Comparison of Alternative Inflation Forecasting Models in OPEC and BRICS countries

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ABSTRACT

We compare the forecasting performance of univariate and multivariate models for BRICS and OPEC economies. For the univariate models, we produce forecasts using ARIMAX models that have a deterministic component to account for structural breaks over the full sample period and different ARIMA specifications over a reduced sample period that avoids the modelling structural breaks. The univariate ARIMA models that we develop over the reduced sample period are, first, a seasonal ARIMA specification identified using the Box-Jenkins method, second, a seasonal ARIMA model identified using EView's automatic model selection tool and third, a non-seasonal ARIMA model identified using EView's automatic model selection tool applied to seasonally adjusted data. The other univariate model we considered include the regime shift threshold Autoregressive model (over the full sample and reduced sample) and the naïve model which added as a benchmark. Multivariate models are estimated over the reduced sample period to avoid modelling structural breaks and are based upon Vector Autoregression (VAR) models that utilise differencing and cointegrating restrictions to ensure the stationarity of the data. In particular, we consider the unrestricted VAR model with differenced (stationary) data, the (unrestricted) Vector Error Correction Model (VECM) that assumes cointegration without imposing cointegrating restrictions and the restricted VEC that imposes a single cointegrating equation on the VECM. Our study shows that the benchmark models (naïve) were never favoured over the best selected univariate and multivariate model. The univariate EView's automatic non-seasonal ARIMA model is generally favoured for the BRICS countries (the exception is South Africa). However, the results are mixed between univariate and multivariate methods for OPEC countries. For OPEC countries that have a history of moderate inflation, for example, Saudi Arabia, the univariate automatic non-seasonal ARIMA model outperforms the multivariate model. In contrast, multivariate models generally outperform univariate automatically selected ARIMA models for countries with high inflation (e.g Angola and Algeria).

DECLARATION

I, Olaoluwa Vincent Ajayi, hereby certify that this thesis, which is approximately 80,000 words in length without references, has been written by me, that it is the record of work carried out by me and that it has not been submitted in any previous application for a higher degree.

DEDICATION

I dedicated this thesis to my late father Justine Safe Ajayi and my two daughters Tiwatope and Temilola Ajayi.

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INTRODUCTION

1.1 Background and Motivation

There is no doubt that accurate forecasts of inflation have an important effect on achieving macroeconomic objectives (price stability, full employment, balance of payments equilibrium and economic growth). Any decision based on wrong inflation forecasts could result in poor allocation of resources and worse economic performance in achieving the goal of macroeconomic objectives. In avoidance of poor economic performance, many academics and policy makers have extensively researched the best inflation model to be used in forecasting inflation (De Brouwer and Ericsson 1998 and Stock and Watson 1999). The evidence remains that none of these researchers has agreed on any best model to forecast inflation. Carlson and Parkin (1975) and Mitra and Rashid (1996) observed that economic agents select different forecasting models in different inflationary environments. When inflation is high and volatile they use sophisticated models whereas simple models are employed during mild and stable inflation periods. Buelens (2012) and Stock and Watson (2008) stated that the accuracy of a forecasting model depends on the sample period in which they are estimated and evaluated. For example, the appropriate forecasting model to be used prior to the economic crisis may be different from that during the economic crisis. Further, some explanatory variables may be good predictors during an economic recession but not in expansion.

Stock and Watson (1999) argued that the Phillips curve model has been more accurate in forecasting US inflation than models involving other macroeconomic variables such as interest rates, money supply and commodity prices. They further revealed that the Phillips curve produced a better forecast when estimated with real economic variables (GDP) than when estimating the Phillips curve with unemployment. That is, the Phillips curve estimated with real economic activity can provide forecasts with smaller mean squared errors than those from unemployment based Phillips curve models. Atkeson and Ohanian (2001) found the Naive model as the most effective in forecasting US inflation for the past fifteen years, when compared with the Phillips curve. Thus, this thesis identifies the following as potential factors that influence the accuracy of inflation forecasts: (i) the type of model in use; (ii) the variables included in the model; (iii) the transformations applied to the data for stationarity, seasonality and strutural breaks (iv) the economic environment (v) the sample period used to estimate the parameters of the model and (vi) the length of the forecasting horizon.

Many researchers have based their inflation forecasting analysis on the study of European countries and the United States. They have often compared inflation forecasting accuracy during periods when inflation targeting policies were adopted with periods when there were no inflation targeting policies in operation.[1] As far as we know, no studies have compared the predictive performance of alternative inflation forecasting models for OPEC and BRICS countries, despite their growing importance in the global economy.[2] This study extends the existing literature by forecasting inflation in these economies that cover sample periods of both high inflation and moderate inflation.[3] In particular, we compare the forecasting performance of univariate and multivariate models for BRICS and OPEC countries with the aim of identifying the most accurate inflation forecasting model for the different economies. Our univariate models are based on ARIMAX, ARIMA specifications, regimes shift threshold autoregressive (TAR) models and Naïve model is added as a benchmark. While the multivariate models are based upon Vector Autoregression (VAR) models that utilise differencing and cointegrating restrictions to ensure the stationarity of the data. In particular, we consider the unrestricted VAR model with differenced (stationary) data, the (unrestricted) Vector Error Correction Model (VECM) that assumes cointegration without imposing cointegrating restrictions and the restricted VECM (or VEC) that imposes a single cointegrating equation on the VECM.

[1] For instance, see Nadal-De Simone (2000), Alles and Horton (2000), Guncavadi et al (2000), Stock and Watson (2007), Lee (2012) and Buelens (2012).

[2] BRICS nations control 43 percent of global foreign exchange reserves and 25 percent of global GDP. OPEC countries account for 81% of the world's crude oil reserves and have a high dependence on oil revenues. See Antoine (2012), Rahman (2004) and World Oil outlook (2012).

[3]Lo and Granato (2008) argue that high inflation hurts growth over the long term. While, Narayan et al (2009) documents that monetary authorities' policies can often be misguided during periods of high inflation. The presence of high inflation has compelled us to examine whether high inflation affects inflation forecasting performance.

1.2 Outline of chapters

We organise the thesis into different inter-linked chapters. Chapter One outlines the background and motivation of the study, research objectives, an overview of BRICS and OPEC countries, that discusses the similarities and differences between OPEC and BRICS countries and contributions of this research. In this chapter, we are able to identify different characteristics of BRICS and OPEC economies that will be later considered when forecasting inflation. In particular, we categorised OPEC countries as an oil exporting economies and BRICS countries (excluding Russia) as an oil importing countries. For instance, all OPEC countries produce crude oil for exportation, and this has contributed to the higher percentage of their export earnings. For example, Nigeria earned 70 percent of its total export revenue from crude oil; Kuwait derived almost 60 percent of its gross domestic product and 93 percent of export revenue from crude oil; Libya acquired almost 95 percent of its government revenues.[4] In contrast, all the BRICS countries except Russia are heavily dependent on oil imports to produce their manufactured products. For example, China is the second largest oil consuming nation in the world and second largest oil importing country from OPEC after the United States in 2010 (Economic Analysis Division, 2004). In addition, BRICS economies are ranked among the G-20 advanced industrial countries in the world whereas the OPEC economic system is classified as a traditional economy where goods and services produced are influenced by traditional beliefs, customs and religion.

Chapter Two discusses the various theoretical models that are commonly used to model and forecast inflation and considers the policies implemented by the central bank to control inflation for BRICS and OPEC countries. This chapter demonstrates that most of the policies implemented by the central bank to regulate inflation focus on the interest rate (for example, via Inflation targeting and Taylor rules as well as through the exchange rate). According to the Taylor rule, the central bank assumes inflation and the interest rate are directly related, especially in the short term. When inflation is above the target rate, the central bank will increase the interest rate to reduce inflation and if inflation is

[4] See: Organization of petroleum exporting countries member, available at http://www.opec.org/opec_web/en/index.htm.

below the target rate, the central bank will decrease the interest rate to raise the rate of inflation (Taylor 2008). For the exchange rate, the government may allow the value of the domestic currency to be fixed at the value of a selected foreign currency to control inflation. In particular, if the government experiences a balance of payments deficit the central bank may be tempted to reduce capital outflows to improve the balance of payments. In this case, the central bank may decide to increase the interest rate to technically increase the cost of borrowing to discourage people from borrowing and decrease consumer spending. However, the use of the interest rate to control inflation is limited in OPEC countries and most of the oil exporting nations. This is due to reasons of religion, social beliefs, the usury activities of financial institutions and the sovereignty of many of these countries that independently regulate their financial institutions.

Chapter Three provides an empirical literature review. The literature is divided into two sections. The first section discusses the various factors that have been considered as determinants of inflation in developed and developing countries. While the second section analyses the empirical literature on inflation forecasting models. This literature suggests a growing consensus that economic relationships change in different inflation environments. The factors that determine inflation in developed countries may be different from the factors that determine inflation in developing countries. For example, the factors that determine inflation in low inflation economies may be different from those in higher inflation economies. In particular, inflation in many developing countries is mostly caused by the external influence of import prices, the foreign interest rate and the exchange rate (Frisch 1977, Dhakal and Kandil 1993, Boujelbene and Thouraya 2010). While the interest rate, money growth and financial assets determine the rate of inflation in developed countries (Tillmann, 2008 Cologni and Manera, 2008). The empirical literature on inflation forecasting suggests the following: (i) theoretical model most especially Phillips curve, are more accurate to forecast inflation when the economy is weak most especially during the economic crises when compared with the univariate ARIMA model (Pretorious and Rensburg 1996, Dotsey et al. 2011 and Buelens, 2012). (ii) ARIMA models outperform other multivariate models (Phillips curve and VAR) during periods of stable and low inflation (Pretorious and Rensburg,1996; Mitra and Rashed, 1996; Nadal – De Simone, 2000 and Dotsey et al. 2011). (iii) When comparing the forecast performance of three and five quarters ahead, the VAR and VECM specifications perform better than the naïve model (Onder, 2004). When comparing VAR models with

VEC models, the VEC models outperform the VAR models over the longer horizon (Fanchon and Wendel, 1999). (iv) The model that account for stochastic volatility and time-varying coefficients (e.g Markov switching models, Dynamic stochastic general equilibrium modelling, Self-exciting TAR models) provide more accurate forecast than those models that do not (D'Agostino et al. (2013), Barnett et al. (2014), Bel and Paap, (2016), Cross and Poon (2016) and Mandalinci, (2017)).

Chapter Four consists of two sections. The first section analyses the graphical features of the quarterly price data and its transformations to assess issues of seasonality, stationarity and structural breaks for each country. While the second section outlines the Box Jenkins ARIMA and ARIMAX methods of univariate modelling employed in this thesis. From the first section, a mixture of visual inspection of the data, autocorrelation functions (ACFs) and unit root test showed that the log of the price is nonstationary in all the growing inflationary economies under consideration. The standard quarterly (one period) difference is generally insufficient to induce stationarity because of seasonal unit roots. Conversely, the annual (four period) difference is generally sufficient to induce stationarity, although only after structural breaks have been accounted for in modelling. For example, a downward shift in the intercept (seasonal indicator variables) coinciding with a move from high to low inflation eras may give a process that is only stationary around a shifting mean. As widely observed from the literature, for instance, Perron (1989), Lee and Chang (2005) and Fernandez and Fernandez (2008), a failure to account for seasonality and structural breaks can lead to model misspecification and make unit root tests biased towards non-rejection of the unit root null hypothesis.

Chapter Five develops the analysis presented in Chapter four and builds ARIMAX models to the annual rate of inflation. We applied the Bai (1997) and Bai and Perron (1998, 2003) tests to a deterministic model of the annual difference of the log of prices to identify structural breaks for each country. Based upon these tests, we used shifting dummy variables to build the deterministic component of an ARIMAX model that accounts for any identified structural breaks in each country. This is achieved by applying the Box-Jenkins method to identify an ARIMA specification to the residuals of the identified deterministic component of the ARIMAX model that accounts for structural shifts. In addition, we develop ARIMA models to inflation using a reduced sample period that avoids the modelling of structural breaks (with at least 39 observations). The following different procedures for developing ARIMA specifications on the reduced sample are employed. First, the Box Jenkins method using the modeller's identification of seasonal ARIMA specifications based upon ACFs and partial (PACFs) is employed. Second, EViews automatic seasonal ARIMA model identification method is used. Third, the data is seasonally adjusted using the Census X11 or X12 program that allows for time-varying seasonality and EViews automatic non-seasonal ARIMA model identification method is used. Forecasts based on the nonseasonal models are reseasonalised using the seasonal indices in 2012 identified by the seasonal adjustment process. The contribution of this chapter is to determine whether using the full sample that generally requires the modelling of structural breaks with an ARIMAX specification produces superior forecasting accuracy to ARIMA models built using a reduced sample with less data that avoids the modelling of structural shifts. Regarding the reduced sample modelling, we compare the forecasting accuracy of ARIMA specifications built using the modeller's judgement and those identified using EViews automatic model selection procedure. The reduced sample models also allow a comparison of ARIMA models built using seasonally adjusted data (with re-seasonalised forecasts) and those using unadjusted data. Further, we estimated the threshold autoregressive (TAR) models over the full sample and reduced sample and compared its forecast performance with the best forecasting model produced by the class of univariate ARIMA specifications. From our results, the TAR models indicate evidence of more than one regime in all selected economies (excluding China) which support the need to for modelling breaks. In terms of forecasting, the nonlinear TAR models (for both full sample and reduced sample) were not favoured over the best selected linear ARIMA models except for China (over all forecasting horizons), Nigeria (over 1 to 4-step ahead horizons) and Saudi Arabia (over 1 to 3 steps ahead horizons) where the TAR model estimated over a reduced sample produced the best forecast. The forecast performance of the TAR model over a few horizons is consistent with the previous study that documents the good performance of the TAR model over linear ARIMA models for the longer horizons (Montgomery et al. (1998)).

Chapter Six discusses the data used in multivariate modelling. We identify the variables that are most commonly employed to model and forecast inflation in the literature and identify the data availability of these series for each country under study. Whilst we give priority to variables available at the quarterly frequency, we also consider the addition of variables that are available only at the annual frequency to ameliorate omitted variable issues. We use frequency conversion tools to generate quarterly series from annual series. The main explanatory variables that we consider for each country are the money supply, real exchange rate, interest rate, output gap, unemployment rate and the oil price.

In Chapter Seven, we considered all variables identified in chapter six for each country and estimated multivariate models (VAR, VECM and VEC) over the reduced sample to avoid the modelling of structural breaks and to use seasonally adjusted data to preclude issues involving seasonal unit roots.[5] The motivation for this chapter is guided by the following principle. Models involving series that are nonstationary may lead to problems of spurious regression that can adversely affect forecasting accuracy. We, therefore, use differencing and cointegration restrictions to transform nonstationary series into stationary variables. VARs estimated with cointegrated data will be misspecified if all of the data are differenced because long-run information will be omitted and will have omitted stationarity inducing constraints if all of the data are used in levels. Therefore, we test for the orders of integration of all variables considered as well as for cointegration. Based on this analysis, we compared the forecasting performance of the following multivariate models: unrestricted stationary VAR, VECM and VEC. Our result shows that including long-run information in the form of a specified cointegrating equation generally improves the forecasting performance compared with VARs and VECMs for BRICS countries. This is consistent with previous findings that stated that

[5] For each of the multivariate model (VAR, VECM and VEC) in each country, we estimate four equations. The first equation includes all available variables as endogenous except unemployment (which is excluded). The second equation includes all available variables as endogenous except for the output gap (which is excluded). The remaining two equations are the same as the first two equations except the oil price is treated as exogenous. The aim is to test whether inclusion of the oil price as exogenous or endogenous will have effect on performance of inflation forecast for oil exporting OPEC and oil importing BRICS countries.

forecasts are most likely to be improved by applying error-correction techniques if the data strongly supports the cointegration hypothesis (see, Timothy and Thomas, 1998).

Further, we investigate whether the multivariate models (VAR, VECM and VEC) are structurally stable in the sense that the regression coefficients are constant. If not, what are the implications of the instability for forecasting future inflation or what forecast methods work well in the face of instability? For instability tests, we perform two different parameter shifts tests that are available in EViews (the CUSUM and Bai and Perron (2003) tests). For the CUSUM test, we apply the CUSUM test that is based on the cumulative sum of the recursive residuals. The condition is that, if the line of the CUSUM test statistics fluctuates within the two 5% critical lines, the estimated models are said to be stable. In contrast, the models are said to be unstable if the line of the CUSUM goes outside the area between the 5% critical lines. For the BRICS countries, the CUSUM test and Bai and Perron (2003) test suggest evidence of instability for all models except all VECMs and VARs specification for India (the exception is the VAR estimated over the full sample that includes all variables as endogenous). The other exceptions are the VECM model that contains all variables as endogenous except unemployment for South Africa; the two valid VECM specifications for Brazil, all four VECMs and the VAR model that includes all variables as endogenous except output gap that excluded for Russia. For OPEC countries, all models also show evidence of instability except the VAR and VECM model that includes all variables as endogenous for Saudi Arabia, the VECM model that specified oil price as exogenous for Angola, the two valid VAR models and two valid VECM specifications for Algeria as well as the VAR model that include oil price as exogenous and other variables as endogenous excluding unemployment for Nigeria.

We also examine whether the instabilities in multivariate models (VAR, VECM and VEC) affects the performance of the inflation forecasting. In our study, the application of the two stability tests (the CUSUM and Bai Perron tests) provide evidence that the stability of the model can enhance the forecasting performance of inflation for few countries. For example, all the favoured forecasting model for the OPEC countries are stable (the exception is for Angola). In general, the VECM specification is stable and produce the best forecasting results over all horizons for Saudi Arabia and the unrestricted VAR model is stable and produce the best forecasting result over all horizon for Nigeria and Algeria. In contrast, all the favoured forecasting models are not stable for BRICS countries according CUSUM and Bai Peron tests. The performance of the favoured forecasting models that are not stable are consistent with the study of (Stock and Watson, 2003, and Rossi 2012) who argued that instability of the theoretical model can be misleading for favoured out-of-sample forecasting.

Moreover, whether the inclusion of oil prices as exogenous or endogenous will improve forecasting performance differs substantially according to the form of the model employed and the country being considered. For BRICS and OPEC countries, the model that includes the oil price as endogenous generally appears to secure better forecasting performance than the model that includes the oil price as exogenous, except for Algeria.

In Chapter Eight, we estimate naïve model as a benchmark model and compare its performance with the best forecasting performance of the multivariate (VAR, VECM and VEC) and univariate models (TAR model, ARIMAX, ARIMAs and EViews automatic selection procedure) to identify the most accurate inflation forecasting model for BRICS and OPEC economies. In our study, naïve models were inferior to the best selected univariate model for all selected countries. The univariate model is generally favoured over the multivariate models for the BRICS countries (except South Africa). However, the results are mixed between univariate and multivariate methods for OPEC countries. For OPEC countries that have a history of moderate inflation, for example, Saudi Arabia, the univariate automatic non-seasonal ARIMA model generally outperforms the multivariate models over the longer horizons (4, 6, 7 and 8). While the TAR model outperforms other selected models over the shorter horizons (1 and 2-steps ahead). In contrast, multivariate models generally outperform univariate automatically selected ARIMA models for the countries with high inflation (e.g Angola and Algeria).

Chapter Nine is the summary and conclusion of this research and includes the discussion on the limitations of this study and identifies some possible areas for future research.

1.3 Aims and Objectives

The performance of inflation forecasting can vary in different economic environments. The factors that influence inflation forecasting in developed countries may be different from developing countries; and the factors that affect inflation forecasting in oil exporting OPEC economies may be different from predominantly oil importing countries such as the BRICS economies.[6] The OPEC economic system can be classified as a traditional economy where goods and services produced are influenced by traditional beliefs, customs and religion whereas BRICS economies are ranked among the G-20 advanced industrial economies in the world. Developed countries have a history of low inflation, stable macroeconomic policies and have control over both monetary and fiscal policies while developing countries are known for higher inflation and unstable macroeconomic policies (Ghazanfar and Sevcik 2008). In our research, we consider the characteristics of oil importing and oil exporting economies when evaluating the forecasting performance of univariate and multivariate models of inflation for BRICS and selected OPEC countries. In our empirical analysis, we address the following issues:

(i) How can we make the price data stationary for each country? In particular, is seasonal differencing required, do structural breaks need to be accounted for and is the logarithmic approximation a valid measure of annual inflation (INF_t= $\frac{P_t - P_{t-4}}{P_{t-4}}$)?

(ii) Can ARIMAX models that pass diagnostic checks be obtained for each country?

(iii) Do ARIMAX models built using the full sample of data (with the benefit of more information) produce superior forecasts to ARIMA models developed using a reduced sample that avoids the modelling of structural breaks (with the disadvantage of less data)?

(iv) Where we applied EViews 9's automatic ARIMA model selection procedure using a reduced sample that avoids modelling breaks, can specifications that pass the diagnostic checks be obtained for all countries?

[6] Ozkan and Yazgan (2015) suggest that the success of inflation forecasts is different in the different monetary-policy regimes that have been implemented in different periods of time.

(v) Does the more time-consuming Box-Jenkins ARIMA model building method that requires modelling skill produce superior forecasts to the quicker automatic ARIMA model selection procedure?

(vi) Do ARIMA specifications that explicitly model seasonality produce superior forecasts to those that apply non-seasonal models to seasonally adjusted data followed by re-seasonalising the forecasts?

(vii) Does regime shift threshold autoregressive model (TAR model) produce superior forecasts over univariate ARIMA model selection?

(viii) Can valid VARs, VECMs and VECs be obtained for each country? Which of these models produces the best forecasting performance for each country? Is there a generally best performing specification across countries and/or for different forecasting horizons?

(ix) When valid VEC models can be found are the coefficients of the long-run equation consistent with theoretical economic expectations?

(x) Is it better to treat the oil price as endogenous or exogenous in multivariate models? Are models that use unemployment to capture the Phillips Curve effect preferred to those that employ the output gap (when both variables are available)?

(xi) Has the multivariate model stable over time? If not, what are the implications of the instability of forecasting inflation?

(xii) Of all the models considered (both univariate and multivariate) which model produces the best forecasting performance over the benchmark model (naïve) across countries and/or for different forecasting horizons?

1.4 Overview of BRICS countries

In recent times, Brazil, Russia, India, China and South Africa (BRICS) have emerged to form an international organization body that will influence global financial trade and form a serious competitor to western economies. Accordingly, many common features exist among the BRICS nations. They share a common thread that they are fast developing nations and one of the largest economies in their regions. For example, China has the largest economy in Asia and is second only to America in the world. Russia is a member of the G8 advanced leading countries in the world, and India has the third-largest economy in Asia. South Africa has the largest economy in Africa, while Brazil has the largest economy in South America. Global Sherpa (2014) reported that BRICS countries ranked among the world's largest and most influential economies in the 21st century. BRICS countries accounted for 25% of world GDP, over one-quarter of the world's land area and more than 40% of the global population.[7] They control almost 43% of global foreign exchange reserves, and their share keeps rising (See Goldman Sachs, 2007, Antoine 2012 and Global Sherpa, 2014). Toloraya (2014) stated that BRICS economies have shown tremendous development in recent decades. The economy has increased by almost two times to reach $300 billion within five years and acquire 30 to 60 percent of the world's most valuable mineral resources.

BRICS countries are heavily dependent on oil imports to produce their manufactured products, and many of these countries have diverse economies particularly about natural resources, higher inflation, as well as exporters of electronics goods. In areas of oil importing and oil consumption, BRICS countries have been playing a leading role in the world.[8] For example, China is the second largest oil consuming nation in the world and second largest oil importing country from OPEC after the United States in 2010 (Economic Analysis Division, 2004). China's oil consumption growth accounted for one-third of the world's oil consumption growth in 2013, and its consumption is increasing by 0.37 million bbl/d 3.5% (EIA, 2014). South Africa has the highest energy consumption in Africa; accounting for about 30% of total primary energy

[7] China and Indian have remarkable population of 1.351 billion and 1.244 billion respectively (World Bank 2012).

[8] Most of BRICS countries are heavily dependent on oil importing and they rank among the highest oil consuming nations in the world apart from Russia. Russia has tremendous oil reserves and is the third largest producer of oil in the world after Saudi Arabia and United states, and most of oil consumption in Russia is producing locally.

consumption in Africa in 2012. Central Intelligence Agency (2010) ranked India as the world's fourth-largest oil-importing and oil consuming nation in the world. India spent $ 15 billion, equivalent to 3% of its GDP on oil importing in 2003 that is 16% higher in 2001 (Economic Analysis Division, 2004). EIA projected that oil consumption in India would grow at an annual average of 1.5% for the next six years. In the case of Brazil, the country is ranked as the 8th largest energy consuming nation in the world. EIA ranked Russia as the second-largest producer of natural gas, second to the United States and the third-largest generator of nuclear power in the world.

In politics and finance, BRICS countries aim to convert their growing economic strength into political power.[9] They believe that by working together, they could carve out the future economic order among themselves. They project that China will continue to dominate in areas of manufacturing goods; India will be providing services; Russia and Brazil will influence in areas of natural resources for the raw materials and providing agriculture inputs. In addition to this plan, they propose to achieve sustainable economic growth and establish an industrial development environment through the launch of the Development Bank. The bank will serve many emerging markets for the development of infrastructure projects and reduce numbers of many countries dependent on the World Bank and the International Monetary Fund (IMF). All the members will provide the total sum of $100bn. China is expected to contribute the highest amount of ($41bn), followed by Brazil, Russia and India contributing $18bn each, and South Africa adding at least $5bn (Wood, 2014). As a result, China won the bid for the bank headquarters which is set to be located in Shanghai and India will provide the New Development Bank’s first president. Nataraj and Sekhani (2014) reported that the new BRICS bank would be based on equality and fairness where individual members will be able to vote and grant loans with fewer restrictions and shorter delays.

[9] This action will bring new development for Russia and China to achieve their foreign and political objectives; In particular, there is no sign that ties between Russia and the Western countries may improve any time soon. As a result, Russia and China would not be totally isolated and forcefully give away their political interest to the Western countries demands.

1.5 BRICS Economies and Their Limitations

Research by Goldman Sachs found that economic growth in South Africa's will increase from an average 3.3% over the last 20 years to 6.7% per annum in 2050 which will produce a region the size of $14tm (Coleman, 2013). The Economist Intelligence Unit predicts that Brazil's economy will be larger than any European country's economy by 2020 and exceed Germany's economy to become the world's fifth biggest global economy (Daly 2013). China's GDP growth is proposed to overtake the United States' GDP before 2030, and the total GDP of the BRICS countries will be more than the combined GDP of the seven largest developed economies by 2050 (see Antoine, 2012 and Kangarlou, 2013).

To achieve this economic plan, BRICS countries need to improve in technology, security, create more jobs, establish good financial institutions, invest in human development, stable political structures and improve on social and economic reforms that will establish sustainable growth. As a result, BRICS countries like India, Brazil, China and South Africa have announced their commitments to the reality of these objectives. For example, China is currently focusing on its 12th five-year plan for building many new airports and creating an additional 45 million new jobs (Jason, 2012). India's is advancing on its 12th five-year plan to invest $1 trillion in infrastructures, with the aim of funding half of it through private sector involvement in public-private partnerships (PPPs). Brazil launched a growth acceleration program in 2007 to provide tax incentives, reduce energy costs, strengthen its investment through foreign participation and restructure its oil royalty payments to increase revenue and provide more capital to the private sector. Moreover, South Africa has engaged in the construction of 56,000 new classrooms; construction of 1,700 new clinics across the country. The country found two million free housing units for low-income families, rehabilitation of 6,000 km of national roads and building of 15,000 km of provincial roads.

Despite these reforms, many studies have questioned the reality of this group becoming a leading economy in 2050. Western analysts and media have criticised the existence of the BRICS nations; they argued that BRICS countries were too different from each other to agree on a common goal (Stuenkel 2014). Consequently, BRICS economies witnessed economic setbacks during the 2007 financial crisis; although its impact varies from one country to another. For example, in the area of financial markets, the toxic assets owned by domestic banks in Brazil and Russia during the 2007 financial crisis was greater than the toxic assets held by India and China. During this period, Brazil owned almost 25%, and Russia owned 12% of toxic assets compared to 0.4% owned by China and 4% belonging to India (Vashisht and Banerjee 2010).[10] Vashisht and Banerjee (2010) also documented that non-performing loans experienced in Brazil and Russia showed the negative impact of the financial crisis in 1997 compared to non-performing loans in India and China. The Non-performing liquidity ratio increased in Russia and Brazil while it decreased in India and China from 4.4% to 2.4% and 8.6% to 1.2% respectively.[11]

World Bank (2014) documents that Russia's GDP growth reduced to 1.3% in 2013 from 3.4 % in 2012 due to inadequate structural reforms. The recent Ukraine Crimea annexation by Russia has been drawing international condemnation and pushed down industrial and investment activities in Russia. The crisis has eroded domestic businesses and consumers' confidence. Russia was accused of supplying heavy weapons to pro-Russian forces in the eastern part of Ukraine. As a consequence, the past United States president (Barack Obama) instigated the G8 economic group to isolate Russia. The European Union and the United States imposed economic sanctions on various Russian financial institutions, imposed asset freezes and visa bans on many Russian politicians. The sanctions restricted access of Russian state-owned banks to obtain funds from Western capital markets, which Russia could turn to and access capital to finance its long-term investment. Consecutively, EU and U.S firms were barred from providing capital for more than 90 days to Russia's key state-owned banks. Recknagel (2014) disclosed that $75 billion of capital has been pulled out from Russia since the crisis started in February 2014 to August 2014. However, this sanction does not target Russian natural gas supplying to the European Union but aimed at the Russian financial industry, whose contribution has powered Russia's economy.

In South Africa, the influence of the previous apartheid political system is another important point to be considered. In the past, the South African population was divided by race; the act was passed to segregate the black race from the white race. As

[10] The toxic asset is an indicator used to measure the soundness of the financial sector. The higher the value of the toxic assets the higher the negative impact of financial crises in selected countries. The lower the value of toxic assets the lesser the impact of financial crises in the selected countries.

[11] Non–performing liquidity ratio is used to determine the ability of financial institution to pay off its short- terms debt obligations. Similarly, the higher the value of non-performing loan ratio, the higher the risk and less safe for the financial institution to cover short- term debts.

a result, many investors believe that the growing population of black races that ought to have provided a good economic market were excluded from the South African economy circuit (Coleman, 2013).

China’s economy has been criticised for currency manipulation, economics "dumping" and caters less for the immediate needs of its population. Aziz (2007) stated China's rapid growth may not be sustainable because many Chinese companies process high cost imported inputs resource into cheap consumer goods for exporting. As a result, when inputs become more expensive, this may undermine China’s economy and investor confidence in achieving sustainable growth. For instance, the competition from other producing countries will make it more difficult for many Chinese companies to increase their market shares. In addition, the growing population of China is another issue to be considered. Overpopulation in China could impede both economic development and economic growth. For instance, an increase in population will increase government expenditure by allocating more resources to social welfare rather than a development of infrastructure. Patel (2013) documented that China’s growing population has increased its environmental pressures and makes the current economic situation in China unstable. For example, agriculture activities in coastal regions of the South China Sea, which should feed fewer people now, cater for more than 300 million persons. The year 2000, more than 11 million tons of fish were eaten in this area, even though, fish stocks in the North East have fallen drastically since the 1990s (Patel 2013). The introduction of the one-child policy in 1979, to curb the rapid growing population, could also reduce the long-run labour force. Currently, 16.6 percent of the total Chinese population is 14-year-old children, whilst 13 percent are over 65 years. If current conditions remain, China will face a shortage of 140 million workers in 2020, and over a quarter of the Chinese will be above 65 years old in 2050 (Patel 2013).

Consequently, corruption remains a threat to the economic growth of the BRICS countries. BRICS countries business environment may not be favourable for many legitimate multinational companies to function. Although the BRICS nations have the potential of being a leading economy, corruption can jeopardize their growth targets. The transparency International civil society organisation scored most of the countries in the world based on their level of corruption in 2014. The group constructed a corruption scale of 0-100, where 0 means that a country is perceived as highly corrupt, and 100 means a very decent country. The table below indicates the level of corruption in BRICS countries.

Table1.1 Corruption ranking table for BRICS countries

Rank	Country	Score
67	South Africa	44
69	Brazil	43
100	China	36
85	India	38
136	Russia	27

Source: Corruption perception index (2014).

From the above table, all the BRICS countries scored less than 50 out of 100 and were ranked above 65. This indicates a serious problem of corruption that exists among the BRICS nations. The Corruption activities in many of these countries include abuse of power, secret dealings, bribery, abuse of human rights and financial violations.

1.6 Overview of OPEC countries

In the late 1950s, the quantities of oil produced in many of the oil producing countries were greater than the global demand for oil. During this period, the oil production sector was dominated by a few individuals, companies and countries. Each of them produced oil and regulated prices independently in the international market until September 14, 1960, when the Organization of Petroleum Exporting Countries (OPEC) was established. This organisation was established in 1960 with five founding members: Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. By the end of 1971, six other nations had joined the group: Qatar, Indonesia, Libya, United Arab Emirates, Algeria and Nigeria. OPEC has a rich diversity of cultures, languages, religions and united by their shared status as oil-producing developing countries. Many of these countries heavily depend on the exportation of petroleum, and this has contributed to the higher percentage of their export earnings. For example, Nigeria earned 70 percent of its total export revenue from crude oil; Kuwait derived almost 60 percent of its gross domestic product and 93 percent of export revenue from crude oil; Libya acquired almost 95 percent of its government revenues. In Qatar, oil and natural gas accounted for 60 percent of the country's gross domestic product and around 85 per cent of export earnings. In Saudi Arabia, the oil and gas sector contributed to 50 percent of the gross domestic product and 90 percent of export earnings and, in Venezuela, oil revenues accounted for about 95 percent of export earnings and 25 percent of the gross domestic product.[12] In total, the OPEC members produce almost 40% of the world's crude oil, which represents almost 60 percent of the total petroleum traded internationally, produces about a third of the world's daily consumption of 90m barrels of crude oil, and controls 78% of the world's crude oil reserves (Energy Inflation Administration, 2013). Apart from petroleum oil, the organization provides other natural resources that include natural gas, tin, iron ore, coal limestone, niobium, lead and zinc.[13]

[12] See: Organization of petroleum exporting countries member, available at http://www.opec.org/opec_web/en/index.htm.

[13] Sala-i Martin and Subramanian (2003) documented that countries that depend heavily on the export of natural resources are liable to various challenges, which include: authoritarian governance, political instabilities, civil wars, high corruption levels, high poverty rates.

The group has the responsibilities of coordinating and unifying petroleum policies, promoting stability and regulating the oil price in the international market. In 2005, the acting general secretary of the organisation (Adnan Shihab-Eldin) emphasised that OPEC is committed to market stability and supplying petroleum products at reasonable prices to both producers and investors.[14] OPEC has responsibilites to safeguard the interests of its members and ensure the stability of the global oil price. For instance, in 1968, OPEC issued a declaratory statement of petroleum policy to protect its members and caution the United Nations on the right expressed by the United Nations that all countries should exercise permanent independent rights over their natural resources for the development of their economy. Accordingly, OPEC maintained that OPEC's resources should benefit the whole OPEC members rather than individual countries by setting a reasonable global oil price. OPEC often regulates the production of the crude oil to set the global oil price and improve the balance of payments. The organization will increases production to increase supply and keep prices low.[15] In contrast, OPEC will decrease oil production to reduce supply of oil and increase oil prices. The first notable example was in October 1973 when the Arab nations in OPEC cut their oil production by 5% per month. The organisation put a supply oil embargo on the United States because of its support for Israel during the Yom Kippur war. The action of the Arab countries led to an increase in global oil prices that increased inflation across the world. A similar example was during the Gulf War, when former Iraqi President (Saddam Hussein) advocated that OPEC should increase the oil price to help Iraq and other member states to generate more revenue and service their debts. However, the aggression and invasion of Iraq on Kuwait did not allow all members of the organization to support the proposal of Saddam Hussein (Basil Ajith, 2011).

[14] A speech delivered by Adnan Shihab-Eldin, Acting for the Secretary General, to the 31st Pio Manzù Conference, Rimini, Italy, 28-30 October 2005. Available at: http://www.opec.org/opec_web/en/883.htm. Accessed on 23 September 2013.

[15] An increase in oil production may leads to excess supply or oversupply and the quantity supply will be greater than the quantity demanded in the equilibrium market. The effect of excess supply of the oil will reduces the price of the oil to encourage consumers to purchase more and suppliers to produce less.

1.7 The similarities and difference between OPEC and BRICS countries

The BRICS and OPEC countries are made of both developed and developing countries. The BRICS economies are ranked among the G-20 advanced industrial countries in the world whereas the OPEC economic system is classified as a traditional economy where goods and services produced are influenced by traditional beliefs, customs and religion. There is evidence that developed countries experienced low inflation and stable macroeconomic policies while higher inflation, unstable macroeconomic policies are attributed to developing countries (Ghazanfar and Sevcik 2008). In developing countries, the analysis of monetary policy is hindered by the absence of a good monetary policy. The developed countries have control over their monetary and fiscal policies and good monetary experts manage their economies.

Many of the BRICS countries are oil importers and high oil consuming nations compared with OPEC countries that are major oil exporters in the world. The majority of OPEC countries are dependent on crude oil and natural resources to generate revenue and import many consumer goods. Therefore, they are more exposed to international trade with crude oil and increases or decreases in the oil price will directly affect their government expenditure. In contrast, incomes for many of the BRICS countries are not only from natural resources but taxes and the financial sector. In addition, BRICS countries are more advanced in technology, and many of them have the ability to process their natural resources for exports.

1.8 Research Contributions

This thesis makes the following contributions to the existing inflation forecasting literature, especially on the empirical front. The most recent literature focuses on developed countries, although some of them focus on developing countries, none of them focuses on BRICS and OPEC economies despite their growing contribution to the global economy. Therefore, this study contributes to the literature by offering evidence that leads to following conclusions in terms of modelling and forecasting inflation for BRICS and selected OPEC countries. We are not aware of any previous study of inflation that draws such conclusions for these countries.

(i) The annual (four periods) difference of the log of prices is a poor approximation of inflation during periods of high inflation. However, the annual (four periods) difference of the log of prices is a reasonable approximation of inflation during periods of low inflation. Given that many BRICS and OPEC countries exhibit periods of both relatively high and moderate inflation this suggests researchers should not automatically assume that the difference of the log of price data can be used as a valid approximation of inflation for modelling in these countries. Further, when using quarterly unadjusted data, it is most appropriate to use the growth rate of prices based on the annual difference rather than the quarterly (one period) difference to obtain stationary data.

(ii) When forecasting with univariate specifications, reducing the sample to avoid modelling large structural breaks improves forecasting performance compared to using the full sample and modelling structural breaks. This implies that the potential benefits of having more data from using the full sample are generally outweighed by being able to avoid modelling structural breaks (even at the cost of a reduced sample for estimation).

(iii) The quick EViews 9 automatic ARIMA model selection procedure is sometimes favoured over the time-consuming Box-Jenkins ARIMA model building method (that requires modelling skill). This is especially the case for the BRICS countries that have a history of moderate inflation. This suggests that automatic selection methods not only have the benefit of saving time they can also produce superior forecasts.

(iv) Utilising the Bai and Perron (2003a and 2003b) test to identify any structural breaks within the ARIMAX modelling context to model inflation is a novelty of our work.

(v) Building ARIMA models to seasonally adjusted data and re-seasonalising the forecasts often yields superior forecasting performance than constructing seasonal ARIMA models to unadjusted series.

(vi) The results from the threshold autoregressive models (TAR model) provides empirical evidence for multiple regimes for inflation in the selected economies. However, our studies revealed that the forecasts from the TAR models were considerably less accurate than the best selected ARIMA specification (EView automatic selection procedure) in all selected countries except in China (all forecasting horizons), Nigeria (over 1 to 4-step ahead horizons) and Saudi Arabia (over 1 to 3 steps ahead horizons). In general, our study provides evidence that modelling of breaks or incorporation of the model that accounts for two or more regimes shifts contributes to improved forecast performance of inflation in few countries.

(vii) Generally, the multivariate models that include the oil price as endogenous appears to secure better forecasting performance than those that include the oil price as exogenous for BRICS and OPEC countries, except for Algeria over all forecasting horizons, Brazil over 1 to 6-steps, Russia over 5 to 6-steps ahead and over 1 to 2-step for South Africa and Nigeria. The exogenous impact of the oil price for few countries implies that inflation may not always be determined by the global effect of the oil price. This may be because of the recent impact of the oil price reductions on inflation.[16] Further, new technology development may have helped many of these countries to reduce the cost of producing oil. This may also be because many of these countries have embarked on different economic policies to diversify their economies from predominantly oil producing states to manufacturing economies. We note that unemployment, money supply, exchange rate, oil price and the interest rate have the highest theoretical consistency rating at 100%, 85%, 75%, 33.3% and 16.6% respectively for OPEC and BRICS countries. For example, an increase in money supply will cause a significant increase in inflation in all countries except China.[17] Further, a rise in unemployment decreases inflation in Brazil and an increase in the exchange rate will raise inflation in Russia, China, South Africa, Nigeria, and

[16] Since 2008, the oil price has traded below $120 per barrel and reached a 12-years low of $27 in January 2016. There is a link between low oil price and economic growth. For instance, low oil prices reduce the cost of production and encourage producers to increase their output.

[17] In general, our study concludes that money supply remains the most effective monetary policy to control inflation in OPEC and selected BRICS countries.

Algeria (see Table 7.1.F2 and 7.1.H2). In contrast, the interest rate has the lowest consistency rating at 16.6% across the countries.[18] This may be because the use of the interest rate to control inflation is limited in OPEC countries and most of the oil exporting nations. This is due to reasons of religion, social beliefs, the usury activities of financial institutions and the sovereignty of many of these countries that independently regulate their financial institutions. This result contrasts with the findings of Hendry (2001) who indicates that the short-long interest-rate spread is an important determinant of inflation in Uk but consistent with the findings of Al-Shammari and Al-Sabaey (2012) who suggest that the interest rate does not significantly affect the general price level for 59 developing countries.

(viii) The VEC specifications often outperform VECMs in terms of forecasting accuracy of the inflation and the oil price. This means that the incorporation of long-run information in the form of specifying a single cointegrating equation is generally beneficial in terms of securing superior forecasting performance. This result is consistent with Timothy and Thomas (1998) who claimed that forecasts are most likely to be improved by applying error-correction techniques if the data strongly supports the cointegration hypothesis.

(ix) The application of the two stability tests (the CUSUM and Bai Perron tests) show that stability of the model can enhance the forecasting performance of inflation. For OPEC countries, the VECM specifications are stable and produce the best forecasts results over all horizons for Saudi Arabia. The VAR model that includes all variables as endogenous except unemployment is stable and produces the best forecast results for Algeria, and the VAR models that specified oil price as exogenous and includes all other variables as endogenous except unemployment is stable and favoured for Nigeria. In contrast, all the favoured forecasting multivariate models for BRICS countries are not stable. The forecast performance of the favoured forecasting models that are not stable is consistent with the study of (Stock and Watson, 2003, and Rossi (2012)) who argued that

[18] Note that the interest rate variable is not available in Saudi Arabia.

instability of the theoretical model can be misleading for out-of-sample forecasting. This may also be because our forecasting comparison is based on out-of-sample forecast instead of the in-sample comparison. Rossi (2012) documents that out-of-sample forecasts comparison are robust to model instabilities because their procedures can minimize the effect of structural breaks on forecasting model. In particular, they re-estimate their parameters over time by either rolling or recursive estimation process.

(x) When comparing forecast performance of the benchmark model (naïve) with the best selecting univariate model regime shift TAR model, (Eview automatic ARIMA selection) and multivariate models (VAR, VECM and VEC). Our study shows that the benchmark models (naïve) were never favoured over the best selected univariate and multivariate model. The univariate EView's automatic non-seasonal ARIMA model is generally favoured for the BRICS countries. However, the results are mixed between univariate and multivariate methods for OPEC countries. For OPEC countries that have a history of moderate inflation, for example, Saudi Arabia, the univariate automatic non-seasonal ARIMA model generally performs better than the multivariate model. In contrast, multivariate models generally outperform univariate automatically selected ARIMA models for countries with high inflation (e.g Angola and Algeria).

CHAPTER 2

THEORIES OF INFLATION DETERMINATION AND CENTRAL BANK POLICIES TO CONTROL INFLATION

2.0. Introduction.

This chapter discusses the various theoretical models that are commonly used to model and forecast inflation and considers the policies implemented by the central bank to control inflation for BRICS and OPEC countries. This chapter demonstrates that most of the policies implemented by the central bank to regulate inflation focus on the interest rate (for example, via Inflation targeting and Taylor rules as well as through the exchange rate). According to the Taylor rule, the central bank assumes inflation and the interest rate are directly related, especially in the short term. When inflation is above the target rate, the central bank will increase the interest rate to reduce inflation and if inflation is below the target rate, the central bank will decrease the interest rate to raise the rate of inflation (Taylor 2008). For the exchange rate, the government may allow the value of the domestic currency to be fixed at the value of a selected foreign currency to control inflation. In particular, if the government experiences a balance of payments deficit. The central bank may be tempted to reduce capital outflows to improve the balance of payments. In this case, the central bank may decide to increase the interest rate to technically increase the cost of borrowing to discourage people from borrowing and decrease consumer spending. However, the use of the interest rate to control inflation is limited in OPEC countries and most of the oil exporting nations. This is due to reasons of religion, social beliefs, the usury activities of financial institutions and the sovereignty of many of these countries that independently regulate their financial institutions.

2.1 The theory of inflation (Phillips curve)

The Phillips curve theory relates the unemployment rate or aggregate economic activity to the rate of inflation. The theory described the relationship between unemployment and wage inflation to be an inverse relation (William Phillips, 1958).[19] In other words, low levels of unemployment could be achieved at a high level of inflation, and a high unemployment rate that is achieved at a low inflation rate. In the principle of the Phillips curve, when demand for labour is increasing, unemployment will be decreasing and employers are expected to increase the wages of the workers to attract the best labour from the labour force. Therefore, an increase in wages will increase the cost of production.

Later, economists substituted price inflation for wage inflation to follow a contemporary relationship between output and demand.[20] Price inflation assumes inflation is caused by excess supply capacity. That is, an increase in output will cause inflation to increase. Specifically, when output is above potential demand there is upward pressure on inflation. However, when output is below potential, this exerts a negative influence or downward pressure on the inflation rate. Consequently, an increase in economic production (economic activity) will increase the demand for labour and decrease the unemployment rate. While a decrease in economic activity will increase the unemployment rate. The effect of the Phillips curve is that employers will employ more labour during the period of economic growth than a period of economic recession. The original Phillips curve is referred to as a short term Phillips curve or expectation augmented Phillips curve.

In practise, an inverse relationship between inflation and unemployment may contradict the macroeconomic objectives of simultaneously achieving full employment and the lowest possible inflation rate.[21] Friedman (1968) argued that the government could not permanently trade higher inflation for lower unemployment and

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[19] Phillips investigates the annual relationship between wage inflation and the unemployment rate in the United Kingdom between the period 1860 and 1957, by plotting a scatter graph.

[20] The source of disagreement between the wages inflation and price inflation are: The wages inflation assumes that; the cost of labour will adjust prices. While the price inflation assumed that, prices are sticky and firms' activities or output will adjust the prices.

[21] The outbreak of stagflation in many countries resulted in the simultaneous occurrence of high levels of inflation and high levels of unemployment.

differentiated between short–run and long–run Phillips curves. He further stated that the inverse relationship between unemployment and inflation was only a short-run phenomenon; and if the government targeted the natural rate of unemployment and allowed real wages to respond to the demand and supply of labour, there would be no trade-off between inflation and unemployment.[22] Accordingly, if unemployment is below the ''natural rate'' there will be an increase in the excess demand for wages and costs of production will be increased and so will inflation. Due to the higher inflation, the real wages that the workers receive will be decreased; purchasing power will be reduced to allow the unemployment rate to return to the natural rate. The condition is that, if the worker realised that inflation has increased more than expected, the real wages have been reduced, and their real purchasing power have been diminished. The worker will agitate for more wages to increase their real purchasing power; the rise in wages will increase the cost of labour and decrease the output profits. As the profit decreased, some workers will be let go to increase the rate of unemployment.[23]

Consequently, the natural rate of unemployment can be described as an equilibrium rate of unemployment i.e. where the supply of labour is equal to demand of labour – this is also known as the natural stability rate.[24] Nevertheless, this theory has two important contributions to the modern-day economy. Firstly, the theory specifies that there is a minimum level of unemployment that the economy can absorb in the long run. Therefore, it could be difficult for any nation to push unemployment below the natural rate for a long period without an upward spiral of wage and price inflation that brings unemployment back to the natural rate. Secondly, the natural rate has made it

[22] The classical economists argue that the long run Phillips curve is vertical and unemployment will always return to its natural rate. This type of Phillips curve can be also described as the non-accelerating rate of unemployment (NAIRU). That is, the level of unemployment that exists in an economy that does not cause inflation to increase.

[23] This also illustrates how the theory of adaptive expectations forecasts operate, that is, there are no long run trade-offs between unemployment and inflation. In the short run, it is possible to lower unemployment at the cost of higher inflation, but, eventually, worker expectations will catch up, and the economy will correct itself to the natural rate of unemployment with higher inflation. However, rational expectations theory predicts that expectation of the worker to catch up and the economy correcting itself to the natural rate of unemployment with higher inflation will undermine the effort of the rational workers. Because, the workers could act rationally to protect their interests. This especially cancels out any intending economic policy that could increase unemployment and increase inflation.

[24] There are several factors that determine the natural rate of employment: employment insurance, availability of unemployment benefits and the desire and ability of the unemployed to search for a job. For example, if unemployment benefits are high enough to cater for unemployed person, this may discourage unemployed person to work or take available jobs.

possible for many nations to handle the short run Phillips curve and allow the temporary combination of low inflation and low unemployment rate. Also, Atkeson and Ohanian (2000) initiated an argument on the stability of the Phillips curve. They examined whether the statistical relationship between unemployment and inflation is stable over time. They found that the relationship between unemployment and inflation is not stable. They suggest that the relationship between the current unemployment rate and future inflation varies and changes with inflation expectations. Since the theory suggests that expectations about inflation may affect the current unemployment rate. Our views support the notion that future inflation forecasts based on the Phillips curve may be influenced by the economic environment or change as the economic environment changes. [25]

[25] In our study, we do not produce direct forecasts for the Phillips curve; instead, we explore the performance of two major indicators of the Phillips curve (unemployment and the output gap) and other selected macroeconomic variables by means of multivariate models to forecast inflation.

2.2 Quantity Theory of money

The quantity theory of money explains the relationship between the money supply, money demand, velocity of money and the real general price level of transactions. The theory defines money supply as the total monetary assets available in the economy at a particular period. Monetarists believe that an increase in the money supply will increase the price and increase inflation as well as reduce the value of money in circulation.

In practise, the reality of how money is created and supplied today is slightly different from the description of the traditional economy. Most of the money in circulation is supplied, not by direct printing of the money by the central bank alone, but by the commercial bank's activities. The commercial banks create money whenever they lend to someone in the economy or buy an asset from consumers. The central bank does not directly control the quantity of money in circulation. Nevertheless, the authority is still able to influence the amount of money in the economy. It does so in normal times by setting monetary policy — through the interest rate that it pays on reserves held by commercial banks. For example, the government often supplies money through commercial banks by making loans. In this case, commercial banks receive deposits from households and the deposit is lent out to the customer inform of loan by the bank to charge interest. As a result, commercial banks simultaneously accept deposits and create new money.

In addition, the loan given out by the commercial bank does not usually come by giving borrowers thousands of pounds' worth of banknotes. Instead, its credit in their bank account with a bank deposit of the actual value.[26] To ensure that money supplied by commercial banks are consistent and conforms to stable inflation the Central Bank usually sets the interest rate on the commercial bank reserve deposits or central bank deposit. Central bank can also buy government securities, assets, or quantitative easing (QE). [27] The quantitative easing is an unconventional monetary policy adopted by a

[26] However, commercial Banks are limited in how much they can lend if they are to remain profitable in a competitive banking system.

[27] QE policy is usually implemented when interest rates are almost at zero; in this case, central banks need to adopt different tactics - such as pumping money directly into the economy. On other hand, central banks could also swap their bank reserves into currency, which would pay a higher interest rate to commercial bank.

central bank to stimulate economic activity, such as increasing consumer spending. The policy aims to purchase government securities or other securities with money it has "printed" - or created electronically. In general, the relationship between deposits and loans and the relationship between reserves and loans given by commercial banks are typically controlled and regulated by the central bank. The central banks decide how much to lend the commercial bank, which depends on the profitable lending opportunities available to them and the interest rate set by central banks. In addition, any decision made by a commercial bank to give out a loan will also influence how the central bank will set interest rates for banking reserve ratio (to meet withdrawals by the public and meet regulatory liquidity requirements).

Traditionally, the quantity of money equation can be stated as follow:

$$M_t V_t = P_t Y_t \quad 2.0$$

Where Y_t is the level of output (real GDP) in period t, P_t is the general price level, M_t is the stock of money/money supply and V_t is the velocity of money (the rate at which money passes from hand to hand).

To generate an inflation equation from the quantity demand for money

We rewrite the equation (2.0) as:

$$P_t = \frac{M_t V_t}{Y_t} \quad 2.1$$

We take natural logarithms of equation (2.1)

$$p_t = m_t + v_t - y_t \quad 2.2$$

We make v_t the subject of the formula.

$$v_t = y_t + p_t - m_t \quad 2.3$$

We followed the approached of Hallman et al. (1991) and write p_t in the form of $p_t{}^*$, where $p_t{}^*$denotes the long run price equilibrium.

$$p_t{}^* = m_t + v_t{}^* - y_t{}^* \quad 2.4$$

We avoid the long-run money supply ($m_t{}^*$) and estimate the price gap by subtracting equation (2.4) from (2.2)[28]

Therefore: $p_t{}^* - p_t = v_t{}^* - v_t + y_t - y_t{}^*$

$$p_t{}^* - p_t = (v_t{}^* - v_t) + (y_t - y_t{}^*) \quad 2.5$$

We substitute the equation (2.3) in the equation (2.5)

$$p_t{}^* - p_t = (v_t{}^* - (y_t + p_t - m_t) + (y_t - y_t{}^*)$$

$$p_t{}^* - p_t = v_t{}^* - p_t - y_t + m_t + y_t - y_t{}^*$$

$$p_t{}^* - p_t = v_t{}^* - p_t - y_t + y_t + m_t - y_t{}^*$$

$$p_t{}^* - p_t = (m_t + v_t{}^* - p_t) - y_t{}^* \quad 2.6$$

Where $(y_t - y_t{}^*)$ represents the output gap, $(p_t{}^* - p_t)$ denotes the price gap and $(v_t{}^* - v_t)$ stands for the liquidity gap. In equation (2.5), the price gap is directly proportional to output y_t and inversely related to velocity v_t. Hence, the price gap is expected to increase after the increase in output (y_t) above its equilibrium value $(y_t{}^*)$. In equation (2.6), the price gap is directly proportional to the money supply m_t, which serves as an important factor to determine the rate of the inflation.

[28] The money supply is assumed to be controlled in both long run and short run by the monetary authority

2.3 Money Demand.

Monetarist economists believe that money is primarily demanded for transactions purposes (for its use as a medium of exchange, store of value and unit of account). The demand for real cash ($^{M_t}/_{P_t}$)^d is typically theorised to be positively related to economic output (Y_t) and negatively related to the real interest rate (R_t).

Theoretically, the traditional demand for money equation is;

$$(^{M_t}/_{P_t})^d = f\,(\overset{+}{Y_{t,}}\ \ \overset{-}{R_t}) \qquad 2.7$$

Where M_t is the money demand, P_t is the general price level, Y_t is the income level, and R_t = $(RL - RD)_t$, where RL is an interest rate that reflects the opportunity cost of holding money and RD is the interest rate that reflects the yield of the deposit.

Thus, $\frac{M_t}{P_t} = f\,(\overset{+}{Y}\ \ \overset{-}{R_t})$ 2.8

Transform the equation (2.8) into natural logarithms

$$m_t - p_t = y_t - (rl - rd)_t \qquad 2.9$$

$$p_t = m_t - y_t + (rl - rd)_t \qquad 2.10$$

In this context, the general price level depends on the actual money stock, the opportunity cost of holding money and real income.[29] Similarly, an increase in the opportunity cost of holding money will increase the general price level and reduce the public demand for money.

[29] This assumes that money demand is equal to money supply.

2.4 Central Bank characteristics and its monetary policies

A central bank is a financial institution that coordinates the monetary actives of a country. The role and functions of a central bank are similar from one country to another. The institution has the power to fix and adjust the interest rate, print money, set a reserve requirement, purchase and sell government securities and act as a lender of last resort to commercial banks or any financial institution during a financial crisis. In addition, the central bank is designed to be independent of any political interference.[30] However, central bank independence has been a major challenge to both developing and developed countries in managing and coordinating its activities. The International Monetary Fund (IMF 1996) observed that central bank independence does not influence inflation performance in industrialized countries (Kumar et al., 2011). Cukierman et al. (2002) also observed that central bank independence does not control price inflation. Gutierrez (2003) reveals that countries with higher independence of central banks tend to have better inflation performance. While Berger et al. (2000) indicate that higher government independence is related to lower inflation in industrialized countries but not in developing countries.

2.5 Central Bank and Inflation Targeting

The history of inflation targeting started from New Zealand in 1990, where the finance minister and the governor of the central bank were jointly set a numerical target value of inflation, with the aim of stabilizing the inflation rate. The plan was adopted by many western countries, including the United Kingdom, Canada, Australia, etc. The policy was later adopted in many developing countries including Brazil, South Africa, Mexico, Philippines, Chile, and Ghana etc. The numerical value of the target rate usually ranges from zero to three percent for most developed countries. Theoretically, inflation and the interest rate are directly related to this policy. When inflation is above the target rate, the central bank will increase the interest rate to decrease inflation and if inflation is below the target rate, the central bank will decrease the interest rate to stimulate the

[30] If the central bank is independent, the institution will be able to implement its own monetary policy and achieve its inflation target without government interference. For example: control its own balance sheet, accountability and transparency,

economy and increase the rate of inflation.[31] Under this system, the central bank's policy intentions become transparent and investors know what would happen to interest rates when inflation is increasing or decreasing. The procedure allows the central bank to react to inflation shocks and provides proper coordination for inflation expectations.[32] Johan (2012) identified two possible requirements for a country to adopt an inflation targeting policy. Firstly, central banks should be able to conduct monetary policy with some degree of independence, policy transparency and accountability. Secondly, the willingness and ability of the central bank to not simultaneously target other indicators, such higher wages, higher employment, or the exchange rate stability. [33]

Consequently, the policy has been more effective than other alternative monetary policies to regulate inflation in developing countries.[34] The performance of macroeconomic variables have improved under this policy (Johan, 2012, Johnson, 1990 and Batini et al. 2006). However, inflation targeting could be difficult to implement in developing countries when compared to developed countries. Firstly, the rates of inflation in developing countries are relatively high and difficult to calculate. Secondly, the large exchange rate movements because of high levels of imports may have adverse effects on inflation. Thirdly, the poor co-ordination of financial institutions and political instabilities in many of these countries may not guarantee the independence of the central bank.

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[31] Increase in an interest rate will reduce supply of money by increasing the cost of borrowing, discouraging consumers from borrowing and spending, attracting more saving, reducing the disposable income of those with mortgages and increase the value of the exchange rate.

[32] Batini and Laxton (2006) identified various advantages of inflation targeting, evidence reveals that interest rates and exchange rates are less volatile, and the risk of currency crises is smaller under this monetary policy.

[33] The condition is that central banks may be inefficient if the authority is pursuing multiple goals, such as low inflation and low unemployment, with only one basic instrument.

[34] Rio de Janeiro (2006) studies the Brazilian experience with inflation targeting between 1999 and 2006. The evidence revealed that inflation targeting policy was successful in reducing inflation in Brazil. However, the policy was affected by the crises caused by an increase in global risk aversion between 2001 and 2002.

Roger (2010) examines performance of inflation targeting for the 26 countries that adopted inflation targeting policy since 1991. He graphically compares the inflation and output performance in these countries with non-inflation-targeting countries over the same period. The evidence revealed that those countries that adopted inflation targeting experienced a larger reduction in inflation volatilities and growing macroeconomic output compared with non-inflation targeting countries.

The lists of 28 countries that have been using inflation targeting policy since 1990 are given in the table below (2.1). Finland, the Slovak Republic and Spain adopted the policy but abandoned it when they started using the euro as their national currency. [35]

[35] Note that all the Euro member countries are subject to European wide inflation targeting policy.

Table 2.1 Countries that have adopted inflation targeting policy

Country	Inflation-targeting adoption date	Inflation rate at Adoption date (%)	Targeted inflation rate (%)
New Zealand	1990	3.30	1 – 3
Canada	1991	6.90	2 +/- 1
United Kingdom	1992	4.00	2
Australia	1993	2.00	2 – 3
Sweden	1993	1.80	2
Czech Republic	1997	6.80	3 +/- 1
Israel	1997	8.10	2 +/- 1
Poland	1998	10.60	2.5 +/- 1
Brazil	1999	3.30	4.5 +/- 1
Chile	1999	3.20	3 +/- 1
Colombia	1999	9.30	2 – 4
South Africa	2000	2.60	3 – 6
Thailand	2000	0.80	0.5 – 3
Hungary	2001	10.80	3 +/- 1
Mexico	2001	9.00	3 +/- 1
Iceland	2001	4.10	2.5 +/- 1.5
Korea	2001	2.90	3 +/- 1
Norway	2001	3.60	2.5 +/- 1
Peru	2002	–0.10	2 +/- 1
Philippines	2002	4.50	4 +/- 1
Guatemala	2005	9.20	5 +/- 1
Indonesia	2005	7.40	5 +/- 1
Romania	2005	9.30	3 +/- 1
Serbia	2006	10.80	4 – 8
Turkey	2006	7.70	5.5 +/- 2
Armenia	2006	5.20	4.5 +/- 1.5
Ghana	2007	10.50	8.5 +/- 2
Albania	2009	3.70	3 +/- 1

Source: International Monetary Fund (IMF) staff publications (Batini et al. 2006 and Johan, 2012)

Empirically, various literatures have shown that the existence inflation targeting has reduced inflation, output shocks and interest rate volatilities (Bernanke et al. 1999; Kamil, 2012; Goncalves and Salles, 2008 and Sikklos, 1999). Others argue that inflation targeting has no effect in reducing inflation, and if it does, the policy only contributes very little to lower inflation and variability (Honda, 2000; Byrne, 2012; Ye Haichun, 2007; George, 2009; Angeriz and Arestis, 2006; Johnson, 2002; Ball and Sheridan, 2003). Hence, the success of inflation targeting may be difficult to measure in both developing and developed countries because many of the developed countries that had adopted inflation targeting had a history of stable and low inflation before the introduction of this policy (for example, New Zealand, Canada and United Kingdom). Therefore, they did not observe recent low inflation as evidence of the success of inflation targeting because inflation also falls in many non-inflations targeting countries (for example, Japan and USA).

2.6 Central Banks and Taylor rules

A Taylor rule can be described as a monetary-policy that defines the rate at which the government should modify the nominal interest rate in response to changes in inflation, output and other macroeconomic variables. The theory gives a guide on how monetary rules should be applied to foster price stability, full employment and achieve other macroeconomic goals. Practically, the central bank will increase interest rates when inflationary pressures appear to be increased and lower interest rates when inflationary pressures are declined. Following Taylor (1993), the below equation is postulated to be used by central banks:[36]

$$i_t = \pi_t + {r_t}^* + a_\pi (\pi_t - {\pi_t}^*) + a_y (y_t - \overline{y_t}) \qquad 2.11$$

In this equation, i_t is the target short-term nominal interest rate (e.g. the federal funds rate), π_t is the rate of inflation, ${\pi_t}^*$ is the inflation target, ${r_t}^*$ is the assumed equilibrium real interest rate, y_t is the logarithm of real GDP, and $\overline{y_t}$ is the logarithm of potential output as determined by the output gap. In addition, a_π and a_y are proposed to be positive (as a rule of thumb) and they were set to be a_π= a_y = 0.5 (Nikolsko and Papell, 2012).

To what rate do we need to change the nominal interest rate? According to the Taylor rule, the central bank should raise the nominal interest rate for the short-term, if inflation rises above its desired level or if the output is above potential output, i.e., $a_y > 0$. Thus, an increase in inflation by 1% should prompt the central bank to increase the nominal interest rate by more than one percentage point (i.e by 1 +a_y). If inflation rises by say 1 percentage point, the central bank should increase the interest rate by 1.5

[36] The equation is available in Taylor (1993) page 202 and expand by (Nikolsko – Rzhevskyy and Papell,2012)

percentage points (Taylor 2008). He added that the interest rate does not always need to be exactly 1.5%, but it is essential to increase the interest rate by more than 1% if inflation increased by 1% to bring inflation down. If GDP starts to fall or inflation is reduced, say by one percentage point, the rule says that the interest rate should be reduced by 0.5 percentage points (Taylor 2008).

2.7 Central Bank and Exchange Rates

An exchange rate is a rate at which the currency of one country is being exchanged for that of another country or the relative price that indicates the price of one currency in terms of another currency. There are three types of exchange rate systems: (i) the gold standard - the process by which countries define its national currencies in term of the weight of gold. (II) Fixed exchange rate system- this process by exchange rate value is determined by the interaction of the government and market forces and (III) floating exchange rate - this a process by which a country’s foreign exchange rate is entirely determined by supply and demand market forces without visible government intervention. Each exchange rate system has different advantages and implications for the conduct of the monetary policy.

2.8 The fixed exchange rate system

A fixed exchange rate, sometimes called a pegged exchange rate, is a process by which government interventions and market forces interact to determine the level of exchange rates. The procedure allows the value of the domestic currency to be fixed at the value of a selected foreign currency. The policy encourages cross-border trade investment, promotes sound macroeconomic policies, reduces uncertainty in transactions costs and controls inflation. However, a fixed exchange rate may limit the government from using other domestic monetary policy to achieve macroeconomic stability.[37] In addition, the lack of credibility may be more destructive under fixed exchange rates than under flexible rates because countries with fixed exchange rates are prone to currency speculation crises (Toulaboe and Terry, 2013 and Guisinger and Andrew, 2010).

[37]Under the fixed exchange rates, the domestic money stock is under the full control of monetary authorities, which means they may help the country to overcome external shocks, such as an unusual inflow of capital but have little influence on domestic shocks.

2.9 The regulation of inflation under the fixed exchange rate regime

When a government experiences a balance of payments deficit, the government usually increases the tax to generate more revenue. Sometimes, governments increase interest rates to mobilise savings from the public. In this regard, an increase in tax, to generate additional revenue, may have extensive implications on economic growth; i.e. technically, increase in government corporate tax will increase the firm's cost of production and decreases the consumers saving and income.[38] In avoidance of this impact, the government may decide to obtain a bond from the central bank. In the process, the central bank will create a bond by printing new money. The printing of the new currency will increase the domestic money supply, reduce short-term interest rates and increase the supply of domestic currency in the foreign exchange market that will likely cause a temporary balance of payments surplus. As a result, the increase in money supply in the foreign exchange market will depreciate the relative value of the domestic currency and keep inflation high if domestic growth does not increase to keep up with the increase in the money supply. To keep the rate of inflation low and prevent further depreciation of the domestic currency under this regime, the increase in the money supply by the domestic investors to the foreign exchange market will be moderated by a government. In this case, the central bank will avoid excess supply of domestic currency by operating a balance of payments deficit where the deficit will be allowed to soak up the excess money created through the printing of additional money.

Specifically, the fixed exchange rate has been used to control inflation and its impact on inflation has been compared with the impact of flexible exchange rates on inflation. For example, Corckett and Goldstein (1976) reported that flexible exchange rates generate more uncertainty than fixed exchange rates. Bleaney (1999) found that a fixed exchange rate is 10 percent less inflationary than a flexible exchange rate regime. Bleaney and Fielding, 2002; Ghosh et al. 2002; McKinnon and Schnabl, 2004 and Bleaney and Francisco, 2005 observed that exchange rate rigidity reduces inflation. Toulaboe and Terry (2013) argue that fixed exchange rates are less inflationary and the anti-inflationary benefit is heavily dependent on the monetary stability and credibility of the regime, which needs to be carefully built in a stable economy. Kiguel (2002) expressed

[38] Poulson and Kaplan (2008) explore the impact of tax policy on economic growth. The analysis supports the hypothesis that higher marginal tax reduces the rate economic growth.

that fixed exchange policy implemented in Argentina in the 1990s reduced the rate of inflation, improved the efficiency of privatization, reduced unemployment and increased GDP in Argentia during the period. Domac and Soledad (2000) argue that a fixed exchange regime minimizes the possibility of a banking crisis in developed countries. Calvo and Mishkin (2003) argue that strong institutions are the best mechanism to achieve macroeconomic success than any exchange rate regime. Jackson and Miles (2008) found that institutional quality and exchange rates reduce the rate of inflation.

2.10 The exchange rate policy in Oil exporting countries

Many of the OPEC countries derive their revenue from oil production; to sustain this revenue, many of these countries have obligations to minimize the cost of production. Consequently, the choice of exchange rate regime is crucial to both oil importing and oil exporting nations because the selection of the appropriate exchange rate regime could guarantee oil price stability and macroeconomic stabilities.[39] Keeping the exchange rate stable, the governments of many of these countries have played various significant roles in the establishment of oil reserves and controlling foreign transactions. In particular, many of the oil importing and oil exporting countries have been avoiding operating flexible exchange rates and focus on fixed exchange rates because of the vulnerability of the global oil price.[40] For example, in 1973, Iraq and Libya pegged their currencies to the US dollar. In 1975, the Kuwait central bank adopted an exchange rate policy pegging the Kuwait dinar to the average weight of currencies of its major suppliers (i.e., United States, Europe and Japan).[41] Since 1975, Qatar, Saudi Arabia and the United Arab Emirates have pegged their exchange rate to the SDR (Special Drawing Rights) to boost

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[39] One country's export is another country's import. Increase in oil price of an exporting country will affect the price level of oil importing nation.

[40] The condition is that, exchange rates are influenced by supply and demand of goods and services through the import and export. If the price of oil reduces in the international market, the export and the revenue of oil exporting countries may be reduced to devalue currency of the oil exporting nations against value of the currency of oil importing countries. On the other hand, if the price of oil increase in international market, the revenue of oil exporting countries will be increased to increase the value of the currency of the oil exporting countries and decrease the value of the oil importing country's currency.

[41] The process is called international currency basket - the value of Kuwait currency was used to set the market value of other countries. In this case, the value of the Kuwait currency was used to construct a currency basket of 40% Euro, 25% British pounds and 35% of the US dollars. The currency basket is a mutual way used to peg a currency without overexposing it to the fluctuations of a single currency.

the confidence and stability of their local currency. Ecuador and Gabon pegged their currencies to the US Dollar and French franc, respectively (see Amuzegar, 1983). The list of BRICS and OPEC countries with fixed exchange rates and the year of adoptions are stated below:

Table 2.2 OPEC countries with fixed exchange rate

Country	**The Pagged Currency**	**Domestic currency**	**Date**
Brazil	US dollar	Brazilian Real	1967 to 1990
Ecuador	Us dollar	Abandon its local currency	Dollarization since 2000 to present
Libya	US dollar	Dinar	1973-1986
Saudi Arabia	US dollar	Riyal	2003 to present
Venezuela	US dollar	Bolivar	2013 to present
Qatar	US dollar	Riyal	2001 to present
United Arab Emirates	US dolar	Dirham	1997 to present
Kuwaiti	US dollar	Dinar	2003 till 2007 and later replaced with basket currency

2.11 Central Bank and Fiscal Policy

Fiscal policy involves the use of budget and taxation by governments to stabilise the economy and allocate resources. A budget reflects government planned expenditure in a period and a source of the revenue that will be used to finance the budget. The Budget can be classified into three categories: surplus, deficits and a balanced budget. When the government is running a budget deficit; it means that total government expenditure exceeds its income for a particular period. On the other hand, a budget surplus occurs when all taxes and other government revenues exceed government expenditures. The balanced budget equates the cost and revenue together. Traditionally, when a government is experiencing a budget deficit, the central bank will either print money or borrow from the public to pay the debt and finance government activities. However, the printing of excess money by central banks could cause inflation and have a direct consequence on economic growth. To avoid this economic consequence, the government could use fiscal policy to regulate the economy. The fiscal policy uses tax to mobilise savings, promote investment and reduce income inequality. For example, if the economic system is threatened with higher inflation; the government may decide to increase income tax, reduce expenditure and reduce the money supply. In this regard, personal income will be reduced, and individual expenditure will also reduce and decrease the aggregate demand for goods and services. However, the direct use of the tax to regulate inflation in developing countries may not be efficient; because it is generally accepted that the developing countries have less efficient tax collection, limited access to external borrowing and political instability (Catao and Terrones, 2005). Tariq et al. (2014) documented that the costs of imposing a tax in many developing countries are high and its effects may harm the living standards and purchasing power of the society.

Furthermore, the relationship between the tax increase and inflation are subject to an academic debate. Researchers have not provided reliable statistical evidence that supports the positive relationship between tax and inflation. For example, recent studies show a positive relationship between the fiscal deficit and inflation in developing countries (Domac and Yucel 2004; Catao and Terrones, 2005; Chukwu, 2013; Tariq et al. 2014). While Haan and Zelhorst (1990) do not provide support for the hypothesis that deficits influence money growth but give evidence of a positive relationship between budget deficits and inflation during high inflation periods. Lin and Chu, (2013) added that the fiscal deficit is strongly related to inflation in high inflation economies and a weak impact on inflation in low inflation economies. Komulainen and Pirttila (2002) show that fiscal deficits increased inflation. While John, 1998; Tekin-Koru and Ozmen, 2003 argue that there was no evidence of a direct relationship between inflation and the budget deficit.

2.12 Interest rates and monetary regulation in OPEC countries

Monetary policy affects economic activities by providing liquidity and credit to the domestic market. The decision to regulate money and inject credit into the economy depends on government initiatives. Governments inject money through public expenditure under the exclusive control of the central bank. In most cases, Central bank uses the interest rate, money supply and the minimum reserve ratio to control inflation. However, the use of the interest rate to control inflation is limited in OPEC countries and most of the oil exporting nations. This is due to reasons of religion, social beliefs, the usury activities of financial institutions and the sovereignty of many of these countries that independently regulate their financial institutions. In many of these countries, religious beliefs are against financial institutions charging interest and when interest rates are charged, they were charged at unreasonably high price to encourage saving. For instance, Islamic law forbids the use of interest as an instrument of monetary policy in Saudi Arabia. In Nigeria, interest rates have not played a significant role in monetary policy due to low incomes. Instead, they use credit control of private firms, statutory reserve requirements and moral suasion as alternative methods to control inflation and regulate monetary policy. For example, in early 1970 before the rise in the price of oil, the annual growth rates in money supply in most of the oil exporting countries were low and estimated at 20% (see: Amuzega, 1983 pg. 49). Following the rise in the oil price; most of the oil exporting countries experienced a rapid increase in domestic liquidity as a result of government expansion in expenditure into the private sectors and the establishment of development banking institutions (see: Amuzega, 1983 pg. 49). Similarly, Algeria established a Development Bank to finance private company investment and supervised the operation of many of the private companies. Iraq created several credit institutions to give loans to private institutions at very low-interest rates.

Nigeria and Venezuela established financial institutions and channelled their credit resources into the agriculture and industrial sectors.[42]

2.13. Chapter summary

In this chapter, we have discussed the various theoretical models that are commonly used to model and forecast inflation and considers the policies implemented by the central bank to control inflation for BRICS and OPEC countries. This chapter demonstrates that most of the policies implemented by the central bank to regulate inflation focus more on the interest rate (for example, via Inflation targeting and Taylor rules as well as through the exchange rate). According to the Taylor rule, the central bank assumes inflation and the interest rate are directly related, especially in the short term. When inflation is above the target rate, the central bank will increase the interest rate to reduce inflation and, if inflation is below the target rate, the central bank will decrease the interest rate to raise the rate of inflation (Taylor 2008). For the exchange rate, the government may allow the value of the domestic currency to be fixed at the value of a selected foreign currency to control inflation. In particular, if the government experiences a balance of payments deficit the central bank may be tempted to reduce capital outflows to improve the balance of payments. In this case, the central bank may decide to increase the interest rate to technically increase the cost of borrowing to discourage people from borrowing and decrease consumer spending. However, the use of the interest rate to control inflation is limited in OPEC countries and most of the oil exporting nations. This is due to reasons of religion, social beliefs, the usury activities of financial institutions and the sovereignty of many of these countries that independently regulate their financial institutions. Instead, central bank use credit control of private firms, statutory reserve requirements and moral suasion as alternative methods to control inflation and regulate monetary policy. The main conclusion of this chapter is that the injection of liquidity into the private sector and direct price control remain the most effective monetary policies to control inflation in many developing countries that include OPEC countries.

[42] In summary, injection of liquidity in to private sector and direct price control remain the most effective monetary policies to control inflation in many OPEC countries.

CHAPTER 3

EMPIRICAL LITERATURE REVIEW

3.0 Introduction

This chapter is divided into two sections. The first section discusses the various factors that have been considered as determinants of inflation for both developed and developing countries. While the second section analyses the empirical literature on inflation forecasting models. This literature suggests a growing consensus that economic relationships change in different inflation environments. The factors that determine inflation in developed countries may be different from the factors that determine inflation in developing countries (that have different economic environments to developed nations). For instance, inflation in many developing countries is high and mostly caused by the external influence of import prices, the foreign interest rate and the exchange rate (Frisch 1977, Dhakal and Kandil 1993, Boujelbene and Thouraya 2010 Ciccarelli and Mojon, 2010). While money growth, financial assets and interest rate determine the rate of inflation in developed countries (Tillmann, 2008 Cologni and Manera, 2008).[43] Further, oil shocks have direct influences on inflation for both developed and developing countries. For example, oil price shocks affect import prices through international trade, exchange rates, production cost, and an increase or decrease in government expenditure (Bloch et al.2006a, LeBlance and Chinn, 2004, Aljebrin 2006 and Mandal et al.2012). Empirical literature on inflation forecasting suggests the following: (i) theoretical model most especially Phillips curve, are more accurate to forecast inflation when the economy is weak most especially during the economic crises when compared with the univariate ARIMA model (Pretorious and Rensburg 1996, Dotsey et al. 2011 and Buelens, 2012). (ii) ARIMA models outperform other multivariate models (Phillips curve and VAR) during periods of stable and low inflation (Pretorious and Rensburg,1996; Mitra and Rashed, 1996; Nadal – De Simone,

[43] This section is important to our study because BRICS and OPEC countries have mixed characteristics of both developed and developing economies and we believe knowing various factors that determine inflation in different economic enviroments will improve our models’ forecasting performance.

2000 and Dotsey et al. 2011). (iii) When comparing the forecast performance of three and five quarters ahead, the VAR and VECM specifications perform better than the naïve model (Onder, 2004). When comparing VAR models with VEC models, the VEC models outperform the VAR models over the longer horizon (Fanchon and Wendel, 1999). (iv) The model that account for stochastic volatility and time varying coefficients (e.g Markov switching models, Dynamic stochastic general equilibrium modelling, Self-exciting TAR models) provide more accurate forecast than those models that do not (D'Agostino et al. (2013), Barnett et al. (2014), Bel and Paap, (2016), Cross and Poon (2016) and Mandalinci, (2017)). (Vi) The literature also reveals that the forecast combination by means of several weights leads to a reduction in forecast error compared to an individual model (Bjornland et al.2008 and Ogunc et al.2013).

3.1. The empirical literature on determinants of inflation for developed and developing countries

Over the years, different policies that include targeting inflation, fiscal policy and pegged exchange rate have been implemented to regulate inflation in both developed and developing countries. Many of these policies have been effective to control inflation in many countries at different periods.[44] In contrast, many of these policies may not be effective to control inflation for developing countries that have a history of high inflation. As a result, it is important for policymakers to know the sources of inflation in many of these countries to address the reasons why many of these policies have not been effective to regulate inflation.

[44] Rio de Janeiro (2006) studies the Brazilian experience with inflation targeting between 1999 and 2006. The evidence revealed that inflation targeting policy was successful in reducing inflation in Brazil. Domac and Soledad (2000) argue that a fixed exchange regime reduces the possibility of a banking crisis in developing countries, while Levy-Yeyati (2002) found evidence that countries with more flexible exchange rate regimes tend to grow faster.

3.2 Literature Review on determinants of inflation

Over the past few decades, different studies have investigated the determinants of inflation across countries. The variables that are reportedly taken by researchers to be the determinants of inflation in many of these countries include: depreciation of the exchange rate, import inflation, government borrowing, money supply, interest rate, output gap, wages, crude oil price, fiscal deficit and Gross domestic product (GDP). Kia (2006) classified many of these variables into two factors: internal and external factors. The external factors are activities from other countries that cause inflation to increase. These factors include: the foreign interest rate, import price, trade, economic sanctions and war. The internal factors are activities within the economic system that causes inflation to increase or factors that shift the aggregate demand curve toward the right side.[45] For example: the nominal exchange rate, money supply, deficits, and debt financing.

Similarly, inflation determinants can also be classified under two categories: Monetarist and Structuralist (Adu George and Marbuah 2011 and Tavakkoli 1996). Monetarists associated inflation to the monetary causes and suggested monetary measures to control it. The dominant view is that money supply is exogenous and can only be controlled by the monetary authority, and the demand for money. In contrast, structuralists assume that monetary factors are not the only factors that cause inflation or control it. They pointed out that most measures put forward by the monetarists to control inflation can only be effective in the short run or offer temporary relief but increase the inflationary pressures in the long run. The structuralist recognised the importance of political wills such as tax reforms and drastic cuts in fiscal expenditure when combating inflation. Consequently, structural factors tend to be treated as a short-run phenomenon and their effects are closely linked to the cost push inflation (See Parkin, 1991 pg 9). Empirical literature highlighted that increases in the cost of production increase the rate of inflation (Gali et al. (2001), LeBlanc and Chinn (2004), Primiceri (2005), Sims and Zha (2006), and Canova, et al. (2007)). For instance, Gali et al. (2001) examined the impact of marginal cost, labour productivity and real wages on inflation in UK, Australia, U.S and other OECD countries between 1970:1 – 1998:1. The

[45] This type of inflation is also known as demand pull inflation

evidence revealed that an increase in real wages generated from union pressures placed consistent upward pressure on real marginal cost to increase inflation in all considered countries. Similarly, Wachter’s (1979) result showed that increases in the cost of agricultural inputs increased the rate of inflation in South American.

According to monetarist theory, money supply is positively linked with inflation. The empirical studies that are consistent with this theory include: Bairam (1990), Ghura (1995), Boschi and Girardi (2007), Bonato (2007), Mosayeb and Mohammad (2009), Korhonen and Mehrotra (2010), Oladipo et al. (2013). For instance, Ghura (1995) stated that an increase in the money stock increases inflation most especially in the long run. That is; a one percent increases in the money stock causes inflation to increase by 0.8 percent in 33 sub-Saharan African countries between the period of 1970 – 1987. Similarly, Bairam (1990) affirms that one percentage point increases in the growth of domestic money supply leads to a 0.20 point increase in domestic inflation in the UK, 0.24 points in Canada and 0.41 points the US. Luca (2005) and Makin (2017) reveal that the relationship between money supply and inflation varies over time. In particular, the rate at which money growth influences inflation during the period of high inflation is different from the period of low inflation or during the period of stable inflation. For example, Luca (2005) shows that correlation between inflation and money growth is weak during the of low inflation of the 1990s (inflation targeting period in the UK) when compared with the period of high inflation in 1970s. This finding is supported by Makin et al. (2017) who found the same relationship between money growth and inflation in Australia during the period of the target and non-targeting inflation.[46] In summary, the conclusion of many of these studies is that money supply determines the rate of inflation in both high inflation and low inflation period. However, the rate at which money supply affects inflation varies, the influence of the money supply on inflation during the period of high inflation is greater than the influence of money supply on inflation during the period of low inflation.

[46] Makin et. al. (2017) document that excess money is the main determinant of the inflation in Australia's, although excess money growth became less important during the inflation targeting era.

Regarding interest rates, there is a strong relationship between inflation and interest rates and monetarists often use interest rates to control inflation. For instance, they increase the interest rate to reduce inflation and decrease the interest rate to increase inflation. Empirically, the relationship between interest rate and inflation has been frequently explored by the Fisher's hypothesis via cointegration. That is, there is a long-run relationship between the nominal interest rate and expected inflation. The nominal interest rate consists of the real rate plus an expected inflation rate. According to the Fisher's hypothesis, the real rate is constant over time; therefore, the nominal rate must change – point-for- point when expected inflation increase or decrease.[47] Different empirical studies have provided support for the Fisher's hypothesis (see Fama 1975., Fama and Schwert 1977., Granville and Mallick, 2004., Gul and Acikalin,2007., Taker et.al.2012 and Ozean and Ari ,2015). This implies interest rate has a direct influence on inflation. In contrast, few studies have argued against the Fisher hypothesis theory (see Ghazali and Ramlee,2003., Bhanumurthy and Agarwal 2003., Abubakar and Sivagnanam (2017)). From those studies that have argued against the theory, there is a consensus that the rejections of the Fisher hypothesis were mainly due to econometric issues and the conduct of the monetary policies. For instance, most of the previous studies do not account for heteroskedasticity and structural breaks to justify their conclusion.

Considering the impact of the oil price on inflation, it is widely accepted that raising the oil price increases the rate of inflation (Shioji and Uchino 2010, Shahiden et al. 2012). Accordingly, if the oil price increases by 10% inflation will increases by 0.4% on average (see: Zahid Ali and Anwar 2013). LeBlanc and Chinn (2004) examine the effect of oil price changes on inflation in the United States, United Kingdom, France, Germany and Japan using an augmented Phillips curve model for the period of 1980:q1 – 2001:q4. The evidence reveals that increases in the oil price increase inflation moderately in all countries. In other words, a 10% increase in the oil price leads to 0.1-0.8 % rise in inflation in the United States and other countries. Alvarez et al. (2010) reveal that the direct impact of oil prices on inflation depends on several factors and varies in different countries. For instance, the effect of oil price shocks on Spanish inflation is found to be

[47] The constant interest rate mean that the interest rate must be independent of changes in inflation and monetary shocks at any given time., i.e. neutrality of monetary policy and independent of central bank.

higher than other European countries. Oil price changes account for more than 50% of the variance of Spanish inflation and 45% of the variance in other European countries. Similarly, Barrell et al. (2011) argue that effects of oil price on inflation depend on the country's relative position in the oil market, i.e. whether the country is a net-importer or net-exporter of oil. The condition is that if one country is exporting another country will be importing. Therefore, increase in the oil price of an exporting country will affect the price level of oil importing nation because all related production costs of oil exporting countries will directly increase, leading to high cost of living and high inflation in oil importing countries.

A few studies also show that an increase in oil prices have a weak effect on macroeconomic variables, most especially inflation, and its impact has been deteriorating relative to the past for most economies. For instance, Hooker (2002) found that oil price affects the US economy and the effect of the oil price has been gradually reducing since the early 1980s. Whilst Chen (2009) obtained similar results for 19 industrialized countries between the period of 1970:q1 -2006:q4. Chen's empirical results reveal that the effect of the oil price on inflation declines through time for most of the countries studied. That is; the impact of the oil price in increasing inflation in the 2000s was weaker than impact in the 1970s. He argues that the appreciation of the domestic currency; active monetary policies and a higher degree of trade openness are the major causes of the decline in the effect of oil price on inflation in the 2000s. The conclusion is similar to the study of Mohanty and John (2014) when examining the determinants of inflation in developing countries (India) between the period of 1996 – 2013. The results show that oil price shocks have a strong influence on inflation during 2009 -2011 and that the influence was moderated in 2012 -2013 when inflation is relatively stable. They conclude that inflation dynamics in India have changed over time with various determinants showing significant time variation in recent years, particularly after the global financial crisis. The main conclusion from this section is that the oil price has a direct relationship with inflation, where an increase in the oil price increases inflation in both developed and developing countries (LeBlanc and Chinn,2004., and Zahid Ali and Anwar 2013). However, the impact of oil prices on inflation has weakened over time. The impact of the oil prices on inflation is relatively small between the period of the 1980s and 1990s than they were in the 1960s and 1970s (Hooker, 2002, Chen

2009, and Mohanty and John, 2014). The reason for the lower inflation in recent years may be because of the higher energy efficiency of production processes and good conduct of monetary policies that have been implemented by policymakers.

3.3 Literature Review on the Performance of inflation forecasting

Most of the empirical literature found that theoretical models are more accurate in forecasting when the economy is weak, most especially during periods of economic crises, when compared with ARIMA, naïve and VAR models (Onder, 2004; Dotsey et al. 2011 and Buelens(2012). For example, Onder (2004) used quarterly data between 1987:q1 and 1999:q4 to forecast Turkish inflation with the Phillips curve, ARIMA, Vector Autoregression (VAR), VECM and Naive models. The evidence revealed that the Phillips curve model outperformed the other models for one-quarter ahead forecasts and the prediction of the 2001 financial crisis. Similarly, Dotsey et al. (2011) compared the predictive performance of the Phillips curve model, an integrated moving average IMA (1, 1) specification and a naïve model in the United States for the period of 1975 - 2010. The evidence suggests that the Phillips curve is more accurate to forecast when the economy is weak and less accurate when the economy is stable. This result is similar to the study of Pretorious and Rensburg (1996) who forecast South African inflation and compared the forecasting abilities of different theoretical models (Phillips curve model, Traditional monetarist and money demand specifications) with time series model (ARIMA) for the period of 1991:q1 - 1995:q3. The estimation period was divided into two different samples to reflect periods of stable inflation and higher inflation. The study found that during periods of higher inflation, the forecast produced by the money demand, Phillips curve and Traditional monetarist forecast models generated the lowest RMSE and MAE when compared to the ARIMA model. Fisher et al. (2002) examine the predictive performance of the Phillips curve with the naïve model for the different sample periods of 1977-84, 1985-1992, 1993-2000 and 1977-2000. These samples described different periods of monetary policy in the United States such as: a high inflation volatility period, the general period of economic turbulence associated with a new monetary policy regime, a period of stable monetary policy and the whole sample period respectively. Evidence reveals that Phillips curve models produced better inflation forecast than the naïve model during the period of higher inflation volatilities (1977-1984). However, different studies have argued against theoretical models most especially the Phillips curve when forecasting inflation. The most famous critics of the Phillips curve are Atkeson and Ohanian (2001) who claimed that for the last 15 years, policymakers had not produced a version of the Philips curve that produced a better inflation forecast than the naïve model. Atkeson and Ohanian argued that economic theory might not predict a stable relationship between current unemployment and future inflation because the historical data changes as a result of changes in the economic environment.[48] Fischer et al. (2002), Sims (2002), Orphanides and Van Norden (2005) and Stock and Watson (2007) also confirm Atkeson and Ohanian' findings. They added that the result of Atkeson and Ohanian depends on the sample period and the forecast horizons. In particular, the Phillips curve forecasts are episodic: there are times, such as the late 1990s, when the Phillips curve forecasts improved upon using univariate forecasts, but there are other times (such as the mid-1990s) when a forecaster would have been better off using a univariate model to forecast. This result is similar to the findings of Fisher, Liu, and Zhou (2002) who suggest that Phillips curve forecasts do relatively poorly in periods of low inflation and after a regime shift. In contrast, this conclusion has been challenged by Sim and Zha (2006) who argued that most of the previous studies that revealed the poor performance of the Phillips curve over the period of low inflation did not account for heteroskedasticity and failure not to account for heteroskedasticity can strongly statistical bias tests in favour of finding significant shifts in the coefficients.[49] Similarly, Stock and Watson (2007) argued that what have changed in the inflation modelling process led to the poor performance of the Phillips curve during the period of low inflation. For instance, there have been substantial changes in the spectra of inflation which led to the apparent changes in the forecast produced by the Phillips curve. Similarly, Giannone (2008) attributed the poor performance of the Phillips curve to changes in the multivariate covariance of the data.

[48] Atkeson and Ohanian (2001) asked whether the Phillips curves capture the stable relationship between unemployment y and future inflation. Atkeson and Ohanian, compared the accuracy of different specification of the Phillips curve (textbook NAIRU Phillips curve, unemployment rate and other measure of economic activates) at a one-year forecast horizon to a naive model that makes a simple prediction: at any date, the inflation rate over the next 12 months will be equal to inflation over the previous 12 months between 1984 - 1999. The result revealed that the forecasts from the all Phillips curve were considerably less accurate than those from the naive models.

[49] Heteroskedasticity occurs when the variance of the error terms differs across observations

In summary, there has been mixed evidence on the accuracy of forecasts from the Phillips curve in different inflation environments. For instance, many of the empirical literatures agree that Phillips curve is more accurate in forecasting inflation when the economy is weak, most especially during periods of the economic crises, when compared with ARIMA, naïve and VAR models (Pretorious and Rensburg, 1996., Fisher et al. 2002., Onder, 2004., Dotsey et al. 2011., and Buelens,2012). In contrast, the Phillips curve performs poorly during periods of stable inflation (Fisher et. al. 2002). Literatures also suggest that when Phillips curve does not account for major econometric problems (e.g heteroskedasticity and changes in covariance) the forecast produced by the Phillips curve is less accurate when compared with naïve and other model (Sim and Zha,2006., Stock and Watson, 2007, and Giannone, 2008).

For the univariate ARIMA model, the model performs better than alternative models (Naive model and multivariate VAR models) during periods of low and stable inflation. For example, Mitra and Rashed (1996) forecast Canadian inflation for one and four quarters ahead and compared the predictive performance of VAR, ARIMA and Static expectation models between 1972:q1 and 1986:q4. The series were divided into different samples to reflect different periods of stable inflation and higher inflation. The evidence revealed that the ARIMA model performed better than the other two models during the period of stable inflation for one- quarter ahead forecasts. For the period of higher inflation and four-quarter ahead forecasts, the VAR model performed better than the ARIMA and Static model. Similarly, Lee (2012) compares the predictive performance of the ARIMA model, Phillips curve and naïve model for twenty-six countries that had adopted a policy of inflation targeting since 1990. The period before the adoption of the policy and the period after the inflation targeting policy were considered. The results specified that inflation forecasts generated by the ARIMA model performed better than inflation forecasts generated by the naïve and Phillips curve models for most countries, especially for the period following the adoption of the inflation targeting policy. The main conclusion from this section is that the univariate ARIMA model produces a better forecast in a period of low inflation volatility than a period of high inflation volatility.

A few studies also found that Multivariate VAR models produce a better forecast than alternative models over the long horizon (Fanchon and Wendel 1992., Fritzer et al. 2002., Onder 2004., Canova 2007). Canova (2007), argued that when the forecast length increases the VAR models improved their forecast performance compared to the univariate ARIMA model. For example, Fritzer et al. (2002) used ARIMA and VAR models to predict Austrian inflation between 1987:q1 and 2001: q1. The results indicate that the VAR model outperformed the univariate ARIMA specifications over a longer forecasting horizon. Similarly, Fanchon and Wendel (1992) specified different multivariate VAR models (Vector error correction (VEC), VAR and Bayesian VAR models) to forecast cattle prices between the period of 1970 and 1989. The (VEC) model differenced the data to achieve stationary and used an error correction term to model the long-run information. The performance of all the estimated models were compared. The evidence revealed that the VAR model generated the lowest mean square error for the 58 - month horizon forecast. The VEC model outperformed the VAR model for 13 and 11-month horizons. The VAR and VEC models outperformed the Bayesian VAR models. They concluded that the predictive performance of VAR and VEC models depend on the length of the forecast horizon.

We now discuss the relative forecasting performance of the survey forecasts. The survey forecast can be described as a forecast view of different professional forecasters on major macroeconomic variables. The forecasters are asked to give projections on each variable over various time horizons. According to Sill (2014), they consisted of 40 to 100 professionals who regularly forecast inflation. Each participant uses their experience to predict quarterly values of major macroeconomic variables for up to five quarters, including the current quarter, and annual projections up to three years ahead. Examples of these type of forecasts include the Federal Reserve Board’s Greenbook, Data Resource, the Michigan Survey of Consumer Sentiment, the Philadelphia Fed’s Livingston Survey, and Blue Chip Survey Professional forecaster. Empirically, there is growing evidence that survey forecasts are among the most accurate forecasts of inflation. The survey forecast performs better than the structural models, ARIMA models and Phillips curve (Sims, 2002., Ang et al.2007., Moreno and Gracia, 2012., and Faust and Wright, 2013). For example, Ang et al. (2007) examine three inflation expectation surveys: the Livingston survey, the Survey of Professional Forecasters (SPF), and the Michigan survey. These are compared with the ARIMA model, the Phillips curve, a structural model (that includes linear, non-linear and an arbitrage-free specification) for post 1985 and post 1995 samples. The results indicate that the survey forecast always performs better than the term structure model, ARIMA model, Phillips curve, and the combined forecast. Similarly, Caralho and Minella (2012) compare the survey forecast with the ARIMA, VAR and BVAR models in Brazil between the period of 1994-2008. Evidence revealed that the survey forecast produces better forecasts than the ARIMA, VAR and BVAR models in all estimated periods. This study suggests that survey forecasts are using more quality information than alternative estimate. Stock and Watson (2009) added that the relatively good performance of the survey forecasts might be due to the ability of professional forecasters to recognize structural change more quickly than automated regression-based forecasts. Giacomini (2015) also documents that survey forecasts perform better than other forecasting models and its forecast has ability to capture information about the current state of the economy. However, some literature that include Thomas (1999), Mehra (2002) and Samuelson (2009) have documented that survey forecasts are biased and exaggerated. Accordingly, in low inflation period, the surveys inflation forecasts are under-predicted and at high levels of inflation the surveys forecasts are over-predicted inflation. Mehra (2002) argued that survey forecasts are not efficient because their projections did not account for past information in making their predictions.[50] The conclusion from this section is that the survey forecasts improved over time when comapared with other forecasting models (such as: structure models,multivariate VAR models, ARIMA models and Phillips curve). The survey forecasts have a higher accuracy than those based on alternative models. One possibility is that the survey forecast generated information from different sources that are captured by a single model (Ang. al. at 2007). However, forecasts produced by this method may be easily undermined by the over predcition (during periods high inflation) and under prediction (during periods of low inflation).

An alternative forecast, so far unmentioned is the time series models that allow for time - varying coefficients and volatilities. This type of model has ability to capture the effects of parameter changes and predict the erratic components of inflation. The model can

[50] Due to these disagreements, we do not include survey forcast in our research.

exist in the inform of univariate, multivariate and nonlinear models to build upon a modern dynamic macroeconomic theory that emphasizes the current state of the economy and the role of expectation (Del Negro and Schorfheide, 2012). Also focus on describing the transformation of macroeconomic dynamics or changes in the monetary policy. For example, the Markov switching model is motivated by a regime-switching process, in which inflation shifts from a low regime to high inflation and vice versa. Similarly, the smooth threshold model describes the switching process between two distinct regimes that smoothly move from one regime to another rather than the threshold autoregressive model that suddenly from one regime to another. The empiricial literature on macroeconomic forecasts that incorporate the time-varying regime shift include: Bradley and Jansen (2004), Sims and Zha (2006), Ang et al. (2007), Groen and Mumtaz (2008), Yuan, (2011).,Barnett et al.(2014) and Hou, (2017). For example, Sim and Zha (2006) argue that a model that incorporates regime switching dynamics has better forecasting performance for United States. Groen and Mumtaz (2008) and Barnett et al.(2014) provide a similar result for the United Kingdom, and show that a regime switching model is useful for describing the change in inflation persistence. For instance, Barnett et. al (2014) used quarterly data between 1976: q1 - 2007: q4 to forecast UK inflation with different regime switching models (Threshold and smooth transition VARs, regime switching VAR, Time- varying VAR, Time-varying factor augmented VAR and unobserved component model with stochastic volatility) and Autoregressive model (AR). The study found that all the regime shift models generated the lowest RMSE when compared to the AR model. Bradley and Jansen (2004) compared the forecasting performance of stock returns and industrial production in the United States using linear (ARIMA model) and nonlinear models' logistic smooth transition autoregressive (LSTAR) between January 1934 to October 2002. The result shows the superiority of the nonlinear models (LSTAR) against linear ARIMA model to forecast industrial production. Montgomery et al (1998) compared the forecasting performance of unemployment rate in the United States using linear (seasonal ARIMA model and bivariate VAR) and nonlinear models (Threshold autoregressive model and Markov switching autoregressive model) as well as combined forecast method using a quarterly data between 1948 and 1993. This period covered the period higher and lower unemployment rate. The study reveals that MSA and TAR model outperform seasonal ARIMA during the rapid increase and decline in unemployment in early 1980. This conclusion also similar to the recent study of (Gupta et al. 2013, 2015 and Diebold et al. 2017) who estimate a Dynamic stochastic general equilibrium (DSGE) models that account for expectation and regular structural changes in many developed and emerging market economies. DSGE is widely used by the central bank to forecast inflation and analyse relevant economic issues. According to Tovar (2008), DSGE model can identify sources of fluctuation, predict the effect of policy changes and answer question about structural changes as well as establishes a link between structural features of the economy and reduced form parameters, something that was not always possible with large scale macroeconomic variables. Empirically, Gupta et al. (2015) estimate DSGE and AR model for South Africa economies using a sample period between 1971q2 to 1999q4 and generate a recursive forecast for inflation over 2000q1 to 2011q4. The study shows that the DSGE model performs better than the AR model during the estimated period. The study of Alpanda et al. (2011) also indicate that DSGE-based inflation forecasts generated the lowest forecast errors compared to forecasts obtained from BVAR and VAR models. Diebold et al. (2017) estimated DSGE models with and without stochastic volatility between 1962:q2 to 2011:q1. The DSGE model that estimated with stochastic-volatility produces superior forecast than the DSGE estimated without stochastic volatility versions during the estimated period. The conclusion from this section is that a model that accounts for regime shifts or time varying coefficients provide accurate forecast than those models that do not (D'Agostino et al. (2013)., Barnett et al. (2014), Bel and Paap, 2016), Cross and Poon (2016) and Mandalinci, (2017)).

A few studies focus exclusively on combined forecasts. A forecast combination is the combination of two or more individual forecasts to produce a single prediction. The empirical success of this model has been demonstrated in a variety of studies during the last decades (see: Stock and Watson (1999, 2003)., Clark and McCracken (2006)., Canova (2007)., Ang, et al. (2007)., Samuelson (2009)., Altavilla and DeGrauw (2010)., Taylor (2010) and Baumeister and Kilian (2015)). The major conclusion from all these studies is that combined forecasts can produce more accurate forecast than individual forecasting models. For example, Garcia et al. (2017) compare the combined forecast model with a Bayesian VAR model in a higher inflation country (Brazil) using monthly data between January 2003 to December 2015. The results show that that the combined forecast produces the best forecasts in the higher inflation environment when compared with the alternative Bayesian VAR model. Similarly, Stock and Watson (2003) show that the combined forecast of aggregate indices of many real activity variables produces better inflation forecasting than individual variables. Samuelson (2009) documents that combined forecasts have a long history of success in an economic application and are less likely to be influenced by structural breaks. The conclusion from this section is that forecasts produce by the combined methods are better than those based on alternative models in the presence of model uncertainty (Samuelson, 2009 and Li and Chen, 2014).

3.4 The chapter summary and conclusion

The empirical literature on the determinants of inflation and forecasting inflation can be grouped into studies that investigate developed and developing economies. Developed economies have well-established institutions that are committed to low inflation. In contrast, developing economies are known for higher inflation, unstable macroeconomic environments and depend heavily on exporting capital (Catao and Terrones, (2005), and Ghazanfar and Sevcik (2008). In developing countries, inflation is mostly caused by the external influence of import prices, the foreign interest rate and the exchange rate (Frisch 1977, Dhakal and Kandil 1993, Boujelbene and Thouraya 2010). Whereas, money growth, financial assets and interest rates determine the rate inflation in developed countries (Hendry 2001, Tillmann, 2008 Cologni and Manera, 2008). For instance, when firms borrow from financial institutions to pay for their production factors. The cost of the interest paid to the financial institution will be added to the production factors to increase inflation. Evidence also revealed that the correlation between money growth and inflation is stronger during periods of high inflation whereas the correlation between inflation and money growth is weaker during periods of stable inflation (Luca, 2005). Besides, there is a direct relationship between the oil price and inflation in both developed and developing countries (LeBlanc and Chinn, 2004 and Cavalcanti and Jalles 2013). For example, oil price shocks affect both the import price and export price through the exchange rate, to increase or decrease the cost of production (Nielsen and Bowdler, 2006 and Bloch et al.2006a). A large amount of the literature suggests that the effect of oil price shocks on macroeconomic variables varies considerably over time (see Burbidge and Harrison, 1984; Chen, 2009; Alvarez et al. 2010 and Mohanty and John, 2014). The impact of the oil price on inflation is typically higher during periods of economic crisis when compared to periods of economic stability. The impact of the oil shock on inflation is considerably lower in developed countries when compared to developing countries (Chen, 2009). This may be because of good financial institutions, active monetary policies, and a higher degree of trade openness in many developed countries, which may have helped to reduce the effect of the oil shocks on inflation when comppared with developing countries.

Regarding the empirical literature on inflation forecasting, many studies suggest the following conclusions:

(i), Phillips curve-based models are more accurate in forecasting when the economy is weak, most especially during periods of the economic crisis, when compared with ARIMA, naïve and VAR models (Onder, 2004; Dotsey et al. 2011 and Buelens 2012).

(ii) During periods of low inflation, univariate ARIMA models outperform the multivariate VAR model (Pretorious and Rensburg,1996; Mitra and Rashed, 1996 and Alles and Hotton, 2000).

(iii) When the forecast length increases the VAR and VECM specifications exhibit improved forecast performance when compared to the Phillips curve, Naïve and ARIMA models (Fanchon and Wendel, 1992 and Onder, 2004).

(iv) Literature also shows that there some gains (in term of forecasting performance) from allowing time variation in the model parameters and from exploiting a large information set. As a result, the model that accounts for stochastic volatility and time varying coefficients (e.g DSGE, Markov switching models and Threshold and smooth transition model) provide more accurate forecast than those models that do not (D'Agostino et al. (2013)., Barnett et al. (2014)., Bel and Paap, 2016)., Cross and Poon (2016) and Mandalinci, (2017)).

(Vi) The survey forecasts improved over time when compared with an individual forecasting model (such as: structure models, multivariate VAR models, ARIMA models and Phillips curve). One possible explanation is that the surveys extract information from different sources, not obtained by a single model or captured by other models.

(VII) Evidence also reveals that the forecast combination using several weights leads to a reduction in forecast error compared to individual models (Bjornland et al.,2008 and Ogunc et al.2013).

CHAPTER 4

FEATURES OF CONSUMER PRICE DATA AND ITS TRANSFORMATIONS

4.0 Introduction

In this chapter, we analyse the feature of the quarterly price data and its transformations to assess issues of seasonality, stationarity and structural breaks. Further, we outline the Box Jenkins ARIMA and ARIMAX methods of univariate modelling employed in this thesis (section 4.4). To identify the main features of the quarterly price, we consider various transformations of the natural logarithm of price data for each country to inform modelling and forecasting. The natural logarithm is used to linearize the exponential trend that is typically expected in price series. It is anticipated that the log of prices will need to be differenced to induce stationarity because in growing inflationary economies this series will not have a mean that is converging to a constant.[51] However, the question is what type of differencing will be required. The two main issues that may need addressing are the potential presence of seasonality in the quarterly data and structural breaks. The presence of seasonality may mean that the standard quarterly (one period) difference may be insufficient to induce stationarity because of seasonal unit roots. Hence, an annual (four period) difference, or other seasonal filters, may be required. It is considered quite possible that an annual difference on its own (instead of a quarterly difference) will be sufficient to induce stationarity. However, the presence of structural breaks may mean that unit root tests indicate that the annual difference is nonstationary because, for example, a downward shift in the intercept (seasonal indices), coinciding with a move from high to low inflation eras, gives a non-constant mean across the whole sample period. Hence, we consider the inspection of sub-samples to determine whether the annual difference is constant around shifting means. If this is not the case it may be necessary to consider the quarterly difference of the annual differenced data, however, our prior belief is that this

[51] In many developed countries that move from a relatively high inflation era in the 1970s and 1980s to a lower inflation era from the 1990s (with smooth transition) may appear like a damped trend that is converging to a constant mean rather than a split trend that simply predicts prices rising at a lower rate in the second era. In terms of unit root testing this split trend can give the inference that the log of prices are stationary. We reject any such inference upon the basis that the log of prices are intrinsically nonstationary and therefore focus our attention on what type of differencing is required to induce stationary.

will represent over-differencing of the data that may reduce our ability to effectively model and forecast the data.

A further issue that we consider is the validity of the (quarterly or annual) difference of the log of prices as a valid approximation of inflation. This approximation is only valid for relatively small rates of inflation (perhaps below 30%). We therefore, compare these approximations to more accurate measures of inflation to determine whether we need to employ the more accurate measures for modelling and forecasting.

Anticipating the graphical features of the data below we discuss the data with the following modelling strategies in mind. We do not use unit root tests that account for seasonality and structural breaks because the currently available tests allow for only one structural break and there is more than one structural break in the data for many countries. Instead, we consider using Box-Jenkins rules of thumb to identify the order of seasonal and non-seasonal differencing in an ARIMAX modelling framework that seeks to first model multiple structural shifts in the data and second models the residuals as an ARMA process. We will apply this to annual differenced data over the full sample of data and use the Bai and Perron (2003a and 2003b) test to identify any structural breaks. Utilising the Bai and Perron (2003a and 2003b) test to identify any structural breaks within the ARIMAX modelling context to model inflation is a novelty of our work. With these issues in mind we analyse various transformations of each country's price series below:

4.1 Data Analysis for the ARIMAX model

For ARIMAX modelling, we considered the consumer price index that is quarterly and available from International Financial Statistics (IFS) published by the International Monetary Fund (IMF) for all selected countries. The availability of the series for each country is summarised below and graphs of various transformations of this data for each country are given in the figures below.

Table 4.1 Consumer price index availability

Country	Period
South Africa	1958q1- 2014q4
Indian	1953q1- 2014q4
Brazil	1980q1 -2014q4
China	1988q1- 2014q4
Russia	1992q1- 2014q4
Nigeria	1960q1- 2014q4
Kuwaiti	1974q1- 2014q4
Algeria	1975q1- 2014q4
Ecuador	1958q1- 2014q4
Saudi Arabia	1971q1 – 2014q4
Angola	1992q4- 2014q4

Source: IMF and IFS

Figure 4.1 Graphs of various transformations of consumer prices for Brazil.

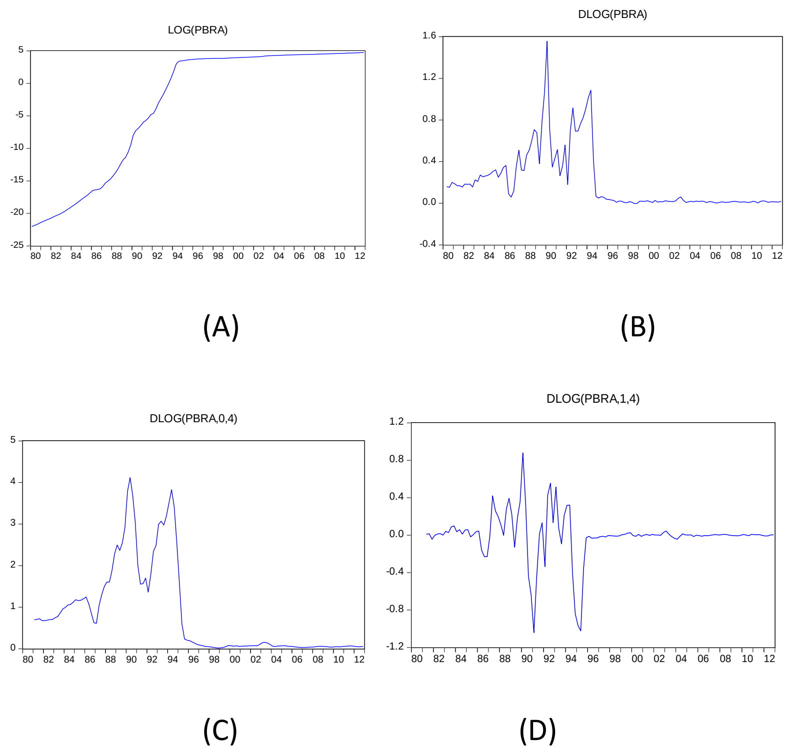


Figure 4.2 Graphs of various transformations of consumer prices for Russia

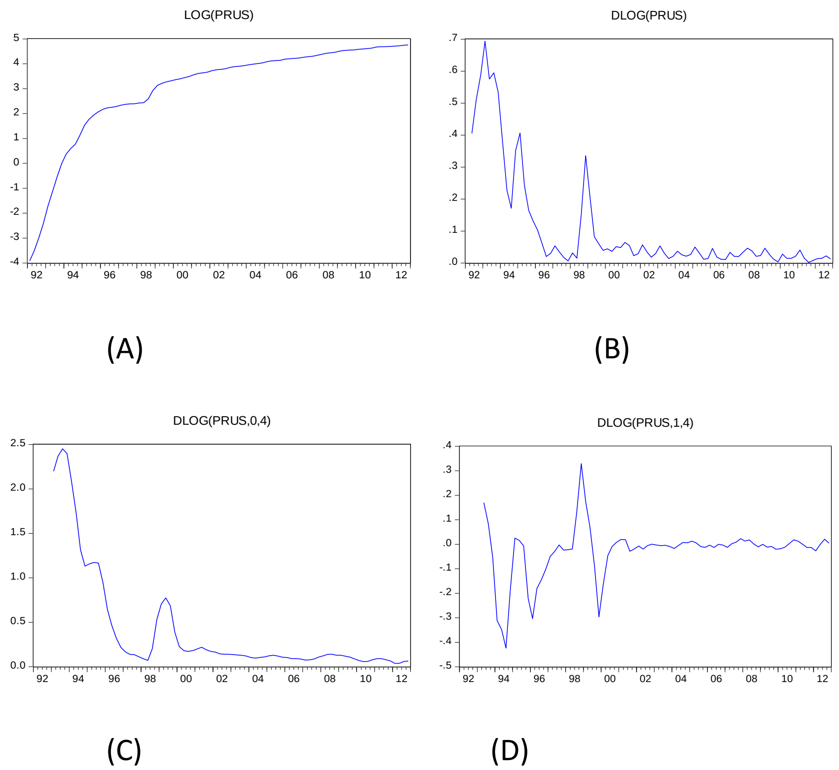


Figure 4.3 Graphs of various transformations of consumer prices for India

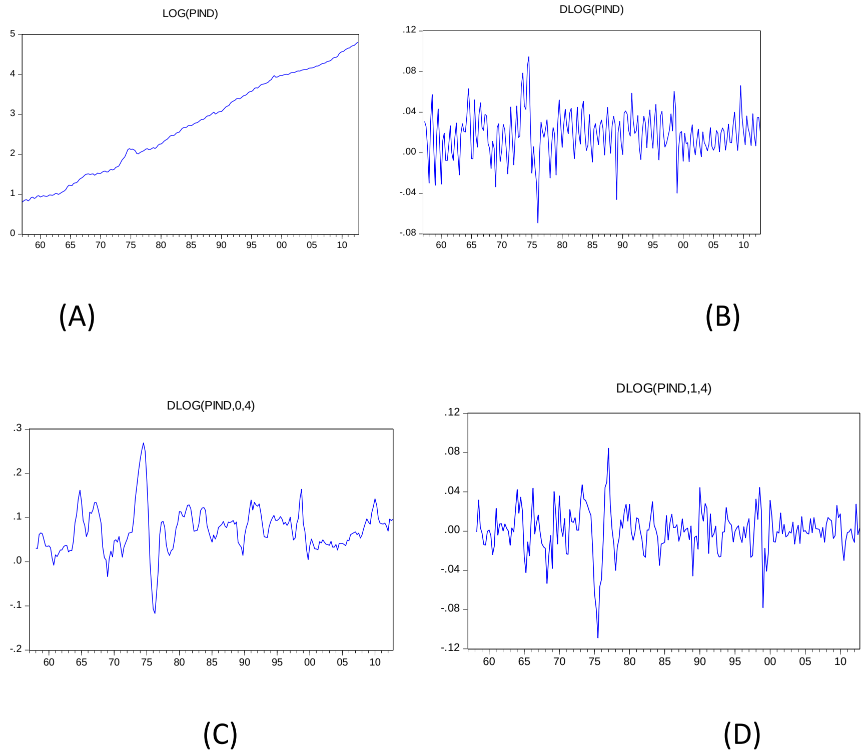


Figure 4.4 Graphs of various transformations of consumer prices for China

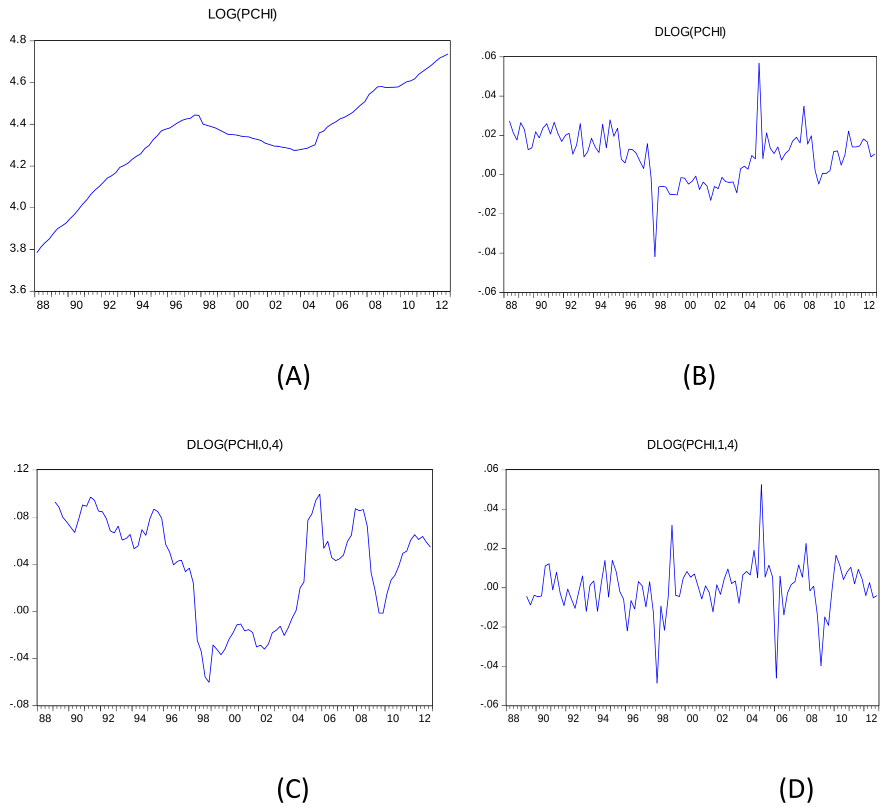


Figure 4.5 Graphs of various transformations of consumer prices for South Africa

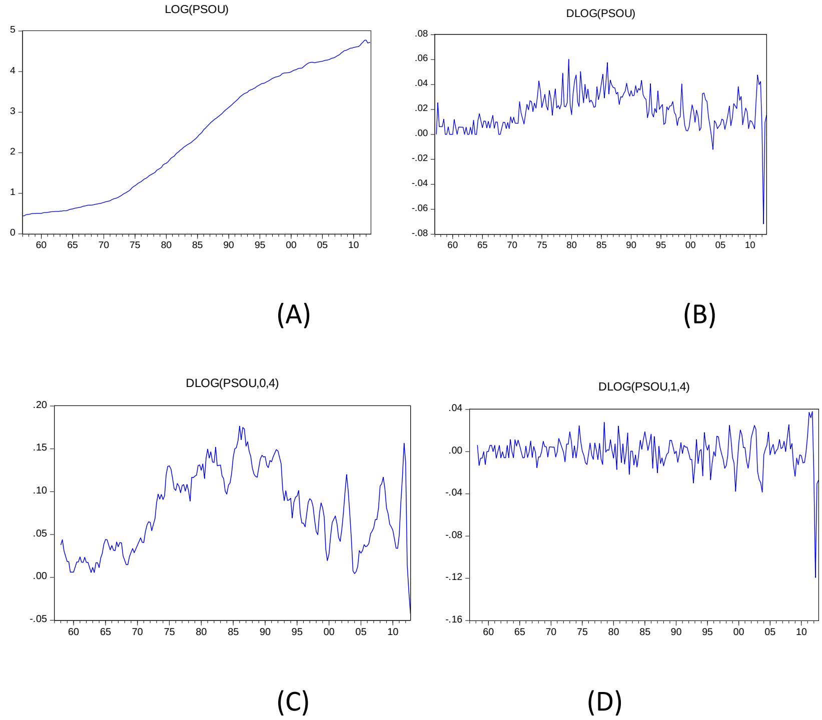


Figure 4.6 Graphs of various transformations of consumer prices for Algeria

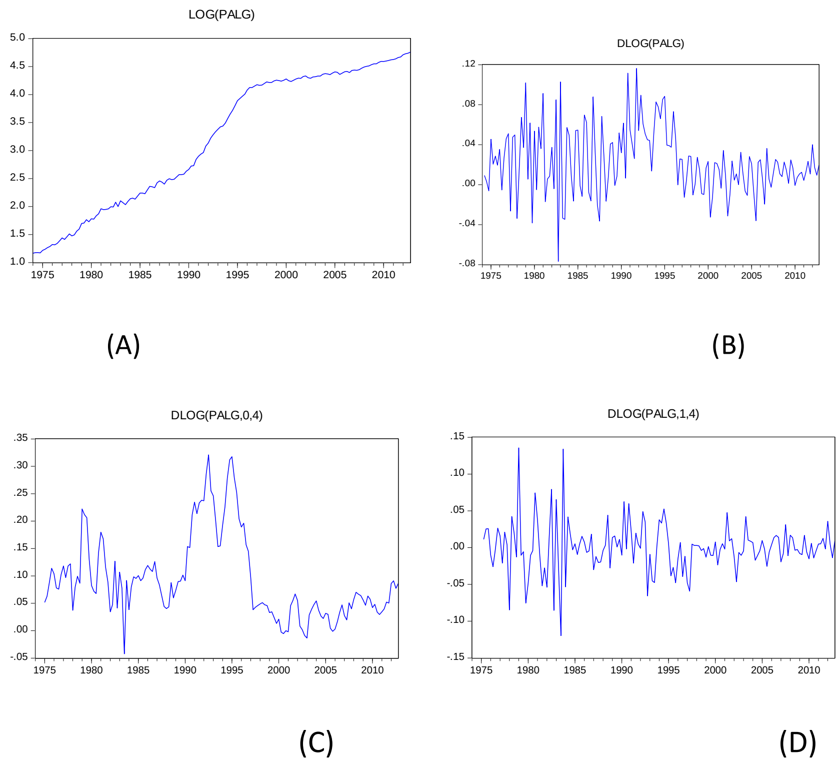
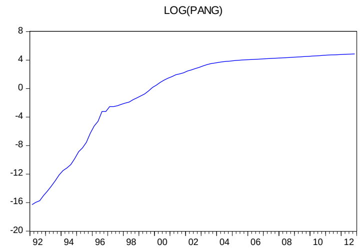
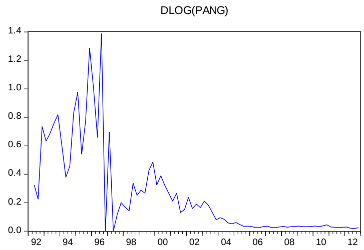
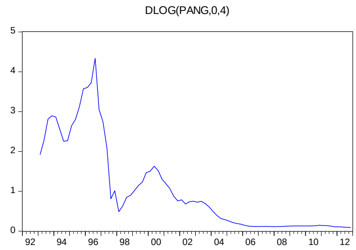


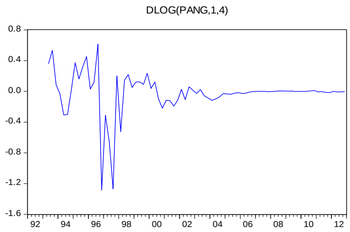
Figure 4.7 Graphs of various transformations of consumer prices for Angola





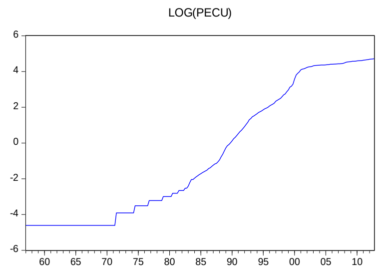
(A) (B)

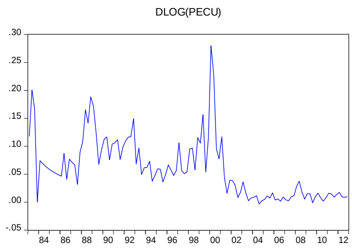




(C) (D)

Figure 4.8 Graphs of various transformations of consumer prices for Ecuador





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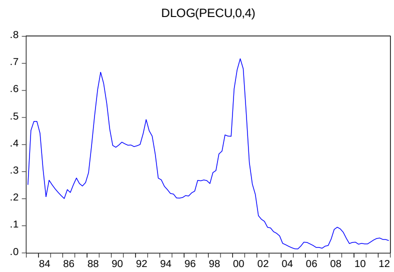
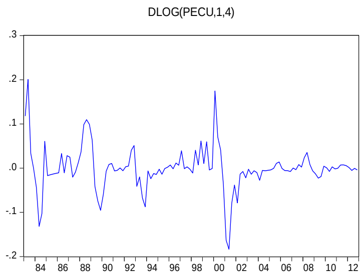
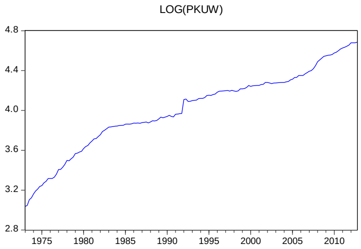
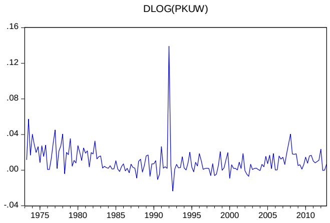




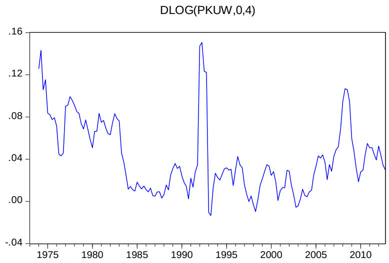
(C) (D)

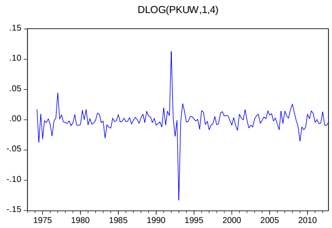
Figure 4.9 Graphs of various transformations of consumer prices for Kuwait





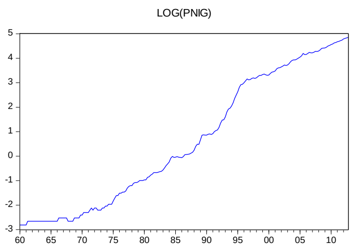
(A) (B)

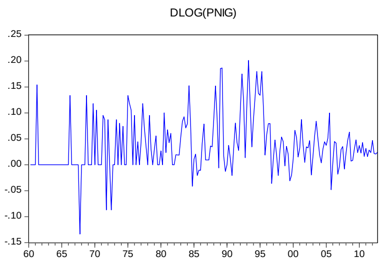




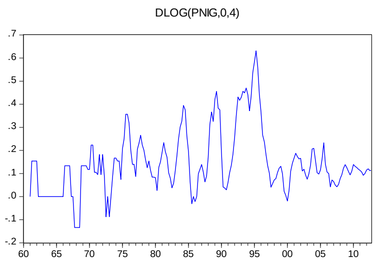
(B) (D)

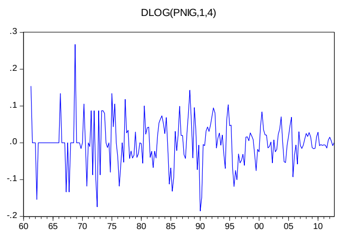
Figure 4.10 Graphs of various transformations of consumer prices for Nigeria





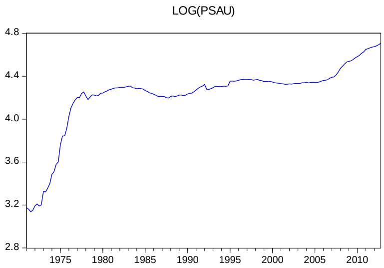
(A) (B)



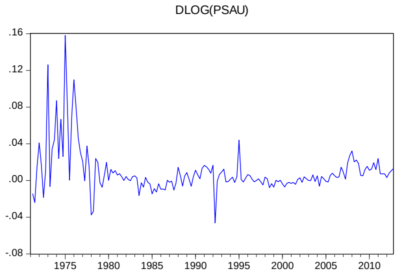


(C) (D)

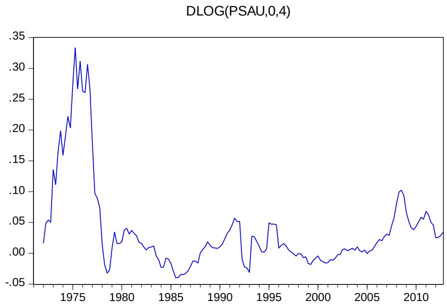
Figure 4.11 Graphs of various transformations of consumer prices for Saudi Arabia



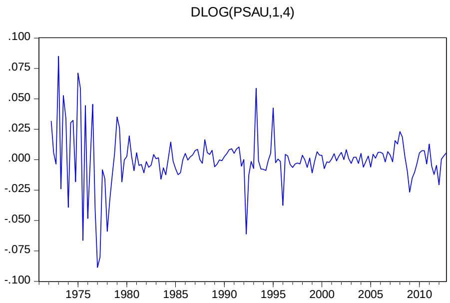
(A)



(B)



(C)



(D)

4.2 The following are the main features of the above graphs

For all countries, the natural logarithm of the consumer prices (given by graph A for each country) has an upward trend and is likely to be nonstationary. For quarterly series seasonality may be expected in price data even if it is not visible in all the log price plots because of the dominant trend; seasonality may be revealed once the trend is removed through differencing. The log of price exhibits a range of trend shifts between 1970s and 2000s that suggest structural breaks for most countries. The breaks between these periods reflect different periods of relatively high inflation and more moderate inflation that may have occurred as a result of the global oil price volatilities, political instabilities and financial crisis across different countries. For example, oil price production was volatile in the early 1970s as a result of the Arab oil Embargo. The oil price increased tremendously during the Iran-Iraq war in the early 1980s and fell back in 1985. The trend in oil prices changed after 1985 and slightly increased and later decreased until beginning of the 1990 when Iraq invades Kuwait. In the middle of 1990s, the price of oil increased until 2007 and fell back in 2008 as a result of the global financial crisis. In 2011, the price of oil picked up and increased until the first quarter of 2014. In the last quarter of 2014, the increase in production of American oil shale drives down the global market price of oil below 50 dollars per barrel (See the graph in Appendix 4).

For Brazil (Graph A figure 4.1), the log of consumer prices shows that the trend is steep up to around 1994q3 (corresponding to a high inflation period) and becomes flattered after 1994q3 (corresponding to a lower inflation period).[52] This suggests that the trend that existed prior 1994q3 does not continue after this time. For Russia, (Graph A from figure 4.2), the graph indicated a trend shift between 1996q1 and 1999q2, slope changes around 1997q1 and a step-shift in 1998q4.[53] Similarly, (Graph A from Figure 4.3) shows a few possible outliers around 1974/1975 for India and two change in slopes around 1997q3 and 2004q3 with some outliers in 2008 for China (see Graph A figure 4.4).[54] The graph for South Africa (Graph A from figure 4.5) shows an S-shaped pattern exhibited by many developed countries between the period of 1970s and 1980s. For instance, there is a shift around 1973 (corresponding to the oil shock) when this slope becomes steeper. Another slope shift occurs around 1991 and becomes flatter. During the 1970s and 1980s inflation was relatively high when compared with the post-1990 period. There is also a possible downward step shift around 2012. For Algeria (Graph A from figure 4.6), two slope shifts appear to have occurred around 1990q4 and 1996q2 with a possible outlier in 1975q1. Similarly, the log of price indicates slow transition (slope shifts) around 1996q3 and 2003q3 for Angola (see Graph A from figure 4.7). For Ecuador (Graph A from figure 4.8), there is a sequence of step shifts with constant prices prior to 1983 and the series appears to be generated by a completely different policy regime to the post-

[52] The graph reflects double-digit annual inflation of the 1970s that turned to triple digits by the 1980s. As a result, the election of Fernando Henrique Cardoso in 1994 (a former finance minister) implemented many successful stabilization programs, such as: introduction of new currency and privatization that are suggested to have helped to stabilize the inflation rate around 1994 (Ito, 1999).

[53] This could be a result of post-Soviet Union economic reforms implemented to reduce inflation. During this period, the Russian government was committed to fiscal policy, privatization, and establishment of various arbitration courts to resolve different economic disputes. As a result, Russia’s inflation was brought under control. However, the 1998 global financial crisis contributed to a sharp decline in the Russian economy.

[54] Due to the role of free markets and different economic reforms, China's economy gained momentum in the early 1990s. During this period, Chinese output increased tremendously with low inflation. However, the influenced of the Asian financial crisis slowed the economy down in 1997 and increased inflation.

1983 data. Hence, using data up to 1983 may be of little value for forecasting data after 2012 and we will therefore not use data in this period for modelling and forecasting Ecuador. Hence, all other graphs for this country (B, C and D) will be for the post 1983 period.[55] After 1983 the data trend upwards with a slope shift around 2001 suggesting a structural break. The log of price has a shift around 1965 for Nigeria and step shift in 1983q1 and 1992q2 for Kuwait. The graphs also suggest a slope shift around 2007 for Kuwait and 1978 and 2008 for Saudi Arabia (see graph A figure 4.9, 4.10 and 4.11 for Kuwait, Nigeria and Saudi Arabia respectively).

B. First differencing of the log price DLOG(P)

We next consider first differencing the log of prices (denoted DLOG(P***) where *** represents the first three letters of each country (BRA, RUS, IND, CHI, SOU, ALG, ANG, KUW, NIG, ECU and SAU). The first difference of the log of price approximates inflation between adjacent periods (quarters), the quarterly inflation rate. In all countries, the first differencing has removed the trend and transformed the structural breaks from slope shifts into an approximate step-shifts with high inflation prior to the break and lower inflation after the break.

For example, in Brazil (see Graph B from figure 4.1), the first differencing has transformed the structural break from a trend (slope) shift in the log of prices into an approximate step-shift in the differenced data with high inflation prior to 1994q3 and lower inflation after 1994q3. For Russia, the breaks between 1996q1 and 1999q2 in the log of prices have also transformed into two sets of outliers in the differenced data with peaks around 1995q1 (approximately a 40% quarterly inflation rate) and 1998q3 (34%) (see Graph B from figure 4.2). Similarly, the slope shifts in 1997q3 and 2004q3 have transformed into step shifts for China with an outlier peak in 2005q1 and a trough in 1998q1 (see Graph B from figure 4.3). For India (see Graph B from figure 4.4), the first difference reveals a peak and trough around 1974 with the highest inflation rate recorded at 9.5% (corresponding to the oil shock). In the case of South Africa, the shifts in the differenced data are roughly divided into step shifts around 1973 and 1991.

[55] This suggests that different economic policies were implemented around this period to control inflation in Ecuador.

However, the shifts do not appear to take place in one period; rather there is a transition over a few periods (see Graph B from figure 4.5).

In Algeria, the first differencing transformed the changes in the slope of the log of prices that occur around 1990q4 and 1996q2 into mean step shifts. The quarterly inflation rate peaks in 1991q4 at approximately 11.6% which is moderately high when compared with after 1996q1 when inflation is much lower and in single digits, averaging approximately 3% (see Graph B from figure 4.6). For Angola, the first differencing transformed the structural breaks from slope shifts in the log of prices into approximate step-shifts (with the slow transition) with high inflation prior to 1996q3 and lower inflation after 2003q3 (see Graph B from figure 4.7). For Ecuador, the slope shifts around 1983q3, 1987q4, 1998q4 and 2000q4 in the log of prices have transformed into outliers and an approximate step-shift with high inflation in 2001q1 and lower inflation around 2004q1 at approximated rates of 28% and -0.3% respectively (see Graph B from figure 4.8). For Kuwait, the step shifts in the log of prices around 1983q1 and 2007 become step shifts in the differenced data. The step shift around 1992q2 in the log of prices becomes a small number of outliers in the differenced data that peaks at 13.9% (see Graph B from figure 4.9). In Nigeria, the slope shift around 1996 in the log of prices is transformed into a possible downward step-shift in the differenced data (the variability of inflation appears to decline from 1996 onwards). The left-hand scale suggests that the quarterly inflation rate peaked at about 20% in around 1995. After 1996 quarterly inflation is generally below 10% which implies that only using data from 1996 onwards for modelling and forecasting may be a strategy worth consideration (see Graph B from figure 4.10). For Saudi Arabia, the first differencing transformed the slope shifts in the log of prices around 1978 and 2008 into approximate step-shifts. The left-hand scale suggests that the quarterly inflation rate peaked at about 16% before 1978 and peaked at 4% in the post 1978 (see Graph B from figure 4.11). This implies that inflation in Saudi Arabia is high before 1978 and moderate after 1978. Additionally, there are clear cycles that appear to have a fixed length in all estimated countries that most likely reflects seasonality.

C. Annual differencing of the log price DLOG (P,0 ,4)

The fourth difference of the log of prices approximates the annual rate of inflation due to the differencing of the logarithm of consumer prices across four quarters. This is a widely used transformation to approximate annual inflation. In all countries except India, the fourth difference transformation has transformed the data into relatively constant mean processes around step shifts (structural breaks). Typically, each country's data is split into approximately two samples: one of high inflation and one of relatively moderate inflation. The period of high inflation is volatile compared to the period of moderate inflation. The annual difference also gives a series that is less cyclical compared to the first differenced data and any seasonality has been substantially reduced. For most countries, the difference of the log approximation of inflation is not appropriate given the relatively high level of inflation during some point in the sample. For consistency across countries we suggest that annual inflation should be measured as: $INF_t = \frac{P_t - P_{t-4}}{P_{t-4}}$.

D. First annual differencing of the log price DLOG (P,1 ,4)

This approximates the first difference of annual inflation. For all countries, the transformation has no trend and gives a relatively constant mean process, although the approximation remains volatile for all countries except Brazil, Russia and Angola. Evidence of volatilities in many of these countries may reflect over differencing that could be avoided by modelling the step shifts in the annual or quarterly differenced data. That is, since both the annual and quarterly differenced series appear to have constant means around step shifts there is no need for both a seasonal and nonseasonal difference to induce stationarity.

4.3 The Summary of the log of price transformations

For all countries, the log of price does not have a constant mean and is therefore intrinsically nonstationary and we will therefore not apply unit root tests to this form of the data as this conclusion is clear. The first (quarterly) differencing and annual differencing of the log price are poor measures of quarterly and annual inflation due to the generally high inflation rate (at least at some point in the sample) for most countries. Therefore, we will not accept these measures for quarterly and annual inflation and we will use the real measures of inflation being: $QINF_t = \frac{P_t - P_{t-1}}{P_{t-1}}$ and $INF_t = \frac{P_t - P_{t-4}}{P_{t-4}}$ for each country (where $QINF_t$ and INF_t represent quarterly and annual rates of inflation respectively). For all countries, the quarterly and annual rates of inflation appear to be constant around their means or constant around shifting means. This implies that once mean shifts are accounted for the data are likely to be stationary. We also observed that quarterly inflation is far more seasonal than annual inflation and this may mean that the former contains some form of seasonal unit root that requires further transformation while the latter does not.[56] Hence, we believe that modelling annual inflation, $INF_t = \frac{P_t - P_{t-4}}{P_{t-4}}$, will be appropriate for most countries and this is our a priori belief. If this is not the case ARIMAX models built to such data will reject the diagnostic checks for stationarity (and invertibility).

Table 4.3 Descriptive statistics for annual inflation between 1994q1 2014q4

	Brazil	Russia	Indian	China	South Africa	Angola	Algeria	Ecuador	Nigeria	Kuwait	Saudi Arabia
Mean	1.697	0.508	0.074	0.031	0.066	4.942	0.074	0.203	0.182	0.030	0.021
Median	0.063	0.137	0.0713	0.034	0.065	0.853	0.047	0.095	0.122	0.030	0.009
Maximum	44.861	7.056	0.179	0.029	0.169	75.344	0.374	1.048	0.881	0.113	0.108
Minimum	0.018	0.038	0.005	0.029	-0.042	0.095	-0.013	0.015	-0.019	-0.01	-0.018
Std. Dev.	7.189	1.081	0.0341	0.0434	0.037	11.619	0.089	0.236	0.182	0.030	0.030
Skewness	4.752	4.061	0.527	-0.754	-0.056	3.902	1.976	1.884	2.296	1.262	0.992
Kurtosis	25.098	21.815	3.123	1.974	3.601	20.75	6.102	6.419	7.727	5.329	3.366
Jarque-Bera	1832.292	1329.775	3.561	10.544	1.181	1190.527	79.927	81.955	137.532	37.347	12.888
Probability	0.000	0.000	0.169	0.005	0.554	0.000	0.000	0.000	0.000	0.000	0.002

To provide additional evidence for the existence of various features of inflation identified in the previous section, statistically, this study employed the Jarque-Bera test, Kurtosis, skewness, mean and standard deviation to describe the rate of annual inflation. The Jarque -Bera test is a test of whether sample data have the skewness and kurtosis matching a normal distribution. Skewness measures the asymmetry of the distribution of a series around its mean. The Kurtosis measures the peakedness or flatness of the distribution of the series. Mean is the average value of the series, obtained by adding up the series and dividing by the number of observations and the

[56] Note that we do not report comparison graphs of quarterly and annual inflation in this paper to save space.

standard deviation is used to measure a dispersion or spread of the series.[57] From Table 4.3, the mean and the standard deviation of annual inflation different across countries. Angola has the highest mean of 494.2% followed by Brazil 169.7% and Russia 50.8%. In contrast, Saudi Arabia has the lowest mean value of 2.1%, followed by Kuwait at 3.0% and China 3.1%. For standard deviation (the rate of volatilities), the country that has the highest mean has the highest deviation value with the rate of 1161.9% for Angola, 718.9% for Brazil, 108.1% for Russia, 23.6% for Ecuador,18.2% for Nigeria, 8.9% for Algeria, 4% for China and South Africa and 3% for both Kuwait and Saudi Arabia. The maximum (minimum) rate of inflation is 4490%(2%) for Brazil, 710% (4%) for Russia, 18%(0.5%) for Indian, 3%(3%) for China and 17%(-4%) for South Africa. In addition, Angola has the maximum (minimum) value of 7500%(9.5%), 40%(-1) for Algeria, 105%(2%) for Ecuador, 90%(-2) for Nigeria, 11%(1%) for Kuwait and 11%(-2%) for Saudi Arabia. In general, the countries that previously known as high inflation has an approximately mean and standard deviation value that is above 10% (see Brazil, Russia, Angola, Ecuador, Nigeria). Whereas, countries with moderate inflation have the mean value that is less than 10% (India, China, South Africa, Kuwait and Saudi Arabia). The skewness values are positive in all selected countries except for China and South Africa, indicating that the asymmetric tail extends more towards positive values than the negative ones. Furthermore, the kurtosis statistics is greater than 3 in all selected countries except China indicating that the rate of inflation for all selected countries are leptokurtic (more peakedness, heavy tails, weak shoulders). This implies that the growth rate of the price display more extreme movements than would be estimated or predicted by a normal distribution. The Jarque–Bera statistics clearly reject the null hypothesis of a normal distribution for inflation in all selected countries except South Africa and India. This suggests that the observed data are mostly inconsistent with the assumption of normality in the selected countries. To help model the non-normality of the data we will utilise specifications that account for structural breaks.

[57] The details and the formula on how we estimate Jarque-Bera test, Kurtosis, skewness, mean and standard deviation are available in Eviews 9 Help guide.

4.4 ARIMA Modelling

Autoregressive integrated moving average (ARIMA) is a univariate time series model. ARIMA models were developed by George Box and Gwilym Jenkins in 1976. The models were often referred to as Box- Jenkins model procedures. ARIMA models have been used to forecast inflation in the past, and it has performed well when compared with other inflation forecasting models (see: Stock and Watson 2007, Ang, Bekaert, and Wei 2007 and Hafer & Hein 1990). In predicting inflation, the model does not need other variables than inflation to forecast. It is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of the error term (the moving average component) as well as an integrated component (which refers to the number of times a series is differenced to induce stationarity).

Modelling and forecasting with ARIMA models involve five stages: (i) identification (ii) estimation (iii) diagnostic checking (iv) model selection, and (v) forecasting. There are two forms of ARIMA model: Non-seasonal and Seasonal Autoregressive Integrated Moving Average models. A seasonal ARIMA model is used when the time series data show seasonal patterns. While the non-seasonal ARIMA model is used to forecast when there is no evidence of seasonality. The non-seasonal ARIMA model is denoted as ARIMA (*p*,*d*,*q*). The parameter *p*, *d*, and *q* are the autoregressive process of order of p, AR(p), an order of integration of order d, I(d) and moving average (MA) process of order q, MA(q), respectively.

The general non-seasonal ARIMA (p,d,q) equation is specified below:

$$\Delta^{d} Y_t = ø_1\Delta^{d}Y_{t-1} + \cdots .... + ø_p\Delta^{d}Y_{t-p} + u_t - \theta_1 u_{t-1} - .... - \theta_p u_{t-q} \qquad 4.1$$

$$\Delta^{d} Y_t = \sum_{i=1}^{p} ø_1\Delta^{d}Y_{t-i} + u_t - \sum_{i=1}^{q} \theta_1 u_{t-J} \qquad 4.2$$

Where u_t is the error term, Δ^{d} indicates the difference (d) times, θ is the coefficients of the moving average term[58].The value of ø denotes the coefficient of autoregressive

[58] The sign in front of $\theta_1, \ldots \ldots, \theta_q$ varies from one text book to another. In some text books the MA(q) model is written as $Y_t = u_t u_{t-1} + \theta_2 u_{t-2} + \theta_1 + ... + \theta_q u_{t-q} = u_t + \sum_{J=1}^{q} \theta_1 u_{t-J}$

terms. In addition, u_t is assumed to be white noise, that is, (E(u_t) = O, E($u_t{}^2$) = б²u and E($u_t\ u_{t+k}$) = E($u_t\ u_{t-k}$) = 0).

ARIMA modelling can only be applied to a stationary time series. If a series is not stationary, steps must be taken to convert the series into a stationary one before ARIMA models can be applied. A non-stationary time series can be converted into a stationary one by differencing and the differencing of a series can be denoted using the backward shift or lag operator. For example, the first difference is stated (d = 1) as:

$$\Delta Y_t = Y_t - Y_{t-1} \qquad 4.3$$

The equivalent back shift notation will be

Y_t – B¹Y_t = Y_t – BY_t= (1-B)Y

The general dth difference can be stated as:

$$\Delta^d Y_t = (1\text{-B})^d Y_t \qquad 4.5$$

The traditional ARIMA model also uses the autocorrelation function (ACF) called the correlogram to examine the stationarity of the data. The correlogram of the stationary series is used to determine the existence of an AR process and order of MA process.[59]

[59] The correlogram can also be described as an autocorrelation plot, i.e., the plotting of the sample autocorrelations versus the time lags. It measures the correlation between the current value of a process and the lagged values up to a kth lag displacement. Consequently, the theoretical autocorrelation coefficient, ρ_k , for a kth lag displacement can be expressed as: $\rho_k = \frac{Cov\ (Y_tY_{t+k})}{s(Y_t)s(Y_{t+k})}$. Where, $Cov\ (Y_tY_{t+k})$ is the covariance between the current value of (Y_t) and the lagged value of k lag displacement (Y_{t+k}). The value $s(Y_{t+k})$ denotes the standard deviation of Y_{t+k}, $s(Y_t)$ represent the standard deviation of (Y_t). If the variance and standard deviation is constant, s(Y_t) = $s(Y_{t+k})$. Therefore, we replace $s(Y_{t+k})$ with the value s(Y_t) i.e $\rho_k = \frac{Cov\ (Y_tY_{t+k})}{s(Y_t)s(Y_{t+k})} = \frac{Cov\ (Y_tY_{t+k})}{s(Y_t)s(Y_t)} = \rho_k = \frac{Cov\ (Y_tY_{t+k})}{[s(Y_t)]^2} = \frac{Cov\ (Y_tY_{t+k})}{Var(Y_t)}$. Note that the variance of a process is equal to the covariance of a variable with itself, i.e., $Cov\ (Y_tY_t)$ = Var (Y_t). Thus, $\frac{Cov\ (Y_tY_{t+k})}{Var(Y_t)} = \frac{Cov\ (Y_tY_{t+k})}{Cov(Y_tY_t)}$. The maximum covariance a series can have is the covariance with itself (Y_t will vary in exactly the same way as (Y_t)). Hence, $Cov\ (Y_tY_{t+k})$ will always be less than $Cov\ (Y_tY_t)$ .., i.e., $Cov\ (Y_tY_{t+k}) \leq Cov\ (Y_tY_t)$ which implies that $-1 \leq \rho_k \leq 1$. Hence, the theoretical autocorrelation coefficient, ρ_k ranges from the value of -1 to +1. The value of -1 means perfect negative correlation and a value of +1 means perfect positive correlation. If ρ_k = 0 then Y_{t+k} and Y_t are not correlated at all in available data. In this research, the tests of whether the autocorrelation coefficients are significantly different from zero will be determined under the null hypothesis of stationarity and the confidence interval will be constructed for to test this hypothesis. Lastly, the theoretical sample autocorrelation coefficient is estimated as: $r_k = \frac{\sum_{t=1}^{T-K}(Y_t - \bar{Y})\ (Y_{t+k} - \bar{Y})}{\sum_{t=1}^{T}\ (Y_t - \bar{Y}\ )^2}$ where $\bar{Y} = \frac{\sum_{t=1}^{T}\ Y_t}{T}$. The value of Y_t is assumed to be stationary, T is the number of the observations and the maximum number of the useful estimated autocorrelations is suggested to be n/4 (Pankratz 1983).

The PACF is used to identify the order of AR process and existence of MA process.[60]

4.4.1 Seasonal ARIMA Modelling

When series are quarterly, it is possible that the series will exhibit seasonality, and modelling of such series requires the non-seasonal ARIMA model to be extended to accommodate additional features of seasonality. Seasonality can be dealt with in two different ways: direct seasonal modelling of unadjusted data and by using seasonal adjustment procedure. The adjusted seasonal method will seasonally adjust the data through, for example, the X-13 or X-12 procedures and a non-seasonal ARIMA model can be used to forecast the adjusted data. After which the identified seasonal indices are used to re-introduce the seasonality into the forecasts. The unadjusted data method directly extends the non-seasonal ARIMA model to capture the seasonal component of the series. In general, the seasonal ARIMA model can be expressed as ARIMA (p,d,q)(P,D,Q)s. That is, there is a combination of two polynomials generated by (p,d,q) and (P, D,Q)s, where P is the seasonal order of the autoregressive component, D denotes the seasonal order of integration and Q represents the seasonal order of moving the average component. The parameter *p*, *d*, and *q* are the corresponding non- seasonal orders of processes. The multiplicative seasonal ARIMA model can be expressed as follows: [61]

$$\o_p(B)\o_P(B^s)(1-B)^d\,(1-B^s)^D Y_t = \theta_q(B)\theta_Q(B^s)u_t \qquad 4.6$$

Where B is the standard backward shift operator defined by $B^K y_t = y_{t-k}$, $\o_p(B)$ denotes the nonseasonal autoregressive model, $\o_P(B^s)$ represents the seasonal autoregressive model, $\theta_q(B)$ describes the nonseasonal moving average process, $\theta_Q(B^s)$ denotes seasonal moving average process, and u_t is a sequence of white noise errors that are

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[60] The partial autocorrelation function (PACF) is the correlation between the lagged variable and the current value after accounting for the correlation with other variables, i.e., it is measure of correlation between Y_t and Y_{t-p} after the effects of $Y_{t-1,}\ Y_{t-2,}$……, Y_{t-p+1} has been taken into account. The theoretical partial autocorrelation coefficient is expressed in the form of an AR_p process i.e., $Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p}$ where $\o_p$ is the partial autocorrelation coefficient that estimates the relationship between Y_t and Y_{t-p}. By including $\emptyset_1, \emptyset_2,\ldots\ldots, \emptyset_{p-1}$ in this regression we are accounting for their effects on Y_t while estimating $\o_p$

[61] Tseng and Tzeng, 2002; Zhang and Qi, 2005; Wang et al. 2012

assumed to have zero mean and constant variance. $(1-B)^d$ and $(1-B^s)^D$ are the nonseasonal and seasonal differencing operators, respectively. Finally, s denotes the number of periods in the seasonal cycle.

Therefore:

$$ø_p(B) = (1 - ø_1 B - ø_2 B^2 - ø_3 B^3 - \ldots\ldots\ldots - ø_p B^p) \quad 4.7$$

$$ø_P(B^s) = (1 - ø_{1S} B^s - ø_{2S} B^{2S} - ø_{3S} B^{3S} - \ldots\ldots - ø_{PS} B^{PS}) \quad 4.8$$

$$θ_q(B) = (1 - θ_1 B - θ_2 B^2 - θ_3 B^3 - \ldots\ldots\ldots - θ_q B^q) \quad 4.9$$

$$θ_Q(B^s) = (1 - θ_{1S} B^s - θ_{2S} B^{2S} - θ_{3S} B^{3S} - \ldots\ldots - θ_{QS} B^{QS}) \quad 4.10$$

Furthermore, an ARIMA model can be amended to incorporate independent exogenous variables to account for outliers and/or structural breaks. This could be referred to as an ARIMAX model.[62] The modelling of the outliers/breaks can take different forms such as: step-shift, pulse, split trend or slope- shift.
In this case, the ARIMAX model can be specified as:

$$Y_t = \beta_0 + \sum_{i=1}^{k-1} \beta_i D_{it} X_{it} + u_t \quad 4.11$$

$$(1 - ø_1 B - ø_2 B^2 - ø_3 B^3 - \ldots\ldots - ø_P B^P)\, u_t = (1 - θ_1 B - θ_2 B^2 - θ_2 B^3 - \ldots. - θ_q B^q)\, e_t \quad 4.12$$

The equation (4.12) can be rearranged as: $u_t \dfrac{(1 - θ_1 B - θ_2 B^2 - θ_2 B^3 \ldots. - θ_q B^q)\, e_t}{(1 - ø_1 B - ø_2 B^2 - ø_3 B^3 - \ldots\ldots - ø_P B^P)}$

[62] Akal (2004) documents that ARIMAX modelling corrects the deficiencies of the econometric causal-effect technique by using dynamic filters to explain the variations in endogenous variables.

Hence $u_t = \frac{\Theta(B)}{\emptyset(B)} e_t$, where $\Theta(B)$ = (1 - $\theta_1 B$ - $\theta_2 B^2$ - $\theta_2 B^3$- …. - $\theta_q B^q$) and $\emptyset(B)$ = (1 - $\emptyset_1 B$ - $\emptyset_2 B^2$ - $\emptyset_3 B^3$ - …… - $\emptyset_P B^P$)

Therefore, the ARIMAX model could be expressed as:

$$Y_t = \beta_0 + \beta_1 D_{it} X_{it} + \beta_2 D_{2t} X_{2t} + \cdots + \beta_{(K-1)} D_{(K-1)t} X_{(K-1)t} + \frac{\Theta(B)}{\emptyset(B)} e_t. \quad 4.13$$

Where Y_t is the dependent variable, $k-1$ is the intervention variable, D_{it} is the dummy variable, β_0 and β_i are the coefficients, X_{it} are the explanatory variables, u_t is the error term that is modelled by a univariate ARIMA(p,d,q) structure – this can be easily extended to a seasonal ARIMA specification (as above). The equation (4.11) is the explanatory component of the ARIMAX model and equation (4.12) specifies the ARIMA model of the error term u_t part of the ARIMAX model. The equation (4.12) is strictly an ARMA(p,q) because it is typically assumed that u_t is stationary (although this can be extended to account for seasonal AR and MA components too). In our models, we focus on modelling outliers and structural shifts using the dummy variables, D_{it}, and we do not add any explanatory variables, X_{it}.

The ARIMAX model involves dummy variables to model the outliers and structural breaks and, take the values of 0 or 1. For example, the pulse intervention specifies the dummy variables as:

$$D_{it} = \begin{cases} 0 & if \quad t \neq t_i \\ 1 & if \quad t = t_i \end{cases}$$

Where X_{it} = 1 (one outlier or break)

And the step intervention allocates dummy variables as follows:

$$D_{it} = \begin{cases} 0 & if \quad t \leq t_i \\ 1 & if \quad t > t_i \end{cases}$$

where X_{it} = 1 (one outlier or break) [63]

[63] The step intervention analysis is associated with permanent changes in the mean of the series while the pusle intervention is associated with a temporary shift in the mean of the series that eventually returns to its stable position.

4.4.2 The identification of AR and MA orders using the ACF and PACF

A stationary autocorrelogram graph is expected to decay geometrically from its initial value and expected to drop to zero within four or five lags. The very slow decaying of the autocorrelation function (ACF) suggests non-stationary. If the ACF sample decays slowly, more differencing is needed to remove non-stationarity. However, over differences should be avoided.[64] Although, the consequences of over differencing is less important in the estimation of AR and MA orders than under differencing the series. When the series is stationary, it becomes possible to use the ACF and partial autocorrelation function (PACF) to identify the order q and p of an ARIMA model. A stationary autoregressive AR process exists when the ACF declines slowly toward zero as k increases. The slow decay of the PACF indicates the existence of an MA process. In the case of seasonal ARIMA models the identification of AR(P) and MA(Q) processess is similar to that of non-seasonal AR(p) and MA(q) procedures except for the displacement lags of the autocorrelation coefficients ocure at every multiple of four, i.e 4, 8 12,16…., instead of 1, 2, 3, 4….., as for non-seasonal components.[65] The order of MA(Q) and MA(q) are indicated by the number of consecutive significant sample autocorrelation coefficients at seasonal and non-seasonal lags, respectively, while the order of AR(P) and AR(p) are identified by the number of consecutive signifcant sample of partial autocorrelation coefficients at seasonal and non-seasonal lags, respectively. However, the PACF is employed to identify the order of an AR process while the ACF is employed to identify the order of an MA process. Note that the number of statistically significant ACF and PACF coefficents do not always indicate the correct specification of ARIMA model due to the sampling error.

Lastly, the ARIMA models will be checked for invertibility stationarity and the absence of residual autocorrelation in the diagnostic checking stage.[66] The ARIMA model

[64] Over differencing can create artificial patterns in data series (spurious MA processes) and can reduce forecast accuracy (Pankratz 1983).
[65] In most cases, the displacement lags of seasonal ARIMA models is denoted as S, 2S, 3S, 4S…., with the requirement that S = 4 for quarterly data.
[66] According to the Wold decomposition theorem, the invertibility rule stated that the MA(1) process is equivalent to an infinite order autoregressive process *AR* (∞).

favoured for forecasting will be chosen by the lowest value of Schwarz's (1978) Bayesian information criterion (SBIC).

4.5 The chapter summary and conclusion

This chapter consists of two sections. The first section analyses the graphical features of the quarterly price data (its transformations) and annual inflation with the descriptive statistics to assess issues of seasonality, stationarity and structural breaks for each country. While the second section outlines the Box Jenkins ARIMA and ARIMAX methods of univariate modelling employed in this thesis. From the first section, a mixture of visual inspection of the data and the result of the descriptive statistics test showed that the log of the price is nonstationary in all the growing inflationary economies under consideration. The standard quarterly (one period) difference is generally insufficient to induce stationarity because of seasonal unit roots. Conversely, the annual (four periods) difference is generally sufficient to induce stationarity, although only after structural breaks have been accounted for in modelling. However, the graphical analysis indicates that annual inflation is stationary around a constant mean or around step-shifts in the mean.[67] In our study, we use annual inflation, $INF_t = \frac{P_t - P_{t-4}}{P_{t-4}}$ to estimate ARIMAX/ARIMA and TAR model for all countries. Our expectation follows that if annual inflation is not stationary the ARIMAX/ARIMA estimate with such data will be rejected by the diagnostic checks for stationarity and invertibility.

[67] Although, the Jarque–Bera statistics clearly reject the null hypothesis of a normal distribution for annual inflation in all selected countries except South Africa and India. This suggests that the observed data are mostly inconsistent with the assumption of normality in the selected countries.

CHAPTER 5

BOX- JENKINS BASED ARIMAX MODELLING OF ANNUAL INFLATION

5.0 Introduction

In this chapter, we develop on the analysis presented in Chapter four and build ARIMAX, different ARIMA specifications and TAR models to the annual difference of inflation, INF_*, where * denotes the three-letter country identifier (section 5.1 to 5.5).[68] Further, we produce forecast for the best selected ARIMAX, different ARIMA specifications and TAR model that passes the standard diagnostic tests (residual autocorrelation, stationarity and invertibility for ARIMAs/ARIMAX and serial autocorrelation for TAR model) and choose the best forecasting model with the lowest value of RMSE, MAPE and U-statistics (section 5.6). For stationarity, our graphical analysis indicates that annual inflation will be stationary around a constant mean or around step-shifts in the mean. Whilst there may be some seasonality our graphical analysis suggests that this will not require transformations to deal with seasonal (unit) roots although it might require seasonal dummy variables (that shift for some countries) and seasonal ARMA components. We use the Bai and Perron (2003a and 2003b) test to help identify potential multiple shifts in the seasonal dummy variables to build a deterministic model of these shifts. Using graphical analysis of the actual and fitted values, we check that this deterministic model has appropriately captured the breaks in the data and make any necessary modifications. The structural breaks are then summarised by a single indicator variable. We then build a potentially seasonal ARMA model (based on the Box-Jenkins method) to the residuals of the deterministic model. The ARIMAX model is the combined deterministic and ARMA model. For each country, we model the full sample of available

[68] TAR model is the threshold autoregressive model estimated over the full sample and reduced sample that avoid modelling structural breaks. ARIMAX is the ARIMA models that have a deterministic component to account for structural breaks over the full sample period. Different ARIMA specifications are estimated over a reduced sample period that avoids the modelling structural breaks.

For different ARIMA specifications, we estimate the followings: first, a seasonal ARIMA specification identified using the Box-Jenkins method, second, a seasonal ARIMA model identified using EView’s automatic model selection tool and, third, a non-seasonal ARIMA model identified using EView’s automatic model selection tool applied to seasonally adjusted data.

data (with a couple of minor exceptions). The modelling of each country is considered in turn below. We provide a detailed discussion of the ARIMAX model developed for Brazil and summarise the results of the ARIMAX modelling process that was applied to the other countries under consideration.

5.1 ARIMAX modelling of annual inflation for Brazil

The maximum available sample period is 1980q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1984q1 – 2012q4. Forecasts (to be discussed in later chapters) will be produced over the period 2013q1 – 2014q4 using this model. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.1.1: Bai and Perron tests for structural breaks in Brazilian annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	48.440	16.19	1995q1	1989q3
1 vs 2	69.432	18.11	1989q3	1995q1
2 vs 3	0.0518	18.93		

In Table 5.1.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. Three of the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is 7.637.

Table 5.1.1 reports the Bai and Perron scaled F-statistics with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.1.2. The test results indicate that there are two significant breakpoints because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1) and the null hypothesis of one break (1 vs 2). However, the scaled F-statistic is less than the critical value for the null hypothesis of 2 breaks (2 vs 3). The sequential and repartition methods indicate the same break point dates of 1995q1 and 1989q3.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variables that give shifts in the seasonal means in 1989q3, denoted $D(1989q3)_{st}$, and 1995q1, denoted $D(1995q1)_{1t}$. The model including the seasonal dummy variables and the shift dummy variables is given in the column headed 2 of Table 5.1.2. All of the shift dummy variables are significant suggesting significant changes in the seasonal means at the identified break points although all 4 of the original seasonal dummy variables are insignificant. The significance of these shift dummy variables and that this model's SC falls to 7.083 supports the need to model the identified breaks.

Figure 5.1.1 plots the actual and fitted values of the model reported in column 2 of Table 5.1.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not capture all of the mean shifts in the actual data. The graph suggests two more mean shifts in 1991q1 and 1992q3 and, we therefore add interaction dummy variables, denoted $D(1991q1)_{st}$ and $D(1992q3)_{st}$, to the model reported in column 2 to capture these shifts. The estimation results of this model are reported in column 3 of Table 5.1.2. All of the shift dummy variables are significant suggesting significant changes in the seasonal means at the identified break points and 3 of the original seasonal dummy variables are significant. The significance of these shift dummy variables and that this model's SC falls to 6.022 supports the inclusion of all of these interaction terms in the model.

Figure 5.1.2 plots the actual and fitted values of the model reported in column 3 of Table 5.1.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts in the actual data than did model 2 (note the relative left-hand scales for the residuals in these two figures and how the fitted values are much closer to the actuals for model 3). We regard model 3 from Table 5.1.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of Brazil's annual inflation.

Table 5.1.2: Deterministic component of ARIMAX models for Brazil

Sample/Observation	1984q1 – 2012q4 (116)			
	1	2	3	4
D_{1t}	4.531 (2.362)	3.733 (1.326)	3.733 (2.551)	
D_{2t}	5.447 (2.839)	3.579 (1.271)	3.579 (2.446)	
D_{3t}	4.380 (2.283)	2.743 (0.889)	2.743 (1.711)	
D_{4t}	3.689 (1.923)	3.499 (1.134)	3.499 (2.182)	
$D(1989q3)_{1t}$		17.010 (4.072)	39.369 (10.167)	
$D(1989q3)_{2t}$		23.318 (5.583)	56.806 (14.670)	
$D(1989q3)_{3t}$		15.908 (3.809)	22.513 (7.506)	
$D(1989q3)_{4t}$		11.191 (2.679)	15.1446 (5.049)	
$D(1991q1)_{it}$			-38.445 (-8.756)	
$D(1991q1)_{2t}$			-56.014 (-12.758)	
$D(1991q1)_{3t}$			-21.456 (-4.887)	
$D(1991q1)_{4t}$			-14.169 (-3.227)	
$D(1992q3)_{1t}$			20.993 (5.856)	
$D(1992q3)_{2t}$			28.309 (7.897)	
$D(1992q3)_{3t}$			15.400 (3.720)	
$D(1992q3)_{4t}$			10.984 (2.653)	
$D(1995q1)_{1t}$		-20.449 (-5.864)	-25.356 (-9.489)	
$D(1995q1)_{2t}$		-26.786 (-7.681)	-32.569 (-12.189)	
$D(1995q1)_{3t}$		-18.574 (-5.712)	-19.122 (-8.554)	
$D(1995q1)_{4t}$		-14.615 (-4.494)	-15.384 (-6.881)	
I_BRA				1.000 (34.979)
Adj R^2	-0.023	0.544	0.877	0.897
SC	7.637	7.083	6.022	5.243
S.E	10.331	6.898	3.585	3.276

Figure 5.1.1: the actual and fitted values of model 2 reported in Table 5.1.2

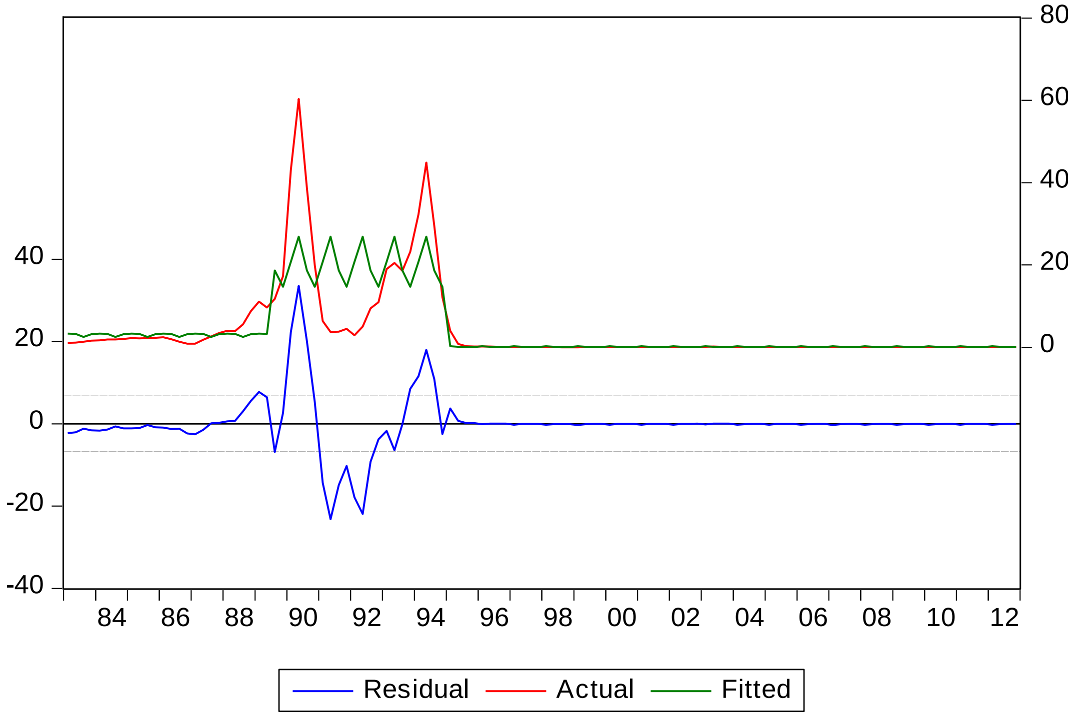
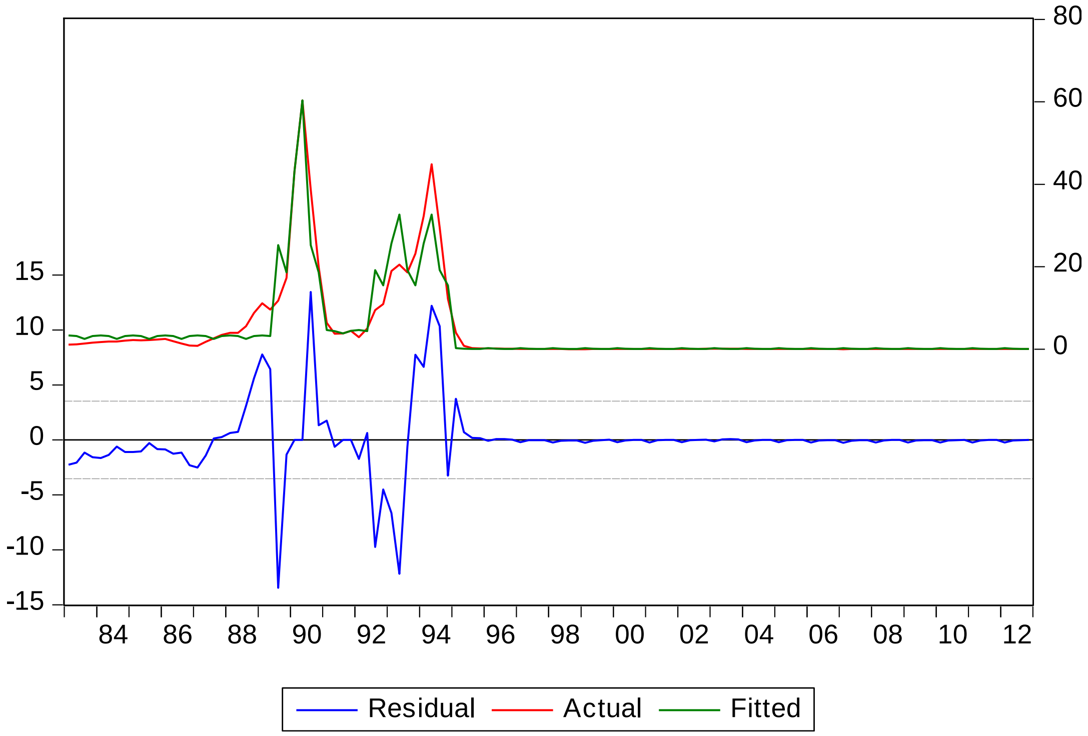


Figure 5.1.2: the actual and fitted values of model 3 reported in Table 5.1.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale et. al. (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.1.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_BRA, as the fitted value of the model reported in column 3 of Table 5.1.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.1.2. The index is significant and has a unit coefficient as is expected. This model's SC is 5.243 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

5.1.2 Developing the ARIMAX model for Brazil

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.1.2 is plotted in Figure 5.1.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lag 1 and insignificant at lags 2, 3, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 1. Further, the seasonal ACs are significant at lags 4 and 8 and insignificant at lags 12, 16, 20, 24 and 28.[69] This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 2 given the significant seasonal lags of 4 and 8.

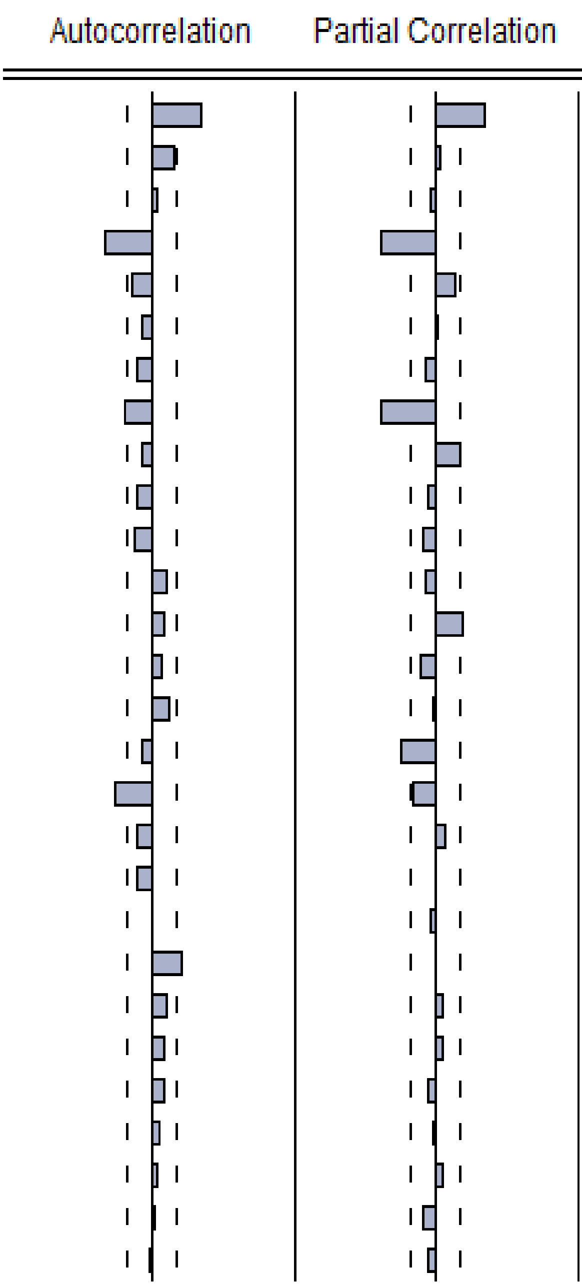
From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1 and insignificant at lags 2 and 3. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 1. The seasonal PACs are

[69] In seasonal ARIMA modelling the ACF is expected to have insignificant autocorrelation coefficients by the fifth or sixth seasonal lag to require no seasonal differencing. The first, second, third, fourth and fifth seasonal lags are represented by the autocorrelation coefficients at the following lag displacements: 4, 8, 12, 16 and 20 respectively. If the ACF sample decays very slowly at the seasonal lags (that is, the first 5 or so seasonal lags are significant) further seasonal differencing is needed.

significant at lags 4, 8 and 16 and insignificant at lags 12, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 2 (because the PAC at lag 12 is insignificant) although could be 4 (given the significance of the PAC at lag 16). Therefore, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(1,1)(2,2)_4$.

Figure 5.1.3: the ACF and PACF of the residuals of model 4 reported in Table 5.1.2

Sample: 1984Q1 2012Q4
Included observations: 116



	AC	PAC	Q-Stat	Prob
1	0.369	0.369	16.188	0.000
2	0.161	0.029	19.299	0.000
3	0.029	-0.046	19.400	0.000
4	-0.341	-0.397	33.606	0.000
5	-0.147	0.135	36.284	0.000
6	-0.079	0.022	37.052	0.000
7	-0.101	-0.067	38.345	0.000
8	-0.195	-0.391	43.165	0.000
9	-0.074	0.176	43.858	0.000
10	-0.107	-0.065	45.344	0.000
11	-0.117	-0.098	47.136	0.000
12	0.102	-0.072	48.500	0.000
13	0.087	0.191	49.509	0.000
14	0.066	-0.101	50.093	0.000
15	0.127	-0.018	52.271	0.000
16	-0.070	-0.257	52.940	0.000
17	-0.271	-0.161	63.093	0.000
18	-0.104	0.078	64.595	0.000
19	-0.110	-0.007	66.306	0.000
20	0.005	-0.033	66.310	0.000
21	0.210	0.003	72.694	0.000
22	0.111	0.065	74.496	0.000
23	0.096	0.042	75.842	0.000
24	0.083	-0.054	76.864	0.000
25	0.060	-0.019	77.397	0.000
26	0.028	0.064	77.514	0.000
27	0.008	-0.088	77.525	0.000
28	-0.018	-0.058	77.577	0.000

We report the multiplicative $ARMA(1,1)(2,2)_4$ specification that includes I_BRA plus 4 seasonal dummy variables as our initial ARIMAX model in the column headed 5 of Table 5.1.3. In this model the SC falls to 4.805 suggesting that the addition of ARMA terms has improved the specification. I_BRA is significant whereas all 4 seasonal dummy variables are insignificant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR (SEA DUM), which has a probability value of 0.687 (given in squared brackets below the reported test statistic). Because this exceeds 0.05 these 4 dummy variables are jointly insignificant. The first non-seasonal autoregressive variable's coefficient, denoted AR(1), is significant as is the first seasonal AR variable's coefficient, denoted SAR(4), however, the second seasonal AR variable's coefficient, denoted SAR(8), is insignificant. The first non-seasonal moving average variable's coefficient, denoted MA(1), is insignificant as is the first seasonal MA variable's coefficient, denoted SMA(4), however, the second seasonal MA variable's coefficient, denoted SMA(8), is significant. These results suggest that the specification can be improved by the exclusion of some combination of deterministic and ARMA terms.

Table 5.1.3: The ARIMAX table for Brazil

Sample/Observations	1984q1 – 2012q4 (116)			
	5	6	7	8
I_BRA	1.021 (73.407)	1.021 (77.081)		
I_BRA2			1.043 (73.462)	1.046 (95.933)
D_1	0.080 (0.956)	0.081 (1.022)	-0.471 (-6.435)	-0.494 (-9.628)
D_2	0.064 (0.670)	0.064 (0.702)	-0.362 (-4.449)	-0.392 (-6.887)
D_3	0.094 (1.098)	0.092 (1.115)	-0.544 (-8.159)	-0.569 (-11.900)
D_4	0.026 (0.337)	0.027 (0.368)	-0.520 (6.163)	-0.472 (-11.089)
AR(1)	0.474 (2.052)	0.366 (4.026)	0.520 (6.163)	0.622 (7.955)
SAR(4)	-0.777 (-7.803)	-0.825 (-18.477)	-0.841 (-17.111)	-0.145 (-1.511)
SAR(8)	0.052 (0.545)			-0.297 (-3.180)
MA(1)	-0.128 (-0.492)			
SMA(4)	0.023 (1.000)	0.024 (0.962)	-0.000 (-0.008)	-0.100 (-26.029)
SMA(8)	-0.977 (-42.532)	-0.977 (-39.905)	-1.000 (-30.695)	
Adj R^2	0.952	0.952	0.958	0.956
SC	4.805	4.730	4.607	4.645
S.E	2.243	2.230	2.100	2.137
AR Root	0.957 0.499 0.474	0.953 0.366	0.958 0.520	0.859 0.622
MA Root	0.999 0.994 0.128	1.000[70] 0.994	0.999	0.999
P[QLB(11)]	0.281	0.447	0.009	0.402
LR (SEA DUM)	2.265 [0.687]	2.378 [0.667]	29.439 [0.000]	29.138 [0.000]
LR (SEA DUM, CON)				36.093 [0.000]
$LR(1989q3)$	4.888 [0.299]	9.734 [0.045]	0.632 [0.959]	1.153 [0.886]
$LR(1991q1)$	4.483 [0.345]	-0.085[71]	0.376 [0.984]	1.536 [0.820]
$LR(1992q3)$	6.794 [0.147]	13.985 [0.007]	0.095 [0.999]	2.191 [0.701]
$LR(1995q1)$	3.360 [0.500]	12.717 [0.013]	0.621 [0.961]	0.305 [0.990]

Where: I_BRA = the fitted value of the model reported in column 3 of Table 5.1.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(11)] = Probability value of the Ljung-Box Q-statistic at the 11th lag - based on the square root of the sample size ($\sqrt{116}$), Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables; $LR(1989q3)$,$LR(1991q1)$, $LR(1992q3)$ and $LR(1995q1)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

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[70] The value is rounded up to one, however, it is less than one which means that invertibility is not violated.

[71] The test statistic has a negative value and therefore no p-value. However, the test statistic is clearly very small and therefore is highly insignificant.

We also conduct variable addition tests for the shift dummy variables included in the I_BRA variable to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA terms. A test of whether the 4 shift dummy variables corresponding to the 1989q3 break can be added to the model with joint significance is reported in the row labelled $LR(1989q3)$. Since the probability value (given in square brackets below the test statistic, being 0.299) exceeds 0.050 these variables cannot be added with joint significance. Similarly, the probability values of the joint tests of the 4 shift dummy variables corresponding to the break dates 1991q1, 1992q3 and 1995q1, reported in the rows labelled $LR(1991q1)$, $LR(1992q3)$ and $LR(1995q1)$ respectively; all exceed 0.050 indicating that no shift variables for these dates can be added with joint significance. This suggests that the coefficients embodied in I_BRA have not significantly changed with the addition of ARMA terms and therefore remains an adequate specification of the deterministic component of the model.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 11th lag, denoted P[QLB(11)], exceeds 0.050 indicating no evident residual autocorrelation – we choose lag 11 based on the square root of the sample size (in this case $\sqrt{116}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests.

However, as indicated above the specification can be improved with the removal of insignificant ARMA variables. The coefficients on the MA(1), SMA(4) and SAR(8) terms are not significant and are candidates for exclusion. Since the SMA(8) term is significant we do not remove the SMA(4) term to retain the full second-order seasonal MA component. Therefore, we remove the MA(1) and SAR(8) terms from the model reported in the column headed 5 from Table 5.1.3 and report the resulting $ARMAX(1,0)(1,2)_4$ specification in the column headed 6 of Table 5.1.3. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification, all variables are significant except for the

SMA(4) term, which we would not exclude because the SMA(8) term is significant. The seasonal dummy variables are jointly insignificant according to LR(SEA DUM) because its probability value is greater than 0.05. However, the tests $LR(1989q3)$, $LR(1992q3)$ and $LR(1995q1)$ indicate that the seasonal shift coefficients embodied in I_BRA have changed significantly. We therefore add the seasonal shift dummy variables corresponding to these dates to the model reported in the column headed 6 of Table 5.1.3 and use the estimated coefficients on these terms to adjust I_BRA. The new index of an indicator variable, I_BRA2, is defined as:

I_ BRA2 = I_BRA + 2.483 [S1*S1989Q3] + 1.264 [S2*S1989Q3] - 0.488 [S3*S1989Q3] + 1.323 [S4*S1989Q3] - 3.987 [S1*S1992Q3] - 3.791 [S2*S1992Q3] + 1.002 [S3*S1992Q3] - 2.270 [S4*S1992Q3] + 1.865 [S1*S1995Q1] + 2.970 [S2*S1995Q1] + 0.113 [S3*S1995Q1] + 1.433 [S4*S1995Q1].

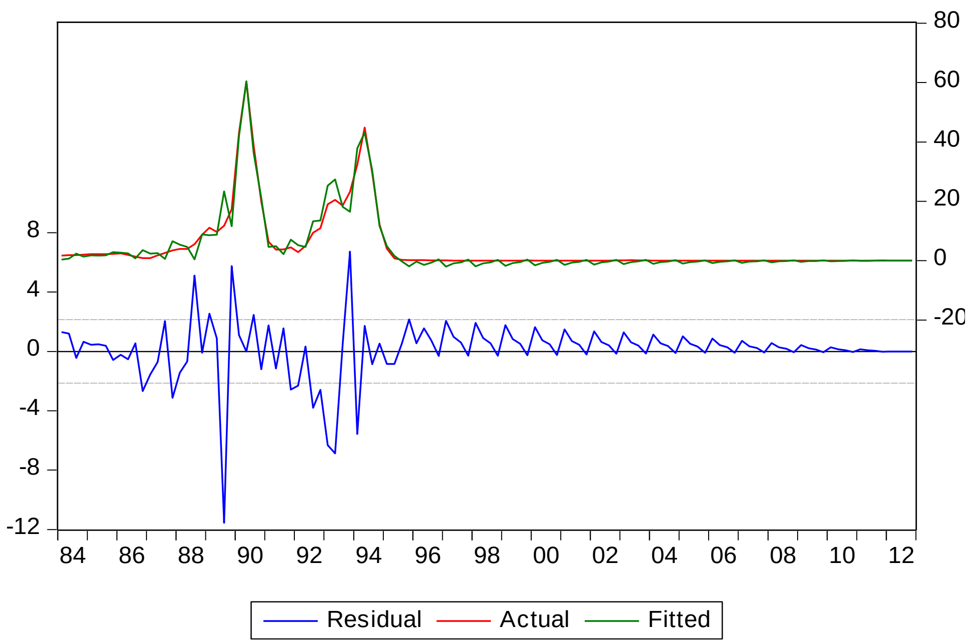
We re-estimate the model reported in the column headed 6 of Table 5.1.3 with I_BRA being replaced with I_BRA2. The resulting model is reported in the column headed 7 of Table 5.1.3. Although this model does not fail the diagnostic checks for invertibility and stationarity, there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model. Experimentation with the ARMA terms demonstrates that an SAR(8) term is significant when included instead of the SMA(8) term included in model 7. Hence, we estimate the $ARMAX(1,0)(2,1)_4$ model reported in the column headed 8 of Table 5.1.3.

This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. Therefore, it is valid for forecasting. All variables are significant except for the SAR(4) term, which we would not remove because the SAR(8) term is significant. Notably, the seasonal dummy variables are now individually and jointly significant (see LR(SEA DUM)).

The tests for the addition of the 4 sets of shift dummy variables, $LR(1989q3)$, $LR(1991q1)$, $LR(1992q3)$ and $LR(1995q1)$, all have probability values that exceed 0.050 indicating that the coefficients embodied in I_BRA2 have not significantly changed as the ARMA specification is amended.

We test the null hypothesis of whether the coefficients of the seasonal dummy variables, D_{1t}, D_{2t}, D_{3t} and D_{4t}, are the same using a Wald test. This test is reported in the row labelled LR (SEA DUM, CON) of column 8 and the probability value is 0.000. Since this value is less than 0.050, we reject the null hypothesis (of no seasonality) and accept the alternative hypothesis. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Further, this model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity, invertibility and the coefficients embodied in I_BRA2 have not significantly changed as the ARMA specification is amended. Therefore, model 8 in Table 5.1.3 is considered the best model to forecast Brazil's annual inflation. Visual inspection of the actual and fitted values graph of this model suggests that the time paths of the actual and fitted values capture all of the mean shifts in the actual data and any unmodelled seasonality is within the confidence limits and diminishes toward zero.

Figure 5.1.4: the actual and fitted values of model 8 reported in Table 5.1.3



Therefore, we regard model 8 from Table 5.1.3 as the best ARIMAX model for forecasting Brazilian annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks and the included deterministic adequately captures the identified structural breaks (according to the conducted variable addition tests). A similar procedure was applied for all countries and (to save space) the discussion for all countries is available in Appendix (Section 5.1, page 285 - 393). The table below summarises the favoured ARIMAX specifications for all BRICS and OPEC countries. These are the ARIMAX specifications used to forecast each country's inflation over the period 2013q1 to 2014q4. We note that all countries' favoured models pass the diagnostic checks and are therefore valid for forecasting. Further, the favoured ARIMAX models include an indicator dummy variable to capture structural breaks for all countries except India.

5.1.5 Summary of the ARIMAX specification for BRICS countries

Countries	**Brazil**	**Russia**	**India**	**China**	**South Africa**
Start	1984q1	1996q1	1961q1	1992q1	1961q1
End	2012Q4	2012q4	2012q4	2012q4	2012q1
Observations	116	68	208	84	208
ARMAX Specifications	(1,0) (2,1)	(0,5)	(4,3)	(2, 3)	(1,1) (1,0)
I_(P)	1.046 (95.933)	1.016 (14.421)		1.037 (5.778)	-0.040 (-6.425)
D_1	-0.494 (-9.628)	-0.009 (-0.443)	0.080 (8.732)	-0.027 (-1.600)	
D_2	-0.392 (-6.887)	-0.009 (-0.434)	0.079 (8.717)	-0.023 (--1.382)	
D_3	-0.569 (-11.900)	-0.004 (-0.198)	0.079 (8.709)	-0.020 (-1.246)	
D_4	-0.472 (-11.089)	-0.007 (-0.339)	0.079 (8.728)	-0.015 (-0.959)	
AR(1)	0.622 (7.955)		0.489 (6.973)	0.378 (2..953)	0.993 (113.433)
AR(2)			0.126 (1.600)	0.341 (2.789)	
AR(3)			0.112 (1.435)		
AR(4)			-0.186 (-2.669)		
SAR(4)	-0.145 (-1.511)				-0.605 (-9.042)
SAR(8)	-0.297 (-3.180)				
MA(1)		0.184 (1.403)	1.005 (61.557)	0.904 (10.427)	0.465 (7.259)
MA(2)		0.511 (4.432)	1.000 (61.251)	0.773 (7.692)	
MA(3)		0.468 (3.633)	0.980 (88.145)	0.868 (11.057)	
MA(4)		-0.431 (-3.397)			
SMA(4)	-0.100 (-26.029)				
MA(5)		0.428 (2.981)			
Adj R^2	0.956	0.932	0.926	0.943	0.945
SC	4.645	-2.278	-5.307	-5.902	-5.951
S.E	2.137	0.062	0.015	0.010	0.012
AR Root	0.859 0.622		0.695 0.621	0.803 0.425	0.993 0.882
MA Root	0.999	0.999 0.992 0.659	0.994 0.992	0.999 0.932	0.465
P[QLB]	0.402[11]	0.519[8]	0.163 [14]	0.163[9]	0.178[14]
LR (SEA DUM)	29.138 [0.000]	9.425 [0.051]	29.925 [0.000]	3.120 [0.540]	
LR (SEA DUM, CON)	36.093 [0.000]	12513.370 [0.000]	12.580 [0.000]	10.986 [0.000]	312.016 [0.000]

MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB]= Probability value of the Ljung-Box Q-statistic at that based on the square root of the sample size, Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables, Rounded Bracket = T – Ratios and Square Bracket = Probability value. I_(P) = is an index indicator variable for seasonal shifts embodied as the deterministic terms, i.e Brazil is estimated at I_ BRA2, Russia at I_ RUS, China is estimated at I_ CHI4 and South Africa is estimated at I_ SOU. However, India does not have an index indicator variable because the Bai Perron test did not specify any break for this country. For South Africa, the seasonal dummy variables are jointly insignificant. Therefore, we exclude the seasonal dummy variables from the model. After the exclusion of these dummies the model passes all the required diagnostic tests for stationarity, invertibility and autocorrelation.

5.1.6 Summary of ARIMAX specification for selected OPEC countries

Countries	Algeria	Angola	Ecuador	Kuwait	Nigeria	Saudi Arabia
Start	1978q1	1996q1	1987q1	1977q1	1964q1	1975q1
End	2012Q4	2012q4	2012q4	2012q4	2012q1	2012q1
Observations	140	68	104	140	196	152
ARMAX Specifications	(4,4)	(1, 2)	(0,2) (0,1)	(1,3)	(1,2) (0,1)	(1,4)(1,0)
I_(P)	0.931 (22.883)	0.219 (65.172)	0.250 (6.677)	0.566 (21.047)	0.413 (6.740)	0.593 (10.889)
D_1		-111.109 (-63.171)	-0.138 (-0.515)	0.016 (4.383)	0.105 (3.402)	
D_2		-1.893 (-4.146)	-0.139 (-0.518)	0.021 (5.968)	0.105 (3.363)	
D_3		33.137 (48.401)	-0.138 (-0.513)	0.019 (5.150)	0.106 (3.389)	
D_4		0.806 (1.747)	-0.139 (-0.517)	0.018 (5.102)	0.104 (3.327)	
AR(1)	-0.482 (-5.905)	0.701 (37.589)		0.355 (4.131)	0.982 (53.154)	-0.578 (-8.389)
AR(2)	0.288 (3.025)					
AR(3)	-0.214 (-2.367)					
AR(4)	-0.648 (-8.371)					
SAR(4)						0.293 (4.148)
MA(1)	1.148 (17.226)	-0.352 (-8.927)	0.696 (7.667)	0.861 (20.914)	0.259 (3.478)	1.747 (173.159)
MA(2)	0.546 (4.587)	0.999 (979.039)	0.485 (5.238)	0.762 (13.532)	0.219 (2.974)	1.590 (86.922)
MA(3)	0.814 (7.323)			0.882 (22.003)		1.719 (130.153)
MA(4)	0.785 (13.321)					0.977 (137.423)
SMA(4)			-0.999 (-32.316)		-0.969 (-63.398)	
Adj R^2	0.893	0.997	0.980	0.949	0.911	0.960
SC	-3.929	2.360	-3.449	-6.646	-2.887	-5.296
S.E	0.029	0.654	0.037	0.008	0.052	0.016
AR Root	0.933 0.863	0.701	0.986	0.355	0.982	0.735 0.578
MA Root	0.986 0.898	0.999	0.999 0.696	0.991 0.943	0.992 0.468	0.996 0.993
P[QLB]	0.061[12]	0.111[8]	0.116[10]	0.330[12]	0.184[14]	0.145[12]
LR (SEA DUM)		298.100 [0.000]	11.295 [0.023]	88.095 [0.000]	18.313 [0.001]	
LR (SEA DUM, CON)	439.,689 [0.000]	1487.189 [0.000]	6.969 [0.000]	647622.300 [0.000]	8.948 [0.000]	499.119 [0.000]

MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB]= Probability value of the Ljung-Box Q-statistic at that based on the square root of the sample size, Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) =

the joint test for the seasonal dummy variables, Rounded Bracket = T – Ratios and Square Bracket = Probability value. I_(P) = is an index indicator variable for seasonal shifts embodied as the deterministic terms, i.e Algeria is significant at I_ ALG, Angola at I_ ANG3, Ecuador at I_ ECU3, Kuwait at I_KUW4, Nigeria at I_NIG3 and Saudi Arabia is significant at I_ SAU. For Saudi Arabia and Algeria, the seasonal dummy variables are jointly insignificant. Therefore, we exclude the seasonal dummy variables from these models. After the exclusion of these dummies the model passes all the required diagnostic tests for stationarity, invertibility and autocorrelation.

5.2.0 Box-Jenkins based ARIMA modelling of annual inflation on reduced samples without structural breaks

In this section, we will build ARIMA models to the countries' annual inflation using a reduced sample period that avoids structural breaks. We use the break dates identified in the above full sample modelling and provided a minimum of 39 observations for estimation and we develop seasonal ARIMA models. Although there may be some seasonality our analysis in Chapter 4 suggests that the annual rate of inflation (based on a 4-period difference) will not require further transformations to deal with seasonal (or nonseasonal) unit roots. Hence, it is this variable that we build seasonal ARIMA models to in all countries. However, we include seasonal dummy variables as the deterministic component of our model which combined with an ARMA specification to the residuals yields our ARIMA model. The purpose of this is to consider whether forecast accuracy is improved by using a shorter sample (reducing efficiency of estimation) to avoid the modelling of structural breaks. The latter entails problems associated with accurately identifying and characterising the breaks (we have typically approximated breaks with an abrupt sample shift which may not be ideal if the break occurs over several periods). Therefore, we consider those countries that meet our minimum requirements. In this study, we consider countries that exhibit structural breaks (we therefore do not model India without a structural break again) and a minimum of 39 observations without structural breaks at the end of their samples. This may be justified by the notion that the end-of-sample period is more relevant for forecasting the future than older samples.

The available countries that meet up with our minimum requirements in the BRICS and selected OPEC countries are summarised below:

Table 5.2

Country	Sample
Brazil	1995q2- 2012q4
Russia	2001q2- 2012q4
South Africa	1993q2- 2012q4
Nigeria	1996q4- 2012q4
Algeria	1997q1- 2012q4
Saudi Arabia	1977q3- 2012q4
Angola	1998q4- 2012q4

5.2.1 Box-Jenkins ARIMA modelling of annual inflation for Brazil

In the full sample ARIMAX model developed for Brazil in section 5.1 we identified the last structural break date as 1995q1. Hence, the maximum available estimation period that avoids structural breaks is 1995q2 to 2012q4.To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 1997q2 – 2012q4 (63 observations). First, we regress inflation on the 4 seasonal dummy variables denoted D_{st} where $s = 1, 2, 3, 4$, to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final seasonal ARIMA model.

Table 5.2.1 reports the benchmark deterministic specification and various seasonal ARIMA models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables' coefficients are significant and the model's Schwarz criterion (SC) is -4.055.

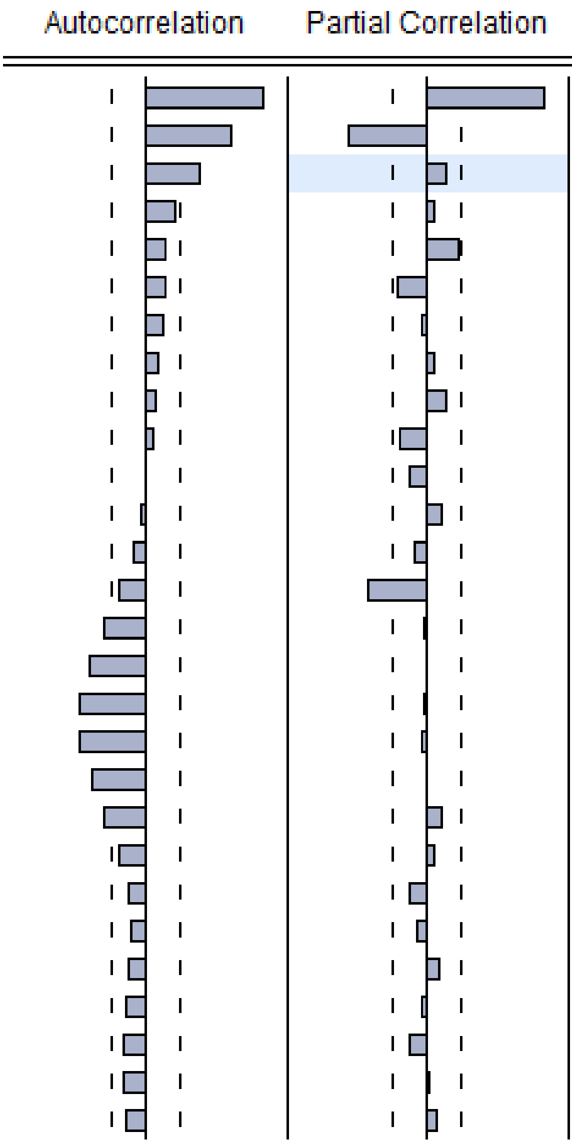
Figure 5.2.1 plots the autocorrelation function (ACF) of the residuals of the model reported in the column headed 1 in Table 5.2.1. The non-seasonal autocorrelation coefficients (ACs) from the ACF are significant at lags 1, 2 and 3 and insignificant at lags 4, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are significant at lags 16 and 20 and insignificant at lags 4, 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1 and 2 and insignificant at lags 3 and 4. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 2. The seasonal PACs are insignificant at lags 4, 8, 12 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process could be 0. Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is a seasonal

$ARMA(2,3)(0,0)_4$, which is equivalent to the non-seasonal $ARMA(2,3)$ specification. We report an ARIMA specification that includes 4 seasonal dummy variables and an $ARMA(2,3)$ model of the residuals in the column headed 2 of Table 5.2.1.

Figure 5.2.1: the ACF and PACF of the residuals of model 1 reported in Table 5.2.1

Sample: 1997Q2 2012Q4
Included observations: 63



	AC	PAC	Q-Stat	Prob
1	0.876	0.876	50.734	0.000
2	0.635	-0.575	77.783	0.000
3	0.395	0.146	88.423	0.000
4	0.220	0.046	91.787	0.000
5	0.154	0.231	93.453	0.000
6	0.142	-0.208	94.895	0.000
7	0.125	-0.044	96.029	0.000
8	0.095	0.065	96.706	0.000
9	0.073	0.144	97.115	0.000
10	0.049	-0.200	97.300	0.000
11	0.008	-0.132	97.305	0.000
12	-0.035	0.109	97.402	0.000
13	-0.089	-0.084	98.047	0.000
14	-0.189	-0.432	101.04	0.000
15	-0.304	-0.011	108.93	0.000
16	-0.411	0.001	123.63	0.000
17	-0.488	-0.023	144.86	0.000
18	-0.482	-0.028	166.03	0.000
19	-0.404	0.001	181.24	0.000
20	-0.300	0.114	189.80	0.000
21	-0.198	0.046	193.64	0.000
22	-0.128	-0.120	195.29	0.000
23	-0.108	-0.068	196.48	0.000
24	-0.122	0.088	198.03	0.000
25	-0.144	-0.037	200.25	0.000
26	-0.164	-0.138	203.22	0.000
27	-0.170	0.016	206.49	0.000
28	-0.147	0.066	209.00	0.000

In this model, the SC falls to -5.981 suggesting that the addition of ARMA terms has improved the specification. All four seasonal dummy variables are significant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.022 (given in square brackets below the reported test statistic). However, all the ARMA components are insignificant. These results suggest that the specification can be improved by the removal of some of the ARMA terms.

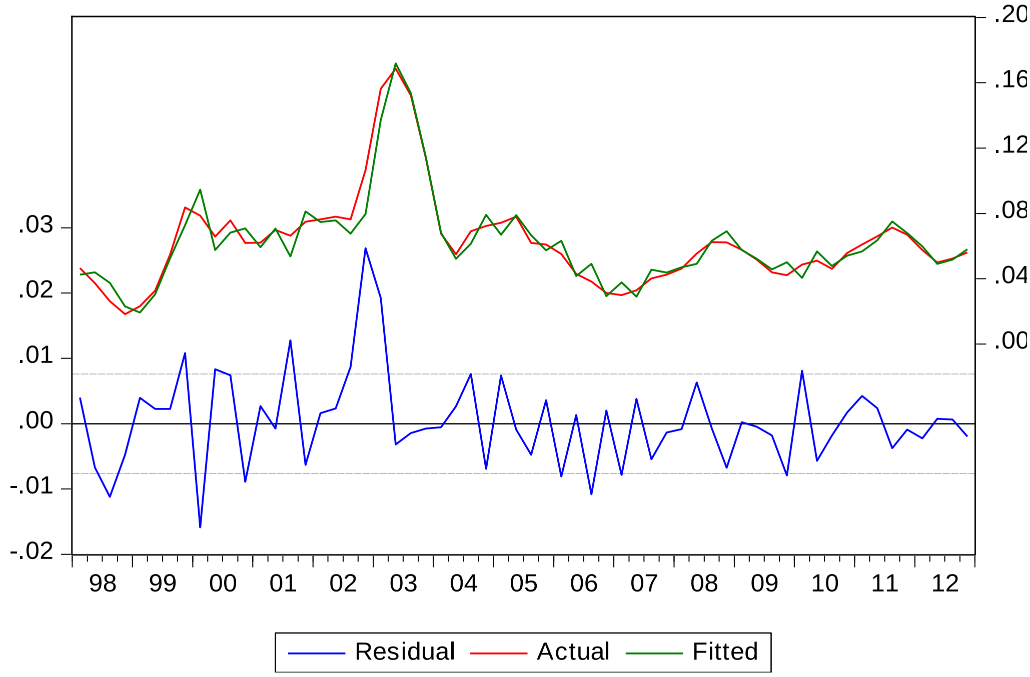
Table 5.2.1: The ARIMA table for Brazil

Observations	1997q2 2012q4 (63)		
	1	2	3
D_1	0.063 (8.421)	0.063 (8.693)	0.056 (46.188)
D_2	0.063 (8.774)	0.063 (8.596)	0.056 (41.780)
D_3	0.062 (8.617)	0.063 (8.442)	0.056 (41.403)
D_4	0.063 (8.686)	0.063 (8.548)	0.056 (46.139)
AR(1)		1.115 (1.442)	
AR(2)		-0.371 (0.727)	
MA(1)		0.597 (0.765)	2.029 (22.789)
MA(2)		-0.250 (-0.288)	2.046 (16.104)
MA(3)		0.152 (0.660)	1.986 (20.354)
MA(4)			0.969 (15.567)
Adj R^2	-0.051	0.892	0.930
SC	-4.055	-5.981	-6.577
S.E	0.028	0.009	0.007
AR Root		0.609	
MA Root		0.999 0.390	0.995 0.989
P[QLB(7)]		0.016	0.355
LR (SEA DUM)		11.413 [0.022]	65.826 [0.000]
LR (SEA DUM, CON)			169.279 [0.000]

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 7th lag, denoted P[QLB(7)], is less than 0.050 indicating evident of residual autocorrelation that suggests unmodelled systematic variation in the dependent variable and the need to adjust the model – we choose lag 8 based on the square root of the sample size (in this case $\sqrt{63}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible. Hence, the model is not valid for forecasting because there is evident autocorrelation.

After experimentation, we find that a non-seasonal $ARMA(0,4)$ specification is an improved model. The results of this $ARMA(0,4)$ model is reported in the column headed 3 of Table 5.2.1. The coefficients on the four dummy variables and all of the moving average components are significant. A Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal is reported in the row denoted LR (SEA DUM, CON). Since the probability value, being 0.000, is less than 0.050 this suggests a significant difference in the coefficients of the individual seasonal dummy variables (significant seasonality) and that they cannot be replaced by a single (non-seasonal) intercept. This model's SC decreases to -6.577. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. Therefore, it is valid for forecasting.

Figure 5.2.2: the actual and fitted values reported in Table 5.2.1 column 3



Visual inspection of the actual and fitted values (Figure 5.2.2) of this model suggests that the time path of the fitted values capture the movements in the actual data well. In terms of model fit the adjusted R^2 of this ARIMA model on the reduced sample is 0.930 which is slightly less than the specification estimated using the full sample that model's structural breaks (Section 5.1), being 0.956. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

A similar procedure was applied for all countries and (to save space) the discussion is available in Appendix. Section 5.2 page 394 - 425. The table below summarises the seasonal ARIMA specifications for both BRICS and OPEC countries. These are the seasonal ARIMA specifications used to forecast each country's inflation over the period 2013q1 to 2014q4. We note that all countries' favoured models pass the diagnostic checks and are therefore valid for forecasting.

Table 5.2.3 Summary of seasonal ARIMA specification for BRICS and selected OPEC countries[72]

Countries	Brazil	Russia	South Africa	Algeria	Angola	Nigeria	Saudi Arabia
Start	1997q2	2003q2	1995Q2	1999Q2	2000q3	1998q4	1979q3
End	2012q4	2012q4	2012q4	2012q4	2012q4	2012q4	2012q4
Observations	63	39	71	55	49	57	134
P_(D)			-0.032 (-6.965)			-0.045 (-2.446)	
ARMA Specifications	(0, 4)	(1, 3)	(1, 1)(0,1)	(1, 0)(1,0)	(1, 3)	(2, 0)(1,0)	(2,1) (1,0)
D_1	0.056 (46.188)	0.096 (13.229)			0.207 (1.845)	0.121 (10.226)	0.038 (0.587)
D_2	0.056 (41.780)	0.096 (13.389)			0.215 (1.910)	0.118 (9.889)	0.038 (0.583)
D_3	0.056 (41.403)	0.096 (13.509)			0.207 (1.879)	0.117 (9.796)	0.038 (0.588)
D_4	0.056 (46.139)	0.096 (13.508)			0.202 (1.802)	0.122 (10.340)	0.038 (0.588)
AR(1)		0.821 (10.849)	0.996 (112.894)	0.999 (32.465)	0.809 (25.825)	1.192 (8.762)	1.867 (21.453)
AR(2)						-0.427 (-2.994)	-0.868 (-9.845)
SAR(4)				-0.580 (-4.760)		-0.427 (-3.000)	-0.970 (-81.718)
MA(1)	2.029 (22.789)	0.777 (8.869)	0.764 (8.761)		0.287 (3.450)		-0.618 (-4.710)
MA(2)	2.046 (16.104)	0.693 (13.154)			0.132 (1.317)		
MA(3)	1.986 (20.354)	0.916 (11.488)			0.844 (9.552)		
MA(4)	0.969 (15.567)						
SMA(4)			-0.899 (-30.058)				
Adj R^2	0.930	0.956	0.897	0.712	0.990	0.711	0.906
SC	-6.577	-6.728	-5.809	-5.551	-2.306	-3.829	-6.366
S. E	0.007	0.001	0.012	0.014	0.061		0.009
AR Root		0.821	0.996 0.974 0.764	0.999 0.873	0.809	0.808 0.654	0.983 0.883
MA Root	0.995 0.989	0.999 0.957	0.974 0.763		0.999 0.918		0.992 0.618
P[QLB]	0.355	0.084	0.103	0.432	0.053	0.406	0.103
LR (SEA DUM)	65.826 [0.000]	19.493 [0.001]			2.584 [0.407]	2.829 [0.034]	1.949 [0.106]
LR (SEA DUM, CON)	169.279 [0.000]	36.149 [0.000]			7.581 [0.000]	18.751 [0.000]	66.771 [0.000]

Note see Table 5.1 6 for details and P_(D) = index pulse dummy variable indicator

[72] Note that we only consider those countries that identified with breaks in the previous section with the minimum of 39 observations after the last break and initialization period of two years. Therefore, we did not consider Ecuador, Kuwait and China in this section because they did not meet our minimum requirement.

In summary, Table 5.2.3 summaries seasonal ARIMA models for both BRICS and selected OPEC countries using a reduced sample period that avoids structural breaks for the following countries: Brazil, Russia, South Africa, Algeria, Angola, Nigeria and Saudi Arabia. We only built models for countries where the reduced sample had at least 39 observations. This will allow us to assess whether forecast accuracy is generally better for seasonal ARIMA specifications using a shorter sample that avoids the modelling of structural breaks or models developed on the full sample where structural breaks are modelled. For Russia, the in-sample fit (according to the $\bar{R}^2$) is superior using the reduced sample specification while for the following countries the in-sample fit is better for the ARIMAX specifications based on the full sample: Brazil, South Africa, Algeria, Angola, Nigeria and Saudi Arabia.[73] For the following countries, there is no in-sample fit comparison because models were not developed on the reduced sample: India, China, Ecuador and Kuwait. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

[73] See Table 5.4.6 for details.

5.3.0 Modelling annual inflation using Eviews 9's automatic seasonal ARIMA model selection tool on reduced samples without structural breaks

In this section, we conduct a further ARIMA modelling experiment to provide an additional model formulation for comparative purposes. We develop seasonal ARIMA models to forecast unadjusted annual inflation variables over the reduced sub-samples (without structural breaks) identified in section 5.2. This is done for the countries where the sub-sample contains at least 39 observations.[74] The difference between these models and those developed in section 5.2 is that we utilise EViews 9's automatic ARMA model selection procedure. This procedure selects seasonal models that minimise the Schwarz (SC) criterion of all ARMA specifications nested within the assumed maximum order of non-seasonal AR and MA components of 3 and maximum seasonal AR and MA components of order 2. A maximum order of 3 for the non-seasonal components is specified because the seasonal terms will capture lag 4 and, in multiplicative specifications, will capture lag 5 (provided a corresponding non-seasonal ARMA component is included). We do not consider the automatic selection of logarithmic or differencing transformations that are also available because we believe that the annual inflation data is stationary. We also include deterministic seasonal dummy variables in the model as exogenous variables when the automatic ARMA selection takes place to yield automatically selected seasonal ARIMA specifications. Whilst we report diagnostic checks (for residual autocorrelation, stationarity and invertibility) for the selected models we do not reject automatically selected models for forecasting that fail these checks because this is not intended in real world applications (it is a cost that needs to be offset against the time saving benefit of the method). However, we will consider whether the forecasting performance of the models that fail these checks notably deteriorates relative to models that do not fail these checks. We will also assess whether EViews 9's automatic ARMA selection procedure leads to the inclusion of statistically insignificant variables.

[74] We include China in this section because the period after the structural breaks are less than 39 observations and relative step shifts for this period also appear to be small which mean that inference regarding unit roots may not be too adversely affected when using the full sample. Hence, the full sample is used for these models for this country.

Table 5.3.1. Automatic Eviews seasonal ARMA specifications: BRICS countries

Countries	Brazil	Russia	India	China	South Africa
Start	1997Q2	2003Q2	1961Q1	1992Q1	1995Q2
End	2012Q4	2012Q4	2012Q4	2012Q4	2012Q4
Observations	63	39	208	84	71
ARMA Specifications	(1,1)(0,1)	(2,2)(2, 2,)	(1,3)(0,0)	(3,2)(0,1)	(1, 1)(0,1)
D_1	0.064 (10.263)	0.105 (9.451)	0.077 (7.149)	0.030 (2.857)	0.063 (30.375)
D_2	0.064 (10.276)	0.106 (9.486)	0.077 (7.139)	0.030 (2.835)	0.062 (26.257)
D_3	0.064 (9.986)	0.106 (9.572)	0.077 (7.145)	0.029 (2.810)	0.062 (28.628)
D_4	0.064 (10.054)	0.106 (9.541)	0.077 (7.138)	0.029 (2.783)	0.063 (32.350)
AR(1)	0.928 (8.247)	1.930 (5.267)	0.569 (12.018)	1.017 (3.118)	0.791 (9.032)
AR(2)		-0.951 (-2.778)		0.835 (1.358)	
AR(3)				-0.870 (-2.814)	
SAR(4)		-0.951 (-1.252)			
SAR(8)		-0.624 (-2.427)			
MA(1)	0.999 (0.000)	-0.360 (-0.211)	0.983 (0.010)	0.310 (0.005)	0.761 (8.526)
MA(2)		0.989 (0.095)	0.983 (0.010)	-0.699 (-0.015)	
MA(3)			0.999 (0.006)		
SMA(4)	-0.999 (-0.001)	-1.908 (-0.000)		-0.999 (-0.006)	-1.000 (-0.001)
SMA(8)		0.999 (0.000)			
Adj R^2	0.928	0.983	0.925	0.944	0.856
SC	-6.236	-6.094	-5.257	-5.669	-5.138
S.E	0.003	0.003	0.015	0.010	0.013
AR Root	0.952	0.975 0.942	0.569	0.972 0.919	0.791
MA Root	0.999	0.999 0.995	0.999	0.999	1.000 0.761
P[QLB]	0.544 [8]	0.000 [6]	0.043 [14]	0.213 [9]	0.606 [8]
LR (SEA DUM)	7.501 [0.000]	36.775 [0.000]	9.737 [0.000]	2.640 [0.041]	3.049 [0.023]
LR (SEA DUM,CON)	213760.000 [0.000]	16.825 [0.000]	32.493 [0.000]	3.392 [0.022]	28.252 [0.000]

Where: MA = the maximum order of non-seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB] = Probability value of the Ljung-Box Q-statistic where the number of ACs included in the ACF is indicated in brackets, Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the test for the joint significance of the seasonal dummy variables and LR (SEA DUM, CON) is the Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal.

Table 5.3.2 Automatic Eviews seasonal ARMA specifications: OPEC countries

Countries	Algeria	Angola	Nigeria	Saudi Arabia
Start	1999Q2	2000Q4	1998Q4	1979Q3
End	2012Q4	2012Q4	2012Q4	2012Q4
Observations	55	49	57	134
ARMA Specifications	(1,0)(0,1)	(3,0)(0,1)	(1,1)(0,1)	(2,1)(0,1)
D_1	0.037 (2.786)	1.541 (0.662)	0.123 (19.261)	0.012 (2.615)
D_2	0.038 (2.840)	1.534 (0.661)	0.119 (16.645)	0.012 (2.577)
D_3	0.040 (3.018)	1.536 (0.662)	0.121 (18.260)	0.012 (2.616)
D_4	0.038 (2.809)	1.540 (0.663)	0.122 (21.520)	0.012 (2.582)
AR(1)	0.986 (4.091)	1.683 (14.890)	0.767 (6.360)	1.962 (33.246)
AR(2)		-0.384 (-2.012)		-0.967 (-15.973)
AR(3)		-0.303 (-3.409)		
MA(1)			0.426 (2.452)	-0.813 (-5.887)
SMA(4)	-0.999 (-0.001)	-1.000 (-0.000)	-1.000 (-0001)	-0.999 (-0.021)
Adj R^2	0.755	0.987	0.787	0.908
SC	-5.295	-1.648	-3.929	-6.249
S.E	0.013	0.069	0.024	0.008
AR Root	0.986	0.996	0.767	0.983
MA Root	0.999	1.000[75]	1.000 0.426	0.999 0.812
P[QLB]	0.725 [7]	0.068 [7]	0.967 [8]	0.082 [12]
LR (SEA DUM)	4.089 [0.006]	3.207 [0.023]	5.498 [0.001]	4.276 [0.003]
LR (SEA DUM,CON)	16.117 [0.000]	0.069 [0.976]	5.497 [0.001]	333.029 [0.000]

See notes to Table 5.3.1

[75] The value is rounded up to one, however, it is less than one indicating that invertibility is not violated.

Table 5.3.3 Automatic Eviews seasonal ARMA specifications for Angola

Countries	Angola
Start	2000Q4
End	2012Q4
Observations	49
ARMA Specifications	(3,0)(0,1)
C	1.501 (0.833)
AR(1)	1.681 (19.990)
AR(2)	-0.383 (-2.527)
AR(3)	-0.302 (-3.890)
SMA(4)	-0.999 (-0.013)
Adj R^2	0.987
SC	-1.800
S.E	0.068
AR Root	0.986
MA Root	0.995 0.305
P[QLB]	0.038 [7]
LR (C, DUM)	8.854 [0.005]

See notes to table 5.3.1. Note that C denotes the intercept and LR(C, DUM) denotes the test for the significance of the intercept that replaced the 4 seasonal dummy variables.

The seasonal ARIMA models automatically selected for the seasonally unadjusted data are reported in Table 5.3.1 (BRICS countries) and Table 5.3.2 (OPEC countries) above. Three of the 5 BRICS countries' automatically selected models fail the standard diagnostic checks for autocorrelation (Russia and India) and invertibility (South Africa). Only Nigeria failed the standard diagnostic checks (for invertibility) in the selected OPEC countries. Hence, 5 of the 9 countries' selected models are valid for forecasting, in the sense that they are not rejected by the diagnostic checks, while there are 4 countries where the automatically selected models are rejected by these diagnostic checks. We therefore might expect that the forecasting performance of the automatically selected models for these 4 countries will be adversely affected relative to those where the checks are not failed. We will see whether this is the case when assessing the ex post forecasting performance of these models.

Regarding the statistical significance of the models' coefficients, we note the following. The seasonal dummy variables are jointly significant in all 9 models indicating the need to include seasonal dummy variables – see LR(SEA DUM). Further, the seasonal dummy variables are significantly different from each other for 8 of the 9 countries (Angola is the exception) suggesting significant deterministic seasonality in these countries' models – see LR(SEA DUM, CON). For Angola, where the seasonal dummy variables are not significantly different, we replace the 4 seasonal dummy variables with a single intercept because seasonality is not significant. This model is reported in the Table 5.3.3 and represents our favoured automatically selected seasonal model for Angola. In all 9 countries, the automatic selection procedure yields models where several ARMA coefficients are statistically insignificant (including the highest order AR or MA terms). This suggests that the automatic selection procedure generally selects models with variables that would be considered for exclusion by a modeller. It will be interesting to see whether this has an impact on the forecasting performance of these models

5.4.0 Modelling annual inflation using Eviews 9's automatic non-seasonal ARIMA model selection tool on reduced samples without structural breaks

In this section, we conduct a further ARIMA modelling experiment to provide an additional model formulation for comparative purposes for chapter 5. These ARIMA models' forecasting performance will be compared to those developed in section 5.1, 5.2 and 5.3. We modify the methodology applied in section 5.3 in the following two ways. First, we seasonally adjust the data on annual inflation prior to developing a non-seasonal ARIMA model using the census X13 method of (multiplicative) seasonal adjustment.[76] This method allows the seasonal indices to vary over time and captures any stochastic seasonality in the data. The non-seasonal ARMA model is used to forecast the seasonally adjusted data for 2013 and 2014 and the four seasonal indices used to adjust the data in 2012 are used to reintroduce seasonality into these forecasts yielding predictions of the original (unadjusted) series. These seasonal forecasts can therefore be compared with those produced by the models developed in section 5.1, 5.2 and 5.3 – these forecasts are compared in later chapters. To ameliorate the impact of the (sometimes very large) structural breaks on the seasonal adjustment procedure we use the reduced sub-samples without structural breaks identified in chapter 5.2 for countries where the sub-sample contains at least 39 observations.

Second, we utilise EViews 9's automatic ARMA model selection procedure that minimises the Schwarz (SC) criterion of all ARMA specifications nested within the assumed maximum non-seasonal ARMA (5, 5) specification. We do not consider the automatic selection of logarithmic or differencing transformations that are also available because we believe that the annual inflation data is stationary (as discussed above). We also include deterministic seasonal dummy variables in the model as exogenous terms when the automatic ARMA selection takes place to yield automatically selected non-seasonal ARIMA specifications. Whilst we report diagnostic checks (for

[76] All the countries are seasonal adjusted with the census X13 multiplicative method except for India, China, South Africa, Algeria, Nigeria and Saudi Arabia that are seasonally adjusted with the census X12 method of (additive) seasonal adjustment. We use the census X- 12 to adjust annual inflation in these countries because the census X13 method of (multiplicative and additive) cannot be implemented with a series with zero or negative values.

residual autocorrelation, stationarity and invertibility) for the selected models we do not reject automatically selected models for forecasting that fail these checks because this is not intended in real world applications (it is a cost that needs to be offset against the time saving benefit of the automatic selection method). However, we will consider whether the forecasting performance of the models that fail these checks notably deteriorates relative to models that do not fail these checks. We will also assess whether EViews 9's automatic non-seasonal ARMA selection procedure leads to the inclusion of statistically insignificant variables. The seasonal factors used in the seasonal adjustment of each country's data for 2012 are presented in Table 5.4.1 (BRICS countries) and Table 5.4.2 (OPEC countries) below.[77]

Table 5.4 .1

Observations	INF_BRA (M)	INF_RUS (M)	INF_IND (A)	INF_CHI (A)	INF_SOU (A)
2012Q1	0.999689	0.988775	0.002035	0.001556	-0.00119
2012Q2	0.993315	0.966174	-0.0001	0.000148	-0.00336
2012Q3	1.003945	1.006558	-0.00012	-0.00114	-0.00547
2012Q4	1.003383	1.040168	-0.00205	-0.00055	0.010634

Table 5.4.2

Observations	INF_ALG (A)	INF_ANG (M)	INF_NIG (A)	INF_SAU (A)
2012Q1	-0.00108	0.997064	0.004994	-0.00100
2012Q2	0.001466	1.00181	0.001509	0.000761
2012Q3	-0.00054	0.996738	-0.00588	4.37E-05
2012Q4	-0.00011	1.00440	-0.00117	0.000229

The non-seasonal ARMA models automatically selected for the seasonally adjusted data are reported in Table 5.4.3 (BRICS countries) and Table 5.4.4 (OPEC countries) below. None of the automatically selected models could be rejected according to the standard diagnostic checks that we conduct for the 5 BRICS countries. However, for 2 of the 4 selected OPEC countries the automatically selected models failed the diagnostic checks for autocorrelation (Angola) and invertibility (Nigeria). Hence, while 7 of the 9 countries'

[77] Where INF_* denotes inflation, * denotes the first three letters of each country, (M) denotes multiplicative indices and (A) denotes additive indices.

selected models are valid for forecasting, in the sense that they are not rejected by the diagnostic checks, there are 2 countries where the automatically selected models are rejected by these checks. We, therefore, might expect that the forecasting performance of the automatically selected models for these 2 countries will be adversely affected. We will see whether this is the case when assessing the ex-post forecasting performance of these models.

Regarding the statistical significance of the models' coefficients, we note the following. The seasonal dummy variables are jointly significant in all 9 models indicating the need to include seasonal dummies – see LR(SEA DUM). Further, the seasonal dummy variables are significantly different from each other for 7 of the 9 countries suggesting significant deterministic seasonality in these countries' models – see LR(SEA DUM, CON). In the 2 countries (Brazil and Angola) where the seasonal dummy variables are not significantly different we replace the 4 seasonal dummy variables with a single intercept because deterministic seasonality is not significant. These models are reported in Table 5.4.5 for Brazil and Angola and they represent the automatically selected non-seasonal models that are favoured for forecasting for these countries. For 8 of the 9 countries (the exception is India) the automatic selection procedure yields models where several ARMA coefficients are statistically insignificant (including the highest order AR or MA term). This suggests that the automatic selection procedure generally selects models with variables that would be considered for exclusion by a modeller. It will be interesting to see whether this has an impact on the forecasting performance of these models.

Table 5.4.3 Automatic Eviews non-seasonal ARMA specifications: BRICS countries

Countries	Brazil	Russia	India	China	South Africa
Start	1997Q2	2003Q2	1961Q1	1992Q1	1995Q2
End	2012Q4	2012Q4	2012Q4	2012Q4	2012Q4
Observations	63	39	208	84	71
ARMA(p,q) Specifications	(0,4)	(1,3)	(1,3)	(1, 4)	(2,2)
D_1	0.064 (6.185)	0.102 (8.357)	0.077 (6.298)	0.041 (1.670)	0.067 (8.556)
D_2	0.064 (6.023)	0.010 (8.468)	0.077 (6.412)	0.041 (1.711)	0.065 (7.702)
D_3	0.063 (5.983)	0.102 (8.432)	0.077 (6.449)	0.042 (1.723)	0.065 (8.383)
D_4	0.063 (6.104)	0.099 (8.320)	0.077 (6.288)	0.041 (1.669)	0.065 (7.838)
AR(1)		0.643 (3.003)	0.632 (13.628)	0.903 (10.732)	1.187 (11.307)
AR(2)					-0.736 (-6.307)
MA(1)	1.571 (0.004)	0.974 (0.002)	0.758 (13.325)	0.353 (1.971)	-0.085 (-0.038)
MA(2)	1.656 (0.002)	0.974 (0.001)	0.720 (12.623)	0.544 (0.386)	0.999 (0.019)
MA(3)	1.564 (0.001)	0.999 (0.001)	0.721 (13.589)	0.332 (0.670)	
MA(4)	0.629 (0.001)			-0.455 (-0.731)	
Adj R^2	0.896	0.924	0.901	0.930	0.830
SC	-5.993	-5.889	-5.033	-5.579	-4.988
S.E	0.009	0.008	0.017	0.012	0.015
AR Root		0.643	0.632	0.903	0.857
MA Root	0.999 0.793	0.999	0.907 0.876	0.998 0.866 0.528	0.999
P[QLB]	0.626 [8]	0.293 [6]	0.269 [14]	0.662 [9]	0.335 [8]
LR (SEA DUM)	23.548 [0.000]	6.399 [0.001]	6.769 [0.000]	3.398 [0.013]	16.153 [0.000]
LR (SEA DUM,CON)	0.658 [0.581]	8.762 [0.000]	663 [0.000]	36.026 [0.000]	40.752 [0.000]

Where: MA = the maximum order of non-seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB] = Probability value of the Ljung-Box Q-statistic where the number of ACs included in the ACF is indicated in brackets, Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the test for the joint significance of the seasonal dummy variables and LR (SEA DUM, CON) is the Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal.

Table 5.4.4 Automatic Eviews non-seasonal ARMA specifications: selected OPEC countries

Countries	Algeria	Angola	Nigeria	Saudi Arabia
Start	1999Q2	2000Q4	1998Q4	1979Q3
End	2012Q4	2012Q4	2012Q4	2012Q4
Observations	55	49	57	134
ARMA(p,q) Specifications	(0, 3)	(1, 3)	(0, 3)	(1, 4)
D_1	0.037 (4.543)	1.202 (0.800)	0.121 (7.493)	0.016 (1.196)
D_2	0.037 (4.708)	1.190 (0.792)	0.118 (7.195)	0.017 (1.258)
D_3	0.041 (5.122)	1.198 (0.799)	0.124 (7.747)	0.017 (1.241)
D_4	0.037 (4.485)	1.190 (0.789)	0.117 (7.776)	0.016 (1.221)
AR(1)		0.982 (9.502)		0.912 (10.520)
MA(1)	0.972 (0.088)	0.537 (0.001)	0.999 (0.001)	0.247 (1.198)
MA(2)	0.971 (0.100)	0.938 (0.000)	0.999 (0.000)	0.401 (0.048)
MA(3)	0.999 (0.068)	0.635 (0.000)	1.000 (0.000)	0.190 (0.117)
MA(4)				-0.607 (-0.122)
Adj R^2	0.748	0.982	0.750	0.900
SC	-5.187	-1.395	-3.808	-6.172
S.E	0.013	0.083	0.026	0.009
AR Root		0.981		0.912
MA Root	0.999	1.000[78] 0.635	1.000	0.999 0.892 0.680
P[QLB]	0.612 [7]	0.025 [7]	0.286 [8]	0.092 [12]
LR (SEA DUM)	12.803 [0.000]	5.428 [0.001]	26.451 [0.000]	3.280 [0.014]
LR (SEA DUM,CON)	6.322 [0.001]	2.443 [0.078]	4.487 [0.007]	34.607 [0.000]

See the notes to Table 5.4.3

[78] This value is rounded up to one, however, it is less than one and therefore does not reject invertibility for this model.

Table 5.4.5 Automatic Eviews non-seasonal ARMA specifications for Brazil and Angola

Countries	Brazil	Angola
Start	1997Q2	2000Q4
End	2012Q4	2012Q4
Observations	63	49
ARMA(p,q) Specifications	(0,4)	(1, 3)
C	0.064 (7.201)	1.196 (0.802)
AR(1)		0.983 (8.900)
MA(1)	1.590 (17.895)	0.477 (0.013)
MA(2)	1.631 (10.161)	0.916 (0.002)
MA(3)	1.467 (6.503)	0.614 (0.003)
MA(4)	0.600 (5.864)	
Adj R^2	0.889	0.982
SC	-6.116	-1.586
S.E	0.009	0.082
AR Root		0.983
MA Root	0.964 0.804	0.999 0.614
P[QLB]	0.774 [8]	0.019 [7]
LR (C, DUM)	9.023 [0.000]	20.202 [0.000]

See notes to table 8.6. Note that C denotes intercept and LR(C, DUM) denotes the test for the significance of the intercept that replaced the 4 seasonal dummy variables.

Table 5.4.6 Comparison of in-sample fit (adjusted R–square) of different ARIMA models

Countries	Chapter 5.1 ARIMAX full sample modelling	Chapter 5.2 seasonal ARIMA reduced sample modelling without breaks	Chapter 5.3 EViews 9's reduced sample automatic ARIMA seasonal modelling	Chapter 5.4 EViews 9's reduced sample automatic ARIMA non-seasonal modelling
Brazil	0.956	0.930	0.928	0.889
Russia	0.932	0.956	0.983	0.924
India	0.926		0.925	0.901
China	0.943		0.944	0.930
South Africa	0.939	0.897	0.856	0.830
Algeria	0.893	0.712	0.755	0.748
Angola	0.997	0.990	0.987	0.982
Ecuador	0.980			
Kuwait	0.949			
Nigeria	0.911	0.711	0.787	0.750
Saudi Arabia	0.960	0.906	0.908	0.900

Table 5.4.6 reports the adjusted R-squares of the favoured ARIMAX/ARIMA models developed in chapters 5.1 and 5.2 with those obtained by Eviews 9's automatic selections procedure. The automatically selected non-seasonal ARIMA models have the lowest R-squares for all countries except Algeria and Nigeria (where the fit is the third best out of the 4 models in both cases).[79] For 7 of the 9 countries (the exception is Russia and China) the adjusted R-squares of the ARIMAX models developed on the full sample that model structural breaks are greater than those of the other models. Whether the generally superior fit to modelling the full sample is due to overfitting the sample (especially overfitting structural breaks in the full sample) or will be reflected in the out-of-sample forecasting performance will be considered in the chapter when the forecasting performance of the models of the different countries is compared.[80]

[79] This may be because the dependent variable is seasonally adjusted for these models whereas they are unadjusted for the other models.
[80] This difference in fit may also be because the models developed in section 5.1 generally use a larger sample than the other models.

5.5.0 Forecast performance and evaluation for Univariate model

In this section, we compare the forecasting performance of ARIMAX models estimated over the full sample and different ARIMA specifications estimated on a reduced sample (with a minimum of 39 observations). When using the full sample, there may be structural breaks that the ARIMAX model accommodates using dummy variables and seasonality that is modelled using seasonal dummy variables and seasonal AR and MA terms. The reduced sample modelling was designed to avoid structural breaks such that there is no need for deterministic terms to model such shifts. Hence, the first set of ARIMA models developed using the reduced sample only include seasonal dummy variables and seasonal AR and MA components. A second set of ARIMA models developed for the reduced sample employ EViews 9's automatic seasonal ARIMA model specification routine. A third set of ARIMA models were developed for the reduced sample where the data are first seasonally adjusted and EViews 9's automatic non-seasonal ARIMA model specification routine is employed. In this latter case forecasts are re-seasonalised using the 2012 seasonal indices obtained from the seasonal adjustment procedure.

We seek to assess the following. First, whether superior forecasts can be obtained by using the full sample (with the benefit of more information) and explicitly modelling the structural breaks (with the possibility of overfitting and difficulty in adequately capturing such effects) or whether using reduced samples (with the disadvantage of fewer data points) is compensated by the avoidance of having to model any structural breaks. Second, whether quick automatic ARIMA selection procedures can produce as good forecasts as specifications produced using more time-consuming model building techniques. Third, whether ARIMA specifications that explicitly model seasonality are superior to specifications that apply non-seasonal models to seasonally adjusted data followed by reseasonalising the forecasts. Each model was estimated over a period that ended in 2012q4 (the start of the estimation period varies across models and countries). These models are used to produce forecasts over the ex-post forecasting period 2013q1 – 2014q4. These produce 1-step ahead forecasts for 2013q1, 2-step ahead forecasts for 2013q2 and so on up to 8-step ahead forecasts for 2014q4.[81] The identified models were

[81] Due to the sample variation (different sample for different country), our forecast comparison is based on out-sample and we did not consider in-sample comparison. It is well known that in-sample

then re-estimated by adding one observation to the end of the sample, hence the models are estimated over a period ending in 2013q1. These estimated models are used to produce 1-step ahead forecasts for 2013q2, 2-step ahead forecasts for 2013q3 and so on up to 7-step ahead forecasts for 2014q4. This process is then repeated with one observation being added to the estimation period (with the last rolling regression's sample period ending in 2014q3), and m-step ahead forecasts produced up to the end of the forecast period. These rolling regressions produce eight 1-step ahead forecasts, seven 2-step ahead forecasts, six 3-step ahead forecasts, five 4-step ahead forecasts and so on up to one 8-step ahead forecast for each estimated model.

Second, we compare the forecasting performance of each model over the different number of step ahead forecasting horizons using the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Theil's inequality coefficient (U). The best forecasting model, on average, over any particular horizon will have the lowest value of forecasting performance measures. The RMSE and U have a quadratic loss function that gives more weight to extreme errors than smaller errors (e.g the square error of 50 is disproportionately more than the square error of 25) while the MAPE has a proportional loss function where small and large errors are weighted similarly. These forecasting performance measures can be classified into two categories: relative measures (MAPE and Theil's U-statistic) and absolute measures (RMSE).[82]The difference between the two types of measure is that relative measures are not determined by the units of measurement of the data and can be used to compare the forecasting performance of different series (including across different countries) while the value of absolute measures are determined by the unit of measurement of the data and only provide valid comparisons of models applied to the same data (for the same country).

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comparison does not guarantee good forecasting performance. A general problem is that in-sample estimation error usually increases with the sample size, and if the forecast sample increase the forecast error may increase.

[82]The root mean squared error (RMSE) = $\sqrt{\frac{\sum e_t^2}{n}} = \sqrt{\frac{\sum (X_t - F_t)^2}{n}}$. The percentage error is (PE_t) = $(\frac{X_t - F_t}{X_t})$ x 100, Mean absolute percentage error is (MAPE) = $\frac{1}{n}\sum_{t=1}^{n}\ /PE_t/$, and Theil's U-statistic is U = $\frac{Rmse}{\sqrt{\frac{\sum X_t^2}{n}}+\sqrt{\frac{\sum F_t^2}{n}}} = \frac{\sqrt{\frac{\sum e_t^2}{n}}}{\sqrt{\frac{\sum X_t^2}{n}}+\sqrt{\frac{\sum F_t^2}{n}}} = \frac{\sqrt{\frac{\sum (X_t - F_t)^2}{n}}}{\sqrt{\frac{\sum X_t^2}{n}}+\sqrt{\frac{\sum F_t^2}{n}}}$, Where $X_{t,}$ is the actual observation for time period $t_,$ F_t is the forecast for the same period with $e_{t,}$ = $X_{t,}$ - F_t and *n* is the number of forecast periods used in the calculation.

5.5.1 Brazil Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA models. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 (Table 5.1.3). The reduced sample models that avoid structural breaks are estimated over the period 1997q2 to 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model discussed in section 5.2 (Table 5.2.1), EViews 9's automatically selected seasonal ARIMA model discussed in section 5.3 (Table 5.3.1) and EViews 9's automatically selected non-seasonal ARIMA model discussed in section 5.4 (Table 5.4.5). The forecast performance measures of these models are given in Table 5.5.1.

Table. 5.5.1: Forecast performance of Univariate models for Brazil

	A Full sample seasonal ARIMAX model with modelling structural breaks			**B** Reduced sample seasonal ARIMA model without modelling structural breaks			**C** Reduced sample EView9 Automatic seasonal ARIMA model without modelling breaks			**D** Reduced sample EView9 Automatic's non-seasonal ARIMA model without modelling structural breaks		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	21.2100	14.2420	0.9960	0.0050	6.3580	0.0360	0.0050*	5.0690*	0.0360*	0.0060	7.8950	0.0490
2-step	24.3500	21.4800	0.9960	0.0060	8.9510	0.0490	0.0060*	8.0390*	0.0470*	0.0070	9.5170	0.0560
3-step	26.4200	25.4060	0.9960	0.0080	10.4100	0.0640	0.0060	10.1500	0.0560	0.0060*	8.2540*	0.0480*
4-step	28.9400	30.4640	0.9960	0.0060	7.1580	0.0460	0.0060	8.6970	0.0500	0.0030*	3.7780*	0.0220*
5-step	32.3600	38.0500	0.9970	0.0040	5.8330	0.0300	0.0070	9.3930	0.0520	0.0002*	0.1580*	0.0010*
6-step	37.3600	50.6330	0.9970	0.0050	7.3880	0.0430	0.0060	7.2460	0.0430	0.0004*	0.5880*	0.0040*
7-step	19.1300	30.0090	0.9940	0.0100	15.7600	0.0790	0.0060	8.2260	0.0490	0.0004*	0.7080*	0.0040*
8-step	14.9000	25.7580	0.9920	0.0020	3.3460	0.0170	0.0090	15.4300	0.0720	0.0004*	0.3390*	0.0020*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The reduced sample univariate model that employs the automatic non-seasonal ARIMA technique, see column D, has the lowest RMSE, MAPE and U-statistics over all forecasting horizons except for the 1 and 2 step-ahead horizons. However, the reduced sample ARIMA model that employs Eviews 9's automatic seasonal selection procedure has the lowest RMSE, MAPE and U values for 1 and 2-step-ahead horizons (Table 5.5.1 column C). Hence, the reduced sample specifications that employ the EView's 9 automatic model selection process produces the best forecasts over all horizons. We note that the univariate ARIMA specification that employs the Box-Jenkins method for the full sample ARIMAX (Table. 5.5.1 column A) and the reduced sample ARIMA (Table. 5.5.1 column B) methods were never favoured. These results imply the following for the univariate modelling on Brazilian data. First, the potential difficulties in explicitly modelling the structural breaks outweighed the benefits of being able to use more data in estimation. Given the extra time and modeller expertise required to model such breaks, this suggests that using reduced samples to avoid structural breaks is the preferred strategy. Second, the quick automatic ARIMA selection procedures produce superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques. Third, the benefits of seasonally adjusting the data and re-seasonalising the forecasts generally outperforms the method of modelling seasonality in ARIMA forecasting (although not always). Finally, note that the MAPE of the favoured ARIMA model is always less than 10 percentage points suggesting a relatively good forecasting performance for this class of models for Brazilian inflation. A similar procedure was applied for all countries and a summary of the favoured methods is given below in the Table 5.5.2 and 5.5.3. The detailed results and discussion are available in Appendix. Section 5.3 page 426 – 443.

Table 5.5.2 Summary of the best forecasting univariate models for BRICS countries

Best forecasting Univariate model for Brazil				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1-to 2-steps	R_A _SARIMA	R_A_SARIMA	R_A_SARIMA	5.0690 – 8.0390
3 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	0.3390 -8.2540
Best forecasting univariate model for Russia				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	6.3660 – 20.6300
Best forecasting univariate model for India				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8- steps	F_SARIMA	F_SARIMA	F_SARIMA	13.5200 -63.4600
Best forecasting univariate model for China				
	RMSE	**U –statistics**	**MAPE**	
1 to 2-steps	F_A_SARIMA	F_A_SARIMA	F_A_SARIMA	7.1980 – 14.0000
3 to 8- steps	F_A_ARIMA	F_A_ARIMA	F_A_ARIMA	14.5800 -19.5400
Best forecasting univariate model for South Africa				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 4 –steps	R_A_SARIMA	R_A_SARIMA	R_A_SARIMA	14.2800 -20.9900
5-step	R_SARIMA	R_A_SARIMA	R_SARIMA	17.2600
6 to 7-steps	R_A_SARIMA	R_A_SARIMA	R_A_SARIMA	12.3600- 13.3600
8-step	R_SARIMA	R_SARIMA	R_SARIMA	10.2000

The best univariate forecasting model is identified by each measure (RMSE, MAPE and U) for each forecasting horizon (1, 2…, 8 steps ahead). The full sample univariate model that employs seasonal Box-Jenkins ARIMA techniques and model's structural breaks is denoted as F_SARIMAX, the full sample univariate model that employs Box-Jenkins ARIMA techniques without modelling structural breaks is denoted as F_SARIMA (this model type is exclusive to India because there were no significant structural breaks to model over the full sample). The full sample specifications that employ EViews 9's automatic seasonal and non-seasonal ARIMA model without modelling breaks are denoted as F_A_SARIMA and F_A_ARIMA respectively (these models are exclusively designed for China because the period after the structural breaks are less than 39 observations and relative step shifts for this period also appear to be small which mean that inference regarding unit roots may not be too adversely affected when using the full sample. Hence, the full sample is used for these models for this country). The reduced sample model that employs seasonal ARIMA technique's without modelling structural breaks is denoted as R_SARIMA. The reduced sample model that employs EViews 9's automatic seasonal ARIMA model selection procedure without modelling breaks is denoted as R_A_SARIMA and the reduced sample model that employs EViews 9's automatic non-seasonal ARIMA model selection method without modelling breaks is represented by R_A_ARIMA. Range gives the range of values for the MAPE for models favoured according to this forecasting measure over the specified horizon.

Table 5.5.3 Summary of the best forecasting univariate models for OPEC countries

Best forecasting univariate model for Angola				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	R_SARIMA	R_SARIMA	R_SARIMA	2.0590 – 13.3300
Best forecasting univariate model for Algeria				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 –step	F_SARIMAX	F_SARIMAX	R_A_SARIMA	61.6300
2 –step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	82.6100
3 to 7-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	27.3800- 136.0000
8-step	F_SARIMAX	R_SARIMA	F_SARIMAX	28.7700
Best forecasting univariate model for Ecuador				
	RMSE	**U- statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	15.4500 -42.9100
Best forecasting univariate model for Saudi Arabia				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 2-steps	R_SARIMA	R_SARIMA	R_SARIMA	8.3720 -14.8500
3 to 8-step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	1.0100 – 15.1400
Best forecasting univariate model for Nigeria				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1-step	R_SARIMA	R_SARIMA	R_SARIMA	19.2400
2-step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	22.8700
3-step	R_SARIMA	R_SARIMA	R_A_ARIMA	38.1200
4 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	40.7200 – 46.5100
Best forecasting univariate model for Kuwait				
	RMSE	U-statistics	MAPE	
Horizon	Type	Type	Type	Rage
1 to 8-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	11.2100 – 38.5900

See note in the Table 5.5.2

For BRICS countries, see Table 5.5.2, the EViews 9 automatic model selection procedure is virtually always favoured for all countries except India. The reduced sample automatic seasonal method is favoured for Brazil over the 1 and 2 steps ahead horizons and for South Africa over the 1 to 4 and 6 to 7-step ahead horizons. The full sample automatic seasonal model is only favoured at the 1 and 2-step ahead horizons for China. The reduced sample automatic non-seasonal method is favoured for Brazil over the 3 to 8 step horizons and for Russia over all horizons. While the full sample automatic non-seasonal method is favoured for China over the 3 to 8 step horizons. The seasonal ARIMA model (without modelling structural breaks) is favoured for India over all horizons (using the full sample) and is preferred for South Africa over the 5 and 8 step horizons (using a reduced sample). For Brazil, Russia, China and South Africa, the MAPE values of all the favoured EViews 9 automatic selection models are always less than 21 percentage points. The MAPE value of the favoured automatic seasonal method is between 5.0690 – 8.0390 for Brazil, 7.1980 – 14.0000 for China and 12.3600- 20.9900 for South Africa. The MAPE values of the automatic non-seasonal method is between 0.3390- 8.2540 for Brazil, 6.3660 – 20.6300 for Russia and 14.5800 -19.5400 for China. The MAPE value for the seasonal ARIMA model (without modelling structural breaks) is between 13.5200 and 63.4600 for India and 10.2000 for South Africa. However, the ARIMAX model was never favoured for any BRICS country.

For OPEC countries, see Table 5.5.3, the EViews 9 automatic model selection procedure applied to the reduced sample is only occasionally favoured and the automatic seasonal method is never favoured for any horizon according to all the 3 forecasting performance measures (which contrasts with the results for BRICS countries). The automatic non-seasonal method is favoured for Algeria over the 2-step horizon, for Saudi Arabia over the 3 to 8 steps ahead horizons and for Nigeria over the 2 (possibly 3) and 4 to 8 step horizons. The seasonal ARIMA model (without modelling structural breaks) is favoured for Angola over all horizons, for Algeria possibly over the 8-step horizon, for Saudi Arabia over the 1 and 2 step horizons and Nigeria over the 1 (and possibly 3) step horizon. The ARIMAX model being the only valid model for Ecuador and Kuwait performs comparatively well for this class of model and produces the best forecast for Algeria over the 3 to 7 (and possibly 1 and 8) step horizons. The MAPE value for the seasonal ARIMA model (without modelling structural breaks) is between 2.0590 – 13.3300 for Angola, 28.7700 for Algeria, 8.3720 -14.8500 for Saudi Arabia and 19.2400 for Nigeria. While the MAPE value for the best automatic non-seasonal model is 82.6100 for Algeria, and 1.0100 – 15.1400 for Saudi Arabia as well as 22.8700 – 46.5100 for Nigeria. The corresponding ARIMAX value for the MAPE is between 11.2100 – 38.5900 for Kuwait, 15.4500 -42.9100 for Ecuador and 27.3800- 136.0000 for Algeria.

When comparing ARIMAX/ARIMA models for BRICS and OPEC countries, the ARIMAX model applied to the full sample is rarely favoured in the class of univariate models (except where it is the only valid model). This suggests that the potential benefits of using a full sample and explicitly modelling the structural breaks are generally outweighed by the benefits of being able to avoid modelling structural breaks at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is typically the preferred strategy. EViews 9's automatic model selection procedure applied to the reduced sample is often favoured (especially for the BRICS countries) although seasonal ARIMA modelling without using automatic model selection is sometimes favoured. Hence, the quick automatic ARIMA selection procedures often (though not always) produce superior forecasts compared to more time-consuming Box-Jenkins ARIMA modelling techniques. Of the two automatic ARIMA model selection procedures considered the non-seasonal method applied to seasonally adjusted data was more generally favoured than the seasonal method applied to unadjusted data. This suggests that the benefit of seasonally adjusting the data and re-seasonalising the forecasts generally outperforms the method of explicitly modelling seasonality.

5.6.0. Nonlinear model

In the previous section, we have seen remarkable success in the application of linear time series models (ARIMA and ARIMAX) to forecast inflation. One of the main conclusions from this section is that, linear time model (ARIMA and ARIMAX) yield specifications that are valid for forecasting. This is in the sense that they are not rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. However, different studies have document poor performance of linear ARIMA model over the nonlinear model most especially when to describe the transformation of macroeconomic dynamics or changes in the monetary policy (Bradley and Jansen (2004), Song et. al. (2003), Teräsvirta et al (2005)). They argue that linear model may not be used to capture features of the data that exist not to be stable. Instead, they argued in favour of nonlinear model. For example, the empirical studies (Tong, 1990, Granger and Terasvirta, 1993) document that the nonlinear model has ability to capture asymmetries, structural breaks that showed in many time series data. In this section, we investigate the forecast performance of nonlinear time series (threshold autoregressive models) and compared its forecasting performance with the best selected ARIMA/ARIMAX models estimated the previous chapter. The threshold autoregressive models (TAR model) is estimated over the full sample that identified with breaks and the reduced sub-samples (without structural breaks) identified in section 5.2.

5.6.1 Threshold Autoregressive model

The threshold autoregressive model (TAR model) was first proposed by Tong (1978) and discussed in detail by Tong and Lim (1980) and Tong (1983). The model is often classified as a nonlinear model that is typically designed to accommodate features of the data that cannot be captured by the linear models. It is used to describe the features of time series variables in two or more different regimes. For several decades, numerous works have been published regarding the application of the threshold model for modelling and forecasting macroeconomic variables. This model has proved successful in describing different economic environments that include periods of high and low inflation (Tiao and Tsay, (1991), Clements and Smith (1997)., Pippenger and Goering, (1998)). For instance, Tiao and Tsay (1991) compare the forecast performance of an AR(2) specification to two- regime Self- Exciting Threshold Autoregressive (SETAR) model for real US quarterly GNP. Evidence reveals that the SETAR model performs better than the AR model during the period of economic recession. This conclusion is similar to the studies of Clement and Smith (1997, 1999) who used the same approach to forecast UK GDP. Montgomery, et al. (1998) also compare the empirical forecasting performance of a set of time-series models for the U.S. unemployment rate. The time series models considered include linear univariate autoregressive integrated moving average (ARIMA) models, bivariate vector autoregressive moving average (VARMA) models, threshold autoregressive (TAR) models, Markov switching autoregressive (MSA), combined forecast and survey forecast method. Evidence reveals that the TAR and MSA models outperform other selected linear models during periods of economic contraction or period of rapidly rising unemployment. For example, the TAR model yields up to a 28% reduction in mean-squared forecast error for longer term forecasts relative to all linear models. The recent literature on inflation forecasting that apply a threshold framework is very rare. Although, the model has been recently used in other field for forecasting, most especially in Science and Engineering. For example, Amiri (2015) compared forecasting performance of 5 different nonlinear time series models, namely Threshold Autoregressive (TAR), Smooth Transition Autoregressive (STAR), Exponential Autoregressive (EXPAR), Bilinear Model (BL) and Markov Switching Autoregressive (MSAR) to forecast daily river flow at Colorado River in U.S.A., from 1/01/2000 to 12/31/2011. The results show that a self-exciting TAR (SETAR) model performs better than other four competing models. Similarly, Tongal and Booij (2016) examine the forecasting performance of two different nonlinear models (SETAR, and a chaotic k-nearest neighbour(k-nn) model) for nine flowing rivers that characterised as low, medium, and high flows in the western United States. Evidence reveals that the SETAR model is superior to the k-nn model for various forecast horizons. In our study, we examine whether the use of the threshold autoregressive model that accounts for different economic environments will improve the forecasting performance for inflation compared to the other models that we consider.

TAR is considered as the self-exciting threshold autoregressive (SETAR) model when the threshold variable is taken as the lagged value of the time series being modelled. The SETAR assumes that a variable y_t is a linear autoregression within a regime but may move between regimes depending on the value taken by a lag of y_t, say, y_{t-d} where d is the length of the delay.

The simple AR(p) model for a time series $\{y_t\}$ follow the process:

$$y_t = \emptyset_0 + \emptyset_1 y_{t-1} + \ldots + \emptyset_p y_{t-p} + \sigma\varepsilon_t \tag{5.0}$$

Where $\emptyset_i$ ($i = 1,2,\ldots, p$) are the AR coefficients, $\varepsilon_t \sim N(0,1)$ and $\sigma > 0$ is the standard deviation of the disturbance term. The model parameters $\emptyset = (\emptyset_0, \emptyset_1, \emptyset_2, \ldots, \emptyset_p)$ and σ are independent of time t and remain constant. To capture nonlinear dynamics, TAR models can be estimated as follow:

$$y_t = \emptyset_o{}^{(j)} + \emptyset_1{}^{(j)} y_{t-1} + \ldots + \emptyset_p{}^{(j)} y_{t-p} + \varepsilon_t{}^{(j)} \text{ if } r_{j-1} < z_t \leq r_j \,, \tag{5.1}$$

Where $j = 1, 2, \ldots, k$, $z_t = y_{t-d,}$. The threshold is $-\infty = r_0 < r_1 < \ldots < r_k = \infty$.; for j. k is the number of regimes separated by $k - 1$ nontrivial thresholds, $\{\varepsilon_t{}^{(j)}\}$ are independent identical distributed sequences with zero mean and variance $\sigma_j{}^2$ and are mutually independent for different j . The parameter d is the delay parameter, r_j are thresholds, p is denotes the AR order and $\emptyset_p$ are the autoregressive coefficients. An interesting feature of SETAR model is that, the stationarity of y_t does not require the model to be stationary in each regime. In this study, we use EViews to apply the Bai and Perron test to determine the number of the regimes and threshold parameter.

Terasvirta and Anderson (1992) and Granger and Terasvirta (1993) estimate a time varying SETAR where parameters are allowed to change smoothly over time. This resulting model is called a smooth threshold autoregressive model (STAR) and has the following general expression.

$$y_t = \pi_0 + \acute{\pi}_1 x_1 + (\theta_0 + \acute{\theta}_1 x_1)\, F(y_{t-d}) + u_t \tag{5.2}$$

Where the error is assumed to be n.i.d (0,σ^2), $x_t = (y_{t-1,\ldots\ldots,} y_{t-p})'$, π_1= $(\pi_{11,\ldots,} \pi_{1p})'$and $\theta_1 = (\theta_{1I,\ldots,} \theta_{1p})'$, and $= F(.)$ is the transition function.

The most common specifications for the transition function are the logistic and the exponential:

$$F(y_{t-d}) = \{1 + \exp[-\gamma(y_{t-d} - r)]\}^{-1} \tag{5.3}$$

$$F(y_{t-d}) = 1 - \exp[-\gamma(y_{t-d} - r)]^2 \tag{5.4}$$

In the logistic STAR (LSTAR) model the parameters change monotonically with y_{t-d}. When γ trends to infinity, $F(y_{t-d})$ becomes a Heaviside function which assumes the value 0 if the threshold variable is equal or smaller than r and the value 1 if is greater than r; in this case the model becomes a SETAR model. On the other hand, if γ tends to zero, the STAR reduces to a linear AR(p) model.

5.6.2 Specification and Modelling of threshold Autoregressive model

In this section, we describe the process of modelling the threshold autoregressive model (TAR model). In estimating the TAR model, we broadly follow the procedure presented in Terasvirta and Anderson (1992).[83] According to this study, the procedure to estimate a TAR model involves three steps. First, select the AR order p for threshold lags. In the second step, we test for the number of regimes and if there is more than one regime we assume a TAR model. However, we do not allow smooth transition between regimes that is estimated in the third procedure of Terasvirta and Anderson (1992). As already indicated, modelling of the TAR models first required to choose an appropriate lag length for linear AR order p. A standard procedure requires to choose appropriate lag length on the basis of a goodness of fit criteria. In practise, different methods can be used to decide the appropriate lag length (e.g Schwarz Information Criteria (SIC) or Akaike Information Criteria and partial autocorrelation function (PACF)). In our study, we use available in EViews (Automatic ARMA model selection procedure) that select Akaike Information Criteria to estimate the lag of the AR. In this method, we estimate the maximum possible AR lags that free from autocorrelation. This procedure selects the maximum 8 lags for non- seasonal AR components and 0 for other ARMA components. We specified maximum order of 8 lags for non-seasonal AR components to capture any possible seasonal AR terms that may occur at lag 4 or 8 lags. Second step is to test for the number of regimes and assuming a TAR model if the regimes are more than one.[84] For each model, we conduct a diagnostic test to the residual of the estimated model for serial correlation using Breusch Godfrey's LM test. If there is no evidence of autocorrelation (of orders 1, 2, … 4) this initial lag length is selected. However, if there is evidence of autocorrelation, we re-estimate the TAR model using a lag length of P*+1 ((where P* = initial lag length). The process is repeated until the model cannot reject the

[83] Our technique is slightly different from procedure presented by Terasvirta and Anderson (1992) in two ways. First, Terasvirta and Anderson (1992) adopts Information Criteria to select AR lag length. In contrast, we apply EVIew automatic ARIMA selection to select AR lag length. Second, Terasvirta and Anderson (1992) tests for linearity before estimating TAR model. In our study, we did not test for linearity before estimating TAR model because evidence suggest that testing linearity may not be relevant when estimating threshold model, but carefully selecting the lag order and delay parameter are important (Terasvirta et al. 2005).

[84] In our study, we did not test for linearity because we only estimate TAR models. The linearity test is to determine whether the TAR specification or STAR specification are appropriate. Preliminary experiment revealed that the STAR model cannot be estimated for most of the selected countries due to the stated error in EViews "specification leads to singular matrix in at least one sub-sample".

hypothesis of no- autocorrelation at the 5% level. For step 3, the TAR model can be examined as long as the model pass the diagnostic test for autocorrelation. [85]

5.6.3. Modelling TAR Models for Brazil

In this section, we construct a TAR model for Brazil over the full sample estimated for ARIMAX for model in section 5.1.2. To identify the lag length in the linear AR of annual inflation, we use the EViews automatic ARIMA selection procedure (without MA terms). First, we select the maximum 8 lags for non- seasonal AR components and 0 for the other ARMA components (such as the MA components). We do not consider the automatic selection of logarithmic or differencing transformations that are available in EViews because we believe that the annual inflation data is stationary following our previous analysis. The automatic ARIMA selection indicates that 3 lags are appropriate for annual inflation. These results are summarized in Table 5.6.1 column 1. Second, we estimate a TAR model using the suggested 3 lags length and d element.[86] The result shows two distinct regimes of the threshold value of 9.658904. This implies that that value of annual inflation in the first regime is less than 965%. While the value of annual inflation in the second regime is more than 965% for Brazil. All the coefficients of the AR terms are significant except AR(3) for the second regime. In contrast, only AR(1) is significant in the first regime (see Table 5.6.1 column 2). The coefficient value of the intercept is also not significant for the first regime and significant in the second regime. The result of the Bai and Perron test associated 5% critical value indicates that there is only one significant breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). However, the scaled F-statistic is less than critical value for the null hypothesis of 1 break (1 vs 2). For the model to be valid we apply the standard diagnostic checks for serial autocorrelation. Our result shows that 3 out of the 4 of the probability values of the residual autocorrelation at the 4th lag, denoted LM[RESID(4)], are less than 0.050 indicating evident of serial autocorrelation up to order four. The probability value of the

[85] In this research, we will not pay more attention into insignificant value of AR coefficients instead we focus on diagnostic test for Autocorrelation because, literature suggests that insignificant value of AR coefficients is not informative when estimating threshold models (Tsay 1989).

[86]In our study, we estimate d = 1 because annual inflation is stationary at level.

LM (Obs*R-squared) also indicates that residuals are serially correlated, and the equation should be re-specified before using for forecasting. These results are summarized in Table 5.6.1 column 2. To maximize the chance of selecting an appropriate lag length that will be free from autocorrelation. We consider models with higher lags for Brazil and re-estimate the TAR model using lag lengths 4 (where P*+ 1= lag length, and P* is the initial lag specified by EView automatic selection) and test the validity of this model. The results of the TAR model with 4 lags is reported in the column headed 3 of Table 5.6.1. This equation also specified the two distinct regimes for the TAR model with the same threshold value of 9.658904 for Brazil. In term of specification, the coefficients of all AR components are not significant for the both regimes except AR (1) and AR(2) for the second regime. The result of the Bai and Perron test associated 5% critical value indicates that there is only one significant breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). However, the scaled F-statistic is less than critical value for the null hypothesis of 1 break (1 vs 2). For the model to be valid we apply the standard diagnostic checks for serial autocorrelation. At least more than two of the probability value of the residual autocorrelation at the 4^{th} lag, denoted LM[RESID(4)], is less than 0.050 indicating evident of serial autocorrelation up to order four. The probability value of the LM (Obs*R-squared) also indicate that residuals are serially correlated, and the equation should be re-specified before using for forecasting. After experimentation with all possible lower and higher lag lengths, we find that a TAR model estimated with 3 lags without intercept passed diagnostic test for serial autocorrelation. The results of this TAR model with 3 lags without intercept is reported in the column headed 4 of Table 5.6.1. Therefore, the TAR model with 3 lags without intercept is valid for forecasting. From the favoured model, the TAR specification reveals that inflation is characterized by only one regime of higher inflation for Brazil between 1984q1 2012q4. A similar procedure was applied for all countries and a summary of the favoured TAR models is given in Table 5.6.2 and 5.6.3 for BRICS and OPEC countries respectively. For both BRICS and selected OPEC countries, we note that TAR specification identified at least two regimes for each country except for Brazil, China and Angola that the TAR model specified only 1 regime. This implies that inflation is characterized by the nonlinearity with at least two distinct regimes for all selected countries except Brazil, China and Angola.

Table 5.6.1. Modelling of the TAR model for Brazil

	1	2	3	4
Countries	AR automatic selections	TAR Specifications	TAR Specifications	TAR specifications
Lags values	3	3	4	3
Number of regimes chosen by Selection Criteria		2	2	1
Threshold value for 1		9.658904 (99)	9.658904 (99)	
C	0.012186 (-0.03231)	-0.00698 (-0.01840)	0.052305 (0.1519)	
Inf_BRA (-1)	1.4767 (3.7804)	1.5001 (3.6066)	1.0988 (1.9655)	1.5648 (17.89374)
Inf_BRA(-2)	-0.3315 (-0.4916)	-0.4071 (-0.5030)	-0.3449 (-0.4755)	-1.0345 (-7.3436)
Inf_Bra(-3)	0.0091 (0.0348)	0.1008 (0.1679)	0.14728 (0.2736)	0.3685 (4.2136)
Inf_Bra(-4)			-0.0549 (-0.2802)	
Threshold value for 2		9.658904 (17)	9.658904 (17)	
C		13.3197 (7.0078)	26.22902 (8.8387)	
Inf_Bra(-1)		1.1266 (10.5001)	1.0130 (10.3225)	
Inf_Bra(-2)		-0.7814 (-4.5167)	-0.8925 (-5.72663)	
Inf_Bra(-3)		-0.1442 (0.5510)	0.1284 (0.5366)	
Inf_Bra(-4)			-0.2770 (-1.0528)	
Adj R^2	0.8971	10.2149	0.9176	-0.0344
SC	5.4670	5.5359	5.3717	5.8180
LM[RESID(1)]		0.2737	0.0386	0.1033
LM[RESID(2)]		0.9055	0.0168	0.7496
LM[RESID(3)]		0.0000	0.1880	0.4015
LM[RESID(4)]		0.0000	0.9456	0.0931
LM (Obs*R-squared)		0.0000	0.0000	0.4592
Bai- Perron test				
0 vs 1		30.9804 {18.23}	45.2648 {20.08}	2.9871 {13.98}
1 vs 2		2.0375 {19.91}	4.0461 {22.11}	

Where Adj R^2 = Adjusted R – square, SC = Schwarz criterion, {} is the critical values for Bai- Perron test, () is the probability value of the coefficient of the TAR model, LM[RESID()] = p value of the residual, LM (Obs*R-squared) = probability value of Breusch- Godfrey LM test. Obs = number of the observations.

Table 5.6.2. Modelling of the TAR models for BRICS

C	Brazil	Russia	India	China	South Africa
Sample	1984Q4 -2012q4	1996Q1-2012q4	1961Q1-2012q4	1992Q1-2012q4	1961q1-2012q4
Lags values	3	6	5	10	6
Number of regime chosen by Selection Criteria	1	2	2	1	2
Threshold value for 1		0.24422(57)	0.11375[166]		0.84756(160)
C		0.000357 (0.0149)	0.0093 (0.0021)	0.0030 (0.0916)	-0.00258 (2.8966)
Inf_Inflation(-1)	1.5648 (17.89374)	3.3516 (10.4292)	1.1860 (0.0000)	1.1258 (0.0000)	0.12435 (7.2658)
Inf_Inflation(-2)	-1.0345 (-7.3436)	-3.7823 (-5.4582)	-0.2492 (0.0400)	0.0345 (0.8485)	0.05411 (-2.3203)
Inf_Inflation(-3)	0.3685 (4.2136)	1.9502 (2.5846)	0.2677 (0.0342)	-0.0922 (0.5862)	0.32112 (0.8475)
Inf_Inflation(-4)		-0.5762 (-1.5505)	-0.8055 (0.0000)	-0.1155 (-0.2850)	-0.1524 (-2.1494)
Inf_Inflation(-5)		0.1568 (0.6781)	0.49022 (6.9147)	0.6105 (0.0064)	-0.51326 (2.0098)
Inf_Inflation(-6)		-0.04433 (-0.4694)		0.3948 (0.2498)	1.4567 (4.2117)
Inf_Inflation(-7)				1.2610 (0.0641)	
Inf_Inflation(-8)				0.1263 (-3.1027)	
Inf_Inflation(-9)				0.3075 (2.8442)	
Inf_Inflation(-10)				0.0436 (0.2225)	
Threshold value for 2		0.24433 (11)	0.11375[42]		0.84756 (48)
C		-0.0094 (-0.1408)	0.03216 (0.0001)		0.043222 (5.72189)
Inf_Inflation(-1)		1.6492 (11.9724)	1.4184 (0.0000)		1.765502 (12.78504)
Inf_Inflation(-2)		-1.07198 (-5.3124)	-0.3499 (0.0457)		-1.74365 (-6.17347)
Inf_Inflation(-3)		0.5727 (2.3572)	-0.2459 (0.1750)		0.997681 (2.95944)
Inf_Inflation(-4)		-0.5693 (-2.3898)	-0.1122 (0.5687)		-0.74486 (-2.01695)
Inf_Inflation(-5)		0.5258 (2.6518)	0.0082 (0.9477)		0.432142 (1.25310)
Inf_Inflation(-6)		-0.1860 (-1.5696)			0.246243 (0.75410)
Adj R^2		0.9421	0.9072	0.9177	0.9450
SC	-0.0344	-2.2685	-5.2469	-5.5347	-6.6892
S.E	5.8180	0.0565	0.0171	0.05150	0.0234
LM[RESID(1)]	0.1033	0.3601	0.4704	1.4736	0.4346
LM[RESID(2)]	0.7496	0.1076	0.1161	0.269391	0.21344
LM[RESID(3)]	0.4015	0.4200	0.2825	0.2108	0.2306
LM[RESID(4)]	0.0931	0.0810	0.0563	0.1879	0.13455
LM (Obs*R-squared)	0.4592	0.2682	8.7239	3.4229	2.5669
Bai- Perron test					
0 vs 1	2.9871 {13.98}	30.5087 {21.87}	40.7161 {27.03}	21.2577 {27.03}	20.6788 {22.0567}
1 vs 2		12.3041 {24.17}	28.7211 {29.7211}		14.5300 {28.7234}

Table 5.6.3. Modelling of the TAR model for selected OPEC countries

C	Algeria	Angola	Nigeria	Saudi Arabia	Kuwait	Ecuador
Sample	1978Q1-2012q4	1996q1 2012q4	1964q1-2012q4	1975Q1-2012q4	1977q1 2012q4	1987q1 2012q4
Lags values	7	3	15	10	5	3
Number of regime chosen by Selection Criteria	3	1	2	2	2	3
Threshold value for 1	0.09372(83)		0.37499(165)	0.0594776(130)	0.06870(115)	0.438485(72)
C	0.006123 (0.91779)	0.454768 (0.468309)	0.026648 (3.316294)	0.00138 (0.8273)	0.0070 (1.11723)	-0.00236 (**-**1.11769)
Inf_Inflation(-1)	0.777401 (0.9177)	0.577528 (4.839734)	1.202501 (13.34657)	1.229157 (9.1675)	0.538022 (2.192908)	1.38968 (4.07459)
Inf_Inflation(-2)	0.199435 (0.9177)	0.199171 (1.448596)	-0.1434 (-1.0616)	-0.37044 (-1.7940)	1.463869 (-3.34909)	-0.27517 (0.749685)
Inf_Inflation(-3)	-0.01111 (-0.0743)	-0.02292 (-0.19502)	-0.13016 (-1.06744)	0.103592 (0.5046)	-2.07862 (4.628368)	
Inf_Inflation(-4)	-0.8886 (-6.7429)		-0.68105 (-6.10123)	-0.4276 (-2.2533)	2.303215 (-1.65001)	
Inf_Inflation(-5)	0.83497 (4.40641)		0.801916	0.594925 (3.19800)	-1.00916 (1.46386)	
Inf_Inflation(-6)	0.0144 (0.0824)		-0.11533 (6.392716)	-0.2916 (-1.4997)		
Inf_Inflation(-7)	-0.0619 (-0.4965)		0.087161 (0.707849)	0.15430 (0.81186)		
Inf_Inflation(-8)			-0.72106 (-6.65902)	-0.3048 (-1.7546)		
Inf_Inflation(-9)			0.719952 (5.816971)	0.3425 (2.1814)		
Inf_Inflation(-10)			-0.15098 (-1.10264)	-0.1312 (-1.5358)		
Inf_Inflation(-11)			0.066229 (0.564039)			
Inf_Inflation(-12)			-0.47435 (-4.4386)			
Inf_Inflation(-13)			0.578215 (4.967618)			
Inf_Inflation(-14)			-0.19689 (1.57349)			
Inf_Inflation(-15)			-0.02775 (-0.3670)			
Threshold value for 2	0.093723(24)		0.37499(28)	0.0594776(22)	0.06870(29)	0.4384858(15)
C	0.135891 (2.836803		0.072 (1.35613)	0.011738 (1.4409)	0.004981 (**1.049287)**	-1.11769 (-4.52669)
Inf_Inflation(-1)	-0.32878 (-0.6567)		1.673 (9.759833)	1.235227 (11.2408)	0.99674 (10.16356)	4.074599 (5.98994)
Inf_Inflation(-2)	0.365933 (1.6358)		-1.155 (4.21423)	-0.37266 (-2.6137)	-0.07437 (0.51907)	0.749685 (1.128554)
Inf_Inflation(-3)	0.0056 (0.0269)		0.432 (1.524301)	-0.3659 (-2.47621)	0.140046 (0.950018)	-1.74153 (-2.78238)
Inf_Inflation(-4)	-0.3060 (-1.2225)		-0.68217 (-2.54981)	0.5141 (2.9287)	-1.00346 (0.950018)	
Inf_Inflation(-5)	-0.02255 (-0.1283)		0.658429 (1.940667)	1.1008 (7.6260)	0.68131 (3.268875)	
Inf_Inflation(-6)	-0.04376 (-0.2096)		0.322021 (0.759652)	-0.76787 (-4.2113)		
Inf_Inflation(-7)	-0.05943 (-0.4185)		-1.44667 (-3.01114)	-0.68419 (-4.85632)		
Inf_Inflation(-8)			1.625617 (3.070437)	0.25619 (1.41498)		
Inf_Inflation(-9)			-0.71065 (-1.29662)	0.9819 (1.4149)		
Inf_Inflation(-10)			0.400739 (0.801632)	-1.2179 (-5.6619)		
Inf_Inflation(-11)			-0.09806 (-0.26301)			

Inf_Inflation(-12)			-0.66393 (-2.54661)			
Inf_Inflation(-13)			0.925057 (3.461555)			
Inf_Inflation(-14)			-0.61483 (-2.00118)			
Inf_Inflation(-15)			0.258236 (1.349004)			
Threshold value for 3	0.15275(33)					0.53901(17)
C	-0.00209 (-0.08217)					0.12946 (2.544994)
Inf_Inflation(-1)	1.270973 (8.481038)					1.5361 (15.2291)
Inf_Inflation(-2)	0.077223 (0.4020)					-0.5439 (-3.36705)
Inf_Inflation(-3)	-0.57528 (-3.15919)					-0.4262 (-2.51298)
Inf_Inflation(-4)	-0.19653 (-1.0505)					
Inf_Inflation(-5)	0.2987 (1.3162)					
Inf_Inflation(-6)	0.5339 (2.3218)					
Inf_Inflation(-7)	-0.44118 (-2.9190)					
Adj R^2	0.8978	0.8750	0.9154	0.9546	0.8310	0.9837
SC	-3.5725	-5.232	-2.4417	-4.7809	-5.1979	-3.2559
LM[RESID(1)]	0.3942	0.1209	0.409307	0.18574	0.5614	0.3098
LM[RESID(2)]	0.5833	0.6689	0.15378	0.18446	0.8699	0.202
LM[RESID(3)]	0.0561	0.122	0.68687	0.16792	0.2108	0.4093
LM[RESID(4)]	0.3275	0.1029	0.25734	0.16918	0.1879	0.9739
LM (Obs*R-squared)	0.2000	0.0841	0.9501	0.1164	0.2754	0.5555
Bai- Perron test						
0 vs 1	3.0927 {23.70}	0.4477 (16.19)	50.2290 {27.3}	90.6243 {27.0}	46.1241 {20.08}	47.0812 {16.7}
1 vs 2	3.2856 {25.75}		26.3329 {29.24}	10.9373 {29.24}	20.0098 {22.11}	27.2727 {18.93}
2 vs 3	0.7421 {26.81}					2.6458 (18.13)

Where *Adj* R^2 *= Adjusted R – square, SC = Schwarz criterion,* **{}** is the critical values for Bai- Perron test, () is the probability value of the coefficient of the TAR model**,** LM[RESID()] = p value of the residual, LM (Obs*R-squared) = probability value of Breusch- Godfrey LM test. Obs = number of the observations

5.6.4. Modelling TAR Models for Brazil

In this section, we use the same sample period used in section 5.2 and 5.3. In particular, we construct TAR models to the countries' annual inflation using a reduced sample period that avoids structural breaks for Brazil. The difference between the TAR model estimated in this section and previous section (5.6.3) is that, we estimate TAR model over a full sample that identify with different multiple breaks in the previous section (5.6.3) and estimate TAR model over a reduced sample that avoid multiple breaks in this section. In particular, we use the Bai Perron tests to identify the number of the possible breaks over the full sample and estimate TAR model on the end of the sample that has no breaks with the minimum of 39 observations.[87] To identify the lag length in the linear AR of annual inflation, we use the EViews automatic ARIMA selection procedure (without MA terms). First, we select the maximum 8 lags for non- seasonal AR components and 0 for the other ARMA components (such as the MA components). We do not consider the automatic selection of logarithmic or differencing transformations that are available in EViews because we believe that the annual inflation data is stationary following our previous analysis. The automatic ARIMA selection indicates that 6 lags are appropriate for annual inflation. These results are summarized in Table 5.6.4 column 1. Second, we estimate a TAR model using the suggested 6 lags length and d element.[88] The result shows two distinct regimes of the threshold value of 0.07492098. The value of annual inflation in the first regime is less than 0. 07492098 while the value of annual inflation in the second regime is more than 0.07492098 for Brazil. All the AR coefficients are not significant for two regimes. The result of the Bai and Perron test associated 5% critical value indicates that there is only one significant breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). However, the scaled F-statistic is less than critical value for the null hypothesis of 1 break (1 vs 2). For the model to be valid we apply the standard diagnostic checks for serial autocorrelation. At least one of the probability value of the residual autocorrelation at the 4th lag, denoted LM[RESID(4)], is less than 0.050 indicating evident of serial autocorrelation up to order four. The probability value of the LM (Obs*R-squared) also indicate that residuals are

[87] See section 5.2.0 for the details

[88]In our study, we estimate d = 1 because annual inflation is stationary at level.

serially correlated, and the equation should be re-specified before using for forecasting. These results are summarized in Table 5.6.4 column 2. To maximize the chance of selecting an appropriate lag length that will be free from autocorrelation. We consider models with higher lags for Brazil and re-estimate the TAR model using lag lengths 7 (where P*+ 1= lag length) and test the validity of this model. The TAR models with 7 lags also indicates evidence of autocorrelation – see column 3 of Table 5.6.4. Therefore, this model is not valid to forecast. After experimentation with valid higher and lower lags, we find that a TAR model estimated with 3 lags and annual inflation passed diagnostic test for serial autocorrelation.[89] The results of this TAR model with 3 lags is reported in the column headed 4 of Table 5.6.4. Therefore, the TAR model with 3 lags is valid for forecasting. From the favoured model, the TAR specification reveals that inflation are characterized by the two distinct regimes for Brazil. For the first regime, the value of annual inflation is less than 6.75% while the value of annual inflation in the second regime is more than 6.75% for Brazil. We categorised the first regime where the value of annual inflation is less than 6.75% as a period of low inflation and the second regime where annual is more than 6.75% as period of high inflation. We also note that the TAR model allocates more observations to the first regime (41 observations) than the second regime (21 observations). This implies that period of economy crisis is less than the period of economic stability for Brazil. This finding is consistent with economic views that duration of economic booms (period lower inflation) tends to be longer than those of economic slumps (period of higher inflation). A similar procedure was applied for all countries and a summary of the favoured TAR models is given in Table 5.6.5 and 5.6.6 for BRICS and OPEC countries respectively. For both BRICS and selected OPEC countries, we noticed that TAR specification identified two regimes for each country except Saudi Arabia that the TAR model specified 3 regimes.[90] This implies that inflation is characterized by the nonlinear with at least two distinct regimes for all selected countries over a reduced sample identified without breaks.[91]

[89]Note that d = 1 because annual inflation is stationary at level.

[90] The available countries that meet up with our minimum requirements in the BRICS and selected OPEC countries are summarised below: Brazil, Russia, South Africa, Nigeria, Algeria, Saudi Arabia and Angola.

[91] The possibility of two regimes mean that inflation parameter in many of these countries is nonlinear.

Table 5.6.4. Modelling of the TAR model for Brazil

	1	2	3	4
Countries	AR automatic selections	TAR Specifications	TAR Specifications	TAR specifications
Lags values	6	6	7	3
Number of regimes chosen by Selection Criteria		2	2	2
Threshold value for 1		0.07492098 [47 Obs]	0.07252098 [47 Obs]	0.06753 [41 Obs]
C	0.0666 (4.9538)	0.01241 (0.0155)	0.0118 (0.0263)	0.0175 (0.0040)
Inf_BRA (-1)	1.5613 (17.0160)	1.4982 (0.0000)	1.4445 (0.0000)	1.6682 (0.0000)
Inf_BRA(-2)	-0.9431 (-4.0581)	-0.9886 (0.0019)	-0.9404 (0.0044)	-1.2603 (0.000)
Inf_Bra(-3)	0.4343 (1.2666)	0.5470 (0.0560)	0.4956 (0.0965)	0.2844) (0.0234)
Inf_Bra(-4)	-0.6202 (-2.0044)	-0.7518 (0.0048)	-0.5417 (0.0294)	
Inf_Bra(-5)	0.7419 (2.9123)	0.6826 (0.0048)	0.2985 (0.0167)	
Inf_Bra(-6)	-0.3171 (-2.2669)	-0.2289 (0.0617)	-0.0462 (-0.1651)	
Inf_Bra(-7)			-0.1569 (-1.1318)	
Threshold value for 2		0.07492098[16 Obs]	0.072592098[16 Obs]	0.06753[22 Obs]
C		0.04309 (0.0000)	0.0452 (0.0000)	0.0296 (0.0001)
Inf_Bra(-1)		1.8115 (0.0000)	1.7609 (0.0000)	1.6623 (0.0000)
Inf_Bra(-2)		-1.7549 (0.0000)	-1.6506 (0.0000)	-0.6623 (0.0000)
Inf_Bra(-3)		0.8854 (0.0151)	0.6478 (0.0678)	-0.0513 (0.8024)
Inf_Bra(-4)		-0.5612 (0.1561)	-0.0991 (0.7653)	
Inf_Bra(-5)		0.48115 (0.1554)	-0.1023 (0.5134)	
Inf_Bra(-6)		-0.2895 (0.0567)	0.2462 (0.7541)	
Inf_Bra(-7)			-0.3700 (-2.2398)	
Adj R^2	0.8865	0.9317	0.9043	0.8927
SC	-5.8305	-6.0816	-6.3189	-6.1436
LM[RESID(1)]		0.9910	0.0078	0.9677
LM[RESID(2)]		0.1452	0.3759	0.9079
LM[RESID(3)]		0.0183	0.0700	0.9056
LM[RESID(4)]		0.1016	0.0407	0.9976
LM (Obs*R-squared)		0.0200	0.0334	0.0831
Bai- Perron test				
0 vs 1		29.1165 {21.87}	32.6372 { 20.08}	22.3885 {16.56}
1 vs 2		9.8978 {24.17}	1.7984 {22.11}	7.8445 {18.11}

Where Adj R^2 = Adjusted R – square, SC = Schwarz criterion, **{}** is the critical values for Bai- Perron test, () is the probability value of the coefficient of the TAR model, LM[RESID()] = p value of the residual, LM (Obs*R-squared) = probability value of Breusch- Godfrey LM test. Obs = number of the observations.

Table 5.6.5. Modelling of the TAR models for BRICS

C	Brazil	Russia	South Africa
Sample	1997Q2 -2012q4	2003Q2-2012q4	1995q2-2012q4
Lags values	3	2	6
Number of regimes chosen by Selection Criteria	2	2	2
Threshold value for 1	0.06753[41]	0.08882[7]	0.1041456[60]
C	0.0175 (0.0040)	-0.0176 (0.1292)	0.01091
Inf_Inflation(-1)	1.6682 (0.0000)	1.844 8 (0.0000)	1.76445 (0.0000)
Inf_Inflation(-2)	-1.2603 (0.000)	-0.7512 (0.0052)	-0.9218 (0.0000)
Inf_Inflation(-3)	0.2844) (0.0234)		0.1061 (0.6246)
Inf_Inflation(-4)			-0.6236 (0.0080)
Inf_Inflation(-5)			0.9907 (0.0000)
Inf_Inflation(-6)			-0.0922 (0.5862)
Threshold value for 2	0.06753[22]	0.08882[32]	0.1041456[11]
C	0.0296 (0.0001)	0.005749 (0.0000)	0.11977 (0.0217)
Inf_Inflation(-1)	1.6623 (0.0000)	1.4510 (0.0000)	0.6328 (0.0147)
Inf_Inflation(-2)	-0.6623 (0.0000)	-0.6962 (0.0000)	-0.8331 (0.0694)
Inf_Inflation(-3)	-0.0513 (0.8024)		0.5035 (0.2592)
Inf_Inflation(-4)			-0.6236 (0.0080)
Inf_Inflation(-5)			0.9907 (0.0000)
Inf_Inflation(-6)			-0.4709 (0.0007)
Adj R^2	0.8927	0.9193	0.9209
SC	-6.1436	-6.3006	-5.4734
S.E	0.0092	0.00850	0.0115
LM[RESID(1)]	0.9677	0.4561	0.7941
LM[RESID(2)]	0.9079	0.9976	0.1848
LM[RESID(3)]	0.9056	0.8773	0.4713
LM[RESID(4)]	0.9976	0.3977	0.7744
LM (Obs*R-squared)	8.2426 [0.0831]	2.1696 [0.7048]	3.6922 (0.4493)
Bai- Perron test			
0 vs 1	22.3885 {16.56}	18.3894 {14.12}	64.2068 {39.1724}
1 vs 2	7.8445 {18.11}	4.7870 {1.5959}	1.5054 {10.5381}

Table 5.6.6. Modelling of the TAR model for selected OPEC countries

C	Algeria	Angola	Nigeria	Saudi Arabia
Sample	1999Q2-2012q4	2000Q4-2012q4	1998Q4-2012q4	1979Q3-2012q4
Lags values	5	2	6	8
Number of regimes chosen by Selection Criteria	2.	2	2	3
Threshold value for 1	0.00902987[25]	1.11950{19]	0.1507519[24]	0.0040835[51]
C	0.0068 (0.1438)	0.01333 (0.2848)	0.0225 (0.1025)	0.00102 (0.5735)
Inf_Inflation(-1)	1.0076 (0.0000)	1.5088 (0.0000)	1.4140 (0.0000)	1.0695 (0.0000)
Inf_Inflation(-2)	-0.1219 (0.4872)	-0.6042 (0.0005)	-0.5406 (0.0323)	-0.3495 (0.0000)
Inf_Inflation(-3)	0.1125 (0.5242)		-0.1649 (0.4461)	0.4034 (0.0000)
Inf_Inflation(-4)	-0.6605 (0.0005)		-0.3952 (0.0211)	-0.8675 (0.0000)
Inf_Inflation(-5)	0.4945 (0.0008)		0.5968 (0.0006)	1.0053 (0.0000)
Inf_Inflation(-6)			-0.1227 (0.3277)	-0.4215 (0.1620)
Inf_Inflation(-7)				0.6420 (0.0146)
Inf_Inflation(-8)				-0.5930 (0.0000)
Threshold value for 2	0.00902987[30]	1.11950[30]	0.1507519[33]	0.0040835[63]
C	0.541 (0.592)	0.33120 (0.0000)	0.27416 (0.0019)	-0.001034 (0.6215)
Inf_Inflation(-1)	-0.447 (-0.1470)	0.4012 (0.0014)	0.2494 (0.2797)	1.4227 (0.0000)
Inf_Inflation(-2)	-0.476 (-0.3529)	-0.6042 (0.0005)	-0.3294 (0.1704)	-0.3105 (0.1533)
Inf_Inflation(-3)	-0.229 (-0.3945)		-0.2923 (0.3802)	-0.0541 (0.7466)
Inf_Inflation(-4)	-0.124 (-0.7531)		-0.5076 (0.2968)	0.0499 (0.7306)
Inf_Inflation(-5)	0.934 (0.6902)		0.7282 (0.1533)	0.0580 (0.6565)
Inf_Inflation(-6)			-0.6508 (0.0190)	-0.0928 (0.4560)
Inf_Inflation(-7)				0.0112 (0.9306)
Inf_Inflation(-8)				0.0055 (0.0055)
Threshold value for 3				0.04761904[20]
C				-0.0129 (0.1234)
Inf_Inflation(-1)				0.9655 (0.0000)
Inf_Inflation(-2)				0.1838 (0.3742)
Inf_Inflation(-3)				-0.1206 (0.6057)
Inf_Inflation(-4)				-0.7086 (0.0050)
Inf_Inflation(-5)				1.0370 (0.0002)
Inf_Inflation(-6)				-0.7635 (0.1432)
Inf_Inflation(-7)				0.1634 (0.8033)

Inf_Inflation(-8)				0.4544 (0.1875)
Adj R^2	0.7107	0.9914	0.8051	0.9158
SC	-5.3230	-2.5734	-3.9300	-5.9484
LM[RESID(1)]	0.8255	0.5092	0.9908	0.2258
LM[RESID(2)]	0.3374	0.1112	0.4948	0.2343
LM[RESID(3)]	0.7580	0.4036	0.6544	0.9313
LM[RESID(4)]	0.1673	0.0581	0.3919	0.3132
LM (Obs*R-squared)	4.4505 (0.3485)	9.2801 (0.0545)	1.6069 (0.8076)	5.3362 (0.2545)
Bai- Perron test				
0 vs 1	1.1571 (6.9423)	23.3253 {69.9760}	5.5717 {39.0019}	4.3041 {38.7376}
1 vs 2		0.4739 {1.4217}	2.4028 {16.8200}	4.9224 {44.3022}
1 vs 3				1.3739 {12.3658}

Where Adj R^2 = Adjusted R – square, SC = Schwarz criterion, **{}** is the critical values for Bai- Perron test, () is the probability value of the coefficient of the TAR model, LM[RESID()] = p value of the residual, LM (Obs*R-squared) = probability value of Breusch- Godfrey LM test. Obs = number of the observations

5.7.1 Forecast performance and evaluation for Threshold Models for Brazil annual inflation

In this section, we follow the rolling regression technique discussed in section 5.5.0 and produce out-of-sample forecasts for two different estimated TAR models given in table 5.6.1 and 5.6.4. The first TAR model is estimated over a full sample with different multiple breaks between the period 1984q1 to 2012q4. The second TAR model is estimated over a reduced sample between the period 1997q2 to 2012q4. The reduced sample are designed to avoid modelling structural breaks. The forecast performance of the two non-linear TAR models for Brazil are given below in Table 5.7.1.

Table 5.7.1. Forecast performance of the nonlinear TAR model for Brazil

	A. Non-linear TAR models estimated over the full sample			B. Non-linear TAR models estimated on a reduced sample that avoid breaks		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
7	0.0070	9.8180	0.0600	0.0050*	6.0080*	0.0360*
2-step	0.0170	25.6600	0.1580	0.0080*	10.9700*	0.0690*
3-step	0.0260	41.1200	0.2640	0.0100*	13.1200*	0.0910*
4-step	0.0310	50.8800	0.3450	0.0110*	13.4300*	0.0990*
5-step	0.0360	57.5300	0.4050	0.0080*	11.1900*	0.0690*
6-step	0.0390	62.300	0.4560	0.0040*	4.8800*	0.0310*
7-step	0.0420	66.7500	0.5070	0.0070*	10.6200*	0.0530*
8-step	0.0420	71.8700	0.5610	0.0060*	10.1600*	0.0480*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for

From Table 5.7.1, the nonlinear TAR model estimated over the reduced sample without multiple breaks (Table 5.7.1 column B) has the lowest RMSE, MAPE and U-statistics over all forecasting horizons. This implies that the TAR model estimated over a reduce sample that avoid modelling breaks is unambiguous outperforms the TAR model estimated over the full sample with different multiple breaks. This result is consistent with our previous findings (in section 5.5.1) that stated that reduced samples to avoid structural breaks is the preferred strategy when modelling and forecasting inflation. A similar procedure was applied to all countries. In summary, for BRICS and selected OPEC countries. The TAR model estimated over a reduce sample that avoid modelling breaks produce superior forecast than the TAR model estimated over a full sample with different multiple breaks except for Saudi Arabia (over 1 to 3-steps ahead horizons). Note that, we did not estimate TAR model over a reduced sample for China, India, Kuwait and Ecuador because the multiple Bai Peron test does not identified breaks over the full sample for China and India. For Kuwait and Ecuador, the end of the sample identified without multiple breaks are less than 39 observations.

5.7.2 Brazil Forecast performance and evaluation

In this section, we compare the forecasting performance of the best selected linear univariate ARIMA model in section 5.5.1 and best selected nonlinear TAR model in section 5.7.1 for Brazil to choose the best univariate model that forecast inflation. The forecast performance of the best selected univariate model for Brazil are given below in Table 5.7.2.

Table. 5.7.2: Comparison of the best performance of the nonlinear TAR model and best selected ARIMA model for Brazil.

	A. Non-linear TAR models estimated on a reduced sample that avoid breaks			B. Reduced sample EView9 Automatic seasonal ARIMA model without modelling breaks			C. Reduced sample EView9 Automatic's non-seasonal ARIMA model without modelling structural breaks		
	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U
1	0.0050	6.0080	0.0360	0.0050*	5.0690*	0.0360*	0.0060	7.8950	0.0490
2-step	0.0080	10.9700	0.0690	0.0060*	8.0390*	0.0470*	0.0070	9.5170	0.0560
3-step	0.0100	13.1200	0.0910	0.0060	10.1500	0.0560	0.0060*	8.2540*	0.0480*
4-step	0.0110	13.4300	0.0990	0.0060	8.6970	0.0500	0.0030*	3.7780*	0.0220*
5-step	0.0080	11.1900	0.0690	0.0070	9.3930	0.0520	0.0002*	0.1580*	0.0010*
6-step	0.0040	4.8800	0.0310	0.0060	7.2460	0.0430	0.0004*	0.5880*	0.0040*
7-step	0.0070	10.6200	0.0530	0.0060	8.2260	0.0490	0.0004*	0.7080*	0.0040*
8-step	0.0060	10.1600	0.0480	0.0090	15.4300	0.0720	0.0004*	0.3390*	0.0020*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each.

From Table 5.7.2, we compare the forecasting performance of the best selected univariate ARIMA model (automatic non-seasonal ARIMA technique) in section 5.5.1 and best selected nonlinear TAR model in section 5.7.2 (Non-linear TAR models estimated on a reduced sample that avoid breaks). From our study, the linear ARIMA model (reduced sample automatic non-seasonal ARIMA technique without modelling breaks) in Table 5.7.2 column C, has the lowest RMSE, MAPE and U-statistics over all forecasting horizons except 1 and 2- step ahead horizons. Similarly, the reduced sample EViews automatic seasonal ARIMA technique without modelling breaks in Table 5.7.2 column B has the lowest RMSE, MAPE and U-statistics values for 1 and 2-step ahead horizon. In contrast, the nonlinear TAR model estimated over the reduced sample that avoid modelling breaks were never favoured for Brazil when compared with other forecasting models. A similar procedure was applied to all countries. In summary, for BRICS and selected OPEC countries. The nonlinear TAR models were not favoured over the best selected linear ARIMA models in Table 5.5.2 and 5.5.3 except for China (over all forecasting horizons), Nigeria (over 1 to 4-steps ahead horizons) and Saudi Arabia (over 1 to 3- steps ahead). Hence, there are 3 countries where the TAR model produces the better forecasts than the best selected ARIMA models over at least some horizons (see table 5.7.3 and 5.7.4 below for details).

Table 5.7.3 Summary of the best forecasting univariate models for BRICS countries

Best forecasting Univariate model for Brazil				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1-to 2-steps	R_A _SARIMA	R_A_SARIMA	R_A_SARIMA	5.0690 – 8.0390
3 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	0.3390 -8.2540
Best forecasting univariate model for Russia				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	6.3660 – 20.6300
Best forecasting univariate model for India				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8- steps	F_SARIMA	F_SARIMA	F_SARIMA	13.5200 -63.4600
Best forecasting univariate model for China				
	RMSE	**U –statistics**	**MAPE**	
1 to 8-steps	F_TAR Model	F_TAR Model	F_TAR model	6.1940 – 10.0800
Best forecasting univariate model for South Africa				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 4 –steps	R_A_SARIMA	R_A_SARIMA	R_A_SARIMA	14.2800 -20.9900
5-step	R_SARIMA	R_A_SARIMA	R_SARIMA	17.2600
6 to 7-steps	R_A_SARIMA	R_A_SARIMA	R_A_SARIMA	12.3600- 13.3600
8-step	R_SARIMA	R_SARIMA	R_SARIMA	10.2000

The best univariate forecasting model is identified by each measure (RMSE, MAPE and U) for each forecasting horizon (1, 2…, 8 steps ahead). The full sample univariate model that employs seasonal Box-Jenkins ARIMA techniques and model's structural breaks is denoted as F_SARIMAX, the full sample univariate model that employs Box-Jenkins ARIMA techniques without modelling structural breaks is denoted as F_SARIMA (this model type is exclusive to India because there were no significant structural breaks to model over the full sample). The full sample specifications that employ EViews 9's automatic seasonal and non-seasonal ARIMA model without modelling breaks are denoted as F_A_SARIMA and F_A_ARIMA respectively (these models are exclusively designed for China because the period after the structural breaks are less than 39 observations and relative step shifts for this period also appear to be small which mean that inference regarding unit roots may not be too adversely affected when using the full sample. Hence, the full sample is used for these models for this country). The reduced sample model that employs seasonal ARIMA technique's without modelling structural breaks is denoted as R_SARIMA. The reduced sample model that employs EViews 9's automatic seasonal ARIMA model selection procedure without modelling breaks is denoted as R_A_SARIMA and the reduced sample model that employs EViews 9's automatic non-seasonal ARIMA model selection method without modelling breaks is represented by R_A_ARIMA. F_TAR Model is denoted as threshold autoregressive model estimated over the full sample and R_TAR model is denoted as the threshold autoregressive model estimated over the reduced sample that avoid modelling breaks. The range gives the range of values for the MAPE for models favoured according to this forecasting measure over the specified horizon.

Table 5.7.4 Summary of the best forecasting univariate models for OPEC countries

Best forecasting univariate model for Angola				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	R_SARIMA	R_SARIMA	R_SARIMA	2.0590 – 13.3300
Best forecasting univariate model for Algeria				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 –step	F_SARIMAX	F_SARIMAX	R_A_SARIMA	61.6300
2 –step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	82.6100
3 to 7-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	27.3800- 136.0000
8-step	F_SARIMAX	R_SARIMA	F_SARIMAX	28.7700
Best forecasting univariate model for Ecuador				
	RMSE	**U- statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	15.4500 -42.9100
Best forecasting univariate model for Saudi Arabia				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 3-steps	F_TAR Model	F_TAR Model	F_TAR Model	4.3720 -8.4800
4 to 8-step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	1.0100 – 15.1400
Best forecasting univariate model for Nigeria				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 4-steps	R_TAR Model	R_TAR Model	R_TAR Model	15.9000- 19.360
5 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	40.7200 – 46.5100
Best forecasting univariate model for Kuwait				
	RMSE	U-statistics	MAPE	
Horizon	Type	Type	Type	Rage
1 to 8-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	11.2100 – 38.5900

See note in the Table 5.5.2

5.7.3 The chapter summary and conclusion

This chapter is divided into two sections, first we discussed the procedure of modelling ARIMAX models that have a deterministic component to account for structural breaks over the full sample period and different ARIMA specifications over a reduced sample period that avoids the modelling structural breaks. The univariate ARIMA models that we develop over the reduced sample period are, first, a seasonal ARIMA specification identified using the Box-Jenkins method, second, a seasonal ARIMA model identified using EView's automatic model selection tool and third, a non-seasonal ARIMA model identified using EView's automatic model selection tool applied to seasonally adjusted data. The other model we considered in this chapter also include the regime shift threshold Autoregressive model estimated over the full sample and reduced sample. Second, we compare the forecasting performance of each valid model over 8-steps ahead forecasting horizons using the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Theil's inequality coefficient (U) to choose appropriate model with the lowest error. The aim of this chapter is to determine whether the valid ARIMA/ARIMAX and TAR models that passes the standard diagnostic test (stationarity and autocorrelation) can be obtained for each country. We also examine whether superior forecasts can be obtained by using the full sample (with the benefit of more information) and explicitly modelling the structural breaks (with the possibility of overfitting and difficulty in adequately capturing such effects) or whether using reduced samples (with the disadvantage of fewer data points) is compensated by the avoidance of having to model any structural breaks. In our study, a valid ARIMA/ARMAX and TAR model can be obtained to forecast inflation for BRICS and selected OPEC countries. To choose the best selected univariate model for both BRICS and OPEC countries. In our study, we observed that the nonlinear TAR models were not favoured over the best selected linear ARIMA/ ARIMAX models except for China (over all forecasting horizons), Nigeria (over 1 to 4-steps ahead horizons) and Saudi Arabia (over 1 to 3- steps ahead). When comparing performance of model estimated over the full sample (ARIMAX and TAR model) to the model estimated over a reduce sample (ARIMAs models and reduced sample TAR model). The ARIMAX and TAR applied to the full sample is rarely favoured when compared with all model estimated over the reduce sample (except where it is the only valid model). This suggests that the potential benefits of using a full sample and explicitly modelling the structural breaks are generally outweighed by the benefits of being able to avoid modelling structural breaks at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is typically the preferred strategy.

CHAPER 6

SELECTION OF VARIABLES FOR MULTIVARIATE ANALYSIS

6.0 Introduction

In this chapter, we discuss the data used in multivariate modelling. We identify the variables that are most commonly employed to model and forecast inflation in the literature and identify the data availability of these series for each country under study. Whilst we give priority to variables available at quarterly frequency we also consider the addition of variables that are available only at annual frequency to ameliorate omitted variable issues. We use frequency conversion tools to generate quarterly series from annual series. The main explanatory variables that we consider for each country are the money supply, real exchange rate, interest rate, output gap, unemployment rate and the oil price. The periods where data are available on most of these variables for each country are given below:

Table 6.1 The summary of available data for multivariate analysis in each country

Countries	Brazil	Russia	India	China	South Africa
Start	1994Q2	2000Q2	1957Q1	1989Q1	1992Q2
End	2014Q4	2014Q4	2014Q4	2014Q4	2014Q4
Countries	Algeria	Angola	Nigeria	Saudi Arabia	
Start	1996Q2	1997Q4	1995Q4	1976Q3	
End	2014Q4	2014Q4	2014Q4	2014Q4	

To allow for lags and transformations we use data up to 3 years prior to the start of the estimation period (2 years for lags and one year for the four-period seasonal difference used to construct inflation from prices). Hence, the sample periods over which multivariate models can be estimated for each country are given in the table below:

Table 6.2. The summary of the estimated samples for each country

Countries	Brazil	Russia	India	China	South Africa
Start	1997Q2	2003Q2	1960Q1	1992Q1	1995Q2
End	2012Q4	2012Q4	2012Q4	2012Q4	2012Q4
Countries	Algeria	Angola	Nigeria	Saudi Arabia	
Start	1999Q2	2000Q4	1998Q4	1979Q3	
End	2012Q4	2012Q4	2012Q4	2012Q4	

Table 6.3. Data availability for Brazil

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1980q1 – 2014q4	1970 – 2008	IMF/IFS & UN DATA
Broad Money Liabilities (Millions of national currency)	2001q4 2014q4		IMF/IFS
Broad Money Liabilities seasonal adjusted (Millions of national currency)	2001q4 2014q4		IMF/IFS
Money Supply (M1) in Million national currency	1971q1 2014q4		IMF/IFS
Money and quasi money (M2) (current LCU)		1990 2014	World Bank
GDP (current) US $		1961 2014	World Bank
Real GDP		1992 2011	Penn World Table
Unemployment rate %	1960q4- 2014q4		IMF/IFS
Industrial production	1975q1 2015q3		OECD
lending interest rate	1997q1 – 2014q4		IMF/IFS
Money market rate	1957q1 2014q4		IMF/IFS
Real interest rate	1997q1 – 2014q4		World Bank
Treasury bill rates %	1995q1 -2014q4		IMF/IFS
Discount rate end of period (% per annum)	1999q2 2014q4		IMF/IFS
Real effective Exchange rate (CPI BASED)	1980q1 2014q4		IMF/IFS
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
GDP DEFLATOR (2000=100) index	1995q1 2014q4		IMF/IFS
Oil price	1980q1 – 2014q4		FRED database[92]

The above table summarises the availability of data for Brazil. For Brazil, we would ideally like to collect data over the period 1994q2 – 2014q4. We implement a VAR analysis using data available over this period involving the following variables: consumer

[92] In this study, we employ quarterly seasonal unadjusted data for the oil price rather than the seasonal adjusted oil price earlier mentioned by external supervisor simply because the graph of the partial autocorrelation for the quarterly oil price shows that oil price does not has the feature of seasonality between the period of 1980q1 to 2014q4.

price index, nominal money supply M1, the money market short-term interest rate, the real effective exchange rate, oil price and unemployment. Quarterly data on industrial production is also available over this sample period which means that the output gap can also be constructed. We will use the EViews frequency conversion tool to generate quarterly versions of these series to additionally use in our VAR analysis. A similar data selection procedure was applied to all countries and (to save space) the full discussion for each country is made available in appendix section 6.1 page 444 – 456. The table below summarises the data availability for each country.

Table 6.4. Summary of data availability for all the countries

Countries	Sample	Variables
Brazil	1999q4 2012q4	P, M, R, REE, UN, GAP and Oilp
Russia	2003Q2 2012q4	P, M, R, REE, UN, GAP and Oilp
India	1963q1 2012q4	P, M, R, GAP and Oilp
China	1992q1 2012q4	P, M, R, REE, GAP and Oilp
South Africa	1995q2 -2012q4	P, M, R, REE, GAP and Oilp
Algeria	1999q2 2012q4	P, M, R, REE, GAP and Oilp
Angola	2002q4 2012q4	P, M, R, GAP and Oilp
Nigeria	1998q4 2012q4	P, M, R, REE GAP and Oilp
Saudi Arabia	1983q1 2012q4	P, M REE, GAP and Oilp

Where P= consumer price, M =money supply, REE= real exchange rate, GAP = output gap, R = interest rate, UN =unemployment and Oilp = oil price. The invalid models indicate the VAR model that do not pass diagnoses test for autocorrelation with all suggesting lags length.

6.1 Phillips Curve

In this section, we utilise the available variables discussed in the previous section to construct the output gap that is based on the Phillips curve. The Phillips curve is a widely used economic model to forecast inflation.[93] The model is based on measures of economic activity such as the unemployment rate or the output gap. The output gap measures the difference between current economic activity (actual output) and the potential output level that could be sustained while keeping inflation stable.[94] The unemployment rate is calculated as a percentage by dividing the number of unemployed individuals by all individuals currently in the labour force.[95] There are many different methods for estimating the output gap. The methods are either based on pure statistical procedures or economic theories. Some statistical procedures are the univariate Hodrick-Prescott (HP) method, multivariate HP method, linear trend method, quadratic time trend, Baxter-King (BK) method, the state-space framework using the Kalman filter etc. The theoretical methods include structural VAR, the Cobb-Douglas production function etc. In practice, each method has advantages and disadvantages and none is unambiguously better than the alternatives.[96] Therefore, we seek to use an appropriate method that is relevant to our research and can be constructed with the available data.[97] Since our focus is on forecasting and comparison, we consider two

[93] See Stock and Watson (1999, 2008), Onder (2004), Faust and Wright (2011) and Ogunc et al. (2013) among others.

[94] See: Office for Budget Responsibility (2011) Estimating the output gap Briefing paper no.2; available on http://budgetresponsibility.org.uk/wordpress/docs/briefing%20paper%20No2%20FINAL.pdf [accessed] on 28 February 2015.

[95] The concept of the output gap is often used to maintain low inflation and stable economic growth. Accordingly, when aggregate demand exceeds potential output, the economy is subject to inflationary pressures and inflation should be expected to increase. Under these circumstances, policymakers will control inflation by restricting aggregate demand. Similarly, when aggregate demand falls short of potential supply, inflation is expected to fall. To maintain stable inflation, the monetary authority aims to adopt expansionary policies.

[96] For example, the Hodrick-Prescott method has the merit of simplicity, but it does not generally exploit additional relevant information apart from information on the variable of interest. Burns et al (2014) suggest that the output gap estimated with a production function and multivariate methods are superior to the Hodrick-Prescott filter and other single variable estimation methods of the output gap. Hendry (2001) argues that the linear trend method can be misleading if the trend-growth changes or becomes inconsistent, especially during periods of economic instability and economic recession.

[97] See Ince and Papell, 2013 on how to estimate different types of output gap.

measures of the output gap when considering the Phillips curve. One uses the unemployment rate and the other uses a version of Stock and Watson's activity index.[98]

[98] See: Stock and Watson (1999) and Atkeson and Ohanian (2001) for a similar methodology. However, Stock and Watson (1999) noted that the Phillips curve estimated with real economic activity provides the best forecast when compared with unemployment-based Phillips curves. They conclude that "the unemployment rate Phillips curve can play a useful role in forecasting inflation, but that relying on it to the exclusion of other forecasts is a mistake". Stock and Watson (2003) document that the ability of output gap models to forecast inflation in Europe is more limited than in the U.S

6.2. Inflation forecasts based on measures of aggregate real activity and unemployment rate

The Phillips curve model that we base our research on is the same as the methodology used by Stock and Watson (1999, 2003), Clark and McCracken (2006) and Nnanna (2007). Their models can be written as:

$$\pi_{t+h} - \pi_t = \mu + \beta(L)x_t + \gamma(L)\Delta\pi_t + v_t \qquad 6.1$$

Where v_t is the random disturbance, μ is a constant, π_t denotes the inflation rate, x_t is an indicator for the activity index or unemployment rate, $\gamma(L)$ and $\beta(L)$ are polynomials in lag operators L and t is the time period. We consider two measures of aggregate activity that are suggested by Stock and Watson (2003) – the index of industrial production and real output measured by real GDP – and utilise the measure where data is most available.[99] We also consider the unemployment rate as measure by International Labour Organization.

In this study we follow Stock and Watson (1999) and estimate x_t in equation 6.1 based on the one-sided version of the Hodrick-Prescott (HP) filter.[100] This method is convenient and preserves the temporal ordering of the data.[101] The one–sided HP trend is constructed as the Kalman filter estimate of τ_t in the model:

$$y_t = \tau_t + \varepsilon_t, \qquad 6.2$$

$$\Delta^2 \tau_t = \eta_t \qquad 6.3$$

[99] Due to the limited data, we use different indicators of the real activity variable for different countries. The industrial production index is available for Brazil, India, Russia, Nigeria and Saudi Arabia while the real output variable measure, real GDP, is estimated by adjusting nominal GDP with the GDP deflator for all the remaining countries.
[100] We use the one-side version because the future value of the observed series (y_t) would not be used in the detrending operation.
[101] See: Stock and Watson (1999, 2003), Clark and McCracken (2006) and Nnanna (2007) for a similar methodology.

Where y_t is the logarithm of the series (the observed series), τ_t is the unobserved trend component and ε_t and η_t are mutually uncorrelated white noise sequences with relative variance q=var(η_t)/var(ε_t). Accordingly, $q = 0.00625$, which corresponds to the usual value of the HP smoothing parameter (Δ^2 = Lambda = 1600). The HP technique computes the smoothed series of the trend component (τ_t) of the log of the real activity variable (y_t) to minimize the variance of the log of this real activity variable around it trend. That is, the output gap is calculated by minimizing the loss-function:

$$\text{Minimise } \{\tau_t\}^{\tau}{}_{t=-1} \quad \{ \textstyle\sum_{t=1}^{\tau} \varepsilon_t{}^2 + \lambda \sum_{t=1}^{\tau}[(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})]^2 \} \qquad 6.4$$

where ε_t = y_t - τ_t, λ is the relative multiplier and the parameter is a positive number. The smoothness parameter λ punishes the variability in the trend component smoother. The larger the value of λ the smoother is the trend component and when λ approaches infinity the trend component becomes a linear trend (Ince and Papell, 2013).[102]

[102] The value of Δ^2 is conventionally set at 100 for annual data, 1600 for quarterly data and 14,400 for monthly series (see: Van Norden Simone 1995, Ceo and McDermott, 1996, Ince and Papell, 2013 and E-views 8 guidelines for estimating the Hodrick-Prescott (HP) filter).

6.3. Multivariate Cointegration Forecast

Our multivariate time series model is based on the VAR method. A standard VAR is used to capture the linear interdependencies of multivariate time series and capture the dynamic behaviours and structural relationship among the variables. That is, it consists of linear relationships among the different variables in which each variable is explained by its own lags, as well as the current and past values of the remaining variables. In estimating a VAR, we face different decisions, namely: the variables to be included and how to deal with the non-stationarity variables.

With regard to nonstationarity, we test for the orders of integration of variables and for those that are nonstationary we consider whether they are cointegrated.[103] We note that modelling and forecasting any series that is not stationary may lead to spurious results. Engle and Granger (1987) establish that a cointegrating equation can be represented as an error correction model which incorporates both changes and levels of variables such that all of the elements are stationary. However, "VARs estimated with cointegrated data will be misspecified if all of the data are differenced because long-run information will be omitted and will have omitted stationarity inducing constraints if all of the data are used in levels. Further, including variables in both levels and differences should satisfy stationarity requirements, however, they will omit cointegrating restrictions that may improve the model. Of course, these constraints will be satisfied asymptotically but efficiency gains and improved multi-step forecasts may be achieved by imposing the constraints" (Engle Granger 1987, p. 259). Therefore, we distinguish between different techniques in modelling using differencing and cointegrating restrictions via an error-correction model to ensure stationary.[104] We focus on the following approaches, three of which are discussed by Timothy and Thomas (1998). The first approach is to construct a VAR model in pure differences (stationary form) to forecast inflation.[105] The second approach is to construct a VECM without imposing

[103] The linear combination of two series which are stationary only after differencing may be cointegrated without differencing (Granger, 1986).
[104] The literature on forecasting variables in cointegrated models that are similar to our approach includes: Engle et al. (1989), Engle and Yoo (1987), Hall et al. (1992), Fanchon and Wendel (1992), Timothy and Thomas (1998) and Sa-ngasoongsong et al. (2012).
[105] As a necessary requirement for this method, all the variables must integrate in the same order, therefore, all the variables will be seasonal adjusted by using census x- 12 or x- 13 and Augmented Dickey-Fuller (ADF) test statistics will be used to test whether each variable has a unit root. The condition is that, the series must be stationary before applying this method.

cointegrating restrictions. The third approach is to construct a VEC that imposes cointegrating restrictions on the VECM. This will allow us to consider whether imposing cointegrating restrictions via an vector error-correction model improves long-run forecasts.[106]

In selecting variables to use we focus on those variables that are commonly and mostly used in explaining and forecasting inflation in the literature and on which we have data. Because there are data constraints we take an eclectic theoretical approach in the sense of combining variables from different economic theories in our VAR specification. Our approach is as follows. We first specify our core VAR model, based on variables that are available at quarterly frequency across the whole sample for any particular country, for example this may include the three variables: money supply, interest rates and prices (from which inflation can be generated). We examine the ability of VARs based on these variables to forecast inflation. To avoid model misspecification (in particular omitted variable issues), we examine whether the inflation forecasting model can be improved by incorporating additional information. In this case we add variables that are available only annually over the available sample and use frequency conversion tools to generate quarterly series and/or variables that are only available quarterly over a reduced sub-sample. In this case, VAR models including all available inflation determinants for each country are considered. In particular, the VARs will be based on (a subset of) consumer prices, money supply, interest rates, real effective exchange rates, the output gap (or, alternatively the unemployment rate) as well as the world oil price (see Table 6.4).[107]

[106] We could use weak/strong exogeneity tests to eliminate irrelevant endogenous variables in the VAR/VECM/VEC, however, this would mean that some variables would not be forecasted by the VAR and would require separate forecasting equations. To avoid this, we will not impose any exogeneity restrictions and therefore do not apply exogeneity tests. The maximum eigenvalue and trace tests will be applied to guide us on whether there is co-integration.

[107] Given the variety of indicators that have been suggested to influence inflation in our literature chapter, we include many of these variables and observe whether incorporation of these variables would provide additional useful information about future inflation as compared to our previous univariate modelling.

6.4 Seasonal adjustment for selected macroeconomic variables

In this section, we identify the general features of selected macroeconomic variables identified in Table (6.4) in each country by mainly focusing on seasonality and stationary characteristics to avoid the issue of seasonal integration.[108] We seasonally adjust each series and compare the adjusted and unadjusted series. If the variances of these series are not significantly different, we regard the data as nonseasonal and utilise the unadjusted data. However, if the variances are significantly different we regard the data as seasonal and use the seasonally adjusted series. We also plot the autocorrelation functions of the series and if these indicate seasonality we will consider seasonally adjusting the data (even if the variances are not significantly different). Anticipating that prices / inflation will be seasonal we will save the seasonal indices in 2012 and use these to reintroduce seasonality into the forecasts that we produce. Using nonseasonal (seasonally adjusted) data will allow us to model using nonseasonal integration and cointegration techniques. For comparison purposes, we plot the graph of the level of the series, the seasonally adjusted data and other transformations of these series. These graphs are discussed for each country below.

[108] We seasonal adjusted these series because seasonal adjusted data are not available from international Financial Statistics/IMF for most of our selected data.

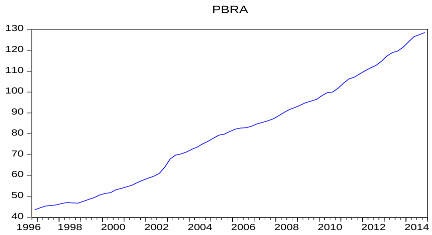
6.5. The graphical features of selected macroeconomic variables for Brazil

In Brazil, we amend the reduced sample identified in chapter 5 from 1994q2- 2014q4 to 1996q4 -2014q4 to avoid an outlier that occurred at the start of this sample.[109] The graphs below depict the following variables. The Brazilian consumer price (denoted PBRA), the seasonally adjusted PBRA series (PBRA_d11) and D_PBRA = PBRA - PBRA_d11, the first (nonseasonal) difference of LPBRA (DLPBRA), the seasonally adjusted LPBRA series (LPBRA_d11) and D_LPBRA = LPBRA - LPBRA_d11 (where LPBRA is the log of PBRA). The seasonally adjusted series PBRA_d11 is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PBRA and PBRA_d11 as well as DLPBRA and DLPBRA_d11. We expect equal variances for both tests if the data are nonseasonal. In contrast, if the data are seasonal we expect the equal variances null hypothesis to be rejected. However, if the data are nonstationary the variances may have equal variances in levels even if they are seasonal. Hence, for the data to be deemed seasonal and require seasonal adjustment we only require the equal variance null to be rejected for the stationary (differenced) form of the data. As a further check, we plot the ACF of LPBRA and DLPBRA. If the seasonal lag (4, 8, 12, 16 and 20) autocorrelation coefficients are significant in the stationary form of the series, we will use the seasonally adjusted data (even if the variance equality null hypothesis is not rejected).

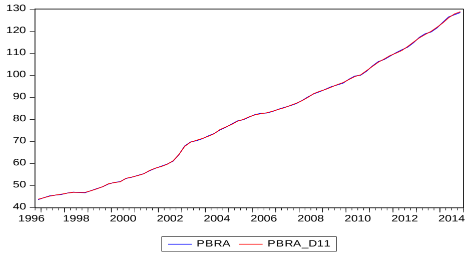
[109] From the preliminary plot of the linear graph of PBRA within 1994q2 – 2014q4, we observed a shift outlier at the beginning of the sample that becomes more visible after the samples were reduced. Although, we do not expect this to be a structural break because the Bai Peron test does not suggest this shift as a break in chapter 5, Table 5.1.1.

6.5.1. The graphs and table of equality test for consumer price in Brazil

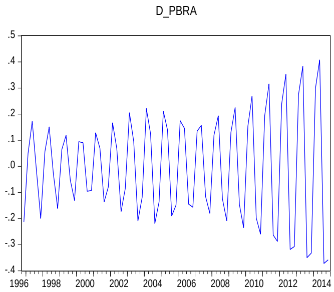
1A.



1B.



1C.

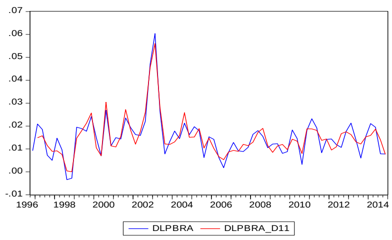


1D.

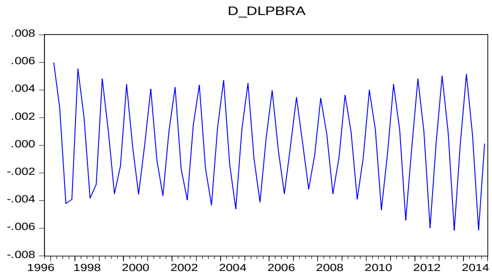
Test for equality of variance between (PBRA) and (PBRA_D11)

Method	Df	Value	Probability
F-test	(72, 72)	1.000523	0.9982
Siegel Turkey		0.003914	0.9969
Bartlett	1	4.88E-06	0.9982
Levene	(1, 144)	1.84E-06	0.9989
Brown-Forsythe	(1, 144)	2.18E-07	0.9996

1E.



1F.

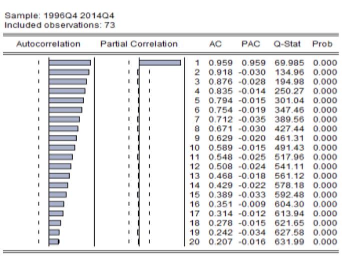


1G.

Test for equality of variance between series (DLPBRA) and (DLPBRA_D11)

Method	Df	Value	Probability
F-test	(71, 72)	1.170530	0.5069
Siegel Turkey		1.433490	0.1517
Bartlett	1	0.439452	0.5074
Levene	(1,143)	0.249246	0.6184
Brown-Forsythe	(1,143)	0.338507	0.5616

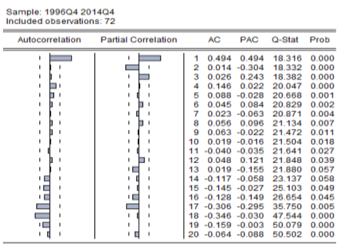
1H.



Sample: 1996Q4 2014Q4
Included observations: 73

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.959	0.959	69.985	0.000
		2	0.918	-0.030	134.96	0.000
		3	0.876	-0.028	194.98	0.000
		4	0.835	-0.014	250.27	0.000
		5	0.794	-0.015	301.04	0.000
		6	0.754	-0.019	347.46	0.000
		7	0.712	-0.035	389.56	0.000
		8	0.671	-0.030	427.44	0.000
		9	0.629	-0.020	461.31	0.000
		10	0.589	-0.015	491.43	0.000
		11	0.548	-0.025	517.96	0.000
		12	0.508	-0.024	541.11	0.000
		13	0.468	-0.018	561.12	0.000
		14	0.429	-0.022	578.18	0.000
		15	0.389	-0.033	592.48	0.000
		16	0.351	-0.009	604.30	0.000
		17	0.314	-0.012	613.94	0.000
		18	0.278	-0.015	621.65	0.000
		19	0.242	-0.034	627.58	0.000
		20	0.207	-0.016	631.99	0.000

1 I.



Sample: 1996Q4 2014Q4
Included observations: 72

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.494	0.494	18.316	0.000
		2	0.014	-0.304	18.332	0.000
		3	0.026	0.243	18.382	0.000
		4	0.146	0.022	20.047	0.000
		5	0.088	-0.028	20.668	0.001
		6	0.045	0.084	20.829	0.002
		7	0.023	-0.063	20.871	0.004
		8	0.056	0.096	21.134	0.007
		9	0.063	-0.022	21.472	0.011
		10	0.019	-0.016	21.504	0.018
		11	-0.040	-0.035	21.641	0.027
		12	0.048	0.121	21.848	0.039
		13	0.019	-0.155	21.880	0.057
		14	-0.117	-0.058	23.137	0.058
		15	-0.145	-0.027	25.103	0.049
		16	-0.128	-0.149	26.654	0.045
		17	-0.306	-0.295	35.750	0.005
		18	-0.346	-0.030	47.544	0.000
		19	-0.159	-0.003	50.079	0.000
		20	-0.064	-0.088	50.502	0.000

As shown in Fig. 1A, the graph of consumer prices for Brazil (PBRA) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing. The time paths of PBRA and PBRA_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between PBRA and PBRA_d11 (denoted D_PBRA) is plotted in Figure 1C. The difference has revealed a cyclical fluctuation that ranges between -0.37 and 0.41. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PBRA and PBRA_d11 that are reported in table 1D. The reported tests are the: F-, Siegel Turkey, Bartlett, Levene and Brown Forsythe tests. For all tests the null hypothesis is that the variances are equal. Hence, if the p-value exceeds 0.05 we cannot reject the null hypothesis of equal variances and therefore infer that there is no significant seasonality. Whereas if the p-value is below 0.05 we reject the null hypothesis and conclude that the difference in the series' variances are statistically significant and there is significant seasonality. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PBRA and PBRA_d11. Hence, we find that seasonality is not significant in the price level. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the logs of the adjusted (DLPBRA_d11) and unadjusted (DLPBRA) data.

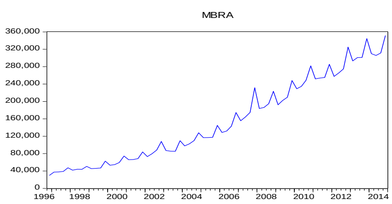
The time paths of DLPBRA and DLPBRA_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after first differencing. The variation in DLPBRA is greater than that of DLPBRA_d11 suggesting seasonality in DLPBRA while DLPBRA_d11 is smoother. This suggests that DLPBRA_ d11 exhibits reduced seasonality as expected. The difference between DLPBRA and DLPBRA_d11 (denoted D_DLPBRA) is plotted in Figure 1F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.006 and 0.005. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPBRA and DLPBRA_d11 that are reported in table 1G. Since the p-values of all of our tests are greater than 0.05 we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLPBRA and DLPBRA_d11. Hence, we find that seasonality is not significant in the difference of the log prices for Brazil.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of PBRA and DLPBRA in figure 1H and 1I. Shown in Fig. 1H is the ACF for PBRA. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPBRA (see fig. 1I) has no significant ACs at seasonal lags. This implies that seasonality is not significant in the price data and confirms the results of the variance equality tests. Hence, we use the unadjusted data PBRA in our VAR analysis.

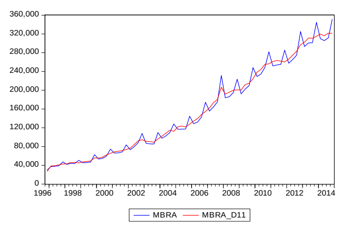
6.5.2. The seasonality features of money supply in Brazil

The graphs below depict the following variables. The Brazilian money supply (denoted MBRA), the seasonally adjusted MBRA series (MBRA_d11) and D_MBRA = MBRA - MBRA_d11, as well as the first (nonseasonal) difference of LMBRA (DLMBRA), the seasonally adjusted LMBRA series (LMBRA_d11) and D_LMBRA = LMBRA - LMBRA_d11 (where LMBRA is the log of MBRA). The seasonally adjusted series MBRA_d11 is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for MBRA and MBRA_d11 as well as DLMBRA and DLMBRA_d11.

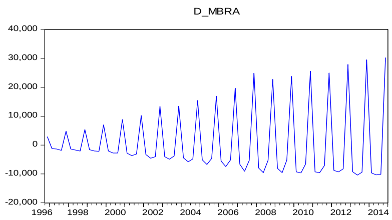
2A.



2B.



2C.

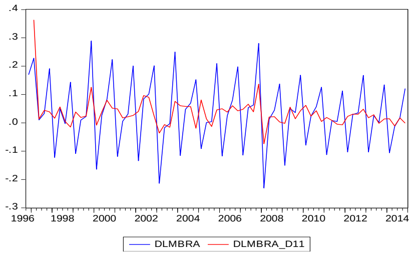


2D.

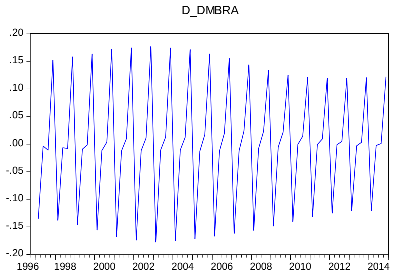
Test for equality of variance between MBRA and MBRA_D11

Method	Df	Value	Probability
F-test	(72, 72)	1.022760	0.9242
Siegel Turkey		0.007828	0.9939
Bartlett	1	0.009053	0.9242
Levene	(1,144)	0.004347	0.9475
Brown-Forsythe	(1,144)	0.002260	0.9621

2E.



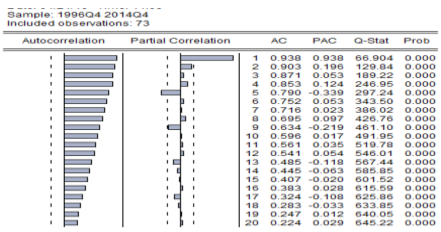
2F.



2G. Test for equality of variance between DLMBRA and DLMBRA_D11

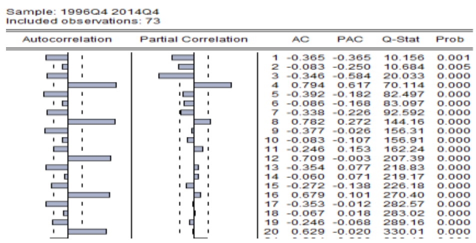
Method	Df	Value	Probability
F-test	(71, 72)	5.141913	0.0000
Siegel Turkey		4.786866	0.0000
Bartlett	1	42.92244	0.0000
Levene	(1,143)	35.65966	0.0000
Brown-Forsythe	(1,143)	34,91378	0.0000

2H.


Sample: 1996Q4 2014Q4
Included observations: 73

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.938	0.938	66.904	0.000
		2	0.903	0.196	129.84	0.000
		3	0.871	0.053	189.22	0.000
		4	0.853	0.124	246.95	0.000
		5	0.790	-0.339	297.24	0.000
		6	0.752	0.053	343.50	0.000
		7	0.716	0.023	386.02	0.000
		8	0.695	0.097	426.76	0.000
		9	0.634	-0.219	461.10	0.000
		10	0.596	0.017	491.95	0.000
		11	0.561	0.035	519.78	0.000
		12	0.541	0.054	546.01	0.000
		13	0.485	-0.118	567.44	0.000
		14	0.445	-0.063	585.85	0.000
		15	0.407	-0.020	601.52	0.000
		16	0.383	0.028	615.59	0.000
		17	0.324	-0.108	625.86	0.000
		18	0.283	-0.033	633.85	0.000
		19	0.247	0.012	640.05	0.000
		20	0.224	0.029	645.22	0.000

2I.


Sample: 1996Q4 2014Q4
Included observations: 73

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.365	-0.365	10.156	0.001
		2	-0.083	-0.250	10.684	0.005
		3	-0.346	-0.584	20.033	0.000
		4	0.794	0.617	70.114	0.000
		5	-0.392	-0.182	82.497	0.000
		6	-0.086	-0.168	83.097	0.000
		7	-0.338	-0.226	92.592	0.000
		8	0.782	0.272	144.16	0.000
		9	-0.377	-0.026	156.31	0.000
		10	-0.083	-0.107	156.91	0.000
		11	-0.246	0.153	162.24	0.000
		12	0.709	-0.003	207.39	0.000
		13	-0.354	0.077	218.83	0.000
		14	-0.060	0.071	219.17	0.000
		15	-0.272	-0.138	226.18	0.000
		16	0.679	0.101	270.40	0.000
		17	-0.353	-0.012	282.57	0.000
		18	-0.067	0.018	283.02	0.000
		19	-0.246	-0.068	289.16	0.000
		20	0.629	-0.020	330.01	0.000

As shown in Fig. 2A, the graph of money supply in Brazil (MBRA) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. There are clear cycles that probably reflect seasonality. Therefore, MBRA may need to be seasonally adjusted.

The time paths of MBRA and MBRA_d11 (see Figure 2B) follow each other. It is obvious that the variation in MBRA is greater than that of MBRA_d11 and the plot of MBRA_d11 is smoother than the plot of MBRA. The difference between MBRA and MBRA_d11 (denoted D_MBRA) is plotted in Figure 2C. The difference reveals a regular cyclical fluctuation that may indicate time-varying seasonality. To ascertain whether the seasonality is significant we refer to a variety of tests for the equality of variance between MBRA and MBRA_d11 that are reported in table 2D. Since the p-values of all tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of MBRA and MBRA_d11. This suggests that seasonality is not significant in the level of the data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLMBRA_d11) and unadjusted (DLMBRA) data.

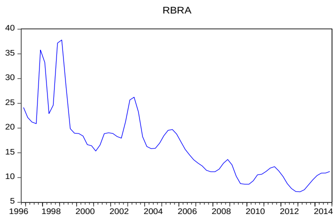
The time paths of DLMBRA and DLMBRA_d11 (see Figure 2E) follow each other closely. The trend has been removed and the series broadly fluctuate around a constant mean as expected after first differencing. The variation in DLMBRA is greater than that of DLMBRA_d11. Therefore, there is seasonality in the DLMBRA series while DLMBRA_d11 is smoother suggesting that DLMBRA_ d11 exhibits reduced seasonality. The difference between DLMBRA and DLMBRA_d11 (denoted D_DLMBRA) is plotted in Figure 2F. The difference reveals a regular fluctuation around a relatively constant mean that ranges between -0.178 and 0.17. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLMBRA and DLMBRA_d11 that are reported in table 2G. Since the p-values of all of our tests is less than 0.05 we reject the null hypothesis and find that there is a significant difference in the variances of DLMBRA and DLMBRA_d11. Hence, seasonality is significant in the difference of the log of the money supply in Brazil.

As a check, we plot the ACFs of MBRA and DLMBRA in figure 2H and 2I. Shown in Fig. 2H is the ACF for MBRA. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLMBRA (see fig. 2I) has significant ACs at all seasonal lags. This implies that seasonality is significant in the money supply data and confirms the results of the variance equality tests. Hence, we will use the seasonally adjusted data MBRA_d11 in our VAR analysis.

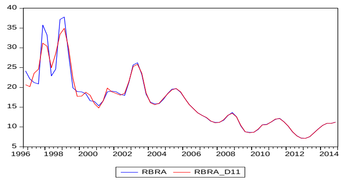
6.5.3. The seasonality features of interest rate in Brazil

The graphs below depict the following variables. The Brazilian interest rate (denoted RBRA), the seasonally adjusted RBRA series (RBRA_d11), D_RBRA = RBRA - RBRA_d11, and the first (nonseasonal) difference of RBRA (DRBRA), the seasonally adjusted DRBRA series (DRBRA_d11) and D_DRBRA = DRBRA – DRBRA_d11. The seasonally adjusted series RBRA_d11 is obtained using the Census X13 procedure in EViews. Table 3D reports various variance equality tests for RBRA and RBRA_d11 while Table 3G reports these tests for variance equality for DRBRA

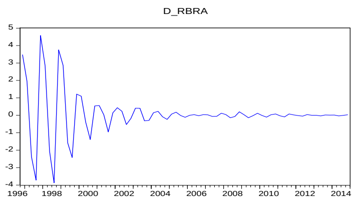
3A.



3B.



3C.

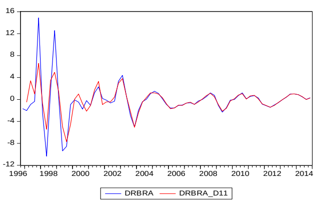


3D

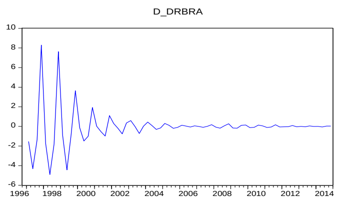
Test for equality of variance between RBRA and RBRA_D11

Method	Df	Value	Probability
F-test	(27, 72)	1.099482	0.6885
Siegel Turkey		0.027397	0.9781
Bartlett	1	0.160724	0.6885
Levene	(1,144)	0.0038	0.9622
Brown-Foresythe	(1,144)	0.003811	0.9509

3E.



3F.

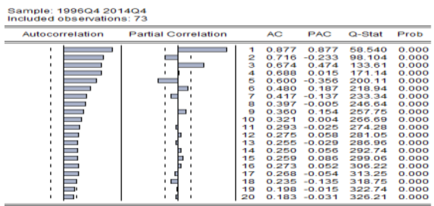


3G.

Test for equality of variance between DRBRA and DRBRA_D11

Method	Df	Value	Probability
F-test	(71, 72)	2.217432	0.0009
Siegel Turkey		0.599102	0.5491
Bartlett	1	10.95152	0.0009
Levene	(1, 143)	0.337148	0.5624
Brown-Foresythe	(1,143)	0.349575	0.5553

3H.



Sample: 1996Q4 2014Q4
Included observations: 73

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.877	0.877	58.540	0.000
		2	0.716	-0.233	98.104	0.000
		3	0.674	0.474	133.61	0.000
		4	0.688	0.015	171.14	0.000
		5	0.600	-0.356	200.11	0.000
		6	0.480	0.187	218.94	0.000
		7	0.417	-0.137	233.34	0.000
		8	0.397	-0.005	246.64	0.000
		9	0.360	0.154	257.75	0.000
		10	0.321	0.004	266.69	0.000
		11	0.293	-0.025	274.28	0.000
		12	0.275	0.058	281.05	0.000
		13	0.255	-0.029	286.96	0.000
		14	0.250	0.056	292.74	0.000
		15	0.259	0.086	299.06	0.000
		16	0.273	0.052	306.22	0.000
		17	0.268	-0.054	313.25	0.000
		18	0.235	-0.135	318.75	0.000
		19	0.198	-0.015	322.74	0.000
		20	0.183	-0.031	326.21	0.000

3I.

Sample: 1996Q4 2014Q4
Included observations: 73

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.194	0.194	2.8612	0.091
		2	-0.530	-0.590	24.531	0.000
		3	-0.258	0.032	29.726	0.000
		4	0.271	0.050	35.562	0.000
		5	0.162	-0.119	37.679	0.000
		6	-0.144	0.021	39.375	0.000
		7	-0.227	-0.191	43.667	0.000
		8	-0.077	-0.141	44.166	0.000
		9	-0.000	-0.203	44.166	0.000
		10	0.059	-0.046	44.467	0.000
		11	0.066	-0.040	44.852	0.000
		12	0.024	-0.005	44.902	0.000
		13	-0.065	-0.070	45.287	0.000
		14	-0.062	-0.111	45.649	0.000
		15	-0.008	-0.156	45.655	0.000
		16	0.082	-0.055	46.308	0.000
		17	0.137	0.078	48.145	0.000
		18	-0.006	-0.065	48.149	0.000
		19	-0.136	0.006	50.020	0.000
		20	-0.054	-0.062	50.323	0.000

As shown in Fig. 3A, the graph of RBRA exhibits a downward trend. Seasonality is not clearly visible in the Brazilian interest rate plot because of the dominant trend.

The time paths of RBRA and RBRA_d11 (see Figure 3B) follow each other closely with the largest difference occurring in 1997q4 when RBRA_d11 is 31.20% and RBRA is 35.80%. While RBRA_d11 is smoother than RBRA this is primarily due to two large cycles at the start of the sample which do not appear to be a year in length. Hence, the difference may not reflect seasonality. We plot the difference between RBRA and RBRA_d11 (denoted D_RBRA) in Figure 3C to further assess whether RBRA is seasonal. The difference indicates time-varying cycles that substantially decline. We refer to a variety of tests for the equality of variance between RBRA and RBRA_d11 that are reported in table 3D. Since the p-values of all of our tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RBRA and RBRA_d11 and hence we find that seasonality is not significant in the level of the data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DRBRA_d11) and unadjusted (DRBRA) data.

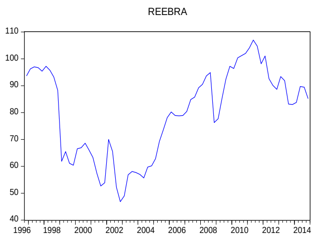
The time paths of DRBRA and DRBRA_d11 (see Figure 3E) follow each other closely if the variation in DRBRA is greater than that of DRBRA_d11 at the start of the sample – if not the end. Therefore, seasonality is not obvious. The difference between DRBRA and DRBRA_d11 (denoted D_DRBRA) is plotted in Figure 3F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -4.90% and 8.30% that substantially declines through time. Variance equality tests between DRBRA and DRBRA_d11 are reported in Table 3G. The p-values for Siegel Turkey, Levene and Brown Forsythe tests are greater than 0.05 indicating equal variances while the p-values of the F-test and Bartlett test are less than 0.05 which reject the null hypothesis of equal variance. Hence, the results regarding equality of variance are ambiguous.

To explore the issue further we plot the ACFs of RBRA and DRBRA in figure 3H and 3I, respectively. Shown in Fig. 3H is the ACF for RBRA. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DRBRA (see fig. 3I) has a marginally significant AC at the first seasonal lag (lag 4) and all other ACs at seasonal lags are insignificant. This provides some evidence that seasonality is significant in the interest rate data. However, because the ACF evidence is not strong, the variance equality tests give ambiguous conclusions, the graphs do not convincingly suggest one-year cycles and seasonality is not expected in interest rates we take the view that RBRA probably is not seasonal. Hence, we use the unadjusted data RBRA in our VAR analysis.

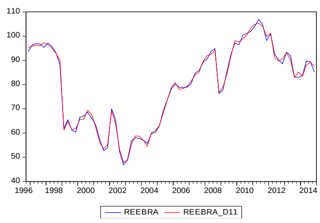
6.5.4. The seasonality features the real effective exchange rate in Brazil

The graphs below depict the following variables. The Brazilian real effective exchange (denoted REEBRA), the seasonally adjusted REEBRA series (REEBRA_d11) and D_REEBRA = REEBRA - REEBRA_d11, as well as the first (nonseasonal) difference of LREEBRA (DLREEBRA), the seasonally adjusted DLREEBRA series (DLREEBRA_d11) and D_DLREEBRA = DLREEBRA - DLREEBRA_d11 (where LREEBRA is the log of REEBRA). The seasonally adjusted series (REEBRA_d11) is obtained using the Census X13 procedure in EViews. Tables 4D and 4G report various tests of the null hypothesis of equality of variance for REEBRA and REEBRA_d11 as well as DLREEBRA and DLREEBRA_d11.

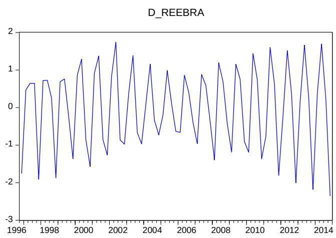
4A.



4B.



4C.

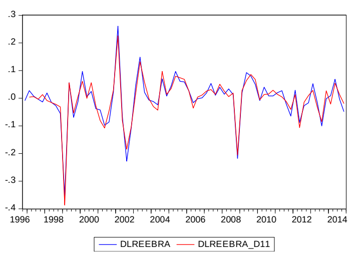


4D.

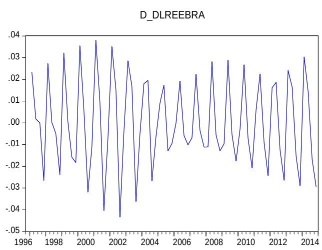
Test for equality of variance between REEBRA and REEBRA_D11

Method	Df	Value	Probability
F-test	(72, 72)	1.001178	0.9960
Siegel Turkey		0.003914	0.9969
Bartlett	1	2.48E-05	0.9960
Levene	(1,144)	0.000654	0.9796
Brown-Foresythe	(1,144)	3.66E-05	0.9952

4E



4F.

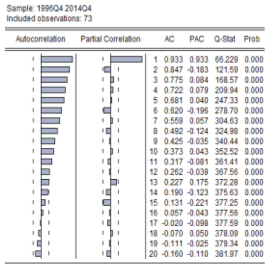


4G.

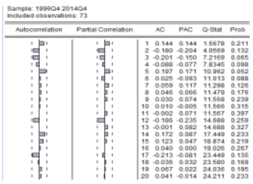
4H.

Test for equality of variance between DLREEBRA and DLREEBRA_D11

Method	Df	Value	Probability
F-test	(71, 72)	1.054191	0.8236
Siegel Turkey		0.231336	0.8171
Bartlett	1	0.049424	0.8241
Levene	(1, 143)	0.024550	0.8757
Brown-Foresythe	(1,143)	0.049137	0.8249



4I



As shown in Fig. 4A, the graph of real effective exchange rate fluctuates around a relatively constant mean. There are large cycles that do not appear to be a year in length.

The time paths of REEBRA and REEBRA_d11 (see Figure 4B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between REEBRA and REEBRA_d11 (denoted D_REEBRA) is plotted in Figure 4C. The difference has revealed a cyclical fluctuation that ranges between -2.40 and 1.70. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between REEBRA and REEBRA_d11 that are reported in table 4D. Since the p-values of all tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REEBRA and REEBRA_d11 and hence find that seasonality is not significant in the level of the real effective exchange rate. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLREEBRA_d11) and unadjusted (DLREEBRA) data.

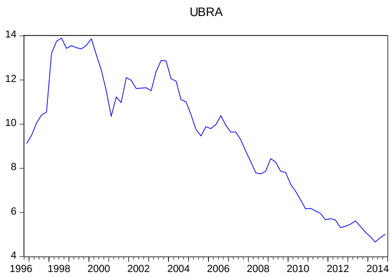
The time paths of DLREEBRA and DLREEBRA_d11 (see Figure 4E) follow each other closely. The variation in DLREEBRA is slightly greater than that of DLREEBRA_D11 suggesting possible seasonality in DLREEBRA while DLREEBRA_D11 is smoother. This suggests that DLREEBRA_D11 exhibits reduced seasonality as expected. The difference between DLREEBRA and DLREEBRA_d11 (denoted D_DLREEBRA) is plotted in Figure 4F. The difference revealed a regular fluctuation around a relatively constant mean that ranges between -0.045 and 0.038. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREEBRA and DLREEBRA_d11 that are reported in table 4G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLREEBRA and DLREEBRA_d11 and hence find that seasonality is not significant in the difference of the log of the real effective exchange rate data for Brazil.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of REEBRA and DLREEBRA in figure 4H and 4I. Shown in Fig. 4H is the ACF for REEBRA. The first 14 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not seasonality. The ACF for DLREEBRA has no significant ACs at seasonal lags (see fig. 4I). This implies that seasonality is not significant in the real effective exchange rate and confirms the results of the variance equality tests. Hence, we will use the unadjusted data REEBRA our VAR analysis.

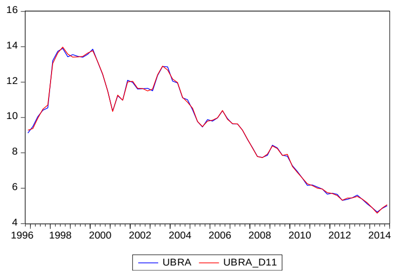
6.5.5. Seasonality and the Brazilian unemployment rate

The graphs below depict the following variables. The Brazilian unemployment rate (denoted UBRA), the seasonally adjusted UBRA series (UBRA_d11) and D_UBRA = UBRA - UBRA_d11, as well as the first (nonseasonal) difference of UBRA (DUBRA), the seasonally adjusted DUBRA series (DUBRA_d11) and D_DUBRA – DUBRA_d11. The seasonally adjusted series (UBRA_d11) is obtained using the Census X13 procedure in EViews. Tables 5D and 5G report various tests of the null hypothesis of equality of variance for UBRA and UBRA_d11 as well as DUBRA and DUBRA_d11.

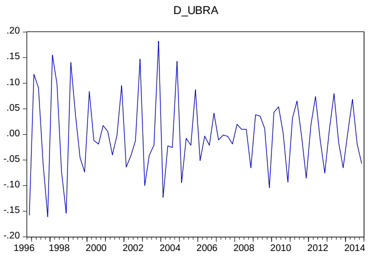
5A.



5B.



5C.

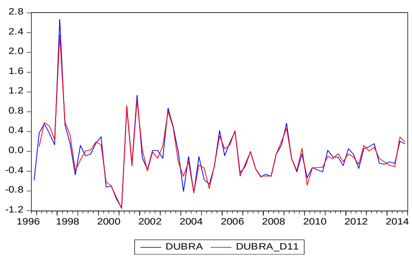


5D

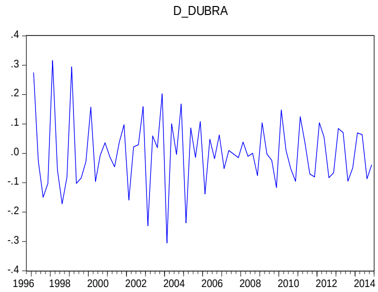
Test for equality of variance between UBRA and UBRA_D11

Method	Df	Value	Probability
F-test	(72, 72)	1.002404	0.9919
Siegel Turkey		-3.56E-15	1.0000
Bartlett	1	0.000103	0.9919
Levene	(1,144)	9.62E-05	0.9922
Brown-Foresythe	(1,144)	0.000105	0.9918

5E.



5F.

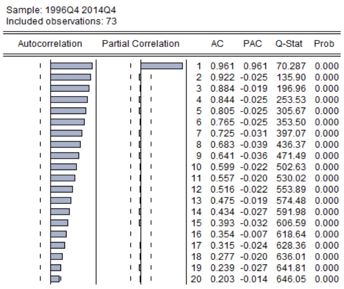


5G.

Test for equality of variance between DUBRA and DUBRA_D11

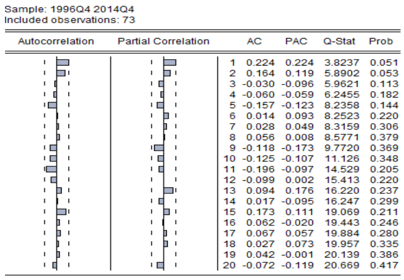
Method	Df	Value	Probability
F-test	(71, 72)	1.125242	0.6188
Siegel Turkey		0.164110	0.8696
Bartlett	1	0.246932	0.6192
Levene	(1, 143)	0.025760	0.8727
Brown-Foresythe	(1,143)	0.029663	0.8635

5H.


Sample: 1996Q4 2014Q4
Included observations: 73

	AC	PAC	Q-Stat	Prob
1	0.961	0.961	70.287	0.000
2	0.922	-0.025	135.90	0.000
3	0.884	-0.019	196.96	0.000
4	0.844	-0.025	253.53	0.000
5	0.805	-0.025	305.67	0.000
6	0.765	-0.025	353.50	0.000
7	0.725	-0.031	397.07	0.000
8	0.683	-0.039	436.37	0.000
9	0.641	-0.036	471.49	0.000
10	0.599	-0.022	502.63	0.000
11	0.557	-0.020	530.02	0.000
12	0.516	-0.022	553.89	0.000
13	0.475	-0.019	574.48	0.000
14	0.434	-0.027	591.98	0.000
15	0.393	-0.032	606.59	0.000
16	0.354	-0.007	618.64	0.000
17	0.315	-0.024	628.36	0.000
18	0.277	-0.020	636.01	0.000
19	0.239	-0.027	641.81	0.000
20	0.203	-0.014	646.05	0.000

5I.


Sample: 1996Q4 2014Q4
Included observations: 73

	AC	PAC	Q-Stat	Prob
1	0.224	0.224	3.8237	0.051
2	0.164	0.119	5.8902	0.053
3	-0.030	-0.096	5.9621	0.113
4	-0.060	-0.059	6.2455	0.182
5	-0.157	-0.123	8.2358	0.144
6	0.014	0.093	8.2523	0.220
7	0.028	0.049	8.3159	0.306
8	0.056	0.008	8.5771	0.379
9	-0.118	-0.173	9.7720	0.369
10	-0.125	-0.107	11.126	0.348
11	-0.196	-0.097	14.529	0.205
12	-0.099	0.002	15.413	0.220
13	0.094	0.176	16.220	0.237
14	0.017	-0.095	16.247	0.299
15	0.173	0.111	19.069	0.211
16	0.062	-0.020	19.443	0.246
17	0.067	0.057	19.884	0.280
18	0.027	0.073	19.957	0.335
19	0.042	-0.001	20.139	0.386
20	-0.072	-0.119	20.669	0.417

As shown in Fig. 5A, the graph of unemployment (UBRA) follows a downward trend. Seasonality is not clearly visible in the unemployment plot because of the dominant trend – although this downward trend could not continue indefinitely because unemployment cannot fall below 0%.

The time paths of UBRA and UBRA_d11 (see Figure 5B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between UBRA and UBRA_d11 (denoted D_UBRA) is plotted in Figure 5C. The difference has revealed cyclical fluctuation that ranges between -0.161 % and 0.182%. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between UBRA and UBRA_d11 that are reported in table 5D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of UBRA and UBRA_d11. Hence, we find that seasonality is not significant in the level of unemployment data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DUBRA_d11) and unadjusted (DUBRA) data.

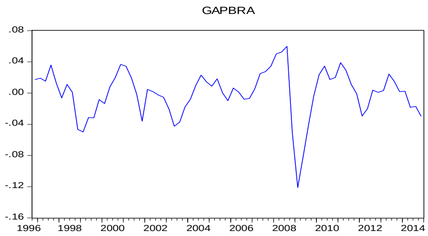
The time paths of DUBRA and DUBRA_d11 (see Figure 5E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean, as expected after first differencing. The variation in DUBRA is greater than that of DUBRA_d11 suggesting seasonality in DUBRA while DUBRA_D11 is smoother. This suggests that DUBRA_D11 exhibits reduced seasonality as expected. The difference between DUBRA and DUBRA_d11 (denoted D_DUBRA) is plotted in Figure 5F. The difference has revealed cyclical fluctuations that range between -0.30% and 0.32%. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DUBRA and DUBRA_d11 that are reported in table 5G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DUBRA and DUBRA_d11 and hence find that seasonality is not significant in the difference of the unemployment rate for Brazil.

To check that we have not missed any significant seasonality we plot the ACFs of UBRA and DUBRA in figure 5H and 5I. In Fig. 5H all ACs are significant (and not just at the seasonal lags) which suggest nonstationary and not necessarily seasonality. The ACF for DUBRA has no significant ACs at seasonal lags (see fig. 5I). This implies that seasonality is not significant in UBRA and confirms the results of the variance equality tests. Hence, we will use the unadjusted data UBRA in our VAR analysis.

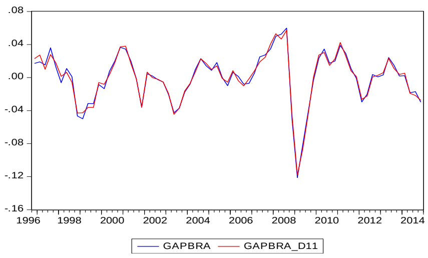
6.5.6. The seasonality features of output gap in Brazil

The graphs below depict the following variables. The Brazilian output gap (denoted GAPBRA), the seasonally adjusted GAPBRA series (GAPBRA_d11) and D_GAPBRA = GAPBRA - GAPBRA_d11, as well as the first (nonseasonal) difference of GAPBRA (DGAPBRA), the DGAPBRA seasonally adjusted (DGAPBRA_d11) and D_DGAPBRA =DGAPBRA – DGAPBRA_d11. The seasonally adjusted series (GAPBRA_d11) is obtained using the Census X13 procedure in EViews. Tables 6D and 6G report various tests of the null hypothesis of equality of variance for GAPBRA and GAPBRA_d11 as well as DGAPBRA and DGAPBRA_d11.

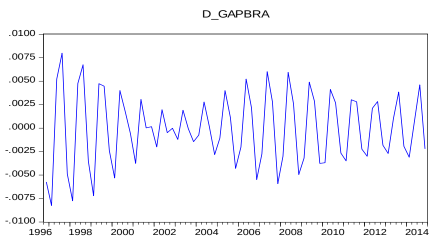
6A.



6B.



6C.

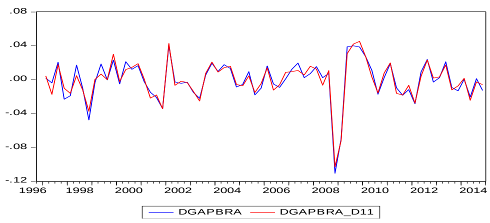


6D.

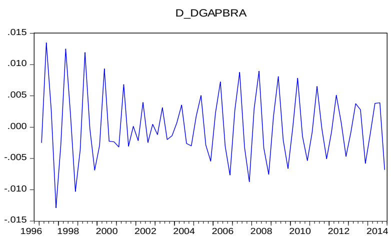
Test for equality of variance between GAPBRA and GAPBRA_D11

Method	Df	Value	Probability
F-test	(71, 72)	1,125242	0.6188
Siegel Turkey		0.164110	0.8696
Bartlett	1	0.246932	0.6192
Levene	(1,143)	0.025760	0.8727
Brown-Foresythe	(1,143)	0.029663	0.8635

6E.



6F.



6G.

Test for equality of variance between DGAPBRA and DGAPBRA_D11

Method	Df	Value	Probability
F-test	(71, 71)	1.078007	0.7525
Siegel Turkey		0.385568	0.6998
Bartlett	1	0.099423	0.7525
Levene	(1,142)	0.057987	0.8101
Brown-Foresythe	(1,142)	0.066293	0.7972

6H.

Sample: 1996Q4 2014Q4
Included observations: 73

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.965	0.965	70.857	0.000
		2	0.921	-0.159	136.26	0.000
		3	0.869	-0.126	195.26	0.000
		4	0.818	0.034	248.38	0.000
		5	0.771	0.019	296.25	0.000
		6	0.730	0.040	339.75	0.000
		7	0.688	-0.048	379.07	0.000
		8	0.644	-0.085	414.02	0.000
		9	0.596	-0.057	444.44	0.000
		10	0.551	0.041	470.85	0.000
		11	0.512	0.064	494.02	0.000
		12	0.480	0.031	514.68	0.000
		13	0.449	-0.041	533.11	0.000
		14	0.417	-0.076	549.23	0.000
		15	0.384	0.000	563.13	0.000
		16	0.345	-0.080	574.57	0.000
		17	0.304	-0.050	583.58	0.000
		18	0.263	-0.012	590.44	0.000
		19	0.223	-0.037	595.47	0.000
		20	0.183	-0.035	598.95	0.000

6I.

Sample: 1996Q4 2014Q4
Included observations: 72

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.245	0.245	4.5083	0.034
		2	-0.199	-0.276	7.5332	0.023
		3	-0.156	-0.030	9.4231	0.024
		4	-0.243	-0.277	14.033	0.007
		5	-0.182	-0.106	16.676	0.005
		6	-0.024	-0.097	16.722	0.010
		7	-0.028	-0.151	16.785	0.019
		8	-0.168	-0.309	19.133	0.014
		9	0.025	-0.031	19.185	0.024
		10	0.073	-0.208	19.647	0.033
		11	0.057	-0.080	19.935	0.046
		12	0.156	-0.061	22.102	0.036
		13	0.169	0.039	24.678	0.025
		14	-0.071	-0.199	25.146	0.033
		15	-0.008	0.123	25.152	0.048
		16	0.050	-0.046	25.387	0.063
		17	-0.140	-0.044	27.289	0.054
		18	-0.125	-0.091	28.843	0.050
		19	-0.053	-0.035	29.127	0.064
		20	-0.046	-0.078	29.342	0.081

From Figure 6A the output gap fluctuates around a relatively constant mean. There are clear cycles however they do not appear to fixed at one-year in length and unlikely reflect seasonality.

The time paths of GAPBRA and GAPBRA_d11 (see Figure 6B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between GAPBRA and GAPBRA_d11 (denoted D_GAPBRA) is plotted in Figure 6C. The difference reveals regular cyclical fluctuations that range between -0.0082 and 0.0079. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between GAPBRA and GAPBRA_d11 that are reported in table 6D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of GAPBRA and GAPBRA_d11. Hence, we find that seasonality is not significant in the level of the output gap. However, because this result may be influenced by any persistence in the level of the data we compare the differences of the adjusted (DGAPBRA_d11) and unadjusted (DGAPBRA) data.

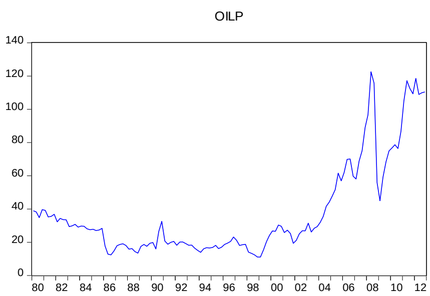
The time paths of DGAPBRA and DGAPBRA_d11 (see Figure 6E) follow each other closely. The difference between DGAPBRA and DGAPBRA_d11 (denoted D_DGAPBRA) is plotted in Figure 6F. The difference has revealed regular cyclical fluctuations. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DGAPBRA and DGAPBRA_d11 that are reported in table 6G. Since the p-values of all of our tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DGAPBRA and DGAPBRA_d11. Hence, seasonality is not significant in the difference of the output gap rate for Brazil.

To check that we have not missed any significant seasonality we plot the ACFs of GAPBRA and DGAPBRA in figure 6H and 6I. In Fig. 6H, all ACs are significant (and not just at the seasonal lags) which suggest nonstationary and not necessarily seasonality. The ACF for DGAPBRA has no significant ACs at seasonal lags (see fig. 6I). This implies that seasonality is not significant in GAPBRA and confirms the results of the variance equality tests. Hence, we will use unadjusted data GAPBRA in our VAR analysis.

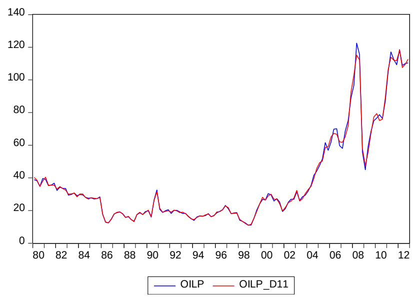
6.5.7. The seasonality features of oil price

The graphs below depict the following variables. The oil price (denoted OILP), the seasonally adjusted OILP series (OILP_d11) and D_OILP =OILP - OILP_d11, as well as the first (nonseasonal) difference of OILP (DOILP), the DOILP seasonally adjusted (DOILP_d11) and D_DOILP =DOILP – DOILP_d11. The seasonally adjusted series (OILP_d11) is obtained using the Census X13 procedure in EViews. Tables 7D and 7G report various tests of the null hypothesis of equality of variance for OILP and OILP_d11 as well as DOILP and DOILP_d11.

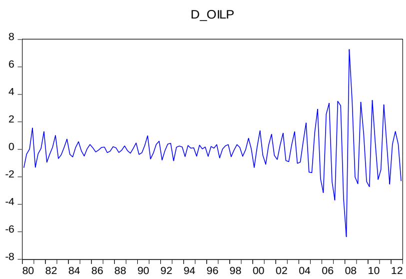
7A



7B



7C

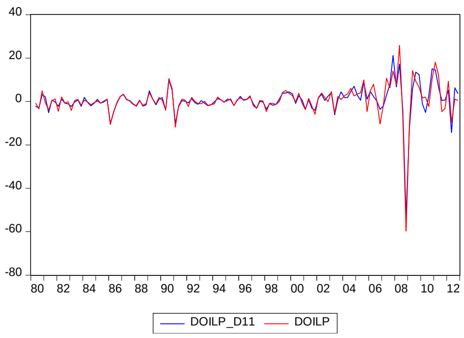


7D

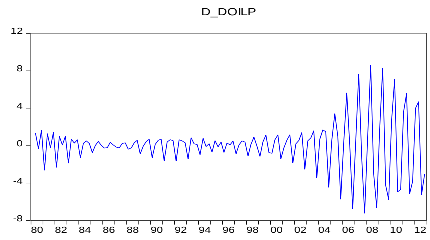
Method	df	Value	Probabilit
F-test	(131, 131)	1.0064	0.9708
Siegel		0.00806	0.9994
Barlett	1	0.001341	0.9708
Levene	(1, 262)	4.66E-06	0.9983
Brown-Fo	(1, 262)	5.60E-06	0.9981

7E

7F



7G



7H

Method	df	Value	Probabilit
F-test	(131, 130)	1.20264	0.2941
Siegel		0.31307	0.2941
Barlett	1	0.10072	0.9708
Levene	(1, 260)	1.70E-01	0.6807
Brown-Fo	(1, 260)	1.64E-01	0.686

Sample: 1980Q1 2012Q4
Included observations: 132

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.941	0.941	119.62	0.000
		2	0.867	-0.167	221.86	0.000
		3	0.813	0.166	312.56	0.000
		4	0.763	-0.056	393.07	0.000
		5	0.725	0.114	466.22	0.000
		6	0.690	-0.033	532.96	0.000
		7	0.652	0.005	593.20	0.000
		8	0.614	-0.039	646.90	0.000
		9	0.582	0.069	695.67	0.000
		10	0.568	0.104	742.41	0.000
		11	0.561	0.045	788.35	0.000
		12	0.548	-0.025	832.68	0.000

7I

Sample: 1980Q1 2012Q4
Included observations: 131

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.231	0.231	7.1678	0.007
		2	-0.304	-0.377	19.631	0.000
		3	-0.156	0.035	22.937	0.000
		4	-0.082	-0.193	23.867	0.000
		5	-0.087	-0.073	24.919	0.000
		6	-0.026	-0.077	25.016	0.000
		7	0.146	0.118	28.008	0.000
		8	0.064	-0.086	28.596	0.000
		9	-0.144	-0.096	31.562	0.000
		10	-0.137	-0.091	34.245	0.000
		11	0.091	0.104	35.440	0.000
		12	0.144	0.020	38.468	0.000

From Figure 7A the oil price fluctuates around a relatively constant mean. There are suspected cycles that do not appear to be of fixed length around the period 1980 to 1985, which is followed by an upward trend. The time paths of OILP and OILP_d11 (see Figure 7B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between OILP and OILP_d11 (denoted D_OILP) is plotted in Figure 7C. The difference has revealed a cyclical fluctuation that ranges between -0.64 and 7.3. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between OILP and OILP_d11 that are reported in table 7D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of OILP and OILP_d11. Hence, we find that seasonality is not significant in the level of the oil price. However, because this result may be influenced by any persistence in the level of the data we compare the differences of the adjusted (DOILP_d11) and unadjusted (DOILP) data.

The time paths of DOILP and DOILP_d11 (see Figure 7E) follow each other closely. The difference between DOIL and DOILP_d11 (denoted D_DOILP) is plotted in Figure 7F. The difference has revealed regular cyclical fluctuations. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DOILP and DOILP_d11 that are reported in table 7G. Since the p-values of all of our tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DOILP and DOILP_d11. Hence, seasonality is not significant in the difference of the oil price.

To check that we have not missed any significant seasonality we plot the ACFs of OILP and DOILP in figure 7H and 7I. In Fig. 7H, all ACs are significant (and not just at the seasonal lags) which suggest nonstationary and not necessarily seasonality. The ACF for DOILP has no significant ACs at seasonal lags (see fig. 7I). This implies that seasonality is not significant in OILP and confirms the results of the variance equality tests. Hence, we will use unadjusted data OILP in our VAR analysis.

A similar procedure was applied for all countries and (to save space) the discussion is made available in appendix. Section 6.2 page 457 - 540. The table below summarises the variables by country and indicate whether they will be used in seasonally adjusted form (indicated by SA) or unadjusted form (denoted with UN).

Table 6.5. Summary of whether the data is seasonally adjusted or not

Countries / Variables	BRA	RUS	IND	CHI	SOU	NIG	ALG	ANG	SAU
Start	1996q4	2000q2	1960q1	1989q1	1992q2	1995q4	1996q2	1999q4	1980q1
End	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4
P	UN	SA	SA	UN	UN	SA	SA	UN	UN
M	SA	UN	A	A	UN	A	A	SA	A
R	UN	UN	UN	UN	UN	UN	UN	UN	
REE	UN	UN		UN	UN	UN	UN		UN
U	UN	SA							
OilP	UN	UN	UN	UN	UN	UN	UN	UN	UN
GAP	UN	SA	UN	A	UN	A	A	A	A

Where SA is seasonal adjusted variables, UN is unadjusted variables, *A* is the variable that has been transformed from annual frequency to quarterly frequency (and is therefore not seasonal) and a blank entry indicates that data is unavailable for the variable in that particular country.

6.6. Unit root tests

Many macroeconomic time-series are subjected to substantial instabilities such as non-stationarity and structural breaks (Stock and Watson, 1988). To ascertain the orders of integration of the variables to be used in our VAR Model we use the widely employed DF-GLS, augmented Dickey-Fuller (ADF), Phillips and Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The null hypothesis of a unit root is tested against the alternative of stationarity for the DF-GLS, ADF and PP tests. We reject the null hypothesis of stationarity when the absolute value of test statistic is greater than the critical value (the variable is stationary). Whereas, we cannot reject the null hypothesis of stationarity when the absolute value of test statistic is less than the critical value (the variable is non-stationary). The null hypothesis of no unit root is observed for the KPSS test.

For non-stationary series. A common example is the random walk:

$$y_t = y_{t-1} + \varepsilon_t, \qquad (6.1)$$

Where ε is a stationary random disturbance term. The series y has a constant forecast value, conditional on t and the variance is increasing over time. To make the series stationary, the nonstationary variable's may be differenced, that is:

$$y_t - y_{t-1} = (1 - L)\, y_t = \varepsilon_t$$

The standard Augmented Dickey- Fuller (ADF) test can be written as:

$$\Delta y_t = \alpha y_{t-1} + x_t \delta + \varepsilon_t \qquad (6.2)$$

Where x_t are optional exogenous regressors which may consist of constant or a constant and trend, δ are parameters to be estimated and the ε_t are assumed to be white noise. $\alpha = \rho - 1$. The null hypothesis of $H_0: \rho = 1$ or $H_0: a = 0$ is tested against the alternative $H_1: \rho < 1$ or $H_1: a < 0$.

For $\rho = 1$ or $a = 0$, y is a nonstationary series and the variance of y increases with time approaches infinity. If $\rho < 1$ or $a < 0$, y is a stationary series except the KPSS test that evaluates the null of $H_0: \rho < 1$ against the alternative $H_1: \rho = 1$. The simple Dickey – Full unit root test described above is valid only if the series is an AR(1) process. If the series is correlated at higher order lags, the assumption of ε_t is violated. The Augmented Dickey Fuller (ADF) test constructs a parametric correction for higher order correlation by assuming that the y series follow an AR(p) process and adding p lagged difference term of the dependent variables y to the right hand side of the test regression:

$$\Delta y_t = \alpha y_{t-1} + x_t\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + v_1. \qquad (6.3)$$

However, the conventional unit root tests could be biased towards finding a unit root when the data is trend stationary with a structural break.[110] Nelson and Plosser (1982) described the nature of these shocks as a permanent. This view was challenged by Perron, (1989 and 1990). He argued that many macroeconomic time series may be better described as having temporary shocks fluctuating around a broken deterministic trend. Perron further argued that his choice of breakpoint is based on prior observation of the data with the underlying asymptotic distribution theory. Perron (1989) introduced three models that based on Dickey- Fuller (ADF) extension by adding dummy variables for different intercept and slopes (the process incorporating the breaks inform of the intervention deterministic suggested by Box and Tiao 1975). The first model is a crash model that permits an exogenous change in the level of the series ("a crash"), i.e., the conventional unit root test (ADF model) is augmented by incorporating a dummy break and a dummy post-break intercept to describe the shifts in the trend. The second model permits an exogenous change in the growth rate. The third model combines changes in the level and the slope of the trend function of the series. Each of these three models has a unit root with breaks under the null hypothesis. According to the Perron (1989), the null hypothesis that a given series $\{y_t\}_1^T$ has a unit root with drift and that an exogenous structural break occur at time $T_B(1 < T_B < T)$ versus the alternative hypothesis that the series is stationary about a deterministic time trend with an exogenous change in the trend function at time T_B.

For null hypothesis

Model (A): $y_t = \mu + dD(T_B)_t + y_{t-1} + e_t,$ (6.4)

Model (B): $y_t = \mu_1 + y_{t-1} + (\mu_2 - \mu_1)DU_t + e_t,$ (6.5)

and

Model (C): $y_t = \mu_1 + y_{t-1} + dD(T_B)_t + (\mu_2 - \mu_1)DU_t + e_t,$ (6.6)

[110] The empirical application of the following studies (Perron, 1989, 1997., Leybourne and Newbold, 2003) generally reaffirmed the conclusion that most macroeconomic time series have unit root.

Where $D(T_B)_t$ = 1 if t = $T_B + 1, 0$ otherwise; $DU_t = 1$ if $t > T_B, 0$ otherwise; $A(L)e_t$ = $B(L)v_t$, $v_t \equiv iid(0, \sigma^2)$, with $A(L)$ and $B(L)$ pth and qth order polynomials in the lag operator. The innovation series $\{e_t\}$ is taken to be of the ARIMA (p, q) type with the orders p and q possibly unknown.

For alternative hypotheses,

Model (A): $y_t = \mu_1 + \beta t + (\mu_2 - \mu_1)DU_t + e_t,$ (6.7)

Model (B): $y_t = \mu + \beta_1 t + (\beta_2 - \beta_1)DT_t^* + e_t,$ (6.8)

and

Model (C): $y_t = \mu + \beta_1 t + (\mu_2 - \mu_1)DU_t + (\beta_2 - \beta_1)DT_t^* + e_t,$ (6.9)

Where $DT_t^*= t - T_B$ if $t > T_B$ and 0 otherwise.

T_B refers to the time of break, i.e., the period at which the change in the parameter of the trend function occur. $\mu_2 - \mu_1$ represents the magnitude of the change in the intercept of the trend function occurring at time T_B. $\beta_2 - \beta_1$ represents the magnitude of the change in the slope of the trend function occurring at time T_B.

The adjusted Dickey- Fuller (ADF) test of the models (A), (B) and (C) involve the following augmented regression equations.

$$y_t = \hat{\mu}^A + \hat{\theta}^A DU_t + \hat{\beta}^A t + \hat{d}^A D(T_B)_t + \hat{a}^A y_{t-1} + \sum_{j-1}^{k} \hat{c}_j^A \Delta y_{t-j} + \hat{e}_{t,} \quad (6.10)$$

$$y_t = \hat{\mu}^B + \hat{\beta}^B t + \hat{\gamma}^B DT_t^* + \hat{a}^B y_{t-1} + \sum_{j-1}^{k} \hat{c}_j^B \Delta y_{t-j} + \hat{e}_t, \quad (6.11)$$

and

$$y_t = \hat{\mu}^C + \hat{\theta}^C DU_t + \hat{\beta}^C t + \hat{\gamma}^C DT_t^* + \hat{d}^C D(T_B)_t + \hat{a}^C y_{t-1} + \sum_{j-1}^{k} \hat{c}_j^C \Delta y_{t-j} + \hat{e}_{t.}$$

(6.12)

The k extra regressors are added to remove possible nuisance- parameters. The number k is determined by a test of the significance of the estimated coefficients $\hat{c}_j^i$ $(i = A, B, C)$.

The idea proposed by Perron (1989) is that the break of trend function is fixed (exogenous) and chosen independently of the data. In addition, the ex-post forecast only predicted the changes that occurred after exogenous event. The condition is that, the impact of these changes on economic activities may vary. As a result, some exogenous events may not have impact on economic actives as some theories would have predicted. Therefore, the argument that relates the choice of break dates to exogenous events or correlated with the data may not be valid because no attempts were made to maximize the chances that the null unit root be may rejected. As a result, different studies have criticized Perron (1989) for treating the time of the break as exogenous (Zivot and Andrews 1992., Christiano, 1992., Vogelsang and Perron,1998., and Banerjee et al. 1992).[111] For example, Zivot and Andrews transform the Perron unit root test that is conditional on structural change at a known point in time into an unconditional unit root test. In particular, the actual breakpoint was assumed not to be known. Instead, a data-dependent algorithm was applied to generate an unobserved components model, which allows yields a new ADF type unit root test that determines breaks at unknow dates.

Perron (1994, 1997) improved on his initial paper (1989) and proposed two different ways of estimating the time of the break endogenously (the additive outlier model and innovational outlier model).[112] These tests overcome many of the shortcoming of the Perron (1989) test with the exogenous breaks.[113]

For the Innovational Outlier Model (IO), the model applies to the case where it is more reasonable to view the break as occurring more slowly over time. The assumption can be captured using the following specification.

Under the null hypothesis of a unit root,

Model (1): $y_t = \mu + \theta DU_t + \beta t + \delta D(T_b)_t + \alpha y_{t-1} + \sum_{j-1}^{k} c_t \Delta y_{t-j} \; e_t,$ (6.13)

Model (2): $y_t = \mu + \theta DU_t + \beta t + \gamma DT_t + \delta D(T_b)_t + \alpha y_{t-1} + \sum_{j-1}^{k} c_t \Delta y_{t-j} \; e_t,$ (6.14)

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[111] Harvie and Pahlavani (2006) document that considering the timing of the break as an exogenously known event invalidates the distribution theory underlying conventional testing.

[112] These studies are closely related to those of Banerjee et al. (1992) and Zivot and Andrews (1992)

[113] (I) the breaks are Endogenously estimated. (II) Minimizing the value of the t statistic on the break parameters associated with the change in either the intercept and slope. (III) Maximizing the absolute value of the t statistic on the break parameters associated with a change in either the intercept or slope.

The first model allows only a change in the intercept. The second model allow changes in both intercept and the slope at time T_b. Both tests are performed using the t −statistic for the null hypothesis that $\alpha = 1$ in the regression. Where DU_t= 1($t > T_b$), $D(T_b)_t$ = 1($t = T_b + 1$) and DT_t = 1($t > T_b)t$ and 0 otherwise.

For the additive outlier model (AO), the model applies to cases where the break is assumed to occur instantly and is not affected by the dynamics of the series. The test follows a two-step procedure. For the first model (6.15), the series is detrended by regressing it on the trend component (including constant, time-trend and dummy break). The second equation (6.16) is estimated without a trend function, using the residual from the first step regression as the dependent variable. The second equation used to test for a unit root.

$$y_t = \mu + \beta t + \gamma D T_t^* + \bar{y}_t. \tag{6.15}$$

$$\bar{y}_t = \alpha \bar{y}_{t-1} + \sum_{i-1}^{k} c_t \Delta y_{t-i} + e_t. \tag{6.16}$$

Where $\bar{y}_t$ = the de-trended series, we denote by $t_{\hat{\alpha}}(i, T_b, k)$ (i =1, 2, 3), the t- statistic for testing $\alpha = 1$ under model i with a break data T_b and truncation lag parameter k, DT_t^*= 1(t $> T_b)(t - T_b)$. Note that T_b and k are usually treated as unknown. Details on how to determine T_b and k can be found Perron (1997).

In this study, we consider both IO and AO versions of the test that allow for a break in the intercept only and a break in both the intercept and trend and consider whether an endogenously determined break causes the finding of a unit root when using conventional tests. All tests allowing for a structural break test the unit root null against the alternative of a stationarity process around a structural break in the intercept (and trend). The tests are applied to the variables discussed in Table 6.4 for the specified countries and are estimated over the reduced sample that avoid modelling structural breaks in inflation (though not necessarily the other variables). All variables are transformed using natural logarithms except for the interest rate, unemployment and output gap. The automatic lag selection procedure in EViews is used to determine the lag augmentation for all tests. The results are tabulated below for each country.

Table 6.6.1. Brazilian unit root tests (the levels data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-0.6192	-3.5271	-1.1409	-3.4753	0.5195	-1.9456	-1.2324	-3.1260
M	-2.8678	-2.9024	-3.4499	-3.4735	1.8444	-1.9455	-1.2560	-3.1196
R	-1.8134	-2.9018	-2.9188	-3.2725	-0.3558	-1.9453	-1.8339	-3.1164
REE	-1.0260	-2.9018	-2.0131	-3.4726	-0.7139	-1.9453	-1.8568	-3.1160
U	0.5943	-2.9024	-3.7005*	-3.4735	-0.0886	-1.9455	-1.1757	-3.1196
OilP	-0.3339	-2.8839	-1.6993	-3.4450	-0.5929	-1.9433	-0.95826	-3.0000
GAP	-5.3191*	-2.9029	-5.2806*	-3.4744	-5.0192*	-1.9455	-5.1618*	-3.1228
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-0.7316	-2.9023	-1.2356	-3.4734	1.1365	0.4630	0.1984	0.1460
M	-2.8677	-2.9023	-3.4499	-3.4734	1.1433	0.4630	0.2614	0.1460
R	-2.0265	-2.9017	-3.0160	-3.4725	0.9466	0.4630	0.0661*	0.1460
REE	-1.1543	-2.9018	-2.1703	-3.4725	0.8237	0.4630	0.1256*	0.1460
U	0.2146	-2.9023	-3.7049*	3.4734	0.9946	0.4630	0.2493	0.1460
OilP	-0.5142	-2.8838	-1.7582	-3.4445	0.7679	0.4630	0.1173*	0.1460
GAP	-3.8571*	-2.9023	-3.8340*	-3.4734	0.0309*	0.4630	0.0309*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.6.1 the absolute values of all the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables (the unit root null cannot be rejected) except for the output gap (in all cases) and unemployment (only for the ADF and PP tests when both intercept and trend are included in the test equation). In addition, the KPSS test statistic is greater than the critical value for all variables (giving rejection of the I(0) null) except for the interest rate, exchange rate (when both intercept and trend are included in the test equation) and the oil price (when both intercept and trend are included in the test equation). Hence, all Brazilian series are unambiguously nonstationary except for the output gap, exchange rate, unemployment rate, oil price and interest rate. The output gap is unambiguously stationary whereas the test results for the unemployment rate, exchange rate, oil price and interest rate are ambiguous (if at least half of the tests indicate non-stationarity in all cases). Therefore, we proceed to the first difference of the data.

Table 6.6.2 Brazilian unit root tests (first difference data)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-5.5984*	-2.9037	-5.5879*	-3.4753	-5.1408*	-1.9455	-5.5228*	-3.1260
M	-12.9459*	-2.9029	-13.1654*	-3.4743	-0.1800	-1.9455	-1.5816	-3.1292
R	-10.1425*	-2.9018	-10.1155*	-3.4725	-0.9579	-1.9453	-0.5928	-3.1228
REE	-6.8752*	-2.9017	-6.7998*	-3.4726	-1.5810	-1.9453	-3.0533	-3.1804
U	-6.4304*	-2.9029	-6.7207*	-3.4744	-3.4465*	-1.9455	-6.6608*	-3.1228
OilP	-9.8839*	-2.8839	-9.9807*	-3.4450	-9.5767*	-1.9433	-10.044*	-3.0010
GAP	-6.6704*	-2.9035	-6.6215*	-3.4753	-6.7116*	-1.9455	-6.6985*	-3.1260
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-4.7011*	-2.9023	-4.6696*	-3.4743	0.1650*	0.4630	0.1082*	0.1460
M	-12.8482*	-2.9030	-13.0718*	-3.4726	0.5275	0.4630	0.0496*	0.1460
R	-9.3289*	-2.9018	-9.4466*	-3.4725	0.2428*	0.4630	0.2142	0.1460
REE	-8.1357	-2.9017	-7.9454*	-3.4726	0.3644*	0.4630	0.3411	0.1460
U	-6.3923*	-2.9029	-6.7044*	-3.4744	0.4206*	0.4630	0.1103*	0.1460
OilP	-9.1476*	-2.8837	-9.6866*	-3.4448	0.3792*	0.4630	0.0490*	0.1460
GAP	-6.4937*	-2.9029	-6.4109*	-3.4743	0.0453*	0.4630	0.0439*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.6.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables (rejecting the unit root null) except the money supply, interest rate and real exchange rate. The null hypothesis cannot be rejected for money supply, interest rate and real exchange rate in the DF-GLS tests in all cases. In addition, the KPSS test statistic is less than critical value for all variables (giving non-rejection of the I(0) null) except for the interest rate, money supply and real exchange rate. For the interest rate and real exchange rate only the version of KPSS test that includes both intercept and trend suggest stationarity while for the money supply only the test equation that just includes an intercept suggests stationarity. Hence, all Brazilian series are unambiguously stationary in first differences except for the money supply, the interest rate and the real exchange rate where the test results are ambiguous (if at least half of the tests indicate stationarity in both cases). That some tests indicate a nonstationary in the first difference for the money supply and interest rates may reflect low power, possibly due to structural breaks.

Table 6.6.3. Brazilian breakpoint unit root tests (the levels data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.2674	-4.4437	-5.6502*	-4.8598	-0.8066	-4.4436	-3.2585	-4.8598
M	-3.3343	-4.4437	-4.7135	-4.8598	-1.3290	-4.4437	-2.4872	-4.8598
R	-3.5261	-4.4437	-4.1541	-4.8598	-3.8697	-4.4436	-5.5040*	-4.8598
REE	-3.2396	-4.4437	-4.2116	-4.8598	-4.2177	-4.4436	-4.3882	-4.8598
U	-2.1215	-4.4437	-4.6588	-4.8598	-2.1435	-4.4436	-4.3587	-4.8598
OilP	-3.1159	-4.4436	-3.0350	-4.8598	-3.9029	-4.4436	-3.8871	-4.8598
GAP	-5.6642*	-4.4436	-5.9677*	-4.8598	-6.0265*	-4.4437	-5.8980*	-4.8598

Table 6.6.4. Brazilian breakpoint unit root tests (first differenced data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**
P	-7.3260*	-4.9491	-6.8188*	-4.8598	-8.89473*	-4.4437	-8.1398*	-4.8598
M	-14.9081*	-4.4436	-14.555*	-4.8598	-13.5161*	-4.4437	-13.5608*	-4.8598
R	-10.3543*	-4.4436	-10.2813*	-4.8598	-10.6216*	-4.4437	-10.6216*	-4.8598
REE	-7.3732*	-4.4437	-7.3059*	-4.8598	-6.9198*	-4.4437	-7.1507*	-4.8598
U	-6.9056*	-4.4436	-7.0550*	-4.8598	-7.1427*	-4.4437	-7.2176*	-4.8598
OilP	-10.2910*	-4.4436	-10.7373*	-4.8598	-10.4723*	-4.4437	-10.6577*	-4.8598
GAP	-8.0128*	-4.4437	-7.9244*	-4.8598	-7.4510*	-4.4436	-7.4195*	-4.8598

In Table 6.6.3 and 6.6.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first differences of the data, respectively. In Table 6.6.3., the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except for consumer prices, interest rates and the output gap. The output gap is unambiguously stationary around a structural break, however, for consumer prices and interest rates the evidence is ambiguous because the unit root null is rejected in 1 of the 4 tests for both variables. For consumer prices (interest rates) the test for the IO (AO) case with intercept and trend indicates stationarity around a structural break, whereas all other cases suggest nonstationarity. Since we expect prices in levels to be intrinsically nonstationary (even if there are structural breaks) we will treat this series as such despite the results of this unit root test. Further, the ambiguity of the results for interest rates suggests that we can treat them as nonstationary, however, we will bear this ambiguity of results in mind in our VAR analysis.

In Table 6.6.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables in Brazil indicating that all series are stationarity around a structural break. However, the finding that all of the first differenced variables are unambiguously stationary without structural breaks (except for the money supply, interest rates and real exchange rates) means that we interpret the evidence that these series are stationary in first differences without structural breaks. Because at least half of the tests indicate that the first differences of the money supply, interest rates and real exchange rates are stationary without structural breaks and we expect them to be stationary we will proceed with our VAR analysis as if these three series are stationary in first differences. Nevertheless, the ambiguity of the results for these three series will be borne in mind if issues arise with the VAR modelling that suggests this assumption is inappropriate.

Overall, despite some ambiguities in results, the unit root tests suggest that we can treat all variables for Brazil as I(1) in our VAR analysis except for the output gap that is unambiguously I(0). Also note that while unit root tests for oil prices have been considered with the variables for Brazil, this series can also be used in the VAR analysis for the other countries. A similar procedure was applied to all variables and countries and (to save space), the summary is given in Table 6.6.5 and the detailed discussion of unit root test results for each country is available in appendix. Section 6.3 page 541-571.

Table 6.6.5. Orders of integration of the data.[114]

Variables/ Countries	BRA	RUS	IND	CHI	SOU	NIG	ALG	ANG	SAU
Start	1996q4	2000q2	1960q1	1989q1	1992q2	1995q4	1996q2	1999q4	1980q1
End	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4	2014q4
P	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)**	I(1)
M	I(1)	I(1)	I(2)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
R	I(1)	I(0)	I(0)	I(1)	I(1)*	I(1)	I(1)	I(1)*	
REE	I(1)	I(1)		I(1)	I(1)	I(1)	I(1)		I(1)
U	I(1)	I(1)							
OilP	I(1)	I(1)		I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
GAP	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

* Indicates a variable that may be stationary around a structural break while ** denotes a variable that may be I(1) around a structural break. Where P= consumer price, M =money supply, REE= real exchange rate, GAP = output gap, R = interest rate, UN =unemployment and OilP = oil price. All variables are transformed using natural logarithms except for the interest rate, unemployment and output gap.[115]

[114] Following a question raised by the external supervisor "Why is R an I(1) variable if it follows a Taylor rule in inflation, given that you have reported inflation as being I(0)". In our study, our forecast modelling is guided by the order of integration of variables obtained from unit root tests rather than economic theory (Taylor rule). In this study, we focused on differencing and cointegrating restrictions to ensure the stationarity of the data in which all available variables are combined and specified based on their level of integration to forecast inflation. For instance, a VAR model is estimated based on differenced variables that are I(0) whereas, VECM and VEC are estimated based on a linear combination of the variables that are I(1). In future research, the forecast combination of interest rate I(0) and inflation I(0) will be considered.

[115] Due to the sample considered for India (1961q1 – 2012q4), the oil price data is not available for this sample, the oil price series we considered in this research is only available between 1980q1 and 2014q4.

6.7 The chapter summary and conclusion

In this chapter, we discussed the data used in multivariate modelling. First, we identify the variables that are most commonly employed to model and forecast inflation in the literature and identify the data availability of these series for each country under study. Whilst we give priority to variables available at quarterly frequency we also consider the addition of variables that are available only at annual frequency to ameliorate omitted variable issues. We use frequency conversion tools to generate quarterly series from annual series. The main explanatory variables that we consider for each country are the money supply, real exchange rate, interest rate, output gap, unemployment rate and the oil price. Second, we identified general features of each variable by mainly focusing on seasonality and stationary characteristics to avoid the issue of seasonal integration. In particular, we seasonally adjust each series and compare the adjusted and unadjusted series. If the variances of these series are not significantly different, we regard the data as nonseasonal and utilise the unadjusted data. However, if the variances are significantly different we regard the data as seasonal and use the seasonally adjusted series. Third, we used the available relevant variable to construct the output gap that is based on the Phillips curve and discussed the procedure involve in estimating cointegrating model.

CHAPTER 7

MULTIVARIATE SPECIFICATIONS AND MODELLING

7.0 Introduction

In this chapter, we develop on the analysis presented in Chapter six and estimate multivariate models based on different cointegration specification over the reduced sample to avoid the modelling of structural breaks (section 7.0 to 7.3). We test whether the estimated multivariate models are structurally stable in the sense that the regression coefficients are constant (section 7.4). Finally, we produce forecast for each multivariate model (VAR, VECM and VEC) that passes the diagnostic test for serial autocorrelation and choose the best forecasting model for multivariate model (section 7.5). The motivation for this chapter is guided by the following principles. Models involving series that are nonstationary may lead to problems of spurious regression that can adversely affect forecasting accuracy. VARs estimated with cointegrated data will be misspecified if all of the data are differenced because long-run information will be omitted and will have omitted stationarity inducing constraints if all of the data are used in levels. Therefore, we consider the test of orders of integration of the data available in chapter 6 (Table 6.6.5) and estimate the following multivariate models: (I) we estimate an unrestricted VAR model in pure differences (stationary form) with variables that have the same order of integration (are I(1)) to forecast inflation. (II) We estimate a VECM with all nonstationary variables and test whether a linear combination of nonstationary variables will be cointegrated, and if cointegrated we produce forecasts for inflation. (III) We construct a VEC model that imposes cointegrating restrictions on the VECM to forecast inflation. Based upon this analysis, we compared the forecasting performance of all three multivariate specifications (VAR, VECM and VEC) and identify the best inflation forecasting model.

7.1 Specification and Modelling of unrestricted VAR

In this section, we describe the process of modelling with an unrestricted VAR model and a Vector Error Correction Model (VECM) using the variables identified in the previous chapter. The unrestricted VAR approach models every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system and can be specified as:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + B x_t + e_t \qquad 7.1$$

where y_t is a k vector of endogenous variables, x_t is a d vector of exogenous variables, $A_1,\ldots\ldots, A_p$ and B are matrices of coefficients to be estimated, and e_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values. The VECM representation of (7.1) is:

$$\Delta y_t = \delta + B x_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + e_t \qquad 7.2$$

Where Γ_i, i =1,…,$p-1$ are functions of A_i, i = 1,…,k.

y_t are independent $I(1)$ variables, $\Delta = (1-L)$ while L is the lag operator, δ is the intercept, Γ is the matrix that reflects the short-run dynamic relationship among the element of $y_{t,}$ Π is the matrix containing long-run equilibrium information and e_t is the residual. Given k endogenous variables, y_t, the Granger representation theorem indicates that if the matrix Π has reduced rank *r* < *k* it can be decomposed as $\Pi = \alpha\beta^{'}$. The dimension of α and β is r x k. The number of cointegrating equations is *r*, where β is the cointegrating vector and α is the speed of adjustment to the long-run equilibrium defined by the cointegrating relationships.

In VAR modelling, the first step is to estimate a VAR model with appropriate lag length that is sufficient to capture the full dynamics of the system. The choice of appropriate lag order (p) is important because too short a lag length may not remove all of the autocorrelation in the residuals and too long a lag length may reduce the precision (efficiency) of the estimates due to a reduction of degrees of freedom (Lack, 2006). Gutierrez et al. (2007) documents that overfitting (selecting a higher order lag length than the true lag length) causes an increase in the mean square-forecast errors of the VAR and that under fitting the lag length often generates autocorrelated errors. They added that impulse response functions and variance decompositions are inconsistently derived from the estimated VAR model when the lag length is misspecified. In this research, we choose the maximum possible lag-length (P*) as 10 for all countries except Brazil, Russia, Algeria, Nigeria and Angola (where only lower orders could be estimated). Different maximum lag lengths are also considered when experimentation reveals that a lag length below 10 cannot reject the hypothesis of no autocorrelation (India, China and Saudi Arabia use 11, 12 and 12 lags, respectively, to remove evident autocorrelation). We employ the Akaike information criterion (AIC) and Schwarz criterion (SC) to help determine the initial lag length, P^{**}. If there is no evidence of autocorrelation (of orders 1, 2, … 10) this initial lag length is selected. However, if there is evidence of autocorrelation, we re-estimate the VAR model using a lag length of P**+1. The process is repeated until the VAR model cannot reject the hypothesis of no-autocorrelation at the 5% level. If a VAR model with more than P^{**} lags that is free from evident autocorrelation cannot be found models with fewer lags will be tested for autocorrelation to see if a model free from autocorrelation can be found.

7.1.2. Model Specification for Unrestricted VARs

Following an eclectic approach to variable selection, we consider four different unrestricted VAR models for Brazil and Russia. For these countries, the output gap (gap) and unemployment (un) variables (which are substitutes for the Phillips curve effect) are available in addition to the other variables (price inflation (p), interest rates (r), real exchange rates (ree), money supply (m) and the oil price ($oilp$)). For the remaining countries (India, China, South Africa, Algeria, Angola, Nigeria and Saudi Arabia), we estimate only two VAR models because the output gap is the only Phillips curve variable available. This is in addition to the other available variables (price inflation, interest rates, real exchange rates, money supply and the oil price). The choice of variables used in each model is motivated by the availability of data in each country.

For Brazil and Russia, we estimate four VARs. The first two VAR models include all variables as endogenous and do not impose a priori restrictions on structural relationships. The first VAR model includes the output gap and excludes unemployment with all other available variables. The second VAR includes unemployment and excludes the output gap with all other available variables. The aim of these two VARs is to consider whether the VAR that includes the output gap provides superior forecasts to the VAR model that includes unemployment. The remaining two VARs are the same as the first two VARs except the oil price is treated as exogenous because international oil prices may be best regarded as determined outside of the system for some countries – although for oil producing countries or large oil consuming countries, such as China, the assumption of endogeneity may be more appropriate.[116] That is, these VARs include the oil price as exogenous and all other available variables as endogenous. The motivation behind the two latter VARs is to examine the impact of oil prices on the inflation forecasts when it is treated as exogenous.

For the remaining countries (China, South Africa, Algeria, Angola, Nigeria and Saudi Arabia) we estimate two VARs. The first VAR model includes all variables as endogenous and does not impose a priori restrictions on structural relationships. The second VAR

[116] For consistency, comparative purposes and to avoid imposing prior assumptions we consider treating oil as both endogenous and exogenous for all countries. Our expectation is that the estimation and forecasting results should reveal which assumption is most appropriate for each country.

model treats the oil price as exogenous and includes all other available variables as endogenous. All VAR models include the intercept as exogenous.

7.1.3 Brazil Model Selection Criterion for Unrestricted VARs

In this section, we describe the process of choosing the appropriate VAR lag order for Brazil. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model (as identified in chapter 6 Table 6.6.5 for Brazil). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. An interesting question is whether the AIC or SC detect the appropriate lag order in the sense that there is no evident autocorrelation**.** The motivation behind this question is to recognise that the AIC and SC may not always choose a lag length where the VAR is free from autocorrelation. However, this does not necessarily imply that the AIC or SC criterion are generally "bad" in selecting appropriate lag lengths. Such a judgment would have to be related to a particular modelling exercise, the nature of the deterministic terms included in the model, the sample size and variable transformations.[117]

First, we estimate an unrestricted VAR model for Brazil where all available variables are included as endogenous except unemployment (which is excluded). We start with the maximum possible lag-length that can be estimated for Brazil (P*= 7). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$).[118] The results are given in Table 7.1.A column 1 and 2 where the lag length selected by the AIC and SC are 7 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing chances that the VAR exhibits autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.1.A. There is evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Brazil with

[117] See: Kapetanios (2004) and Lack (2006) for similar discussion.

[118] Where the variables are denoted as follows: prices (p), interest rate(r), real exchange rate (ree), money supply (m), output gap (gap), unemployment (un) and oil price ($oilp$).

more than 7 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR model using lag length of 6 (where P*-1) and test the validity of the model. Given a lag length of 7 is indicated by the AIC this suggests VARs with more lags are preferred to those with less hence we consider a lag length of 6 rather than a higher lag length. The VAR model cannot reject the hypothesis of no-autocorrelation at the 5% level for all of the orders of autocorrelation considered – see column 4 of Table 7.1.A. This indicates that this model is valid for forecasting Brazilian inflation. Hence, we choose 6 as the lag length for this Brazilian VAR model.

Table 7.1.A

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$.				
	1	2	3	4
	AIC	SC	Prob.	Prob.
Lag			7	6
0	-15.5061	-15.2984		
1	-17.5058	-16.0524*	0.000	0.1040
2	-17.3584	-14.6592	NA	0.6037
3	-17.7366	-13.7917	NA	0.7218
4	-17.4705	-12.2799	NA	0.9196
5	-17.1274	-10.691	0.000	0.5208
6	-17.6675	-9.98533	0.000	0.4551
7	-18.7040*	-9.77609	NA	0.9050
8			0.000	0.3130
9			0.000	0.3392
10			0.000	0.2725

The table indicates the selected lag from the AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for Brazil where all available variables are included as endogenous except the output gap (which is excluded). We start with the maximum possible lag-length that can be estimated for Brazil (P*= 7). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, ΔR, $\Delta InREE$, Δun and $\Delta InOilp$). The results are given in Table 7.1.B column 1 and 2 where the lag length selected by the AIC and SC are 7 and 0 respectively. To maximize the chance of selecting an appropriate lag length and minimize the chances that the VAR exhibits autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, …

10). There is evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Brazil with more than 7 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 6 and 5 lags and report the autocorrelation tests in columns 4 and 5, respectively. Given a lag length of 7 is indicated by the AIC this suggests VARs with more lags are preferred to those with less hence we do not consider lower lag length VARS than necessary. The VAR models with 6 lags indicates evidence of autocorrelation whereas the VAR with 5 lag exhibits no evident autocorrelation at 5% level for all of the orders of autocorrelation considered – see column 5 of Table 7.1.B. Hence, we select the 5 lag VAR of this model for forecasting Brazilian inflation.

Table 7.1.B

	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, ΔUN and $\Delta InOilp$.				
	1	2	3	4	5
	AIC	SC	Prob.		Prob.
Lag			7	6	5
0	-9.95798	-9.74549*			
1	-10.8855	-9.4195	0.000	0.9283	0.1582
2	-10.8621	-8.13948	NA	0.3202	0.0963
3	-10.9592	-6.9799	NA	0.1913	0.6831
4	-11.2014	-5.96552	NA	0.4621	0.6040
5	-11.1313	-4.63884	0.000	0.7915	0.2058
6	-11.9563	-4.20723	0.000	0.7506	0.2608
7	-13.9126*	-4.90693	NA	0.2430	0.6681
8			0.000	0.9347	0.9896
9			0.000	0.0108	0.6924
10			0.000	0.5223	0.4124

The table indicates the selected lag from AIC and SC criterion by an asterisk

Third, we estimate an unrestricted VAR model for Brazil where we treat oil price as exogenous and all other available variables except unemployment (which is excluded) as endogenous. We start with the maximum possible lag-length that can be estimated for Brazil (P*= 9). The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP). The results are given in Table 7.1.C column 1 and 2 where the lag length selected by both the AIC and SC is 9. There is evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05 (see the column headed 3). The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Brazil with more than 9 lags and because experience suggests that models with too many lags can exhibit autocorrelation we consider lower lag length VARs. As a result, we re-estimate the VAR models with 8 and 7 lags and report the autocorrelation tests in columns 4 and 5 of Table 7.1.C, respectively. Given a lag length of 9 is indicated by the AIC and SC this suggests VARs with more lags are preferred to those with less hence we do not consider VARs with lag lengths lower than that which removes the evident autocorrelation. The VAR models with 9 and 8 lags indicate evidence of autocorrelation whereas the VAR with 7 lags exhibits no evident autocorrelation. Hence, we select the 7 lag VAR of this model for forecasting Brazilian inflation.

Table 7.1. C

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$					
	1	2	3	4	5
	AIC	SC	Prob.	Prob.	Prob.
Lag			9	8	7
0	-13.5636	-13.1918			
1	-15.6417	-14.3405	NA	0.1869	0.5835
2	-15.4462	-13.2157	NA	0.0870	0.1821
3	-15.8655	-12.7056	NA	0.0087	0.3868
4	-15.2929	-11.2036	NA	0.6377	0.1908
5	-15.1721	-10.1534	NA	0.1131	0.8807
6	-15.6379	-9.68988	0.000	0.1673	0.8418
7	-16.2944	-9.41695	0.000	0.1632	0.8389
8	-18.1713	-10.3645	0.000	0.2311	0.3212
9	-23.37272*	-14.63652*	0.000	0.3396	0.6262
10			0.000	0.0248	0.4811

The table indicates the selected lag from AIC and SC criterion by an asterisk

Fourth, we estimate an unrestricted VAR model for Brazil where we treat oil price as exogenous and all other available variables except for the output gap (which is excluded) as endogenous. The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and Δun). The results are given in Table 7.1.D column 1 and 2 where the lag length selected by both the AIC and SC is 9. There is evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05 (see the column headed 3). The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Brazil with more than 9 lags and experience suggests that models with too many lags can exhibit autocorrelation we consider lower lag length VARs. As a result, we re-estimate the VAR models with 8, 7 and 6 lags and report the autocorrelation tests in columns 4, 5 and 6 of Table 7.1.D, respectively. Given a lag length of 9 is indicated by the AIC and SC this suggests VARs with more lags are preferred to those with less hence we do not consider VARs with lag lengths lower than that which removes the evident autocorrelation. The VAR model with 8 and 7 lags indicate evidence of autocorrelation whereas the VAR with 6 lags exhibits no evident autocorrelation. Hence, we select the 6 lag VAR of this model for forecasting Brazilian inflation.

Table 7.1D

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and ΔUN Exogenous: $\Delta InOilp\_f$,						
	1	2	3	4	5	6
Lag			9	8	7	6
	AIC	SC	Prob	Prob	Prob	
0	-8.05062	-7.67887				
1	-8.99371	-7.69258	0.000	0.0746	0.4870	0.7934
2	-9.08246	-6.85194	NA	0.8010	0.5188	0.7240
3	-9.24438	-6.08448	NA	0.0101	0.2108	0.7115
4	-9.29958	-5.21029	0.000	0.7066	0.8261	0.7529
5	-9.47729	-4.45862	NA	0.6799	0.1656	0.4303
6	-10.4646	-4.51658	0.000	0.9425	0.9184	0.5407
7	-11.3105	-4.43303	0.000	0.6852	0.4917	0.7872
8	-13.4715	-5.66463	0.000	0.9171	0.9445	0.8883
9	-19.86108*	-11.1248*	0.000	0.7715	0.6611	0.5500
10			0.000	0.3680	0.0120	0.5613

The table indicates the selected lag from AIC and SC criterion by an asterisk

A similar procedure was applied for all countries and the tables of results are available in appendix section 7. 2 page 576 -602. A summary of the VAR models and their selected lag lengths for all countries is given in Table 7.1.E. Forecasts will be produced for all models summarised in Table 7.1.E where a valid specification (models that are free from evident autocorrelation) could be found. In addition, where oil prices are specified as exogenous, we will use the oil price forecast produced between 2013q1 – 2014q4 that is based on ARIMA model. The details are available in Appendix. Section 7.1 page 572 - 575.

Table 7.1.E. Summary of the VAR model specification

Countries	Sample	Variable specifications	The maximum lag length suggested by EVIews	Chosen lag length
Brazil	1999q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	7	6
Brazil	1999q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, ΔUN and $\Delta InOilp$	7	5
Brazil	1999q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$,	9	7
Brazil	1999q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and ΔUN Exogenous: $\Delta InOilp\_f$	9	6
Russia	2003Q2 2012q4	Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$, ΔGAP and $\Delta InOilp$	5	No valid model
Russia	2003Q2 2012q4	Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$, ΔUN and $\Delta InOilp$	5	4
Russia	2003Q2 2012q4	Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$ and ΔGAP Exogenous: $\Delta InOilp\_f$	6	No valid model
Russia	2003Q2 2012q4	Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$ and ΔUN Exogenous: $\Delta InOilp\_f$	6	4
India	1963q1 2012q4	Endogenous: ΔlnP, $\Delta\Delta lnM$, R, and GAP	7	11
India	1984q1 2012q4	Endogenous: ΔlnP, $\Delta\Delta lnM$, R, $\Delta InOilp$ and GAP	3	19
India	1984q1 2012q4	Endogenous: ΔlnP, $\Delta\Delta lnM$, R, and GAP Exogenous: $\Delta InOilp\_f$	7	16
China	1992q1 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	10	9
China	1992q1 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$	10	11
South Africa	1995q2 -2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	10	7
South Africa	1995q2 -2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$	10	10
Algeria	1999q2 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	7	5
Algeria	1999q2 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$	9	5
Angola	2002q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, GAP and $\Delta InOilp$	6	4
Angola	2002q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR and GAP Exogenous: $\Delta InOilp\_f$	7	7
Nigeria	1998q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	8	6
Nigeria	1998q4 2012q4	Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$	9	5
Saudi Arabia	1983q1 2012q4	Endogenous: ΔlnP, ΔlnM, $\Delta InREE$, GAP and $\Delta InOilp$	4	12
Saudi Arabia	1983q1 2014q4	Endogenous: ΔlnP, ΔlnM, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp\_f$	4	12

Where P= consumer price, M =money supply, REE= real exchange rate, GAP = output gap, R = interest rate, UN =unemployment and Oilp = oil price. The invalid models indicate the VAR models that do not pass the diagnostic test for autocorrelation with all possible lag lengths.

7.2 Modelling Vector Error Correction Model (VECM)

This section describes procedures for modelling using the Vector Error Correction Model (VECM) stated in equation (7.2). The model adds an error-correction (long-run) feature into the VAR model and captures the dynamic relationships among the variables in the short-run. It provides the framework for estimating a co-integrated model with the aim of improving long-term forecasting. Engle and Granger (1987) argued that, if cointegrating relationships exist between variables that are integrated of order 1, a model may be specified as a VECM rather than a VAR. Hence, we expect variables that are I(1) may be cointegrated, that is, there may be a long-run equilibrium relationship between the variables. As a result, we estimate a VECM model for each country and focus only on variables that are integrated of order 1 (as identified in chapter 6 (Table 6.6.5). To avoid model misspecification and the possibility of imposing false restrictions, we do not impose any a priori restrictions on this model – although some other researchers have imposed a priori restrictions on the VECM. To choose an appropriate lag length for this model, we follow the same procedure used in the previous chapter (section 7.1). We estimate a VAR model in levels and use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum possible lag-length (P* =10) to determine the initial lag length P^{**} and test for autocorrelation. If there is no evidence of autocorrelation (of orders 1, 2, … 10) this initial lag length is selected. However, if there is evidence of autocorrelation, we re-estimate the VAR model using a lag length of P**+1. The process is repeated until a VAR model that cannot reject the hypothesis of no-autocorrelation at the 5% level is obtained. If a VAR model with more than P^{**} lags that is free from evident autocorrelation cannot be found models with fewer lags will be tested for autocorrelation to see if a model free from autocorrelation can be found. This yields the lag length that will be used in the VECM.

Using this VECM, we run the Johansen cointegration test with unrestricted intercept and no trend to determine whether the variables cointegrate. We use the trace and maximum eigenvalue tests to determine the cointegrating rank. In this case, we test the null hypotheses from $r = 0$ to $r = n - 1$ until we fail to reject the null hypothesis. If there is evidence of cointegration this means that long-run information should be included in the model. We therefore use the unrestricted VECM, that does not specify the number or form of cointegrating relations to produce forecasts.[119] In addition, if there is evident cointegration we estimate a restricted VECM, denoted by VEC, by assuming a single cointegrating relation (based on the Johansen estimates) and use this model for forecasting. We assume one cointegrating equation because it is not theoretically obvious how we should specify more cointegrating equations. Further, the Johansen procedure is known to tend to reject the less cointegration null more often than it should when the null is for the number of cointegrating equations being greater than 0.[120]

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[119] The difference between the VECM specified in this section and an unrestricted VAR model discussed in the previous section is that the former includes nonstationary, in particular I(1), variables that may be cointegrated while the latter is applied only to variables that are made stationary through differencing.

[120] The Johansen procedure severely over-rejects the null of "less cointegration" versus the alternative of "more cointegration" when using sample sizes typically employed in time-series analysis – see Hanck C (2006 p. 6). "Cross-Sectional Correlation Robust Tests for Panel Cointegration", Mimeo, Department of Economics, University of Dortmund.

7.2.1 Modelling Vector Error Correction Model (VECM) for Brazil

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for Brazil. We focus only on those variables that are I(1) in Table 6.6.5. First, we include all variables except the output gap (which is I(0)) as endogenous and do not impose a priori restrictions on structural relationships. The following variables are considered: lnP, lnM, R, $InREE$, UN and $InOilp$ (all are I(1)). To choose an appropriate lag length for this model, we estimate a levels VAR model and use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum possible lag-length that can be estimated (P* =7) to determine the initial lag length P^{**}. The results are given in Table 7.2.1.A. Column 1 and 2 indicate that the lag length selected by both the AIC and SC is 7. We tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.2.1.A. There is evidence of autocorrelation at the 5% level because all of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Brazil with more than 7 lags and experience suggests that models with too many lags can exhibit autocorrelation we consider lower lag length VARs and re-estimate the VAR model using lag lengths 6 and 5 (where lags = P* - 1;) and test the validity of each model. The VAR models with 6 lags indicate evidence of autocorrelation whereas the VAR with 5 lags exhibits no evident autocorrelation. Hence, we select the 5 lag VAR of this model for cointegration analysis.

Table 7.2.1. A. The VAR lags order selection criteria

Endogenous: lnP, lnM, R, $InREE$, UN and $InOilp$					
	1	2	3	4	5
Lags			7	6	5
	AIC	SC	Prob.	Prob.	Prob.
0	2.139911	2.3629			
1	-10.922	-9.36068	0.0018	0.1726	0.1745
2	-10.8347	-7.93504	0.0000	0.0258	0.7827
3	-11.2047	-6.96667	0.0000	0.0618	0.8204
4	-11.0758	-5.49954	0.0000	0.6897	0.1111
5	-12.8521	-5.93752	0.0000	0.0312	0.6912
6	-12.7817	-5.62883	0.0000	0.1808	0.6926
7	-14.78175*	-6.52883*	0.0000	0.8630	0.5209
8			0.0000	0.8666	0.2921
9			0.0000	0.4360	0.4999
10			0.0000	0.7357	0.9144

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value of a test for autocorrelation.

Using a VECM based on 5 lagged level terms (4 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.2.1.B. Based on the trace and maximum eigenvalue statistics, we reject the null hypothesis of no cointegrating equations at the 5% level. However, the null hypothesis of at most 4 cointegrating equations cannot be rejected at the 5% significance level according to the trace test. Therefore, we assume one cointegrating equation because it is not theoretically obvious how we should specify more cointegrating equations and the Johansen procedure has a tendency to indicate too many cointegrating equations (see discussion above).

Table 7.2.1.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	390.3386	95.75366	0.0001	148.0977	40.07757	0.0001
At most 1*	242.241	69.81889	0.0000	100.6393	33.87687	0.0000
At most 2*	141.6017	47.85613	0.0000	69.065	27.58434	0.0000
At most 3*	72.53672	29.79707	0.0000	54.44726	21.13162	0.0000
At most 4*	18.08946	15.49471	0.0199	17.13844	14.2646	0.0171
At most 5	0.95102	3.841466	0.3295	0.95102	3.841466	0.0001

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.2.1.C to forecast inflation. This specification does not impose the number or form of cointegrating equations on the model.

Table 7.2.1. C. The Vector Error Correction Model

Standard errors in ( ) & t-statistics in [ ]						
Table 7.2.1.D. The Vector Error Correction Model						
	DLOG(PBRA)	DLOG(MBRA_D11)	D(RBRA)	DLOG(REEBRA)	D(UBRA)	DLOG(OILP)
DLOG(PBRA(-1))	-0.02505	0.459901	8.027274	1.713247	0.498807	4.892168
	-0.20863	-1.36955	-32.7435	-3.14106	-15.1613	-5.97748
	[-0.12006]	[0.33580]	[0.24516]	[0.54544]	[0.03290]	[0.81843]
DLOG(PBRA(-2))	-0.64034	0.104678	-63.7641	-0.66796	-3.49175	-0.97568
	-0.18627	-1.22278	-29.2345	-2.80445	-13.5366	-5.3369
	[-3.43773]	[0.08561]	[-2.18113]	[-0.23818]	[-0.25795]	[-0.18282]
DLOG(PBRA(-3))	-0.11974	0.08268	-21.5148	-1.22243	-8.48606	-0.08844
	-0.19527	-1.28188	-30.6473	-2.93997	-14.1907	-5.59481
	[-0.61320]	[0.06450]	[-0.70201]	[-0.41580]	[-0.59800]	[-0.01581]
DLOG(PBRA(-4))	-0.17503	-0.66971	-54.221	1.871178	-28.7315	0.904799
	-0.16538	-1.08564	-25.9557	-2.48991	-12.0183	-4.73833
	[-1.05835]	[-0.61688]	[-2.08899]	[0.75151]	[-2.39064]	[0.19095]
DLOG(MBRA_D11(-1))	0.030531	-0.70857	3.334608	-0.38737	-1.23705	0.445273
	-0.03072	-0.20164	-4.82086	-0.46246	-2.23222	-0.88007
	[0.99397]	[-3.51400]	[0.69170]	[-0.83762]	[-0.55418]	[0.50595]
DLOG(MBRA_D11(-2))	0.05914	-0.41333	7.109911	-0.3501	0.902908	2.415929
	-0.0342	-0.2245	-5.36736	-0.51489	-2.48527	-0.97984
	[1.72934]	[-1.84112]	[1.32466]	[-0.67996]	[0.36330]	[2.46564]
DLOG(MBRA_D11(-3))	0.127499	-0.25542	7.110853	-0.10436	4.928344	3.083513
	-0.04004	-0.26283	-6.28367	-0.60279	-2.90955	-1.14711
	[3.18456]	[-0.97180]	[1.13164]	[-0.17312]	[1.69385]	[2.68806]
DLOG(MBRA_D11(-4))	0.096886	-0.31859	9.749591	-1.12315	7.034013	0.583007
	-0.05082	-0.33364	-7.97668	-0.7652	-3.69347	-1.45618
	[1.90632]	[-0.95490]	[1.22226]	[-1.46780]	[1.90444]	[0.40037]
D(RBRA(-1))	0.00137	-0.004	0.26786	-0.00868	0.067052	-0.04629
	-0.00102	-0.00672	-0.16075	-0.01542	-0.07443	-0.02935
	[1.33768]	[-0.59541]	[1.66627]	[-0.56309]	[0.90082]	[-1.57720]
D(RBRA(-2))	-0.00069	-0.00597	-0.25438	0.011572	0.094198	-0.01369
	-0.00117	-0.00766	-0.18324	-0.01758	-0.08485	-0.03345
	[-0.59352]	[-0.77832]	[-1.38821]	[0.65833]	[1.11022]	[-0.40923]
D(RBRA(-3))	0.004033	-0.00591	0.187726	-0.01648	0.122438	0.027893
	-0.00112	-0.00734	-0.17549	-0.01683	-0.08126	-0.03204
	[3.60703]	[-0.80534]	[1.06974]	[-0.97883]	[1.50681]	[0.87066]

D(RBRA(-4))	0.00043	-0.00598	-0.07125	-0.00886	0.1961	0.004426
	-0.00076	-0.005	-0.11963	-0.01148	-0.05539	-0.02184
	[0.56435]	[-1.19496]	[-0.59563]	[-0.77238]	[3.54022]	[0.20265]
DLOG(REEBRA(-1))	-0.05491	-0.02813	-3.05574	0.158792	-1.07576	0.857222
	-0.01557	-0.10223	-2.44422	-0.23447	-1.13176	-0.4462
	[-3.52560]	[-0.27511]	[-1.25019]	[0.67723]	[-0.95053]	[1.92114]
DLOG(REEBRA(-2))	-0.04935	0.24348	-6.91508	-0.42095	0.275846	0.396617
	-0.01983	-0.13016	-3.11182	-0.29851	-1.44088	-0.56808
	[-2.48921]	[1.87066]	[-2.22220]	[-1.41016]	[0.19144]	[0.69817]
DLOG(REEBRA(-3))	-0.05803	0.28468	-3.34386	-0.11563	0.492672	0.34053
	-0.02247	-0.14748	-3.52598	-0.33825	-1.63265	-0.64369
	[-2.58318]	[1.93029]	[-0.94835]	[-0.34184]	[0.30176]	[0.52903]
DLOG(REEBRA(-4))	-0.04455	0.191369	-3.84498	-0.21947	-2.15527	-0.35162
	-0.02394	-0.15718	-3.75785	-0.36049	-1.74001	-0.68601
	[-1.86060]	[1.21753]	[-1.02318]	[-0.60881]	[-1.23865]	[-0.51255]
D(UBRA(-1))	-0.00315	0.027035	-0.24267	0.063859	-0.54615	-0.02537
	-0.0029	-0.01902	-0.45471	-0.04362	-0.21055	-0.08301
	[-1.08590]	[1.42148]	[-0.53368]	[1.46397]	[-2.59394]	[-0.30567]
D(UBRA(-2))	-0.006	0.038407	-0.99963	0.053643	-0.26842	-0.07914
	-0.00285	-0.01869	-0.44686	-0.04287	-0.20691	-0.08158
	[-2.10758]	[2.05489]	[-2.23702]	[1.25140]	[-1.29728]	[-0.97013]
D(UBRA(-3))	-0.00468	0.038277	-0.36425	0.050164	-0.47173	-0.08278
	-0.00288	-0.01888	-0.45131	-0.04329	-0.20897	-0.08239
	[-1.62820]	[2.02774]	[-0.80710]	[1.15870]	[-2.25738]	[-1.00468]
D(UBRA(-4))	-0.00169	0.029846	-0.66812	0.020312	-0.73462	-0.13526
	-0.00294	-0.01928	-0.46089	-0.04421	-0.21341	-0.08414
	[-0.57483]	[1.54824]	[-1.44965]	[0.45941]	[-3.44236]	[-1.60760]
DLOG(OILP(-1))	0.003258	-0.00556	0.823192	0.016615	-0.82134	-0.36459
	-0.00877	-0.05758	-1.37652	-0.13205	-0.63738	-0.25129
	[0.37151]	[-0.09649]	[0.59802]	[0.12583]	[-1.28862]	[-1.45087]
DLOG(OILP(-2))	0.008811	-0.09016	1.845928	0.037176	-0.94655	-0.54557
	-0.00802	-0.05264	-1.25855	-0.12073	-0.58275	-0.22975
	[1.09880]	[-1.71264]	[1.46671]	[0.30792]	[-1.62428]	[-2.37459]
DLOG(OILP(-3))	-0.0015	-0.07368	-0.76849	0.069967	-0.46031	-0.34807
	-0.00862	-0.05659	-1.35285	-0.12978	-0.62642	-0.24697
	[-0.17421]	[-1.30203]	[-0.56805]	[0.53913]	[-0.73483]	[-1.40935]
DLOG(OILP(-4))	-0.00302	-0.07522	-0.60699	-0.08065	-0.50957	-0.28783
	-0.00873	-0.05734	-1.37091	-0.13151	-0.63478	-0.25027
	[-0.34564]	[-1.31180]	[-0.44277]	[-0.61325]	[-0.80276]	[-1.15008]

LOG(PBRA(-5))	-0.17045	0.652487	-16.8	1.428985	-7.99718	0.439702
	-0.05783	-0.37966	-9.07688	-0.87074	-4.2029	-1.65703
	[-2.94722]	[1.71862]	[-1.85086]	[1.64112]	[-1.90278]	[0.26536]
LOG(MBRA_D11(-5))	0.093528	-0.29722	9.530508	-0.57464	3.81829	0.056674
	-0.02896	-0.19014	-4.54584	-0.43608	-2.10488	-0.82986
	[3.22912]	[-1.56318]	[2.09653]	[-1.31775]	[1.81402]	[0.06829]
RBRA(-5)	0.002147	-0.00984	0.038328	-0.01984	0.250899	0.01918
	-0.00095	-0.00623	-0.14903	-0.0143	-0.06901	-0.02721
	[2.26065]	[-1.57798]	[0.25718]	[-1.38801]	[3.63589]	[0.70497]
LOG(REEBRA(-5))	-0.06122	0.21591	-6.69862	0.178297	-2.48866	-0.17408
	-0.02176	-0.14287	-3.41566	-0.32766	-1.58157	-0.62355
	[-2.81288]	[1.51128]	[-1.96115]	[0.54415]	[-1.57354]	[-0.27917]
UBRA(-5)	-0.00674	0.028098	-0.45536	0.051163	-0.48722	-0.09761
	-0.00227	-0.0149	-0.35628	-0.03418	-0.16497	-0.06504
	[-2.96777]	[1.88551]	[-1.27810]	[1.49697]	[-2.95341]	[-1.50082]
LOG(OILP(-5))	-0.01134	-0.07256	-1.50277	-0.08445	0.357234	-0.36792
	-0.0065	-0.04264	-1.01943	-0.09779	-0.47203	-0.1861
	[-1.74642]	[-1.70170]	[-1.47413]	[-0.86357]	[0.75680]	[-1.97700]
R-squared	0.88738	0.697224	0.884123	0.6062	0.739249	0.654417
Adj. R-squared	0.745381	0.315462	0.738017	0.109669	0.410475	0.218683
Sum sq. resids	0.000526	0.022665	12.9551	0.119218	2.777579	0.431745
S.E. equation	0.004782	0.031391	0.75051	0.071996	0.347512	0.137009
F-statistic	6.249191	1.826332	6.051247	1.220871	2.248503	1.501871
Log likelihood	230.0931	130.3631	-37.8705	86.36913	2.937135	52.26687
Akaike AIC	-7.55068	-3.78729	2.561151	-2.12714	1.02124	-0.84026
Schwarz SC	-6.43542	-2.67203	3.67641	-1.01188	2.1365	0.275
Mean dependent	0.0159	0.033944	-0.23962	0.007017	-0.15173	0.031932
S.D. dependent	0.009477	0.037941	1.46629	0.076301	0.452604	0.155002
Determinant resid covariance (dof adj.)		2.66E-14				
Determinant resid covariance		1.77E-16				
Log likelihood		509.8871				
Akaike information criterion		-12.4486				
Schwarz criterion		-5.75701				

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.2.1.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Brazil inflation since there is no evidence of autocorrelation.

Table 7.2.1.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.1745
2	0.7827
3	0.8204
4	0.1111
5	0.6912
6	0.6926
7	0.5209
8	0.2921
9	0.4999
10	0.9144

In this section, we seek to produce a VECM for Brazil where we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a level's VAR using the maximum possible lag-length that can be estimated for Brazil (P*= 9). The VAR model considered includes five nonstationary endogenous variables (lnP, lnM, R, $InREE\ and\ UN$) with the difference of the log of oil prices as exogenous ($\Delta InOilp$). The results are given in Table 7.2.1.E column 1 and 2 where the lag length selected by both the AIC and SC is 9. There is evidence of autocorrelation at the 5% level in this 9-lag model because all the tests' probability values are less than 0.05 (see column 3). The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Brazil with more than 9 lags and because experience suggests that models with too many lags can exhibit autocorrelation we consider lower lag length VARs. As a result, we re-estimate VAR models with 8 ,7 and 6 lags and report the autocorrelation tests in columns 4, 5 and 6 of Table 7.2.1.E, respectively. The VAR models with 8 and 7 lags indicate evidence of autocorrelation whereas the VAR with 6 lags exhibits no evident autocorrelation. Hence, we select the 6 lag VAR of this model for cointegration analysis.

Table 7.2.1. E

Endogenous: $lnP, lnM, R, lnREE\ and\ UN$ Exogenous: $\Delta InOilp$						
	1	2	3	4	5	6
	AIC	SC	Prob.	Prob.	Prob.	
Lag			9	8	7	6
0	6.051451	6.237327				
1	-9.49954	-8.38428	0.000	0.0284	0.0321	0.1575
2	-9.47911	-7.43447	0.000	0.0348	0.4982	0.1833
3	-9.64925	-6.67523	0.000	0.367	0.1017	0.3612
4	-9.8226	-5.91919	0.000	0.9978	0.1355	0.5404
5	-10.739	-5.90624	0.000	0.0138	0.8474	0.9888
6	-11.4478	-5.68559	0.000	0.3043	0.7347	0.4096
7	-12.5219	-5.83038	0.000	0.8661	0.7619	0.8324
8	-14.4782	-6.85723	0.000	0.8875	0.2745	0.2845
9	-19.58900*	-11.03868*	0.000	0.9024	0.9127	0.9355
10			0.000	0.8407	0.7105	0.7257

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 6 lagged level terms (5 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.2.1.F. Based on the trace and maximum eigenvalue statistics, we reject the null hypothesis of no cointegrating equations at the 5% level. However, the null hypothesis of at most 4 cointegrating equations cannot be rejected at the 5% significance level. Therefore, we assume one cointegrating equation because it is not theoretically obvious how we should specify more cointegrating equations and the Johansen procedure tends to indicate too many cointegrating equations (see the discussion above).

Table 7.2.1.F Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	176.6939	69.8189	0.0000	63.5116	33.8768	0.0000
At most 1*	113.1823	47.8561	0.0000	42.5288	27.5843	0.0003
At most 2*	70.6535	29.7970	0.0000	31.5575	21.1316	0.0012
At most 3*	39.0960	15.4949	0.0000	25.5497	14.2646	0.0006
At most 4*	13.5462	3.8415	0.0002	13.5462	3.8414	0.0002

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.2.1.G to forecast inflation. This specification does not impose the number or form of cointegrating equations on the model.

Table 7.2.1.G. The Vector Error Correction Model

Standard errors in ( ) & t-statistics in [ ]					
	DLOG(PBRA)	DLOG(MBRA_D11)	D(RBRA)	DLOG(REEBRA)	D(UBRA)
DLOG(PBRA(-1))	-0.22833	0.550628	15.92621	6.707261	-3.36615
	-0.23504	-1.51386	-39.7417	-3.64915	-19.1466
	[-0.97145]	[0.36373]	[0.40074]	[1.83803]	[-0.17581]
DLOG(PBRA(-2))	-0.61565	0.80644	-46.4207	-2.04527	-15.0712
	-0.2029	-1.30686	-34.3075	-3.15018	-16.5285
	[-3.03422]	[0.61708]	[-1.35308]	[-0.64925]	[-0.91183]
DLOG(PBRA(-3))	-0.35833	-0.26896	-24.4989	3.069599	-3.31068
	-0.23682	-1.52534	-40.0431	-3.67683	-19.2918
	[-1.51308]	[-0.17633]	[-0.61181]	[0.83485]	[-0.17161]
DLOG(PBRA(-4))	-0.27821	0.065003	-62.0859	0.229944	-28.7151
	-0.16374	-1.05462	-27.6859	-2.54217	-13.3384
	[-1.69908]	[0.06164]	[-2.24251]	[0.09045]	[-2.15281]
DLOG(PBRA(-5))	-0.33275	0.548354	-69.6121	2.654713	-1.71647
	-0.20626	-1.32849	-34.8754	-3.20232	-16.8022
	[-1.61324]	[0.41277]	[-1.99602]	[0.82900]	[-0.10216]
DLOG(MBRA_D11(-1))	0.055006	-0.76841	3.80544	-0.28874	-0.77874
	-0.03391	-0.21841	-5.73366	-0.52647	-2.76234
	[1.62212]	[-3.51822]	[0.66370]	[-0.54844]	[-0.28191]
DLOG(MBRA_D11(-2))	0.094216	-0.43396	8.990891	-0.20847	0.939916
	-0.03916	-0.25224	-6.62173	-0.60802	-3.1902
	[2.40578]	[-1.72046]	[1.35778]	[-0.34287]	[0.29463]
DLOG(MBRA_D11(-3))	0.182573	-0.30003	16.23415	0.056639	1.961149
	-0.03697	-0.23814	-6.25167	-0.57404	-3.01191
	[4.93791]	[-1.25989]	[2.59677]	[0.09867]	[0.65113]
DLOG(MBRA_D11(-4))	0.165389	-0.56076	23.42301	-1.35653	4.238154
	-0.0537	-0.34587	-9.07983	-0.83373	-4.37445
	[3.07986]	[-1.62130]	[2.57967]	[-1.62707]	[0.96884]
DLOG(MBRA_D11(-5))	0.168829	-0.65018	22.42615	-0.66791	3.744489
	-0.06017	-0.38756	-10.1742	-0.93422	-4.90171
	[2.80574]	[-1.67762]	[2.20421]	[-0.71494]	[0.76391]
D(RBRA(-1))	0.002927	-0.00671	0.032361	-0.00591	-0.01983
	-0.00125	-0.00802	-0.21055	-0.01933	-0.10144
	[2.35093]	[-0.83648]	[0.15370]	[-0.30554]	[-0.19552]
D(RBRA(-2))	-0.0004	-0.01036	-0.40443	-0.00101	0.110014
	-0.00117	-0.00757	-0.19862	-0.01824	-0.09569
	[-0.34332]	[-1.36967]	[-2.03616]	[-0.05516]	[1.14966]
D(RBRA(-3))	0.004297	-0.0089	-0.07483	-0.00339	0.116696
	-0.00128	-0.00827	-0.21701	-0.01993	-0.10455
	[3.34777]	[-1.07663]	[-0.34481]	[-0.17014]	[1.11618]
D(RBRA(-4))	0.003661	-0.00901	0.11791	-0.02578	0.08291
	-0.00138	-0.00887	-0.23279	-0.02138	-0.11215
	[2.65934]	[-1.01609]	[0.50650]	[-1.20588]	[0.73925]
D(RBRA(-5))	0.003431	-0.01634	0.091489	-0.01094	0.188937
	-0.00103	-0.00664	-0.17426	-0.016	-0.08395
	[3.32952]	[-2.46187]	[0.52503]	[-0.68351]	[2.25052]
DLOG(REEBRA(-1))	-0.04162	0.020023	-3.25675	0.112973	-1.56708
	-0.01435	-0.09244	-2.42661	-0.22282	-1.16908
	[-2.90028]	[0.21662]	[-1.34210]	[0.50702]	[-1.34043]
DLOG(REEBRA(-2))	-0.05716	0.184606	-6.45632	-0.08169	-1.05372
	-0.01979	-0.12745	-3.3457	-0.30721	-1.61188

	[-2.88853]	[1.44850]	[-1.92974]	[-0.26590]	[-0.65372]
DLOG(REEBRA(-3))	-0.06114	0.206331	-6.41581	0.027907	-0.66153
	-0.01868	-0.1203	-3.15823	-0.28999	-1.52156
	[-3.27341]	[1.71507]	[-2.03146]	[0.09623]	[-0.43477]
DLOG(REEBRA(-4))	-0.0738	0.072569	-6.36373	0.087077	-3.03819
	-0.02243	-0.14448	-3.79278	-0.34826	-1.82727
	[-3.28994]	[0.50229]	[-1.67785]	[0.25003]	[-1.66269]
DLOG(REEBRA(-5))	-0.10528	0.115865	-14.7356	0.292799	-0.88359
	-0.02434	-0.15676	-4.1153	-0.37787	-1.98265
	[-4.32556]	[0.73912]	[-3.58070]	[0.77486]	[-0.44566]
D(UBRA(-1))	-0.00628	0.033757	-0.95329	0.072754	-0.28129
	-0.00316	-0.02036	-0.53456	-0.04908	-0.25754
	[-1.98492]	[1.65776]	[-1.78332]	[1.48221]	[-1.09223]
D(UBRA(-2))	-0.01095	0.046217	-1.76546	0.062539	-0.13762
	-0.0035	-0.02254	-0.59164	-0.05433	-0.28504
	[-3.13057]	[2.05073]	[-2.98401]	[1.15119]	[-0.48281]
D(UBRA(-3))	-0.01039	0.031164	-1.04321	0.10108	-0.33214
	-0.00376	-0.02419	-0.63503	-0.05831	-0.30594
	[-2.76557]	[1.28831]	[-1.64277]	[1.73351]	[-1.08564]
D(UBRA(-4))	-0.00761	0.028342	-1.52258	0.054157	-0.55844
	-0.00365	-0.02351	-0.61712	-0.05667	-0.29731
	[-2.08504]	[1.20565]	[-2.46723]	[0.95573]	[-1.87828]
D(UBRA(-5))	-0.0088	0.040856	-2.09478	0.054035	-0.36201
	-0.004	-0.02573	-0.67554	-0.06203	-0.32546
	[-2.20324]	[1.58769]	[-3.10089]	[0.87112]	[-1.11231]
C	-0.00094	1.938028	43.13157	-2.22898	1.790133
	-0.14002	-0.90184	-23.675	-2.17388	-11.4061
	[-0.00670]	[2.14897]	[1.82182]	[-1.02534]	[0.15695]
LOG(PBRA(-6))	-0.30203	0.774999	-31.4358	1.854344	-6.87639
	-0.08491	-0.54691	-14.3576	-1.31834	-6.91714
	[-3.55694]	[1.41704]	[-2.18949]	[1.40658]	[-0.99411]
LOG(MBRA_D11(-6))	0.153826	-0.48194	14.92527	-0.73317	3.355336
	-0.04436	-0.2857	-7.50014	-0.68868	-3.61339
	[3.46787]	[-1.68687]	[1.99000]	[-1.06460]	[0.92858]
RBRA(-6)	0.005166	-0.01674	0.236499	-0.0245	0.141011
	-0.0014	-0.00899	-0.23611	-0.02168	-0.11375
	[3.69913]	[-1.86109]	[1.00164]	[-1.13021]	[1.23962]
LOG(REEBRA(-6))	-0.10031	0.128217	-16.3053	0.487939	-2.3447
	-0.03043	-0.19597	-5.14471	-0.4724	-2.4786
	[-3.29677]	[0.65426]	[-3.16932]	[1.03290]	[-0.94598]
UBRA(-6)	-0.01278	0.01875	-1.66752	0.106514	-0.33277
	-0.0037	-0.02385	-0.62606	-0.05749	-0.30162
	[-3.45228]	[0.78624]	[-2.66350]	[1.85287]	[-1.10328]
DLOG(OIL_EXOG(6))	0.003883	-0.00839	-0.1242	0.013946	-0.42059
	-0.00595	-0.03829	-1.00525	-0.0923	-0.48431
	[0.65318]	[-0.21920]	[-0.12355]	[0.15109]	[-0.86844]
R-squared	0.904085	0.751771	0.885459	0.643363	0.720968
Adj. R-squared	0.762496	0.385339	0.716376	0.116899	0.309064
Sum sq. resids	0.000448	0.018581	12.80568	0.107968	2.972307
S.E. equation	0.004618	0.029746	0.780893	0.071703	0.376216
F-statistic	6.385291	2.051595	5.236811	1.222046	1.750328
Log likelihood	234.3479	135.6272	-37.5631	88.99596	1.141524
Akaike AIC	-7.63577	-3.91046	2.625021	-2.15079	1.164471
Schwarz SC	-6.632457	-2.72085	3.814631	-0.96118	2.354081

Mean dependent	0.0159	0.033944	-0.23962	0.007017	-0.15173
S.D. dependent	0.009477	0.037941	1.46629	0.076301	0.452604
Determinant resid covariance (dof adj.)		3.43E-12			
Determinant resid covariance		3.35E-14			
Log likelihood		446.2034			
Akaike information criterion		-10.8001			
Schwarz criterion		-4.85208			

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.2.1.H. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Brazilian inflation since there is no evidence of autocorrelation.

Table 7.2. 1. H. Probability value of the residual autocorrelation

Lags	Prob.
1	0.1635
2	0.0623
3	0.6131
4	0.6911
5	0.2286
6	0.9306
7	0.9577
8	0.8703
9	0.4300
10	0.5233

A similar procedure was applied for all countries and the tables of results are available in appendix section 7.3 page 603 - 671. A summary of the unrestricted VECM models and their selected lag lengths for all countries is given in Table 7.2.1.I. Forecasts will be produced for all models summarised in Table 7.2.1.I where a valid specification (that is free from evident autocorrelation) could be found.

Table 7.2.1. I. Summary of the VECM equations specification

Countries	Sample	Variable specifications	Chosen lag length	Number of cointegration
Brazil	1999q4 2012q4	Endogenous: lnP, lnM, R, $InREE$, UN and $InOilp$	5	4
Brazil	1999q4 2012q4	Endogenous: lnP, lnM, R, $InREE$ and UN Exogenous: $\Delta InOilp\_f$	6	4
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$, gap and $InOilp$	No models free from autocorrelation	
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$, UN and $InOilp$	3	1
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$ and gap Exogenous: $\Delta InOilp\_f$	5	4
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$ and UN Exogenous: $\Delta InOilp\_f$	6	3
India	1963q1 2012q4	Endogenous: lnP and lnM	9	2
India	1984q1 2012q4	Endogenous: lnP lnM and $lnOilp$	9	1
India	1984q1 2012q4	Endogenous: lnP and lnM Exogenous: $\Delta InOilp\_f$	9	1
China	1992q1 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	10	1
China	1992q1 2012q4	Endogenous: lnP, lnM, R, and $InREE$ Exogenous: $\Delta InOilp\_f$	10	2
South Africa	1995q2 - 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	2	1
South Africa	1995q2 - 2012q4	Endogenous: lnP, lnM, R and $lnREE$ Exogenous: $\Delta lnOilp\_f$	2	1
Algeria	1999q2 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	7	5
Algeria	1999q2 2012q4	Endogenous: lnP, lnM, R, and $InREE$ Exogenous: $\Delta InOilp\_f$	10	4
Angola	2002q4 2012q4	Endogenous: lnP, lnM, R and $InOilp$	6	3
Angola	2002q4 2012q4	Endogenous: lnP, lnM, and R Exogenous: $\Delta InOilp$	6	3
Nigeria	1998q4 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	No models free from autocorrelation	
Nigeria	1998q4 2012q4	Endogenous: lnP, lnM, R, $and\ InREE$ Exogenous: $\Delta InOilp\_f$	No models free from autocorrelation	
Saudi Arabia	1983q1 2012q4	Endogenous: lnP, lnM, $InREE$ and $InOilp$	11	4
Saudi Arabia	1983q1 2014q4	Endogenous: lnP, lnM and $InREE$ Exogenous: $\Delta InOilp\_f$	5	1

Where P= consumer price, M =money supply, REE= real exchange rate, GAP = output gap, R = interest rate, UN =unemployment, Oilp = oil price and $\Delta InOilp\_f$ is the ARIMAX forecast of the oil price. Note that all the models in this table passed the diagnostic tests for autocorrelation at the 5% level of significance except those where "No models free from autocorrelation" is specified. In these cases, the models did not pass the diagnostic test for autocorrelation for all available lag lengths.

7.3.0. Modelling Vector Error Correction (VEC) model

In this section, we focus on the main problem of the vector error correction model (VECM) discussed in the previous section (7.2) with the aim of improving our inflation forecast performance. The problem with the VECM model is the large number of parameters that must be estimated. Each equation involves estimating $m \text{ x } k$ lagged coefficients plus one or more parameters for the deterministic components. For example, with a maximum of 6 lags, if six variables are treated as endogenous, each equation requires estimating 36 parameters, and the system as a whole has 216 coefficients. However, the large number of parameters in a model could cause over-parameterisation, loss of degrees of freedom, model misspecification and poor forecasting performance (Sa-ngasoongsong et al.2012). In practice, this problem can be addressed by imposing restrictions on the VECM. For example, testing the cointegrating rank in the system and imposing restrictions on the cointegrating vector β, long-run matrix (Π), short-run dynamic coefficients Γ and cointegrating rank. Another approach is to form a single equation and impose zero restrictions on insignificant coefficients. Based upon the cointegration results from the VECM models discussed in the previous chapter (chapter 7.2) we estimate a restricted VECM specification (called the VEC). The restriction that we impose on the VECM is to specify the cointegrating equations and thereby produce the VEC. In particular, for the models where there is evidence of at least one cointegrating equation we impose a single cointegrating equation on the model to produce the VEC. We assume one cointegrating equation because it is not theoretically obvious how we should specify more cointegrating equations. Further, the Johansen procedure is known to tend to reject the less cointegration null more often than it should when the null is for the number of cointegrating equations being greater than zero.[121] The difference between the previous model in section (7.2) (VECM) and the VEC model is that that cointegrating equations are imposed in the latter case and not the former.

[121] see Hanck C (2006 p. 6). "Cross-Sectional Correlation Robust Tests for Panel Cointegration", Mimeo, Department of Economics, University of Dortmund.

7.3.1. Brazilian Modelling Vector Error Correction (VEC) Model

In this section, we describe the process of modelling a VEC model for Brazil and focus only on those valid models where the variables were found to be cointegrated in section 7.2. First, we consider the cointegration results for the VECM model reported in (Table 7.2.1.I) for Brazil where the stationary form of the oil price is treated as exogenous and all other variables as endogenous (which are I(1)). In this case, there was evidence of four cointegrating equations; therefore, we accept that there is one equilibrium relationship among the variables because it is not theoretically obvious how we should specify more cointegrating equations. The estimation results for the error-correction term (denoted CointEq1), its associated cointegrating equation (CE1) and its VEC model are reported in Table 7.3.1.A and 7.3.1.B respectively. Note that the only difference in the coefficients of the error-correction term and the cointegrating equation is that their signs are reversed. The error-correction term (CointEq1) has a negative and significant coefficient in the inflation equation [in the column headed D(LOG(PBRA) Table 7.3.1.1.B)] suggesting that inflation is forced back to the cointegrating equation defined by CE1. All the explanatory variables in the cointegrating equation are significant (because their t-ratios exceed approximately 2 in magnitude). Based on the cointegrating equation results (CE1) in the Table 7.3.1.A it can be said that most of the signs of the equation parameters are in accordance with suggested economic theory as expected. The positive sign on the coefficients for the money supply supports the quantity theory of money. This implies that increases in money leads to rising prices in the long-run. The coefficient shows that a 1% increase in the money supply results in a 0.51% increase in prices. Surprisingly, there is a positive relationship between the interest rate and prices in Brazil which does not appear to be consistent with the basic economic theory. This result indicates that a 1%-point increase in the interest rate results in a 0.02% increase in prices.

We expect a positive long-run relationship between the exchange rate and inflation However, the negative sign contradicts our expectations. The coefficient indicates that a 1% increase in the exchange rate (currency depreciation) decreases the prices by 0.31%. Considering the Phillips curve, we would expect unemployment to have a negative influence on the rate of inflation over a long run. Our estimation results show that unemployment has a negative influence on the prices which is in line with our theoretical expectations. This implies that a 1%-point decrease in unemployment leads to 0.042% increase in prices in the long run.

We expect a positive short-run relationship between the exogenous oil price and inflation. Our results indicate that the oil price has positive short-run impact on prices; however, this is insignificant at the 5% level, but significant at 10% level. Hence, while oil prices have the expected sign it is not expected that their effect would be insignificant.

Table 7.3.1.A. Cointegrating equation.[122]

	1	2
Cointegrating Eq:	CointEq1	CE1
LOG(PBRA(-1))	1	
LOG(MBRA_D11(-1))	-0.51207	0.51207
	[-43.0127]	[43.0127]
RBRA(-1)	-0.01756	0.01756
	[-14.6649]	[14.6649]
LOG(REEBRA(-1))	0.31263	-0.31263
	[10.9281]	[-10.9281]
UBRA(-1)	0.04204	-0.04204
	[9.7558]	[-9.7558]
C	0.19989	-0.19989

Where [ ] = the *t* statistics

Error Correction:	D(LOG(PBRA))	D(LOG(MBRA_D11))	D(RBRA)	D(LOG(REEBRA))	D(UBRA)
CointEq1	-0.32473	0.967426	-21.582	1.361218	-2.94749
	-0.07028	-0.54213	-14.8918	-1.11563	-5.38306
	[-4.62030]	[1.78449]	[-1.44926]	[1.22013]	[-0.54755]
D(LOG(PBRA(-1)))	0.030065	0.799288	47.64822	3.060759	18.02426
	-0.17334	-1.33704	-36.7271	-2.75145	-13.2761
	[0.17345]	[0.59780]	[1.29736]	[1.11242]	[1.35765]
D(LOG(PBRA(-2)))	-0.25654	-0.41991	-50.3474	-2.13264	-15.7947
	-0.16831	-1.29824	-35.6614	-2.67161	-12.8908
	[-1.52428]	[-0.32345]	[-1.41182]	[-0.79826]	[-1.22527]
D(LOG(PBRA(-3)))	-0.04491	-0.0685	-5.09861	2.007329	13.02149
	-0.1571	-1.21179	-33.2865	-2.49369	-12.0324
	[-0.28588]	[-0.05653]	[-0.15317]	[0.80496]	[1.08221]
D(LOG(PBRA(-4)))	0.083827	-0.51799	-34.3806	-0.84522	-25.1915
	-0.13028	-1.00491	-27.604	-2.06798	-9.97825
	[0.64345]	[-0.51546]	[-1.24549]	[-0.40872]	[-2.52464]
D(LOG(PBRA(-5)))	-0.00563	1.351132	-1.55782	0.738437	14.23351
	-0.10603	-0.81786	-22.4658	-1.68305	-8.12092
	[-0.05313]	[1.65203]	[-0.06934]	[0.43875]	[1.75270]
D(LOG(MBRA_D11(-1)))	-0.09359	0.086796	-2.76808	0.231685	-1.77358

[122] Column 1 in the table 7.3.1.A is the equation that describe the error-correction term and Column 2 is the cointegrating equation. Note that the only difference in the coefficients of the error-correction term and cointegrating equation is that their signs are reversed.

	-0.03229	-0.24905	-6.84122	-0.51252	-2.47295
	[-2.89851]	[0.34851]	[-0.40462]	[0.45205]	[-0.71719]
D(LOG(MBRA_D11(-2)))	-0.05875	0.536467	3.352753	-0.00652	1.576656
	-0.03462	-0.26707	-7.33605	-0.54959	-2.65182
	[-1.69688]	[2.00874]	[0.45702]	[-0.01185]	[0.59456]
D(LOG(MBRA_D11(-3)))	0.020484	0.521586	4.011097	0.344894	2.676611
	-0.03225	-0.24874	-6.83262	-0.51187	-2.46984
	[0.63521]	[2.09692]	[0.58705]	[0.67379]	[1.08372]
D(LOG(MBRA_D11(-4)))	0.017821	-0.16072	1.787225	-0.14817	-0.12839
	-0.0295	-0.22754	-6.2502	-0.46824	-2.25931
	[0.60414]	[-0.70635]	[0.28595]	[-0.31644]	[-0.05683]
D(LOG(MBRA_D11(-5)))	0.019859	-0.28127	1.044583	0.56876	-0.64271
	-0.02971	-0.2292	-6.29597	-0.47167	-2.27586
	[0.66833]	[-1.22716]	[0.16591]	[1.20585]	[-0.28240]
D(RBRA(-1))	-0.00241	0.012606	0.081015	0.020555	-0.12714
	-0.00143	-0.011	-0.3021	-0.02263	-0.1092
	[-1.69306]	[1.14623]	[0.26817]	[0.90820]	[-1.16422]
D(RBRA(-2))	-0.00598	0.005914	-0.56012	0.020291	0.014307
	-0.00114	-0.00882	-0.24236	-0.01816	-0.08761
	[-5.22604]	[0.67027]	[-2.31112]	[1.11755]	[0.16331]
D(RBRA(-3))	-0.00142	0.013539	0.023159	0.000268	0.077277
	-0.00141	-0.01086	-0.29833	-0.02235	-0.10784
	[-1.01013]	[1.24656]	[0.07763]	[0.01198]	[0.71658]
D(RBRA(-4))	-0.00141	0.007549	-0.15675	0.005206	-0.06343
	-0.00072	-0.00555	-0.15256	-0.01143	-0.05515
	[-1.96245]	[1.35918]	[-1.02742]	[0.45547]	[-1.15013]
D(RBRA(-5))	-0.00217	0.000127	-0.07732	0.00724	0.097467
	-0.00074	-0.00569	-0.1563	-0.01171	-0.0565
	[-2.94058]	[0.02234]	[-0.49472]	[0.61832]	[1.72515]
D(LOG(REEBRA(-1)))	0.059506	-0.24959	5.741729	-0.26926	0.058135
	-0.02598	-0.20037	-5.50409	-0.41234	-1.98961
	[2.29073]	[-1.24562]	[1.04317]	[-0.65300]	[0.02922]
D(LOG(REEBRA(-2)))	0.044882	-0.02756	3.236278	-0.47452	0.695389
	-0.01602	-0.12355	-3.39379	-0.25425	-1.22678
	[2.80213]	[-0.22308]	[0.95359]	[-1.86637]	[0.56684]
D(LOG(REEBRA(-3)))	0.041149	-0.08981	4.117703	-0.25811	0.488141
	-0.0171	-0.13186	-3.62219	-0.27136	-1.30934
	[2.40708]	[-0.68110]	[1.13680]	[-0.95117]	[0.37281]
D(LOG(REEBRA(-4)))	0.02784	-0.23064	3.14604	-0.12376	-1.84714
	-0.01338	-0.10319	-2.83455	-0.21235	-1.02463
	[2.08105]	[-2.23507]	[1.10989]	[-0.58281]	[-1.80274]
D(LOG(REEBRA(-5)))	0.000714	-0.11841	-1.70401	0.10803	0.451376
	-0.01217	-0.09391	-2.57951	-0.19325	-0.93244
	[0.05864]	[-1.26094]	[-0.66060]	[0.55903]	[0.48408]
D(UBRA(-1))	0.007642	0.012935	0.242379	0.016083	0.00983
	-0.00252	-0.01942	-0.53334	-0.03996	-0.19279
	[3.03598]	[0.66622]	[0.45446]	[0.40253]	[0.05099]
D(UBRA(-2))	0.001998	0.011599	-0.68404	-0.01093	0.10984
	-0.00199	-0.01537	-0.42232	-0.03164	-0.15266
	[1.00252]	[0.75446]	[-1.61972]	[-0.34534]	[0.71951]
D(UBRA(-3))	0.00193	-0.00387	0.236347	0.016364	-0.04374
	-0.00201	-0.01552	-0.42628	-0.03194	-0.15409
	[0.95943]	[-0.24932]	[0.55444]	[0.51241]	[-0.28385]
D(UBRA(-4))	0.004983	-0.01107	-0.12605	-0.02061	-0.3412
	-0.00187	-0.01439	-0.39538	-0.02962	-0.14292

	[2.67023]	[-0.76928]	[-0.31879]	[-0.69589]	[-2.38733]
D(UBRA(-5))	0.004013	0.011579	-0.10744	-0.02995	-0.0848
	-0.00187	-0.01445	-0.39703	-0.02974	-0.14352
	[2.14165]	[0.80108]	[-0.27062]	[-1.00696]	[-0.59085]
C	0.018528	0.016349	-0.21274	-0.05505	-0.29713
	-0.00393	-0.03028	-0.8317	-0.06231	-0.30064
	[4.72027]	[0.53997]	[-0.25579]	[-0.88353]	[-0.98834]
DLOG(OILP_EXOG)	0.006747	-0.03865	-0.72811	0.238065	-1.10628
	-0.00578	-0.04458	-1.22461	-0.09174	-0.44267
	[1.82874]	[-0.86695]	[-0.59456]	[2.59493]	[-2.49911]
R-squared	0.904344	0.64493	0.820616	0.628202	0.75399
Adj. R-squared	0.801035	0.261454	0.626882	0.22666	0.4883
Sum sq. resids	0.000447	0.026579	20.05519	0.112558	2.620547
S.E. equation	0.004227	0.032606	0.89566	0.067099	0.323762
F-statistic	8.753793	1.6818	4.235775	1.564474	2.837851
Log likelihood	234.4194	126.1411	-49.4509	87.89268	4.479342
Akaike AIC	-7.78941	-3.70344	2.922677	-2.2601	0.887572
Schwarz SC	-6.7485	-2.66253	3.963586	-1.21919	1.928481
Mean dependent	0.0159	0.033944	-0.23962	0.007017	-0.15173
S.D. dependent	0.009477	0.037941	1.46629	0.076301	0.452604
Determinant resid covariance (dof adj.)		3.77E-12			
Determinant resid covariance		8.79E-14			
Log likelihood		420.6304			
Akaike information criterion		-10.4012			
Schwarz criterion		-5.01073			

For the model to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.3.1.C. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Brazilian inflation since there is no evidence of autocorrelation.

Table 7.3 1.C Probability value of the residual autocorrelation

Lags	Prob.
1	0.1278
2	0.4065
3	0.4941
4	0.6218
5	0.9122
6	0.2788
7	0.6143
8	0.8679
9	0.8799
10	0.5094

A similar procedure was applied for all countries (to avoid similar repetition, the details these tables are available on request, to save space). A summary of the VEC models, adjustment coefficients on the error correction term in the inflation equation and the cointegrating equations for all countries are given in Table 7.3.1.D, 7.3.1.E and 7.3.1.F respectively. The forecasts will be produced for all models summarised in Table 7.3.1.D. where a valid specification that is free from evident autocorrelation and cannot reject cointegration could be found.

Table 7.3.1.D Summary of the VEC specifications

Countries	Sample	Variable specifications	Chosen lag length	Number of cointegration rank imposed	SC	AIC
Brazil	1999q4 2012q4	Endogenous: lnP, lnM, R, $InREE$, UN and $InOilp$	5	1	-6.5481	-7.7377
Brazil	1999q4 2012q4	Endogenous: lnP, lnM, R, $InREE$ and UN Exogenous: $InOilp\_f$	5	1	-6.7485	-7.7894
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$, UN and $InOilp$	2	1	-6.5293	-7.0412
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$, gap and $InOilp$	4	1	-5.93014	-6.8685
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$ and gap Exogenous: $InOilp\_f$	6	1	-5.78105	-6.9327
Russia	2003Q2 2012q4	Endogenous: lnP, lnM, $InREE$ and UN Exogenous: $InOilp\_f$	6	1	-12.5695	-16.6645
India	1963q1 2012q4	Endogenous: lnP and lnM	13	1	-5.3968	-5.8618
India	1984q1 2012q4	Endogenous: lnP lnM and $lnOilp$	8	1	-5.2883	-5.9054
India	1984q1 2012q4	Endogenous: lnP and lnM Exogenous: $InOilp\_f$	16	1	- 10.7993	- 11.7488
China	1992q1 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	10	1	-6.9911	-14.657
China	1992q1 2012q4	Endogenous: lnP, lnM, R, and $InREE$ Exogenous: $InOilp\_f$	12	1	-7.6633	-13.7252
South Africa	1995q2 - 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	2	1	-9.97811	-11.2523
South Africa	1995q2 - 2012q4	Endogenous: lnP, lnM, R and $lnREE$ Exogenous: $lnOilp\_f$	2	1	-9.03415	-10.0539
Algeria	1999q2 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	7	1	-10.1217	- 16.14376
Algeria	1999q2 2012q4	Endogenous: lnP, lnM, R, and $InREE$ Exogenous: $InOilp\_f$	8	1	-10. 6614	-16.5009
Angola	2002q4 2012q4	Endogenous: lnP, lnM, R and $InOilp$	5	1	-6.1447	-7.06425
Angola	2002q4 2012q4	Endogenous: lnP, lnM, and R Exogenous: $InOilp\_f$	6	1	-5.4583	-6.3340
Nigeria	1998q4 2012q4	Endogenous: lnP, lnM, R, $InREE$ and $InOilp$	5	1	-3.6665	-4.6343
Nigeria	1998q4 2012q4	Endogenous: lnP, lnM, R, $and\ InREE$ Exogenous: $InOilp$	7	1	-3.5021	- 4.61333
Saudi Arabia	1983q1 2012q4	Endogenous: lnP, lnM, $InREE$ and $InOilp$	9	1	-11.7962	-15.7916
Saudi Arabia	1983q1 2014q4	Endogenous: lnP, lnM and $InREE$ Exogenous: $InOilp\_f$	10	1	-6.1675	-6.5160

Where P= consumer price, M =money supply, REE= real exchange rate, GAP = output gap, R = interest rate, UN =unemployment, Oilp = oil price. Note that all the models in this table passed the diagnostic tests for autocorrelation at the 5% level of significance except those where "No valid model" is specified. In these cases, the models did not pass the diagnostic test for autocorrelation for all available lag lengths.

7.3.1.E. The summary of the adjustment coefficient on the error correction terms in the inflation equation (where the stationary transformation of the oil price is treated as exogenous)

	Brazil	Russia (Un')	Russia (gap')	India	China	South Africa	Nigeria	Algeria	Angola	Saudi Arabia
CointEq1	-0.3247	-0.0894	-0.1118	-0.0281	0.0129	-0.0052	0.0546	-0.0250	-0.1389	-0.0089
t []ratio statistics	[-4.6203]	[-1.5458]	[-1.1178]	[-1.6829]	[2.068]	[-0.6501]	[1.2095]	[-1.3898]	[-3.6324]	[-3.0094]

Where [] = t ratio statistics, Russia (gap') = when the output gap is excluded and Russia (Un')= when the unemployment variable is excluded.

7.3.1.F. The summary of the estimated cointegrating equations (where the stationary transformation of the oil price is treated as exogenous)

CE1	Brazil	Russia (gap')	Russia (Un')	India	China	South Africa	Algeria	Angola	Nigeria	Saudi Arabia
lnP										
lnM	0.51207	0.20096	0.18827	0.47112	-0.83780	0.08997	0.82095	0.4466	0.5161	0.47582
	[43.0137]	[4.7798]	[3.5071]	[15.9553]	[-2.9561]	[0.6202]	[9.52665]	[11.8215]	[14.0402]	[2.62970]
R	0.01756				-0.26812	-0.0519	0.30119	0.00274	0.0108	
	[14.6649]				[-1.3309]	[-1.9619]	[4.9237]	[2.4888]	[1.3798]	
$InREE$	-0.31263	0.67519	0.55554		5.16488	1.1295	3.24607		0.4010	-0.63910
	[-10.928]	[3.4647]	[2.4541]		[2.83337]	[2.3671]	[4.81036]		[4.4520]	[-1.5618]
UN	-0.04204	0.02153								
	[-9.7558]	[2.7635]								
GAP			-0.41819							
			[-2.1665]							
C	-0.19989	3.56E-01	1.0969	-10.2708	8.67335	-0.72231	-37.07347	-1.811372	12.7541	-5.178497

Where [] = t ratio statistics, Russia (gap') = when the output gap is excluded and Russia (Un')= when the unemployment variable is excluded.

The summary of the adjustment coefficient on the error correction terms in the inflation equation and the cointegrating equations (where the stationary transformation of the oil price is treated as exogenous) are provided in the Table 7.3.1.E and 7.3.1.F respectively. Table 7.3.1.E indicates that for Brazil, Angola and Saudi Arabia, the error-correction term (CointEq1) has a negative and significant coefficient in the inflation equation. This result shows evidence of a long-run equilibrium relationship between prices and the other selected macroeconomic variables in these countries. This long-run relationship implies that the selected variables move together over time such that the short-term deviations of prices from its long-run trend will be corrected. For Russia, India, South Africa and Algeria, the coefficient on the error-correction term (CointEq1) is negative however it is not significant. Hence, while the price is forced towards its long-run value the adjustment is statistically insignificant. For China and Nigeria, the coefficient on the error-correction term (CointEq1) is positive and significant for China but insignificant for Nigeria, neither of which are consistent with theory. This suggesting that the price variable is continually forced away from its long-run value as defined by the estimated cointegrating equation. This raises questions over the validity of specified cointegrating equation as an equilibrium specification for prices and as such might be expected to adversely affect the accuracy of inflation forecasts from this model for China and Nigeria.

Table 7.3.1.F reports the estimated cointegrating equations. For Brazil, Russia (both models), India, Algeria, Angola, Saudi Arabia and Nigeria, the money supply variable has the theoretically expected positive and significant long-run relationship with prices. However, for China the coefficient on money supply is negative and significant while for South Africa this coefficient is positive and insignificant. Most of these countries' estimates are consistent with the quantity theory of money and this general consistency may be expected to enhance the forecasts for inflation.

For China and South Africa, interest rates have the theoretically expected negative long-run relationship with prices; however, the coefficient estimates are insignificant which suggests caution in interpreting these results as consistent with theoretical expectations.[123] For Nigeria, the coefficient on the interest rate is positive and insignificant. However, the coefficient on the interest rate is positive and significant for Brazil, Algeria and Angola which is not consistent with theory. The general inconsistency of the interest rate coefficient may have an adverse impact on these models' forecasts of inflation. The real exchange rate has the theoretically expected positive and significant coefficient for Russia (both equations), China, South Africa, Algeria and Nigeria. However, the coefficient on the real exchange rate is negative and significant

[123] According to monetary economics (for both Money demand and Money supply theory), there is an inverse relationship between inflation and interest rate. For example, interest rates are determined by the interaction of the quantity supplied and the quantity demanded of money. For supply of money, if interest rates are reduced, consumers will be able to borrow more money. The result is that consumers have more money to spend, causing the economy to grow and inflation to increase. The opposite holds for demand for money. If government increase the interest rate, consumers tend to save more to get higher returns. The result is that consumers will have less money to spend, causing the economy to slow and inflation to decrease.

for Brazil and negative and insignificant for Saudi Arabia, neither of which are consistent with theory.

The coefficient on unemployment is negative and significant for Brazil, which is consistent with economic theory. However, the coefficient on unemployment is positive and significant in the Russian cointegrating equation which is not consistent with theoretical expectations. Finally, the output gap has a theoretically unexpected negative and significant coefficient in the Russian cointegrating equation.

We now consider the plausibility of the cointegrating equations by country. When a coefficient is significant and has the expected coefficient sign it is regarded as fully consistent with an equilibrium equation for prices and is assigned a value of 1 in Table 7.3.1.F2 below. When a coefficient is insignificant and has the expected sign it is regarded as semi-consistent with an equilibrium equation for prices and is assigned a value of 0.5 in Table 7.3.1.F2. Finally, a coefficient that has an unexpected coefficient sign and is insignificant is considered as completely inconsistent with an equilibrium equation for prices and is assigned a value of 0 in Table 7.3.1.F2. Based on these assigned values we report a percentage of coefficients that are consistent with an equilibrium equation for prices for each country in the row labelled "plausible" to provide an indication of each cointegrating equation's plausibility for each country. This should also give some indication of the likely forecasting performance of the inflation equation in the VEC for each country. It may well be that the potential benefits (in terms of forecasting accuracy) of using theory to build multivariate VEC models of inflation may be undermined by the practical difficulty in securing statistically valid and theoretically consistent specifications. This is an issue that we will assess when the forecasting performance of multivariate and univariate models are compared and evaluated. It may be that such practical difficulty in producing valid multivariate specifications justifies the use of univariate models for forecasting purposes.

7.3.1.F2. The plausibility of the estimated cointegrating equations as long-run inflation models (where the stationary transformation of the oil price is treated as exogenous)

CE1	Brazil	Russia (gap')	Russia (Un')	India	China	South Africa	Algeria	Angola	Saudi Arabia	Nigeria	Consistent
lnP											
lnM	1	1	1	1	0	0.5	1	1	1	1	85%
R	0				0.5	0.5	0	0		0	16.6%
$InREE$	0	1	1		1	1	1		0	1	75%
UN	1	0									50%
GAP			0								0%
CointEq1	1	0.5	0.5	0.5	0	0.5	0.5	1	1	0	55%
Plausible	60%	62.5%	62.5%	75%	37.5%	62.5%	62.5%	66.7%	66.7%	50%	

Where Russia (gap') = when the output gap is excluded and Russia (Un')= when the unemployment variable is excluded. Values of 0, 0.5 and 1 indicate coefficients that are completely inconsistent, semi consistent and completely consistent with a plausible long-run equation for inflation. The row and column labelled Plausible indicates the percentage of coefficients that are consistent with a plausible long-run equation for inflation.

Our results from the row labelled "Plausible" in Table 7.3.1.F2 indicates that the most plausible cointegrating equation as a long-run model of inflation is for India with 75% of the coefficients being plausible. The next most plausible equations are for Angola and Saudi Arabia (66.7% plausibility); followed by Russia (both equations), South Africa and Algeria (62.5%), Brazil (60%) and Nigeria. The least plausible cointegrating equation is for China (37.5%). It will be interesting to see whether the relative plausibility of the different countries' VEC models (as measured above) is reflected in their forecasting performance.

We also assess the relative theoretical consistency of each variable's long-run coefficient in the VEC in the column headed "Consistent" of Table 7.3.1.F2. The coefficient on the money supply has the highest consistency rating at 85%, followed by the real exchange rate (75%), unemployment (50%), interest rates (16.6%) and the output gap (0%). Finally, we note that in 55% of models the equation is forced to its long-run equilibrium model of prices as defined by the cointegrating equation.

7.3.1.G. The summary of the adjustment coefficient on the error correction terms in the inflation equation (where all variables are included as endogenous)

	Brazil (gap')	Russia (gap')	China	India	South Africa	Algeria	Nigeria	Angola	Saudi Arabia
Error Correction (CointEq1)	-0.18864	0.002438	-0.0088	-0.01519	-0.00053	0.042605	-0.01115	-0.27439	0.006082
t- statistics	[-1.8099]	[0.46400]	[-0.6739]	[-0.72605]	[-0.2820]	[1.19416]	[-0.2483]	[-6.7085]	[3.59405]

Where [] = t ratio statistics and (gap') = when the output gap is excluded

7.3.1.H. The summary of the estimated cointegrating equations (where all variables are included endogenous)

CE1	Brazil (gap')	Russia (gap')	India	China	South Africa	Algeria	Angola	Nigeria	Saudi Arabia
lnP									
lnM	0.57787	-2.679846	0.55395	0.3469	-1.1292	0.46909	0.26359	0.3693	4.46189
	[34.5678]	[- 5.1112]	[31.3397]	[2.2419]	[1.97561]	[6.41509]	[1.6940]	[7.4333]	[3.99688]
R	0.00233			-0.2780	0.020597	0.09369	0.00201	-00456	
	[11.5847]			[3.8548]	[0.18569]	[2.62987]	[4.32512]	[3.9024]	
$InREE$	0.36215	18.8124		3.8339	2.09799	1.07726		0.2247	8.35233
	[10.5416]	[5.8172]		[4.3998]	[0.97392]	[2.71960]		[5.2953]	[4.43181]
UN	-0.05602	-0.235514							
	[9.59924]	[-2.5977]							
$InOilp$	0.0769	-10.8959	-0.00351	-1.2456	1.91205	-0.16232	0.35191	0.1354	-4.777097
	[5.09120]	[-4.6990]	[-3.5685]	[3.6547]	[2.94489]	[- 2.1170]	[6.59163]	[1.5650]	[-4.3012]
C	-0.18864	-52.1268	-12.5968	17.059	-0.14245	-14.3692	-0.82686	8.1215	-138.2281

Where [] = t ratio statistics and (gap') = when the output gap is excluded

The summary of the adjustment coefficient on the error correction terms in the inflation equation and the cointegrating equations (where all the variables are treated as the endogenous) are provided in the Table 7.3.1.G and 7.3.1.H respectively. In the Table 7.3.1.G, for Angola, the error-correction term (CointEq1) has a negative and significant coefficient in the inflation equation. This result shows evidence of a long-run equilibrium relationship between prices and the other selected macroeconomic variables in these countries. The long-run relationship implies that the selected variables move together over time such that the short-term deviations of price from its long-run trend will be corrected. For Brazil, India, China, South Africa and Nigeria, the coefficient on the error-correction term (CointEq1) is negative however it is not significant. Hence, while the price variable is forced towards its long-run value the adjustment is statistically insignificant. For Saudi Arabia, the coefficient on the error-correction term (CointEq1) is positive and significant suggesting that the price variable is continually forced away from its long-run value as defined by the estimated cointegrating equation. This raises questions over the validity of specified cointegrating equation as an equilibrium specification for prices and as such might be expected to adversely affect the accuracy of inflation forecasts from this model in this country.

Table 7.3.1.H reports the corresponding estimated cointegrating equations. For Brazil, India, China, Algeria, Angola, Nigeria and Saudi Arabia, the money supply has the theoretically expected positive and significant long-run relationship with prices. However, for Russia the coefficient on money supply is negative and significant. Most of these countries' estimates are consistent with the quantity theory of money and this general consistency may enhance the forecasts for inflation.

For interest rates, China and Nigeria have significant theoretically expected negative long-run relationship with prices. However, the coefficient on the interest rate is positive and significant for Brazil, Algeria and Angola, which is not consistent with theory. The general inconsistency of the interest rate's coefficients may have an adverse impact on these models' forecasts of inflation. The real exchange rate has the theoretically expected positive and significant coefficient for Brazil, Russia, China, Nigeria, Algeria and Saudi Arabia.

For the endogenous oil price, Angola, Brazil and South Africa have the theoretically expected positive and significant long-run relationship with prices. However, for Russia, India, China, Algeria and Saudi Arabia the coefficient on the oil price is negative and significant. The general inconsistency of the oil price coefficients may have an adverse impact on these models' forecasts of inflation.

Further, we consider the plausibility of the cointegrating equations by country. As before, when a coefficient is significant and has the expected coefficient sign it is regarded as fully consistent with an equilibrium equation for prices and is assigned a value of 1 in Table 7.3.1.H2 below. When a coefficient is insignificant and has the expected sign, it is regarded as semi-consistent with an equilibrium equation for prices and is assigned a value of 0.5 in Table 7.3.1.H2. Finally, a coefficient that has an unexpected coefficient sign and is insignificant is considered as completely inconsistent with an equilibrium equation for the price variable and is assigned a value of 0 in Table 7.3.1.H2. Based on these assigned values we report a percentage of coefficients that are consistent with an equilibrium equation for prices for each country in the row labelled "plausible" to provide an indication of each cointegrating equation's plausibility for each country. This should also give some indication of the likely forecasting performance of the inflation equation in the VEC for each country. It may well be that the potential benefits (in terms of forecasting accuracy) of using theory to build multivariate VEC models of inflation may be undermined by the practical difficulty in securing statistically valid and theoretically consistent specifications. This is an issue that we will assess when the forecasting performance of multivariate and univariate models are compared and evaluated. It may be that such practical difficulties in producing valid multivariate specifications justify the use of univariate models for forecasting purposes.

7.3.1.H2. The plausibility of the estimated cointegrating equations as long-run inflation models (where all variables are included as endogenous)

CE1	Brazil (gap')	Russia (gap')	India	South Africa	China	Algeria	Angola	Saudi Arabia	Nigeria	Consistent
lnP										
lnM	1	0	1	0	1	1	1	1	1	77%
R	0	0	0	0.5	1	0	0	0	1	27.8%
$InREE$	0	1	0	0.5	1	1	0	1	1	61.1%
UN	1	1								100%
$InOilp$	1	0	0	0.5	0	0	1	0	0.5	33.3%
CointEq1	0.5	0	0.5	0.5	0.5	0	1	0	0.5	38.9%
Plausible	58.3%	33.3%	30%	40%	70%	40%	60%	40%	80%	

Where Russia (gap') = when the output gap is excluded, and unemployment rate is included. Values of 0, 0.5 and 1 indicate coefficients that are completely inconsistent, semi consistent and completely consistent with a plausible long-run equation for inflation. The row and column labelled Plausible indicates the percentage of coefficients that are consistent with a plausible long-run equation for inflation

Our results from the row labelled "Plausible" in Table 7.3.1.H2 indicates that the most plausible cointegrating equation as a long-run model of inflation is for Nigeria with 80% of the coefficients being plausible. The next most plausible equations are for China (70 plausibility), Angola (60% plausibility), Brazil, South Africa, Algeria and Saudi Arabia (40% plausibility); followed by Russia (33%) and India (30%). It will be interesting to see whether the relative plausibility of the different countries' VEC models (as measured above) is reflected in their forecasting performance.

We also assess the relative theoretical consistency of each variable's long-run coefficient in the VEC in the column headed "Consistent" of Table 7.3.1.H2. The coefficient on unemployment has the highest consistency rating at 100%, followed by the money supply (77%), real exchange rate (61.1%), oil price (33.3%) and interest rate (27.8%). Finally, we note that in 38.9% of the models the price variable is forced to its long-run equilibrium value as defined by the cointegrating equation.

7.4 Stability test for multivariate models

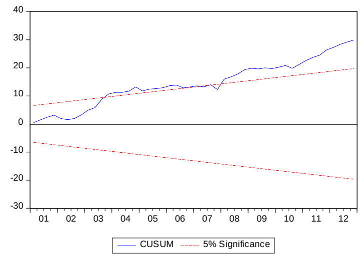
This section aims to test whether the multivariate models are structurally stable in the sense that the regression coefficients are constant. Over the past three decades, the stability of different forecasting models has been a major concern in the monetary economics literature because if the relationship that exists between two different macroeconomic variables are not stable the forecast produced by this model can be inaccurate and policy recommendations can be misleading (Hansen, 2001). For the Phillips curve, relationships between inflation and unemployment or economic activities can also be affected because of this dilemma (Atkeson and Ohanian, 2001, Fischer et al. 2002, Sims, 2002, Orphanides and Van Norden, 2005, and Stock and Watson, 2007). The original studies (Phillips, 1958) established that the Phillips curve is a stable negative relationship that exists between inflation and unemployment. However, the simultaneous occurrence of high inflation and high unemployment in many developed countries during the 1970s and after the economic crisis of 2008 has led to the alternative conclusion among the scholars that Phillips curve may not stable. For instance, Friedman (1977) argued that there is a positive relationship between inflation and unemployment. He claimed that higher inflation is often accompanied by higher unemployment. The possible explanation for this result has been attributed to the contribution of lags of inflation in the Phillips curve and changes in historical data as a result of changes in the economic environment (Atkeson and Ohanian, 2001, Stock and Watson 1999a and 2003).[124] In our study, we investigate whether the multivariate models (VAR, VECM and VEC) are stable. If not, what are the implications of the instability for forecasting future inflation or what forecast methods work well in the face of instability? For instability tests, we perform two different parameter shifts tests that are available in Eviews (the CUSUM and Bai and Perron (2003) tests). For the CUSUM test, we apply the CUSUM test that is based on the cumulative sum of the recursive residuals. The condition is that, if the line of the CUSUM test statistics fluctuates within the two 5% critical lines, the estimated models are said to be stable. In contrast, the models are said to be unstable if the line of the CUSUM goes outside the area between the 5% critical lines. In our results, the graph of the CUSUM test went outside the area

[124] Stability test is developed to detect structural breaks of unknown origin and identify factors that behind the empirical failure.

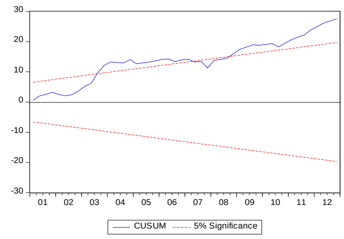
between the two 5% critical lines for the VAR models that specified all variables as endogenous for Brazil (see Figure 7.4.1. A and B). This result implies that the CUSUM test suggests evidence of instabilities in the two models that specified all variables as endogenous. For the two models that specified oil price as exogenous (Figure 7.4.1. C and D), the line of the CUSUM tests lie within the two 5% critical lines. This result suggests evidence of stability for these models.[125] This is despite the incidence of several major shocks that affect the Brazilian economy (e.g the Asian financial crisis in the middle of 1997, the global financial crisis in 2007, the recent oil crisis and political instabilities). To further check, we also applied the multiple structural breaks test suggested by Bai and Perron (2003). This test indicates no breaks for the two specifications that include all variables as endogenous (see the Table 7.4.1). However, the result of the multivariate breaks test suggests two potential structural breaks around 2001 and 2003 for two model that specified the oil price as exogenous (see Table 7.4.1). The overall results of the CUSUM tests indicate evidence of instability for the two models that include all variables as endogenous. Whereas, the multiple structural breaks test suggested by Bai and Perron (2003) shows evidence of stability for two models that specified oil price as exogenous. In conclusion, that there is some evidence of parameter instability for multivariate VAR model in Brazil according to at least one test for all VAR models for Brazil.

[125] Note that the CUSUM test line intercept the upper critical line around 2003 that may also imply evidence instabilities for the two models.

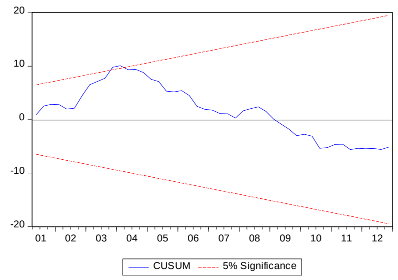
Figure 7.4.1. CUSUM test for four different unrestricted VAR models for Brazil



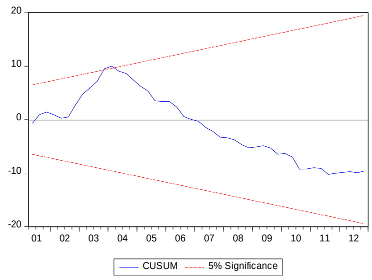
A



B



C



D

Where
A = All variables included as endogenous except Unemployment that excluded
B. All variables included as endogenous except output gap that excluded
C. Oil price is specified as exogenous variable and all other variables included as endogenous except unemployment variable
D. Oil price is specified as exogenous variables and all other variables included as endogenous variable except output gap variable.

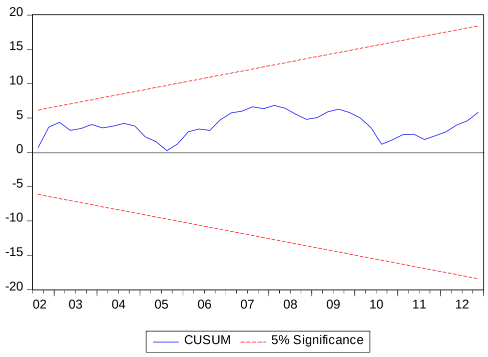
Table 7.4.1. unrestricted VAR stability result test result for Brazil

Model	Sample	CUSUM tests	Bai and Perron (2003) tests
VAR(GAP)	1999q4 2012q4	Unstable	No breaks
VAR(UN)	1999q4 2012q4	Unstable	No breaks
VAR (GAP)_Exo	1999q4 2012q4	Stable	2001q3 and 2003q3
VAR (UN)_Exo	1999q4 2012q4	Stable	2001q3 and 2003q4

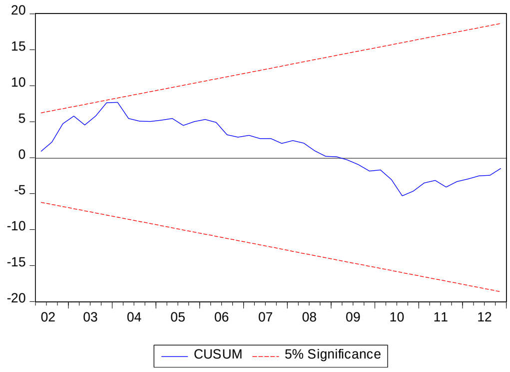
VAR(UN) = Unrestricted VAR where all variables included as endogenous except output gap that excluded, VAR(GAP) = Unrestricted VAR where all variables included as endogenous except unemployment variable that excluded, VAR (UN)_Exo) = Unrestricted VAR where Oil price is specified as exogenous and all other variables included as endogenous variable except output gap. variable, VAR (GAP)_Exo = Unrestricted VAR where Oil price is specified as exogenous and all other variables included as endogenous variables except unemployment variable. Stable = result of the CUSUM test where the line of CUSUM tests lie within the two critical lines and Unstable = result of CUSUM test where the line of CUSUM tests lie outside the two critical lines, No breaks = where Bai and Perron (2003) tests do not specified any break date.

For the two valid Vector Error Correction Models (VECM) for Brazil in Table 7.2.1. I., the CUSUM test is the only test that could be implemented.[126] For the CUSUM test, the line of CUSUM tests lie within the two 5% critical lines for the two valid models (see Figure E and F in 7.4.2). This suggests evidence of stability for the two models.

7.4.2. CUSUM test for two VECM specifications for Brazil



E



F

E = VECM(UN) = specification that include all variables as endogenous except output gap.

F = VECM(UN)_EXO) = specification that include oil price as exogenous and other variables as endogenous except output gap.

Table 7.4.2. VECM stability result for Brazil

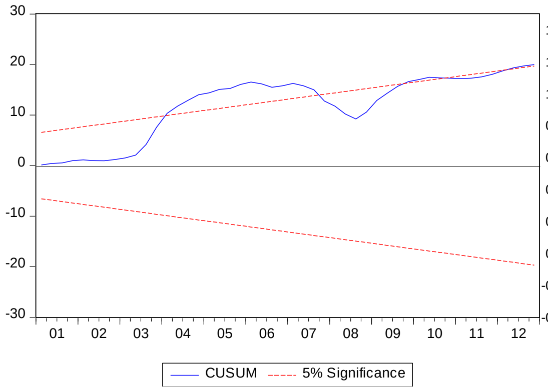
Model	Sample	CUSUM test
VECM(UN)	1999q4 2012q4	Stable
VECM(UN)_EXO)	1999q4 2012q4	Stable

VECM(UN)= specification that include all variables as endogenous except output gap, VECM(UN)_EXO = specification that include oil price as exogenous and other variables as endogenous except output gap. Stable = result of CUSUM test where the line of CUSUM tests lie within the two critical lines and Unstable = result of CUSUM test where the line of CUSUM tests lie outside the two critical lines.

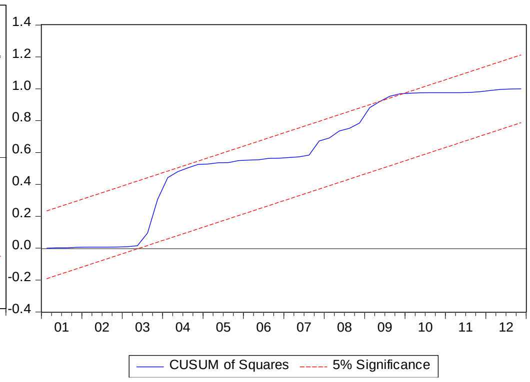
[126] The multiple breaks Bai and Perron (2003) test could not be implemented for the two VECM specifications. Eviews gave an error message indicating a near singular matrix.

For two valid VECs models for Brazil in Table 7.3.1.D., the model that includes all variables as endogenous including unemployment and excluding the output gap is not stable according to the CUSUM test. In particular, the line of the CUSUM test statistics went outside the area between the two 5% critical lines (see Figure I in 7.4.3). In contrast, the line of the CUSUM tests lie within the two 5% critical lines for the model that specified oil price as exogenous and includes all other variables as endogenous except for the output gap (see Figure J in 7.4.3). This suggests no evidence instability for this model. However, the result of the Bai and Perron (2003) test suggests evidence of instabilities for the two VEC specifications (the model that specified the oil price as exogenous and the model that included the oil price as endogenous). The overall results suggest that the two VEC models show evidence of instabilities according to at least one test. A similar method is applied to all countries and the results are summarised in Table 7.4.4.

7.4.3. CUSUM test for VEC specification for Brazil



I



J

Where
I. All variables included as endogenous except output gap that excluded
J. Oil price is specified as exogenous variables and all other variables included as endogenous variable except output gap variable.

Table 7.4.3. VEC stability result for Brazil

Model	Sample	CUSUM test	Bai and Perron (2003) tests
VEC(UN)	1999q4 2012q4	Instable	2003q3, 2006q3 2009q1
VEC (UN)_Exo	1999q4 2012q4	Stable	2003q2,2003q3,2006q3,2008q3,2009 q1 and 2011q1

All variables included as endogenous except output gap that excluded (VEC(UN), Oil price is specified as exogenous variables and all other variables included as endogenous variable except output gap variable (VEC (UN)_Exo). Stable = result of CUSUM test where the line of CUSUM tests lie within the two critical lines and Unstable = result of CUSUM test where the line of CUSUM tests lie outside the two critical lines, no breaks = where Bai and Perron (2003) tests does not specified any break date.

Table 7.4.4 Summary of the stability tests for BRICS countries

Brazil			
Model	**Sample**	**CUSUM test**	**Bai and Perron (2003) tests**
VAR(GAP)	1999q4 -2012q4	Unstable	No breaks
VAR(UN)	1999q4 -2012q4	Unstable	No breaks
VAR(GAP)_Exo	1999q4 -2012q4	Stable	2001q3 and 2003q3
VAR (UN)_Exo	1999q4 -2012q4	Stable	2001q3 and 2003q4
VECM_UN	1999q4 -2012q4	Stable	Unavailable
VECM(UN)_Exo	1999q4 -2012q4	Stable	Unavailable
VEC_UN	1999q4 -2012q4	Unstable	2003q3, 2006q3 and 2009q1
VEC(UN)_Exo	1999q4 -2012q4	Stable	2003q2,2003q3,2006q3,2008q3,2009q and 2011q1
Russia			
VAR(UN)	2003Q2- 2012q4	Stable	No breaks
VAR(UN)_Exo	2003Q2 -2012q4	Unstable	Unavailable
VECM (UN)	2003Q2 -2012q4	Stable	Unavailable
VECM(GAP)	2003Q2 -2012q4	Stable	Unavailable
VECM(GAP)_Exo	2003Q2 -2012q4	Stable	Unavailable
VECM(UN)_Exo	2003Q2 -2012q4	Stable	Unavailable
VEC(UN)	2003Q2 -2012q4	Unstable	2002q2,2007q3 and 2010q2
VEC(GAP)	2003Q2 -2012q4	Unstable	2005q2, 2007q3, 2009q2
VEC(GAP)_Exo	2003Q2 -2012q4	Unstable	2009q1
VEC(UN)_Exo	2003Q2 -2012q4	stable	2008q1
India			
FVAR	1963q1 -2012q4	Instable	1971q1 and 1979q1
VAR	1984q1- 2012q4	Stable	Unavailable
VAR_EXO	1984q1- 2012q4	Stable	No breaks
FVECM	1963q1 -2012q4	Stable	No breaks
VECM	1984q1- 2012q4	Stable	No breaks
VECM_Exo	1984q1- 2012q4	Stable	Unavailable
FVEC	1963q1 -2012q4	Unstable	No breaks
VEC	1984q1- 2012q4	Unstable	1990q1, 1994q2, 1998q3 and 2008q4
VEC_Exo	1984q1- 2012q4	Unstable	1991q1, 1995q2, 1999q3 and 2008q4
China			
VAR	1992q1- 2012q4	Unstable	2005Q1
VAR_exo	1992q1 -2012q4	Unstable	No breaks
VECM	1992q1 -2012q4	Stable	2004q4
VECM_exo	1992q1 -2012q4	Stable	1998q1
VEC	1992q1 -2012q4	Unstable	1996q3, 2000q3 and 2006q4
VEC_exo	1992q1 -2012q4	Unstable	1995q1, 2000q3, 2005q1 and 2009q3
South Africa			
VAR	1995q2- 2012q4	Unstable	2010q3
VAR_exo	1995q2-2012q4	Stable	2010q3
VECM	1995q2-2012q4	Stable	Unavailable
VECM_exo	1995q2- 2012q4	Stable	2005q2 and 2010q2
VEC	1995q2- 2012q4	Unstable	1999q1, 2003q3 and 2008q2
VEC_exo	1995q2- 2012q4	unstable	1999q1, 2003q1 and 2008q2

Stable = result of CUSUM test where the line of CUSUM tests lie within the two critical lines and Unstable = result of CUSUM test where the line of CUSUM tests lie outside the two critical lines., VAR = unrestricted VAR model that include all variables as endogenous, VECM = multivariate model estimated with all nonstationary variables that include all variables as endogenous, VEC = Multivariate model that imposes cointegrating restrictions on the VECM and include all variables as endogenous. VAR_Exo = unrestricted VAR model that include oil price as exogenous and other variables as endogenous. VECM_EXO = VECM specification that include oil price as exogenous and other variables as endogenous, VEC_Exo = VEC model that include oil price as exogenous and other variables as endogenous. For Brazil and Russia where unemployment and Output gap variables are available, VAR(UN) = Unrestricted VAR where all variables included as endogenous except output gap that excluded, VAR(GAP) = Unrestricted VAR where all variables included as endogenous except unemployment variable that excluded, VAR (UN)_Exo) = Unrestricted VAR where Oil price is specified as exogenous and all other variables included as endogenous variable except output gap. VAR (GAP)_Exo = Unrestricted VAR where Oil price is specified as exogenous and all other variables included as endogenous variables except unemployment variable. FVAR =unrestricted VAR estimated over the full sample, FVECM = VECM estimated over full sample, No breaks = where Bai and Perron (2003) tests does not specified any break date (hence suggesting no instability). Unavailable = where the Bai and Perron (2003) is not available due to the error of the singular matrix indicated by EViews.

Table 7.4.5 Summary of the stability tests for OPEC countries

Algeria		CUSUM test	Bai and Perron (2003) tests
VAR	1992q2-2012q4	Stable	No breaks
VAR_exo	1992q2- 2012q4	Stable	No breaks
VECM	1992q2- 2012q4	Stable	Unavailable
VECM_exo	1992q2- 2012q4	Stable	Unavailable
VEC	1992q2- 2012q4	Unstable	Unavailable
VEC_exo	1992q2- 2012q4	Unstable	2002q2, 2008q3 and 2011q1
Angola			
VAR	2002q4 2012q4	Unstable	No breaks
VAR_exo	2002q4 2012q4	Unstable	2004q2 and 2005q4
VECM	2002q4 2012q4	Unstable	Unavailable
VECM_oil_exo	2002q4 2012q4	Stable	Unavailable
VEC	2002q4 2012q4	Unstable	2003q4 and 2010q2
VEC_exo	2002q4 2012q4	Unstable	2010q1 and 2004q4
Nigeria			
VAR	1998q4 2012q4	Unstable	No breaks
VAR_exo	1998q4 2012q4	Stable	No breaks
VEC	1998q4 2012q4	Unstable	2001q2,2003q3 and 2009q1
VEC_exo	1998q4 2012q4	Unstable	2002q1,2004q1 and 2009q2
Saudi Arabia			
VAR	1983q1- 2012q4	Stable	No breaks
VAR_exo	1983q1- 2012q4	Stable	1992q2, 2006q4 and 2007q3
VECM	1983Q1- 2012Q4	Stable	No breaks
VECM_Exo	1983Q1- 2012Q4	Stable	2007q3
VEC	1983Q1- 2012Q4	Unstable	1989q1, 2000q2 and 2008q3
VEC_exo	1983Q1- 2012Q4	unstable	1987q4, 2000q2 and 2008q3

Note see Table 7.4.4

For the BRICS countries (Table 7.4.4), the CUSUM test and Bai and Perron (2003) test suggest evidence of instability for all models except all VECMs and VARs specification for India (the exception is the VAR estimated over the full sample that includes all variables as endogenous). The other exceptions are the VECM model that includes all variables as endogenous for South Africa; the two VECM specifications for Brazil, all four VECMs and the VAR model that contains all variables as endogenous except output gap that excluded for Russia.

For OPEC countries (Table 7.4.5), all models show evidence of instability except the VAR and VECM model that includes all variables as endogenous for Saudi Arabia, the VECM model that specified oil price as exogenous for Angola, the two VAR models and two VECM specifications for Algeria.

In general, our CUSUM and Bai and Perron (2003) tests yield evidence of instabilities in the coefficients for the VAR, VECM and VEC for both BRICS and OPEC countries. In our study, we produce forecasts for all models that are free from autocorrelation in Table

7.1.E., Table 7.2.1. I., and Table 7.3.1.D.[127] We do this despite the evidence of instability for many of these specifications because the literature suggests that if instabilities have occurred, they may or may not affect their forecasting performance (Stock and Watson (1999), Rudebusch (2005), Clark and Mccacken, (2006). Hence, it will be interesting to see whether models with evident instabilities produce poor forecasting performance.

[127] Our empirical work is similar to the study of Clark and Mccacken, (2006) who argues whether model instabilities can affect the forecast performance of macroeconomic variables.

7.5.0 Forecast performance and evaluation

In this section, we apply the same forecast evaluation procedure that was applied to univariate models in chapter 5 (section 5.5.0) and produce m-step ahead forecasts for different multivariate models and compare their forecasting performance using rolling regressions following, for example, Sarantis and Stewart (1995), Alles and Hotton (2000) and Ogunc et al. (2013). First, we conduct a series of rolling regressions and calculate out-of-sample forecasts for all the multivariate models identified in previous sections (sections 7.1, 7.2 and 7.3). Each model is estimated over a reduced sample that avoids modelling breaks with the period ended in 2012q4 (the start of the estimation period varies across models and countries). These models are used to produce forecasts over the ex-post forecasting period 2013q1 – 2014q4. These produce 1-step ahead forecasts for 2013q1, 2-step ahead forecasts for 2013q2 and so on up to 8-step ahead forecasts for 2014q4. The identified models were then re-estimated by adding one observation to the end of the sample; hence the models are estimated over a period ending in 2013q1. These estimated models are used to produce 1-step ahead forecasts for 2013q2, 2-step ahead forecasts for 2013q3 and so on up to 7-step ahead forecasts for 2014q4. This process is then repeated with one observation being added to the estimation period (with the last rolling regression's sample period ending in 2014q3), and m-step ahead forecasts produced up to the end of the forecast period. These rolling regressions produce eight 1-step ahead forecasts, seven 2-step ahead forecasts, six 3-step ahead forecasts, five 4-step ahead forecasts and so on up to one 8-step ahead forecast for each estimated model.

Second, we compare the forecasting performance of each model over the different number of the step ahead forecasting horizons using the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Theil's inequality coefficient (U). The best forecasting model, on average, over any particular horizon will have the lowest value of forecasting performance measures.

7.5.1 Brazil Forecast performance and evaluation

In this section, we compare the forecasting performance of the four-alternative unrestricted VAR model specifications in Table 7.1.E, the VECM specifications (that does not restrict the cointegrating equation into the model) in Table 7.2.1. I and the VEC (that restricts a single cointegrating equation into the model), in Table 7.3.1.D. To produce out-of-sample ex-post forecasts on a rolling basis, we first estimate the models over the period 1999q4 – 2012q4 and generate forecasts over the period 2013q1 to 2014q4. Second, the models are re-estimated over the period 1999q4 – 2013q1 and forecasts are produced over the period 2013q2 to 2014q4 and so on. The last estimation sample period is 1999q4 - 2014q3 and a single 1-step ahead forecast is produced for 2014q4. These forecasts are used to compute forecast error measures for each forecast horizon, which are compared across models. The first unrestricted VAR model includes all available variables as endogenous except unemployment (which is excluded). The second unrestricted VAR includes all available variables as endogenous except for the output gap (which is excluded). The remaining two unrestricted VARs are the same as the first two VARs except the oil price is treated as exogenous. The forecast performance measures for these models are given in the columns headed A, B, C and D, respectively, of Table 7.5.1.1.

Table. 7.5.1.1: Inflation forecast performance of unrestricted VARs for Brazil

	A All variables endogenous output gap included unemployment excluded			**B** All variables endogenous output gap excluded unemployment included			**C** Oil price exogenous output gap included unemployment excluded			**D** Oil price exogenous output gap excluded unemployment included		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	**0.0050**	**6.5320**	**0.0430**	**0.0060**	**8.5330**	**0.0460**	**0.0049**	**6.9540**	**0.0390**	**0.0048***	**6.4700***	**0.0380***
2-step	**0.0080***	**11.0500***	**0.0620***	**0.0120**	**17.6600**	**0.0900**	**0.0101**	**14.2600**	**0.0770**	**0.0100**	**13.8600**	**0.0780**
3-step	**0.0090***	**10.6500***	**0.0700***	**0.0130**	**18.4700**	**0.0970**	**0.0200**	**30.5600**	**0.1500**	**0.0150**	**20.8500**	**0.1120**
4-step	**0.0120**	**17.0700***	**0.0930**	**0.0110***	**17.6500**	**0.0850***	**0.0260**	**32.5500**	**0.1910**	**0.0180**	**25.1800**	**0.1360**
5-step	**0.0140***	**18.4500***	**0.1000***	**0.0150**	**23.5100**	**0.1100**	**0.0300**	**41.9900**	**0.2090**	**0.0230**	**32.2200**	**0.1620**
6-step	**0.0180***	**19.6100***	**0.1280***	**0.0200**	**28.9700**	**0.1430**	**0.0270**	**37.260**	**0.1850**	**0.0320**	**50.2700**	**0.2020**
7-step	**0.0180**	**28.0700**	**0.1250**	**0.0140***	**19.7900***	**0.1020***	**0.0330**	**53.1900**	**0.2090**	**0.0330**	**53.6600**	**0.2130**
8-step	**0.0260**	**45.2600**	**0.1850**	**0.0070***	**12.4400***	**0.0590***	**0.0370**	**63.6300**	**0.2410**	**0.0270**	**46.3100**	**0.1880**

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting

The unrestricted VAR model where all variables included as endogenous except unemployment, see column A of Table 7.5.1.1 has the lowest RMSE, MAPE and U values for all forecasting horizons except for 1, 4 (RMSE and U -statistics) 7 and 8 steps ahead. The unrestricted VAR model where all variables included as endogenous except out gap, see column B of Table 7.5.1.1 produces a superior forecast for 4 steps ahead horizons according to the RMSE and U-statistics and for 7 and 8 steps ahead horizons according to the RMSE, MAPE and U-statistics. While the best forecasting model for 1 -step ahead according to RMSE, MAPE and U-statistics is the unrestricted VAR model that treats the oil price as exogenous and all other variables as endogenous (unemployment is included) and the output gap is excluded, see column D of the table 7.5.1.1. In general, our results indicate that the specification of the unrestricted VAR models that include the oil price as endogenous instead of the exogenous enhance the forecasting performance of inflation for Brazil over the short and long horizons.

We next consider the relative forecasting performance of the alternative Vector Error Correction Model (VECM) specifications discussed in section 7.2. The first VECM incorporates all available variables as endogenous (including unemployment) and excludes the output gap. The second model treats the oil price as exogenous and incorporates all available variables as endogenous (including unemployment) and excludes the output gap. The forecast performance measures for these VECMs are given in the column headed E and F (in Table 7.5.1.2).

Table. 7.5.1.2: Forecast performance of the Modelling Vector Error Correction Model for Brazil

	E All variables endogenous output gap excluded unemployment included			F Oil price exogenous output gap excluded unemployment included		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	**0.0050**	**7.085**	**0.0300***	**0.0060**	**8.3790**	**0.0470**
2-step	**0.0080***	**10.3500***	**0.0590***	**0.0150**	**20.7300**	**0.1310**
3-step	**0.0130**	**17.1700**	**0.0990**	**0.0300**	**35.3500**	**0.2860**
4-step	**0.0220**	**28.0000**	**0.1600**	**0.0360**	**47.4900**	**0.3640**
5-step	**0.0320**	**42.8600**	**0.2100**	**0.0300**	**41.1600**	**0.2960**
6-step	**0.0430**	**64.2700**	**0.2590**	**0.0360**	**45.5400**	**0.3450**
7-step	**0.0490**	**75.2900**	**0.2850**	**0.0430**	**52.8000**	**0.3970**
8-step	**0.0650**	**111.4000**	**0.35800**	**0.0080**	**14.4600**	**0.0670**

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

From the Table. 7.5.1.2, the two valid VECM specifications rarely improved the forecasting performance relative to the VAR models. The VECM specification that incorporates all available variables as endogenous (including unemployment) and excludes the output gap model (see a column headed E in the table 7.5.1.2) has lower RMSE, MAPE and U values over 2- step and 1-step ahead according to the U-statistics compared to the best selected VAR models. The VECM specification that includes the oil price as an exogenous instead of endogenous (see column headed F in the table 7.5.1.2) was never favoured. Like the best performing unrestricted VAR model, the VECM that includes oil prices as an endogenous variable confirming that this strategy appears to produce better forecasts for Brazil (of the model considered so far). However, the inclusion of (unrestricted) long-run information in the form of levels variables in the VECM has not unambiguously improved the forecasting performance over the VAR that includes only stationary variables for forecasting horizons considered here for Brazil.

We next consider the two VEC models discussed in section 7.3 for Brazil. The first model incorporates all variables as endogenous including unemployment and excluding the output gap. The second model treats the oil price as exogenous, incorporates all available variables as endogenous (including unemployment) and excludes the output gap. The forecast performance measures for these VECs are given in the column headed G and H in Table 7.5.1.3.

Table. 7.5.1.3: Forecast performance of the Modelling Vector Error Correction Model for Brazil

	G. All variables endogenous output gap excluded unemployment included			H. Oil price exogenous output gap excluded unemployment included		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	**0.0040**	**5.1800**	**0.0290**	**0.0040***	**5.0840***	**0.0290***
2-step	**0.0070**	**10.1000**	**0.0560**	**0.0060***	**7.0540***	**0.0440***
3-step	**0.0060**	**6.8780***	**0.0450***	**0.0060***	**7.3040**	**0.0520**
4-step	**0.0040**	**4.9060**	**0.0290**	**0.0030***	**4.4790***	**0.0250***
5-step	**0.0090**	**9.9190**	**0.0660**	**0.0030***	**3.5420***	**0.0220***
6-step	**0.0190**	**24.4600**	**0.1370**	**0.0130***	**17.8300***	**0.0920***
7-step	**0.0180**	**24.1100**	**0.1330**	**0.0190**	**29.0400**	**0.1340**
8-step	**0.0110**	**18.0800**	**0.0830**	**0.0170**	**28.8600**	**0.1260**

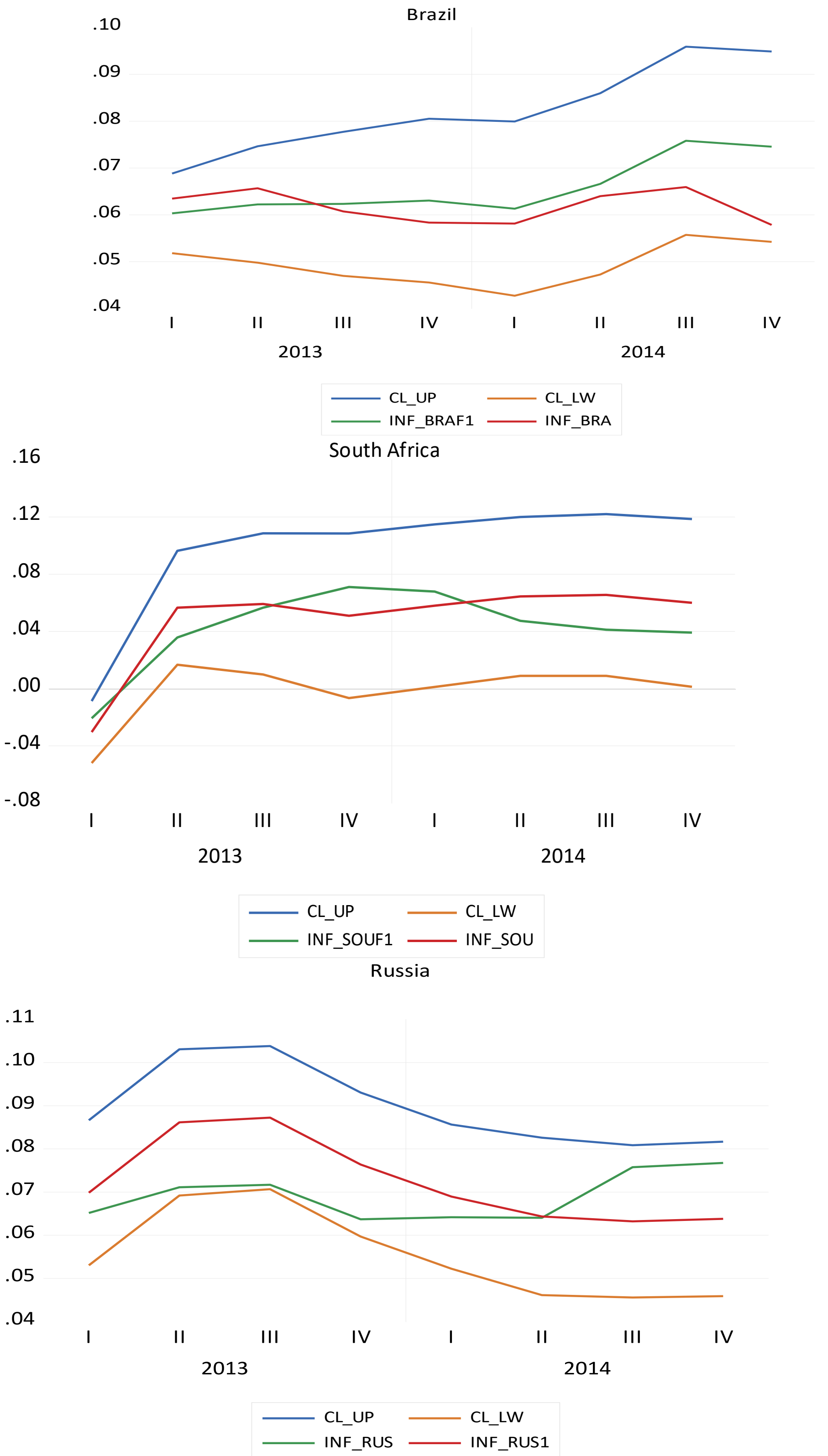
An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

According to the above table, the VEC model where the oil price is included as exogenous has the best forecasting performance of both VARs and VECM over the 1, 2, 3, 4, 5 and 6- step ahead horizons according to the RMSE, MAPE and U-statistics (MAPE and U-statistics are not favoured for 3-step ahead forecasting horizon). The VEC model that treats all variables as endogenous has superior forecasting accuracy at the 3-step ahead horizons according to the MAPE and U-statistics. At the longer forecasting horizons (over 7 to 8 steps ahead), the VEC model generally exhibits inferior forecasting performance relative to the favoured unrestricted VAR and VECM. However, the inclusion of long-run information and imposing the restriction of a single cointegration equation has generally improved the forecasting performance over the unrestricted VAR for the shorter horizon. While unrestricted VAR (that includes only stationary variables) produces the best forecasting performance for the longer horizons (7 to 8-step forecasting horizons). Further, the best forecast model is typically produced when the oil price is estimated as exogenous rather than endogenous. We also note that the MAPE values of all the favoured multivariate models are less than 20 percentage points suggesting moderately good relative forecasting performance for Brazil.

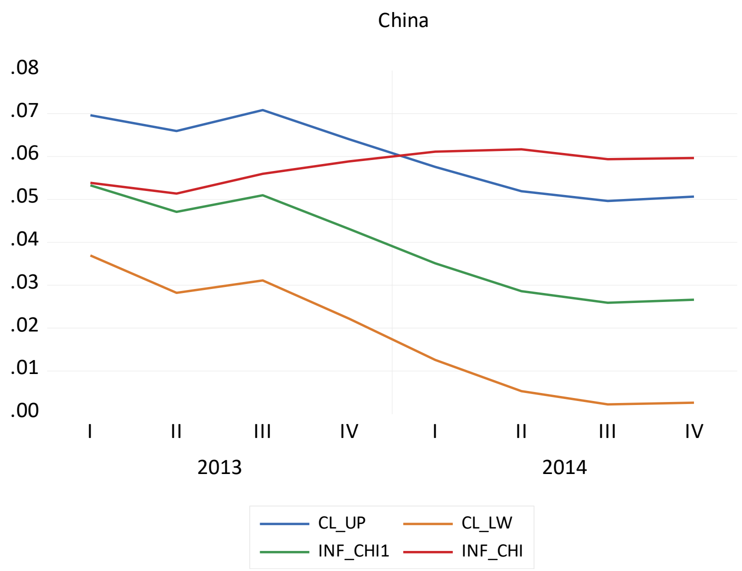
A similar procedure is applied to all countries, and a summary of the models with superior forecasting performance in each case is given below in Table 7.5.1 and 7.5.2.

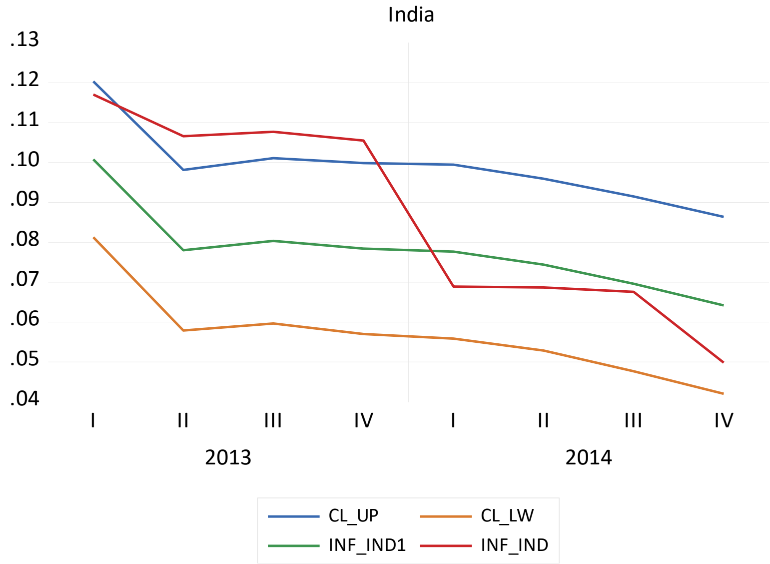
The BRICS and OPEC graphs of actual inflation (INF_***), the point forecast of inflation (INF_***1) and the associated 90% confidence interval (CL_UP and CL_LW) over the 8 step-ahead forecast period (2013 and 2014) are given in figure 7.5.1.3 for BRICS and 7.5.1.4 for OPEC countries. For the best forecasting multivariate model for each BRICS and OPEC country. The confidence interval of the favoured model (VEC model that specified oil price exogenous and all other variables as endogenous including unemployment and excluding output gap) shows that we can be 90% confident that inflation will lie between 4.3% and 9.6% during the period of 2013 and 2014 (see figure 7.5.1.3. for Brazil). This confidence interval is quite wide and suggests evidence of uncertainty over the forecasts especially in 2014. However, it is also noticeable that actual inflation (INF_BRA) lies within the interval and is quite close to the forecast with no systematic over or under prediction visible. While the graphs for South Africa, Russia, Angola, Saudi Arabia and Nigeria yield a broadly similar picture to Brazil, it is noticeable that actual inflation is outside of the 90% confidence interval for some of the forecast periods for China, India and Algeria (see Figure 7.5.1.3 and 7.5.1.4). It is also notable that while the width of the forecast confidence intervals is in single digits for most countries, they are in double digits for South Africa (up to around 12 percentage points) Angola (up to about 20 percentage points) and Nigeria (up to around 12 percentage points).

Figure 7.5.1.3: The VEC 90% confidence interval graphs for the inflation forecasting performance of BRICS countries[128]



[128] To avoid graphs repetition, we only include the 90% confidence interval graphs for all the favoured VEC model in each country because the graph of the 90% confidence interval for other multivariate model yields the similar patterns.

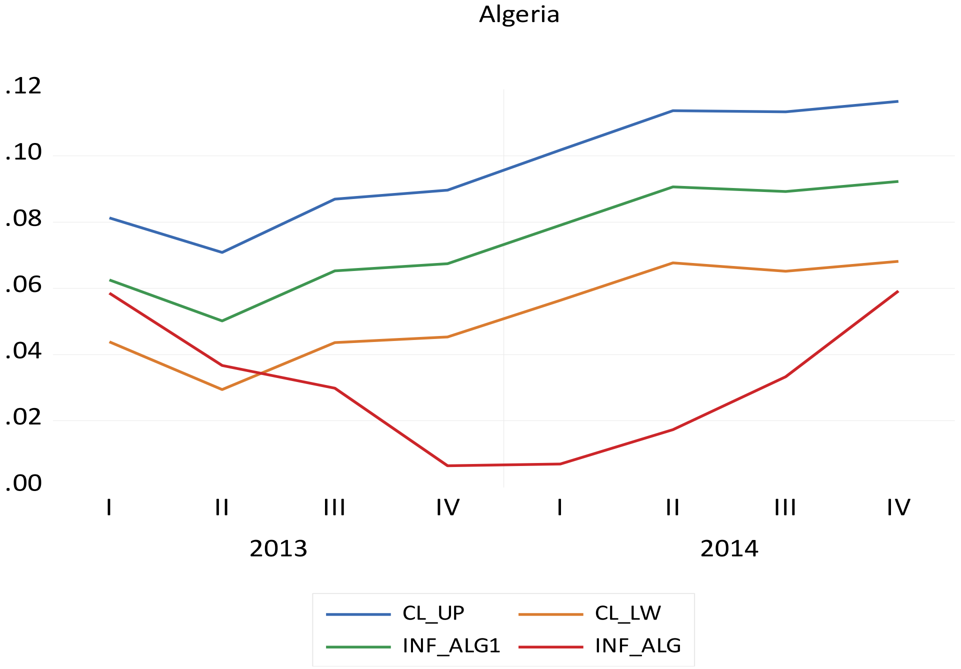


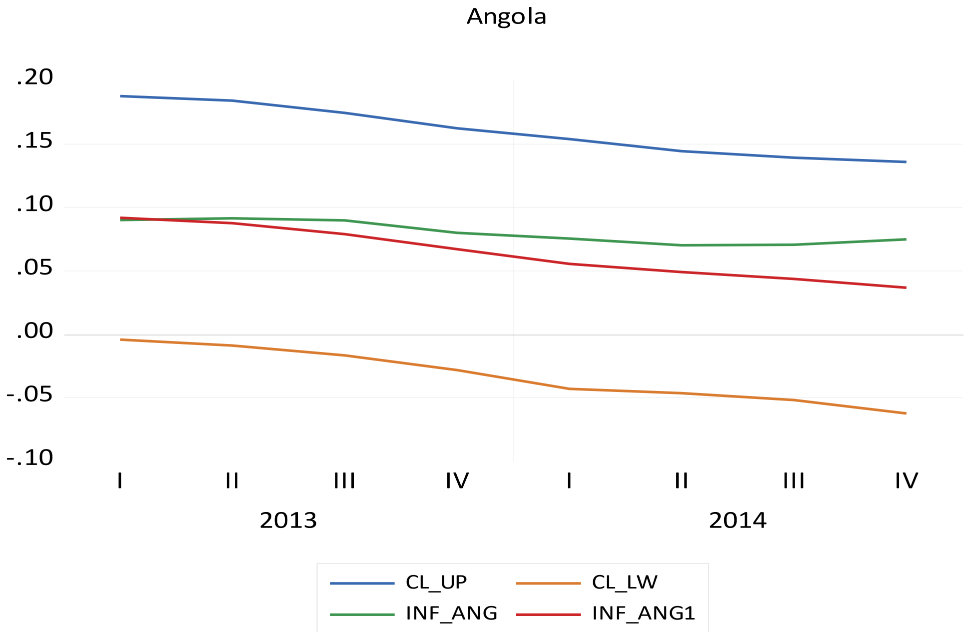


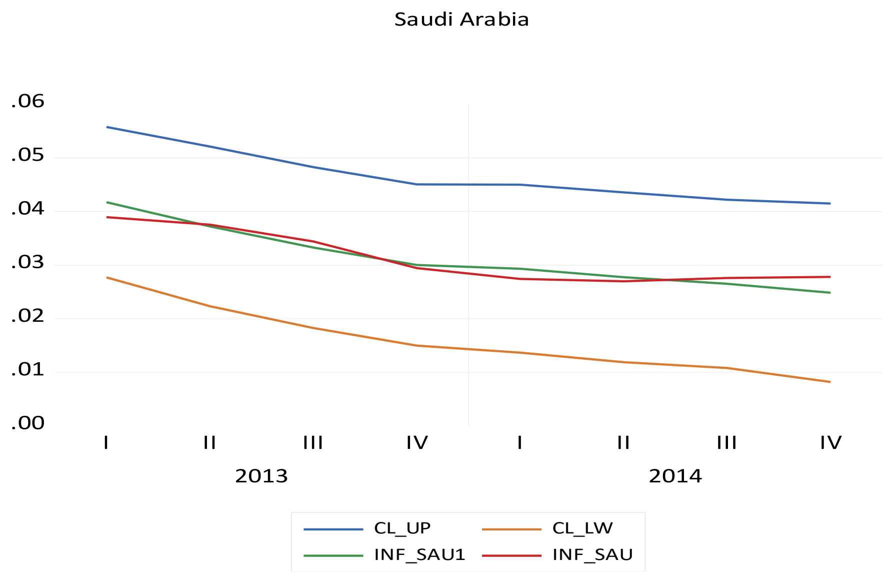
Key

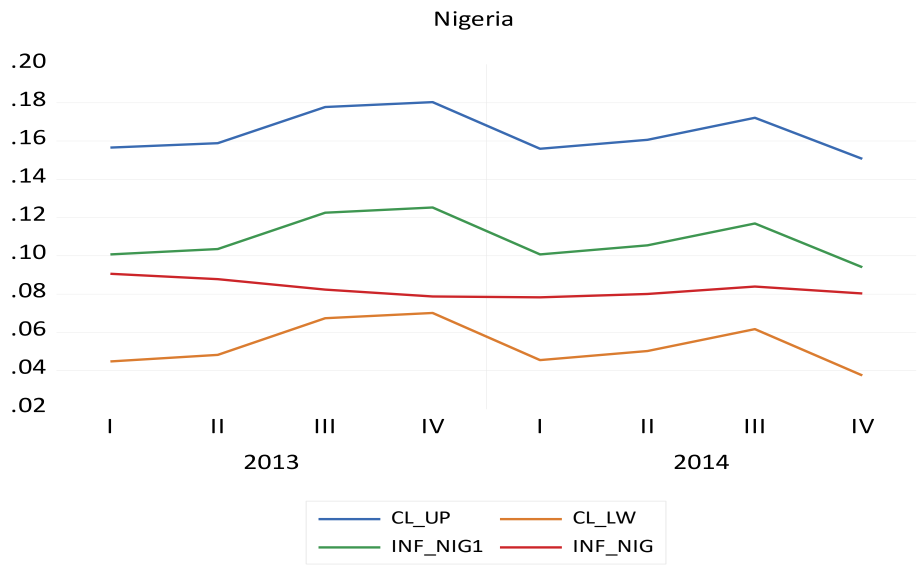
1. CL_UP (indicated with the blue colour) represents the confidence interval for the upper bound.
2. CL_LW (indicated with the orange colour) gives the confidence interval for the lower bound.
3. INF_*** (indicated with the green colour) denotes the actual inflation rate.
4. INF_***1 (indicated with the red colour) is the forecast of the inflation over the whole 8-step ahead horizon.
5. *** denotes the first three letters of each country (e.g BRA, IND, RUS, CHI, SOU).

Figure 7.5.1.4: The VEC 90% confidence interval graphs for the inflation forecasting performance of OPEC countries.









Key

1. CL_UP (indicated with the blue colour) represents the confidence interval for the upper bound.
2. CL_LW (indicated with the orange colour) gives the confidence interval for the lower bound.
3. INF_*** (indicated with the green colour) denotes the actual inflation rate.
4. INF_***1 (indicated with the red colour) is the forecast of the inflation over the whole 8-step ahead horizon.
5. *** denotes the first three letters of each country (e.g ALG, ANG, NIG and SAU).

Table 7.5.1 Summary of the best forecasting multivariate models for BRICS countries

Best forecasting multivariate model for Brazil (1994q4 -2012q4)										
	RMSE			**MAPE**				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1 to 2-step	VEC	Exo	lnP, lnM, R, $InREE$, UN and $InOilp\_f$	VEC	Exo	lnP, lnM, R, $InREE$, UN and $InOilp\_f$	5.0840 - 7.0540	VEC	Exo	lnP, lnM, ΔR, $InREE$, UN and $InOilp\_f$
3 -step	VEC	Exo	lnP, lnM, R, $InREE$, UN and $InOilp$_f	VEC	End	lnP, lnM, R, $InREE$, UN and $InOilp$	6.8780	VEC	End	lnP, lnM, R, $InREE$, UN and $InOilp$
4 to 6 - steps	VEC	Exo	lnP, lnM, R, $InREE$, UN and $InOilp\_f$	VEC	Exo	lnP, lnM, R, $InREE$, UN and $InOilp\_f$	4.4790 - 17.8300	VEC	Exo	lnP, lnM, R, $InREE$, UN and $InOilp\_f$
7 and 8-step	VAR	End	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, ΔUN and $\Delta InOilp$	VAR	End	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, ΔUN and $\Delta InOilp$	12.0000— 19. 8000	VAR	End	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, ΔUN and $\Delta InOilp$
Best forecasting multivariate model for Russia (2003q2-2012q4)										
	RMSE			**MAPE**				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1-step	VEC	End	lnP, lnM, $InREE$, gap, $InOilp$	VEC	End	lnP, lnM, $InREE$, gap, $InOilp$	7.9400	VEC	End	lnP, lnM, $InREE$, gap, $InOilp$
2 -step	VAR	End	lnP, lnM, $InREE$, GAP, $InOilp$	VAR	End	lnP, lnM, $InREE$, UN, $InOilp$	12.800	VEC	Exo	lnP, lnM, $InREE$, GAP and $InOilp\_f$
3 to 4-step	VAR	End	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp$	VAR	End	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp$	14.0000 - 15.2100	VAR	End	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp$
5 to 6-step	VAR	Exo	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp\_f$	VAR	Exo	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp\_f$	17.0900 – 22.8200	VAR	Exo	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp\_f$
7 to 8-step	VAR	End	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp$	VAR	End	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp$	28..0100-33.3700	VAR	End	ΔlnP, ΔlnM, R $\Delta InREE$, ΔUN, $\Delta InOilp$
Best forecasting multivariate model for India (1984q1- 2012q4)										
	RMSE			**MAPE**				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1 – 8 steps	VEC	End	lnP, lnM, $InOilp$	VEC	End	lnP, lnM, $InOilp$	7.4500-12.6570	VEC	End	lnP, lnM, $InOilp$
Best forecasting multivariate model for China (1992q1 -2012q4)										
	RMSE			**MAPE**				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1 -5 steps	VEC	End	lnP, R lnM, $InREE$ and $InOilp$	VEC	End	lnP, R lnM, $InREE$ and $InOilp$	5.001 - 22.099	VEC	End	lnP, R lnM, $InREE$ and $InOilp$
6 – 8 steps	VAR	End	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, gap, $\Delta InOilp$	VAR	End	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, gap, $\Delta InOilp$	25.1000 – 51.6500	VAR	End	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, gap, $\Delta InOilp$
Best forecasting multivariate model for South Africa (1995q2 -2012q4)										
	RMSE			**MAPE**				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1-2	VEC	Exo	lnP, R lnM, $InREE$ $InOilp\_f$	VEC	Exo	lnP, R lnM, $InREE$ $InOilp\_f$	6.0450-15.4560	VEC	Exo	lnP, R lnM, $InREE$ $InOilp\_f$
3 - 8 steps	VEC	End	lnP, R lnM, $InREE$ $InOilp$	VEC	End	lnP, R lnM, $InREE$ $InOilp$	8.4560-12.8700	VEC	End	lnP, R lnM, $InREE$ $InOilp$

The best multivariate forecasting model is identified by measure (RMSE, MAPE and U) for each forecasting horizon (1, 2, …, 8 steps ahead). The heading Type indicates the specification (VAR, VECM or VEC) while the Oil heading indicates whether oil is treated as an endogenous variable (End), exogenous variable (Exo) or is excluded from the model (None). The heading Variables specify the variables included in the model while Range gives the range of values for the MAPE for models favoured according to this forecasting measure over the specified horizon.

Table 7.5.2 Summary of the best forecasting multivariate models for OPEC countries.

Best forecasting multivariate model for Algeria (1999q2 -2012q4)										
	RMSE			**MAPE**				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1-3 steps	VAR	Exo	ΔlnP, ΔlnM, ΔR, ΔInREE, GAP and ΔInOilp_f	VAR	Exo	ΔlnP, ΔlnM, ΔR, ΔInREE, GAP and ΔInOilp_f	44.0700 - 101.600	VAR	Exo	ΔlnP, ΔlnM, ΔR, ΔInREE, GAP and ΔInOilp_f
4 to 6 steps	VEC	Exo	lnP, lnM, $InREE$, R and $InOilp\_f$	VEC	Exo	lnP, lnM, $InREE$, R and $InOilp\_f$	30.555 – 163.600	VEC	Exo	lnP, lnM, $InREE$, R and $InOilp\_f$
7 and 8	VAR	Exo	ΔlnP, ΔlnM, ΔR, ΔInREE, GAP and ΔInOilp_f	VEC	Exo	lnP, lnM, $InREE$, R and $InOilp\_f$	30.5500 - 48.9500	VAR	Exo	ΔlnP, ΔlnM, ΔR, ΔInREE, GAP and ΔInOilp_f
Best forecasting multivariate model for Angola (2002q4 - 2012q4)										
	RMSE			MAPE				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1- 8 steps	VAR	End	ΔlnP, ΔlnM, ΔR, gap, $\Delta InOilp$	VAR	End	ΔlnP, ΔlnM, ΔR, gap, $\Delta InOilp$	0.0800 – 0.1360	VAR	End	ΔlnP, ΔlnM, ΔR, gap, $\Delta InOilp$
Best forecasting multivariate model for Saudi Arabia (1983q1- 2012q4)										
	RMSE			MAPE				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	**Range**	**Type**	**Oil**	**Variables**
1-8steps	VECM	End	lnP, lnM, $InREE$ and $InOilp$	VECM	End	lnP, lnM, $InREE$ and $InOilp$	2.4270 - 12.710	VECM	End	lnP, lnM, $InREE$ and $InOilp$
Best forecasting multivariate model for Nigeria (1998q4 -2012q4)										
	RMSE			MAPE				**U**		
Horizon	**Type**	**Oil**	**Variables**	**Type**	**Oil**	**Variables**	Range	**Type**	**Oil**	**Variables**
1 to 2- steps	VAR	Exo	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp\_f$	VAR	Exo	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp\_f$	18.0800	VAR	Exo	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp\_f$
3 to 8 -steps	VAR	Endo	ΔlnP ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	VAR	Endo	ΔlnP ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$	17.1500 – 59.5958	VAR	Endo	ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$

The best multivariate forecasting model is identified by measure (RMSE, MAPE and U) for each forecasting horizon (1, 2, …, 8 steps ahead). The heading Type indicates the specification (VAR, VECM or VEC) while the Oil heading indicates whether oil is treated as an endogenous variable (End), exogenous variable (Exo) or is excluded from the model (None). The heading Variables specify the variables included in the model while Range gives the range of values for the MAPE for models favoured according to this forecasting measure over the specified horizon.

7.6 Summary and conclusions of the multivariate models' forecasting performance

In this section, Table 7.5.1 summarises the multivariate models (VAR, VECM and VEC) with the superior forecasting performance for the BRICS countries while Table 7.5.2 summarises the best forecasting models for the OPEC nations. A general impression from the table is that no single model that dominates across all the countries and the best forecasting method varies considerably across the models. However, the following general findings can be useful for future research. Where both unemployment and the output gap are available as indicators of the Phillips curves (for Brazil and Russia), models including unemployment outperform those that use the output gap. This view is contrary to Bjornland et al. (2008) and Stock and Watson (1999), who argue that models including the output gap contain the most valuable information in inflation forecasting than models based on alternative indicators (unemployment).

Further, the unrestricted VAR model often produces the best forecasting performance for OPEC countries except in Saudi Arabia that has the history of lower inflation. VAR models have the superior forecasting performance over all forecasting horizons for Algeria, Angola and Nigeria. The exception is for Algeria over 4 to 6-steps ahead horizons. In contrast, unrestricted VAR model has rarely produced the best forecasts for BRICS countries over both shorter and longer horizons and was only favoured over 7 to 8-steps ahead horizon for Brazil, 6 to 8-steps for China and all forecasting horizons except 1-step ahead horizon for Russia. The VECM only favoured for 1 out of 4 selected OPEC countries (Saudi Arabia overall forecasting horizons) and never favoured for BRICS countries.

Further, the VEC models produce better forecasts over all forecasting horizons for all BRICS countries. The exception is for China over 6 to 8-steps ahead horizons, Brazil over 7 to 8 horizons and Russia over 2 to 8-steps ahead horizon. Whereas, the VEC only favoured over 4 to 6 or 4 to 8-steps for Algeria. On average, our result indicates that unrestricted VAR models over both short and long horizons produce the best forecasting performance for OPEC countries. While the VEC model produces a better forecast for BRICS countries. The forecasting performance of the VEC model for BRICS countries and possible VECM for Saudi Arabia may also be because inflation in many of these countries is relatively moderate and kept in check by good monetary policy, especially when compared with other OPEC countries. Accordingly, the explicit nature of the variables and characteristics of the system can influence the accuracy of the forecasting performance (Zapata and Garcia, 1990). Furthermore, VEC also has the ability to minimize the effect of model misspecification as a result of unstable macroeconomic variables and avoid information lost due to differencing when including the stationary inducing restriction on non-stationary time series (see: Christoffersen and Diebold 1998, Mccrae et al. 2002 and Sa-ngasoongsong et al.2012). Indeed, our results generally support the view that the inclusions of cointegrating equations improve the inflation forecasting performance most especially for the BRICS countries and OPEC countries that has a history of low inflation (Saudi Arabia).[129] However, we note that many countries' VEC specifications contain variables in the cointegrating equation that are not statistically significant or exhibit unexpected coefficients signs (see table 7.3.1.F2 and 7.3.1.H2.). Nevertheless, the VECs of most countries include variables with theoretically plausible coefficients that are statistically significant and the incorporation of this information in the models appears to be useful for forecasting future inflation.

Moreover, whether the inclusion of oil prices as exogenous or endogenous will improve forecasting performance differs substantially according to the form of the model employed and the country being considered. For BRICS and OPEC countries, the model that includes the oil price as endogenous appears to secure better forecasting performance than the model that includes the oil price as exogenous, except for Algeria over all forecasting horizons, Brazil over 1 to 6-steps, Russia over 5 to 6-steps ahead and over 1 to 2-step for South Africa and Nigeria. This is interesting for many of our selected countries because both BRICS and OPEC countries are heavily dependent on oil importing for domestic consumption and oil exporting for revenue. Therefore, increases or decreases in the global oil price will directly affect government revenue and expenditure of many these countries. However, the impact of oil shocks on inflation in few economies most especially Algeria, Brazil, South Africa, Russia and Nigeria over a few steps may not be a surprise because many of these the countries have recently implemented monetary policies to manage their inflationary pressures; therefore it is possible that good monetary policy could have helped to minimize the impact of

[129] "Forecasts are most likely to be improved by applying error-correction techniques if the data strongly supports the cointegration hypothesis" (See: Timothy and Thomas, 1998).

changes in the global oil price for this country.[130] The 90% confidence interval for the best forecasting multivariate models are given for BRICS countries. These show that we can be 90% confident that, for the period of 2013 to 2014, inflation will lie between 4.3% to 9.6% for Brazil, - 5.2% to 12.2% for South Africa, 4.7% to 10.2% for Russia, 0.2% to 7.2% for China, 4.2% to 12% for India. Similarly, we can also be 90% confident that inflation lies between 0.7% to 11. 6% for Algeria, -6.2% to 18.8% for Angola, 3.7% to 18% for Nigeria and 0.8% to 5.6% for Saudi Arabia using the best forecasting multivariate model for these OPEC countries.

We also examine whether the instabilities in multivariate models (VAR, VECM and VEC) affect the performance of the inflation forecasting. In our study, the application of the two stability tests (the CUSUM and Bai Perron tests) provide evidence that stability of the model can enhance the forecasting performance of inflation for few countries (see Table 7.4.4 and 7.4.5). For example, the best multivariate models that are stable produce the best result for 3 out of 4 selected OPEC countries. In particular, the unrestricted VAR specifications are stable and produce the best forecasts results over all horizons for Algeria and Nigeria, and the VECM specification that includes all variables as endogenous including oil price is stable and favoured for Saudi Arabia over all forecasting horizons. In contrast, all the best forecasting multivariate models for BRICS countries are not stable. The forecast performance of the favoured multivariate models that are not stable for BRICS countries are consistent with the study of (Stock and Watson, 2003, and Rossi 2012) who argued that instability of the theoretical model can be misleading for out-of-sample forecasting.[131] This may also be because our forecasting

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[130] For example, Brazil launched a growth acceleration program in 2007 to provide tax incentive and reduce energy costs, strengthen its investment through foreign participation and restructure its oil royalty payment to increase revenue and provide more capital to the private sector. Similarly, Algeria government has recently imposed a policy that reduces licensing of importation of luxury furniture and building materials. The government approved the quantitative easing of printing almost 570 billion dinars (about 5 billion dollars) to help the Central Bank lend money to Public Treasury. Also, the government has also approved the plan to diversify its economy by boosting domestic engineering, petrochemical and pharmaceutical and food industries to make them more globally competitive. (The Reuter (2016) "Algeria's economic policy may accelerate inflation - IMF Online" available on https://af.reuters.com/article/algeriaNews/idAFL5N1UJ512 [accessed] on 17th September 2018.

[131] Gabrielyan (2016) compares the forecast performance of the Phillips curve and random walk for Swedish inflation over the period 1980 – 2014. The author reports evidence of instability for Phillips curve. However, the Phillips curve instabilities do not affect its forecast performance when compared

comparison are based on out-of-sample forecast instead of the in-sample comparison. Rossi (2012) documents that out-of-sample forecasts comparison are robust to model instabilities because their procedures can minimize the effect of structural breaks on forecasting model. In particular, they re-estimate their parameters over time by either rolling or recursive estimation process.

with the random walk model. For instance, the Phillips curve outperforms the random walk model for the period of 2004 to 2013.

7.7 The chapter summary and conclusion

In this chapter, we estimate multivariate models (VAR, VECM and VEC) based on different level of integration of the variables identified in chapter six for each country. In particular, we distinguished between different techniques in modelling using differencing and cointegrating restrictions via an error-correction model to ensure stationary. We estimate the following multivariate models (VAR, VECM and VEC). First, we estimate the VAR model in pure differences (stationary form) to forecast inflation.[132] Second, we construct a VECM without imposing cointegrating restrictions.[133] Third, we estimate a VEC that imposes cointegrating restrictions on the VECM. This allows us to examine whether imposing cointegrating restrictions via a vector error-correction model improves long-run inflation forecasts.

Further, we investigate whether the multivariate models (VAR, VECM and VEC) are structurally stable in the sense that the regression coefficients are constant. If not, what are the implications of the instability for forecasting future inflation or what forecast methods work well in the face of instability? For instability tests, we perform two different parameter shifts tests that are available in EViews (the CUSUM and Bai and Perron (2003) tests). Further, we produce a forecast for each multivariate model (VAR, VECM and VEC) that passes the diagnostic test for serial autocorrelation and choose the best forecasting model for the multivariate model. For each model, we estimate four different models. The first model includes all available variables as endogenous except unemployment (which is excluded). The second model includes all available variables as endogenous except for the output gap (which is excluded). The aim of these two models is to consider whether the model that includes the output gap provides superior forecasts to the model that includes unemployment. The remaining two models are the same as the first two models except the oil price is treated as exogenous.

For multivariate inflation forecast, a general impression is that there is no single model that dominates across all the countries and the best forecasting method varies considerably across the models. For example, where both unemployment and the

[132] As a necessary requirement for this method, all the variables must be stationary and integrated in the same order

[133] For this model, we consider all variables that are not stationary and test for the cointegration. Accordingly, linear combination of two series which are stationary only after differencing may be cointegrated without differencing (Granger, 1986).

output gap are available as indicators of the Phillips curves (for Brazil and Russia), models including unemployment outperform those that use the output gap. Similarly, the unrestricted VAR model often produces the best forecasting performance for OPEC countries except in Saudi Arabia that has a history of lower inflation. For instance, VAR models have the superior forecasting performance over 1, 2, 3, 7 and 8-steps ahead for Algeria and all horizons for Nigeria and Angola. In contrast, the VEC is virtually favoured for BRICS countries over 1-step for Russia, 1 to 5-steps ahead for China, 1 to 6- steps ahead for Brazil and all horizons for South Africa and India. The VECM specification only favoured for Saudi Arabia. In general, we find that including long-run information in the form of a specified cointegrating equation generally improves the forecasting performance of inflation compared with VARs and VECMs for BRICS. While unrestricted VAR model outperforms other selected models for OPEC countries. To examine whether the instabilities in multivariate models (VAR, VECM and VEC) affects the performance of the inflation forecasting. In our study, the application of the two stability tests (the CUSUM and Bai Perron tests) provide evidence that the stability of the model can enhances the forecasting performance of inflation for few countries. For example, the favoured forecasting models are stable for 3 (Algeria, Nigeria and Saudi Arabia) out of 4 OPEC countries. The unrestricted VAR models are stable produce the best forecast results for Angola and Algeria. Similarly, the VECM specification that includes all variables as endogenous is stable and favoured for Saudi Arabia. In contrast, all the favoured forecasting model for BRICS countries are not stable. The performance of the favoured forecasting models that are not stable are consistent with the study of (Stock and Watson, 2003, and Rossi 2012) who argued that instability of the theoretical model could be misleading for favoured out-of-sample forecasting.

CHAPTER 8

COMPARISON OF THE BEST FORECASTING PERFORMANCE OF THE MULTIVARIATE AND UNIVARIATE MODELS

8.0 Introduction

In this chapter, we estimate a benchmark model (naïve model) and compare its forecasting performance with the best - selected multivariate (unrestricted VAR, VECM and VEC) and univariate models (TAR, ARIMAX and ARIMAs) to choose the best model that forecasts inflation in each country.

8.1 Naïve Model

In this section, we apply the same forecast evaluation procedure applied to the univariate models in chapter 5 (section 5.5.0) and multivariate specifications developed in chapter 7 to produce m-step ahead forecast for the naïve model. Our approach follows the studies of Atkeson and Ohanian (2001) who use the same model as the benchmark model. Atkeson and Ohanian argued that an inflation forecasting model based on some hypothesized economic relationship cannot be considered a useful guide for policy if its forecasting performance is not better than a simple naïve model. We estimate the naïve model by equating the observed value in the last quarter of the estimation period to forecast the present quarter. In other words, the inflation rate over the coming quarter is expected to be the same as the inflation rate over the previous quarter. In our study, we applied a Naïve model to the growth rate of prices to produce forecasts over the ex-post forecasting period 2013q1 – 2014q4. In particular, we conduct the rolling forecast for the Naïve model as follows. For models estimated up to 2012q4, we use the 2012q4 observed value of data to produce a 1-step ahead forecast for 2013q1, as the 2-step ahead forecast for 2013q2, 3-step ahead forecast for 2013q3, and up to 8- step ahead forecast for 2014q4. For Brazil, we produce out-of-sample ex-post forecast for naïve model based on a rolling basis. The forecast generated by the naïve model for Brazil is compared with the other class of the models. Table 8.1 and 8.2 reports the new generated naïve forecast performance measures, and those for the best selected univariate model in Chapter 5 Table 5.6.4 (TAR model, Automatic EView ARIMA selection) and best selected multivariate model in Chapter 7 Table 7.4.1.2 and 7.4.1.3 (the VECM and VEC models).

The forecast performance measures for these models are given in the columns headed A, B, C, D, E, F and G, of Table 8.1 and 8.2.

Table. 8.1. The best univariate models selected for Brazil

	A. Naive Model			B. Nonlinear TAR model over a reduced sample that avoid breaks			C. Reduced sample EView9 Automatic seasonal ARIMA model without modelling breaks			D. Reduced sample EView9 Automatic's non-seasonal ARIMA model without modelling structural breaks		
	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U
1-step	0.0050	6.6990	0.0400	0.0050	6.0080	0.0360	0.0050	5.0690*	0.0360	0.0060	7.8950	0.0490
2-step	0.0060	9.6120	0.0520	0.0080	10.9700	0.0690	0.0060	8.0390	0.0470	0.0070	9.5170	0.0560
3-step	0.0060	8.7380	0.0490	0.0100	13.1200	0.0910	0.0070	10.150	0.0560	0.0060	8.2540	0.0480
4-step	0.0040	4.8850	0.0290	0.0110	13.4300	0.0990	0.0060	8.6970	0.0500	0.0030*	3.7780*	0.0220*
5-step	0.0020	2.4170	0.0150	0.0080	11.1900	0.0690	0.0070	9.3930	0.0520	0.0002*	0.1580*	0.0010*
6-step	0.0070	9.8590	0.0530	0.0040	4.8800	0.0310	0.0060	7.2460	0.0430	0.0004*	0.5880*	0.0040*
7-step	0.0080	12.3100	0.0660	0.0070	10.6200	0.0530	0.0060	8.2260	0.0490	0.0004*	0.7080*	0.0040*
8-step	0.0020	3.0140	0.0150	0.0060	10.1600	0.0480	0.0090	15.4300	0.0720	0.0004*	0.3390*	0.0020*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance

Table 8.2. The best multivariate models selected for Brazil

	E. VAR: All variables endogenous output gap excluded unemployment included			F. VEC: All variables endogenous output gap excluded unemployment included			G. VEC: Oil price exogenous output gap excluded unemployment included		
	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U
1-step	0.0060	8.5330	0.0460	0.0040	5.1800	0.0290	0.0040	5.0840	0.0290*
2-step	0.0120	17.6600	0.0900	0.0070	10.1000	0.0560	0.0060	7.0540*	0.0440*
3-step	0.0130	18.4700	0.0970	0.0060	6.8780	0.0450	0.0060	7.3040	0.0520
4-step	0.0110	17.6500	0.0850	0.0040	4.9060	0.0290	0.0030	4.4790	0.0250
5-step	0.0150	23.5100	0.1100	0.0090	9.9190	0.0660	0.0030	3.5420	0.0220
6-step	0.0200	28.9700	0.1430	0.0190	24.4600	0.1370	0.0130	17.8300	0.0920
7-step	0.0140	19.7900	0.1020	0.0180	24.1100	0.1330	0.0190	29.0400	0.1340
8-step	0.0070	12.4400	0.0590	0.0110	18.0800	0.0830	0.0170	28.8600	0.1260

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

From the table (8.1 and 8.2), the reduced sample univariate model that employs EViews 9's automatic non-seasonal ARIMA technique, see column D, has the lowest RMSE, MAPE and U-statistics over all forecasting horizons except for the 1 to 3 step-ahead horizons. Similarly, the reduced sample that employs EView9 Automatic seasonal ARIMA model without modelling breaks has the lowest value for MAPE over the 1-step ahead horizon, (see column C table 8.1). In contrast, the reduced sample multivariate VEC model that specified oil price as exogenous and include other variables as endogenous including unemployment and excluding output gap, see column G table 8.2, has the lowest RMSE and U-statistics values for 1 and 2-steps-ahead horizons according to the RMSE, MAPE and U-statistics. The VEC model that includes all variables as an endogenous including oil price (see column F table 8.2) has lowest value for 3-step according to the RMSE, MAPE and U-statistics. Our results indicate that univariate ARIMA model that employs Eviews 9's automatic non-seasonal ARIMA unambiguously produces the best forecasting performance over long horizons for Brazil. While the multivariate VEC model generally produces a better forecast for Brazil inflation over the short horizons (1, 2 and 3-steps forecast ahead). We note that the benchmark model (naïve) and nonlinear TAR model were never favoured over the best selected multivariate models and univariate ARIMA model for all forecasting horizons according to the RMSE, MAPE and U-statistics. Our result is a contrast to the study of Atkeson and Ohanian (2001) who produces a better forecast for the naïve model than the multivariate VAR model. A similarly procedure was applied to all countries and summary is available in the table 8.3 and 8.4.

8.3 Summary of the best forecasting multivariate and univariate models for BRICS countries

Best forecasting model for Brazil							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1	VEC	Exo	R_A_SARIMA		5.0690	VEC	Exo
2 Step	VEC	Exo	VEC	Exo	**7.0540**	VEC	Exo
3	VEC	Exo	VEC	End	**6.8780**	End	End
4 to 8- steps	R_A_ARIMA	-	R_A_ARIMA	-	0.3390 - 8.2540	R_A_ARIMA	-
Best forecasting model for Russia							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 8 –steps	R_A_ARIMA	**-**	R_A_ARIMA	-	6.3660 – 20.8700	R_A_ARIMA	-
Best forecasting multivariate model for India							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 8 steps	F_A_SARIMA	**-**	F_A_SARIMA	-	13.5200 - 63.4600	F_A_SARIMA	-
Best forecasting model for China							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 8- steps	F_TAR Model	-	F_TAR Model	-	**6**.1940 – 10.0800	F_TAR Model	
Best forecasting model for South Africa							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 2-steps	VEC	Exo	VEC	Exo	6.0450-15.4560	VEC	Exo
3 to 8-steps	VEC	End	VEC	End	8.4560-12.8700	VEC	End

See notes for Table 5.5.2 and 7.5.1. VAR = unrestricted VAR model with differenced (stationary) data, VECM = unrestricted Vector Error Correction Model (VECM) that assumes cointegration without imposing cointegrating restrictions. VEC = restricted VECM that imposes a single cointegrating equation on the VECM.

8.4. Summary of the best forecasting multivariate and univariate models for OPEC countries

Best forecasting model for Angola							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**Oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 8 steps	VAR	End	R_SARIMA	-	2.05900 - 13.5000	VAR	End
Best forecasting model for Algeria							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**Oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 3-steps	VAR	**Exo**	VAR	Exo	44.0100-101.600	VAR	Exo
4 to 6 -steps	VEC	**Exo**	VEC	Exo	30.555 – 163.600	VEC	Exo
7 to 8-steps	VAR	**Exo**	VAR	Exo	0.0550 - 37.6500	VAR	Exo
Best forecasting model for Ecuador							
	RMSE		**MAPE**			**U**	
Horizon	Type	**Oil**	Type	Oil	Range	Type	oil
1 to 8-steps	F_SARIMAX	**-**	F_SARIMA X	-	15.4500 - 42.9100	F_SARIMAX	-
Best forecasting model for Nigeria							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**Oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 4- steps	R_TAR Model		R_TAR Model		15.9000-19.360	R_TAR Model	
5 to 8-steps	VAR	**End**	VAR	End	28.7600 - 37.7700	VAR	End
Best forecasting model for Saudi Arabia							
	RMSE		**MAPE**			**U**	
Horizon	**Type**	**Oil**	**Type**	**Oil**	**Range**	**Type**	**Oil**
1 to 2-steps	R_TAR Model	-	R_TAR Model	-	5.6470 – 7.8200	R_TAR Model	-
3 and 5-steps	VECM	End	VECM	End	4.3590 – 8.1710	VECM	End
4, 6, 7 and 8-steps	R_A_ARIMA	-	R_A_ARIMA	-	1.0100 - 13.2000	R_A_ARIMA	-
Best forecasting model for Kuwait							
Horizon	RMSE		**MAPE**			U	
1-8-steps	F_SARIMAX	-	F_SARIMA X		11.2100 – 38.5900	F_SARIMAX	-

See notes for Table 5.5.2 and 7.5.1. The best univariate forecasting model is identified by each measure (RMSE, MAPE and U) for each forecasting horizon (1, 2…, 8 steps ahead). The full sample univariate model that employs seasonal Box-Jenkins ARIMA techniques and model's structural breaks is denoted as F_SARIMAX, the full sample univariate model that employs Box-Jenkins ARIMA techniques without modelling structural breaks is denoted as F_SARIMA (this model type is exclusive to India because there were no significant structural breaks to model over the full sample). The full sample specifications that employ EViews 9's automatic seasonal and non-seasonal ARIMA model without modelling breaks are denoted as F_A_SARIMA and F_A_ARIMA respectively (these models are exclusively designed for China because the period after the structural breaks are less than 39 observations and relative step shifts for this period also appear to be small which mean that inference regarding unit roots may not be too adversely affected when using the full sample. Hence, the full sample is used for these models for this country). The reduced sample model that employs seasonal ARIMA technique's without modelling structural breaks is denoted as R_SARIMA. The reduced sample model that employs EViews 9's automatic seasonal ARIMA model selection procedure without modelling breaks is denoted as R_A_SARIMA and the reduced sample model that employs EViews 9's automatic non-seasonal ARIMA model selection method without modelling breaks is represented by R_A_ARIMA. F_TAR Model is denoted as threshold autoregressive model estimated over the full sample and R_TAR model is denoted as the threshold autoregressive model estimated over the reduced sample that avoid modelling breaks. The range gives the range of values for the MAPE for models favoured according to this forecasting measure over the specified horizon.

From table 8.3, the EViews 9 automatic ARIMA model selection procedure applied to the reduced sample is virtually favoured for all the BRICS countries except South Africa and China (all horizons) and Brazil (for 1 up to 3- step ahead horizon). The reduced sample automatic nonseasonal method is favoured for all forecasting horizons for Russia and over 4 to 8 steps for Brazil. The full sample automatic seasonal method is favoured for all forecasting horizons for India and over 1-step ahead horizon for Brazil according to the MAPE measure. [134] Similarly, the full sample TAR model is only favoured for China over all forecasting horizon. However, the VEC that specified the oil price as exogenous produces the best forecasts over all forecast horizons for South Africa and over the 1 to 3-step ahead period for Brazil. We note that the MAPE of all favoured non-seasonal automatic ARIMA models is always less than 21 percentage points suggesting a relatively good forecasting performance for this class of models for BRICS nations while the MAPE value of the automatic seasonal ARIMA model is between 13.5200 and 63.4600 for India and 5 percentage point for Brazil. The MAPE value for the TAR model is less than 11 percentage point. While the MAPE value for the VEC is between 6.0450 and 15.4560 for South Africa and 7.0540 for Brazil.

For OPEC countries (table 8.4), the univariate ARIMA model is rarely favoured and, this is in contrast with the results for the BRICS nations. For all the selected OPEC countries, the automatic ARIMA specification is only favoured for Saudi Arabia over the longer horizons (4, 6, 7 and 8-steps ahead). Whereas the TAR model produces the best forecasting results over the shorter 1 to 2-step ahead horizons and the VECM is favoured over 3 and 5 steps ahead horizons. For Angola, the best forecasting models depend upon the forecaster's loss function and whether they are especially averse to large errors or whether they treat the size of all forecasting errors equally. According to MAPE, the reduced sample seasonal Box-Jenkins ARIMA technique is favoured over all forecasting horizons. While the unrestricted VAR model produces the best results for 1 to 8- step ahead horizons according to the RMSE and U-statistics value. Similarly, the unrestricted VAR is favoured for Algeria over 1, 2, 3, 7 and 8 -steps ahead while the VEC produces the best forecasting results over 4 to 6-steps ahead horizons. For Nigeria, unrestricted VAR

[134] Note that the automatic seasonal method is applied to the reduced sample for Brazil.

is favoured over the longer horizons (5 to 8-steps ahead) and, the TAR model produces the best forecasting results over the shorter horizons (1 to 4-steps ahead).

For Ecuador and Kuwait, the valid ARIMAX model and TAR model outperform the benchmark naïve model. The MAPE value for ARIMA specification is between 11.2100 and 38.5900 for Kuwait, and 15.4500 - 42.9100 for Ecuador. The MAPE value for the favoured automatic ARIMA model is less than 14 percentage point for Saudi Arabia. While the MAPE value for the TAR model for Nigeria is between 15.9000 and 19.360 and 5.6470 – 7.8200 for Saudi Arabia.

To sum up, our study shows that the naïve models were never over the univariate and multivariate models which is contrast to the study of Atkeson and Ohanian (2001). Our research also shows that the univariate model is generally favoured over the multivariate models for the BRICS countries (except South Africa). However, the results are mixed between univariate and multivariate methods for OPEC countries. These results suggest that multivariate models do not clearly outperform univariate ARIMA models when forecasting inflation for the countries considered here (especially for Russia, China, and India). This result is consistent with the findings of Stock and Watson (2007) and Atkeson and Ohanian (2001) who note that the univariate models outperform multivariate models during periods of stable and low inflation. Their result is because an increase in economic instabilities (requiring modelling of these instabilities) could reduce forecasting accuracy, especially in multivariate models. Other possible explanation may also be because all the multivariate model specified by BRICS countries failed the two-stability tests (CUSUM and Bai Peron test) specified in this research. Therefore, it may be possible that instabilities have reduced forecast performance of the multivariate model for the BRICS countries.

When examining the sensitivity of forecast performance, we compare the full sample that explicitly models breaks and the reduced sample that avoids modelling breaks. We note that reducing the sample to avoid modelling instabilities increases the forecasting performance of both univariate and multivariate models. In our work on BRICS and OPEC countries, we find that reducing the sample to avoid modelling structural breaks improves forecasting performance, where the univariate models tend to forecast best (especially for BRICS countries).

8.2 The chapter summary and conclusion

In this chapter, we follow the study of Atkeson, and Ohanian (2001) and produced forecast for inflation using a naïve model. Atkeson and Ohanian argued that an inflation forecasting model based on some hypothesized economic relationship cannot be considered a useful guide for policy if its forecasting performance is not better than a simple naïve model. Therefore, we examine whether the forecast produce by the naïve model will outperforms forecast produced by the multivariate (VAR, VECM and VEC) and univariate models (TAR model, ARIMAX, ARIMAs and EViews automatic selection procedure). In our study, the naïve models were inferior to the best selected univariate and multivariate model for all selected countries. This result confirms the relatively good forecast performance of both multivariate and univariate models estimated in our study.

CHAPTER 9

9.1 SUMMARY AND CONCLUSION

The evidence from previous studies indicate that the performance of inflation forecasting depends on different monetary regimes over different periods (Lee 2012, Ozkan and Yazgan, 2015). In particular, inflation forecasting performance is generally superior under inflation targeting monetary regime compared to periods without inflation targeting policy. Buelens (2012) and Stock and Watson (2008) stated that the accuracy of a forecasting model depends on the sample period in which they are estimated and evaluated. For example, the appropriate forecasting model to be used prior to the economic crisis may be different from that during the economic crisis. Pretorious and Rensburg (1996) revealed that univariate ARIMA models are better in the prediction of inflation when the inflation rate is relatively stable, and multivariate models are better at forecasting inflation when inflation is volatile. The empirical studies of (Sim and Zha 2006, Groen and Mumtaz 2008, and Barnett et al. (2014)) revealed that a model that incorporates different regime shifts have better forecasting performance than the alternative model without regime shifts. Fanchon and Wendel (1992) observed that the predictive performance of VAR and VEC models depends on the length of the forecasting horizon. For instance, the multivariate VEC model outperformed the VAR model for 13 and 11-month ahead forecasting horizons. This study extends the existing literature by forecasting inflation in BRICS and selected OPEC countries over an 8-steps ahead forecasting horizon. To the best of our knowledge, no study has previously analysed the relative performance of inflation forecasting in OPEC and BRICS economies that cover sample periods of both high inflation and moderate inflation. In this study, we fill this gap by evaluating the forecasting performance of univariate and multivariate models in the selected economies.

For the univariate models, we produce a forecast for ARIMAX models that have a deterministic component to account for structural breaks over the full sample period and different ARIMA specifications over a reduced sample period (with a minimum of 39 observations) that avoids structural breaks. The univariate models that we develop over the reduced sample period are, first, a seasonal ARIMA specification identified using the Box-Jenkins method, second, a seasonal ARIMA model identified using EView's automatic model selection tool, third, a non-seasonal ARIMA model identified using

EView's automatic model selection tool applied to seasonally adjusted data, fourth, a regime shifts threshold autoregressive model (over the reduced sample and full sample) and fifth, naïve model as a benchmark model. The aims are as follows. First, how can we make the price data stationary for each country? In particular, is seasonal differencing required, do structural breaks need to be accounted for and is the logarithmic approximation a valid measure of annual inflation. Second, can ARIMAX models that pass diagnostic checks be obtained for each country. Third, to determine whether forecasting accuracy is improved by using models developed over a shorter sample period that avoids the modelling of structural breaks or using specifications estimated over the full sample where structural breaks are modelled. Fourth, to determine whether using modeller judgement in selecting models by applying the Box-Jenkins identification method delivers superior forecasting performance to models developed using automatic model selection tools. Fifth, to determine whether forecasts based on the models applied to seasonally adjusted data (with re-seasonalised forecasts) are more accurate than those based on unadjusted data. Sixth, to determine whether the model that incorporates different regimes or structural breaks will produce a better forecast than the alternative model without the incorporation of a regime shift. Seventh, to examine whether the inflation forecast generated by a naïve model will outperforms other selected models.

For multivariate analysis, we produce a forecast for annual inflation; all models are estimated using reduced sample periods that avoid the modelling of structural breaks and use seasonally adjusted data to avert the need to deal with issues of seasonal integration and seasonal cointegration. The multivariate specifications developed are based on unrestricted VAR, VECM and VEC formulations involving stationarity inducing transformations. Each model formulation has potentially four specifications. The first specification excludes unemployment and includes the output gap, where the oil price and all other variables are treated as endogenous. The second specification excludes the output gap and includes unemployment, where the oil price and all other variables are treated as endogenous. Comparison of these two models are determined whether the specification that includes the output gap provides superior forecasts to the model that includes unemployment. In the third specification, the oil price is treated as exogenous and all other available variables as endogenous except unemployment (which is excluded). For the fourth specification, the oil price is also treated as exogenous and includes all available variables as endogenous except the output gap (which is excluded). Fifth, has multivariate model stable over time? If not, what are the implications of the instability of forecasting inflation? These multivariate models provide insights that include the following. First, they indicate which economic determinants are essential for modelling and forecasting inflation and suggest the extent to which there are similarities or differences in this regard across countries. Second, they determine whether VAR, VECM or VEC formulations are favoured in any country and/or across countries generally. Third, they facilitate the assessment of whether the use of explanatory factors in these multivariate formulations can improve forecasting performance relative to univariate models that have specifications that are not based on economic theory. Fourth, of all the models considered (both univariate and multivariate) which model produces the best forecasting performance over the benchmark model (naïve) across countries and/or for different forecasting horizons?

The main conclusions of this thesis are summarised below.

1. For all countries, the price data is highly seasonal such that they appear to be a seasonal, rather than autoregressive, unit root requiring measures of inflation based upon four periods (rather than one period) differencing to induce stationarity. However, for all countries except India, there are evident of structural shifts in inflation such that inflation based upon a four period (annual) difference is only stationary after accounting for structural breaks. In the majority of countries, the annual differencing transformed the change in the slope of prices into step shifts in inflation such that a period of relatively high inflation is followed by a period of more moderate inflation. This implies the need to model structural breaks when using the full sample of data or reduce the sample to avoid the modelling of such shifts in all countries (except for India). In this study, our results indicate that the annual (four periods) difference of the log of prices is a poor approximation of inflation for the periods of high inflation or countries that have a history of high inflation, for example, Brazil, Russia, Angola, Algeria and Nigeria. However, the annual (four periods) difference of the log of prices is a reasonable approximation

of inflation for the period of low inflation or countries that have a history of low inflation, for example, India, China, South Africa and Saudi Arabia.[135]

2. For all the selected countries ARIMAX models estimated over the full sample that cannot be rejected according to the standard diagnostic tests are obtained. The diagnostic tests considered are for residual autocorrelation, stationarity and invertibility. We additionally require that the included deterministic component of the model adequately captures the identified structural breaks. Therefore, ARIMAX models that are valid for forecasting are obtained for all countries.

3. The ARIMA models estimated over the reduced sample that avoids the modelling of structural breaks exhibit superior forecasting performance compared to ARIMAX models estimated over the full sample in most countries except Ecuador and Kuwait that only available in that class model. This result implies that the potential benefits of having more data from using the full sample are generally outweighed by being able to avoid modelling structural breaks, even at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks this suggests that using reduced samples to avoid the issue of structural breaks is generally the preferred strategy. This is consistent with the notion that models with many regressors, as required when modelling structural breaks, can overfit the sample and exhibit a poor forecasting performance (Yohei, 2013 and Carlos, 2014).

4. In some countries, the EView's automatic (non-seasonal and seasonal) ARIMA model selection procedure yields specifications that are valid for forecasting. This is in the sense that the diagnostic checks do not reject them for residual autocorrelation, stationarity and invertibility. One exception is for Nigeria that failed the standard diagnostic checks for both the non-seasonal and seasonal ARIMA specifications. In addition, the EViews automatic seasonal ARIMA model

[135] Note, we do not use the log approximation for inflation in any country and instead use the more standard growth rate measure of inflation, ($INF_t = \frac{P_t - P_{t-4}}{P_{t-4}}$).

selection method yielded specifications that failed at least one of the standard diagnostic checks for 4 of the 9 countries (being, Russia, India, Nigeria and South Africa). For the automatic non-seasonal ARIMA model selection procedure, 7 of the 9 countries' selected models are valid for forecasting where 2 (Angola and Nigeria) of the 4 selected OPEC countries' models failed at least one of the diagnostic checks. We also note that in 8 of the 9 countries (the exception is India) the automatic selection procedure yields models where the ARMA coefficients are statistically insignificant (including the highest order AR or MA term). Overall, this suggests that the automatic ARIMA model selection procedure often selects specifications that would be considered invalid (fails at least one diagnostic check) or would not be favoured by the modeller (includes an irrelevant regressor).

5. ARIMA specifications based upon the EViews 9 automatic model selection procedure are favoured for the class of univariate model (according to forecasting accuracy measures) for virtually all countries. In particular, the automatic seasonal model selection method is favoured: for Brazil and China over the 1 and 2 steps ahead horizons, for South Africa over the 1 to 4 and 6 to 7 steps ahead horizons and never favoured over any horizon for Angola, Nigeria, Saudi Arabia and Algeria. The automatic non-seasonal model selection method is favoured for Russia over all horizons, for Algeria over the 2-step ahead horizon, for Brazil, Saudi Arabia and China over the 3 to 8 step horizons and for Nigeria over the 2 (possibly 3) and 4 to 8 steps ahead horizons. Whereas, the seasonal Box-Jenkins ARIMA model without using the automatic selection technique is favoured for Angola over all horizons, for Algeria possibly over the 8-step horizon, for Saudi Arabia over the 1 and 2 step horizons, for Nigeria over the 1 (and probably 3) step horizon, for South Africa over the 5 and 8 step horizons and for India over all forecasting horizons. In general, the EViews 9 automatic model selection procedure is favoured over the seasonal Box-Jenkins ARIMA model (that does not use the automatic selection technique), especially for the BRICS countries. This suggests that automatic selection methods not only have the benefit of saving time they often also produce superior forecasts. This is despite our finding that ARIMA models based on automatic selection procedures often fail standard diagnostic checks and/or include irrelevant regressors.

6. We compare automatic ARIMA model selection specifications that explicitly model seasonality to those that apply non-seasonal models to seasonally adjusted data and re-seasonalize the forecasts. We observed that non-seasonal specifications produce superior forecasting performance over the 3 to 8 steps ahead horizon for Brazil, China and Saudi Arabia, for all forecasting horizons for Russia, over the 2 and 4 to 8 step horizons for Nigeria and the 2-step ahead horizon for Algeria. The automatically selected seasonal ARIMA model is favoured for Brazil, China and Saudi Arabia over 1 to 2 steps ahead horizons, for all forecasting horizons for India and Angola, over the 1 to 4 and 6 to 7 steps ahead horizons for South Africa and over the 1 and 3 steps ahead horizons for Nigeria. In general, we find that building ARIMA models to seasonally adjusted data and re-seasonalising the forecasts generally yields superior forecasting performance relative to constructing seasonal ARIMA models when using automatic ARIMA model selection procedures.

7. When we compared the forecast performance of the regime shift TAR model estimated over the full sample and reduced sample that avoid modelling breaks. The TAR model estimated over a reduced sample that avoid modelling breaks produce superior forecast than the TAR model estimated over a full sample for all countries except for Saudi Arabia (over 1 to 3-steps ahead horizons). Similarly, when we compared the best selected ARIMA specifications in each country with the best selected threshold autoregressive model (TAR model). We observed that the best selected TAR models were not favoured over the best selected linear ARIMA models for all countries except for China (over all forecasting horizons), Nigeria (over 1 to 4-steps ahead horizons) and Saudi Arabia (over 1 to 3-steps ahead). The performance of the TAR model for a few countries are consistent with the studies of (Montgomery et al. (1998)) who argued that the nonlinear threshold models (TAR model) produce a superior forecast for five steps ahead over a linear ARIMA model during periods of high unemployment for the selected country.

8. For all selected OPEC and BRICS countries, the unrestricted VAR, VECM and VEC models that pass the standard diagnostic check for autocorrelation can be obtained. Unrestricted VAR models produce superior forecasts for the class of multivariate models over all forecasting horizons for 3 (Algeria, Angola and Nigeria) of the 4

selected OPEC countries. The exception is for Algeria over 4 to 6 steps ahead horizons). In contrast, unrestricted VAR model has rarely produced the best forecasts for BRICS countries over both shorter and longer horizons and was only favoured over 7 to 8-steps ahead horizon for Brazil, 6 to 8-steps for China and all forecasting horizons except 1-step ahead horizon for Russia. The VECM is only favoured for 1 (Saudi Arabia) out of 4 selected OPEC countries and never favoured for BRICS countries. Further, the VEC models produce better forecasts over all forecasting horizons for all BRICS countries. The exception is for China over 6 to 8-steps ahead horizons, Brazil over 7 to 8 horizons and Russia over 2 to 8-steps ahead horizon. Whereas, the VEC only favoured over 4 to 6 or 4 to 8-steps for Algeria. In summary, our results show that the unrestricted VAR models over both short and long horizons produce the best forecasting performance for OPEC countries. While the VEC model produces a better forecast for BRICS countries. The forecasting performance of the VEC model for BRICS countries and possible VECM for Saudi Arabia may be because inflation in many of these countries is relatively moderate and kept in check by good monetary policy, especially when compared with other OPEC countries. Accordingly, the explicit nature of the variables and characteristics of the system can influence the accuracy of the forecasting performance (Zapata and Garcia, 1990). Also, the relatively good performance of the unrestricted VAR model over the VEC model for OPEC countries is consistent with the findings of Ogunc et al. (2013) who stated that VAR models appear to produce the best forecasting model for Turkish inflation for a period that covers the effect of the global financial crisis. Our results also reveal that VECs often outperform VECMs, which means that restricting the long-run component into a single cointegrating equation is beneficial. This is consistent with Timothy and Thomas (1998) who stated that forecasts are most likely to be improved by applying error-correction techniques if the data strongly supports the cointegration hypothesis.

9. From the VECs, we specify a single cointegrating equation that indicates the extent to which models are consistent with our theoretical expectations. For 2 (Angola, and Saudi Arabia) of the OPEC countries where valid models could be obtained, the error-correction term (CointEq1) has a negative and significant adjustment coefficient in the inflation equation indicating error-correction toward the

equilibrium price level specified by the cointegrating equation. However, while the coefficient on the error-correction term is negative, it is insignificant for Nigeria (where all variables are included as endogenous except unemployment that is excluded) and Algeria (where oil price is treated as exogenous). The insignificance of the adjustment coefficient questions whether there is valid error-correction towards an equilibrium price level for this country, although it may just indicate slow adjustment given the coefficient has the expected negative coefficient sign. The coefficients in the cointegrating equations can also be assessed for their consistency with theoretical expectations. For 4 OPEC countries (Angola, Algeria, Nigeria and Saudi Arabia), the long-run coefficients on the money supply are significant and positive, which is consistent with the quantity theory of money. In contrast, the long-run coefficients on the interest rate do not have the expected negative sign for these OPEC countries except Nigeria where all variables include as endogenous including the oil price. This contradicts theoretical expectations for many OPEC countries. The long-run coefficients on the real exchange rate are positive and significant for 3 (Algeria, Nigeria and Saudi Arabia) of the 4 OPEC countries and this is consistent with economic theory. However, the long-run coefficient on the real exchange rate is negative and insignificant for Angola which is inconsistent with economic theory. We similarly summarise the theoretical plausibility of the cointegrating equations for the BRICS countries. The error-correction term has a negative and significant adjustment coefficient in the inflation equation only for Brazil. This indicates valid error-correction towards the equilibrium price level for Brazil. The adjustment coefficient is negative and insignificant for Russia, India and South Africa. Whilst this is strictly not consistent with valid error-correction behaviour it may just indicate a slow adjustment to equilibrium given the coefficient has the expected negative coefficient sign. However, the coefficient on the error correction term in the inflation equation is positive and significant for China. This suggests that the price level is being forced away from the specified cointegrating equation for China. The long-run coefficients on the money supply are significant and have the theoretically expected positive sign for 3 (Brazil, Russia and India) of the BRICS countries. However, the long-run coefficient on the money supply is not consistent with economic theory for China (its coefficient is negative and significant) and South Africa (negative and insignificant). The long-run coefficient on the interest rate has a sign that is not consistent with economic theory for 2 (Brazil and South Africa) of the BRICS countries where this variable is available.[136] The long-run coefficient on the real exchange rate is significant and has the expected positive coefficient for 4 (Brazil, Russia, China and South Africa) of the BRICS countries. However, the long-run coefficient on the real exchange rate is negative and significant for Brazil (where the oil price is treated as exogenous), which contradicts the basic economic theory. The long-run coefficient on the oil price is positive and significant for Angola, South Africa, and Brazil which is consistent with economic theory. However, the coefficient is positive and not significant for Nigeria. Where the unemployment variable is available (Brazil and Russia), the long-run coefficient on unemployment's is negative and significant for Russia which is consistent with economic theory. However, the coefficient on unemployment is positive and significant for Brazil which is not consistent with theoretical expectation. To summarise, we consider the consistency of each variable with theory across all countries where that variable is available. To provide an indicative summary, we measure and utilise the following rules. If the variable is significant and has the expected sign for any country, it is considered fully consistent and has a 100% rating for that nation. If a variable has the expected sign and is insignificant, it has a 50% consistency rating for that country. Whereas, if a variable has the unexpected sign it is given a 0% consistency rating for that country. In particular, the coefficients on the unemployment, money supply, exchange rate, oil price and the interest rate have the highest theoretical consistency rating at 100%, 85%, 75%, 33.3% and 16.6% respectively for OPEC and BRICS countries (see Table 12.1.F2 and 12.1.H2).[137] The relatively low consistency rating for the interest rate across the countries except Saudi Arabia is consistent with the findings of Al-Shammari and Al-Sabaey (2012) who indicate that the interest rate does not significantly affect the general price level for 59 developing countries.[138] However, our results may not be surprising because the literature

[136] Note that the interest rate is not included in the VEC specifications for India and Russia because the variable is I(0). In addition, interest rate is consistent and significant for China where oil price is included as endogenous.
[137] Salehi (2013) documents that the exchange rate and money supply are appropriate variables to consider in monetary policies aimed at controlling inflation.
[138] Note that the interest rate variable is not available in Saudi Arabia.

suggests a limited role for the interest rate in controlling inflation in OPEC countries and many developing nations. This is due to reasons of religion, social beliefs, the usury activities of financial institutions and the sovereignty of many these countries to regulate their financial institutions independently. The explanatory variables with relatively high consistency with theory are unemployment (100%), the money supply (85%) and the exchange rate (75%).[139] For instance, an increase in money supply will cause a significant increase in inflation in all countries except China. Further, a rise in unemployment increases inflation (Brazil) decreases inflation in Russia and an increase in the exchange rate will raise inflation in Russia, China, South Africa, Nigeria, Saudi Arabia and Algeria (see Table 7.1.F2 and 7.1.H2).

We also assess the consistency and plausibility of each country's cointegrating equation (from the VEC) with theory. Algeria (62.5%), Nigeria (80%) and Angola (66.7%) have relatively high consistency with theory, although they are not generally favoured when compared with other multivariate models in terms of forecasting performance. In contrast, Brazil, (60%), China (70%), and India (75%) have relatively high consistency with theory and their forecasting performance is generally superior to VARs and VECMs. In general, the valid VEC models that are broadly (if not entirely) consistent with economic theory can be found for BRICS and OPEC countries, most especially BRICS countries and they are generally favoured over the VARs and VECMs in terms of forecasting performance. This implies that the potential benefits (in terms of forecasting accuracy) of using theory to build multivariate VEC models of inflation may be undermined by the practical difficulty in securing statistically valid and completely theoretically consistent specifications.

10. In general, the model that includes the oil price as endogenous appears to secure better forecasting performance than the model that includes the oil price as exogenous for all BRICS countries except for Brazil and South Africa (for at least 1 to 2 steps ahead) as well as Russia over 5 and 6 -steps ahead. Similarly, the model that includes the oil as endogenous also produces the best forecasting performance for

[139] Our literature review documents that inflation in developing countries were mostly caused by the external influence of the import price, higher interest rates, money supply and exchange rates (Frisch 1977, Dhakal and Kandil 1993, Wesche et al. 2008, Boujelbene and Thouraya 2010).

all the OPEC countries except for Algeria over all forecasting horizons and Nigeria over the shorter horizon (1 to 2-steps ahead). The endogenous impact of the oil price on inflation for many OPEC and BRICS countries suggest that fluctuation of the global oil price has a considerable influence on inflation for the selective economy. For instance, a fall in the global oil price is expected to reduce government revenue and lead to a higher government budget deficit that requires either higher taxes or a reduction in government expenditure that may increase the cost of production. However, this result remains tentative because the oil price has a coefficient sign that is inconsistent with economic theory for 3 (Russia, India and China) out of 5 selected BRICS countries and 2 (Algeria and Saudi Arabia) out of 4 selected OPEC countries. This suggests caution in interpreting these results for these countries. The exogenous impact of oil prices on inflation for few countries most especially Algeria, Brazil, Nigeria and South Africa implies that inflation may not always determine by the oil price. This may be because oil price reductions in recent years have reduced the impact of oil shocks on inflation for this economy.[140] We also suggest that many of these economies may recently have good monetary policies to manage their inflationary pressures. Therefore, it is possible that good monetary policy could have helped to minimize the impact of changes in the global oil price for these countries.[141] This view is supported by the findings of Hooker (2002), Taylor (2000), Chen (2009), Mandal et al. (2012) and Dedeoglu and Kaya (2014) who indicate that the effect of the oil price on inflation is weak when adequate monetary policies are implemented.

11. When examining whether the instabilities in multivariate models (VAR, VECM and VEC) affects the performance of the inflation forecasting. In our study, the application of the two stability tests (the CUSUM and Bai Perron tests) provide evidence that the stability of the model can enhance the forecasting performance

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[140] Since 2008, the oil price has been traded at less than $120 per barrel and reached a 12-year low of $27 in January 2016. There is a link between the lower oil price and economic growth. For instance, low oil prices reduce the cost of production and encourage producers to increase their output.

[141] Abraham (2016), stated that devaluation of the naira in Nigeria was found to have been effective reduce the effect of crude oil price decline on the performance of the Nigerian stock market.

of inflation for few countries. For example, the best multivariate models that are stable produce the best result for 3 out of 4 selected OPEC countries. In particular, the unrestricted VAR specifications are stable and produce the best forecasts results over all horizons for Algeria and Nigeria, and the VECM specification that includes all variables as endogenous including oil price is stable and favoured for Saudi Arabia over all forecasting horizons. In contrast, all the best forecasting multivariate models for BRICS countries are not stable according to the CUSUM and Bai Perron tests. The forecast performance of the favoured multivariate models that is not stable for BRICS countries are consistent with the study of (Stock and Watson, 2003, and Rossi 2012) who argued that instability of the theoretical model can be misleading for out-of-sample forecasting.

12. We now summarise which models have the superior forecasting performance across both univariate and multivariate specifications. From our study, the EViews 9 automatic ARIMA model selection procedure applied to the reduced sample is virtually favoured for all the BRICS countries except South Africa and China (all horizons) and Brazil (for 1 up to 3- step ahead horizon). The reduced sample automatic nonseasonal ARIMA is favoured for all forecasting horizons for Russia and over 4 to 8 steps for Brazil. The full sample automatic seasonal method ARIMA is favoured for all forecasting horizons for India and the reduced sample automatic seasonal method is favoured over 1-step ahead horizon for Brazil according to the MAPE measure. Similarly, the full sample TAR model is only favoured for China over all forecasting horizon. However, the VEC that specified the oil price as exogenous produces the best forecasts over all forecast horizons for South Africa and over the 1 to 3-step ahead period for Brazil.

For OPEC countries, the univariate ARIMA model is rarely favoured and this is in contrast with the results for the BRICS nations. For all the selected OPEC countries, the automatic ARIMA specification is only favoured for Saudi Arabia over the longer horizons (4, 6, 7 and 8-steps ahead). Whereas the TAR model produces the best forecasting results over the shorter 1 to 2-step ahead horizons and the VECM is favoured over 3 and 5 steps ahead horizons. For Angola, the best forecasting models depend upon the forecaster’s loss function and whether they are especially averse to large errors or whether they treat the size of all forecasting errors equally. According to MAPE, the reduced sample seasonal Box-Jenkins ARIMA technique is favoured over all forecasting horizons. While the unrestricted VAR model produces the best results for 1 to 8- step ahead horizons according to the RMSE and U-statistics value. Similarly, the unrestricted VAR is favoured for Algeria over 1, 2, 3, 7 and 8 -steps ahead while the VEC produces the best forecasting results over 4 to 6-steps ahead horizons. For Nigeria, unrestricted VAR is favoured over the longer horizons (5 to 8-steps ahead) and, the TAR model produces the best forecasting results over the shorter horizons (1 to 4-steps ahead). For Ecuador and Kuwait, the valid ARIMAX model outperforms the TAR model and naïve model.

To sum up, our study shows that the naïve models were never over the best selected univariate and multivariate models which is contrast to the study of Atkeson and Ohanian (2001). Our research shows that the univariate model is generally favoured over the multivariate models for the BRICS countries (except South Africa). However, the results are mixed between univariate and multivariate methods for OPEC countries. For OPEC countries that have a history of moderate inflation, for example, Saudi Arabia, the univariate automatic non-seasonal ARIMA model generally outperforms the multivariate models. In contrast, multivariate models generally outperform univariate automatically selected ARIMA models for the countries with high inflation (e.g. Angola and Algeria). These results suggest that multivariate models do not clearly outperform univariate ARIMA models when forecasting inflation for the countries considered here (especially for India, China and Russia that has the history of moderate inflation compared to the OPEC countries). This finding is consistent with the previous literature that finds that univariate models are better in a prediction of inflation when inflation rate is relatively stable and theory-based models are better at forecasting inflation when the inflation is volatile (Pretorius and Rensburg 1996, Onder 2004, Stock and Watson, 2007 and Atkeson and Ohanian, 2001). Given this evidence, this study adds to the existing literature by providing information on the best inflation forecasting models for OPEC and BRICS countries. It also indicates that the modelling strategy of reducing the sample to avoid modelling structural breaks improves forecasting performance relative to using the full sample and modelling structural breaks.

CHAPTER 10

10. Limitations and Future research

It is widely accepted that Inflation in developing countries is caused by monetary and structural issues while inflation in the developed countries is caused by mainly monetary reasons (Tavakkoli, 1996). For inflation forecasting, most studies have argued in favour of using multivariate models over univariate although other studies have questioned the performance of multivariate models over different forecasting horizons (Fritzer et al. 2002, Onder 2004, Alnaa and Abdalla, 2005). In contrast, our empirical results predominantly favoured that univariate ARIMA model outperforms the benchmark model (naïve), threshold autoregressive model (TAR model) and Multivariate model (VAR, VECM and VEC) during the period of moderate inflation while multivariate model performs better than the univariate during the period of high inflation. Nevertheless, our research is limited in terms of data availability. For instance, not all potential determinants were available at the quarterly frequency for all nations and this limited the variables that we could consider for some countries. In an attempt to ameliorate this (and omitted variable issues) we considered the addition of variables only available at the annual frequency and used frequency conversion tools to generate quarterly series from annual series. Even so, not all determinants that we wanted to consider were available and were, therefore, not considered in our models for some countries.

Further, many of our selected macroeconomic variables have a variety of different measures that can be used as their proxies. For example, the output gap can be estimated by different methods, and each of these methods has their advantages and disadvantages.[142] Similarly, the GDP deflator, for example, could be used instead of the consumer price index to measure inflation. Therefore, different proxies for different variables may lead to different forecasting results.[143] As more data become available on

[142] The Hodrick-Prescott method we considered in our study has the merit of simplicity, but it does not generally exploit additional relevant information apart from information on the variable of interest. Burns et al. (2014) suggest that the output gap estimated by a production function and multivariate methods are superior to those based on the Hodrick-Prescott filter and other single variable estimation methods. Hendry (2001) argues that the linear trend can be misleading if the trend-growth changes or becomes inconsistent, especially during periods of economic instability and economic recession.

[143] CPI is a good proxy of inflation because it is arguably closer to the actual price while the GNP deflator may be better because it includes more commodities than the CPI (see Tavakkoli, 1996).

the potential determinants of inflation and their different proxies in BRICS and OPEC countries expanded models of inflation may be considered. However, we faced data constraints and considered a comprehensive set of variables and models for modelling and forecasting inflation in countries where there has previously been little such work.

In this study, we consider modelling structural breaks over the full sample for the univariate ARIMAX and TAR specification only. In future research, more appropriate multivariate models (such as Bayesian vector autoregressions, BVARs, or ARDL specifications) can be extended for modelling structural breaks over the full sample and used to compare their forecasting performance with the univariate ARIMAX model.

Further, our multivariate models are focused on differencing and cointegrating restrictions to ensure the stationarity of the data, in which all available variables are combined and specified based on their level of integration to forecast inflation. For instance, a VAR model is estimated based on differenced variables that are I(0) as well as VECM and VEC models where differenced variables and linear combinations of I(I) covariates are stationary. In future, we recommend consideration of multivariate models that are guided by economic theory rather than the order of integration of variables. For example, the ARDL model of Pesaran et al. (2001) that uses the bounds testing approach is appropriate when there is uncertainty over the order of integration of variables.

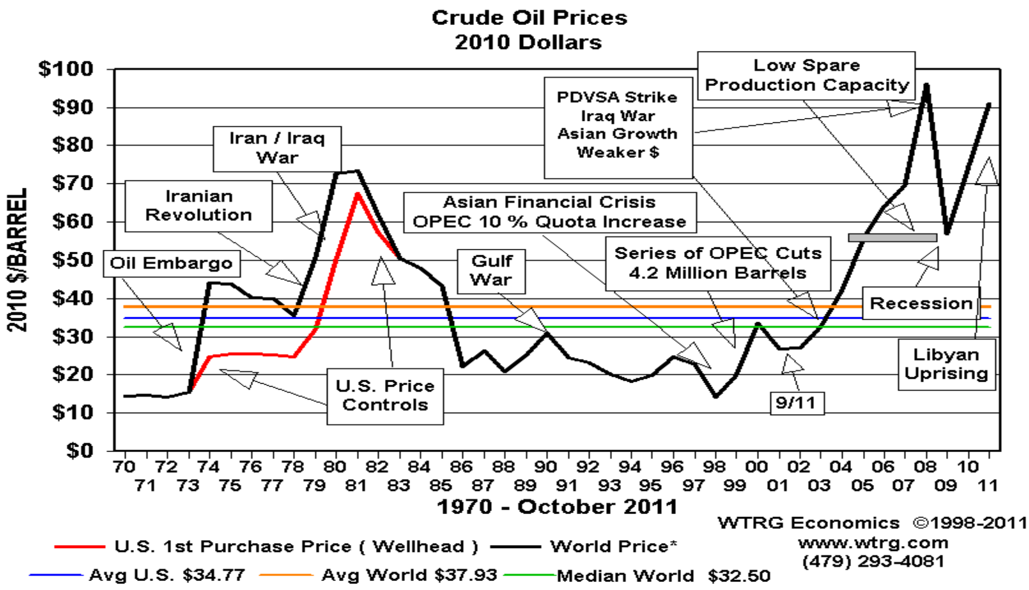
Further, throughout this study, we restricted ourselves to a minimum of 39 observations for the reduced sample that avoids modelling breaks. This limited our use of seasonal ARIMA specifications for some OPEC countries (e.g Ecuador and Kuwait). In future research, as more data becomes available, this restriction may no longer be binding, and a broader set of models can be considered for countries where our restriction meant certain models were not considered.

Also, this study only compares the forecasting performance of the univariate ARIMA, multivariate models (VAR, VECM and VEC), naive model and nonlinear TAR model. Therefore, we recommend that more non-linear models (such as switching Markov, Dynamic stochastic general equilibrium modelling and Neural network) should be considered for forecasting in both OPEC and BRICS countries in the future, to develop our work further. In addition to studying both linear and nonlinear models, survey forecast, and combined model forecasts of inflation could also be examined.[144]

Lastly, due to time constraints, we were not able to consider all alternative modelling strategies suggested by the referee and agree that producing forecasts based on stochastic volatility or time-varying MA specifications would be desirable for future work in these countries.

[144]Forecast combination captures important information from many different forecasts while lowering the risk of choosing the worst forecast (Gibbs, 2017).

Appendix 4.



Crude Oil Prices
2010 Dollars
$100
$90
$80
$70
$60
$50
$40
$30
$20
$10
$0
2010 $/BARREL
Low Spare
Production Capacity
PDVSA Strike
Iraq War
Asian Growth
Weaker $
Iran / Iraq
War
Iranian
Revolution
Asian Financial Crisis
OPEC 10 % Quota Increase
Oil Embargo
Gulf
War
Series of OPEC Cuts
4.2 Million Barrels
Recession
Libyan
Uprising
U.S. Price
Controls
9/11
70 72 74 76 78 80 82 84 86 88 90 92 94 96 98 00 02 04 06 08 10
71 73 75 77 79 81 83 85 87 89 91 93 95 97 99 01 03 05 07 09 11
1970 - October 2011
WTRG Economics ©1998-2011
www.wtrg.com
(479) 293-4081
U.S. 1st Purchase Price (Wellhead)
World Price*
Avg U.S. $34.77
Avg World $37.93
Median World $32.50

Appendix. Section 5.1

5.2 ARIMAX modelling of annual inflation for Russia

The maximum available sample period is 1992q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1996q1 – 2012q4. The first sub - section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.2: 1 Bai and Perron tests for structural breaks in Russian annual inflation

	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	39.849	16.19	2000q1	2000q1
1 vs 2	0.528	18.11		

In Table 5.2.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is 0.170.

Table 5.2.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.2.2. The test result indicates only one breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). However, the scaled F-statistic is less than critical value for the null hypothesis of one break date (1 vs 2). Both sequential and repartition methods indicate the same break point date of 2001q1.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the

seasonal dummy variables that give shifts in the seasonal means in 2001q1, denoted $D(2001q1)_{st}$. The model including the seasonal dummy variables and the shift dummy variables is given in the column headed 2 of Table 5.2.2. All the seasonal dummy variables and the shift dummy variables are significant suggesting significant changes in the seasonal means at the identified break points. The significance of these shift dummy variables and that this model's SC falls to -0.091 supports the need to model the identified breaks.

Figure 5.2.1 plots the actual and fitted values of the model reported in column 2 of Table 5.2.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not capture all of the mean shifts in the actual data. The graph suggests two more mean shifts in 1997q2 and 1998q3 and we therefore add interaction dummy variables, denoted $D(1997q2)_{st}$ and $D(1998q3)_{st}$ to the model reported in column 2 to capture these shifts. The estimation results of these model break dates are reported in column 3 of Table 5.2.2. All the seasonal and the shift dummy variables are significant except $D(1997q2)_{3t}$ and $D(1997q2)_{4t}$. The SC of this model falls to -0.746 supports the inclusion of all of these interaction terms to in the model.

Figure 5.2.2 plots the actual and fitted values of the model reported in column 3 of Table 5.2.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts in the actual data than did model 2 (note the relative left-hand scales for the residuals in these two figures and how the fitted values are much closer to the actuals for model 3). We regard model 3 from Table 5.2.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of Russia's annual inflation.

Table 5.2.2: Deterministic component of ARIMAX models for Russia

Sample/Observation	1996q1 – 2012q4 (68)			
	1	2	3	4
D_{it}	0.229 (3.940)	0.551 5.735	0.541 (6.592)	
D_{2t}	0.211 (3.632)	0.494 (5.145)	0.587 (5.057)	
D_{3t}	0.194 (3.330)	0.431 (4.492)	0.374 (3.221)	
D_{4t}	0.181 (3.107)	0.381 (3.999)	0.242 (2.084)	
$D(1997q2)_{it}$			-0.447 (-3.147)	
$D(1997q2)_{2t}$			-0.476 (-3.352)	
$D(1997q2)_{3t}$			-0.229 (-1.394)	
$D(1997q2)_{4t}$			-0.124 (-0.753)	
$D(1998q3)_{1t}$			0.934 (5.690)	
$D(1998q3)_{2t}$			1.058 (7.449)	
$D(1998q3)_{3t}$			0.458 (3.226)	
$D(1998q3)_{4t}$			0.467 (3.307)	
$D(2000q1)_{1t}$		-0.420 (-3.827)	-0.897 (-7.449)	
$D(2000q1)_{2t}$		-0.370 (-3.367)	-1.045 (-8.675)	
$D(2000q1)_{3t}$		-0.311 (-2.829)	-0.483 (-5.478)	
$D(2000q1)_{4t}$		-0.266 (-2.421)	-0.470 (-5.334)	
I_RUS				1.000 (30.248)
Adj R^2	-0.041	0.333	0.757	0.880
SC	0.170	-0.091	-0.746	-2.128
S.E	0.240	0.192	0.116	0.082

Figure 5.2.1: the actual and fitted values of model 2 reported in Table 5.2.2

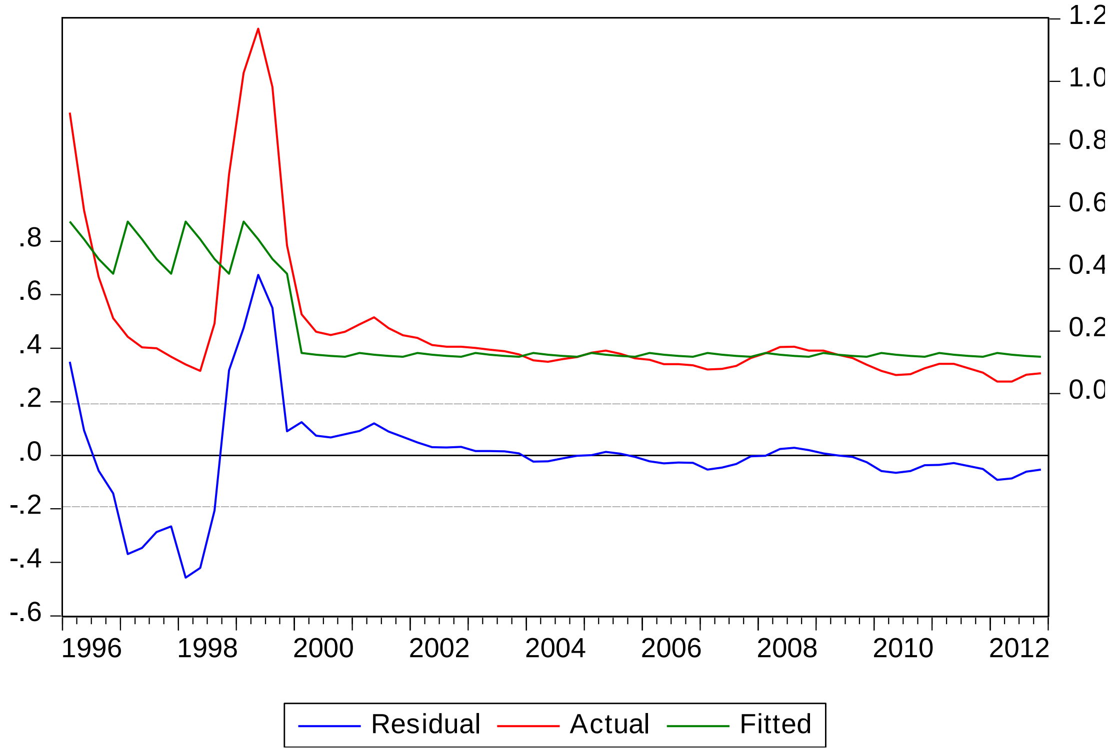
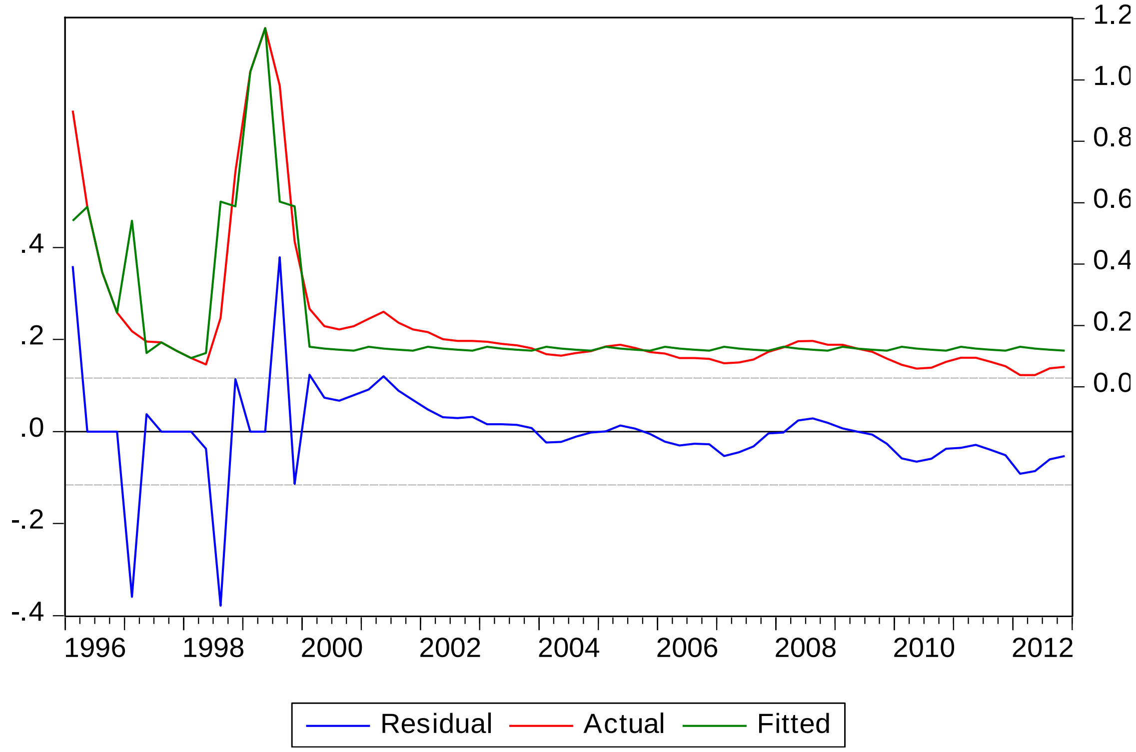


Figure 5.2.2: the actual and fitted values of model 3 reported in Table 5.2.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.2.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variables, denoted I_RUS, as the fitted value of the model reported in column 3 of Table 5.2.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.2.2. The index is significant and has a unit coefficient as is expected. This model's SC is -2.128 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

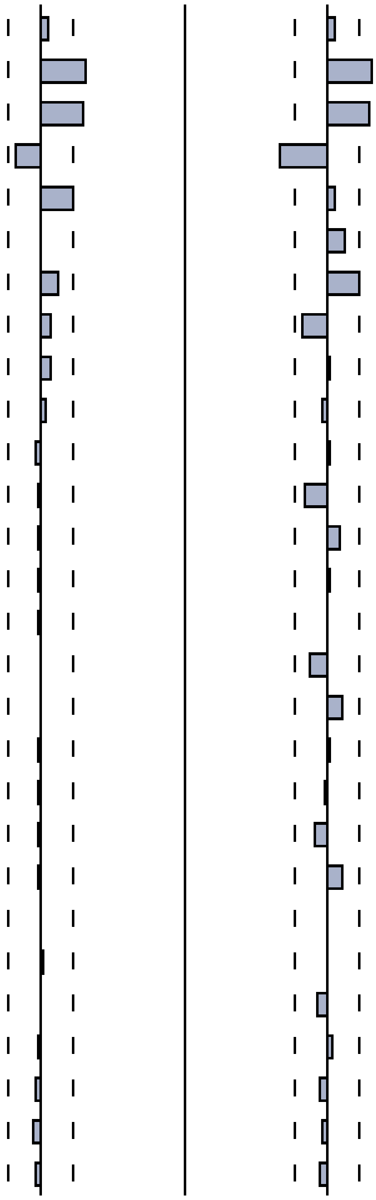
5.2.2 Developing the ARIMAX model for Russia

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.2.2 is plotted in Figure 5.2.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lag 2, 3 and 5 and insignificant at lags 1 and 4. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably equal to 0 although could be 3 or 5 (given the significance of the ACs at lag 2, 3 and 5). Further, all the seasonal ACs are insignificant at lags 4, 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12 16 and 20) are significant. This also indicates the maximum order of seasonal moving average (MA) component is probably equal to 0 or 1 (given the significance of the ACs at lag 5).

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 2, 3, 4 and insignificant at lags 1 and 5. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 0 although could be 3 (given the significance of the PAC at lag 2). The seasonal PACs are significant at lags 4 and insignificant at lags 8, 12, 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 1. The maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(3,3)(1,1)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_ RUS plus 4 seasonal dummy variables and an $ARMA(3,3)(1,1)_4$ model of the residuals in the column headed 5 of Table 5.2.3.

Figure 5.2.3: the ACF and PACF of the residuals of model 4 reported in Table 5.2.2

Sample: 1996Q1 2012Q4
Included observations: 68



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.061	0.061	0.2612	0.609
		2	0.326	0.323	7.9153	0.019
		3	0.304	0.304	14.705	0.002
		4	-0.175	-0.343	16.989	0.002
		5	0.227	0.051	20.894	0.001
		6	0.000	0.120	20.894	0.002
		7	0.124	0.230	22.090	0.002
		8	0.067	-0.179	22.447	0.004
		9	0.071	0.012	22.854	0.007
		10	0.039	-0.026	22.978	0.011
		11	-0.048	0.020	23.173	0.017
		12	-0.024	-0.166	23.222	0.026
		13	-0.020	0.093	23.257	0.039
		14	-0.022	0.022	23.302	0.056
		15	-0.010	-0.000	23.310	0.078
		16	-0.004	-0.127	23.312	0.106
		17	-0.005	0.104	23.314	0.139
		18	-0.017	0.012	23.340	0.178
		19	-0.018	-0.011	23.371	0.221
		20	-0.013	-0.083	23.387	0.270
		21	-0.011	0.105	23.398	0.323
		22	0.007	0.007	23.404	0.379
		23	0.017	0.001	23.433	0.436
		24	0.001	-0.075	23.433	0.494
		25	-0.014	0.038	23.455	0.551
		26	-0.025	-0.055	23.528	0.603
		27	-0.050	-0.034	23.823	0.640
		28	-0.047	-0.054	24.086	0.677

We report the multiplicative $ARMA(3,3)(1,1)_4$ specification that includes I_RUS plus 4 seasonal dummy variables as our initial ARIMAX model in the column headed 5 Table 5.2.3. In this model the SC increase to -1.835 suggesting that the addition of ARMA terms has not improved the specification. I_RUS is significant whereas all 4 seasonal dummy variables are insignificant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.782 (given in squared brackets below the reported test statistic). Because this exceeds 0.05 these 4 dummy variables are jointly insignificant. The non-seasonal moving average MA (1) and MA(3) terms are significant in model while all other ARMA components are insignificant. These results suggest that the specification can be improved by the inclusion or exclusion of some combination of deterministic and ARMA terms.

Table 5.2.3. The ARIMAX table for Russia

Sample/Observations	1996q1 – 2012q4 (68)			
	5	6	7	8
I_RUS	1.084 (14.642)	1.049 (12.663)	1.016 (14.421)	1.030 (30.170)
D_1	-0.0123 (-0.601)	-0.014 (-0.601)	-0.009 (-0.443)	
D_2	-0.016 (-0.771)	-0.009 (-0.387)	-0.009 (-0.434)	
D_3	-0.012 (-0.606)	-0.003 (-0.142)	-0.004 (-0.198)	
D_4	-0.016 (-0.838)	-0.009 (-0.418)	-0.007 (-0.339)	
AR(1)	-0.207 (-1.683)	0.069 (0.371)		
AR(2)	0.145 (1.742)	-0.003 (-0.026)		
AR(3)	-0.163 (-1.743)	-0.064 (-0.566)		
AR(4)		0.016 (0.241)		
SAR(4)	0.042 (0.779)			
MA(1)	0.371 (2.733)	0.034 (0.164)	0.184 (1.403)	0.177 (0.324)
MA(2)	0.170 (1.548)	0.475 (2.603)	0.511 (4.432)	0.852 (0.930)
MA(3)	0.799 (7.049)	0.527 (3.167)	0.468 (3.633)	0.671 (1.075)
MA(4)		-0.479 (-2.896)	-0.431 (-3.397)	-0.798 (-1.791)
SMA(4)	-0.299 (-1.750)			
MA(5)		0.434 (2.245)	0.428 (2.981)	0.563 (1.215)
Adj R^2	0.907	0.923	0.932	0.955
SC	-1.835	-1.985	-2.278	-2.351
S.E	0.071	-1.985	0.062	0.050
AR Root	0.721 0.475 0.452	0.439 0.404 0.219		
MA Root	0.999 0.894 0.739	0.999 0.980 0.673	0.999 0.992 0.659	1.189 1.066 0.611
P[QLB(8)]	0.000	0.000	0.519	0.069
LR (SEA DUM)	1.751 [0.782]	-46.099[145]	9.425 [0.051]	
LR (SEA DUM, CON)			12513.370 [0.000]	
$LR(1997q2)$	11.149 [0.025]	-3.200[146]	3.178 [0.529]	7.144 [0.129]
$LR(1998q3)$	25.805 [0.000]	8.751 [0.068]	6.261 [0.181]	24.910 [0.000]
$LR(2000q1)$	19.393 [0.001]	40.402 [0.000]	7.891 [0.096]	32.681 [0.000]

[145] The test statistic has negative value and therefore no p- value. However, the test statistic is clearly very small and therefore is highly insignificant.

[146] The test statistic has negative value and therefore no p- value. However, the test statistic is clearly very small and therefore is highly insignificant.

Where: I_RUS = the fitted value of the model reported in column 3 of Table 5.2.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(8)] = Probability value of the Ljung-Box Q-statistic at the 8th lag from - based on the square root of the sample size ($\sqrt{68}$), Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables; $LR(1997q2)$,$LR(1998q3)$ and $LR(2001q1)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We also conduct variable addition tests for the shift dummy variables included in the I_RUS variable to determine whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA terms. A test of whether the shift dummy variable corresponding to the 1997q2 break can be added to the model with joint significance is reported in the row labelled $LR(1997q2)$. Since the probability value (0.025) is less than 0.050, this variable can be added with joint significance. Similarly, the probability values of other joint test for shift dummy variables corresponding to the break dates 1998q3 and 2000q1 reported in the rows labelled $LR(1998q3)$ and $LR(2001q1)$ respectively, are also less than 0.050 indicating that the shift variables for these dates can be added with joint significance. This suggests that the coefficients embodied in $ARMA(3,3)(1,1)_4$ have significantly changed with the addition of ARMA terms.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 8th lag, denoted P[QLB(8)], is less than 0.050 indicating evident of residual autocorrelation that suggests unmodelled systematic variation in the dependent variable and the need to adjust the model – we choose lag 8 based on the square root of the sample size (in this case $\sqrt{68}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible.

However, this model cannot be valid for forecasting due to the evidence of residual autocorrelation. Therefore, we amend the model reported in the column headed 5 of

Table 5.2.3 and estimate an ARMA $(4, 5)_4$.[147] This result is reported in the column headed 6 Table 5.2.3. The SC of this model decrease to -1.985 suggesting that the addition of ARMA terms has improved the specification. In terms of specification, the coefficient of I_RUS is significant whereas the 4 seasonal dummy variables are insignificant. The non-seasonal moving average terms MA(2), MA(3), MA(4) and MA(5) are significant while the non-seasonal autoregressive variables' coefficients, denoted AR(1) AR(2), AR(3) AR(4) and non-seasonal moving average MA(1) term are insignificant.

According to the standard diagnostic checks the model is stationarity and invertible however there is an evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model.

Therefore, we exclude the insignificant components of AR terms from the model reported in the column headed 6 from Table 5.2.3 and report the resulting $ARMAX(0, 5)$ in the column headed 7 of Table 5.2.3. Therefore, we exclude insignificant coefficients of AR(1) AR(2), AR(3) and AR(4). We did not exclude the insignificant MA(1) term because the higher order MA components are included. The SC of this model has decreased to -2.278 suggesting that the exclusion of insignificant of ARMA terms has improved the specification. The coefficient of I_RUS is significant whereas all 4 seasonal dummy variables are insignificant. All the ARMA components are significant except for the MA(1) term, which we would not remove because the other MA terms are significant.

The tests for the addition of the 3 sets of shift dummy variables, the tests $LR(1997q2)$, $LR(1998q3)$ and $LR(2001q1)$, all have probability values that exceed 0.050 indicating that the coefficients embodied in I_RUS have not significantly changed as the ARMA specification is amended.

This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. However, the seasonal dummy variables are jointly insignificant (see LR(SEA DUM)). Therefore, we exclude the seasonal dummy variables that are jointly insignificant (see LR(SEA DUM)) from the model reported in the

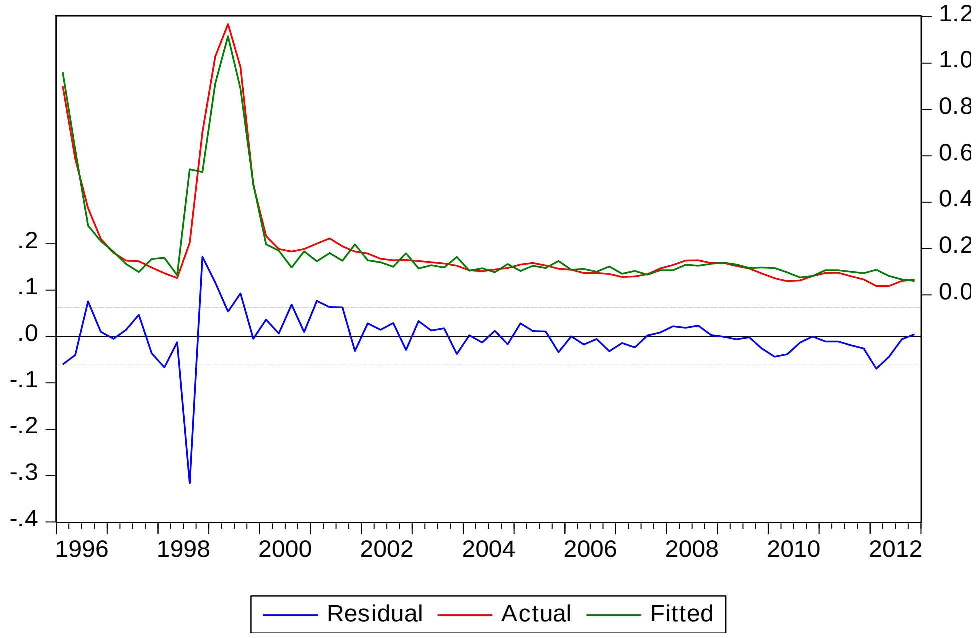
[147] Since (MA) component is significant at lag 2, 3 and 5 and (AR) component is at significant at lag 2, 3 and 4 (see figure 6.2.3). However, we avoid inclusion of seasonal SAR (4) since the presence of AR(4)

column headed 7 in the Table 5.2.3 and this result is reported in the Table 5.2.3 column 8. In this model the SC falls to -2.351 and the coefficient of I_RUS is significant.

The test for the shift dummy variable corresponding to $LR(1997q2)$ is insignificant while $LR(1998q3)$ and $LR(2001q1)$ are significant. Notably, this test indicates the warning of MA backcasts differ for the original test equation and under the null hypothesis, the impact of this difference vanishes asymptotically. Consequently, the two of the MA inverse roots is greater than one suggesting that this model could not be valid in the sense that the model is non- invertible.

Therefore, we regard model 7 from Table 5.2.3 as the best ARIMAX model for forecasting Russia's annual inflation because the model passed diagnostic test for stationary, autocorrelation and invertible. Although the seasonal dummy variables are jointly insignificant and required to be significant. Since the probability value of the dummy variable of this model is close to 0.05 (see LR(SEA DUM)). Furthermore, we test the null hypothesis of whether the coefficients of the seasonal dummy variables, D_{1t}, D_{2t}, D_{3t} and D_{4t}, are the same using a Wald test. This test is reported in the row labelled LR (SEA DUM, CON) of column 7 and the probability value is 0.000. Since this value is less than 0.050, we reject the null hypothesis (of no seasonality) and accept the alternative hypothesis. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 7 in Table 5.2.3 is considered the best model to forecast Russia's annual inflation.

Figure 5.2.4: the actual and fitted values reported in Table 5.2.3 column 7



The visual inspection of the above figure revealed that the actual and fitted values graph of this model suggests that the time paths of the actual and fitted values capture all of the mean shifts in the actual data well.

5.3 ARIMAX modelling of annual inflation for India

The maximum available sample period is 1957q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1961q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARIMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.3.1 Bai and Perron tests for structural breaks in India annual inflation

Break Test	F-statistic	Scaled F-statistic	Critical Value
0 vs 1	1.380	5.521	16.19

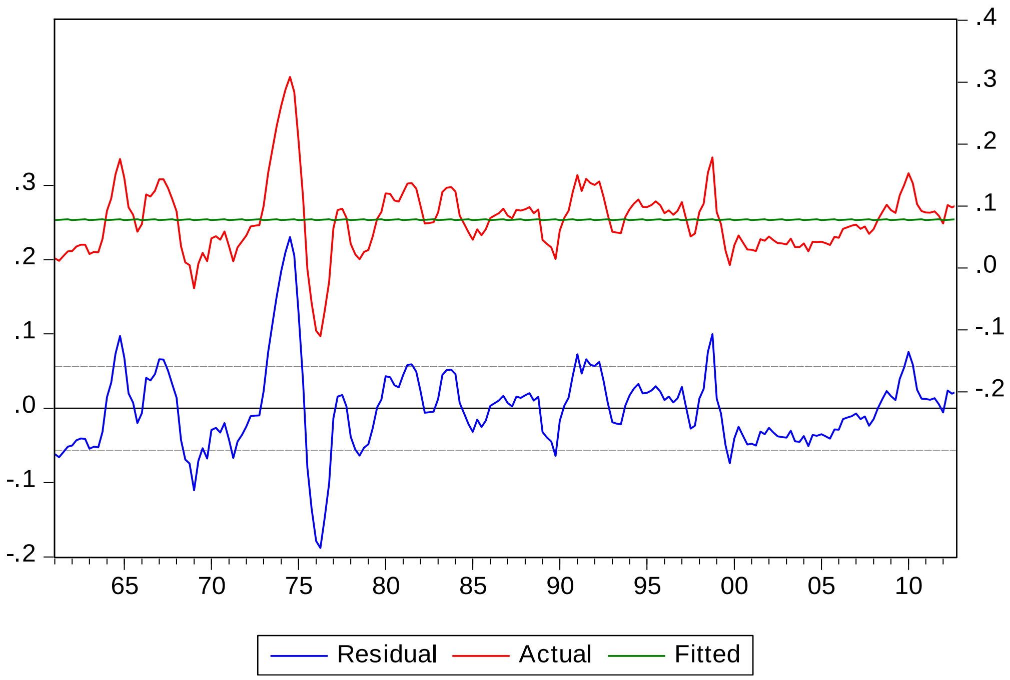
In Table 5.3.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -2.828 which supports the need to include these dummy variables.

Table 5.3.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.3.2. The evidence revealed that there is no substantial break because the scaled F- Statistic is less than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). Figure 5.3.1 plots the actual and fitted values of the model reported in column 1 of Table 5.3.2. Visual inspection of this graph suggests that this deterministic model captures the actual data well. Therefore, we use this model as the basis of the deterministic component of our ARIMAX model of Indian's annual inflation.

Table 5.3.2: Deterministic component of ARIMAX models for India

Sample/Observation	208
	1
D_{1t}	0.077 (9.859)
D_{2t}	0.078 (9.912)
D_{3t}	0.078 (9.965)
D_{4t}	0.079 (10.048)
Adj R^2	-0.015
SC	-2.828
S.E	0.057

Figure 5.3.1: the actual and fitted values reported in Table 5.3.2



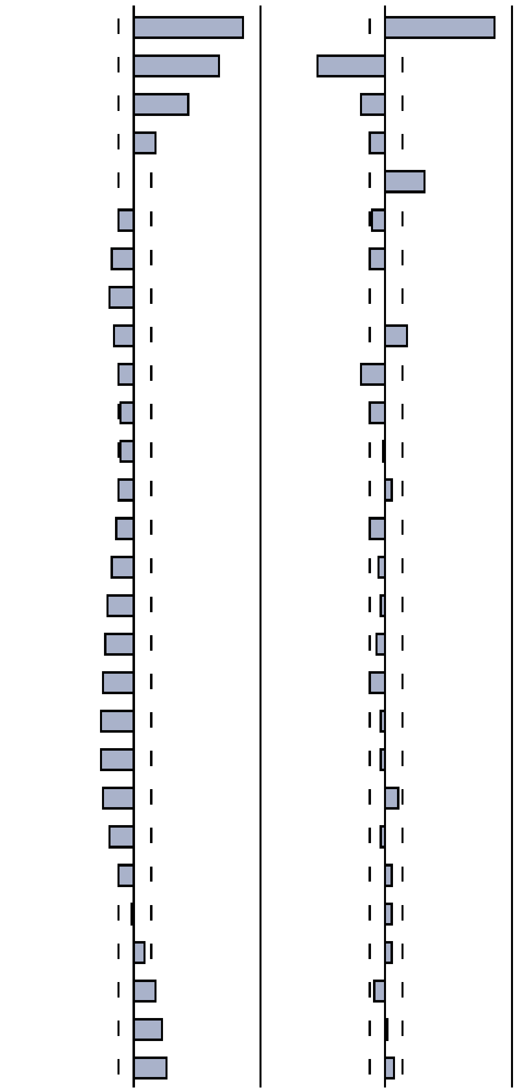
5.3.1 Developing the ARIMAX model for India

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in Table 5.3.2 is plotted in Figure 5.3.1. The ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lag 1, 2, 3 and insignificant at lag 5. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are significant at lags 4, 8, 16, 20, 28 and insignificant at lags 12, and 24. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 2 (the seasonal lags 4 and 8).

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1, 2 and 3. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 3. The seasonal PACs are significant at lags 4 and insignificant at lags 8, 12, 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 1 or 2 given the significance of PAC at lag 9. Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(3,3)(2,2)_4$. Assuming a multiplicative specification, we report an ARIMAX specification that includes 4 seasonal dummy variables and an $ARMA(3,3)(2,2)_4$ model of the residuals in the of Table 5.3.2.

Figure 5.3.2: the ACF and PACF of the residuals of model reported in Table 5.3.2

Sample: 1961Q1 2012Q4
Included observations: 208



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.898	0.898	170.24	0.000
		2	0.698	-0.565	273.44	0.000
		3	0.448	-0.189	316.28	0.000
		4	0.188	-0.122	323.88	0.000
		5	-0.000	0.328	323.88	0.000
		6	-0.120	-0.109	327.01	0.000
		7	-0.188	-0.133	334.68	0.000
		8	-0.199	0.008	343.37	0.000
		9	-0.169	0.180	349.61	0.000
		10	-0.135	-0.200	353.66	0.000
		11	-0.111	-0.138	356.38	0.000
		12	-0.103	-0.013	358.73	0.000
		13	-0.121	0.063	362.01	0.000
		14	-0.154	-0.124	367.33	0.000
		15	-0.184	-0.059	374.98	0.000
		16	-0.212	-0.043	385.23	0.000
		17	-0.239	-0.080	398.29	0.000
		18	-0.258	-0.120	413.58	0.000
		19	-0.270	-0.026	430.42	0.000
		20	-0.275	-0.042	447.98	0.000
		21	-0.250	0.108	462.57	0.000
		22	-0.198	-0.029	471.78	0.000
		23	-0.123	0.052	475.32	0.000
		24	-0.019	0.062	475.41	0.000
		25	0.089	0.050	477.32	0.000
		26	0.180	-0.097	485.10	0.000
		27	0.245	0.018	499.57	0.000
		28	0.276	0.077	518.08	0.000

The SC of the $ARMA(3,3)(2,2)_4$ decreases to -5.332 and all 4 seasonal dummy variables are significant suggesting that the addition of ARMA terms has improved the specification. We test for the joint exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.001 (given in square brackets below the reported test statistic). Because this less than 0.05 these 4 dummy variables are jointly significant. All the ARMA components are significant except the second non seasonal MA variables' and second seasonal AR variable coefficients, denoted MA(2) and AR(8) respectively.

Table 5.3.3: The ARIMAX table for India

Sample/Observations		1961q1 2012q4 (208)			
	2	3	4	5	6
D_1	0.080 (69.333)	0.080 (83.215)	0.080 (52.248)	0.080 (9.585)	0.080 (8.732)
D_2	0.080 (68.652)	0.079 (82.259)	0.080 (52.137)	0.080 (9.572)	0.079 (8.717)
D_3	0.080 (68.490)	0.079 (82.750)	0.080 (52.101)	0.080 (9.562)	0.079 (8.709)
D_4	0.080 (69.085)	0.080 (83.042)	0.079 (52.256)	0.080 (9.581)	0.079 (8.728)
AR(1)	0.755 (6.889)	0.670 (5.189)	1.556 (3.496)	0.195 (0.398)	0.489 (6.973)
AR(2)	0.886 (20.233)	0.861 (15.289)	-0.503 (-0.730)	0.272 (1.101)	0.126 (1.600)
AR(3)	-0.693 (-6.664)	-0.610 (-4.722)	-0.090 (-0.342)	0.168 (1.746)	0.112 (1.435)
AR(4)				-0.094 (-1.127)	-0.186 (-2.669)
AR(5)				-0.180 (-1.780)	
SAR(4)	-0.781 (-5.807)	-0.672 (-7.383)	-0.911 (-27.788)		
SAR(8)	-0.147 (-1.948)				
MA(1)	0.712 (5.644)	0.790 (5.670)	-0.121 (-0.271)	1.279 (2.570)	1.005 (61.557)
MA(2)	-0.220 (-1.164)	-0.077 (-0.354)		1.279 (2.559)	1.000 (61.251)
MA(3)	0.062 (-2.531)	0.129 (1.163)		1.246 (2.519)	0.980 (88.145)
MA(4)				0.263 (0.542)	
SMA(4)	-0.258 (-2.531)	-0.229 (-2.715)	-0.019 (-0.999)		
SMA(8)	-0.258 (-2.531)	-0.771 (-9.180)	-0.955 (-51.184)		
Adj R^2	0.933	0.932	0.931	0.927	0.926
SC	-5.332	-5.341	-5.367	-5.271	-5.307
S.E	0.041	0.015	0.015	0.015	0.015
AR Root	0.949 0.855 0.751	0.939 0.905 0.806	0.977 0.846 0.126	0.778 0.691 0.622	0.695 0.621
MA Root	0.999 0.995 0.928	0.999 0.937 0.359	0.997 0.992 0.121	0.992 0.989 0.269	0.994 0.992
P[QLB(14)]	0.076	0.065	0.026	0.260	0.163
LR (SEA DUM)	18.427 [0.001]	15.371 [0.004]	16.409 [0.003]	9.560 [0.049]	29.925 [0.000]
LR (SEA DUM, CON)					12.580 [0.000]

Where: S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non-seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(14)] = Probability value of the Ljung-Box Q-statistic at the 14th lag from - based on the square root of the sample size ($\sqrt{208}$), Adj R^2 = Adjusted R – square , **SC =** Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 14th lag, denoted P[QLB(14)], exceeds 0.050 indicating no evident residual autocorrelation – we choose lag 14 based on the square root of the sample size (in this case $\sqrt{208}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests.

However, as indicated above the specification can be improved with the removal of some variables that are not significant. The coefficients on the MA(2) and SAR(8) terms are not significant and are candidates for exclusion. Since the MA(3) term is significant we do not remove the MA(2) term to retain the full third-order non seasonal MA component. Therefore, we remove the SAR(8) term from the model reported in the column headed 2 from Table 5.3.3 and report the resulting $ARMA(3,3)(1,2)_4$ in the column headed 3 of Table 5.3.3.

This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification all variables are significant except for the MA(2) and MA(3) terms. The seasonal dummy variables are jointly significant according to LR(SEA DUM) because its probability value is less than 0.05.

However, as indicated above the specification can be improved with the removal of some variables that are not significant. The coefficients on the MA(2) and MA(3) terms are not significant. Therefore, we remove the MA(2) and MA(3) terms from the model reported in the column headed 3 from Table 5.3.3 and report the resulting $ARMA(3,1)(1,2)_4$ in the column headed 4 of Table 5.3.3. In this model, the ARMA coefficient of MA(1), SMA(4), AR(2) and AR(3) are insignificant while the ARMA coefficient for AR(1) , SAR(4) and SMA(8) are significant.

According to the standard diagnostic checks, this model is stationary and invertible however there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model. We confirmed the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM) has a probability value that is less than 0.05 suggesting that theses dummy variables are jointly significant.

Therefore $ARMA(3,1)(1,2)_4$ needs to be re-amended, hence we estimate an $ARMAX(5,4)$ that based on experimentation.[148] The results of this model is reported in the column headed 5 Table 5.3.3. The coefficients on the four dummy variables are significant. The non-seasonal autoregressive variables' coefficients, denoted AR(1) AR(2), AR(3), AR(4), AR(5) and non-seasonal moving average MA(4) are insignificant. While the non-seasonal moving average terms, MA(1), MA(2) and MA(3) are significant.

We apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic test exceeds 0.050 indicating no evident residual autocorrelation.

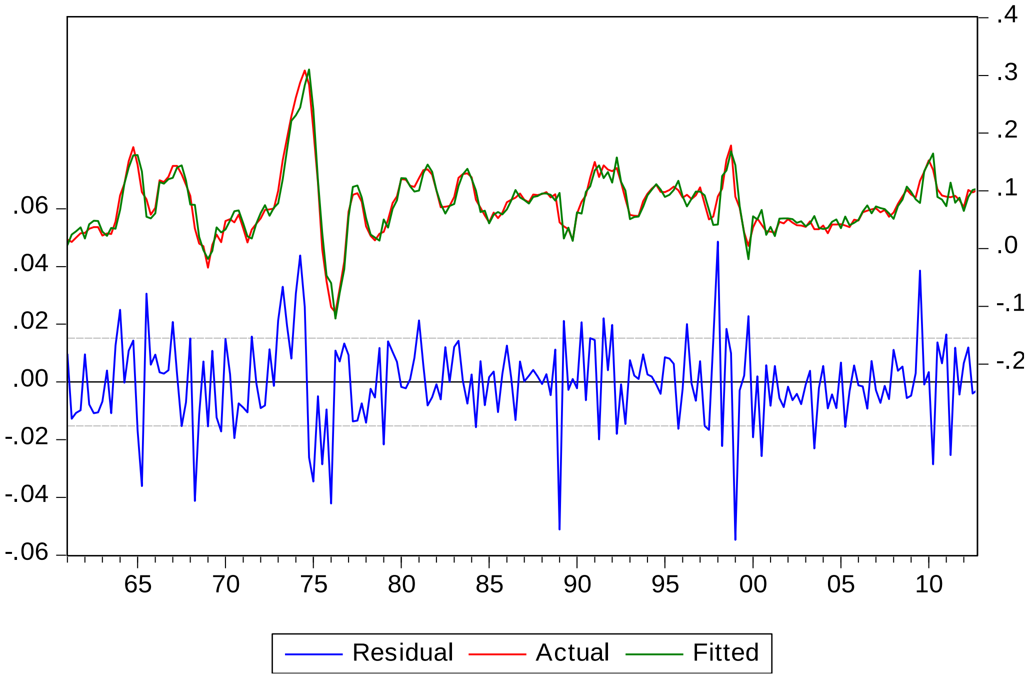
However, as indicated above the specification can also be improved with the removal of some variables. The coefficients on the AR(1) AR(2) AR(3) AR(4) AR(5) and MA(4) terms that are not significant and are candidates for exclusion. Hence, experimentation with the ARMA terms suggest excluding the MA(4) and AR(5) terms from the model reported in the column headed 5 Table 5.3.3 is significant. The resulting $ARMAX(4,3)$ specification is reported in the column headed 5 of Table 5.3.3.

This model's SC decreases to -5.307 suggesting that the exclusion of the MA(4) and AR(5) terms from the model reported in the column headed 6 Table 5.3.3 has improved the specification. The coefficients on all the ARMA components are significant except for the AR(2) and AR(3) terms, which we would not exclude because the AR(4) term that is significant. Notably, the seasonal dummy variables are now individually and jointly significant (see LR(SEA DUM)). This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility Therefore it is valid for forecasting. We test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 6. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients

[148] The (MA) component is significant at lag, 1,2, 3 and 4 and (AR) component is significant at lag 1, 2, 3, 4 and 5 (see figure 5.3.2). However, we did not include seasonal SAR (4) and SMA(4) since the presence of AR(4) and MA(4).

of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 6 in Table 5.3.3 is considered the best model to forecast India's annual inflation.

Figure 5.3.3: the actual and fitted values reported in Table 5.3.3 column 6



The visual inspection of the actual and fitted values graph of this model suggests that the time paths of the fitted values capture the movements in the actual data well.

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5.4 Box-Jenkins ARIMAX modelling of annual inflation for China

The maximum available sample period for estimation is 1988q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1992q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.4.1: Bai and Perron tests for structural breaks in Chinese annual inflation

	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	21.631	16.19	1996q3	1998q1
1 vs 2	26.220	18.11	2004q4	2004q4
2 vs 3	11.552	18.93		

In Table 5.4.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -3.239.

Table 5.4.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.4.2. The test results indicate that there are two significant breakpoints because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1) and the null hypothesis of one break (1 vs 2). However, the scaled F-statistic is less than critical value for the null hypothesis of 2 breaks (2 vs 3). The sequential and repartition methods indicate different break point dates. The sequential method indicates the multiple break point dates of 1996q3 and 2004q4 while repartition method indicates the multiple break point dates of 1998q1 and 2004q4.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the

seasonal dummy variables that give shifts in the seasonal means in 1996q3, denoted $D(1996q3)_{st}$, 1998q1, denoted $D(1998q1)_{st}$ and 2004q4, denoted $D(2004q4)_{st}$.

Table 5.4.2 column 2 estimates the seasonal dummy and the shift dummy variables $D(1996q3)_{st}$ and $D(2004q4)_{st}$ indicated by Bai and Perron's sequential test (see Table 5.4.1). In this table, all the four seasonal dummy variables and the shift dummy variables are significant. The significance of these variables and that the model's SC falls to -3.967 supports the need to model the identified breaks.

Figure 5.4.1 plots the actual and fitted values of the model reported in column 2 of Table 5.4.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not properly capture all of the mean shifts in the actual data in the late 1990s. Therefore, we consider the model including the shift seasonal dummy variables $D(1998q1)_{st}$ and $D(2004q4)_{st}$as indicated by Bai and Perron's repartition test, which is given in the column headed 3 of Table 5.4.2. We note that all four seasonal dummy variables and the shift dummy variables are significant and that this new model's SC falls to -4.253.

Figure 5.4.2 plots the actual and fitted values of the model reported in column 3 of Table 5.4.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts in the actual data than did model 2 (which is confirmed by model 3 having the lowest SC). We regard model 3 from Table 5.4.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of Chinese annual inflation.

Table 5.4.2: Deterministic component of ARIMAX models for China

Sample/Observation	1992q1 2012q4 (84)			
	1	2	3	4
D_{it}	0.033 (3.421)	0.072 (6.105)	0.067 (7.228)	
D_{2t}	0.032 (3.372)	0.069 (5.857)	0.063 (6.783)	
D_{3t}	0.032 (3.323)	0.074 (5.616)	0.062 (6.683)	
D_{4t}	0.032 (3.287)	0.071 (5.430)	0.059 (6.331)	
$D(1996q3)_{it}$		-0.083 (-5.612)		
$D(1996q3)_{2t}$		-0.082 (-5.503)		
$D(1996q3)_{3t}$		-0.081 (-5.168)		
$D(1996q3)_{4t}$		-0.083 (-5.175)		
$D(1998q1)_{it}$			-0.087 (-6.918)	
$D(1998q1)_{2t}$			-0.083 (-6.582)	
$D(1998q1)_{3t}$			-0.085 (-6.572)	
$D(1998q1)_{4t}$			-0.085 (-6.544)	
$D(2004q4)_{1t}$		0.066 (5.069)	0.075 (6.340)	
$D(2004q4)_{2t}$		0.070 (5.308)	0.076 (6.498)	
$D(2004q4)_{3t}$		0.064 (5.013)	0.077 (6.561)	
$D(2004q4)_{4t}$		0.065 (5.087)	0.080 (6.684)	
I_CHI				1.000 (21.485)
Adj R^2	-0.037	0.635	0.726	0.762
SC	-3.239	-3.967	-4.253	-4.833
S.E	0.044	0.026	0.002	0.021

Figure 5.4.1: the actual and fitted values of model 2 reported in Table 5.4.2

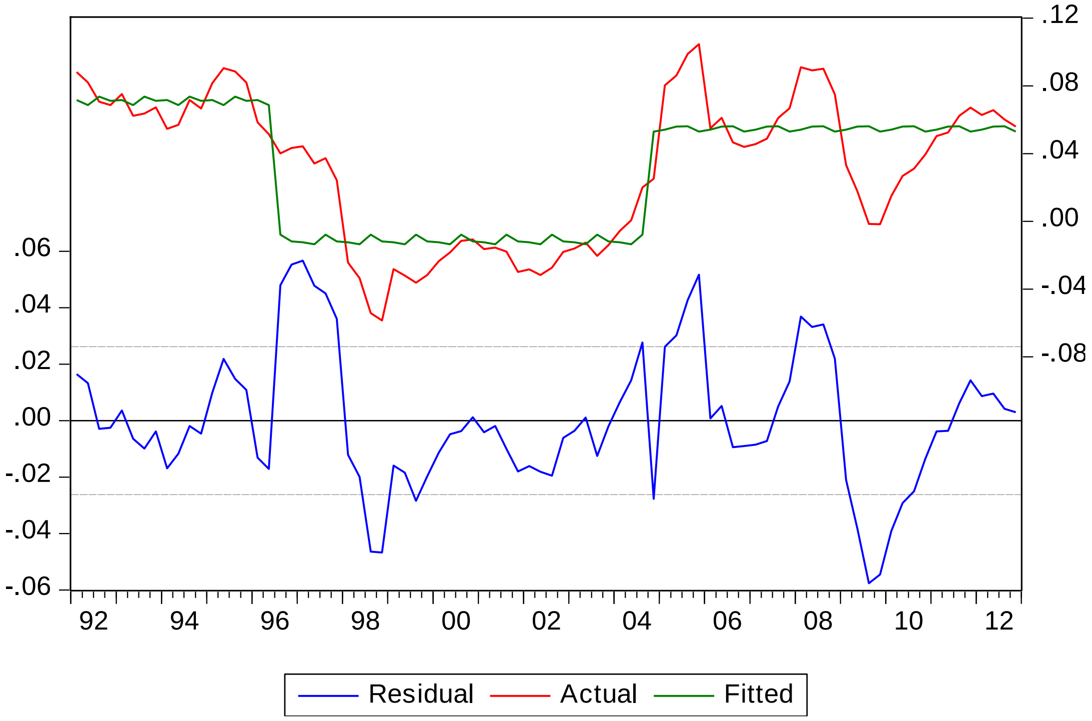
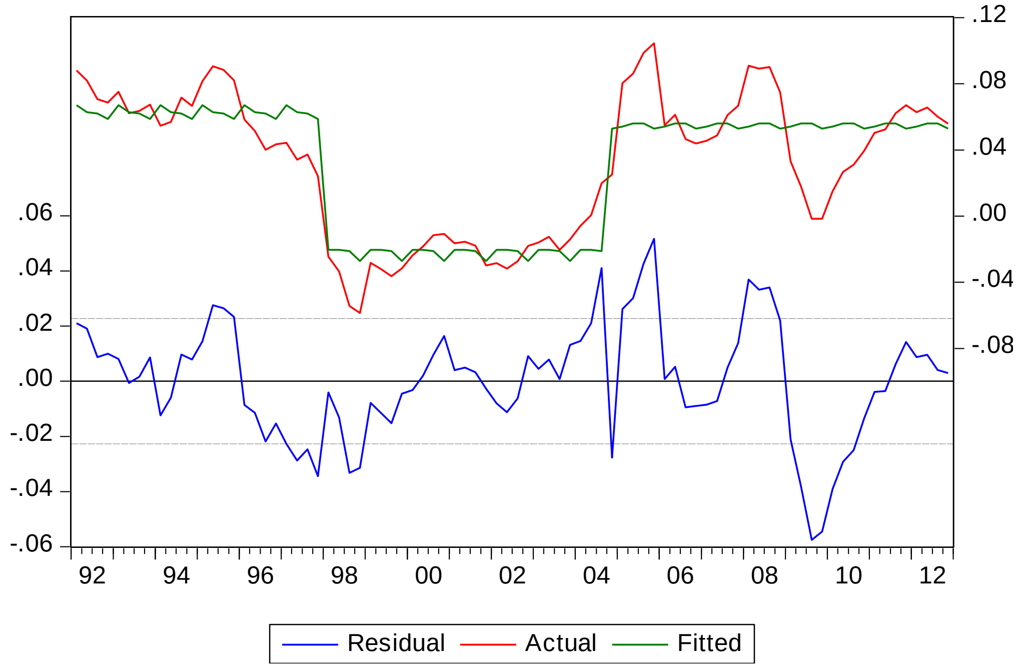


Figure 5.4.2: the actual and fitted values of model 3 reported in Table 5.4.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.4.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_CHI, as the fitted value of the model reported in column 3 of Table 5.4.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.4.2. The index is significant and has a unit coefficient as is expected. This model's SC is -4.833 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

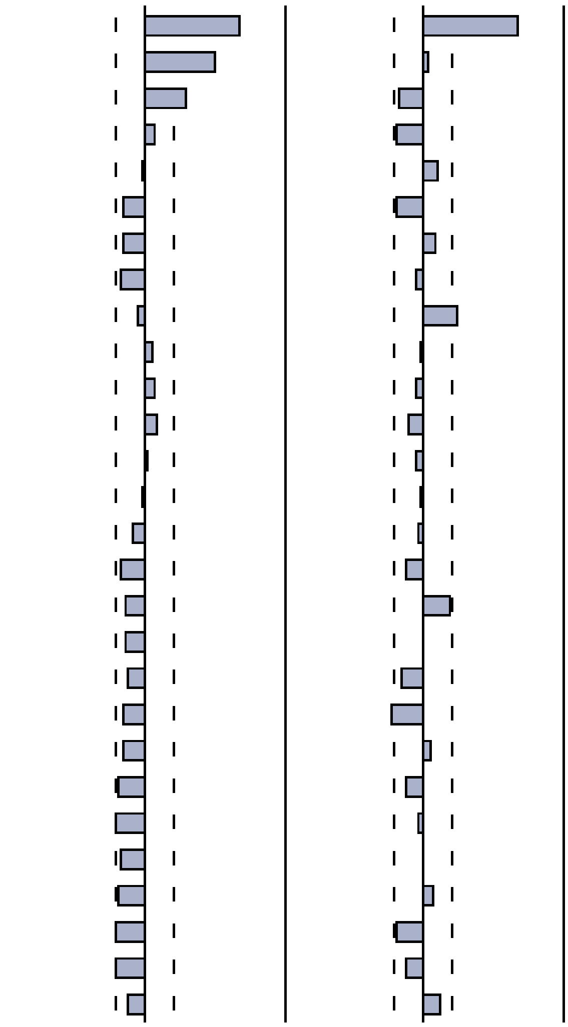
5.4.2 Developing the ARIMAX model for China

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.4.2 are plotted in Figure 5.4.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1, 2, 3 and insignificant at lags 4 and 5. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are insignificant at lags 4, 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates that the maximum order of seasonal moving average (MA) component is probably equal to zero.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1 and insignificant at 2, 3, 4 and 5. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 1. Furthermore, the seasonal PACs are insignificant at lags 4, 8, 12, 16, 24 and 28. However, PAC is significant at lag 9 and 20. Therefore, the maximum order of seasonal AR process is probably equal to 0 or 2 (in multiplicative form) given the significance of PAC at lag 9. Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(1,3)(2,0)_4$. Assuming a multiplicative specification we report an ARIMAX model that includes I_CHI plus 4 seasonal dummy variables and an $ARMA(1,3)(2,0)_4$ model of the residuals in the column headed 5 of Table 5.4.3.

Figure 5.4.3: the ACF and PACF of the residuals of model 4 reported in Table 5.4.2

Sample: 1992Q1 2012Q4
Included observations: 84



Lag	AC	PAC	Q-Stat	Prob
1	0.712	0.712	44.078	0.000
2	0.524	0.036	68.298	0.000
3	0.296	-0.182	76.092	0.000
4	0.066	-0.197	76.485	0.000
5	-0.013	0.112	76.499	0.000
6	-0.163	-0.189	78.952	0.000
7	-0.161	0.085	81.384	0.000
8	-0.175	-0.053	84.300	0.000
9	-0.052	0.256	84.565	0.000
10	0.053	-0.018	84.839	0.000
11	0.076	-0.062	85.415	0.000
12	0.096	-0.106	86.337	0.000
13	0.010	-0.058	86.347	0.000
14	-0.019	-0.016	86.385	0.000
15	-0.091	-0.036	87.254	0.000
16	-0.185	-0.130	90.871	0.000
17	-0.150	0.200	93.291	0.000
18	-0.147	-0.006	95.671	0.000
19	-0.135	-0.162	97.694	0.000
20	-0.166	-0.237	100.81	0.000
21	-0.172	0.049	104.18	0.000
22	-0.199	-0.131	108.79	0.000
23	-0.220	-0.027	114.53	0.000
24	-0.179	-0.007	118.41	0.000
25	-0.196	0.070	123.09	0.000
26	-0.207	-0.197	128.44	0.000
27	-0.216	-0.124	134.38	0.000
28	-0.123	0.122	136.33	0.000

In this model the SC falls to -5.529 suggesting that the addition of ARMA terms has improved the specification. I_CHI is insignificant and all 4 seasonal dummy variables are insignificant. The joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM) has a probability value of 0.929. Because this greater than 0.05 these 4 dummy variables are jointly insignificant. The first non-seasonal autoregressive variable's coefficients, denoted AR(1) is significant while the first and second seasonal autoregressive variable's coefficient, denoted as SAR(4) and SAR(8) are significant. All the moving average terms are significant except MA(3).

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 9th lag, denoted P[QLB(9)], exceeds 0.050 indicating no evident residual autocorrelation – we choose lag 9 based on the square root of the sample size (in this case $\sqrt{84}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible.

We conduct variable addition tests for the shift dummy variables included in the model to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA components. A test of whether the shift dummy variables corresponding to the 1998q1 break can be added to the model with joint significance is reported in the row labelled $LR(1998q1)$. Since the probability value (given in square brackets below the test statistic, being 0.148) exceeds 0.050 these variables cannot be added with joint significance. However, the probability values of the joint tests of the shift dummy variable corresponding to the break date 2004q4, reported in the rows labelled $LR(2004q4)$ is less than 0.050.

Table 5.4.3: The ARIMAX table for China

Sample/Observations		1992q1 – 2012q4 (84)				
	5	6	7	8	9	10
I_CHI	0.167 (1.933)					
I_CHI2		0.250 (2.237)				
I_CHI3			0.323 (2.743)	0.297 (2.546)		
I_CHI4					1.037 (5.778)	0.094 (1.281)
D_{it}	0.021 (0.971)	0.026 (1.072)	0.032 (1.187)	0.035 (2.270)	-0.027 (-1.600)	
D_{2t}	0.022 (0.980)	0.026 (1.072)	0.031 (1.179)	0.034 (2.252)	-0.023 (--1.382)	
D_{3t}	0.022 (0.985)	0.026 (1.071)	0.032 (1.175)	0.034 (2.244)	-0.020 (-1.246)	
D_{4t}	0.021 (0.974)	0.026	0.032 (1.197)	0.035 (2.278)	-0.015 (-0.959)	
AR(1)	0.937 (18.392)	0.943 (18.914)	0.946 (18.723)	0.412 (3.562)	0.378 (2..953)	0.429 (3.174)
AR(2)				0.306 (2.704)	0.341 (2.789)	0.486 (3.959)
SAR(4)	-0.522 (-3.722)	-0.519 (-3.769)	-0.480 (-3.315)			
SAR (8)	-0.350 (-2.740)	-0.361 (-2.839)	-0.372 (-2.917)			
MA(1)	0.321 (2.442)	0.342 (2.628)	0.422 (3.229)	0.992 (16.255)	0.904 (10.427)	1.089 (7.452)
MA(2)	0.431 (3.069)	0.368 (2.593)	0.229 (1.602)	0.999 (13.958)	0.773 (7.692)	0.676 (5.838)
MA(3)	0.105 (0.718)	0.155 (1.051)	0.324 (2.185)	0.991 (19.831)	0.868 (11.057)	0.891 (7.474)
Adj R^2	0.924	0.926	0.928	0.941	0.943	0.944
SC	**-5.529**	**-5.556**	**-5.577**	**-5.878**	**-5.902**	**-6.079**
S.E	0.012	0.012	0.012	0.010	0.010	0.010
AR Root	0.937 0.877	0.943 0.881	0.946 0.884	0.796 0.384	0.803 0.425	0.944 0.515
MA Root	0.643 0.254	0.624 0.397	0.724 0.669	0.999 0.991	0.999 0.932	1.165 0.874
P[QLB(9)]	0.055	0.050	0.014	0.128	0.163	0.058
LR (SEA DUM)	0.868 [0.929]	0.843 [0.933]	1.392 [0.846]	6.525 [0.163]	3.120 [0.540]	
LR (SEA DUM, CON)					10.986 [0.000]	
$LR(1998q1)$	6.787 [0.148]	7.334 [0.119]	19.887 [0.001]	14.569 [0.005]	-2.119	3.259 [0.515]
$LR(2004q4)$	11.472 [0.022]	9.619 [0.047]	7.846 [0.097]	-5.777	-31.095	-14.687

Where: I_CHI = the fitted value of the model reported in column 3 of Table 5.4.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(9)] = Probability value of the Ljung-Box Q-statistic at the 9th lag from - based on the square root of the sample size ($\sqrt{84}$), Adj R^2 = Adjusted R – square , **SC =** Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables, , $LR(1998q1)$ and $LR(2000q4)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

Therefore, we add the seasonal shift dummy variable corresponding to this date $(2004q4)$ to the model reported in the column headed 5 of Table 5.4.3 and use the estimated coefficients on this term to adjust I_CHI. The new index of indicator variables, I_CHI2, is defined as:

I_CHI2 = I_CHI - 0.0416 [S1*S2004Q4] - 0.0408 [S2*S2004Q4] - 0.0410 [S3*S2004Q4] - 0.0405 [S4*S2004Q4]

We re-estimate the model reported in the column headed 5 of Table 5.4.3 with I_CHI being replaced with I_CHI2. The resulting model is reported in the column headed 6 of Table 5.4.3. In terms of specification, all the seasonal dummy variables are insignificant and all the ARMA components are significant except for the MA(3) term. This model does not fail the diagnostic checks for invertibility, stationarity and autocorrelation. However, the test for $LR(2004q4)$ indicates that the seasonal shift coefficients embodied in I_CHI have changed significantly. We therefore add the seasonal shift dummy variable corresponding to this date to the model reported in the column headed 6 of Table 5.4.3 and use the estimated coefficients on these terms to adjust I_CHI2. The new index of indicator variables, I_CHI3, is defined as:

CHI3 = CHI2 - 0.0280 [S1*S2004Q4] - 0.028 [S2*S2004Q4] - 0.028 [S3*S2004Q4] - 0.027 [S4*S2004Q4]

We re-estimate the model reported in the column headed 6 of Table 5.4.3 with I_CHI2 being replaced with I_CHI3. The resulting model is reported in the column headed 7 of Table 5.4.3. In terms of specification, the seasonal dummy variables are insignificant and all the ARMA components are significant except for the MA(2) term. Although this model does not fail the diagnostic checks for invertibility and stationarity, there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model.

In column 8 Table 5.4.3, we consider a nonseasonal $ARMA(2,3)$ specification that is chosen based upon experimentation. In this model the SC falls to -5.878. All 4 seasonal dummy variables and all the ARMA components are significant. This model does not fail the diagnostic checks for invertibility, stationarity and autocorrelation. However, the joint test for $LR(1998q1)$ is significant. We therefore add the seasonal shift dummy variables corresponding to this date to the model reported in the column headed 8 of Table 6.4.3 and use the estimated coefficients on these terms to adjust I_CHI3. The new index of indicator variable, I_CHI4, is defined as:

CHI4 = CHI3 + 0.061 [S1*S1998Q1] + 0.056 [S2*S1998Q1] + 0.053 [S3*S1998Q1] + 0.051 [S4*S1998Q1].

We re-estimate the model reported in the column headed 8 of Table 5.4.3 with I_CHI3 being replaced with I_CHI4. The resulting model is reported in the column headed 9 of Table 5.4.3. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility and is therefore valid for forecasting. In this model the SC falls to -5.902. All 4 seasonal dummy variables are insignificant and all the ARMA components are significant. Notably, the seasonal dummy variables are now individually and jointly insignificant (see LR(SEA DUM)).

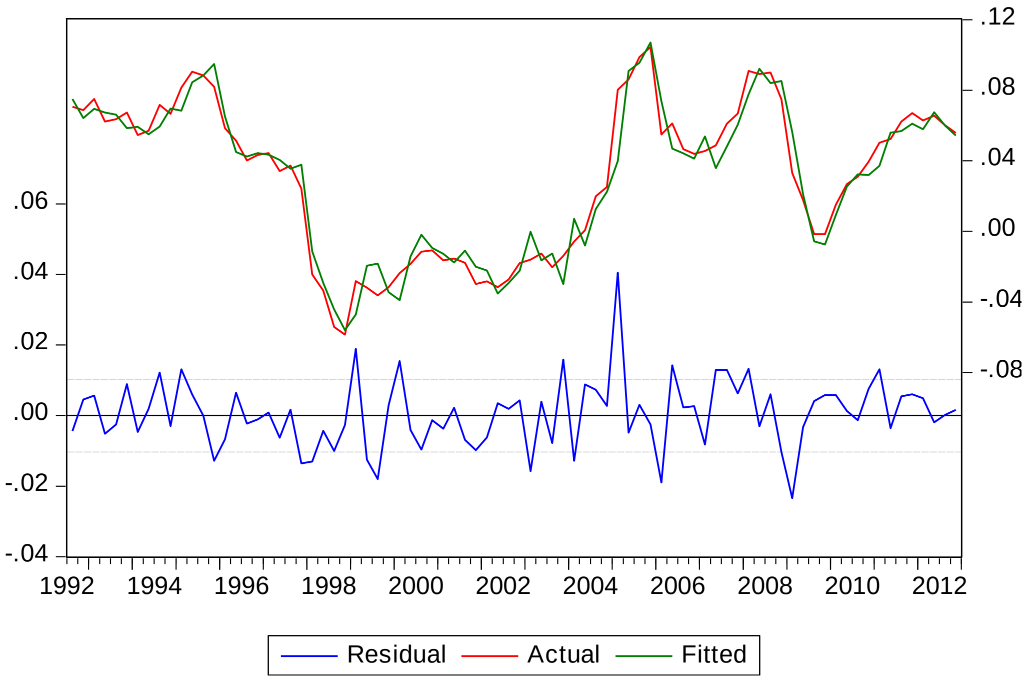
The probability values of the joint tests of the shift dummy variables corresponding to the break dates $LR(1998q1)$ and $LR(2004q4)$ all have the negative values and therefore no p-values. However, the test statistic is clearly very small and therefore is highly insignificant indicating that no shift variables for these dates can be added with joint significance. This suggests that the coefficients embodied in I_CHI4 have not significantly changed as the ARMA specification is amended.

In Table 5.4.3 column 10, we exclude the seasonal dummy variables that are jointly insignificant (see LR(SEA DUM)) from the model reported in the column headed 9. In this model the SC decreases to -6.079, the coefficient of I_CHI4 becomes insignificant and all the ARMA components' coefficients are significant. The tests for shift dummy variables corresponding to the break dates $LR(1998q1)$ and $LR(2004q4)$ are all insignificant. Although this model does not exhibit evident autocorrelation or nonstationarity one of the MA inverse roots is greater than one suggesting that this model is non-invertible. Hence, this model is not valid for forecasting.

Therefore we regard model 9 from Table 5.4.3 as the best ARIMAX model to forecast China's annual inflation because it has the lowest SC of the models that pass the diagnostic tests for stationarity, autocorrelation and invertibility. Although the seasonal dummy variables are jointly insignificant their exclusion causes the model to become non-invertible and invalid for forecasting. Hence the model in the column headed 9 is considered as the favoured model to forecast China's annual inflation compared to the other models considered.

We test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 9. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 9 in Table 5.4.3 is considered the best model to forecast China's annual inflation.

Figure 5.4.4: the actual and fitted values reported in Table 5.4.3 column 9



Visual inspection of Figure 5.4.4 gives the actual and fitted values of the favoured model for China. It suggests that the time paths of the actual and fitted values capture the mean shifts and variation in the actual data generally well.

5.5 ARIMAX modelling of annual inflation for South Africa

The maximum available sample period is 1957q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1961q1 – 2012q4. The first sub- section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.5.1: Bai and Perron tests for structural breaks in South African annual inflation

	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	99.548	16.19	1972q4	1973q1
1 vs 2	217.840	18.11	1993q1	1980q4
2 vs 3	25.899	18.93	1980q4	1993q1
3 vs 4	10.453	19.64		

In Table 5.5.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -3.058.

Table 5.5.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.5.2. The test results indicate that there are three significant breakpoints because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1), the null hypothesis of one break (1 vs 2) and the null hypothesis of two breaks (2 vs 3). However, the scaled F-statistic is less than critical value for the null hypothesis of 3 breaks (3 vs 4). The sequential and repartition methods indicate different break point dates. The sequential method indicates the multiple breaks point dates of 1972q4, 1980q4 and 1993q1 while the repartition method indicates the multiple breaks point dates of 1973q1, 1980q4 and 1993q1.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variables that give shifts in the seasonal means in 1972q4, denoted $D(1972q4)_{st}$, 1973q1 denoted $D(1973q1)_{st}$, 1980q4, denoted $D(1980q4)_{st}$ and 1993q1, denoted $D(1993q1)_{st}$.

The results of the model including the seasonal dummy variables and the shift dummy variables identified by the sequential method, ($D(1972q4)_{st}$, $D(1980q4)_{st}$ and $D(1993q1)_{st}$,) are given in the column headed 2 of Table 5.5.2. In this model, all the seasonal dummy variables and shift dummy variables are significant suggesting significant changes in the seasonal means at the identified break points. The significance of these shift dummy variables and that this model's SC falls to -4.028 supports the need to model the identified breaks.

Figure 5.5.1 plots the actual and fitted values of the model reported in column 2 of Table 5.5.2. Visual inspection of this graph suggests that this deterministic model captures the main mean shifts in the actual data. However, we also consider the model including the seasonal dummy variables and the shift dummy variables identified by the repartition method, $D(1973q1)_{st}$, $D(1980q4)_{st}$ and $D(1993q1)_{st}$.This model is reported in column 3 of Table 5.5.2. All the shift dummy variables and seasonal dummy variables are significant. The significance of these shift dummy variables and that this model's SC falls to -4.032 supports the inclusion of these dummy variables in the model.

Figure 5.5.2 plots the actual and fitted values of the model reported in column 3 of Table 5.5.2. Visual inspection of this graph suggests that this deterministic model also captures the main mean shifts in the actual data. We prefer the model reported in column 3 to that reported in column 2 because the model reported in column 3 has the lowest SC. Hence, we regard model 3 from Table 5.5.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of South Africa's annual inflation.

5.5.2: Deterministic component of ARIMAX models for South Africa

Sample/Observation		1961 q1 – 2012q4 (208)		
	1	2	3	4
D_{it}	0.087 (12.421)	0.031 (4.057)	0.032 (4.066)	
D_{2t}	0.085 (12.168)	0.032 (4.057)	0.032 (4.066)	
D_{3t}	0.085 (12.186)	0.034 (4.259)	0.035 (4.267)	
D_{4t}	0.085 (12.253)	0.032 (3.892)	0.035 (4.486)	
$D(1972\text{q}4)_{it}$		0.082 (6.568)		
$D(1972\text{q}4)_{2t}$		0.084 (6.719)		
$D(1972\text{q}4)_{3t}$		0.085 (6.800)		
$D(1972\text{q}4)_{4t}$		0.081 (6.340)		
$D(1973\text{q}1)_{1t}$			0.082 (6.582)	
$D(1973\text{q}1)_{2t}$			0.084 (6.733)	
$D(1973\text{q}1)_{3t}$			0.085 (6.814)	
$D(1973\text{q}1)_{4t}$			0.083 (6.414)	
$D(1993\text{q}1)_{1t}$		-0.077 (-7.687)	-0.077 (-7.702)	
$D(1993\text{q}1)_{2t}$		-0.082 (-8.200)	-0.082 (-8.217)	
$D(1993\text{q}1)_{3t}$		-0.081 (-8.014)	-0.081 (-8.158)	
$D(1993\text{q}1)_{4t}$		-0.078 (-8.014)	-0.078 (-8.029)	
$D(1980\text{q}4)_{it}$		0.035 (2.785)	0.035 (2.791)	
$D(1980\text{q}4)_{2t}$		0.032 (2.572)	0.032 (2.577)	
$D(1980\text{q}4)_{3t}$		0.028 (2.251)	0.028 (2.255)	
$D(1980\text{q}4)_{4t}$		0.031 (2.542)	0.025 (2.977)	
I_SOU				1.000 (52.311)
Adj R^2	-0.015	0.699	0.701	0.723
SC	-3.058	-4.028	-4.032	-4.417
S.E	0.050	0.144	0.027	0.026

Figure 5.5.1: the actual and fitted values of model 2 reported in Table 5.5.2

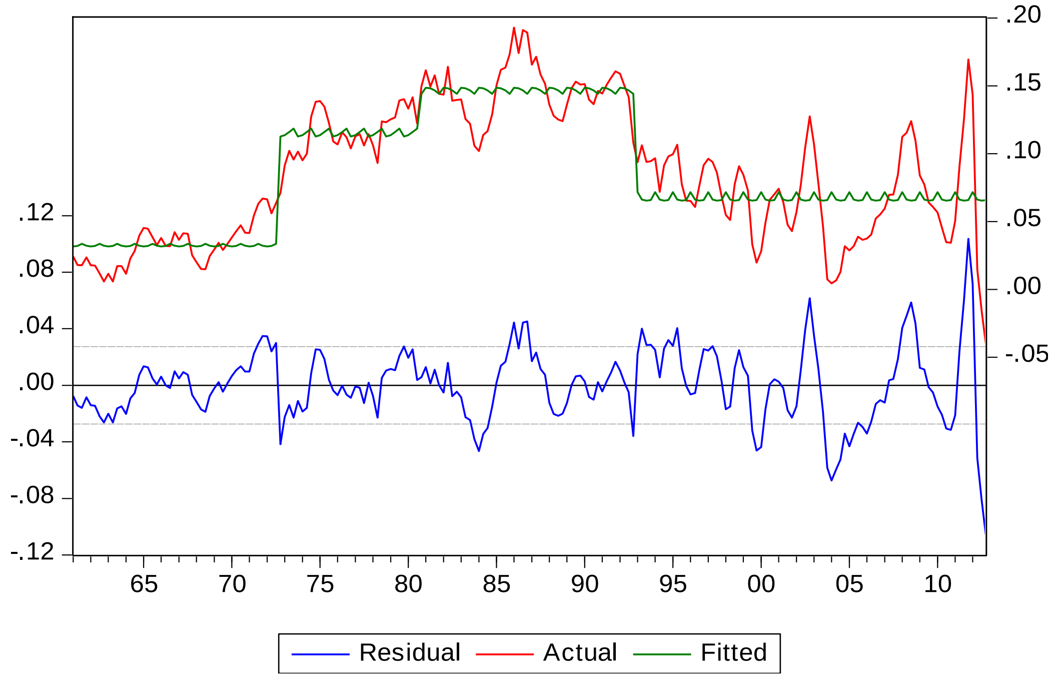
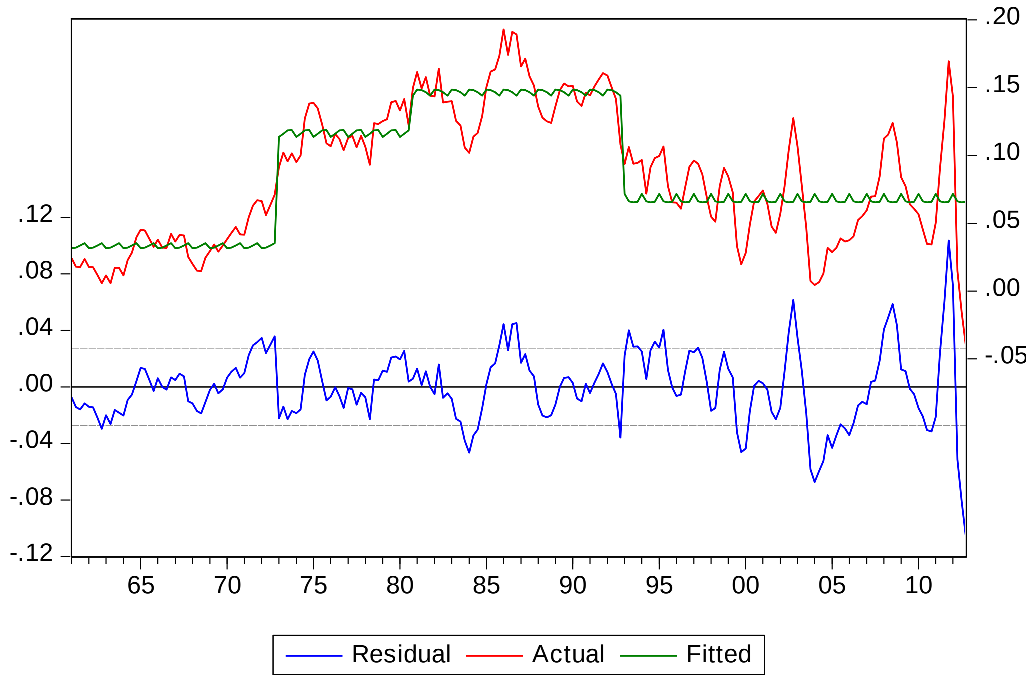


Figure 5.5.2: the actual and fitted values of model 3 reported in Table 5.5.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale et al (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.5.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_SOU, as the fitted value of the model reported in column 3 of Table 5.5.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.5.2. The index is significant and has a unit coefficient as is expected. This model's SC is -4.417 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

5.5.2 Developing the ARIMAX model for South Africa

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of table 5.5.2 are plotted. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lag 1, 2 and insignificant at lags 3, 4 and 5. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. The maximum order of non-seasonal moving average (MA) component is probably equal to 2. Further, the seasonal AC is significant at lag 12 and insignificant at lags 4, 8, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates that the maximum order of seasonal moving average (MA) component is probably equal to zero.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1, 2, 3 and 5 and insignificant at lag 4. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 3. The seasonal PACs are not significant at lags 4, 8, 12, 16, 20, 24 and 28. Hence, the maximum order of seasonal AR process is probably be equal to 0 or 1 (given the significance of lag 5 assuming a multiplicative functional form). The maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(3,2)(1,0)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_SOU plus 4 seasonal dummy variables and an $ARMA(3,2)(1,0)_4$ model of the residuals in the column headed 5 of Table 5.5.3.

Figure 5.5.3: the ACF and PACF of the residuals of model 3 reported in Table 5.5.2

Sample: 1961Q1 2012Q4
Included observations: 208

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.749	0.749	118.49	0.000
		2	0.408	-0.351	153.76	0.000
		3	0.086	-0.165	155.35	0.000
		4	-0.088	0.075	157.01	0.000
		5	-0.083	0.155	158.48	0.000
		6	-0.040	-0.111	158.82	0.000
		7	-0.008	-0.046	158.84	0.000
		8	-0.017	-0.011	158.90	0.000
		9	-0.068	-0.053	159.91	0.000
		10	-0.131	-0.092	163.71	0.000
		11	-0.168	-0.016	169.96	0.000
		12	-0.151	0.030	175.06	0.000
		13	-0.091	0.010	176.92	0.000
		14	-0.047	-0.083	177.41	0.000
		15	-0.028	-0.012	177.59	0.000
		16	-0.063	-0.074	178.48	0.000
		17	-0.096	0.001	180.60	0.000
		18	-0.093	0.019	182.61	0.000
		19	-0.076	-0.050	183.94	0.000
		20	-0.002	0.091	183.94	0.000
		21	0.083	0.065	185.56	0.000
		22	0.118	-0.070	188.82	0.000
		23	0.133	0.060	193.02	0.000
		24	0.087	-0.032	194.84	0.000
		25	0.042	0.019	195.25	0.000
		26	0.009	-0.027	195.27	0.000
		27	-0.016	-0.034	195.34	0.000
		28	-0.008	0.032	195.35	0.000

In this model the SC falls to -5.669 suggesting that the addition of ARMA terms has improved the specification. I_SOU is significant and all 4 seasonal dummy variables are also significant. However, the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM) indicates that they are jointly insignificant. The second non-seasonal autoregressive variable's coefficient, denoted AR(2), and the first seasonal AR variable's coefficient, denoted SAR(4) are significant, while the first and third non-seasonal AR variable's coefficient, denoted AR(1) and AR(3) respectively are insignificant. The first non-seasonal moving average variable's coefficient, denoted MA(1), is significant, however, the second non-seasonal MA variable's coefficient, denoted MA(2), is insignificant. These results suggest that the specification can be improved by the exclusion of some combination of deterministic and ARMA terms.

Table 5.5.3: The ARIMAX table for South Africa

Sample/Observations	1961q1 2012q4 (208)					
	5	6	7	8	9	10
I_SOU	0.463 (4.507)	0.177 (2.129)	0.186 (2.177)	0.175 (2.127)	0.126 (1.716)	
I_SOUA						0.318 (4.480)
D_{it}	0.032 (2.521)	0.073 (3.441)	0.072 (3.573)			
D_{2t}	0.032 (2.575)	0.072 (3.424)	0.071 (3.557)			
D_{3t}	0.032 (2.561)	0.072 (3.438)	0.072 (3.572)			
D_{4t}	0.033 (2.635)	0.073 (3.462)	0.072 (3.596)			
P(2012Q2)					-0.040 (-6.425)	
AR(1)	0.245 (1.223)	0.963 (49.209)	0.959 (47.996)	0.991 (104.011)	0.993 (113.433)	0.988 (88.045)
AR(2)	0.871 (16.442)					
AR(3)	-0.233 (-1.197)					
SAR(4)	-0.593 (-7.473)	-0.639 (-8.539)	-0.641 (-8.687)	-0.642 (-8.844)	-0.605 (-9.042)	-0.616 (-8.772)
MA(1)	1.044 (4.856)	0.407 (5.448)	0.415 (6.165)	0.408 (6.193)	0.465 (7.259)	0.411 (6.296)
MA(2)	-0.001 (-0.004)	-0.062 (-0.801)				
Adj R^2	0.936	0.934	0.934	0.934	0.945	0.939
SC	-5.669	-5.689	-5.712	-5.794	-5.951	-5.866
S.E	0.012	0.013	0.013	0.013	0.012	0.012
AR Root	0.942 0.917 0.877 0.270	0.963 0.894	0.956 0.894	0.992 0.894	0.993 0.882	0.988 0.886
MA Root	1.045 0.001	0.524 0.118	0.415	0.408	0.465	0.411
P[QLB(14)]	0.127	0.242	0.299	0.182	0.178	0.243
LR (SEA DUM)	-5.787	3.848 [0.427]	4.301 [0.367]			
LR (SEA DUM, CON)					312.016 [0.000]	
$LR(1973\text{q}1)$	10.844 [0.028]	0.157 [0.997]	0.194 [0.996]	0.526 [0.971]	0.719 [0.949]	2.927 (0.570)
$LR(1993\text{q}1)$	13.035 [0.011]	1.513 [0.824]	1.540 (0.820]	2.537 [0.638]	2.964 [0.564]	8.733 [0.068]
$LR(1980\text{q}4)$	14.976 [0.005]	5.280 [0.260]	4.505 [0.342]	5.983 [0.200]	7.958 [0.093]	4.495 [0.343]

Where: I_SOU = the fitted value o3f the model reported in column 3 of Table 5.5.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(14)] = Probability value of the Ljung-Box Q-statistic at the 14th lag from - based on the square root of the sample size ($\sqrt{208}$), Adj R^2 = Adjusted R – square , **SC** = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables; $LR(1972q4)$, $LR(1993q1)$ and $LR(1980q4)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We conduct variable addition tests for the shift dummy variables included in the I_SOU variable to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA terms. A test for whether the shift dummy variables corresponding to the 1973q1 break can be added to the model with joint significance is reported in the row labelled $LR(1973\text{q}1)$. Since the probability value (0.028) is less than 0.050 these variables can be added with joint significance. Similarly, the probability values of the joint tests of the other sets of shift dummy variables corresponding to the break dates 1993q1 and 1980q4 are reported in the rows labelled $LR(1993\text{q}1)$ and $LR(1980\text{q}4)$ respectively. These probability values are all less than 0.050 indicating that all shifts variables for these dates can be added with joint significance. This suggests that the coefficients embodied in I_SOU have significantly changed with the addition of ARMA terms.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 14th lag, denoted P[QLB(14)], is above 0.050 indicating that no evident of residual autocorrelation. We choose lag 14 based on the square root of the sample size (in this case $\sqrt{208}$). The inverse roots of the AR process denoted AR Root, are all less than one indicated that the model could be significant. Although, one value of the inverse roots of the MA process, denoted MA Root, is greater than one indicating that the model is non-invertible. Therefore, the model is not valid for forecasting according to the standard tests.

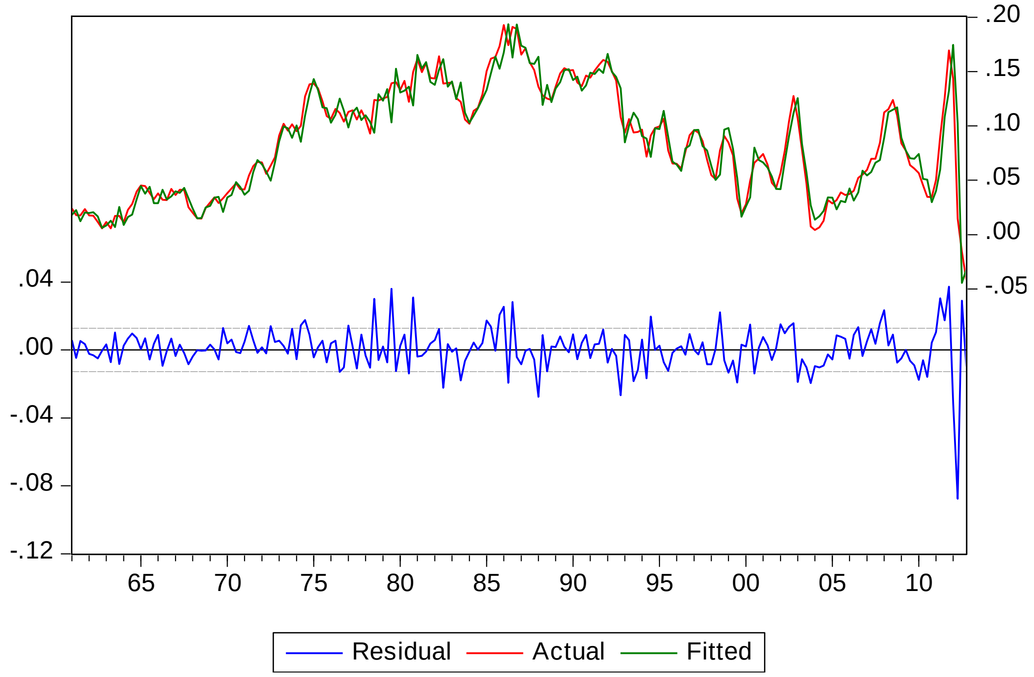
Experimentation with the ARMA terms demonstrate that the model is invertible when the AR(2) and AR(3) terms are excluded from the model reported in column 5 of Table 5.5.3.[149] Hence, we estimate the $ARMAX(1,2)(1,0)_4$ model reported in the column headed 6 of Table 5.5.3. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of

[149] As indicated from Table 5.5.3 column 5, the specification can be improved with the removal of some insignificant ARMA components. The coefficients on the AR(1), AR(3) and MA(2) terms are not significant and are candidates for exclusion. Since the AR(2) term is significant we do not remove the AR(1) term to retain the full second-order of non- seasonal AR component. Therefore, we remove the AR(3) and MA(2) terms from the model reported in the column headed 5 from Table 5.5.3. To our surprise, this model cannot be valid for forecasting and it is rejected base on the diagnostic checks for stationarity and invertibility. The result indicates that the root MA process of this model is too large and the singular covariance- coefficients of this model are not unique as well as estimated MA process is non-invertible

specification, all variables are significant except for the MA(2) term (if the seasonal dummies are jointly insignificant) and shift dummies cannot be added with significance to I_SOU. This suggests that the specification can be improved by the exclusion of the MA(2) term that is not significant. Therefore, we remove the MA(2) term from the model reported in the column headed 6 in Table 5.5.3 and report the resulting $ARMAX(1,1)(1,0)_4$ specification in the column headed 7 of Table 5.5.3.

In this model, all the ARMA coefficients are significant. The tests for the joint significance of the shift dummy variables corresponding to $LR(1973q1)$, $LR(1993q1)$ and $LR(1980q4)$, all have probability values that exceed 0.050 indicating that the coefficients embodied in I_SOU have not significantly changed as the ARMA specification is amended. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. However, the seasonal dummy variables are jointly insignificant. Therefore, we exclude the seasonal dummy variables from the model reported in the column headed 7 and the resulting specification is reported in column 8 of Table 5.5.3. In this model the SC falls to -5.794, the coefficients of I_SOU and all ARMA components are significant and shift variables cannot be added to I_SOU with significance. This model passes all the required diagnostic tests for stationarity, invertibility and autocorrelation and is therefore valid for forecasting.

Figure 5.5.4: the actual and fitted values of model reported in Table 5.5.3 in column 8



In Figure 5.5.4, we plot the actual and fitted values of the model reported in column 8 of Table 5.5.3. Visual inspection of this graph suggests that this model adequately capture all of the mean shifts in the actual data. However, the graph has an outlier in 2012q2 and we therefore add a new pulse dummy variable, denoted $P(2012q2)$, to the model reported in column 8 to capture the outlier. [150]

This result is reported in the Table 5.5.3 column 9, the SC of this model fall -5.951 and all the ARMA coefficients are significant. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. However, the coefficient of I_SOU becomes insignificant.

In Table 5.5.3 column 10, we construct an index of a new indicator variable to summarise the deterministic terms for the new outlier. We add the pulse dummy variable to the model reported in the column 9 and use the estimated coefficient on this term to adjust I_SOU. The new index of indicator variables, I_SOUA, is defined as:

I_SOUA = I_SOU - 0.0401 [P2012Q2]

We re-estimate the model reported in the column headed 10 of Table 5.5.3 with I_SOU being replaced with I_SOUA. In this model, all the ARMA components including the coefficient of I_SOUA are significant. The tests for the shift dummy variables corresponding to $LR(1973q1)$, $LR(1993q1)$ and $LR(1980q4)$ are all insignificant. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. Therefore valid for forecasting.

Notably, there are two models in Table 5.5.3 (column 9 and column 10) that are valid for forecasting. The model in column 9 has the minimum SC although the coefficient of I_SOU is not significant. In contrast the model in column 10 does not has minimum SC but the coefficient of I_SOUA is significant and the model does not suggest any variables should be excluded according to the t-ratios and P-value. Hence, we test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 9. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This

[150] The aim is to examine whether the new pulse dummy variable, $P(2012q2)$, outlier will improve the specified model.

suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Therefore, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 9 in Table 5.5.3 could be considered as the best model to forecast South Africa's annual inflation.

5.6. ARIMAX modelling of annual inflation for Algeria

The maximum available sample period for estimation is 1974q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1978q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.6.1: Bai and Perron tests for structural breaks in Algeria annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	86.795	16.19	1997q2	1990q4
1 vs 2	165.984	18.11	1990q4	1997q1
2 vs 3	5.703	18.93		

In Table 5.6.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -1.816.

Table 5.6.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 6.6.2. The test results indicate that there are two significant breakpoints because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1) and the null hypothesis of one break (1 vs 2). However, the scaled F-statistic is less than critical value for the null hypothesis of 2 breaks (2 vs 3). The sequential and repartition methods indicate different break point dates. The sequential method indicates the multiple breaks point dates of 1990q4 and 1997q2 while the repartition method indicates the multiple breaks point dates of 1990q4 and 1997q1.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the

seasonal dummy variables that give shifts in the seasonal means in 1990q4, denoted $D(1990q4)_{st}$, 1997q1, denoted $D(1997q1)_{st}$ and 1997q2, denoted $D(1997q2)_{st}$. The model including the seasonal dummy variables and the shift dummy variables based on the sequential method is given in the column headed 2 of Table 5.6.2. All of the shift dummy variables and seasonal dummy variables are significant suggesting significant changes in the seasonal means at the identified break points. The significance of these shift dummy variables and that this model's SC falls to -2.870 supports the need to model the identified breaks.

Figure 5.6.1 plots the actual and fitted values of the model reported in column 2 of Table 5.6.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results broadly captures all of the mean shifts in the actual data.

We also consider the model indicated by the repartition version of the Bai and Perron test and report this model in column 3 of Table 5.6.2. The model's SC falls to -2.936 and all dummy variables are significant.

Figure 5.6.2 plots the actual and fitted values of the model reported in column 3 of Table 5.6.2. Visual inspection of this graph suggests that this deterministic model also captures the main mean shifts in the actual data, as did model 2. However, we favour model 3 from Table 5.6.2 because it has the lowest SC and use this as the basis of the deterministic component of our ARIMAX model of Algeria's annual inflation.

5.6.2: Deterministic component of ARIMAX models for Algeria

Sample/Observation	1978q1 – 2012q4 (140)			
	1	2	3	4
D_{1t}	0.102 (6.522)	0.100 (7.414)	0.100 (7.663)	
D_{2t}	0.103 (6.591)	0.107 (7.937)	0.107 (8.203)	
D_{3t}	0.102 (6.536)	0.104 (7.705)	0.104 (7.963)	
D_{4t}	0.100 (6.440)	0.098 (6.988)	0.098 (7.222)	
$D(1990q4)_{1t}$		0.144 (6.289)	0.167 (7.189)	
$D(1990q4)_{2t}$		0.157 (6.516)	0.157 (6.734)	
$D(1990q4)_{3t}$		0.160 (6.650)	0.160 (6.873)	
$D(1990q4)_{4t}$		0.146 (6.305)	0.145 (6.517	
$D(1997q1)_{it}$			-0.227 (-10.047)	
$D(1997q1)_{2t}$			-0.225 (-9.983)	
$D(1997q1)_{3t}$			-0.225 (-9.959)	
$D(1997q1)_{4t}$			-0.206 (-9.616)	
$D(1997q2)_{1t}$		-0.207 (-9.291)		
$D(1997q2)_{2t}$		-0.225 (-9.659)		
$D(1997q2)_{3t}$		-0.225 (-9.636)		
$D(1997q2)_{4t}$		-0.206 (-9.303)		
I_ALG				1.000 (33.667)
Adj R^2	-0.022	0.715	0.733	0.754
SC	-1.816	-2.870	-2.936	-3.325
S.E	0.092	0.048	0.047	0.045

Figure 5.6.1: the actual and fitted values of model 2 reported in Table 5.6.2

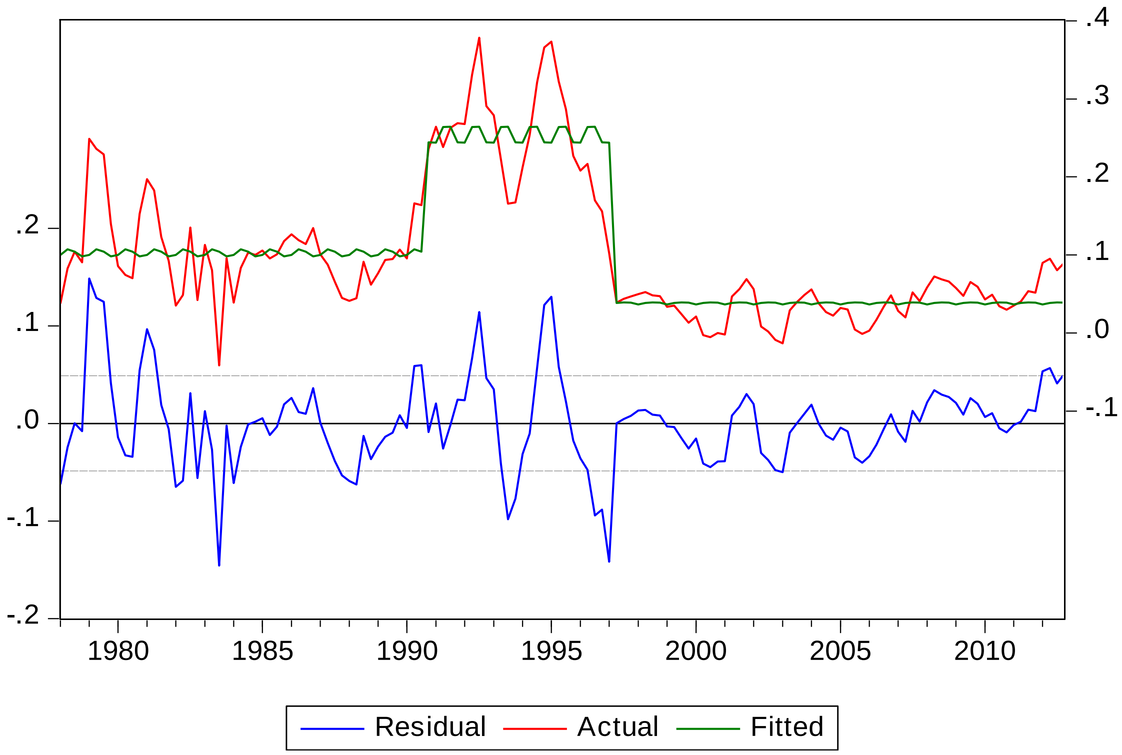
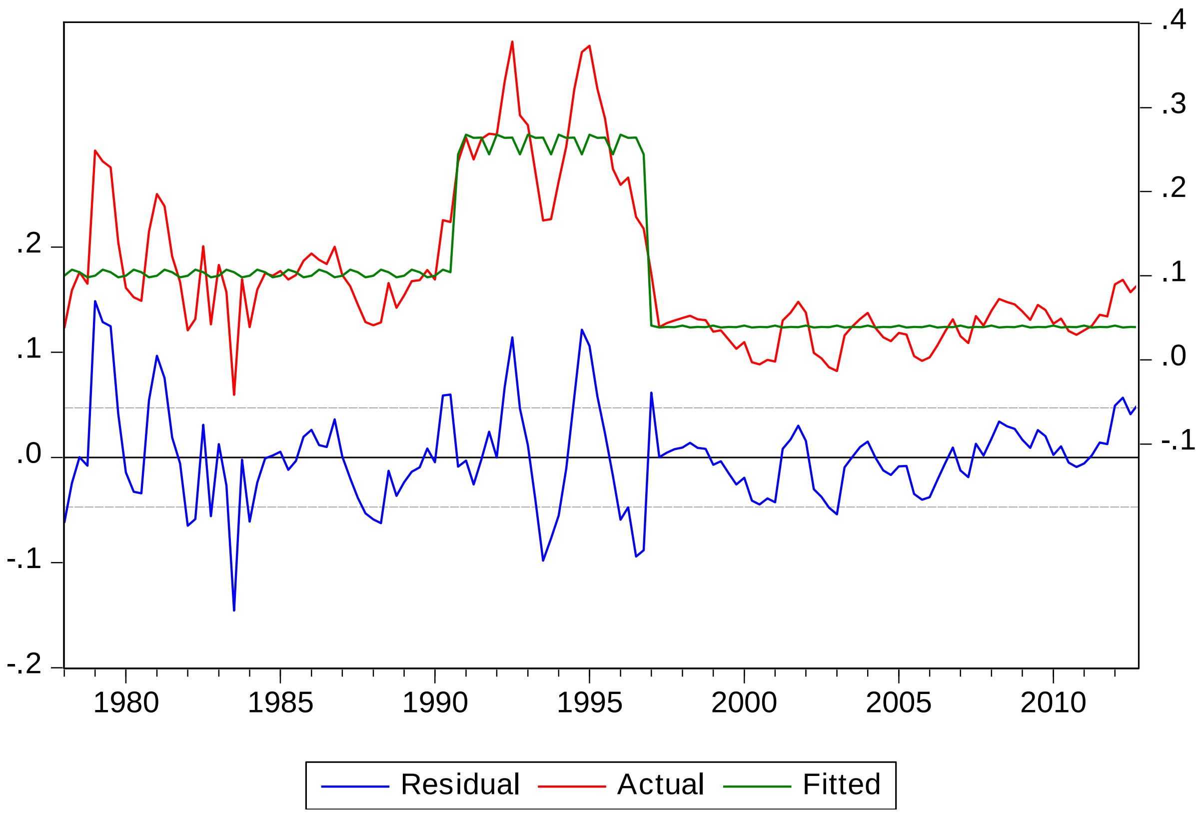


Figure 5.6.2: the actual and fitted values of model 3 reported in Table 5.6.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.6.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicators variable, denoted I_ALG, as the fitted value of the model reported in column 3 of Table 5.6.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.6.2. The index is significant and has a unit coefficient as is expected. This model's SC is -3.325 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

5.6.2 Developing the ARIMAX model for Algeria

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.6.2 is plotted in Figure 5.6.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1, 2, 4, 5 and 6 and insignificant at lags 3. This implies that there is no need for further non-seasonal differencing because no more than the first 5 or 6 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 2. Further, the seasonal ACs are significant at lags 4 and insignificant at lags 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 1 at the seasonal lags 4 (using a multiplicative functional form can capture the significant AC at lag 5 with a seasonal MA term).

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1, 3, 4, 5 and insignificant at lags 2 and 6. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 1 or 3 (given the significant third lag). The seasonal PACs are significant at lags 4, 20, 24, 28 and insignificant at lags 8, 12 and 16. Therefore, the maximum order of seasonal AR process is probably be equal to 1 (the marginal significance of the higher order seasonal lags is probably due to chance while a multiplicative functional form can capture the significant

PAC at lag 5). Therefore, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(3,2)(1,1)_4$. Assuming a multiplicative specification, we report an ARIMAX specification that includes I_ALG plus 4 seasonal dummy variables and an $ARMA(3,2)(1,1)_4$ model of the residuals in the column headed 5 of Table 5.6.3.

Figure 5.6.3: the ACF and PACF of the residuals of model 4 reported in Table 5.6.2

Sample: 1978Q1 2012Q4
Included observations: 140

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.606	0.606	52.590	0.000
		2	0.303	-0.102	65.814	0.000
		3	0.004	-0.219	65.816	0.000
		4	-0.330	-0.357	81.699	0.000
		5	-0.266	0.257	92.142	0.000
		6	-0.180	0.022	96.949	0.000
		7	-0.011	0.079	96.968	0.000
		8	0.119	-0.126	99.117	0.000
		9	0.130	0.042	101.69	0.000
		10	0.066	-0.098	102.35	0.000
		11	-0.001	0.104	102.35	0.000
		12	-0.014	0.049	102.38	0.000
		13	-0.050	-0.043	102.77	0.000
		14	-0.038	-0.090	103.00	0.000
		15	-0.075	-0.097	103.89	0.000
		16	-0.071	0.081	104.69	0.000
		17	-0.056	-0.005	105.19	0.000
		18	-0.034	0.041	105.38	0.000
		19	0.055	0.011	105.88	0.000
		20	-0.017	-0.218	105.93	0.000
		21	0.043	0.161	106.23	0.000
		22	0.071	0.108	107.08	0.000
		23	0.027	0.047	107.21	0.000
		24	0.037	-0.201	107.44	0.000
		25	-0.015	0.019	107.48	0.000
		26	0.005	0.104	107.48	0.000
		27	-0.020	0.012	107.55	0.000
		28	-0.078	-0.162	108.63	0.000

In this model the SC falls to -3.893 suggesting that the addition of ARMA terms has improved the specification. I_ALG is significant and all the seasonal dummy variables are individually significant. However, the latter is not confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.572 (given in square brackets below the reported test statistic). Because this exceeds 0.05 these 4 dummy variables are jointly insignificant. All the ARMA terms are significant except the first seasonal moving average term SMA(4). These results suggest that the specification can be improved by the exclusion of some combination of deterministic and ARMA terms.

Table 5.6.3: The ARIMAX table for Algeria

Sample/Observations	1978q1 2012q4 (140)			
	5	6	7	8
I_ALG	0.502 (6.159)	0.509 (6.361)	0.486 (6.107)	0.931 (22.883)
D_1	0.052 (2.291)	0.052 (2.365)		
D_2	0.051 (2.257)	0.052 (2.327)		
D_3	0.052 (2.240)	0.051 (2.309)		
D_4	0.052 (2.267)	0.051 (2.342)		
AR(1)	0.225 (3.699)	0.215 (4.090)	0.259 (5.907)	-0.482 (-5.905)
AR(2)	-0.204 (-4.401)	-0.204 (-4.427)	-0.172 (-4.125)	0.288 (3.025)
AR(3)	0.786 (16.739)	0.784 (16.646)	0.826 (20.999)	-0.214 (-2.367)
AR(4)				-0.648 (-8.371)
SAR(4)	-0.471 (-3.075)	-0.511 (-6.372)	-0.519 (-6.716)	
MA(1)	0.664 (31.131)	0.664 (31.301)	0.665 (34.170)	1.148 (17.226)
MA(2)	0.988 (84.594)	0.988 (84.035)	0.986 (85.816)	0.546 (4.587)
MA(3)				0.814 (7.323)
MA(4)				0.785 (13.321)
SMA(4)	-0.063 (-0.333)			
Adj R^2	0.898	0.898	0.898	0.893
SC	-3.893	-3.928	-4.045	-3.929
S.E	0.029	0.029	0.029	0.029
AR Root	0.925 0.922 0.828	0.923 0.920 0.845	0.966 0.925 0.849	0.933 0.863
MA Root	0.994 0.501	0.994	0.993	0.986 0.898
P[QLB(12)]	0.041	0.052	0.034	0.061
LR (SEA DUM)	2.918 [0.572]	3.234 [0.520]		
LR (SEA DUM, CON)				439.,689 [0.000]
$LR(1990q4)$	0.922 [0.922]	0.879 [0.928]	2.182 [0.702]	1.673 [0.796]
$LR(1997q1)$	0.623 [0.960]	0.660 [0.956]	3.552 [0.470]	3.656 [0.455]

Where: I_ALG = the fitted value of the model reported in column 3 of Table 5.6.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} =

the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(12)] = Probability value of the Ljung-Box Q-statistic at the 14th lag from - based on the square root of the sample size ($\sqrt{140}$), Adj R^2 = Adjusted R – square , **SC =** Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables; $LR(1990q4)$ and $LR(1997q1)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We also conduct variable addition tests for the shift dummy variables included in the I_ALG variable to assess whether the coefficients on the terms embodied in this index have changed significantly with the addition of ARMA terms. A test of whether the 4 shift dummy variables corresponding to the 1990q4 break can be added to the model with joint significance is reported in the row labelled $LR(1990q4)$. Since the probability value (0.922) exceeds 0.050 these variables cannot be added with joint significance. Similarly, the probability values of the joint tests for the shift dummy variables corresponding to the break date 1997q1 reported in the row labelled $LR(1997q1)$ exceeds 0.050 indicating that no shift variables for these dates can be added with joint significance. This suggests that the coefficients embodied in I_ALG have not significantly changed with the addition of ARMA terms and therefore remains an adequate specification of the deterministic component of the model.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 12th lag, denoted P[QLB(12)], is less than 0.050 indicating evident of residual autocorrelation suggesting unmodelled systematic variation in the dependent variable– we choose lag 12 based on the square root of the sample size (in this case $\sqrt{140}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible. Due to the evident autocorrelation this model is not valid for forecasting and needs to be respecified.

In the model reported in Table 5.6.3 column 5 that $ARMA(3,2)(1,1)_4$ the SMA(4) term is not significant and is a candidate for exclusion. Therefore, we remove SMA(4) from the model reported in the column headed 5 in Table 5.6.3 and report the resulting $ARMAX(3,2)(1,0)_4$ in the column headed 6 of Table 5.6.3. The SC decreases to -3.928

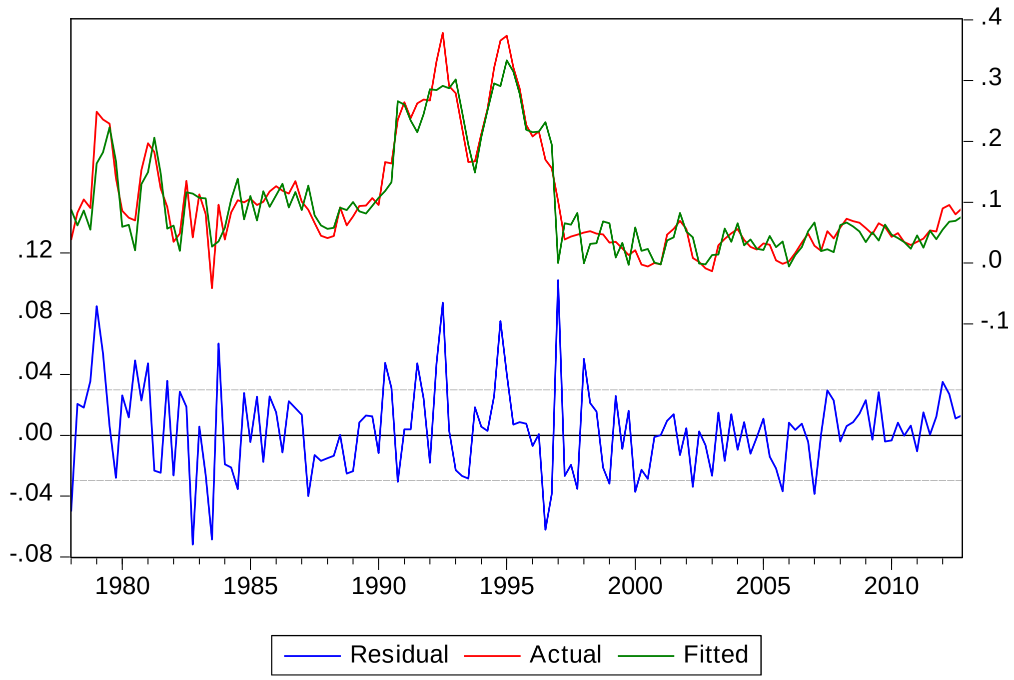
and all the ARMA components are significant. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility, hence this respecification has removed the previously evident autocorrelation.

We conduct variable addition tests for the shift dummy variables to assess whether the coefficients on these terms embodied in this index have changed significantly with the adjustment of ARMA terms. The test for the 2 sets of shift dummy variables corresponding to $LR(1990q4)$, and $LR(1997q1)$ are all insignificant indicating that these coefficients have not changed and no need to respecify the index of indicators. However, the test for the joint significance seasonal dummy variables, denoted LR(SEA DUM), indicates that they are insignificant.

In Table 5.6.3 column 7, we exclude the seasonal dummy variables that are jointly insignificant from the model reported in the column headed 6 in Table 5.6.3. In this model the SC decreases to -4.045 and the coefficient of I_ALG and all the ARMA components are significant. The tests for shift dummy variables corresponding to the break dates $LR(1990q4)$ and $LR(1997q1)$ are all insignificant indicating no need to respecify the index of indicators variable. However, while this model does not fail the diagnostic checks for invertibility and stationarity, there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and a need to respecify the model. Experimentation with the ARMA terms demonstrate that the MA(3), MA(4) and AR(4) terms are significant when included instead of the SAR(4) term in model 7. Hence, we estimate the $ARMAX(4,4)$ model reported in the column headed 8 of Table 5.6.3. In terms of specification, all the ARMA components are significant and this model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility.

The tests for the shift dummy variables corresponding to $LR(1990q4)$ and $LR(1997q1)$ suggest that the coefficients embodied within the I_ALG index have not changed significantly with the adjustment of ARMA terms. In addition, the visual inspection of the actual and fitted values of this model suggests that the time path of the fitted values capture all of the mean shifts and fit the data well (see figure 5.6.4).

Figure 5.6.4: the actual and fitted values reported in Table 5.6.3 Column 8



We regard model 8 from Table 5.6.3 as the best ARIMAX model for forecasting Algeria's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks and because the included deterministic terms adequately capture the identified structural breaks (according to the conducted variable addition tests).

We also test the null hypothesis of whether the coefficients of the seasonal dummy variables, D_{1t}, D_{2t}, D_{3t} and D_{4t}, are the same using a Wald test. This test is reported in the row labelled LR (SEA DUM, CON) of column 8 and the probability value is 0.000. Since this value is less than 0.050, we reject the null hypothesis (of no seasonality) and accept the alternative hypothesis. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 8 in Table 5.6.3 is considered the best model to forecast Algeria's annual inflation.

5.7 ARIMAX modelling of annual inflation for Angola

The maximum available sample period is 1992q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1996q1 – 2012q4. The first sub- section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.7.1: Bai and Perron tests for structural breaks in Angola annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	51.644	16.19	1998q3	1998q3
1 vs 2	0.567	18.11		
2 vs 3				

In Table 5.7.2 we report various deterministic models based upon these results. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. Three of the four seasonal dummy variables are insignificant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is 7.898

Table 5.7.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.7.2. The test results indicate that there is only one significant breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). However, the scaled F-statistic is less than critical value for the null hypothesis of 1 breaks (1 vs 2). Both sequential and repartition methods indicate the same break point date of 1998q3.

Based on the Bai and Perron test results we specify a shift dummy variable (that is zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variables that give shifts in the seasonal means in 1998q3, denoted $D(1998q3)_{st}$. The model including the seasonal dummy variables and the shift dummy variables are given in the column headed 2 of Table 5.7.2. All of the shift dummy variables are significant except $D(1998q3)_{4t}$ and all the seasonal dummy variables are significant. The general significance of these shift dummy variables and the fall of the SC to 7.526 supports the need to model the identified break.

Figure 5.7.1 plots the actual and fitted values of the model reported in column 2 of Table 5.7.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not properly capture all of the mean shifts in the actual data. The graph suggests one more shift in 1997q1 and we therefore add interaction dummy variables, denoted $D(1997q1)_{st}$, to the model reported column 2. The estimation results of this model are reported in column 3 of Table 5.7.2. All the seasonal and shift dummy variables are significant except $D(1998q3)_{3t}$ *and* $D(1998q3)_{4t}$. The general significance of these shifts dummy variables and that this model's SC falls to 4.530 supports the inclusion of these interaction terms in the model.

Figure 5.7.2 plots the actual and fitted values of the model reported in column 3 of Table 5.7.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts in the actual data than did model 2. We regard model 3 from Table 5.7.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of Angola's annual inflation.

5.7.2: Deterministic component of ARIMAX models for Angola

Sample/Observation	1996q1 – 2012q4 (68)			
	1	2	3	4
D_{1t}	3.672 (1.324)	16.918 (3.384)	35.655 (20.144)	
D_{2t}	3.530 (3.530)	16.064 (3.213)	40.316 (22.778)	
D_{3t}	5.229 (1.885)	38.297 (6.255)	75.344 (42.568)	
D_{4t}	1.991 (0.717)	10.942 (6.123)	20.134 (11.375)	
$D(1997q1)_{it}$			-28.104 (-12.964)	
$D(1997q1)_{2t}$			-36.379 (-16.781)	
$D(1997q1)_{3t}$			-74.094 (-29.600)	
$D(1997q1)_{4t}$			-18.384 (-7.344)	
$D(1998q3)_{1t}$		-16.086 (-2.920)	-6.718 (-5.021)	
$D(1998q3)_{2t}$		-15.219 (-2.763)	-3.093 (-2.311)	
$D(1998q3)_{3t}$		-37.477 (-5.750)	-0.430 (-0.235)	
$D(1998q3)_{4t}$		-10.145 (-1.557)	-0.953 (-0.521)	
I_ANG				1.000 (59.170)
Adj R^2	-0.036	0.406	0.975	0.979
SC	7.898	7.526	4.530	3.848
S.E	11.435	8.659	1.770	1.618

Figure 5.7.1: the actual and fitted values of model 2 reported in Table 5.7.2

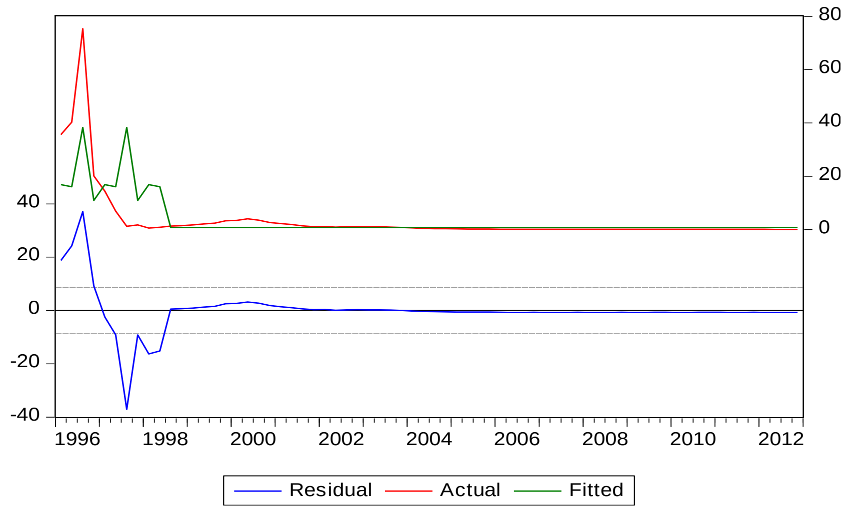
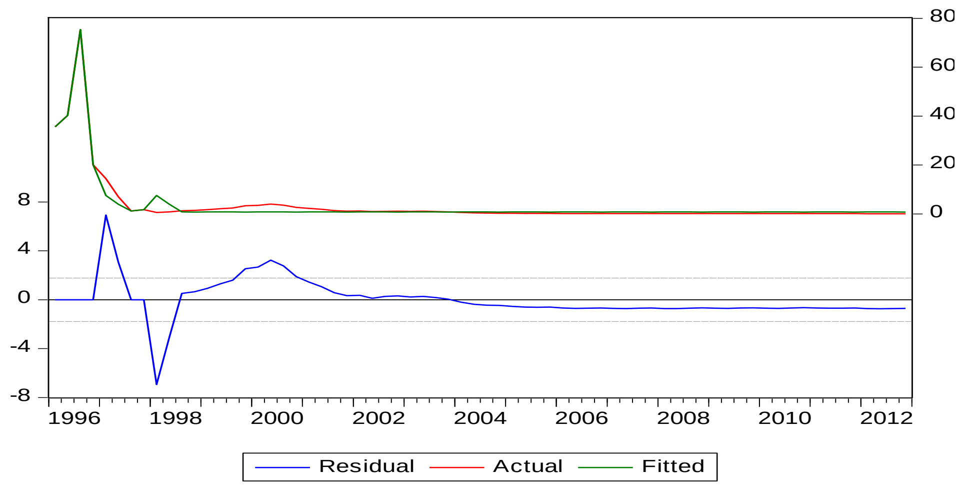


Figure 5.7.2: the actual and fitted values of model 3 reported in Table 5.7.3



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.7.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_ANG, as the fitted value of the model reported in column 3 of Table 5.7.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.7.2. The index is significant and has a unit coefficient as is expected. This model's SC is 3.848 which provides a benchmark for comparison with the ARIMAX models to be developed from this deterministic specification that are discussed below.

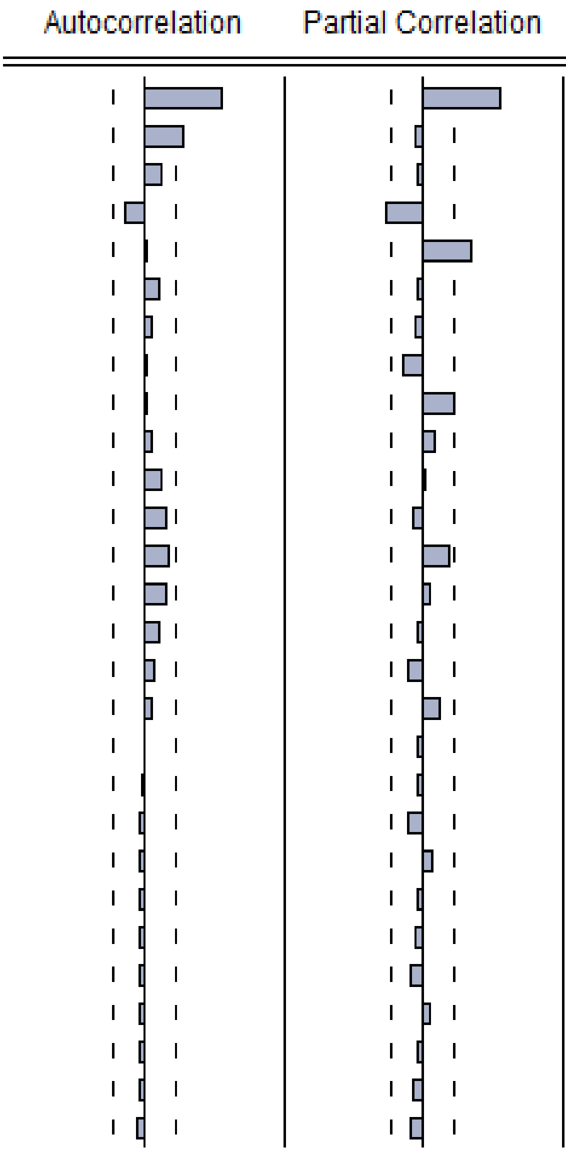
5.7.2 Developing the ARIMAX model for Angola

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.7.2 is plotted in Figure 5.7.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lag 1 and 2 and insignificant at lags 3, 4, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 2. Further, the seasonal ACs are insignificant at lags 4, 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1, 4, 5 and insignificant at lags 2, 3 and 6. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 1. The seasonal PACs are significant at lags 4 and insignificant at lags 8, 12, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 1 or 2 (assuming a multiplicative functional form given the significant PAC at lag 9, although this could be result of sampling error). The maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(1,2)(2,0)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_ANG plus 4 seasonal dummy variables and an $ARMA(1,2)(2,0)_4$ model of the residuals in the column headed 5 of Table 5.7.3.

Figure 5.7.4: the ACF and PACF of the residuals of model 4 reported in Table 5.7.2

Sample: 1996Q1 2012Q4
Included observations: 68



	AC	PAC	Q-Stat	Prob
1	0.567	0.567	22.860	0.000
2	0.280	-0.062	28.516	0.000
3	0.117	-0.025	29.517	0.000
4	-0.142	-0.274	31.019	0.000
5	0.019	0.363	31.046	0.000
6	0.101	-0.028	31.832	0.000
7	0.045	-0.062	31.991	0.000
8	0.024	-0.152	32.035	0.000
9	0.012	0.229	32.046	0.000
10	0.060	0.090	32.346	0.000
11	0.130	0.020	33.754	0.000
12	0.157	-0.069	35.854	0.000
13	0.183	0.203	38.747	0.000
14	0.158	0.056	40.956	0.000
15	0.110	-0.026	42.043	0.000
16	0.075	-0.108	42.553	0.000
17	0.044	0.124	42.730	0.001
18	0.001	-0.028	42.730	0.001
19	-0.020	-0.046	42.769	0.001
20	-0.030	-0.111	42.861	0.002
21	-0.046	0.078	43.072	0.003
22	-0.040	-0.032	43.240	0.004
23	-0.037	-0.054	43.382	0.006
24	-0.033	-0.093	43.498	0.009
25	-0.029	0.050	43.594	0.012
26	-0.036	-0.044	43.744	0.016
27	-0.048	-0.067	44.009	0.021
28	-0.059	-0.082	44.424	0.025

In this model the SC falls to 3.065 suggesting that the addition of ARMA terms has improved the specification. I_ANG is significant whereas all 4 seasonal dummy variables are individually insignificant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.296 (given in square brackets below the reported test statistic). Because this exceeds 0.05 these 4 dummy variables are jointly insignificant. All the ARMA terms are significant.

Table 5.7.3: The ARIMAX table for Angola

Sample/Observations	1996q1 – 2012q4 (68)				
	5	6	7	8	9
I_ANG	0.700 (48.041)	0.690 (11.423)			
I_ANG2			0.775 (12.507)		
I_ANG3				0.293 (44.504)	0.219 (65.172)
D_{it}	0.493 (0.858)	0.486 (1.151)	0.672 (1.561)	-147.422 [-42.370]	-111.109 (-63.171)
D_{2t}	0.474 (0.817)	0.486 (1.152)	0.505 (1.161)	-2.090 [-3.102]	-1.893 (-4.146)
D_{3t}	0.715 (1.229)	0.497 0.497 (1.184)	0.032 (0.073)	44.710 [40.144]	33.137 (48.401)
D_{4t}	0.806 (1.401)	0.582 (1.393)	1.659 (3.884)	2.045 [3.103]	0.806 (1.747)
AR(1)	0.498 (4.494)				0.701 (37.589)
SAR(4)	-0.374 (4.493)				
SAR(8)	-0.065 (-7.839)				
MA(1)	1.716 (101.758)	0.855 (45.799)	0.966 (10.370)	1.305 (10.340)	-0.352 (-8.927)
MA(2)	0.985 (79.977)	0.851 (0.0186)	0.970 (10.607)	1.150 (7.639)	0.999 (979.039)
MA(3)		0.985 (156.022)	0.996 (69.185)	0.129 (1.009)	
Adj R^2	0.994	0.994	0.994	0.986	0.997
SC	3.065	2.979	2.999	3.784	2.360
S.E	0.889	0.891	0.900	1.333	0.654
AR Root	0.710 0.498				0.701
MA Root	0.993	0.995 0.994	0.999 0.996	0.999 0.130	0.999
P[QLB(8)]	0.013	0.085	0.195	0.006	0.111
LR (SEA DUM)	4.918 [0.296]	32.889 [0.000]	90.069 [0.000]	233.55 [0.000]	298.100 [0.000]
LR (SEA DUM, CON)					1487.189 [0.000]
$LR(1997\text{q}1)$	85.686 [0.000]	3.576 [0.466]	13.871 [0.008]	67.215 [0.000]	-68.066
$LR(1998\text{q}3)$	7.216 [0.125]	10.758 [0.029]	12.096 [0.017]	-138.289	-224.802

Where: I_ANG = the fitted value of the model reported in column 3 of Table 5.7.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(8)] = Probability value of the Ljung-Box Q-statistic - based on the square root of the sample size ($\sqrt{68}$), Adj R^2 = Adjusted R – square , **SC =** Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables, $LR(1997q1)$ and $LR(1998q3)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We also conduct variable addition tests for the shift dummy variables included in the I_ANG variable to assess whether the coefficients on the terms embodied in this index have changed significantly with the addition of ARMA components. A test of whether the shift dummy variables corresponding to the 1997q1 break can be added to the model with joint significance is reported in the row labelled $LR(1997q1)$. The probability value (given in square brackets below the test statistic, being 0.000) less than 0.050 suggesting that the variables corresponding to this break date can be added with joint significance. Similarly, the probability value of the joint test of the shift dummy variable corresponding to the break date 1998q3 reported in the row labelled $LR(1998q3)$ exceeds 0.050 indicating that the variable corresponding to this break date cannot be added with joint significance.

To assess whether the model is valid for forecasting we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 8th lag, denoted P[QLB(8)], is less than 0.05 indicating evident residual autocorrelation and the need to respecify the model – we choose lag 8 based on the square root of the sample size (in this case $\sqrt{68}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible.

This model is not valid for forecasting in the sense that there is evidence of residual autocorrelation and that the $ARMAX(1,2)(2,0)_4$ specification reported in column 5 of Table 5.7.3 should be amended. After experimentation with the ARMA components we estimate an $ARMAX(0\ ,3)$ specification and report this in the column headed 6 of Table 5.7.3. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification, all the ARMA components are significant and the seasonal dummy variables are also jointly significant according to LR(SEA DUM) because its probability value is less than 0.05. However, the test denoted $LR(1998q3)$ indicates that the seasonal shift coefficients embodied in I_ANG have changed significantly in this year. We therefore add the coefficients of the seasonal shift dummy variables corresponding to this date to the I_ANG variable. The new index of indicator variables, I_ANG2, is defined as:

I_ANG2 = I_ANG - 0.949 [S1*S1998Q3] - 0.710 [S2*S1998Q3] - 0.081 [S3*S1998Q3] - 2.140 [S4*S1998Q3]

We re-estimate the model reported in the column headed 6 of Table 6.7.3 with I_ANG being replaced with I_ANG2. The resulting model is reported in the column headed 7 of Table 5.7.3. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification all the ARMA components are significant and the seasonal dummy variables are jointly significant according to LR(SEA DUM). However, the tests $LR(1997q1)$ and $LR(1998q3)$ indicate that the seasonal shift coefficient embodied in I_ANG2 have changed significantly. We therefore use the estimated coefficients on these terms to adjust I_ANG2. The new index of indicator variables, I_ANG3, is defined as: [151]

I_ANG3 = I_ANG2 + 508.111 [S1*S1997Q1] + 10.495 [S2*S1997Q1] - 149.406 [S3*S1997Q1] - 0.625 [S4*S1997Q1]

We re-estimate the model reported in the column headed 7 of Table 5.7.3 with I_ANG2 being replaced with I_ANG3. The resulting model is reported in the column headed 8 of Table 5.7.3. According to the diagnostic tests this model is consistent with stationarity and invertibility however there is evident residual autocorrelation. In terms of specification all the ARMA components are significant except MA(3) and the seasonal dummy variables are jointly significant according to LR(SEA DUM). Further, the set of shift dummy variables corresponding to $1997q1$ cannot be added with significance whereas the shift dummy variables corresponding $1998q3$ can be added with significance.

To deal with the evident autocorrelation we experiment with the ARMA components and find that replacing the MA(3) term with an AR(1) term yields a model that cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. This model is reported in the column headed 9 of Table 5.7.3.

The tests for the two sets of shift dummy variables, corresponding to $LR(1997q1)$ and $LR(1998q3)$, both have negative values and therefore no p-value. This implies that the

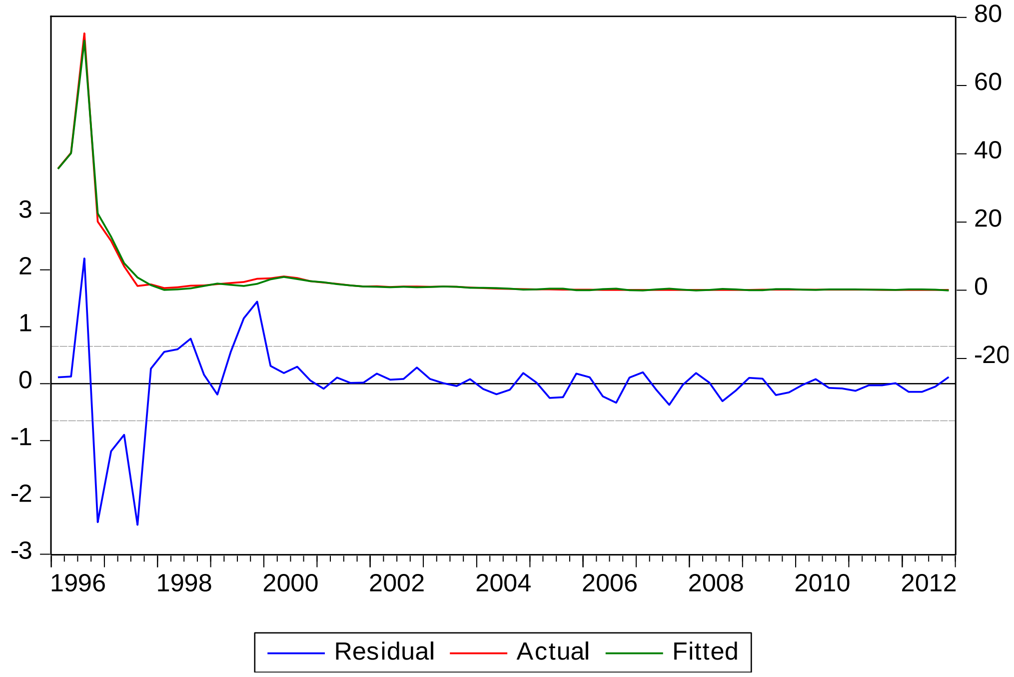
[151] Due to the error of a singular matrix as a result of possible multiple collinearity, we are unable to estimate $LR(1997q1)$ and $LR(1998q3)$ with $ARMAX(0\,,3)$ at a time. Experimentation with the two breaks dates revealed that interaction term associated with $LR(1997q1)$ has lowest SC when added to the $ARMAX(0\,,3)$ model. Therefore, we use this to estimate I_ANG3.

test statistic is clearly very small and is therefore highly insignificant indicating that the coefficients embodied in I_ANG3 have not significantly changed as the ARMA specification is amended. The ARMA terms are all significant and the seasonal dummy variables are jointly significant suggesting that no variables should be excluded. Further, this model has the lowest SC of all those reported.

We test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 9. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 9 in Table 5.7.3 is considered the best model to forecast Angola's annual inflation.

Visual inspection of the actual and fitted values of this model are given in Figure 5.7.4 also suggests that the time path of the fitted values capture the mean shifts in the actual data and broadly tracks the data well if there is some evident seasonality in the residuals (although this declines towards the end of the sample).

Figure 5.7.4: the actual and fitted values of model 9 reported in Table 5.7.3



Therefore, we regard model 9 from Table 5.7.3 as the best ARIMAX model for forecasting Angola's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks and the included deterministic terms adequately capture the identified structural breaks (according to the conducted variable addition tests).

5.8. ARIMAX modelling of annual inflation for Ecuador

The maximum available sample period is 1983q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1987q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.8.1: Bai and Perron tests for structural breaks in Ecuador annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	149.442	16.19	2001q4	2001q4
1 vs 2	10.366	18.11		

In Table 5.8.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is 0.321.

Table 5.8.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.8.2. The test indicates one significant breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). However, the scaled F-statistic is less than critical value for the null hypothesis of 1 breaks (1 vs 2). Both sequential and repartition methods indicate the same break point date of 2001q4

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variable that shift the seasonal mean in 2001q4, denoted $D(2001q4)_{st}$. The model including the seasonal dummy variables and the shift dummy variables is given in the column headed 2 of Table 5.8.2. Both the seasonal dummy variables and the shift dummy variables are all significant suggesting significant changes in the seasonal means at the identified break point. The significance of these shift dummy variables and that this model's SC falls to -0.439 supports the need to model the identified breaks.

Figure 5.8.1 plots the actual and fitted values of the model reported in column 2 of Table 5.8.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not adequately capture all of the mean shifts in the actual data. Therefore, the graph suggests two sets of pulse outliers in around 1989 and 2000 and experimentation gives rise to new break date in 2002q1 to replace the previously identified one in 2001q4. The dummy variables corresponding to the new break date are denoted with $D(2002q1)_{st}$ and the pulse outliers are denoted as $D(1989)$ and $D(2000)$ respectively.[152] We add these new shifts and pulse dummy variables to the model reported in column 2 giving the estimation results are reported in column 3 of Table 5.8.2. All of the seasonal, shift and pulse dummy variables are significant. The significance of these dummy variables and that this model's SC falls to -1.392 supports the inclusion of all of these terms in the model.

Figure 5.8.2 plots the actual and fitted values of the model reported in column 3 of Table 5.8.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts in the actual data than did model 2. We regard model 3 from Table 5.8.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of Ecuador's annual inflation.

[152] The dummy variables for $D(1989)_{st}$ and $D(2000)$ are estimated as follow: $D(1989)$ = $\begin{cases} 0 \ \ if \ t \neq 1988q4, 1989q1, 1989q2 \ and \ 1989q3 \\ 1 \ \ if \ t = \ 1988q4, 1989q1, 1989q2 \ and \ 1989q3 \end{cases}$ and $D(2000)$ = $\begin{cases} 0 \ \ if \ t \neq 2000 \\ 1 \ \ if \ t = 2000 \end{cases}$

5.8.2: Deterministic component of ARIMAX models for Ecuador

Sample/Observation		1987q1 – 2012q4 (104)		
	1	2	3	4
D_{1t}	0.293 (5.637)	0.467 (10.684)	0.399 (14.950)	
D_{2t}	0.289 (5.562)	0.462 (10.587)	0.395 (14.792)	
D_{3t}	0.288 (5.543)	0.461 (10.561)	0.394 (14.749)	
D_{4t}	0.285 (5.483)	0.473 (10.474)	0.391 (14.626)	
$D(2001q4)_{1t}$		-0.411 (-6.114)		
$D(2001q4)_{2t}$		-0.409 (6.101)		
$D(2001q4)_{3t}$		-0.409 (-6.095)		
$D(2001q4)_{4t}$		-0.409 (-6.139)		
$D(2002q1)_{1t}$			-0.342 (-8.448)	
$D(2002q1)_{2t}$			-0.342 (-8.427)	
$D(2002q1)_{3t}$			0.342 (-8.411)	
$D(2002q1)_{4t}$			-0.342 (-8.411)	
$D(1989)$			0.451 (8.564)	
$D(2000)$			0.560 (10.633)	
I_ECU				1.000 (39.581)
Adj R^2	-0.030	0.580	0.849	0.862
SC	0.321	-0.439	-1.392	-1.800
S.E	0.265	0.169	0.101	0.097

Figure 5.8.1: the actual and fitted values of model 2 reported in Table 5.8.2

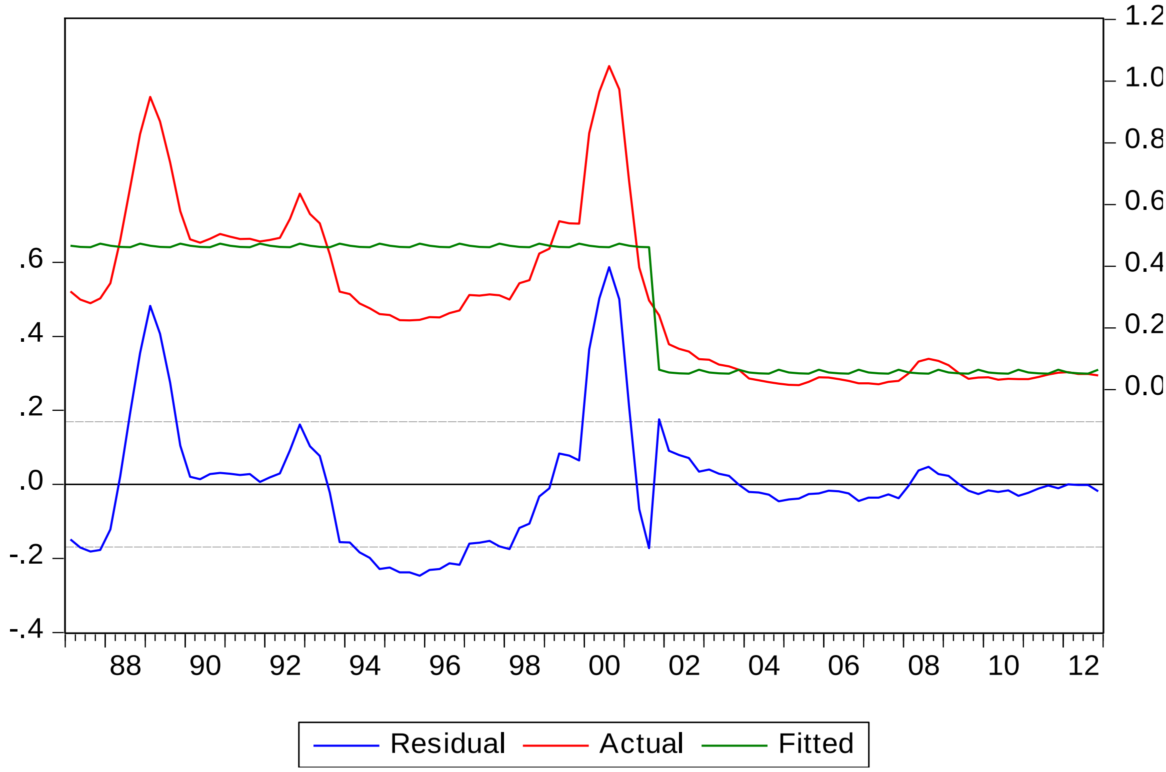
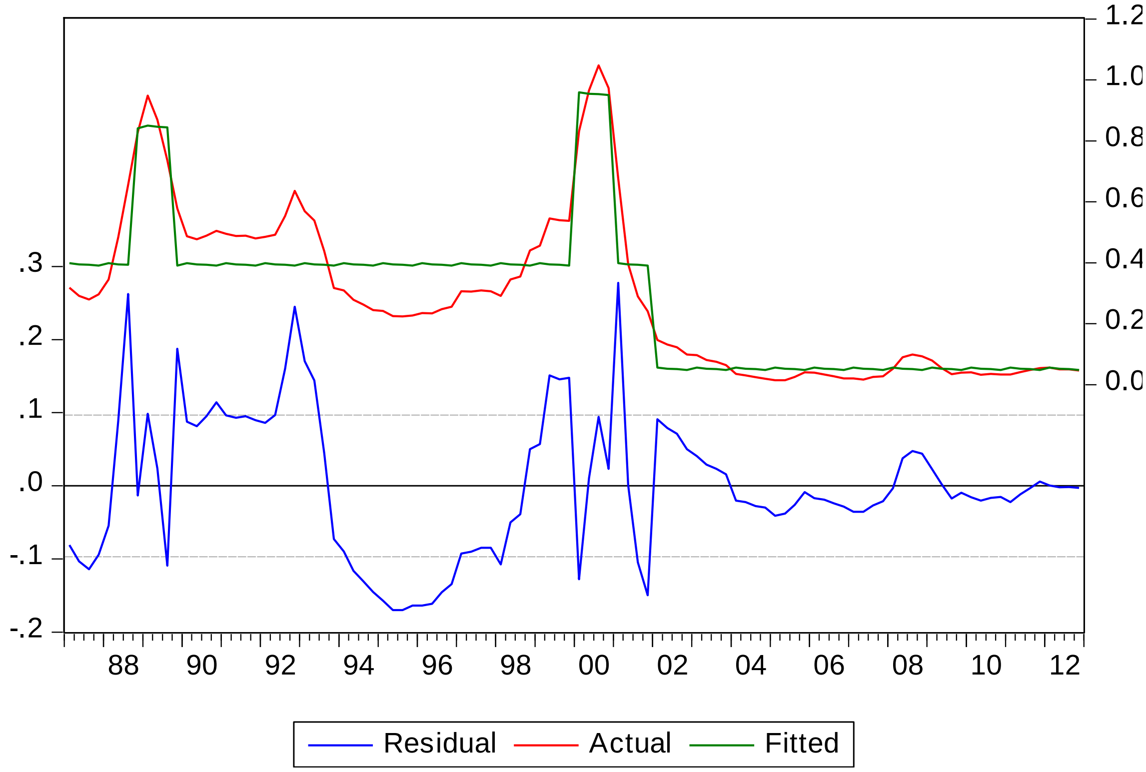


Figure 5.8.2: the actual and fitted values of model 3 reported in Table 5.8.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.8.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_ECU, as the fitted value of the model reported in column 3 of Table 5.8.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.8.2. The index is significant and has a unit coefficient as is expected. This model's SC is -1.800 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

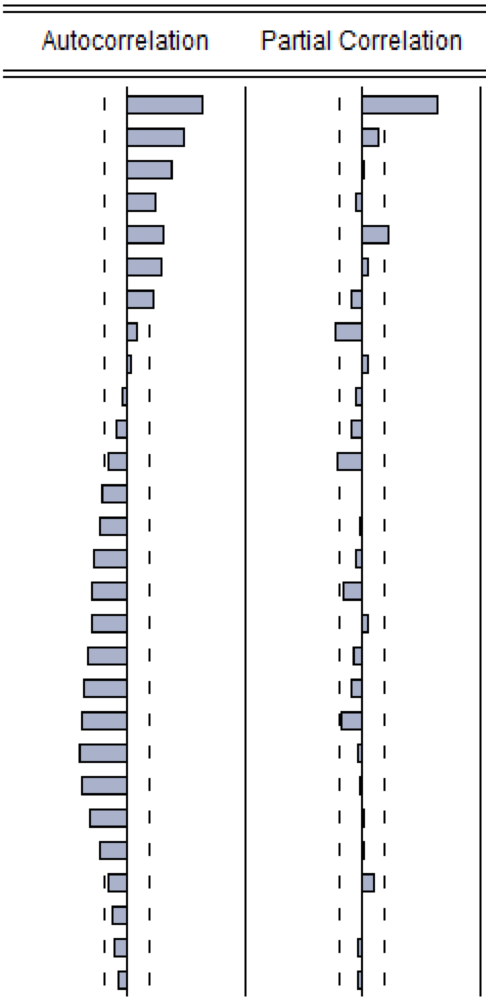
5.8.2 Developing the ARIMAX model for Ecuador

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.8.2 is plotted in Figure 5.8.3. Although the first 7 autocorrelation coefficients (ACs) are significant which, being greater than 5, is normally indicative of nonstationarity, the insignificance of the ACs at lags 8, 9, 10, 11 and 12 and the clear sinusoidal (rather than persistently significant) nature of the ACF suggests that the data are stationary and do not require any further nonseasonal differencing. If this is not the case it will become apparent from our diagnostic tests for stationarity and we therefore proceed being mindful of not over differencing the data. We also note that this sinusoidal geometric decay of the ACF is suggestive of the existence of an AR process. The seasonal ACs are significant at lags 4, 16, 20 and 24 and insignificant at lags 8 and 12. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant and, as already mentioned, the sinusoidal decay of the ACF is probably indicative of an AR process rather than the need for any further differencing (be it seasonal or nonseasonal). It also indicates the maximum order of seasonal MA component is probably equal to 1 (given the significant AC at the seasonal lag of 4 and the insignificance of the seasonal AC at lag 8). The sinusoidal nature of the ACF makes it difficult to identify the order of nonseasonal MA process with the first 7 ACs being significant. We initially specify this to be 3 to account for the significant ACs at lags 1, 2 and 3 and given that we have identified a seasonal MA component to account for the significant AC at lag 4. Since we do not expect a higher nonseasonal MA process as it would imply nonstationarity we do not, at least initially, specify a higher order nonseasonal MA process.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1, and insignificant at lags 2 and 3. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 1. The seasonal PACs are significant at lags 8 and 12 and insignificant at lags 4, 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 3 (given the significance of the PAC at lag 5, 8 and 12). Therefore, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(1,3)(3,1)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_ECU plus 4 seasonal dummy variables and an $ARMA(1,3)(3,1)_4$ model of the residuals in the column headed 5 of Table 5.8.3.

Figure 5.8.3: the ACF and PACF of the residuals of model 4 reported in Table 5.8.2

Sample: 1987Q1 2012Q4
Included observations: 104



	AC	PAC	Q-Stat	Prob
1	0.658	0.658	46.331	0.000
2	0.511	0.138	74.581	0.000
3	0.388	0.012	90.984	0.000
4	0.259	-0.063	98.399	0.000
5	0.312	0.232	109.26	0.000
6	0.307	0.062	119.84	0.000
7	0.239	-0.086	126.32	0.000
8	0.088	-0.239	127.21	0.000
9	0.038	0.060	127.38	0.000
10	-0.041	-0.063	127.58	0.000
11	-0.090	-0.095	128.55	0.000
12	-0.160	-0.210	131.60	0.000
13	-0.209	0.004	136.88	0.000
14	-0.245	-0.014	144.24	0.000
15	-0.283	-0.065	154.17	0.000
16	-0.316	-0.164	166.66	0.000
17	-0.307	0.064	178.63	0.000
18	-0.347	-0.073	194.08	0.000
19	-0.376	-0.094	212.38	0.000
20	-0.399	-0.182	233.27	0.000
21	-0.425	-0.037	257.21	0.000
22	-0.397	-0.022	278.44	0.000
23	-0.335	0.018	293.73	0.000
24	-0.239	0.011	301.60	0.000
25	-0.158	0.110	305.07	0.000
26	-0.115	0.006	306.94	0.000
27	-0.105	-0.035	308.53	0.000
28	-0.081	-0.043	309.49	0.000

In this model the SC falls to -2.545 suggesting that the addition of ARMA terms has improved the specification. I_ECU is significant whereas all 4 seasonal dummy variables are individually insignificant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of -0.822 (given in square brackets below the reported test statistic). Because the actual value exceeds 0.05 these 4 dummy variables are jointly insignificant while all the ARMA components are significant except the AR(1), SAR(8), SAR(12) and SMA(4) terms that are insignificant. The latter suggests the removal of ARMA components to improve the model.

Table 5.8.3: The ARIMAX table for Ecuador

Sample/Observations 1987q1 2012q4 (104)						
	5	6	7	8	9	10
I_ECU	0.677 (11.470)	0.452 (8.135)	0.229 (6.087)			
I_ECU2				0.270 (6.763)		
I_ECU3					0.357 (8.588)	0.250 (6.677)
D_1	0.047 (1.791)	0.108 (2.410)	0.042 (0.634)	0.063 (1.387)	0.104 (1.249)	-0.138 (-0.515)
D_2	0.047 (1.787)	0.109 (2.424)	0.041 (0.621)	0.062 (1.366)	0.104 (1.240)	-0.139 (-0.518)
D_3	0.044 (1.666)	0.107 (2.339)	0.042 (0.644)	0.064 (1.396)	0.105 (1.239)	-0.138 (-0.513)
D_4	0.045 (1.666)	0.104 (2.339)	0.042 (0.632)	0.063 (1.378))	0.101 (1.204)	-0.139 (-0.517)
AR(1)	0.075 (0.539)		0.970 (61.259)	0.962 (54.31	0.936 (24.989)	0.986 (87.391)
SAR(4)	0.842 (2.499)	0.535 (5.536)	0.259 (2.280)	0.287 (2.492	-0.863 (-26.139)	
SAR(8)	-0.223 (-1.182)					
SAR(12)	-0.086 (-0.727)					
MA(1)	0.817 (6.969)	1.059 (13.406)	0.582 (5.815)	0.580 (5.892)	0.423 (4.519)	0.696 (7.667)
MA(2)	0.944 (13.280)	1.066 (11.494)	0.400 (4.166)	0.440 (4.672)	0.467 (4.822)	0.485 (5.238)
MA(3)	0.881 (10.456)	0.992 (23.952)				
SMA(4)	-0.450 (-1.280)		-0.999 (-21.133)	-0.999 (-26.787)	0.999 (46.013)	-0.999 (-32.316)
Adj R^2	0.957	0.964	0.979	0.980	0.976	0.980
SC	-2.545	-2.867	-3.354	-3.398	-3.213	-3.449
S.E	0.054	0.049	0.038	0.037	0.041	0.037
AR Root	0.900 0.668 0.075	0.855	0.970 0.713	0.962 0.732	0.964 0.936	0.986
MA Root	0.999 0.881 0.819	0.999 0.992	0.999 0.632	0.999 0.63l	0.999 0.683	0.999 0.696
P[QLB(10)]	0.030	0.002	0.224	0.214	0.037	0.116
LR (SEA DUM)	-0.822	14.818 (0.005)	4.188 [0.381]	3.151 [0.533]	1.660 [0.798]	11.295 [0.023]
LR (SEA DUM, CON)						6.969 [0.000]
$LR(2002q1)$	21.365 [0.000]	1.453 (0.835)	-0.376	-23.008	23.025 [0.000]	-1.985
$LR(1989)$	87.435 [0.000]	30.563 (0.000)	10.776 [0.001]	6.245 [0.013]	25.523 [0.000]	2.778 [0.100]
$LR(2000)$	55.828 [0.000]	0.155 (0.693)	10.006 [0.002]	5.937 [0.015]	28.242 [0.000]	0.964 [0.326]

Where: I_ECU = the fitted value of the model reported in column 3 of Table 5.8.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(10)] = Probability value of the Ljung-Box Q-statistic at the 10th lag from the sample size ($\sqrt{10}$), Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables; $LR(1989)$, $LR(2000)$ and $LR(2002q1)$, = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We conduct variable addition tests for the shift dummy variables included in the I_ECU variable to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA terms. We test whether the shift dummy variables corresponding to the 2002q1 break can be added to the model with joint significance is reported in the row labelled $LR(2002q1)$. Since the probability value is less than 0.05, this variable is highly significant and the variable can be added with joint significance. Similarly, the probability values of the joint tests of the pulse outlier dummy variables corresponding to the break dates $LR(1989)$ and $LR(2000)$, reported in the rows labelled $LR(1989)$ and $LR(2000)$ are also significant indicating that both variables can be added with joint significance. This suggests that the coefficients embodied in I_ECU have significantly changed with the addition of ARMA terms.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 10th lag, denoted P[QLB(10)], is less than 0.050 indicating evident residual autocorrelation – we choose lag 10 based on the square root of the sample size (in this case $\sqrt{104}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible.

This model cannot be valid for forecasting due to the evidence of residual autocorrelation and should be respecified. Therefore, we amend the model reported in the column headed 5 of Table 5.8.3 by removing insignificant ARMA variables. The coefficients on the AR(1), SAR(8), SAR(12) and SMA(4) terms are not significant and are therefore removed from the model given in the column headed 5 of Table 5.8.3 and the resulting $ARMAX(0,3)(1,0)_4$ specification is reported in the column headed 6 of Table 5.8.3. Although this model does not fail the diagnostic checks for invertibility and stationarity, there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable that indicates the need to further adjust the model.

Experimentation with the ARMA components yields the $ARMAX(1,2)(1,1)_4$ model reported in the column headed 7 of Table 5.8.3. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. All the ARMA components are significant. The seasonal dummy variables are jointly insignificant according to LR(SEA DUM) because its probability value is greater than 0.05. However, the joint tests for $LR(1989)$ and $LR(2000)$ indicate that the coefficients embodied in I_ECU have changed significantly. We therefore add the dummy variables corresponding to these dates to the model reported in the column headed 7 of Table 5.8.3 and use the estimated coefficients on these terms to adjust I_ECU. The new index of indicator variables, I_ECU2, is defined as:

I_ECU2 = I_ECU - 0.139 [D1989] + 0.002 [D2000]

We re-estimate the model reported in the column headed 7 of Table 5.8.3 with I_ECU being replaced with I_ECU2. The resulting model is reported in the column headed 8 of Table 5.8.3. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The seasonal dummy variables are jointly insignificant. However, the joint tests for $LR(1989)$ and $LR(2000)$ indicate that the coefficients embodied in I_ECU2 have changed significantly. We therefore add the dummy variables corresponding to these dates to the model reported in the column headed 8 of Table 5.8.3 and use the estimated coefficients on these terms to adjust I_ECU2. The new index of indicator variables, I_ECU3, is defined as:

I_ECU3 =I_ECU2 - 0.089 [D1989] + 0.001 [D2000]

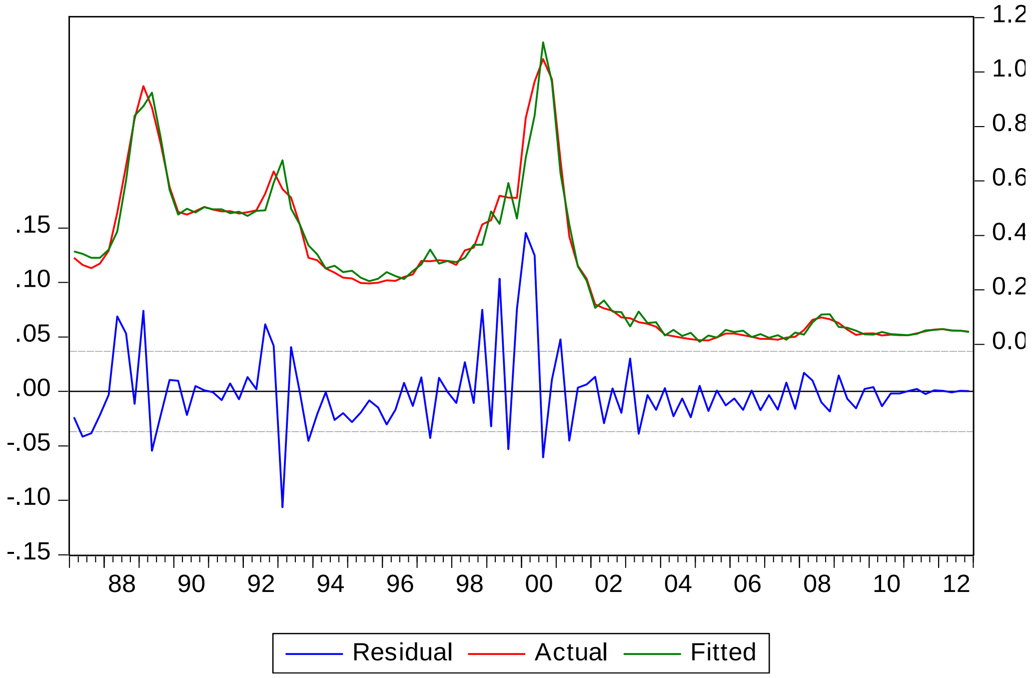
We re-estimate the model reported in the column headed 8 of Table 5.8.3 with I_ECU2 being replaced with I_ECU3. The resulting model is reported in the column headed 9 of Table 5.8.3. This model is rejected based on residual autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model. After experimentation with the ARMA components we select an

$ARMAX(1,2)(0,1)_4$ with I_ECU3 which is reported in the column headed 10 of Table 5.8.3. In this model, all the ARMA components are significant. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The tests for the addition of the 3 sets of dummy variables corresponding to $LR(1989)$, $LR(2000)$ and $LR(2002q1)$, are all insignificant indicating that coefficients embodied in I_ECU3 have not significantly changed with the amendment of ARMA terms. However, although the four seasonal dummy variables are individually insignificant the joint test for the exclusion of these dummy variables is significant and we therefore do not exclude these insignificant dummy variables from this model.[153]

We test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 10. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 10 in Table 5.8.3 is considered the best model to forecast Ecuador's annual inflation.

[153] Experimentation with the exclusion of these seasonal variables caused further problems of autocorrelation that suggest unmodelled systematic variation in the dependent variable.

Figure 5.8.4: the actual and fitted values of model 10 reported in Table 5.8.3



Visual inspection of the actual and fitted values of this graph shows that the fitted values broadly captures the mean shifts and general time path of the actual data .Therefore we regard model 10 from Table 5.8.3 as the best ARIMAX model for forecasting Ecuador's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks. Although there is some concern with the seasonality in the residuals (this declines to zero at the end of the sample).

5.9 Box-Jenkins ARIMAX modelling of annual inflation for Kuwait

The maximum available sample period estimated is 1973q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1977q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.9.1: Bai and Perron tests for structural breaks in Kuwait annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	58.174	16.19	1983q2	1983q2
1 vs 2	24.299	18.11	2007q1	2007q1
2 vs 3	5.484	18.93		

In Table 5.9.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -3.777.

Table 5.9.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.9.2. The test results indicate that there are two significant breakpoints because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1) and the null hypothesis of one break (1 vs 2). However, the scaled F-statistic is less than critical value for the null hypothesis of 2 breaks (2 vs 3). Both sequential and repartition methods indicate the same break point dates of 1983q2 and 2007q1.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variables that give shifts in the seasonal means in 1983q2, denoted $D(1983q2)_{st}$, and 2007q1, denoted $D(2007q1)_{st}$. The model including the seasonal dummy variables and the shift dummy variables is given in the column headed 2 of Table 5.9.2. All the shifts and seasonal dummy variables are significant. The significance of the shift dummy variables and that this model's SC falls to -4.027 supports the need to model the identified breaks.

Figure 5.9.1 plots the actual and fitted values of the model reported in column 2 of Table 5.9.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not capture a large set of outliers in around 1992. We therefore add a pulse dummy variable, denoted $D(1992)$ to the model reported in column 2 to capture these outliers.[154] The estimation results of this model are reported in column 3 of Table 5.9.2. All of the dummy variables are significant suggesting significant justifying their inclusion. The significance of these dummy variables and that this model's SC falls to -4.968 supports the inclusion of all of these terms to in the model.

Figure 5.9.2 plots the actual and fitted values of the model reported in column 3 of Table 5.9.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts and outliers in the actual data than did model 2. We regard model 3 from Table 5.9.2 as capturing the main shifts and outliers in the data and use this as the basis of the deterministic component of our ARIMAX model of Kuwait's annual inflation.

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[154]The dummy variables for $D(1992)$ is estimated as follow: $= \begin{cases} 0 \ \ if \ t \neq 1992 \\ 1 \ \ if \ t = 1992 \end{cases}$

Table 5.9.2: Deterministic component of ARIMAX models for Kuwait

Sample/Observation		1977q1- 2012q4 (144)		
	1	2	3	4
D_{1t}	0.039 (6.780)	0.077 (7.378)	0.077 (11.967)	
D_{2t}	0.039 (6.781)	0.082 (7.296)	0.082 (11.833)	
D_{3t}	0.039 (6.692)	0.082 (7.282)	0.082 (11.811)	
D_{4t}	0.038 (6.571)	0.079 (7.033)	0.079 (11.407)	
$D(2007q1)_{it}$		0.033 (2.645)	0.038 (4.997)	
$D(2007q1)_{2t}$		0.032 (2.580)	0.038 (4.866)	
$D(2007q1)_{3t}$		0.029 (2.364)	0.035 (4.516)	
$D(2007q1)_{4t}$		0.029 (2.293)	0.034 (4.400)	
D(1992)			0.127 (14.707)	
$D(1983q2)_{1t}$		-0.053 (-4.496)	-0.059 (-8.038)	
$D(1983q2)_{2t}$		-0.058 (-4.593)	-0.063 (-8.127)	
$D(1983q2)_{3t}$		-0.057 (-4.584)	-0.063 (-8.112)	
$D(1983q2)_{4t}$		-0.055 (-4.369)	-0.060 (-7.764)	
I_KUW				1.000 (36.379)
Adj R^2	-0.021	0.360	0.757	0.777
SC	-3.777	-4.027	-4.968	-5.382
S.E	0.035	0.027	0.017	0.016

Figure 5.9.1: the actual and fitted values of model 2 reported in Table 5.9.2

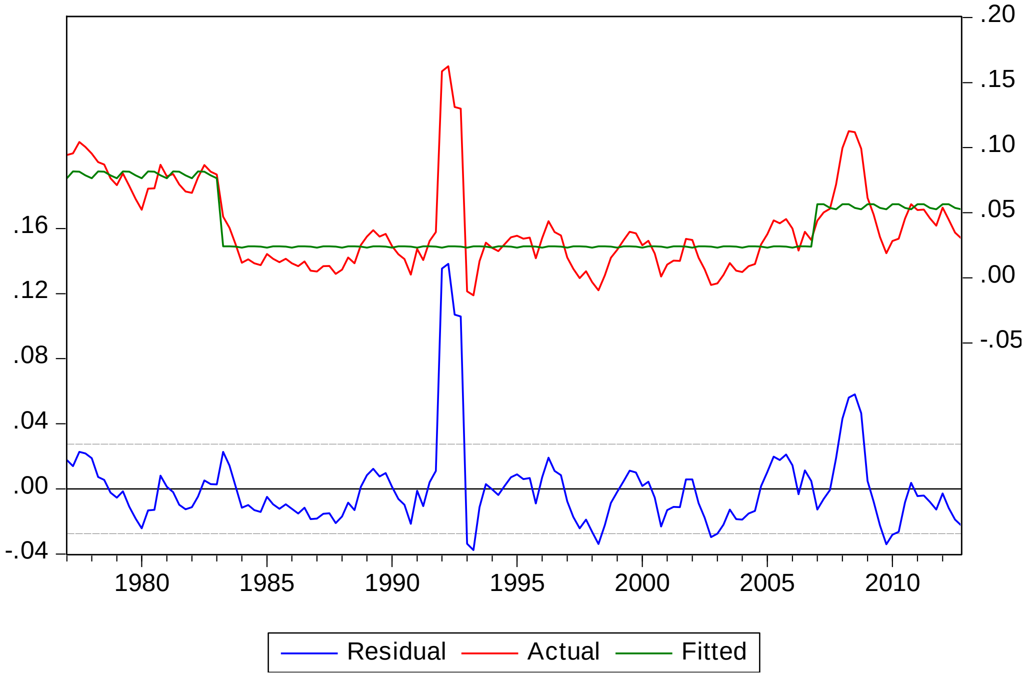
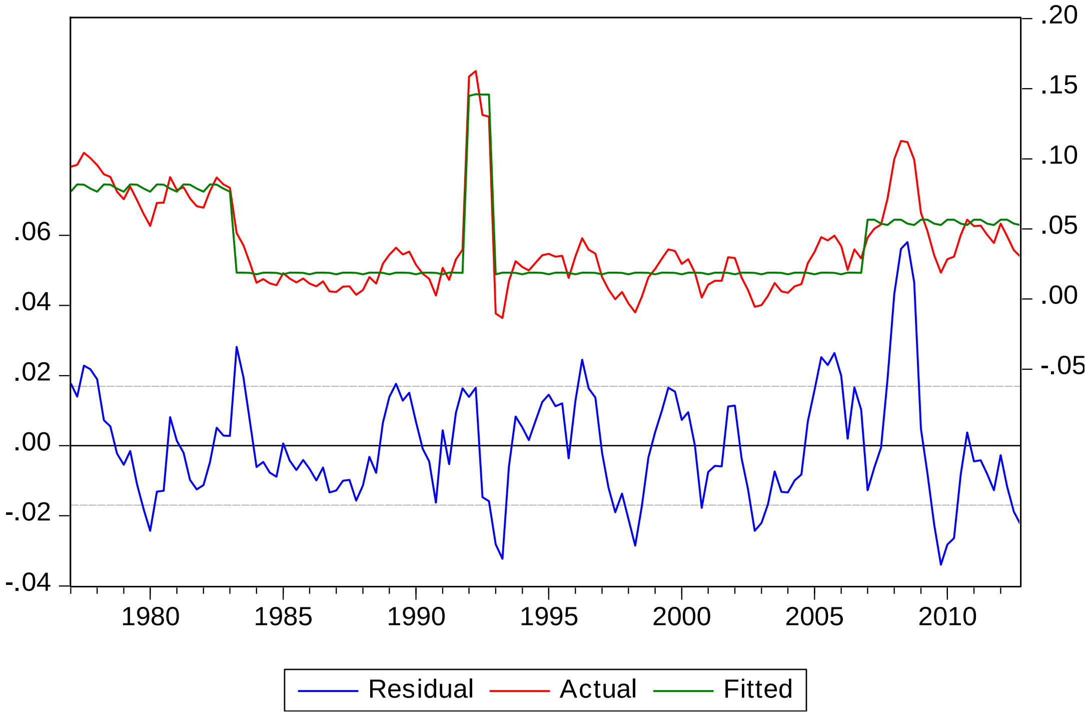


Figure 5.9.2: the actual and fitted values of model 3 reported in Table 5.9.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.1.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_KUW, as the fitted value of the model reported in column 2 of Table 5.9.2 and report the regression of annual inflation on this indicator variable in column 3 of Table 5.9.2. The index is significant and has a unit coefficient as is expected. This model's SC is -5.382 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

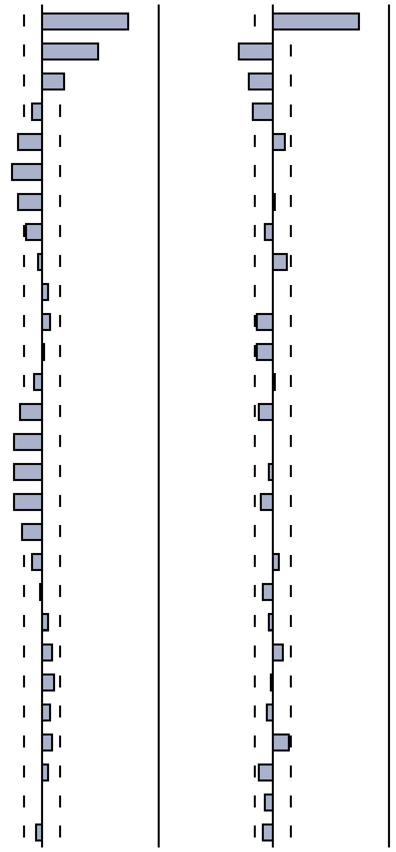
5.9.2 Developing the ARIMAX model for Kuwait

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.9.2 is plotted in Figure 5.9.2. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1, 2 and 3 insignificant at lag 4. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant (the significance of the ACs at lags 5, 6 and 7 is interpreted as part of the sinusoidal pattern of the ACF rather than nonstationarity). It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are insignificant at lags 4, 8, 16, 20, 24 and 28 (if significant at lag 16, which is interpreted as part of the sinusoidal pattern of the ACF). This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1, 2 and 3 and insignificant at lag 5. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 3. The seasonal PACs are significant at 4 and insignificant at lags, 8 12, 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 1. Therefore, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(3,3)(1,\ 0)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_KWU plus 4 seasonal dummy variables and an $ARMA(3,3)$ (1, 0)$_4$ model of the residuals in the column headed 5 of Table 5.9.3.

Figure 5.9.3: the ACF and PACF of the residuals of model 4 reported in Table 5.9.2

Sample: 1977Q1 2012Q4
Included observations: 144



Autocorrelation / Partial Correlation (lag)	AC	PAC	Q-Stat	Prob
1	0.782	0.782	90.007	0.000
2	0.496	-0.299	126.50	0.000
3	0.192	-0.222	132.01	0.000
4	-0.087	-0.178	133.15	0.000
5	-0.227	0.106	140.95	0.000
6	-0.264	0.006	151.56	0.000
7	-0.217	0.014	158.76	0.000
8	-0.145	-0.077	162.00	0.000
9	-0.030	0.128	162.14	0.000
10	0.065	0.005	162.82	0.000
11	0.073	-0.150	163.66	0.000
12	0.011	-0.151	163.68	0.000
13	-0.073	0.016	164.54	0.000
14	-0.191	-0.117	170.45	0.000
15	-0.256	0.007	181.15	0.000
16	-0.259	-0.043	192.15	0.000
17	-0.247	-0.106	202.29	0.000
18	-0.184	0.007	207.95	0.000
19	-0.085	0.048	209.17	0.000
20	-0.008	-0.092	209.18	0.000
21	0.042	-0.040	209.48	0.000
22	0.093	0.086	210.96	0.000
23	0.099	-0.018	212.66	0.000
24	0.068	-0.050	213.47	0.000
25	0.085	0.148	214.75	0.000
26	0.060	-0.136	215.40	0.000
27	0.007	-0.080	215.41	0.000
28	-0.051	-0.095	215.88	0.000

In this model the SC falls to -6.477 suggesting that the addition of ARMA terms has improved the specification. I_KUW is significant and all 4 seasonal dummy variables are individually insignificant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.681 (given in square brackets below the reported test statistic). Because this exceeds 0.05 these 4 dummy variables are jointly insignificant. The first non-seasonal autoregressive variable's coefficient denoted AR(1), the first, second and third non-seasonal moving average variables' coefficients, denoted as MA(1), MA(2) and MA(3) respectively, are significant. However, the first seasonal AR variable's coefficient, denoted SAR(4), as well as the second and third non-seasonal AR variables' coefficients, denoted AR(2) and AR(3) respectively, are insignificant. These results suggest that the specification can be improved by the exclusion of some combination of deterministic and ARMA terms.

Table 5.9.3: The ARIMAX table for Kuwait

Sample/Observations	1977q1 – 2012q4 (140)				
	5	6	7	8	9
I_KUW	0.940 (17.022)				
I_KUW2		0.605 (18.930)			
I_KUW3			0.607 (20.111)	0.617 (20.977)	
I_KUW4					0.566 (21.047)
D_1	0.002 (0.393)	0.016 (4.022)	0.015 (3.685)	0.014 (4.022)	0.016 (4.383)
D_2	0.002 (0.507)	0.020 (5.220)	0.020 (5.256)	0. 020 (5.773)	0.021 (5.968)
D_3	0.002 (0.546)	0.018 (4.690)	0.017 (4.431)	0.017 (4.858)	0.019 (5.150)
D_4	0.002 (0.643)	0.018 (4.601)	0.017 (4.371)	0.017 (4.814)	0.018 (5.102)
AR(1)	0.301 (2.357)	0.281 (3.176)	0.330 (3.775)	0.350 (4.000)	0.355 (4.131)
AR(2)	0.019 (0.136)	-0.046 (-0.492)	-0.088 (-0.939)		
AR(3)	-0.154 (-1.201)	0.036 (0.396)	0.066 (0.770)		
SAR(4)	0.130 (1.130)	0.100 (1.297)	0.073 (1.017)		
MA(1)	0.697 (6.772)	0.902 (42.399)	0.896 (44.438)	0.845 (18.758)	0.861 (20.914)
MA(2)	0.593 (5.657)	0.889 (36.176)	0.886 (0.886)	0.716 (11.461)	0.762 (13.532)
MA(3)	0.687 (7.026)	0.963 (64.208)	0.968 (68.851)	0.852 (19.346)	0.882 (22.003)
Adj R^2	0.929	0.946	0.949	0.949	0.949
SC	-6.477	-6.502	-6.560	-6.635	-6.646
S.E	0.009	0.008	0.008	0.008	0.008
AR Root	0.601 0.577 0.462	0.562 0.395 0.300	0.521 0.458 0.382	0.350	0.355
MA Root	0.894 0.877	0.988 0.987	0.990 0.988	0.991 0.927	0.991 0.943
P[QLB(12)]	0.216	0.113	0.027	0.271	0.330
LR (SEA DUM)	2.299 [0.681]	69.407 [0.000]	86.087 [0.000]	90.051 [0.000]	88.095 [0.000]
LR(SEA DUM,CON)					647622.300 [0.000]
$LR(1983q2)$	25.391 [0.000]	9.968 [0.041]	1.614 [0.806]	1.137 (0.888)	1.546 [0.819]
$LR(1992)$	19.515 [0.000]	1.512 [0.220]	1.851 [0.174]	4.109 [0.043]	2.516 [0.113]
$LR(2007q1)$	8.033 [0.090]	4.264 [0.372]	2.711 [0.607]	8.574 [0.072]	7.585 [0.108]

Where: I_KUW = the fitted value of the model reported in column 3 of Table 5.9.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(12)] = Probability value of the Ljung-Box Q-statistic at the 12th lag from - based on the square root of the sample size ($\sqrt{114}$), Adj R^2 = Adjusted R – square , **SC =** Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables, $LR(1983q2)$,$LR(1992)$, and $LR(2007q1)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We also conduct variable addition tests for the shift dummy variables included in the I_KUW variable to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA terms. Tests of whether the dummy variables corresponding to the 1983q2, 1992 and 2007q1 periods can be added to the model with joint significance are reported in the rows labelled $LR(1989q3)$ and $LR(1992)$, $LR(2007q1)$. Since the probability values for 1983q2 and 1992 (given in square brackets below the test statistics, both being 0.000) are less than 0.050 the variables corresponding to these dates can be added with joint significance. Similarly the probability value of the joint test for the shift dummy variable corresponding to the 2007q1 break date exceeds 0.050 indicating that the shift variable for this date cannot be added with joint significance.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 12th lag, denoted P[QLB(12)], exceeds 0.050 indicating no evident residual autocorrelation – we choose lag 12 based on the square root of the sample size (in this case $\sqrt{144}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible.

Since, shift dummy variables test for $LR(1983q2)$ and $LR(1992)$ indicate that the seasonal shift coefficients embodied in I_KUW have changed significantly; we add the seasonal shift dummy variables corresponding to these dates to the model reported in the column headed 5 of Table 5.9.3 and use the estimated coefficients on these terms to adjust I_KUW. The new index of indicator variables, I_KUW2, is defined as:

I_kuw2 = I_kuw - 0.007 [S1*S1983Q2] - 0.0146 [S2*S1983Q2] - 0.0109 [S3*S1983Q2] - 0.0101 [S4*S1983Q2] + 0.088 [D1992]

We re-estimate the model reported in the column headed 5 of Table 5.9.3 with I_KUW2 being replaced with I_KUW. The resulting model is reported in the column headed 6 of Table 5.9.3. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification all variables are significant except for the AR(2), AR(3) and SMA(4) terms. The seasonal dummy variables are jointly significant according to LR(SEA DUM). The tests for $LR(2007q1)$ and $LR(1992)$ indicate that the coefficients embodied in I_KUW2 have not changed significantly (insignificant). The test $LR(1983q2)$ break date is significant. Therefore, we add the seasonal shift dummy variables corresponding to $LR(1983q2)$ to the model reported in the column headed 6 of Table 5.9.3 and use the estimated coefficients on these terms to adjust I_KUW2. The new index of indicator variables, I_KUW3 is defined as:

I_kuw3 = i_kuw2+ 0.002 [S1*S1983Q2] - 0.000 [S2*S1983Q2] + 0.002 [S3*S1983Q2] + 0.001 [S4*S1983Q2]

We re-estimate the model reported in the column headed 6 of Table 5.9.3 with I_KUW2 being replaced with I_KUW3. The resulting model is reported in the column headed 7 of Table 5.9.3. This model does not fail the diagnostic checks for invertibility and stationarity, however there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model. In terms of specification all variables are significant except for the AR(2), AR(3), SAR(4) and MA(2) terms, which are insignificant.

Therefore, we remove all insignificant ARMA terms, except for the MA (2) term (because the MA(3) term is significant) from the model reported in the column headed 7 from Table 5.9.3 and report the resulting $ARMAX(1,3)$ in the column headed 8 of Table 5.9.3. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. All the ARMA terms in this model are significant. The tests $LR(2007q1)$ and $LR(1983q2)$ indicate that the seasonal shifts coefficient embodied in I_KUW3 have not changed significantly however the $LR(1992)$ break date is significant. Therefore, we add the dummy variables corresponding to $LR(1992)$ to the model reported in the column headed 8 of Table 5.9.3 and use the estimated coefficients on these terms to adjust I_KUW3. The new index of indicator variables, I_KUW4 is defined as:

I_kuw4 = I_kuw3 + 0.024 [D1992]

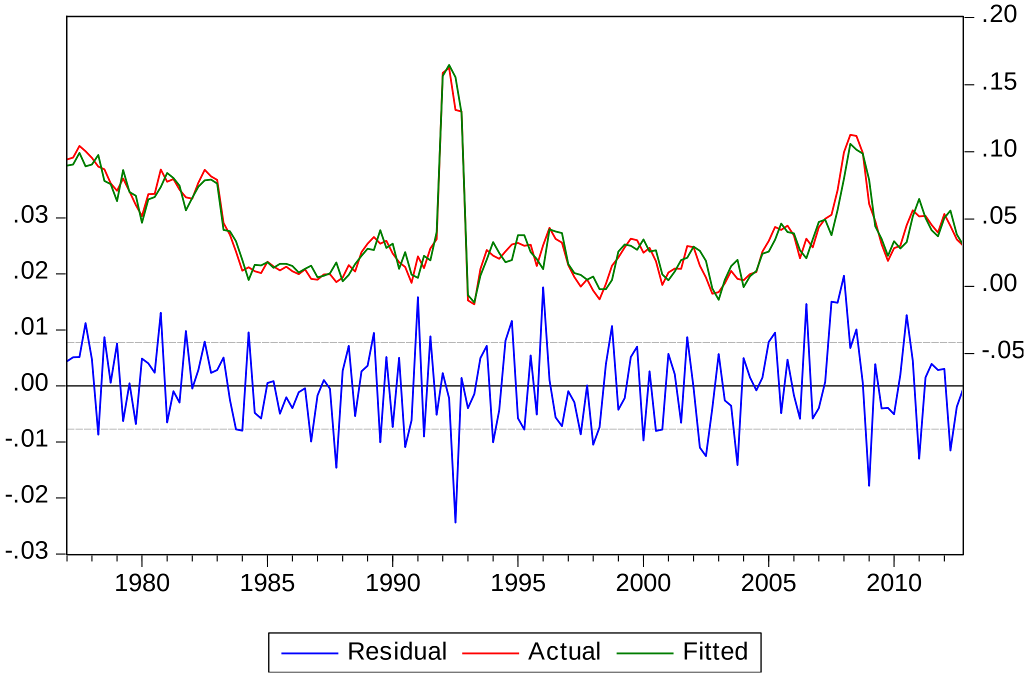
We re-estimate the model reported in the column headed 8 of Table 5.9.3 with I_KUW3 being replaced with I_KUW4. The resulting model is reported in the column headed 9 of Table 5.9.3. According to standard diagnostic test, this model cannot be rejected for residual autocorrelation, stationarity and invertibility. In terms of specification all the ARMA components are significant and the seasonal dummy variables are individually and jointly significant, see LR(SEA DUM).

The tests for the addition of the 3 sets of shift dummy variables, $LR(1983q2)$, $LR(1992)$, and $LR(2007q1)$, all have probability values that exceed 0.050 indicating that the coefficients embodied in I_KUW4 have not significantly changed as the ARMA specification is amended.

We test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 9. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 9 in Table 5.9.3 is considered the best model to forecast Kuwait's annual inflation.

Visual inspection of the actual and fitted values graph of this model suggests that the time path of the fitted values broadly track the data well including the identified mean shifts.

Figure 5.9.4: the actual and fitted values of model 9 reported in Table 5.9.3



We regard model 9 from Table 5.9.3 as the best ARIMAX model for forecasting Kuwait's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks and the included deterministic adequately capture the identified structural breaks (according to the conducted variable addition tests).

5.10 ARIMAX modelling of annual inflation for Nigeria

The maximum available sample period is 1960q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1964q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and discusses the development of the final ARIMAX model.

Table 5.10.1: Bai and Perron tests for structural breaks in Nigeria annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	25.101	16.19	1973q4	1973q4
1 vs 2	37.619	18.11	1997q1	1988q2
2 vs 3	71.560	18.98	1988q2	1996q3
3 vs 4	0.696	19.64		

In Table 5.10.2 we report various deterministic models of annual inflation. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -0.560.

Table 5.10.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.10.2. The test results indicate that there are three significant breakpoints because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1,), the null hypothesis of one break (1 vs 2) and the null hypothesis of two breaks (2 vs 3). However, the scaled F-statistic is less than critical value for the null hypothesis of 3 breaks (3 vs 4). Both sequential and repartition methods indicate different break point dates. The sequential method indicates break dates of 1973q4, 1988q2 and 1997q1 while the repartition method specifies the dates as 1973q4, 1988q2 and 1996q3.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variables that give shifts in the seasonal means in 1973q4, 1988q2, 1996q3 and 1997q1, denoted as: $D(1973q4)_{st}$, $D(1988q2)_{st,}$ $D(1996q3)_{st}$ and $D(1997q1)_{st}$ respectively. The model that include the seasonal dummy variables and the shift dummy variables indicated by the sequential method are given in the column headed 2 of Table 5.10.2. All the shift dummy variables are significant suggesting significant changes in the seasonal means at the identified breaks point; however, all four seasonal dummy variables are insignificant. The significance of the shift dummy variables and that this model's SC falls to -0.883 supports the need to model the identified breaks.

Figure 5.10.1 plots the actual and fitted values of the model reported in column 2 of Table 5.10.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron sequential test results captures all of the mean shifts in the actual data. We also report a model with break dates based on the repartition method in column 3 of Table 5.10.2. All the shift dummy variables are significant. The significance of these shift dummy variables and that this model's SC falls to -0.898 suggests that this deterministic model should be preferred to the one reported in the column headed 2.

Figure 5.10.2 plots the actual and fitted values of the model reported in column 3 of Table 5.10.2. Visual inspection of this graph suggests that this deterministic model also captures the main mean shifts in the actual data. We regard model 3 from Table 5.10.2 as capturing the main mean shifts in the data and use this as the basis of the deterministic component of our ARIMAX model of Nigeria annual inflation because it has the lowest SC.

Table 5.10.2: Deterministic component of ARIMAX models for Nigeria

Sample/Observation	1966q1 2012q4 (196)			
	1	2	3	4
D_{1t}	0.175 (7.000)	0.051 (1.240)	0.051 (1.250)	
D_{2t}	0.177 (7.057)	0.060 (1.453)	0.060 (1.464)	
D_{3t}	0.178 (7.1011)	0.062 (1.493)	0.062 (1.550)	
D_{4t}	0.177 (7.057)	0.055 (1.265)	0.055 (1.274)	
$D(1973q4)_{1t}$		0.131 (2.447)	0.131 (2.465)	
$D(1973q4)_{2t}$		0.116 (2.148)	0.116 (2.164)	
$D(1973q4)_{3t}$		0.119 (2.199)	0.119 (2.215)	
$D(1973q4)_{4t}$		0.121 (2.192)	0.121 (2.209)	
$D(1988q2)_{it}$		0.245 (4.269)	0.245 (4.301)	
$D(1988q2)_{2t}$		0.238 (4.250)	0.238 (4.282)	
$D(1988q2)_{3t}$		0.237 (4.232)	0.256 (4.440)	
$D(1988q2)_{4t}$		0.237 (4.167)	0.256 (4.499)	
$D(1996q3)_{1t}$			-0.307 (-5.452)	
$D(1996q3)_{2t}$			(-0.299) (-5.665)	
$D(1996q3)_{3t}$			-0.316 (-5.665)	
$D(1996q3)_{4t}$			-0.311 (-5.589)	
$D(1997q1)_{1t}$		-0.307 (-5.412)		
$D(1997q1)_{2t}$		-0.299 (-5.479)		
$D(1997q1)_{3t}$		-0.306 (-5.605)		
$D(1997q1)_{4t}$		-0.290 (-5.322)		
I_NIG				1.000 (23.961)
Adj R^2	-0.016	0.432	0.441	0.484
SC	-0.560	-0.883	-0.898	-1.301
S.E	0.175	0.131	0.130	0.125

Figure 5.10.1: the actual and fitted values of model 2 reported in Table 5.10.2

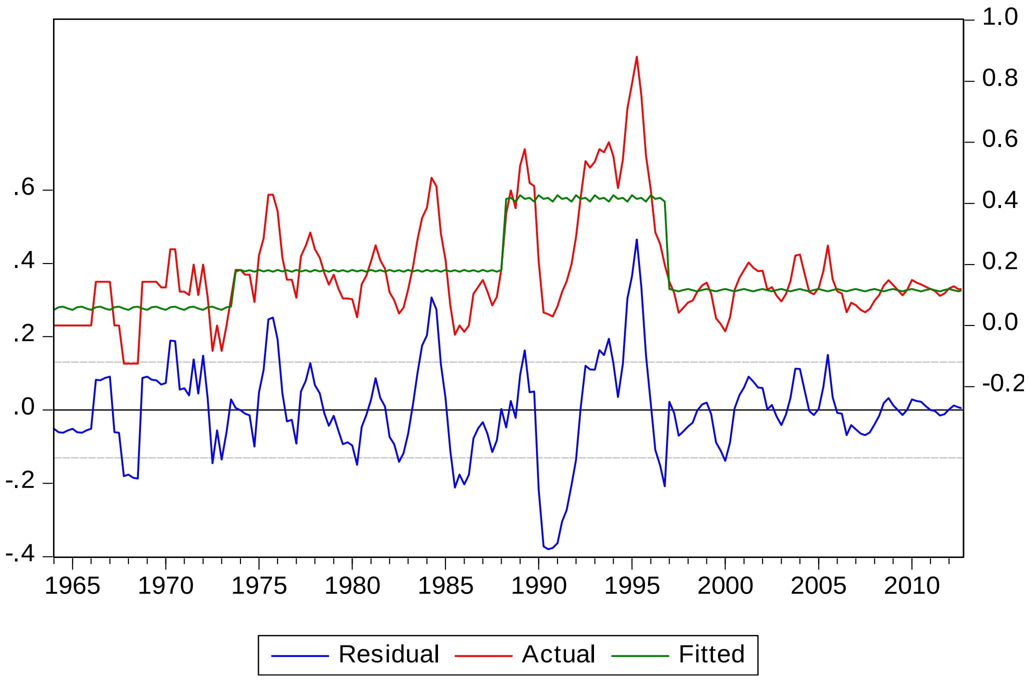
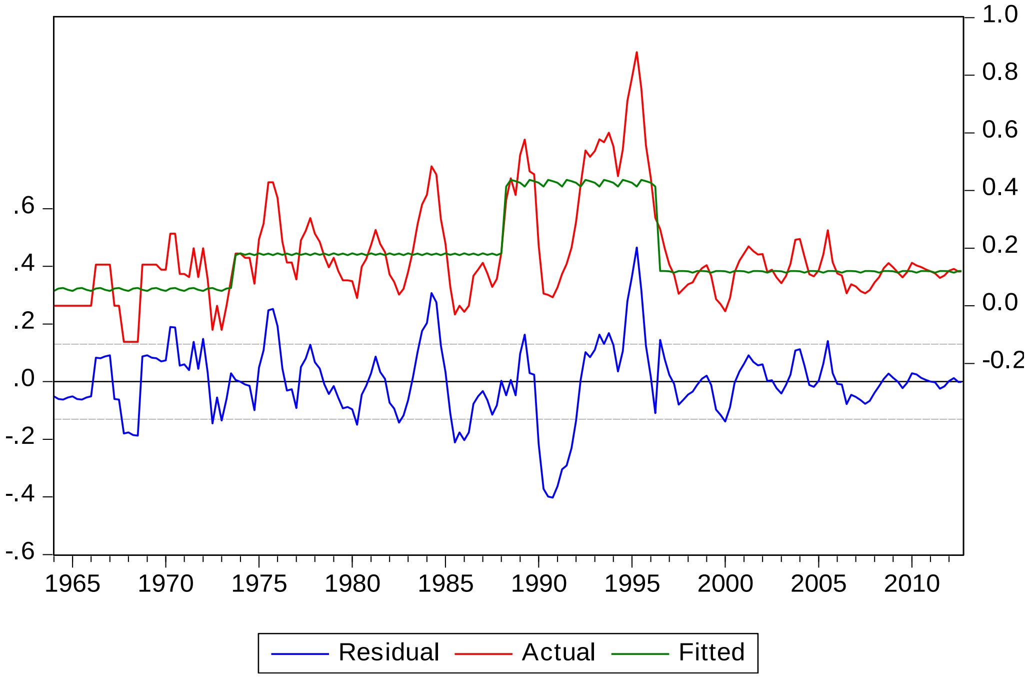


Figure 5.10.2: the actual and fitted values of model 3 reported in Table 5.10.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 3 of Table 5.10.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_NIG, as the fitted value of the model reported in column 3 of Table 5.10.2 and report the regression of annual inflation on this indicator variable in column 4 of Table 5.10.2. The index is significant and has a unit coefficient as is expected. This model's SC is -1.301 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

5.10.2 Developing the ARIMAX model for Nigeria

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 4 of Table 5.10.2 is plotted in Figure 5.10.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1, 2 and 3 and insignificant at lags 4 and 5. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are significant at lags 16 and 28 and insignificant at lags 4, 8, 12, 20 and 24. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1, 2, 3 and insignificant at lags 4. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 3. The seasonal PACs are significant at lags 12 and insignificant at lags 4, 8, 12, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 0 or 3 (given the significance of PACs at lags 5, 9, 12 and 13). Therefore, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(3,3)(3,0)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_NIG plus 4 seasonal dummy variables and an $ARMA(3,3)(3,0)_4$ model of the residuals in the column headed 5 of Table 5.10.3.

Figure 5.10.3: the ACF and PACF of the residuals of model 4 reported in Table 5.10.2

Sample: 1964Q1 2012Q4
Included observations: 196

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.829	0.829	136.64	0.000
		2	0.598	-0.282	208.23	0.000
		3	0.337	-0.225	231.08	0.000
		4	0.112	-0.048	233.59	0.000
		5	0.023	0.269	233.70	0.000
		6	-0.038	-0.162	234.00	0.000
		7	-0.074	-0.119	235.11	0.000
		8	-0.114	-0.074	237.81	0.000
		9	-0.124	0.195	240.98	0.000
		10	-0.125	-0.097	244.23	0.000
		11	-0.120	-0.099	247.26	0.000
		12	-0.134	-0.147	251.06	0.000
		13	-0.131	0.219	254.69	0.000
		14	-0.157	-0.211	259.97	0.000
		15	-0.181	-0.080	267.01	0.000
		16	-0.167	0.040	273.02	0.000
		17	-0.197	-0.074	281.47	0.000
		18	-0.173	0.032	287.99	0.000
		19	-0.127	0.059	291.53	0.000
		20	-0.063	0.048	292.40	0.000
		21	0.028	0.016	292.58	0.000
		22	0.076	-0.111	293.86	0.000
		23	0.068	-0.124	294.91	0.000
		24	0.014	0.010	294.96	0.000
		25	-0.049	0.010	295.50	0.000
		26	-0.110	-0.150	298.28	0.000
		27	-0.127	0.031	301.97	0.000
		28	-0.149	-0.088	307.06	0.000

In this model the SC falls to -2.673 suggesting that the addition of ARMA terms has improved the specification. I_NIG is significant and all 4 seasonal dummy variables are individually significant. The latter is not confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.169 (given in square brackets below the reported test statistic). Because this exceeds 0.05 these 4 dummy variables are jointly insignificant. All the ARMA terms are significant except second and third non-seasonal autoregressive variables' coefficients, denoted AR(2) and AR(3), which are not significant. These results suggest that the specification can be improved by the exclusion of some combination of deterministic and ARMA terms.

Table 5.10.3: The ARIMAX model for Nigeria

Sample/Observations	1964q1- 2012q4 (196)				
	5	6	7	8	9
I_NIG	0.298 (3.057)				
I_NIG2		0.316 (3.827)			
I_NIG3			0.390 (6.306)	0.379 (5.058)	0.413 (6.740)
D_1	0.127 (3.416)	0.128 (3.936)	0.111 (4.091)	0.053 (1.809)	0.105 (3.402)
D_2	0.128 (3.416)	0.128 (3.910)	0.112 (4.043)	0.052 (1.786)	0.105 (3.363)
D_3	0.128 (3.434)	0.128 (3.911)	0.112 (4.077)	0.052 (1.791)	0.106 (3.389)
D_4	0.127 (3.406)	0.127 (3.911)	0.109 (4.009)	0.051 (1.746)	0.104 (3.327)
AR(1)	0.485 (2.391)	0.421 (2.856)	0.303 (3.757)	0.363 (4.470)	0.982 (53.154)
AR(2)	0.261 (1.128)	0.289 (1.800)	0.213 (2.457)	0.286 (3.119)	
AR(3)	0.095 (0.526)	0.083 (0.597)	-0.004 (-0.045)		
SAR(4)	-0.423 (-3.249)	-0.342 (-2.631)	-0.002 (-0.022)	-0.041 (-0.422)	
SAR(8)	-0.4227 (-4.557)	-0.392 (-3.955)	-0.163 (-2.051)	-0.237 (-3.460)	
SAR(12)	-0.316 (-3.645)	-0.280 (-3.050)	-0.079 (-0.987)		
MA(1)	0.827 (4.365)	0.892 (7.004)	0.981 (23.982)	1.036 (16.963)	0.259 (3.478)
MA(2)	0.630 (2.941)	0.707 (4.306)	0.923 (16.707)	0.827 (10.609)	0.219 (2.974)
MA(3)	0.443 (3.148)	0.565 (4.574)	0.942 (20.773)	0.889 (12.501)	
SMA(4)					-0.969 (-63.398)
Adj R^2	0.901	0.904	0.909	0.912	0.911
SC	-2.673	-2.696	-2.762	-2.834	-2.887
S.E	0.055	0.054	0.052	0.051	0.052
AR Root	0.925 0.895 0.876 0.326	0.919 0.866 0.310	0.844 0.745 0.631 0.325 0.017	0.835 0.835 0.747 0.383	0.982
MA Root	0.763	0.846 0.817	0.999 0.971	1.052 0.919	0.992 0.468
P[QLB(14)]	0.671	0.550	0.666	0.160	0.184
LR (SEA DUM)	6.533 [0.163]	7.539 [0.110]	14.907 [0.005]	23.013 [0.000]	18.313 [0.001]
LR (SEA DUM, CON)					8.948 [0.000]
$LR(1973q4)$	23.030 [0.000)	23.134 [0.000]	13.016 [0.011]	**-10.386**	**1.523** **(0.823)**
$LR(1988q2)$	30.951 [0.000)	25.332 [0.000]	16.528 [0.002]	0.165 [0.997]	0.566 [0.967]
$LR(1996q3)$	2.903 [0.574]	16.296 [0.003]	6.347 [0.175]	-7.714	1.132 [0.889]

Where: I_NIG = the fitted value of the model reported in column 3 of Table 5.10.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(14)] = Probability value of the Ljung-Box Q-statistic at the 11th lag from - based on the square root of the sample size ($\sqrt{196}$), Adj R^2 = Adjusted R – square , **SC =** Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables, $LR(1973q4)$ $LR(1988q2)$,$LR(1996q3)$ and = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 14th lag, denoted P[QLB(14)], exceeds 0.050 indicating no evident residual autocorrelation – we choose lag 14 based on the square root of the sample size (in this case $\sqrt{196}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests.

We conduct variable addition tests for the shift dummy variables included in the model to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA components. The test whether the shift dummy variables corresponding to the 1973q4 and 1988q2 breaks can be added to the model with joint significance were reported in the rows labelled $LR(1973q4)$ and $LR(1988q2)$. Since the probability values (given in square brackets below the test statistic, both being 0.000) are less than 0.050 these variables can be added with joint significance. In contrast, the probability values of the joint tests of the shift dummy variables corresponding to the break date 1996q3, reported in the row labelled $LR(1996q3)$ exceeds 0.050 indicating that no shift variables for this date can be added with joint significance.

Since the tests $LR(1973q4)$ and $LR(1988q2)$ indicate that the seasonal shift coefficients embodied in I_NIG have changed significantly (the probability values are less than 0.050) we add seasonal shift dummy variables corresponding to these dates to the model reported in the column headed 5 of Table 5.10.3 and use the estimated coefficients on these terms to adjust I_NIG. The new index of indicator variables, I_NIG2, is defined as:

I_NIG2 = I_NIG - 0.073 [S1*S1973Q4] - 0.072 [S2*S1973Q4] - 0.069 [S3*S1973Q4] - 0.069 [S4*S1973Q4] + 0.088 *[S1*S1988Q2] + 0.087 [S2*S1988Q2] + 0.085 [S3*S1988Q2] + 0.087 [S4*S1988Q2]

We re-estimate the model reported in the column headed 5 of Table 5.10.3 with I_NIG being replaced with I_NIG2. The resulting model is reported in the column headed 6 of Table 5.10.3. In this model, all the ARMA terms are significant except for the AR(2) and AR(3) terms. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. However, all the shift dummy variables corresponding to the statistics $LR(1973q4)$, $LR(1988q2)$ and $LR(1996q3)$ are significant which indicates that the seasonal shift coefficients embodied in I_NIG2 have changed significantly. We therefore add the seasonal shift dummy variables corresponding to these dates to the model reported in the column headed 6 of Table 5.10.3 and use the estimated coefficients on these terms to adjust I_NIG2. The new index of indicator variables, I_NIG3, is defined as:[155]

I_NIG3 = I_NIG2 + 0.050 [S1988Q2] + 0.051 [S1988Q2] + 0.048 [S1988Q2] + 0.0507 [S1988Q2] + 0.030 [*S1996Q3] + 0.027 [S1996Q3] + 0.028 [S1996Q3] + 0.030 [S1996Q3].

We re-estimate the model reported in the column headed 6 of Table 5.10.3 with I_NIG2 being replaced with I_NIG3. The resulting model is reported in the column headed 7 of Table 5.10.3. All variables are significant except for the AR(3), SAR(4) and SAR(12) terms. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The shift dummy variable corresponding to $LR(1996q3)$ is insignificant while $LR(1988q2)$ and $LR(1973q4)$ are statistical significant. This indicates that the seasonal shift coefficients embodied in I_NIG3 have changed significantly. In this model, there are two issues that arise (insignificant of ARMA terms and significant shift dummy variables). Therefore, we first address issue relating to insignificant of ARMA terms and remove variables that are not significant from this model. The coefficients on the AR(3), SAR(4) and SAR(12) terms are not

[155] Due to the error of a singular matrix as a result of non-invertibility, we are unable to estimate the $LR(1973q4)$, $LR(1988q2)$ *and* $LR(1996q3)$ *with* $ARMA(3,3)(3,0)_4$ together at a time. Experimentation with the three break dates revealed that their interaction are not invertible. However, interaction between $LR(1988q2)$ and $LR(1996q3)$ with $ARMA(3,3)(3,0)_4$ model are invertible. Therefore, we use interaction between $LR(1988q2)$ and $LR(1996q3)$ with $ARMA(3,3)(3,0)_4$ to estimate I_NIG3 in column 7.

significant in column 7 and are candidates for exclusion. Since the SAR(8) term is significant we do not remove the SAR(4) term to retain the full second-order seasonal AR component. Therefore, we remove the AR(3) and SAR(12) terms from the model reported in the column headed 7 from Table 6.10.3 and report the resulting $ARMA(2,3)(2,0)_4$ in the column headed 8 of Table 5.10.3.

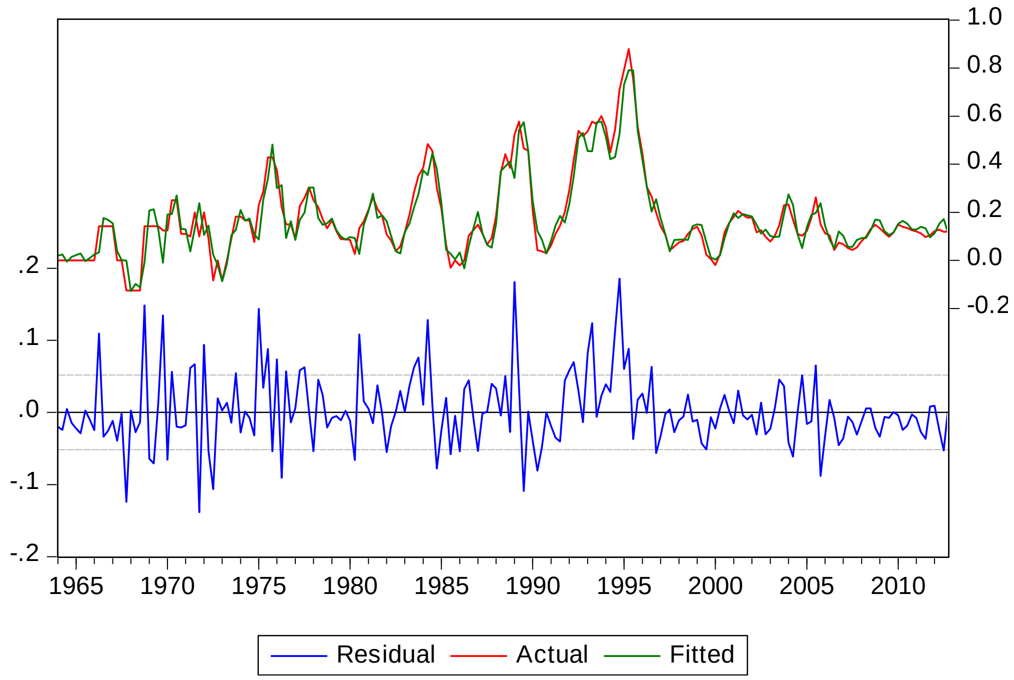
In this model, all the ARMA components are significant except for the SAR(4) term, which we would not remove because of the SAR(8) term that is significant. The tests for shift dummy variables corresponding to the break dates$(1973q4)$, $LR(1988q2)$ and $LR(1996q3)$ are all insignificant. This model does not exhibit evident autocorrelation and nonstationarity. However, one of the MA inverse roots is greater than one suggesting that this model is non-invertible. Hence, this model is not valid for forecasting.

After experimentation with the ARMA components we estimate an $ARMA(1,2)(0,1)_4$ and report this result in the column headed 9 of Table 5.10.3. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification, all the ARMA components are significant and the seasonal dummy variables are also jointly significant according to LR(SEA DUM) because its probability value is less than 0.05. The test denoted , $LR(1973q4)$, $LR(1988q2)$ and $LR(1996q3)$ indicating that the seasonal shift coefficients embodied in I_NIG3 have not changed significantly as the ARMA specification is amended.

We test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 9. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 9 in Table 5.10.3 is considered the best model to forecast Nigeria's annual inflation.

Visual inspection of the actual and fitted values graph of this model suggests that the time paths of the actual and fitted values capture the mean shifts in the actual data.

Figure 5.10.4: the actual and fitted values of model 9 reported in Table 5.10.3



Therefore we regard model 9 from Table 5.10.3 as the best ARIMAX model for forecasting Nigeria's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks.

5.11 Box-Jenkins ARIMAX modelling of annual inflation for Saudi Arabia

The maximum available sample period is 1971q1 to 2012q4. To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1975q1 – 2012q4. The first sub-section discusses the development of the deterministic component of the model that allows for structural breaks (shifts in the seasonal means). The second sub-section identifies the ARMA component to the residuals of this model and hence discusses the development of the final ARIMAX model.

Table 5.11.1: Bai and Perron tests for structural breaks in Saudi Arabia annual inflation

Break Hypothesis	Scaled F-statistic	Critical Value	Sequential	Repartition
0 vs 1	76.031	16.19	1980q3	1980q3
1 vs 2	12.479	18.11		

In Table 5.11.2 we report various deterministic models based upon these results. The model reported in the column labelled 1 is the benchmark model that includes the 4 seasonal dummy variables denoted, D_{st} where $s = 1, 2, 3, 4$, and does not model any structural breaks. All the four seasonal dummy variables are significant according to the t-ratios (reported in brackets below the dummy variables' coefficients) and the model's Schwarz criterion (SC) is -2.132

Table 5.11.1 reports the Bai and Perron scaled F-statistic with the associated 5% critical values for the benchmark model reported in the column labelled 1 in Table 5.11.2. The test results indicate only one significant breakpoint because the scaled F-statistic is greater than the corresponding critical value for the null hypothesis of no breaks (denoted 0 vs 1). Both sequential and repartition methods indicate the same break point date of 1980q3.

Based on the Bai and Perron test results we specify shift dummy variables (that are zero prior to the break date and unity from the break date onwards) interacted with the seasonal dummy variables that give shifts in the seasonal means in 1980q3, denoted $D(1980q3)_{st}$. The model including the seasonal dummy variables and the shift dummy variables that is given in the column headed 2 of Table 5.11.2. The shift dummy variable,

$D(1980q3)_{st}$, is significant suggesting significant changes in the seasonal means at this identified break point and all the four seasonal dummy variables are also significant. The significance of these shift dummy variables and that this model's SC falls to -2.424 supports the need to model the identified break.

Figure 5.11.1 plots the actual and fitted values of the model reported in column 2 of Table 5.11.2. Visual inspection of this graph suggests that this deterministic model based on the Bai and Perron test results does not appropriately capture the mean shifts in the actual data. The graph suggests two new breaks dates (1977q2 and 2008q4). Therefore, we add interaction of these new breaks, denoted as $D(1977q2)_{st}$ and $D(2008q4)_{st}$ respectively to the model reported in column 3 of Table 5.11.2. All the seasonal dummy variables and shift dummy variables are significant except for $D(1980q3)_{st}$ where three out of its four seasonal shift terms are insignificant. In this model's the SC falls to -3.918 to support the addition of the specified interaction terms. Since three out four seasonal dummy variables in the $D(1980q3)_{st}$ set are insignificant we exclude the $D(1980q3)_{st}$ term from the model given in Table 5.11.2 column 3. The estimation results of this model are reported in column 4 of Table 5.11.2. All of the seasonal and shift dummy variables are significant. The significance of these shift dummy variables and that this model's SC falls to -3.997 to support the exclusion of insignificant $D(1980q3)_{st}$ term.

Figure 5.11.2 plots the actual and fitted values of the model reported in column 4 of Table 5.11.2. Visual inspection of this graph suggests that this deterministic model better captures the main mean shifts in the actual data than did model 2. We regard model 4 from Table 5.11.2 as capturing the main mean shifts in the data (based on its lowest SC and from visual inspection of the graph) and use this as the basis of the deterministic component of our ARIMAX model of Saudi Arabia's annual inflation.

Table 5.11.2: Deterministic component of ARIMAX models for Saudi Arabia

Sample/Observation	1975q1- 2012q4 (152)				
	1	2	3	4	5
D_{1t}	0.034 (2.673)	0.142 (5.374)	0.271 (16.927)	0.271 (16.722)	
D_{2t}	0.034 (2.658)	0.142 (5.359)	0.347 (17.711)	0.347 (17.496)	
D_{3t}	0.032 (2.526)	0.148 (5.119)	0.332 (16.967)	0.332 (16.907)	
D_{4t}	0.032 (2.496)	0.147 (5.075)	0.335 (17.115)	0.335 (16.907)	
$D(1977q2)_{1t}$			-0.257 (-11.360)	-0.264 (-15.557)	
$D(1977q2)_{2t}$			-0.308 (-12.822)	-0.337 (16.483)	
$D(1977q2)_{3t}$			-0.308 (-12.121)	-0.323 (-15.811)	
$D(1977q2)_{4t}$			-0.306 (-12.396)	-0.326 (-15.960)	
$D(1980q3)_{it}$		-0.128 (-4.444)	-0.008 (-0.477)		
$D(1980q3)_{2t}$		-0.128 (-4.436)	-0.033 (-2.291)		
$D(1980q3)_{3t}$		-0.134 (-4.294)	-0.019 (-1.116)		
$D(1980q3)_{4t}$		-0.133 (-4.261)	-0.014 (-0.859)		
$D(2008q4\ )_{1t}$			0.052 (3.930)	0.052 (3.854)	
$D(2008q4)_{2t}$			0.055 (4.066)	0.050 (3.733)	
$D(2008q4)_{3t}$			0.051 (3.805)	0.049 (3.652)	
$D(2008q4)_{4t}$			0.048 (3.548)	0.046 (3.427)	
I_SAU					1.000 (36.715)
Adj R^2	-0.020	0.314	0.875	0.872	0.881
SC	-2.132	-2.424	-3.918	-3.997	-4.360
S.E	0.079	0.065	0.027	0.028	0.027

Figure 5.11.1: the actual and fitted values of model 2 reported in Table 5.11.2

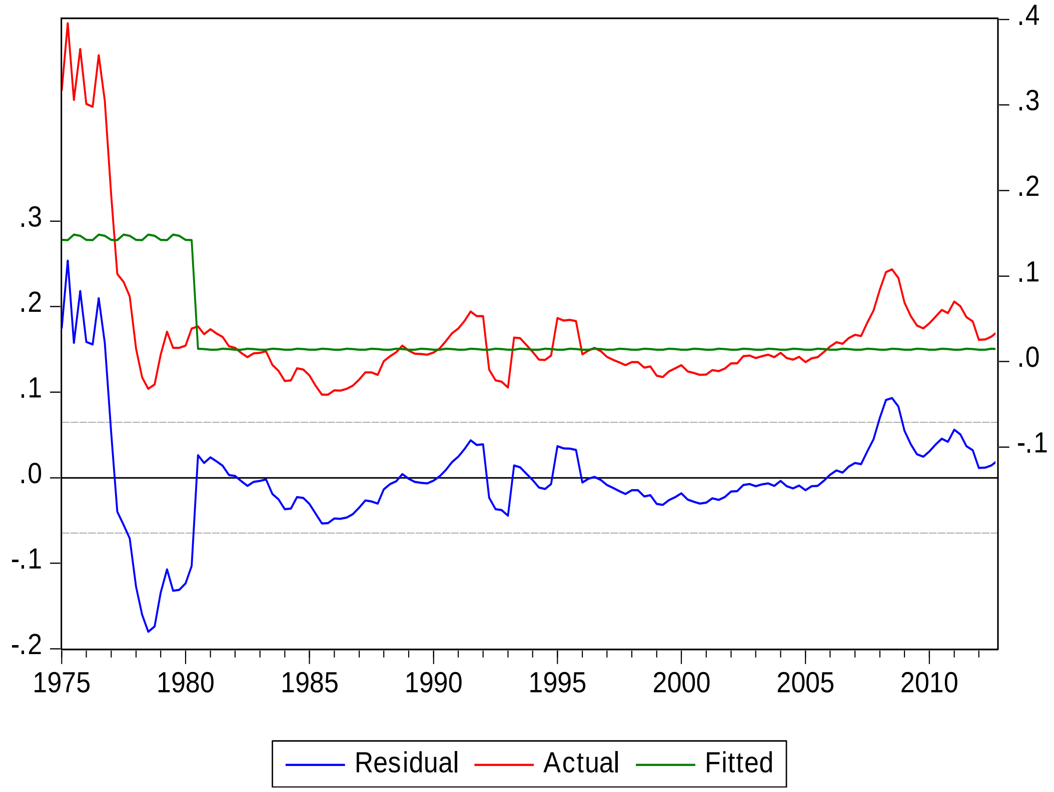
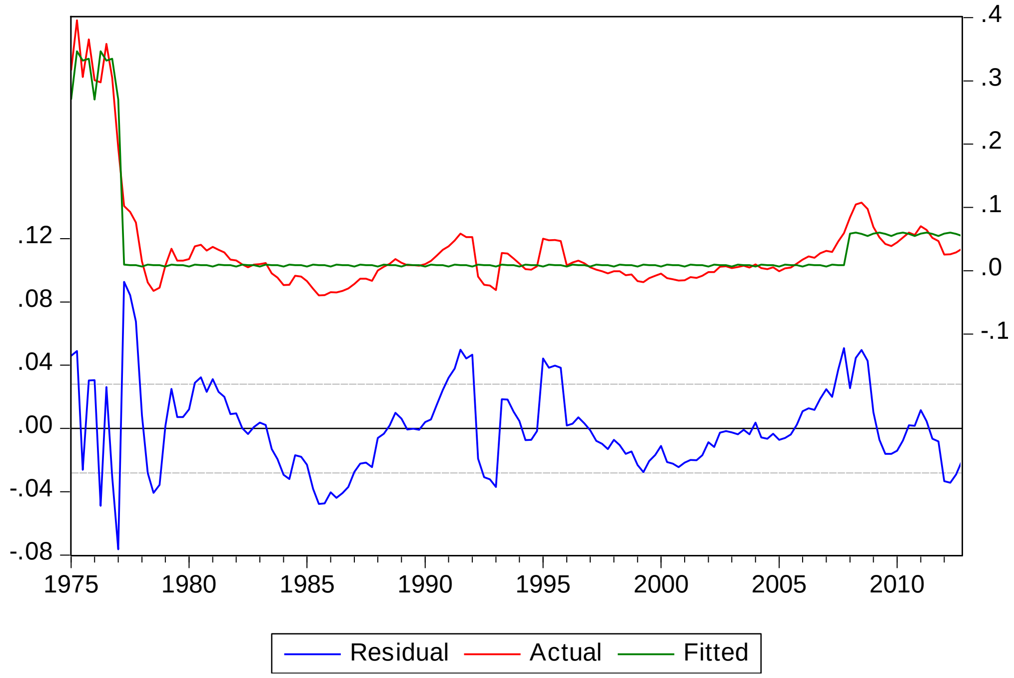


Figure 5.11.2: the actual and fitted values of model 4 reported in Table 5.11.2



Following Hendry (2001), Hendry and Santos (2005) and Caporale *et al* (2012) we construct an index of indicator variables to summarise the deterministic terms reported in column 4 of Table 5.11.2 in a single variable to enhance the efficiency of estimation of the ARIMAX model. We therefore define the index of indicator variable, denoted I_SAU, as the fitted value of the model reported in column 4 of Table 5.11.2 and report the regression of annual inflation on this indicator variable in column 5 of Table 5.11.2. The index is significant and has a unit coefficient as is expected. This model's SC is -4.360 which provides a benchmark for comparison with potential ARIMAX models to be developed from this deterministic specification that are discussed below.

5.11.2 Developing the ARIMAX model for Saudi Arabia

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the deterministic model reported in column 5 of Table 5.11.2 is plotted in Figure 5.11.3. From the ACF the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1, 2 and 3 and insignificant at lags 4 and 5. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are significant at lags 20 and 24 and insignificant at lags 4, 8, 12, 16 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags 4, 8, 12, 16 and 20) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0. From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1 and insignificant at lags 2 and 3. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 1. The seasonal PACs are significant at lag 4 and insignificant at lags 8, 12, 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 1. Thus, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is $ARMA(1,3)(1,0)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes I_SAU plus 4 seasonal dummy variables and an $ARMA(1,3)(1,0)_4$ model of the residuals in the column headed 6 of Table 5.11.3.

Figure 5.11.4: the ACF and PACF of the residuals of model 5 reported in Table 5.11.2

Sample: 1975Q1 2012Q4
Included observations: 152

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.617	0.617	59.097	0.000
		2	0.370	-0.018	80.470	0.000
		3	0.285	0.102	93.193	0.000
		4	0.044	-0.275	93.498	0.000
		5	0.125	0.342	95.995	0.000
		6	0.219	0.037	103.68	0.000
		7	0.165	0.026	108.06	0.000
		8	0.150	-0.122	111.73	0.000
		9	0.120	0.103	114.10	0.000
		10	0.094	0.055	115.54	0.000
		11	0.036	-0.121	115.76	0.000
		12	-0.002	-0.055	115.76	0.000
		13	-0.039	-0.054	116.01	0.000
		14	-0.081	0.032	117.11	0.000
		15	-0.087	-0.096	118.42	0.000
		16	-0.107	-0.062	120.40	0.000
		17	-0.132	-0.053	123.43	0.000
		18	-0.151	-0.026	127.42	0.000
		19	-0.169	-0.043	132.46	0.000
		20	-0.178	-0.065	138.09	0.000
		21	-0.168	0.010	143.12	0.000
		22	-0.165	-0.042	148.04	0.000
		23	-0.182	-0.044	154.08	0.000
		24	-0.189	-0.056	160.62	0.000
		25	-0.194	-0.012	167.56	0.000
		26	-0.182	0.006	173.68	0.000
		27	-0.147	-0.011	177.72	0.000
		28	-0.122	-0.010	180.53	0.000

In this model the SC falls to -5.015 suggesting that the addition of ARMA terms has improved the specification. I_SAU is significant and two of the four seasonal dummy variables are insignificant. The joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), has a probability value of 0.056, which exceeds 0.05 indicating that they are jointly insignificant. All the ARMA components are significant except the AR(1) term.

Table 5.11.3: The ARIMAX table for Saudi Arabia

Sample/Observations	1975q1 – 2012q4 (152)				
	6	7	8	9	10
I_SAU	0.622 (9.588)	0.671 (12.526)	0.550 (8.841)	0.475 (7.683)	0.593 (10.889)
D_{it}	0.014 (1.985)	0.011 (1.771)	0.008 (1.199)		
D_{2t}	0.013 (1.805)	0.010 (1.548)	0.007 (1.119)		
D_{3t}	0.015 (2.062)	0.012 (1.821)	0.008 (1.335)		
D_{4t}	0.015 (2.082)	0.012 (1.861)	0.009 (1.441)		
AR(1)	0.129 (1.312)		0.411 (4.148)	0.476 (4.869)	-0.578 (-8.389)
AR(2)			-0.206 (-2.369)	-0.203 (-2.382)	
SAR(4)	0.189 (2.479)	0.194 (2.596)	-0.626 (-11.777)	-0.607 (-11.820)	0.293 (4.148)
MA(1)	0.845 (49.962)	0.848 (59.916)	0.731 (13.121)	0.743 (14.623)	1.747 (173.159)
MA(2)	0.846 (46.572)	0.846 (54.209)	0.867 (40.325)	0.878 (66.322)	1.590 (86.922)
MA(3)	0.985 (86.143)	0.982 (108.804)	0.881 (18.431)	0.863 (17.564)	1.719 (130.153)
MA(4)					0.977 (137.423)
SMA(4)			1.135 (11.541)	1.204 (13.018)	
SMA(8)			0.265 (2.968)	0.351 (4.193)	
Adj R^2	0.951	0.951	0.966	0.966	0.960
SC	-5.015	-5.038	-5.299	-5.408	-5.296
S.E	0.017	0.017	0.014	0.014	0.016
AR Root	0.659 0.129	0.664	0.889 0.454	0.883 0.450	0.735 0.578
MA Root	0.996	0.995 0.992	0.999 0.947 0.882 0.757	0.995 0.918 0.872 0.839	0.996 0.993
P[QLB(12]	0.014	0.042	0.106	0.006	0.145
LR (SEA DUM)	9.178 [0.056]	30.845 [0.000]	3.567 (0.468)		
LR (SEA DUM, CON)					499.119 [0.000]
$LR(1977q2)$	121.409 [0.000]	91.722 [0.000]	-44.387	7.528 [0.111]	5.999 [0.199]
$LR(2008q4)$	5.525 [0.238]	3.506 [0.477]	-57.678	2.510 [0.643]	3.948 [0.413]

Where: I_SAU = the fitted value of the model reported in column 4 of Table 5.11.2, S E = S E of regression, MA = the maximum order of non-seasonal moving average component, SMA = the maximum order of seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , D_{st} = the seasonal dummy variables, denoted as D_{1t}, D_{2t}, D_{3t} and D_{4t}, P[QLB(12)] = Probability value of the Ljung-Box Q-statistic at the 12th lag from - based on the square root of the sample size ($\sqrt{152}$), Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average , MA Roots = Stationary Moving average, LR(SEA DUM) = the joint test for the seasonal dummy variables; $LR(1977q2)$ and $LR(2008q4)$ = Joint shift significance of each break date, Rounded Bracket = T – Ratios and Square Bracket = Probability value.

We also conduct variable addition tests for the shift dummy variables included in the I_SAU variable to assess whether the coefficients on these terms embodied in this index have changed significantly with the addition of ARMA terms. A test whether the 4 shift dummy variables corresponding to the 1977q2 break can be added to the model with joint significance is reported in the row labelled $LR(1977q2)$. Since the probability value (given in square brackets below the test statistic, being 0.000) is less than 0.050 these variables can be added with joint significance. Similarly, the probability values of the joint tests of the shift dummy variable corresponding to the break date 2008q4, reported in the rows labelled $LR(2008q4)$ exceed 0.050 indicating that the shift variable for this date cannot be added with joint significance. This suggests that the coefficients embodied in I_SAU have significantly changed with the addition of ARMA terms for $LR(1977q2)$ in this year.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 12th lag, denoted P[QLB(12)], is less than 0.050 indicating evident of residual autocorrelation that suggests unmodelled systematic variation in the dependent variable and the need to adjust the model – we choose lag 12 based on the square root of the sample size (in this case $\sqrt{152}$). The inverse roots of the AR process, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible.

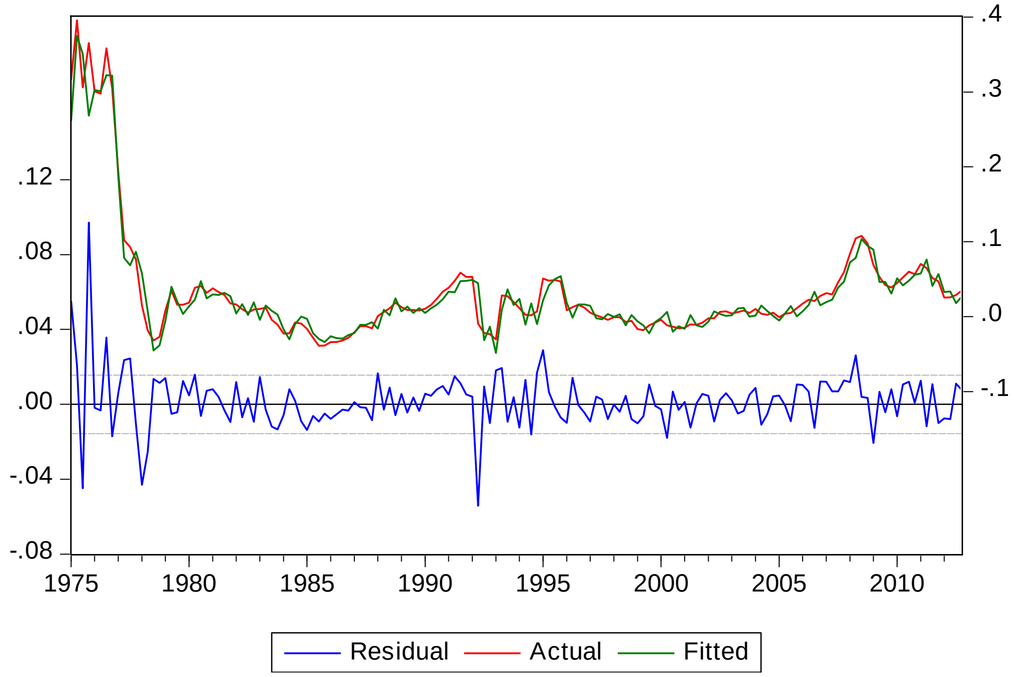
As a first step in respecifying the model reported in the column headed 6 of Table 5.11.3 we exclude the insignificant AR(1) variable and report the resulting $ARMA(0,3)(1,0)_4$ in the column headed 7 of Table 5.11.3. This model does not fail the diagnostic checks for invertibility and stationarity, however there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable which suggests the need to further adjust the model. The tests for 2 sets of shift dummy variables corresponding to $LR(1977q2)$ and $LR(2008q4)$ indicate that $LR(1977q2)$ is significant while $LR(2008q4)$ is insignificant.

After experimentation we produce the $ARMA(2,3)(1,2)_4$ model reported in Table 5.11.3 column 8. According to the standard diagnostic checks, this model cannot be rejected based on stationarity, invertibility and autocorrelation. In terms of specification, all the ARMA components are significant although the seasonal dummy variables are individually insignificant. The latter is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value that exceeds 0.05.

Therefore, we exclude seasonal dummy variables that are jointly insignificant and report the resulting model in the column headed 9 of Table 5.11.3. In this model the SC reduces to -5.408 and the coefficient of I_SAU is significant as well as all the ARMA components. The tests for the shift dummy variables corresponding to the $LR(1977q2)$ and $LR(2008q4)$ are insignificant. This model does not fail the diagnostic checks for invertibility and stationarity, however there is evidence of autocorrelation that suggests this model is not valid for forecasting.

After further experimentation with the ARMA components we report an $ARMAX(1,4)(1,0)_4$ model in the column headed 10 of Table 5.11.3. In this model, all the ARMA components are significant and this model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The tests for the shift dummy variables $LR(1977q2)$ and $LR(2008q4)$ are all insignificant suggesting that the coefficients in I_SAU have not changed with the changes in specification.

Figure 5.11.4: the actual and fitted values of model 10 reported in Table 5.11.3



Visual inspection of the actual and fitted values of this model suggests that the fitted values capture the mean shifts in the data and broadly track the data well (see Figure 5.11.4). We regard this model as the best model for forecasting Saudi Arabia's annual inflation. However, there are two models in Table 5.11.3 (column 8 and column 10) that are valid for forecasting. The model in column 8 has the minimum SC although it includes a variable that should be excluded according to t-ratios. In contrast the model in column 10 does not suggest any variables should be excluded according to the t-ratios although it does not exhibit the minimum SC.

Since model in column 10 does not suggest any variable should be included, we test the null hypothesis of whether the coefficients of the seasonal dummy variables are the same using a Wald test in the row labelled LR (SEA DUM, CON) of column 10. The probability value is 0.000 which rejects the null hypothesis of no deterministic seasonality. This suggests a significant difference in the coefficients of the individual seasonal dummy variables indicating significant deterministic seasonality. Hence, these seasonal dummy variables cannot be replaced by a single deterministic intercept. Therefore, model 10 in Table 5.11.3 is considered the best model to forecast Saudi Arabia annual inflation.

Appendix. Section 5.2

5.2.2 Box-Jenkins ARIMA modelling of annual inflation for Russia

In the full sample ARIMAX model developed for Russia in section 5.1 we identified the last structural break date in 2001q1. Hence, the maximum available estimation period is 2001q2 to 2012q4.To allow for lags, transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 2003q2 – 2012q4 (39 observations). First, we regress inflation on the 4 seasonal dummy variables, D_{st},to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final ARIMA model.

Table 5.2.2 reports the benchmark deterministic specification and various ARIMAX models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables coefficients are significant and the model's Schwarz criterion (SC) is -3.831.

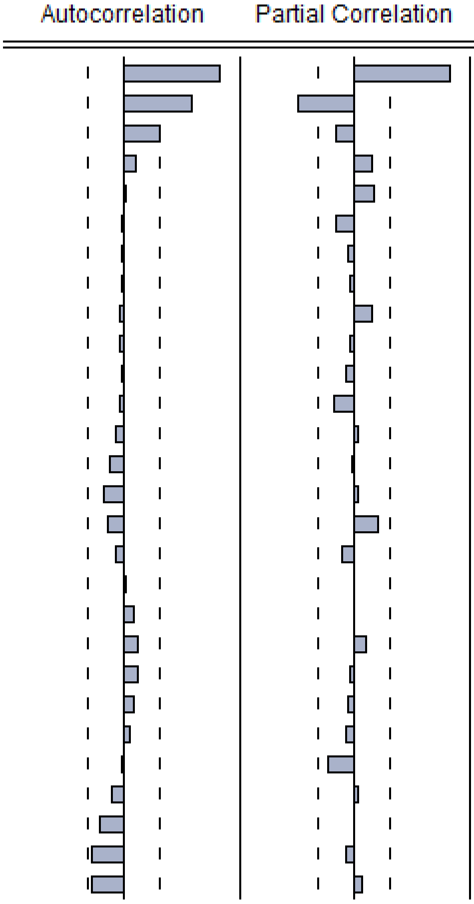
Figure 5.2.2.1 plots the autocorrelation function (ACF) of the residuals of the model reported in the column headed 1 of Table 5.2.2. The non-seasonal autocorrelation coefficients (ACs) from the ACF are significant at lags 1, 2 and 3 and insignificant at lags 4, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 3. Further, the seasonal ACs are insignificant at lags 4, 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1 and 2 and insignificant at lags 3 and 4. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 2. The seasonal PACs are insignificant at lags 4, 8, 12 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 0. Hence, the maximum ARMA specification that we initially identify to the residuals of the deterministic model is

$ARMA(2,3)(0,0)_4$, which is equivalent to the non-seasonal $ARMA(2,3)$ specification. We report an ARIMAX specification that includes 4 seasonal dummy variables and an $ARMA(2,3)$ model of the residuals in the column headed 2 of Table 5.2.2.

Figure 5.2.2.1 the ACF and PACF of the residuals of model 1 reported in Table 5.2.2

Sample: 2003Q2 2012Q4
Included observations: 39



	AC	PAC	Q-Stat	Prob
1	0.861	0.861	31.223	0.000
2	0.612	-0.503	47.422	0.000
3	0.329	-0.157	52.233	0.000
4	0.113	0.166	52.812	0.000
5	0.015	0.188	52.823	0.000
6	-0.014	-0.171	52.833	0.000
7	-0.010	-0.062	52.839	0.000
8	-0.021	-0.038	52.861	0.000
9	-0.026	0.165	52.897	0.000
10	-0.028	-0.033	52.939	0.000
11	-0.021	-0.066	52.965	0.000
12	-0.036	-0.185	53.044	0.000
13	-0.074	0.030	53.382	0.000
14	-0.132	-0.024	54.489	0.000
15	-0.178	0.039	56.591	0.000
16	-0.147	0.209	58.092	0.000
17	-0.077	-0.108	58.526	0.000
18	0.021	-0.006	58.561	0.000
19	0.094	0.006	59.268	0.000
20	0.126	0.111	60.607	0.000
21	0.122	-0.029	61.921	0.000
22	0.093	-0.052	62.739	0.000
23	0.062	-0.068	63.129	0.000
24	-0.014	-0.243	63.150	0.000
25	-0.104	0.033	64.396	0.000
26	-0.206	-0.007	69.609	0.000
27	-0.284	-0.081	80.330	0.000
28	-0.290	0.078	92.521	0.000

In this model the SC falls to -6.336 suggesting that the addition of ARMA terms has improved the specification. All four seasonal dummy variables are significant, which is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.007. In this model, all of the ARMA components are significant except for the AR(1), AR(2) and MA(2) terms. This suggests that the specification can be improved by the exclusion of the insignificant ARMA terms.

Table 5.2.2: The ARMA table for Russia

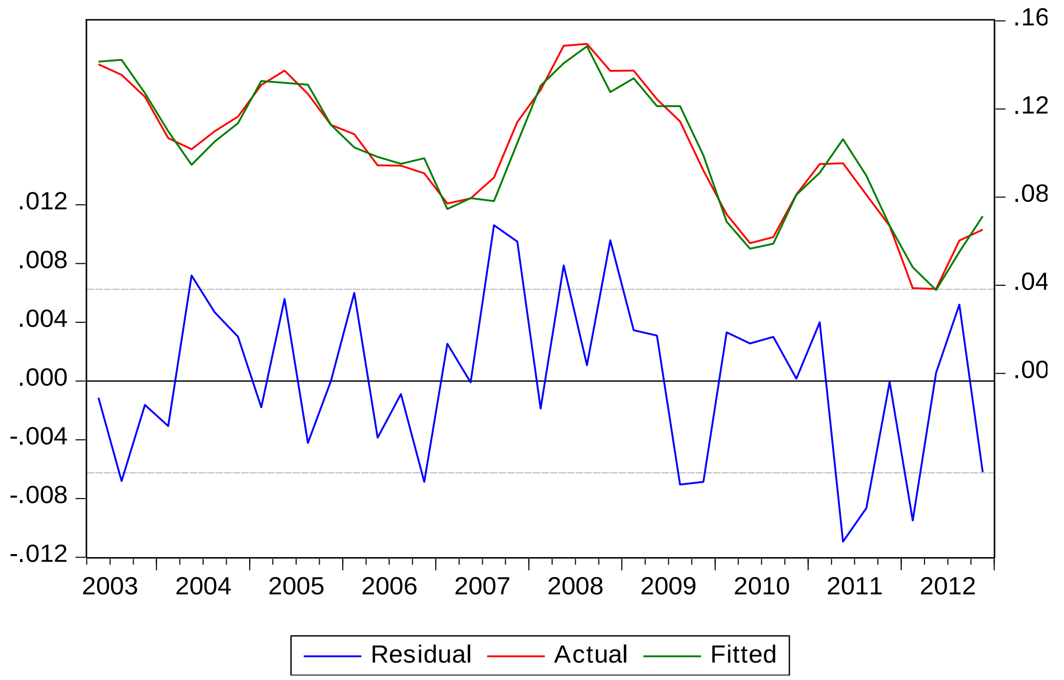
Observations		2003q2 2012q4 (39)		
	1	2	3	4
D_1	0.099 (9.572)	0.095 (7.048)	0.097 (14.101)	0.096 (13.229)
D_2	0.102 (10.340)	0.095 (6.992)	0.097 (13.689)	0.096 (13.389)
D_3	0.102 (10.371)	0.098 (7.179)	0.098 (14.090)	0.096 (13.509)
D_4	0.100 (10.169)	0.097 (7.260)	0.098 (14.258)	0.096 (13.508)
AR(1)		0.648 (1.915)		0.821 (10.849)
AR(2)		0.012 (0.040)		
MA(1)		0.977 (2.814)	1.203 (29.247)	0.777 (8.869)
MA(2)		0.654 (1.855)	1.233 (29.998)	0.693 (13.154)
MA(3)		0.670 (2.977)	0.959 (8.849)	0.916 (11.488)
Adj R^2	-0.084	0.905	0.892	0.956
SC	-3.831	-6.336	-5.941	-6.728
S.E	0.032	0.009	0.010	0.001
AR Root		0.681 0.032	0.999 0.959	0.821
MA Root		0.999 0.900		0.999 0.957
P[QLB(6)]		0.119	0.003	0.084
LR (SEA DUM)		19.043 [0.007]	61.965 [0.000]	19.493 [0.001]
LR(SEA DUM,CON)				36.149 [0.000]

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 6th lag, denoted P[QLB(6)], exceeds 0.050 indicating no evident of residual autocorrelation– we choose lag 6 based on the square root of the sample size (in this case $\sqrt{39}$). The inverse roots of the AR and MA processes are all less than one indicating that the model is consistent with a stationary and invertible process. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests.

However, as indicated above the specification can be improved with the removal of insignificant ARMA variables. The coefficients on the AR(1), AR(2) and MA(2) terms are not significant and are candidates for exclusion. Since the MA(3) term is significant we do not remove the MA(2) term to retain the full second-order seasonal MA component. Therefore, we remove the AR(1) and AR(2) terms from the model reported in the column headed 2 from Table 5.2.2 and report the resulting $ARMAX(0,3)$ in the column headed 3. This model does not fail the diagnostic checks for invertibility and stationarity, however there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and the need to adjust the model.

After further experimentation with the ARMA components we report an improved $ARMAX(1,3)$ model in the column headed 4 of Table 5.2.2. In this model, all of the variables are significant and this model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. Therefore, it is valid for forecasting. Further, the Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal, denoted LR (SEA DUM, CON), is rejected. This suggests significant deterministic seasonality and that these dummies cannot be replaced by a single (non-seasonal) intercept.

Figure 5.2.2.2: the actual and fitted values reported in Table 5.2.2 column 4



Visual inspection of the actual and fitted values (Figure 5.2.2.2) of this model suggests that the time path of the fitted values capture the movements in the actual data well. In terms of model fit the adjusted R^2 of this ARIMAX model on the reduced sample is 0.956 which is slightly higher than the specification estimated using the full sample that models structural breaks (Appendix A. Section 5.1 Table 5.2.3), being 0.932. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

5.2.3 Box-Jenkins ARIMA modelling of annual inflation for South Africa

In the full sample ARIMAX model developed for South Africa in section 5.1 we identified the last structural break date in 1993q1. Hence, the maximum available estimation period without a structural break is 1993q2 to 2012q4. To allow for lags and transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 1995q2 – 2012q4 (71 observations). First, we regress inflation on the 4 seasonal dummy variables, D_{st}, to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final ARIMA model.

Table 5.2.3 reports the benchmark deterministic specification and various ARIMAX models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables coefficients are significant and the model's Schwarz criterion (SC) is -3.539.

Figure 5.2.3.1 plots the ACF of the residuals of the model reported in the column headed 1 of Table 5.2.3. The ACF of the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1 and 2 and insignificant at lags 3, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 2. Further, the seasonal ACs are significant at lag 4 and insignificant at lags 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags) are significant. It also indicates the maximum order of seasonal MA component is probably equal to 1.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1 and 2 and insignificant at lags 3, 4 and 5. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 2. The seasonal PACs are insignificant at lags 4, 8, 12 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably be equal to 0. Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is ARMA $(2, 2)(0,1)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes 4 seasonal dummy variables and an $ARMA(2,2)(0,1)_4$ model of the residuals in the column headed 2 of Table 5.2.3.

Figure 5.2.3.1: the ACF and PACF of the residuals of model 1 reported in Table 5.2.3

Sample: 1995Q2 2012Q4
Included observations: 71

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.728	0.728	39.294	0.000
		2	0.302	-0.487	46.160	0.000
		3	-0.098	-0.197	46.885	0.000
		4	-0.247	0.220	51.592	0.000
		5	-0.183	0.047	54.226	0.000
		6	-0.070	-0.172	54.617	0.000
		7	0.024	0.065	54.663	0.000
		8	0.036	-0.001	54.768	0.000
		9	-0.026	-0.149	54.826	0.000
		10	-0.104	-0.024	55.744	0.000
		11	-0.146	0.032	57.578	0.000
		12	-0.124	-0.039	58.926	0.000
		13	-0.052	0.004	59.168	0.000
		14	-0.021	-0.117	59.207	0.000
		15	-0.033	-0.039	59.308	0.000
		16	-0.092	-0.053	60.114	0.000
		17	-0.158	-0.109	62.513	0.000
		18	-0.162	0.022	65.092	0.000
		19	-0.124	-0.037	66.633	0.000
		20	-0.034	0.002	66.753	0.000
		21	0.059	0.040	67.114	0.000
		22	0.116	0.002	68.540	0.000
		23	0.141	0.044	70.674	0.000
		24	0.119	0.011	72.224	0.000
		25	0.063	-0.064	72.672	0.000
		26	-0.001	-0.028	72.672	0.000
		27	-0.061	-0.037	73.110	0.000
		28	-0.098	-0.086	74.275	0.000

In this model the SC falls to -5.206 suggesting that the addition of ARMA terms has improved the specification. Although the four seasonal dummy variables are individually significant they are jointly insignificant according to the test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.126. In this model, all the ARMA components are significant except for the MA(1), which we would not remove because the MA(2) term is significant.

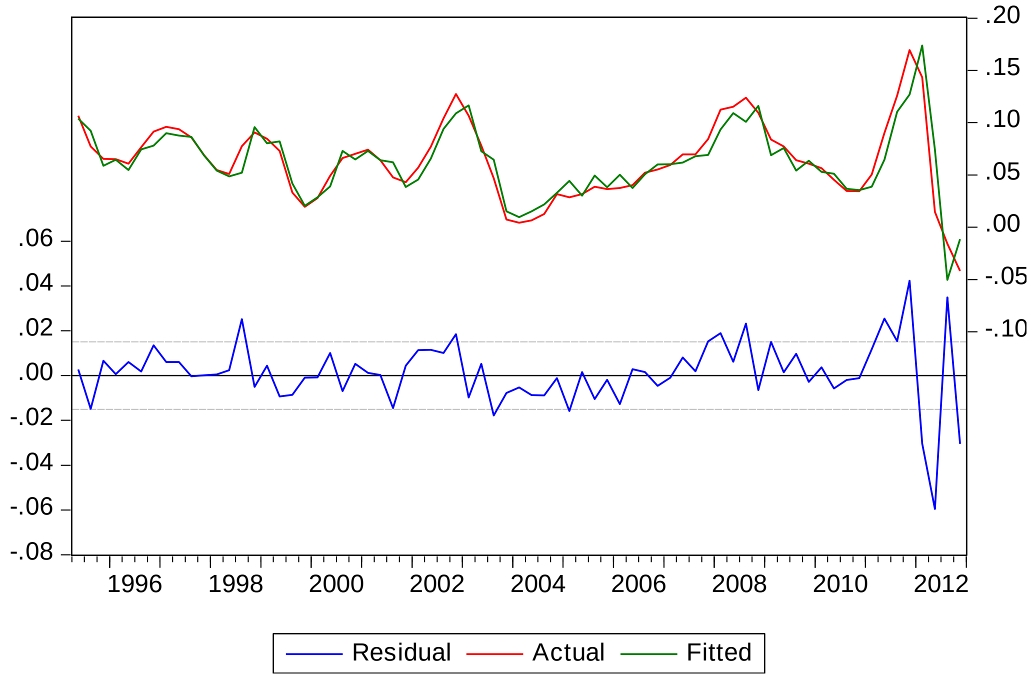
Table 5.2.3 The ARMA table for South Africa

Observations	1995Q2 2012q4(71)				
	1	2	3	4	5
P(2012q2)				-0.036 (-6.343)	-0.032 (-6.965)
D_1	0.067 (7.367)	0.060 (28.149)			
D_2	0.064 (7.170)	0.059 (26.976)			
D_3	0.062 (7.023)	0.060 (28.687)			
D_4	0.062 (7.041)	0.061 (28.688)			
AR(1)		1.679 (14.509)	1.688 (13.773)	0.909 (1.770)	0.996 (112.894)
AR(2)		-0.728 (-7.163)	-0.689 (-5.641)	0.087 (0.170)	
MA(1)		-0.098 (-0.777)	-0.067 (-0.677)	0.949 (1.901)	0.764 (8.761)
MA(2)		-0.729 (-4.828)	-0.762 (-6.342)	0.284 (0.760)	
SMA(4)		-0.826 (-8.823)	-0.080 (-10.188)	-0.902 (-31.243)	-0.899 (-30.058)
Adj R^2	-0.042	0.843	0.834	0.892	0.897
SC	-3.539	-5.206	-5.332	-5.720	-5.809
S.E	0.038	0.015	0.015	0.012	0.012
AR Root		0.853 0.827 0.032	0.998 0.690	0.997 0.087	0.996 0.974 0.764
MA Root		0.953 0.953 0.904 0.807	0.951 0.907	0.975 0.533	0.974 0.763
P[QLB(8)]		0.312	0.294	0.115	0.103
LR (SEA DUM)		1.873 [0.126]			

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 8th lag, denoted P[QLB(8)], exceed 0.050 indicating that there is no residual autocorrelation– we choose lag 8 based on the square root of the sample size (in this case $\sqrt{71}$). The inverse roots of the AR and MA processes are all less than one indicating that the model is consistent with a stationary and invertible process. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests.

Since the seasonal dummy variables are jointly insignificant, we exclude them from the model reported in the column headed 2 of Table 5.2.3 and the result is reported in the column headed 3. The SC of this model falls to -5.332 and all of the ARMA components are significant except for the MA(1) term, which we would not remove because the MA(2) term is significant. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility and is therefore valid for forecasting.

Figure 5.2.3.2.the actual and fitted values reported in Table 5.2.3 column 3

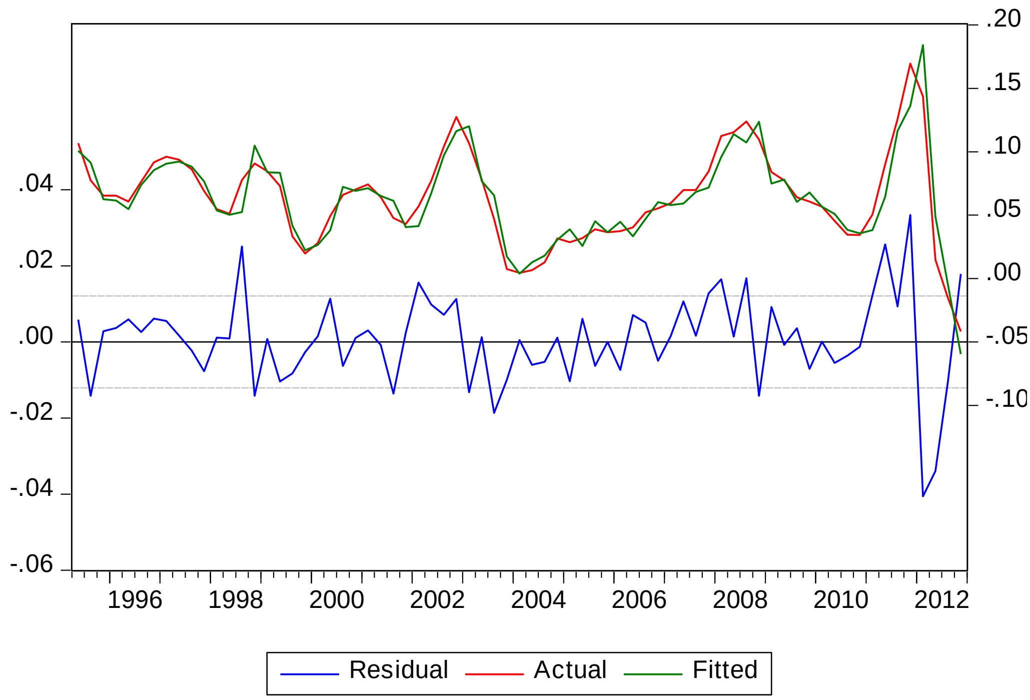


In Figure 5.2.3.2 we plot the actual and fitted values of the model reported in column 3 of Table 5.2.3. Visual inspection of this graph suggests that the fitted values capture the mean in the actual data well. However, the graph has an outlier in 2012q2 and we therefore add a new pulse dummy variable, denoted $P(2012q2)$, to the model to capture the outlier. This new model is reported in column 4. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. However, all of the ARMA coefficients are insignificant except for the SMA(4) term .

Hence, this specification can be improved with the removal of insignificant ARMA variables. We remove the highly insignificant AR(2) and MA(2) terms and report the resulting $ARIMA(1,1)(0,1)_4$ specification in the column headed 5 of Table 5.2.3. In this model, all the variables are significant and the SC fall to -5.809. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. Therefore, we regard model 5 from Table 5.2.3 as the best ARIMAX model for forecasting South Africa's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks (based on the reduced sample).

In addition, the adjusted R^2 of the reduced sample model is 0.897 which is lower than the specification estimated using the full sample that models structural breaks (Appendix A. Section 5.1 Table 5.5.3), being 0.945. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

Figure 5.2.3.3: the actual and fitted values reported in Table 5.2.3 column 5



In Figure 5.2.3.3 we plot the actual and fitted values of the model reported in column 5 of Table 5.2.3 Visual inspection of this graph suggests that the fitted values capture the mean in the actual data well. Therefore, we consider this model as the best model to forecast South Africa's annual inflation based on reduced sample.

5.2.4 Box-Jenkins ARIMA modelling of annual inflation for Algeria

In the full sample ARIMAX model developed for Algeria in section 5.1 we identified the last structural break date in 1997q1. Hence, the maximum available estimation period without an identified structural break is 1997q2 to 2012q4. To allow for lags and transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 1999q2 – 2012q4 (55 observations). First, we regress inflation on the 4 seasonal dummy variables, D_{st}, to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final ARIMA model.

Table 5.2.4 reports the benchmark deterministic specification and various ARIMAX models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables' coefficients are significant and the model's Schwarz criterion (SC) is -4.133

Figure 5.2.4.1 plots the ACF of the residuals of the model reported in the column headed 1 of Table 5.2.4. The autocorrelation coefficients (ACs) are significant at lag 1 and 2 and insignificant at lags 3, 4, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal MA component is probably 2. Further, the seasonal ACs are insignificant at lags 4, 8, 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1 and insignificant at lags 2, 3, 4 and 5. This suggests the maximum order of non-seasonal AR component is probably 1. The seasonal PACs are insignificant at lags 4, 8, 12 16, 20, 24 and 28. However, the maximum order of seasonal AR process is may be equal to 1 given the notable significance of the PAC at lag 5 (assuming a multiplicative functional form). Therefore, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is ARMA $(1,2)(1,0)_4$.
Assuming a multiplicative specification we report an ARIMAX specification that includes

4 seasonal dummy variables and an ARMA $(1,2)(1,0)_4$ model of the residuals in the column headed 2 of Table 5.2.4.

Figure 5.2.4.1: the ACF and PACF of the residuals of model 1 reported in Table 5.2.4

Sample: 1999Q2 2012Q4
Included observations: 55

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.761	0.761	33.652	0.000
		2	0.503	-0.182	48.615	0.000
		3	0.235	-0.194	51.943	0.000
		4	-0.026	-0.198	51.984	0.000
		5	-0.028	0.420	52.033	0.000
		6	0.005	-0.035	52.035	0.000
		7	0.072	-0.022	52.370	0.000
		8	0.145	-0.059	53.770	0.000
		9	0.162	0.183	55.551	0.000
		10	0.206	0.147	58.519	0.000
		11	0.201	-0.073	61.407	0.000
		12	0.177	-0.059	63.683	0.000
		13	0.174	0.131	65.935	0.000
		14	0.123	0.041	67.090	0.000
		15	0.073	-0.121	67.504	0.000
		16	0.059	0.031	67.782	0.000
		17	0.065	0.167	68.132	0.000
		18	0.102	0.049	69.014	0.000
		19	0.116	-0.200	70.190	0.000
		20	0.086	-0.121	70.848	0.000
		21	0.042	0.156	71.010	0.000
		22	-0.031	0.014	71.101	0.000
		23	-0.080	-0.217	71.730	0.000
		24	-0.108	-0.177	72.902	0.000
		25	-0.128	0.170	74.604	0.000
		26	-0.183	-0.199	78.223	0.000
		27	-0.166	0.008	81.314	0.000
		28	-0.155	-0.111	84.099	0.000

In this model the SC falls to -5.200 suggesting that the addition of ARMA terms has improved the specification. Although the four seasonal dummy variables are individually significant they are jointly insignificant according to the test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.668. In this model, all the ARMA components are significant except for the MA(1) and MA(2) terms. This suggests that the specification can be improved by exclusion of insignificant ARMA terms.

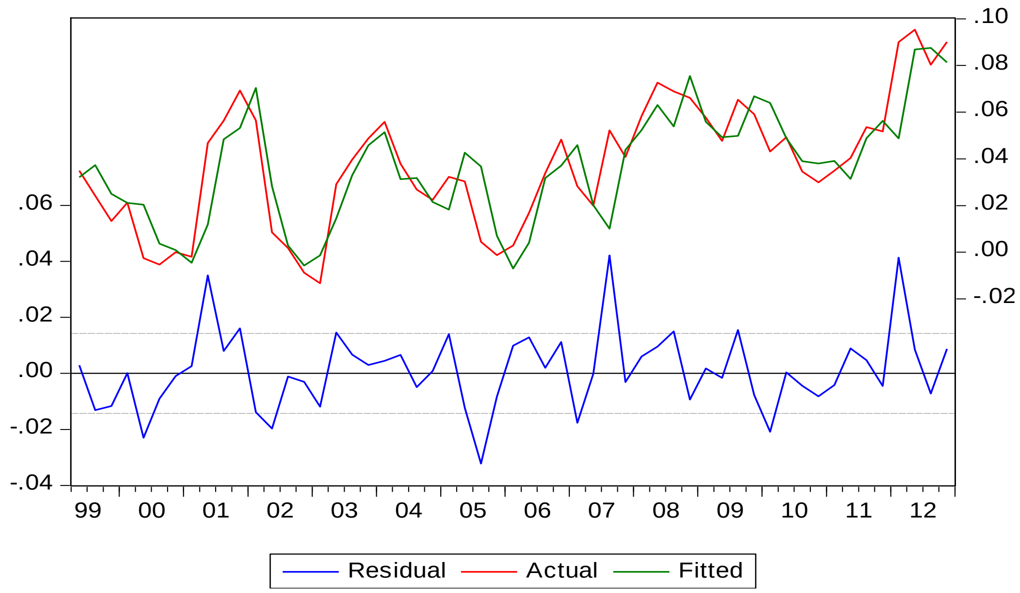
Table 5.2.4: The ARMA table for Algeria

Observations	1999Q2 2012q4 (55)			
	1	2	3	4
D_1	0.036 (4.698)	0.042 (2.739)	0.043 (2.417)	
D_2	0.038 (5.121)	0.042 (2.810)	0.045 (2.488)	
D_3	0.038 (5.215)	0.043 (2.837)	0.045 (2.511)	
D_4	0.037 (5.148)	0.042 (2.756)	0.044 (2.443)	
AR(1)		0.898 (8.392)	0.922 (12.664)	0.999 (32.465)
AR(2)				
SAR(4)		-0.583 (-4.301)	-0.578 (-4.354)	-0.580 (-4.760)
MA(1)		0.247 (1.247)		
MA(2)		-0.098 (-0.557)		
SMA(4)				
Adj R^2	-0.058	0.705	0.704	0.712
SC	-4.133	-5.200	-5.301	-5.551
S.E	0.027	0.015	0.015	0.014
AR Root		0.898 0.874	0.922 0.870	0.999 0.873
MA Root		0.448 0.221		
P[QLB(7)]		0.588	0.523	0.432
LR (SEA DUM)		2.369 [0.668]	2.430 [0.681]	

We apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 7th lag, denoted P[QLB(7)], exceeds 0.050 indicating that there is no residual autocorrelation– we choose lag 7 based on the square root of the sample size (in this case $\sqrt{55}$). The inverse roots of the AR and MA processes are all less than one indicating that the model is consistent with a stationary and invertible process. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests. However, as indicated above the specification can be improved with the amendment of the ARMA terms. The coefficients on the MA(1) and MA(2) terms are not significant and are candidates for exclusion. Therefore, we remove the MA(1) and MA(2) terms from the model reported in the column headed 2 from Table 5.2.4 and report the resulting $ARMAX(1,0)(1,0)_4$ in the column headed 3 of Table 5.2.4. This model's SC decreases to -5.301. All of the ARMA components as well as the coefficients on the four seasonal dummy variables are significant. However, the test for the exclusion of all 4 seasonal dummy variables is jointly insignificant.

We exclude seasonal dummy variables that are jointly insignificant and report this model in the column headed 4 in Table 5.2.4. In this model the SC reduces to -5.551 and all the ARMA components are significant. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility and is therefore valid for forecasting.

Figure 5.2.4.2: the actual and fitted values reported in Table 5.2.4 column 4



Visual inspection of the actual and fitted values (Figure 5.2.4.2) of this model suggests that the time path of the fitted values capture the movements in the actual data reasonably. In terms of model fit the adjusted R^2 of this ARIMAX model on the reduced sample is 0.712 which is much lower than the specification estimated using the full sample that models structural breaks (Appendix A. Section 5.1. Table 5.6.3:), being 0.893. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

5.2.5 Box-Jenkins ARIMA modelling of annual inflation for Angola

In the full sample ARIMAX model developed for Angola in section 5.1 we identified the last structural break in 1998q3. Hence, the maximum available estimation period without an identified structural break is 1998q4 to 2012q4. To allow for lags and transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 2000q4 – 2012q4 (49 observations). First, we regress inflation on the 4 seasonal dummy variables, D_{st}, to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final ARIMA model.

Table 5.2.5 reports the benchmark deterministic specification and various ARIMA models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables coefficients are significant and the model's Schwarz criterion (SC) is -2.136.

Figure 5.2.5.1 plots the ACF of the residuals of the model reported in the column headed 1 of Table 5.2.5. Visual inspection of this graph suggests that the first 9 autocorrelation coefficients (ACs) are significant which, being greater than 5, is normally indicative of nonstationarity. However, the sinusoidal pattern of ACF and that the ACs are not highly significant suggests the existence of an AR process rather than nonstationarity. We therefore assume that the series is stationary and does not require any further nonseasonal differencing – if this turns out to be incorrect it should result in the rejection of the diagnostic check for stationarity. We initially specify the maximum order of non-seasonal MA component as 3 and seasonal MA component as 2 given that ACs are significant at lag 4 and 8 and insignificant at lags 12, 16, 20, 24 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs (at the seasonal lags) are significant. Given the difficulty in clearly identifying the (especially non-seasonal) orders of MA process alternative orders will be considered if an adequate model cannot be identified.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lag 1 and insignificant at lags 2, 3, 4 and 5. This suggests the maximum order of non-seasonal AR component is probably 1. The seasonal PACs are insignificant at lag 4, 8, 12 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process is probably equal to 0. Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is ARMA $(1,3)(0,2)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes 4 seasonal dummy variables and an ARMA $(1,3)(0,2)_4$ model of the residuals in the column headed 2 of Table 5.2.5

Figure 5.2.5.1: the ACF and PACF of the residuals of model 1 reported in Table 5.2.5

Sample: 2000Q4 2012Q4
Included observations: 49

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.835	0.835	36.294	0.000
		2	0.696	-0.004	62.045	0.000
		3	0.579	-0.003	80.270	0.000
		4	0.506	0.080	94.513	0.000
		5	0.467	0.084	106.91	0.000
		6	0.421	-0.022	117.20	0.000
		7	0.401	0.087	126.78	0.000
		8	0.359	-0.051	134.62	0.000
		9	0.308	-0.039	140.55	0.000
		10	0.258	-0.019	144.80	0.000
		11	0.185	-0.109	147.04	0.000
		12	0.106	-0.101	147.80	0.000
		13	0.041	-0.028	147.92	0.000
		14	-0.002	-0.019	147.92	0.000
		15	-0.035	-0.032	148.01	0.000
		16	-0.066	-0.021	148.34	0.000
		17	-0.088	-0.005	148.95	0.000
		18	-0.104	0.009	149.82	0.000
		19	-0.121	-0.003	151.04	0.000
		20	-0.143	-0.023	152.79	0.000
		21	-0.155	0.014	154.95	0.000
		22	-0.161	0.013	157.36	0.000
		23	-0.169	-0.024	160.11	0.000
		24	-0.183	-0.045	163.47	0.000
		25	-0.188	-0.000	167.14	0.000
		26	-0.189	-0.019	171.04	0.000
		27	-0.197	-0.046	175.44	0.000
		28	-0.211	-0.057	180.73	0.000

In this model the SC falls to -2.255 suggesting that the addition of ARMA terms has improved the specification. All four seasonal dummy variables are individually insignificant. This is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 0.728. In this model all of the ARMA components are significant except for the SMA(4) and SMA(8) terms.

For the model to be valid we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 7^{th} lag, denoted P[QLB(7)] is less than 0.050 indicating evidence of autocorrelation in the dependent variable – we choose lag 7 based on the square root of the sample size (in this case $\sqrt{49}$). The inverse roots of the AR and MA processes are all less than one indicating that the model is consistent with a stationary and invertible process. Hence, the model is not valid for forecasting in the sense that there is evidence of autocorrelation.

Table 5.2.5: The ARMA table for Angola

Observations	2000q3 2012q4(49)				
	1	2	3	4	5
D_1	0.533 (2.944)	0.217 (1.862)	0.207 (1.845)		
D_2	0.467 (2.583)	0.225 (0.116)	0.215 (1.910)		
D_3	0.413 (2.280)	0.220 (1.903)	0.207 (1.879)		
D_4	0.551 (3.172)	0.211 (1.828)	0.202 (1.802)		
AR(1)		0.802 (20.642)	0.809 (25.825)	0.831 (31.618)	0.465 (1.717)
AR(2)					0.281 (1.281)
MA(1)		0.280 (3.427)	0.287 (3.450)	0.378 (5.530)	0.684 (2.497)
MA(2)		0.195 (2.473)	0.132 (1.317)	0.203 (2.289)	0.060 (0.266)
MA(3)		0.916 (12.022)	0.844 (9.552)	0.823 (11.134)	0.375 (2.005)
SMA(4)		0.219 (1.353)			
SMA(8)		-0.209 (-1.405)			
Adj R^2	-0.057	0.996	0.990	0.990	0.987
SC	-2.136	-2.255	-2.306	-2.543	-2.172
S.E	0.627	0.059	0.061	0.060	0.071
AR Root		0.802	0.809	0.831	0.811 0.347
MA Root		0.999 0.957 0.873 0.775	0.999 0.918	0.999 0.907	0.999 0.612
P[QLB(7)]		0.002	0.053	0.017	0.002
LR (SEA DUM)		2.041 [0.728]	2.584 [0.407]		
LR (SEA DUM, CON)			7.581 [0.000]		

As indicated above the specification can be improved with the removal of insignificant ARMA variables. The coefficients on the SMA(4) and SAR(8) terms are not significant and are candidates for exclusion. Therefore, we remove these variables from the model reported in the column headed 2 Table 5.2.5 and report the resulting non-seasonal $ARMAX(1,3)$ in the column headed 3 of Table 5.2.5. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. In terms of specification all ARMA variables are significant. However, the four seasonal dummy variables are individually and jointly insignificant.

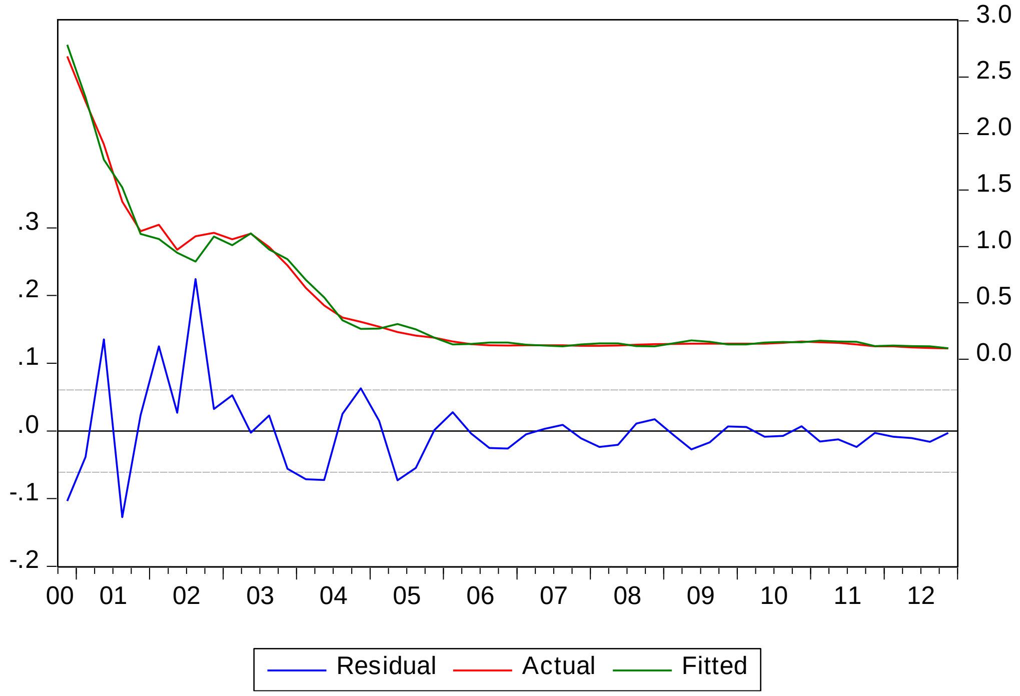
We exclude the seasonal dummy variables that are jointly insignificant and report the resulting model in column 4. This model's SC decreases to -2.543 and all the included variables are significant. According to the standard diagnostic checks, this model is stationary and invertible however there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variables.

We also experiment with adding an AR(2) term to model in Colum 4 to examining whether the model will passes the diagnostic check and report the resulting model in column 5. This model is rejected based on evidence of autocorrelation.

Since model 4 and 5 are rejected due to autocorrelation we regard model 3 as the best ARIMA model for forecasting Angola annual inflation because the model has the lowest SC of those that cannot be rejected according to the diagnostic checks.

Further, the Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal, denoted LR (SEA DUM, CON), is rejected. This suggests significant deterministic seasonality and that these dummies cannot be replaced by a single (non-seasonal) intercept.

Figure 5.2.5.2: the actual and fitted values reported in Table 5.2.5 column 3



Visual inspection of the actual and fitted values (Figure 5.2.5.2) of this model suggests that the time path of the fitted values capture the movements in the actual data well. In terms of model fit the adjusted R^2 of this ARIMAX model on the reduced sample is 0.990 which is slightly lower than the specification estimated using the full sample that models structural breaks (Appendix A. Section 5.1 Table 5.7.3), being 0.997. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

5.2.6 Box-Jenkins ARIMAX modelling of annual inflation for Nigeria

In the full sample ARIMAX model developed for Nigeria in section 5.1 we identified the last structural break date in 1996q3. Hence, the maximum available estimation period without a structural break is 1996q4 to 2012q4. To allow for lags and transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 1998q4 – 2012q4 (57 observations). First, we regress inflation on the 4 seasonal dummy variables, D_{st}, to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final ARIMA model.

Table 5.2.6 reports the benchmark deterministic specification and various ARIMA models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables coefficients are significant and the model's Schwarz criterion (SC) is -2.741

Figure 5.2.6.1 plots the autocorrelation function (ACF) of the residuals of the model reported in the column headed 1 of Table 5.2.6. The non-seasonal autocorrelation coefficients (ACs) from the ACF are significant at lags 1 and 2 and insignificant at lags 3, 4, 5 and 6. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal MA component is probably 2. Further, the seasonal ACs are significant at lag 24 and insignificant at lags 4, 8, 12, 16, 20 and 28. This suggests that there is no need for further seasonal differencing because no more than the first 5 seasonal ACs are significant. It also indicates the maximum order of seasonal MA component is probably equal to 0.

From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1 and 2 and insignificant at lags 3 and 4. This suggests the maximum order of non-seasonal AR component is probably 2. The seasonal PACs are insignificant at lags 4, 8, 12 16, 20, 24 and 28. Nevertheless, the maximum order of seasonal AR process could be 1 given the notable significance of the PAC at lag 5 (assuming a multiplicative specification). Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is ARMA $(2,2)(1,0)_4$. Assuming a multiplicative specification we report an ARIMAX specification that includes

4 seasonal dummy variables and an ARMAX $(2,2)(1,0)_4$ of the residuals in the column headed 2 of Table 5.2.6.

Figure 5.2.6.1: the ACF and PACF of the residuals of model 1 reported in Table 5.2.6

Sample: 1998Q4 2012Q4
Included observations: 57

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.755	0.755	34.199	0.000
		2	0.372	-0.458	42.666	0.000
		3	0.028	-0.105	42.715	0.000
		4	-0.205	-0.081	45.374	0.000
		5	-0.193	0.298	47.786	0.000
		6	-0.130	-0.264	48.908	0.000
		7	-0.116	-0.127	49.811	0.000
		8	-0.137	-0.077	51.107	0.000
		9	-0.133	0.254	52.346	0.000
		10	-0.094	-0.142	52.976	0.000
		11	-0.007	0.047	52.980	0.000
		12	0.054	-0.166	53.198	0.000
		13	0.017	0.022	53.219	0.000
		14	-0.066	-0.127	53.562	0.000
		15	-0.183	-0.098	56.241	0.000
		16	-0.208	0.095	59.797	0.000
		17	-0.097	0.156	60.590	0.000
		18	0.024	-0.147	60.640	0.000
		19	0.085	-0.170	61.275	0.000
		20	0.007	-0.196	61.278	0.000
		21	-0.196	-0.148	64.866	0.000
		22	-0.335	0.038	75.629	0.000
		23	-0.337	-0.104	86.874	0.000
		24	-0.245	-0.116	92.997	0.000
		25	-0.072	0.077	93.541	0.000
		26	0.061	0.028	93.951	0.000
		27	0.120	0.003	95.557	0.000
		28	0.146	-0.171	98.013	0.000

In this model the SC falls to -3.763 suggesting that the addition of ARMA terms has improved the specification. All four seasonal dummy variables are significant although this is not confirmed by the test for the joint exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM). In this model all the ARMA components are significant except for those associated with the AR(1) and MA(2) terms.

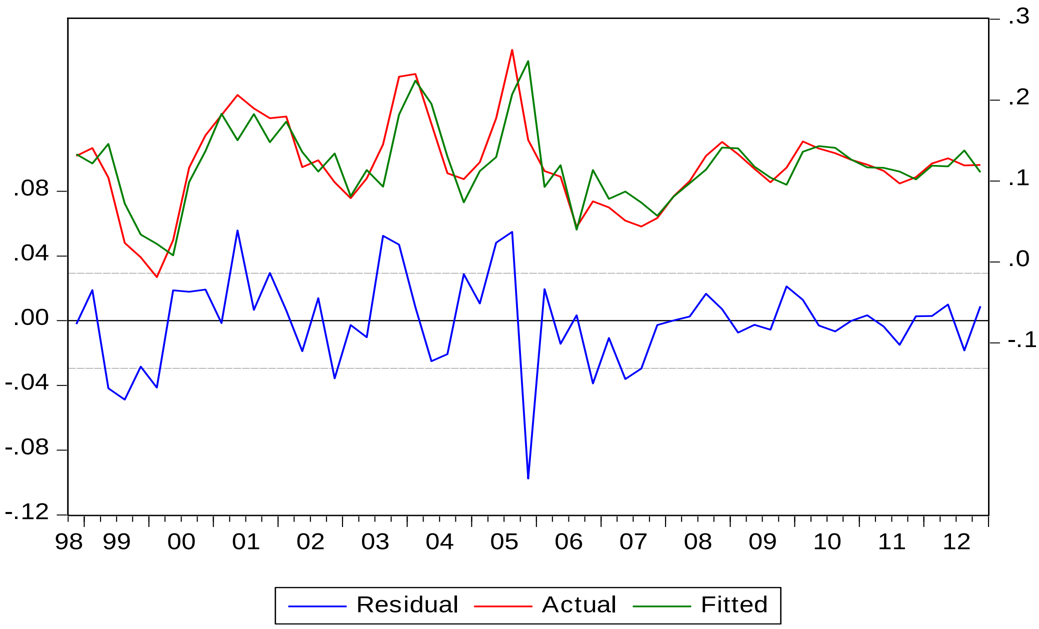
Table 5.2.6. The ARMA table for Nigeria

Observations	1998q4 2012q4(57)					
	1	2	3	4	5	6
D_1	0.122 (8.226)	0.128 (10.133)	0.124 (7.947)	0.121 (9.632)	0.123 (6.904)	0.121 (10.226)
D_2	0.119 (8.013)	0.122 (8.811)	0.119 (7.593)	0.117 (9.301)	0.119 (6.691)	0.118 (9.889)
D_3	0.117 (7.923)	0.126 (8.777)	0.119 (7.539)	0.117 (9.223)	0.118 (6.641)	0.117 (9.796)
D_4	0.120 (8.387)	0.126 (10.125)	0.121 (7.774)	0.123 (9.727)	0.124 (6.977)	0.122 (10.340)
P(2005q4)				-0.043 (-2.370)	-0.039 (-1.713)	-0.045 (-2.446)
AR(1)		-0.034 (-0.123)	0.220 (1.636)	1.072 (3.231)	0.843 (10.796)	1.192 (8.762)
AR(2)		0.531 (3.144)	0.425 (2.963)	-0.324 (-1.071)		-0.427 (-2.994)
SAR(4)		-0.436 (-3.081)	-0.434 (-3.090)	-0.442 (-3.028)	-0.527 (-4.252)	-0.427 (-3.000)
MA(1)		1.289 (3.753)	0.981 (38.690)	0.144 (0.411)		
MA(2)		0.290 (0.969)				
Adj R^2	-0.056	0.706	0.639	0.706	0.657	0.711
SC	-2.741	-3.763	-3.804	-3.762	-3.711	-3.829
S.E	0.055	0.029	0.029	0.029	0.032	
AR Root		0.812 0.812 0.746	0.812 0.772 0.551	0.815 0.570	0.852 0.843	0.808 0.654
MA Root		0.999 0.290	0.981	0.144		
P[QLB(8)]		0.450	0.508	0.659	0.049	0.406
LR (SEA DUM)		-3.028	10.717 [0.030]	1.351 [0.265]	1.448 [0.232]	2.829 [0.034]
LR (SEA DUM, CON)						18.751 [0.000]

We apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 8th lag, denoted P[QLB(8)], exceeds 0.050 indicating evidence of no autocorrelation in the dependent variable– we choose lag 8 based on the square root of the sample size (in this case $\sqrt{57}$). The inverse roots of the AR and MA processes are all less than one indicating that the model is consistent with a stationary and invertible process. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests.

However, as indicated above the specification can be improved with the removal of insignificant ARMA variables. The coefficients on the AR(1) and MA(2) terms are not significant and are candidates for exclusion. Since the AR(2) term is significant we do not remove the AR(1) term to retain the full second-order specification of the non-seasonal AR component. However, we remove the MA(2) term from the model reported in the column headed 2 from Table 5.2.6. and report the resulting $ARMAX(2,1)(1,0)_4$ in the column headed 3. In this model all of the coefficients of the variables are significant except for the AR(1) term, which we would not exclude because the AR(2) term is significant. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility and is therefore valid for forecasting.

Figure 5.2.6.2: the actual and fitted values of model reported in Table 5.2.6 in column 3



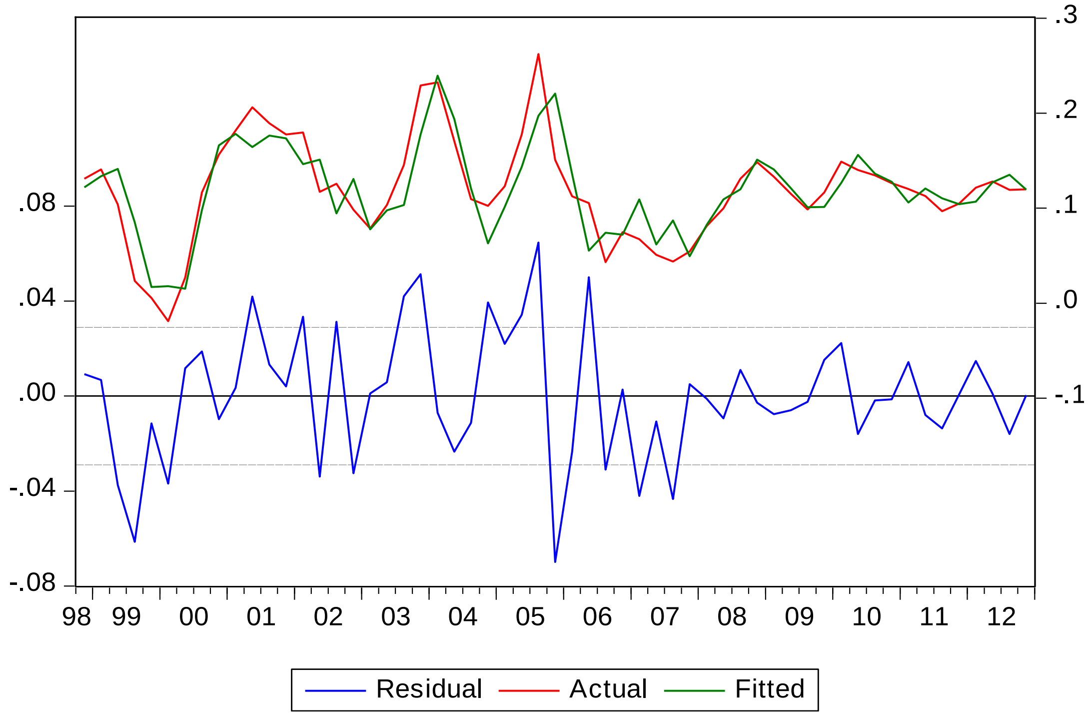
In the Figure 5.2.6.2 we plot the actual and fitted values of the model reported in column 3 of Table 5.2.6. Visual inspection of this graph suggests that there is an outlier in 2005q4 and we therefore add a new pulse dummy variable, denoted $P(2005q4)$, to the model reported in column 3 to capture this outlier. This model, reported in column 4, cannot be rejected according to the diagnostic checks and all of the ARMA coefficients are significant except for the AR(2) and MA(1) terms.

We remove the insignificant MA (1) and AR (2) terms from the model reported in the column headed 4 Table 5.2.6 and report the resulting $ARMAX(1,0)(1,0)_4$ in the column headed 5. In this model, the coefficient of the new pulse dummy variable becomes insignificant. While this model does not fail the diagnostic checks for invertibility and stationarity there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and a need to respecify the model.

After experimentation we estimate the $ARIMAX(2,0)(1,0)_4$ which is reported in the column headed 6 of Table 5.2.6. In this specification all of the variables are significant and this model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility.

Further, the Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal, denoted LR (SEA DUM, CON), is rejected. This suggests significant deterministic seasonality and that these dummies cannot be replaced by a single (non-seasonal) intercept.

Figure 5.2.6.3: the actual and fitted values of model reported in Table 5.2.6 in column 6



Visual inspection of the actual and fitted values (Figure 5.2.6.3) of this model suggests that the time path of the fitted values reasonable capture the movements in the actual data. Therefore, we regard model 6 from Table 5.2.6 as the best ARIMAX model for forecasting Nigeria's annual inflation because the model has the lowest SC and it cannot be rejected according to the diagnostic checks for stationarity, invertibility and autocorrelation. The adjusted R^2 of the ARIMAX model using this reduced sample is 0.711 which is much lower than the specification estimated using the full sample that models structural breaks (Appendix A. Section 5.1 Table 5.10.3), being 0.911. It will be interesting to see if the comparative fit of these two models is indicative of their relative forecasting performance.

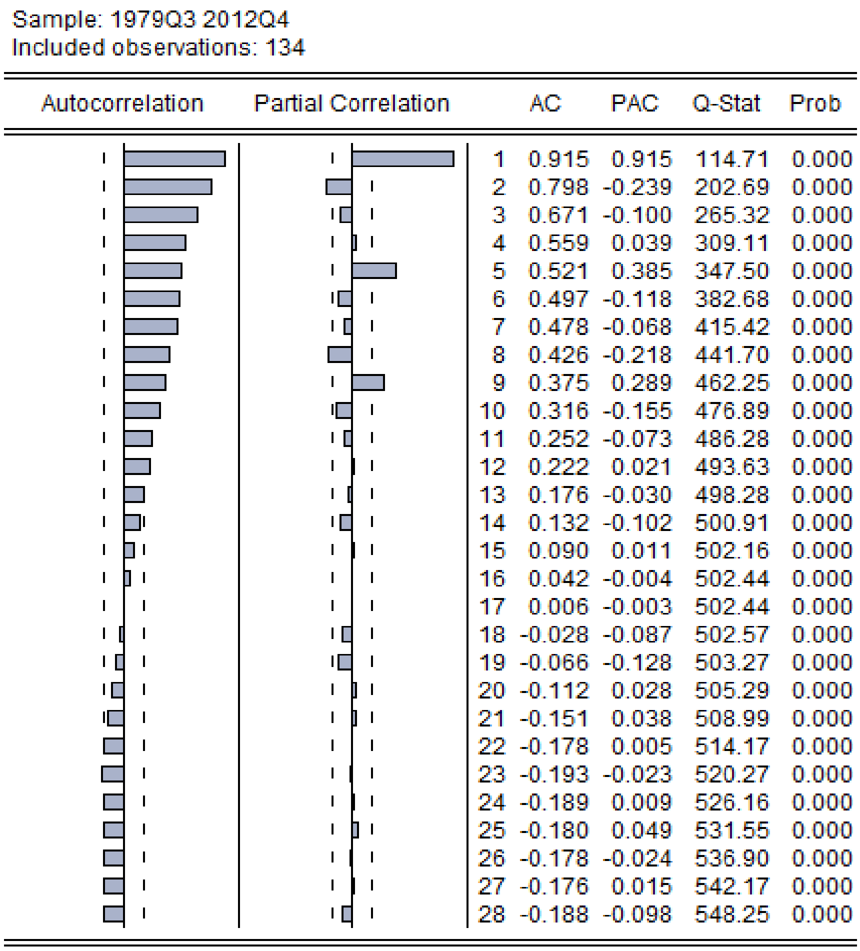
5.2.7 Box-Jenkins ARIMA modelling of annual inflation for Saudi Arabia

In the full sample ARIMAX model developed for Saudi Arabia in section 5.1 we identified the last structural break date in 1977q2. Hence, the maximum available estimation period without a structural break is 1977q3 to 2012q4. To allow for lags and transformations and have a consistent estimation period for all models we specify an initialization period of two years and estimate all models over the period 1979q3 – 2012q4 (134 observations). First, we regress inflation on the 4 seasonal dummy variables, D_{st} to yield the benchmark deterministic specification. Second, we identify the ARMA components to the residuals of this model and discuss the development of the final ARIMA model.

Table 5.2.7 reports the benchmark deterministic specification and various ARIMAX models. The model reported in the column labelled 1 is the benchmark deterministic model. The results indicate that all of the seasonal dummy variables coefficients are significant and the model's Schwarz criterion (SC) is -4.098.

Figure 5.2.7.1 plots the ACF of the model reported in the column headed 1 of Table 5.2.7 Visual inspection of this graph suggests that the first 13 autocorrelation coefficients (ACs) are significant which, being greater than 5, is normally indicative of nonstationarity. However, the sinusoidal pattern of the ACF and that the ACs are not highly significant suggests the existence of an AR process rather than nonstationarity. We therefore assume that the series is stationary and does not require any further nonseasonal differencing – if this turns out to be incorrect it should result in the rejection of the diagnostic check for stationarity. We initially specify the maximum order of non-seasonal MA component as 3 and seasonal MA component as 3 given that ACs are significant at lags 4, 8, 12, 24 and 28 and insignificant at lags 16 and 20. This suggests that there is no need for further seasonal differencing because the seasonal ACs cut to zero by seasonal lag 5 (the seasonal ACs are insignificant at lag 16 and 20). Given the difficulty in clearly identifying the (especially non-seasonal) orders of MA process alternative orders will be considered if an adequate model cannot be identified. From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1 and 2 and insignificant at lags 3 and 4. This suggests the maximum order of non-seasonal AR component is probably 2. The seasonal PACs are significant at lags 4 and 8 and insignificant at lags 12, 16, 20, 24 and 28. Therefore, the maximum order of seasonal AR process could be 2. Hence, the maximum seasonal ARMA specification that we initially identify to the residuals of the deterministic model is ARMA $(2,3)(2,3)_4$. Assuming a multiplicative specification we report an ARIMAX model that includes 4 seasonal dummy variables and an ARMA$(2,3)(2,3)_4$ process for the residuals in the column headed 2 of Table 5.2.7.

Figure 7.7.1: the ACF and PACF of the residuals of model 1 reported in Table 7.7.1



Sample: 1979Q3 2012Q4
Included observations: 134

Lag	AC	PAC	Q-Stat	Prob
1	0.915	0.915	114.71	0.000
2	0.798	-0.239	202.69	0.000
3	0.671	-0.100	265.32	0.000
4	0.559	0.039	309.11	0.000
5	0.521	0.385	347.50	0.000
6	0.497	-0.118	382.68	0.000
7	0.478	-0.068	415.42	0.000
8	0.426	-0.218	441.70	0.000
9	0.375	0.289	462.25	0.000
10	0.316	-0.155	476.89	0.000
11	0.252	-0.073	486.28	0.000
12	0.222	0.021	493.63	0.000
13	0.176	-0.030	498.28	0.000
14	0.132	-0.102	500.91	0.000
15	0.090	0.011	502.16	0.000
16	0.042	-0.004	502.44	0.000
17	0.006	-0.003	502.44	0.000
18	-0.028	-0.087	502.57	0.000
19	-0.066	-0.128	503.27	0.000
20	-0.112	0.028	505.29	0.000
21	-0.151	0.038	508.99	0.000
22	-0.178	0.005	514.17	0.000
23	-0.193	-0.023	520.27	0.000
24	-0.189	0.009	526.16	0.000
25	-0.180	0.049	531.55	0.000
26	-0.178	-0.024	536.90	0.000
27	-0.176	0.015	542.17	0.000
28	-0.188	-0.098	548.25	0.000

In this model the SC falls to -6.167 suggesting that the addition of ARMA terms has improved the specification. All four seasonal dummy variables are individually insignificant, which is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM), which has a probability value of 1.000. The coefficients on the AR(1), AR(2) SAR(4), SAR(8), MA(3), SMA(8) and SMA(12) are not significant. These results suggest that the specification can be improved by the exclusion of insignificant ARMA terms.

Table 5.2.7: The ARMA table for Saudi Arabia

Observations	1979q3 2012q4 (134)							
	1	2	3	4	5	6	7	8
D_1	0.014 (2.766)	0.025 (1.017)	0.014 (3.375)	0.014 (3.626)	0.038 (0.587)		0.029 (0.810)	
D_2	0.0146 (2.856)	0.025 (1.006)	0.014 (3.433)	0.015 (3.689)	0.038 (0.583)		0.030 (0.810)	
D_3	0.015 (2.941)	0.026 (1.022)	0.014 (3.434)	0.015 (3.689)	0.038 (0.588)		0.030 (0.812)	
D_4	0.014 (2.893)	0.026 (1.022)	0.015 (3.421)	0.015 (3.663)	0.038 (0.588)		0.030 (0.812)	
P1992q2							-0.005 (-1.355)	-0.006 (-2.853)
AR(1)		0.616 (1.999)			1.867 (21.453)	1.849 (17.978)	1.863 (20.997)	1.820 (16.999)
AR(2)		0.356 (1.235)			-0.868 (-9.845)	-0.846 (-8.031)	-0.866 (-9.622)	-0.816 (-7.459)
SAR(4)		0.144 (0.702)						
SAR(8)		0.241 (1.673)						
MA(1)		0.709 (2.279)	0.914 (9.679)	0.971 (13.492)	-0.618 (-4.710)	-0.596 (-4.022)	-0.969 (-69.890)	-0.535 (-3.499)
MA(2)		0.452 (2.581)	0.546 (5.794)	0.582 (8.115)				
MA(3)		0.310 (1.768)						
SMA(4)		-0.858 (-3.515)	0.115 (0.972)		-0.970 (-81.718)	-0.967 (-58.179)	-0.969 (-69.890)	-0.974 (-88.157)
SMA(8)		-0.338 (-1.217)						
SMA(12)		0.245 (1.671)						
Adj R^2	-0.000	0.903	0.726	0.725	0.906	0.903	0.906	0.908
SC	-4.098	-6.167	-5.327	-5.352	-6.366	-6.452	-6.343	-6.476
S.E	0.029	0.009	0.015	0.015	0.009	0.009	0.009	-6.476
AR Root		0.979 0.864 0.807 0.363		0.763	0.983 0.883	1.019 0.830	0.976 0.887	1.020 0.799
MA Root		0.985 0.863 0.828 0.698 0.667	0.739 0.582		0.992 0.618	0.992 0.596	0.992 0.605	0.993 0.535
P[QLB(12)]		0.000	0.000	0.000	0.103	0.064	0.039	0.027
LR (SEA DUM)		0.219 [1.000]	3.826 [0.006]	4.556 [0.002]	1.949 [0.106]		0.423 [0.792]	
LR (SEA DUM, CON)					66.771 [0.000]			

We apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 12th lag, denoted P[QLB(12)], is less than 0.050 indicating evident of residual autocorrelation – we choose lag 12 based on the square root of the sample size (in this case $\sqrt{134}$). The inverse roots of the AR and MA processes are all less than one indicating that the model is consistent with a stationary and invertible process. Hence, the model is not valid for forecasting in the sense that there is evident autocorrelation.

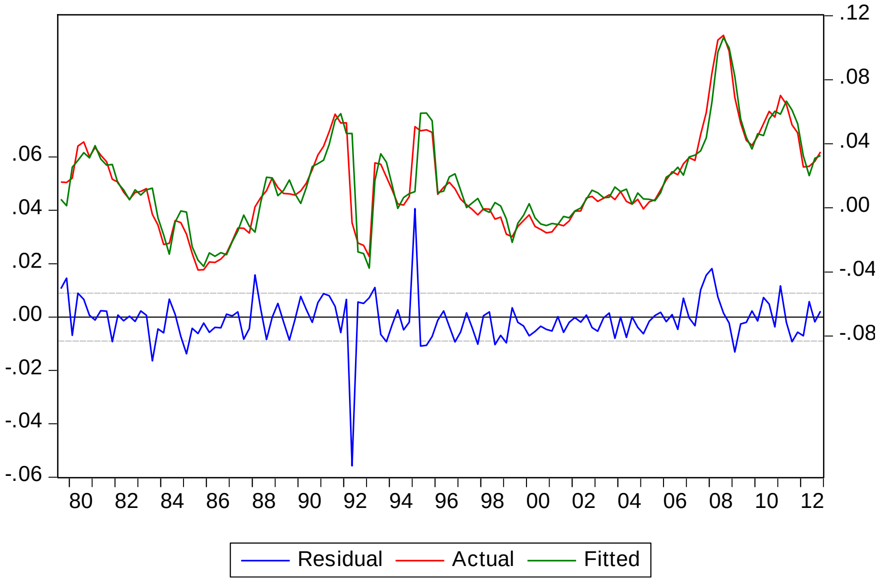
However, as indicated above the specification can be improved with the removal of some variables that are not significant. Therefore, we remove the variables AR(1), AR(2) SAR(4), SAR(8), MA(3), SMA(8) and SMA(12) from the model reported in the column headed 2 and report the resulting $ARMAX(0,2)(0,1)_4$ in the column headed 3. In this model, all the ARMA components are significant except for the SMA(4) term. This model does not fail the diagnostic checks for invertibility and stationarity however there is evidence of autocorrelation suggesting unmodelled systematic variation in the dependent variable and a need to re-specify the model.

Therefore, we remove the insignificant SMA(4) term and report the resulting $ARMAX(0,2)$ model in the column headed 4. This model is rejected because there is evidence of autocorrelation and there is a need to re-specify this model.

Based on experimentation we estimate the $ARMAX(2,1)(1,0)_4$ that is reported in the column headed 5. In terms of specification, all of the ARMA coefficients are significant. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. However, the seasonal dummy variables are individually insignificant. This is confirmed by the joint test for the exclusion of all 4 seasonal dummy variables, denoted LR(SEA DUM). Therefore, we exclude the seasonal dummy variables and report the result in column 6.

In this model, the SC falls to -6.452. Although this model does not exhibit evident autocorrelation or violates invertibility one inverse root of MA, however, the AR inverse roots is greater than one suggesting that this model is non-stationary. Hence, this model is not valid for forecasting and we prefer the valid model reported in column 5.

Figure 5.2.7.2: the actual and fitted values reported in Table 5.2.7 column 5



In Figure 5.2.7.2 we plot the actual and fitted values of the valid model reported in column 5 of Table 5.2.7. Visual inspection of this graph suggests that there is an outlier in 1992q2 and we therefore add a new pulse dummy variable, denoted $P(1992q2)$, to the model reported in column 5 to capture this outlier. This model is reported in column 7 and all of the ARMA components are significant except the coefficient on the pulse dummy and individual seasonal dummy variables. This model cannot be rejected according to the diagnostic checks for stationarity and invertibility, however, there is evident residual autocorrelation indicating that the model is not valid for forecasting

Therefore, we exclude the seasonal dummy variables that are jointly insignificant from the model reported in the column headed 7 and the result is reported in column 8. In this model, the SC falls to -6.476. Although this model is invertible there is evidence of autocorrelation and non-stationarity (one of the AR inverse roots is greater than one). Hence, this model is not valid for forecasting.

Therefore, we regard model 5 from Table 5.2.7 as the best ARIMAX model for forecasting Saudi Arabia's annual inflation because it has the minimum SC from those that cannot be rejected according to the diagnostic checks.

Further, the Wald test for the null hypothesis that all of the seasonal dummies' coefficients are equal, denoted LR (SEA DUM, CON), is rejected. This suggests significant deterministic seasonality and that these dummies cannot be replaced by a single (non-seasonal) intercept.

Section 5.3.

5.5.2 Russia Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA models. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality for Russia in section 5.1 (Table 5.1.5). The reduced sample models that avoid modelling structural breaks are estimated over the period 2003q2 – 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model for Russia in section 5.2 (Table 5.2.3), EViews 9's automatic selected seasonal ARIMA specification discussed in section 5.3 (Table 5.3.1) and EViews 9's automatically selected non-seasonal ARIMA model discussed in section 5.4 (Table 5.4.3). The forecast performance measures of these models are given in Table 5.5.2.

Table. 5.5.2: Forecast performance of Univariate models for Russia

	A Full sample seasonal ARIMAX model with modelling structural breaks			B Reduced sample seasonal ARIMA model without modelling structural breaks			C Reduced sample EView9 Automatic seasonal ARIMA model without modelling breaks			D Reduced sample EView9 Automatic's non-seasonal ARIMA model without modelling structural breaks		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	0.0290	33.6800	0.1710	0.0110	11.6700	0.0770	0.0160	14.9600	0.1080	0.0090*	10.1800*	0.0630*
2-step	0.0310	37.2200	0.1790	0.0180	21.7300	0.1180	0.0280	24.0900	0.1740	0.0080*	9.4120*	0.0520*
3-step	0.0340	42.9100	0.1940	0.0220	25.9800	0.1420	0.0400	39.0600	0.2330	0.0150*	17.5500*	0.0960*
4-step	0.0460	59.8300	0.2380	0.0230	27.2600	0.1360	0.0530	45.5300	0.2810	0.0160*	20.6300*	0.0990*
5-step	0.0360	43.7300	0.1920	0.0220	22.7000	0.1280	0.0560	48.3300	0.2920	0.0168*	18.8700*	0.1040*
6-step	0.0350	41.3700	0.1760	0.0240	28.4300	0.1320	0.0490	43.4500	0.2500	0.0140*	15.5900*	0.0800*
7-step	0.0320	36.2100	0.1570	0.0260	31.0900	0.1330	0.0480	50.8000	0.2360	0.0160*	15.1500*	0.0870*
8-step	0.0170	18.0000	0.0830	0.0100	9.8920	0.0470	0.0290	30.2200	0.1310	0.0060*	6.3660*	0.0310*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The reduced sample univariate model that employs Eviews 9's automatic non-seasonal ARIMA model, see column D of Table 5.5.2 has the lowest RMSE, MAPE and U values over all forecasting horizons across the four specifications. This implies that this specification unambiguously has the best forecasting performance over both short and long horizons. We note that the ARIMAX forecasts modelling structural breaks, see column A, reduced seasonal Box-Jenkins ARIMA, see column B and EViews 9's automatic selected seasonal ARIMA, see column C, were never favoured. These results imply the following for the univariate modelling on Russian data. First, the potential difficulties in explicitly modelling the structural breaks over the full sample outweighed the loss of data from using the reduced sample. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is the preferred strategy. Second, the quick automatic ARIMA selection procedures produce superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques. Third, the ARIMA specifications that explicitly model seasonality are inferior to the specification that applies non-seasonal models to seasonally adjusted data and then reseasonalises the forecasts. Finally, note that the MAPE of the favoured ARIMA model is between 6 and 21 percentage points suggesting a relatively moderate forecasting performance for this class of models for Russian inflation.

5.5.3 India Forecast performance and evaluation

We compare the forecasting performance of the three ARIMA models over the period of 1961q1 – 2012q4 for India.[156] The following ARIMA specifications are used for forecasting: the seasonal Box-Jenkins ARIMA method discussed in section 5.1 summarised for India in Table 5.1.5**,** EViews 9's automatically selected seasonal ARIMA model discussed in section 5.3 (Table 5.3.1) and EViews 9's automatically selected non-seasonal ARIMA model discussed in section 5.4 (5.4.3).[157] The forecast performance measures for this model are given in Table 5.5.3.

Table. 5.5.3: Forecast performance of Univariate models for India

	A Seasonal ARIMA modelling			**B** EViews 9's automatic seasonal ARIMA modelling			**C** EViews 9's automatic non-seasonal ARIMA modelling		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	0.0120*	13.5200*	0.0680*	0.0140	16.3300	0.0800	0.0160	17.3300	0.0890
2-step	0.0180*	23.1400*	0.1060*	0.0210	25.7800	0.1190	0.0210	26.9600	0.1240
3-step	0.0190*	22.3400*	0.1130*	0.0190	24.0200	0.1150	0.0220	29.7000	0.1340
4-step	0.0230*	33.8600*	0.1480*	0.0250	36.1500	0.1580	0.0260	38.5400	0.1590
5-step	0.0200*	31.5000*	0.1360*	0.0220	34.4200	0.1490	0.0230	36.8100	0.1530
6-step	0.0220*	35.3200*	0.1520*	0.0230	36.8900	0.1590	0.0240	38.8300	0.1650
7-step	0.0240*	42.3800*	0.1780*	0.0260	44.5000	0.1870	0.0250	43.3500	0.1790
8-step	0.0300*	63.4600*	0.2400*	0.0300	64.8100	0.2450	0.0300	64.3600	0.2440

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The univariate model employing the seasonal Box-Jenkins ARIMA method, see column A, has the lowest RMSE, MAPE and U values over all forecasting horizons, see Table 5.5.3. Hence, the method that employs seasonal Box-Jenkins ARIMA specification unambiguously has the superior forecasting performance over all forecasting horizons. We note that EViews 9's automatic selections procedures (Table. 5.5.3 column and B and C) are never favoured. These results imply, first, that there is no evidence that quick automatic ARIMA selection procedures can produce as good forecasts as specifications

[156] Note that we do not produce forecast for ARIMAX model in India since Bai and Perron test did not indicates any break date for modelling deterministic.

[157] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

produced using more time-consuming traditional Box-Jenkins ARIMA method. Second, the ARIMA specifications that explicitly model seasonality are superior to the specification that applies non-seasonal models to seasonally adjusted data and then reseasonalises the forecasts. Finally, we note that the MAPE of the favoured ARIMA model is above 13 percentage points suggesting a relatively poor forecasting performance for this class of models for Indian inflation.

5.5.4 China Forecast performance and evaluation

We compare the forecasting performance of the ARIMAX model and two EViews 9's automatic specifications over the period of 1992q1 – 2012q4 for China. The ARIMAX model includes deterministic dummy variables to model structural breaks and seasonality as summarised for China in section 5.1 (Table 5.1.5).[158] The following EViews 9 automatically selected models are used for forecasting: EViews 9's automatically selected seasonal ARIMA model discussed in section 5.3 (Table 5.3.1) and the EViews 9's automatic non-seasonal ARIMA model (with re-seasonalised forecasts) discussed in section 5.4 (Table 5.4.3).[159] The forecast performance measures of these models are given in Table 5.5.4

Table. 5.5.4: Forecast performance of Univariate models for China

	A **ARIMAX forecasts**			**B** **EViews 9's automatic seasonal ARIMA forecast**			**C** **EViews 9 automatic's non-seasonal ARIMA forecast**		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	0.0060	9.2670	0.0530	0.0040*	7.1980*	0.0390*	0.0070	10.4700	0.0600
2-step	0.0100	14.3200	0.0880	0.0090*	14.0000*	0.0870*	0.0110	17.0200	0.0980
3-step	0.0150	22.7500	0.1420	0.0150	24.4200	0.1450	0.0120*	16.1100*	0.1100*
4-step	0.0210	33.4300	0.2050	0.0230	36.3400	0.2290	0.0110*	14.0200*	0.0990*
5-step	0.0250	41.4400	0.2630	0.0260	41.4800	0.2660	0.0130*	17.8800*	0.1160*
6-step	0.0280	45.7500	0.2980	0.0300	49.3800	0.3310	0.0150*	24.1300*	0.1410*
7-step	0.0280	47.1100	0.3080	0.0280	46.1800	0.3010	0.0160*	25.6000*	0.1550*
8-step	0.0310	52.6000	0.3570	0.0280	47.1300	0.2450	0.0120*	19.5400*	0.1080*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The univariate model that employs EViews 9's automatic non-seasonal ARIMA model, see column C, Table 5.5.4 has the lowest RMSE, MAPE and U-statistic values for 3, 4,5,6,7 and 8-step ahead horizons. While the model that employs EViews 9's automatic

[158] We did not estimate reduced sample model for China because the period after the structural breaks are less than 39 observations. However, the relative step shifts for this period appear to be small which mean that inference regarding (seasonal) unit roots may not be too adversely affected when using the full sample, Therefore, we apply EView 9's automatic specifications over the full sample for China to determine whether the effect of moderate mean shifts can affect the performance of inflations for this class of the model.

[159] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

seasonal ARIMA model, see column B, has the lowest RMSE, MAPE and U-statistic values for the 1 and 2-step ahead horizons. Hence, the EViews 9 automatic non-seasonal ARIMA model generally has the superior forecasting performance over all forecasting horizons although EViews 9's automatic seasonal model selection processes produce the best forecast for 1 and 2 steps ahead. We note that the ARIMAX that explicitly models structural breaks (Table. 5.5.4 column A) is never favoured. These results imply the following for the univariate modelling of Chinese data. First, the potential difficulties in explicitly modelling the structural breaks outweighed the benefits of using Eviews 9's automatic selection method. Given the extra time and modeller expertise required to model such breaks, this suggests that avoiding modelling structural breaks is the preferred strategy than modelling structural breaks. Second, the quick automatic ARIMA selection procedures produce superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques even when applied over the full sample. Third, the benefit of seasonally adjusting data and re-seasonalising the forecasts generally outperforms the method of modelling seasonality in ARIMA forecasting. Finally, note that the MAPE of the favoured ARIMA models is between 7 and 26 percentage points suggesting a relatively moderate forecasting performance for this class of models for Chinese inflation.

5.5.5. South Africa univariate Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA models for South Africa. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality as discussed section 5.1 and summarised in Table 5.1.5. The reduced sample models that avoid structural breaks are estimated over the period 1995q2 – 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model discussed in section 5.2 and summarised for South African in Table 5.2.3**,** EViews 9's automatic seasonal ARIMA model discussed in section 5.3 (Table 5.3.1) and EViews 9's automatic non-seasonal ARIMA model discussed in section 5.4 (Table 5.4.3).[160] The forecast performance measures of these models are given in Table 5.5.5.

Table. 5.5.5: Forecast performance of Univariate models for South Africa

	A Full sample seasonal ARIMAX model with modelling breaks			**B** Reduced sample seasonal ARIMA model without modelling breaks			**C** Reduced sample EView automatic 9's seasonal ARIMA without modelling breaks			**D** Reduced sample EView automatic 9's non-seasonal ARIMA without modelling breaks		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	0.0320	44.5700	0.2750	0.0250	41.0900	0.2160	0.0080*	14.2800*	0.0640*	0.0400	70.7100	0.3030
2-step	0.0500	67.4000	0.3940	0.0230	35.2600	0.1880	0.0130*	19.5400*	0.1010*	0.0590	76.2700	0.3830
3-step	0.0560	82.7900	0.4480	0.0260	34.0600	0.2150	0.0130*	17.4100*	0.1010*	0.0550	88.8900	0.3560
4-step	0.0500	66.3800	0.4230	0.0210	28.5400	0.1770	0.0130*	20.9900*	0.1010*	0.0470	59.8600	0.3110
5-step	0.0430	62.9200	0.4020	0.0120*	17.2600*	0.1060	0.0140	20.0300	0.1030*	0.0230	30.6000	0.1740
6-step	0.0430	63.4500	0.4660	0.0120	15.4000	0.1010	0.0090*	13.3600*	0.0690*	0.0150	23.4800	0.1350
7-step	0.0520	82.6000	0.6780	0.0120	18.9000	0.1040	0.0080*	12.3600*	0.0580*	0.0310	34.7200	0.2920
8-step	0.0510	85.1100	0.7410	0.0060*	10.2000*	0.0540*	0.0120	19.7400	0.0900	0.0200	33.7900	0.2030

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon

[160] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

From the above Table, the EViews 9 automatic seasonal ARIMA selection method, see column C, has the lowest U-statistics over all forecasting horizons except for 8-steps ahead. This specification also has the lowest RMSE and MAPE values over all forecasting horizons except for 5 and 8-steps ahead. The model that employs the reduced sample seasonal ARIMA model without modelling breaks has the lowest RMSE and MAPE for the 5 step horizon and has the best 8 step ahead forecasting performance according to all the three measures. Hence, the EViews 9 automatic seasonal ARIMA model selection procedure generally produces the best forecasting performance over most (though not all horizons). We note that the ARIMAX forecasts produced using the full sample that explicitly model structural breaks (Table. 5.5.5 column A) and reduced sample ARIMA model that employs Eviews 9's automatic non-seasonal ARIMA selection routine (Table. 5.5.5 column D) were never favoured. These results imply the following for the univariate modelling of South African data. First, the potential benefits of using a full sample and explicitly modelling the structural breaks were outweighed by the benefits of being able to avoid modelling structural breaks at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is the preferred strategy. Second, the quick automatic ARIMA selection procedures generally (though not always) produce superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques. Third, there is no evidence to support the application of non-seasonal models to seasonally adjusted data and reseasonalising the forecasts produces superior forecast to explicitly modelling seasonality with the ARIMA technique. Finally, note that the MAPE of the favoured ARIMA models is between 10 and 21 percentage points suggesting a relatively moderate forecasting performance for this class of models for South African inflation.

5.5.6 Angola Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA model for Angola. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 and summarised in Table 5.1.6. The reduced samples that avoid modelling structural breaks are estimated over the period 2000q4 – 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model discussed in section 5. 2 (Table 5.2.3)**,** EViews 9's automatically selected seasonal ARIMA model discussed in section 5.3 (Table 5.3.1) and EViews 9's automatically selected non-seasonal ARIMA model discussed in section 5.4 (Table 5.4.4).[161] The forecast performance measures of these models are given in Table 5.5.6.

Table 5.5.6: Forecast performance of Univariate models for Angola

	A Full sample seasonal ARIMAX model with modelling breaks			**B** Reduced sample seasonal ARIMA model without modelling breaks			**C** Reduced sample EViews 9's automatic seasonal ARIMA without modelling breaks			**D** Reduced sample EViews 9's automatic non-seasonal ARIMA without modelling breaks		
	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U
1-step	0.1220	13.1000	0.4540	0.0180*	2.05900*	0.0990*	0.0310	3.50100	0.1680	0.0650	4.34100	0.3170
2-step	0.1900	20.2900	0.5530	0.0270*	3.25600*	0.1440*	0.0690	6.46900	0.3170	0.1450	9.70900	0.5320
3-step	0.2600	29.7300	0.6350	0.0400*	5.11300*	0.2060*	0.1070	12.2000	0.4200	0.1790	14.1300	0.5900
4-step	0.2930	35.9700	0.6720	0.0570*	7.63000*	0.2760*	0.1740	22.5400	0.5450	0.1900	17.6000	0.5960
5-step	0.3990	53.7600	0.7360	0.0720*	9.81300*	0.3320*	0.2510	33.9000	0.6350	0.2430	24.0800	0.6540
6-step	0.4330	59.5600	0.7520	0.0860*	11.7500*	0.3740*	0.3170	43.0200	0.6890	0.2810	29.2500	0.6820
7-step	0.4250	58.1700	0.7450	0.0940*	12.8000*	0.3920*	0.3350	46.0000	0.6970	0.1130	14.5200	0.4440
8-step	0.2880	38.5100	0.6580	0.1000*	13.3300*	0.4000*	0.4000	53.4800	0.7280	0.1540	20.6000	0.5070

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The reduced sample univariate model that employs seasonal Box-Jenkins ARIMA technique's, see column B, and has the lowest RSME, MAPE and U values over all forecasting horizons. This implies that the reduced that employs seasonal Box-Jenkins ARIMA technique unambiguously produces the best forecasting performance across the four models. We note that the ARIMAX forecasts produced using the full sample that explicitly model structural breaks (Table. 5.5.6 column A) and reduced sample ARIMA

[161] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

model that employs Eviews 9's automatic ARIMA selection routine (Table. 5.5.6 of the column C and D) were never favoured. These results imply the following for the univariate modelling on Angolan data. First, the potential benefits of using a full sample and explicitly modelling the structural breaks were outweighed by the benefits of being able to avoid modelling structural breaks at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is the preferred strategy. Second, the quick automatic ARIMA selection procedures never produced superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques. Third, there is no evidence to support the application of non-seasonal models to seasonally adjusted data and reseasonalising the forecasts produces superior forecast to explicitly modelling seasonality with the ARIMA technique. Finally, note that the MAPE of the favoured ARIMA models is between 2 and 14 percentage points suggesting a relatively good forecasting performance for this class of models for Angolan inflation.

5.5.7 Algeria Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA models. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 and summarised for Algeria in Table 5.1.6. The reduced sample models that avoid structural breaks are estimated over the period 1999q2 – 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model discussed in section 5.2 (Table 5.2.3)**,** EViews 9's automatic seasonal ARIMA model discussed in section 5.3 (Table 5.3.3) and EViews 9's automatic non-seasonal ARIMA model discussed in section 5.4 (Table 5.4.4).[162] The forecast performance measures of these models are given in Table 5.5.7.

5.5.7. Forecast performance of Univariate models for Algeria

	A Full sample ARIMAX model with modelling breaks			**B** Reduced sample ARIMA model without modelling breaks			**C** Reduced sample Eviews 9's automatic seasonal ARIMA without modelling breaks			**D** Reduced sample Eviews 9's automatic non-seasonal ARIMA without modelling breaks		
	RMSE	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**	**RMSE**	**MAPE**	**U**
1-step	0.0120*	76.7400	0.1730*	0.0140	84.7400	0.1800	0.0150	61.6300*	0.1900	0.0140	63.3700	0.1950
2-step	0.0170	111.2000	0.2670	0.0270	189.9000	0.3540	0.0250	99.4900	0.3270	0.0160*	82.6100*	0.2380*
3-step	0.0160*	108.2000*	0.2650*	0.0380	313.0000	0.4500	0.0310	183.3000	0.3940	0.0190	158.100	0.2930
4-step	0.0160*	136.0000*	0.2430*	0.0480	459.1000	0.5010	0.0410	369.2000	0.4990	0.0240	218.100	0.3480
5-step	0.0200*	147.2000*	0.2660*	0.0490	371.9000	0.4710	0.0430	326.3000	0.4790	0.0220	150.800	0.2970
6-step	0.0160*	55.9600*	0.1950*	0.0440	166.0000	0.3830	0.0420	151.7000	0.4240	0.0180	61.4700	0.2310
7-step	0.0160*	27.3800*	0.1670*	0.0330	78.74000	0.2650	0.0420	100.3000	0.3600	0.0160	27.6800	0.1790
8-step	0.0170*	28.7700*	0.1680	0.0210	35.6200	0.1510*	0.0260	43.1600	0.1780	0.0210	36.1300	0.2200

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The full sample univariate ARIMAX specification that models' structural breaks has the lowest MAPE values over all forecasting horizons except 1 and 2 steps ahead (Table. 5.5.7 column A). This model also has the lowest RMSE and U-statistic values for all forecasting horizons except 2 and 8-steps ahead. The reduced sample model that employs the Box-Jenkins ARIMA technique has the lowest U-statistic value for 8-steps ahead, see Table 5.5.7 column B and the EViews 9 automatic seasonal selection

[162] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

procedure has the lowest MAPE for the 1-step horizon, see Table 5.5.7 column C. While the reduced sample model that employs the EViews 9 automatic non- seasonal ARIMA selection method has lowest RMSE, MAPE and U-statistics for the 2-step horizon. Hence, the ARIMAX forecasts produced using the full sample that model structural breaks generally has superior forecasting performance (although not over all forecasting horizons). These results imply the following for the univariate modelling on Algerian data. First, the benefits of modelling the structural breaks with more information outperform the benefits of avoiding modelling structural breaks using a reduced sample. Second, the univariate models that employ the Eviews 9 automatic model selection procedures are rarely favoured. Finally, note that the MAPE of the favoured ARIMA models is always over 27 percentage points suggesting a relatively poor forecasting performance for this class of models for Algerian inflation.

5.5.8. Saudi Arabia Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA models. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 and summarised for Saudi Arabia in Table 5.1.6. The reduced sample models that avoid structural breaks are estimated over the period 1977q3 to 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model discussed in section 5.2 (Table 5.2.3)**,** EViews 9's automatic seasonal ARIMA model discussed in section 5.3 (Table 5.3.3) and EViews 9's automatic non-seasonal ARIMA model discussed in section 5.4 (Table 5.4.4).[163] The forecast performance measures of these models are given in Table 5.5.8.

Table. 5.5.8: Forecast performance of Univariate models for Saudi Arabia

	A Full sample ARIMAX model with modelling breaks			B Reduced sample ARIMA model without modelling breaks			C Reduced sample EViews 9's automatic seasonal ARIMA without modelling breaks			D Reduced sample EViews 9's automatic non-seasonal ARIMA without modelling breaks		
	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U
1-step	0.0060	18.1000	0.0940	0.0030*	8.3720*	0.0450*	0.0040	10.9800	0.0700	0.0050	14.2500	0.0810
2-step	0.0080	20.0500	0.1160	0.0050*	14.8500*	0.0800*	0.0070	21.8100	0.1280	0.0070	22.3000	0.1130
3-step	0.0070	20.7300	0.1170	0.0090	25.9900	0.1310	0.0110	36.9100	0.2380	0.0050*	15.1400*	0.0840*
4-step	0.0060	19.6800	0.0940	0.0130	43.0800	0.1860	0.0140	50.8800	0.3420	0.0020*	7.0610*	0.0420*
5-step	0.0090	29.9900	0.1470	0.0150	53.4200	0.2190	0.0170	62.0600	0.4500	0.0040*	12.6800*	0.0660*
6-step	0.0090	30.6400	0.1480	0.0180	63.3100	0.2440	0.0200	72.9600	0.5740	0.0040*	13.2000*	0.0720*
7-step	0.0080	27.6000	0.1300	0.0210	73.8200	0.2700	0.0250	87.8300	0.7710	0.0010*	4.2320*	0.0220*
8-step	0.0050	16.9700	0.0780	0.0220	78.7200	0.2820	0.0260	92.6100	0.8620	0.00-04*	1.0100*	0.0050*

The reduced sample that employs Eviews 9's automatic non-seasonal selection procedure, see column D, has the lowest RMSE, MAPE and U over all forecasting horizons except for 1 and 2-steps ahead (Table 5.5.8 column C). However, the reduced sample model that employs the seasonal Box Jenkins ARIMA specification has the lowest RMSE, MAPE and U value for the 1 and 2-step ahead horizons (Table 5.5.8 column B). Hence, the reduced sample specification that employs Eviews 9's automatic non-seasonal model selection procedures has the best forecasting performance over the medium to long term horizons if the model that employs seasonal Box Jenkin ARIMA has

[163] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

the best forecast performance over the shorter horizons. We note that the ARIMAX forecasts produced using the full sample that explicitly model structural breaks (Table. 5.5.8 column A) and reduced sample ARIMA model that employs Eviews 9's automatic seasonal ARIMA selection routine (Table. 5.5.8 column C) were never favoured. These results imply the following for the univariate modelling on Saudi Arabian data. First, the potential benefits of using a full sample and explicitly modelling the structural breaks were outweighed by the benefits of being able to avoid modelling structural breaks at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is the preferred strategy. Second, the quick automatic ARIMA selection procedures generally (though not always) produce superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques. Third, the benefits of seasonally adjusting the data and re-seasonalising the forecasts generally (if not always) outperforms the method of modelling seasonality. The MAPE of the favoured model is between 1 and 16 percentage points suggesting a relatively good forecasting performance for Saudi Arabian univariate ARIMA models.

5.5.9 Nigeria Forecast performance and evaluation

We compare the forecasting performance of the full sample ARIMAX and the reduced sample ARIMA models. The full sample specification includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 and summarised for Nigeria in Table 5.1.6. The reduced sample models that avoid structural breaks are estimated over the period 1999q2 – 2012q4. The following ARIMA models estimated over the reduced sample are used for forecasting: seasonal Box-Jenkins ARIMA model discussed in section 5.2 (Table 5.2.3)**,** EViews 9's automatic seasonal ARIMA method discussed in section 5.3 (Table 5.3.3) and EViews 9's automatic non-seasonal ARIMA method discussed in section 5.4 (Table 5.4.4).[164] The forecast performance measures of these models are given in Table 5.5.9

Table. 5.5.9: Forecast performance of Univariate models for Nigeria

	A Full sample ARIMAX model with modelling breaks			**B** Reduced sample ARIMA model without modelling breaks			**C** Reduced sample EViews 9's automatic seasonal ARIMA without modelling breaks			**D** Reduced sample EViews 9's automatic non-seasonal ARIMA without modelling breaks		
	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U	RMSE	MAPE	U
1-step	0.0250	21.8300	0.1390	0.0170*	19.2400*	0.0930*	0.0240	21.3000	0.1300	0.0230	23.4500	0.1270
2-step	0.0440	48.0400	0.2180	0.0280	31.8500	0.1450	0.0380	43.6400	0.1880	0.0200*	22.8700*	0.1120*
3-step	0.0660	72.6500	0.2960	0.0380*	46.2800	0.1930*	0.0530	62.6500	0.2470	0.0410	38.1200*	0.2080
4-step	0.0780	92.7600	0.3300	0.0460	56.6400	0.2210	0.0610	75.3600	0.2740	0.0370*	45.6400*	0.1870*
5-step	0.0860	101.5000	0.3500	0.0470	57.6400	0.2240	0.0580	71.2400	0.2650	0.0380*	46.5100*	0.1910*
6-step	0.0900	107.800	0.3590	0.0440	53.9200	0.2120	0.0490	60.6800	0.2330	0.0350*	43.0300*	0.1780*
7-step	0.0990	116.5000	0.3770	0.0430	51.6700	0.2070	0.0480	57.6700	0.2240	0.0340*	40.7200*	0.1690*
8-step	0.1230	153.000	0.4330	0.0430	53.9700	0.2130	0.0460	57.2000	0.2220	0.0350*	43.1000*	0.1770*

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

The reduced sample univariate model that employs seasonal Box-Jenkins ARIMA technique's, see column B, has the lowest RMSE and U-statistic over the 1 and 3-step ahead horizons. This model also has the lowest MAPE for the 1-step ahead horizon. The reduced sample model that employs Eviews 9's automatic non-seasonal selection procedure, see column D, has the lowest RMSE and U-statistic over all forecasting horizons except for 1 and 3 steps ahead and the lowest MAPE values for all forecasting horizons except for 1-step ahead. Hence, the reduced sample model that employs

[164] The Eviews 9's automatically selected non-seasonal ARIMA specification is used to model and forecast the seasonally adjusted (annual) inflation data for 2013 and 2014. The four seasonal indices from 2012 are then used to reintroduce seasonality into these forecasts yielding predictions for the original (unadjusted).

Eviews 9's automatic non-seasonal selection procedure generally has the superior forecasting performance although the reduced sample seasonal method that employs Box-Jenkins ARIMA procedures produces the best forecasts over some of the shorter horizons.

We note that the ARIMAX forecasts produced using the full sample that explicitly model structural breaks (Table. 5.5.9 column A) and reduced sample ARIMA model that employs Eviews 9's automatic seasonal ARIMA selection routine (Table. 5.5.9 column C) were never favoured. These results imply the following for the univariate modelling on Nigerian data. First, the potential benefits of using a full sample and explicitly modelling the structural breaks were outweighed by the benefits of being able to avoid modelling structural breaks at the cost of a reduced sample for estimation. Given the extra time and modeller expertise required to model such breaks suggests that using reduced samples to avoid structural breaks is the preferred strategy. Second, the quick automatic ARIMA selection procedures generally (though not always) produce superior forecasts compared to using more time-consuming Box-Jenkins ARIMA modelling techniques. Third, the benefit of seasonally adjusting the data and re-seasonalising the forecasts generally outperforms the method of explicitly modelling seasonality. Finally, note that the MAPE of the favoured ARIMA models is always over 19 percentage points suggesting a relatively poor forecasting performance for this class of models for Nigerian inflation.

5.5.10 Ecuador Forecast performance and evaluation

In this section, we produce forecasts for the only valid model for Ecuador, being the full sample ARIMAX specification that includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 and summarised in Table 5.1.6 for Ecuador[165]. To produce out-of-sample ex post forecasts on a rolling basis, we first estimate the models over the period 1987q1 to 2012q4 and generate forecasts over the period 2013q1 to 2014q4. Second, the models are re-estimated over the period 1987q1 – 2013q1 and forecasts are produced over the period 2013q2 to 2014q4 and so on. The last estimation sample period is 1987q1 - 2014q3 and a single 1-step ahead forecast is produced for 2014q4. These forecasts are used to compute forecast error measures for each forecast horizon. The forecast performance measures for this model are given in Table 5.5.10.

Table. 5.5.10: Forecast performance of Univariate model for Ecuador

	Full sample ARIMAX model with modelling breaks		
	RMSE	MAPE	U
1-step	0.0070	19.0500	0.1140
2-step	0.0090	23.4900	0.1570
3-step	0.0130	37.3100	0.2240
4-step	0.0160	42.9100	0.2830
5-step	0.0150	37.0800	0.2450
6-step	0.0150	25.7600	0.2360
7-step	0.0080	15.4500	0.1190
8-step	0.0110	28.5700	0.1670

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

There is only one valid model it is the favoured univariate specification for Ecuador. However, we note that the MAPE of the favoured model is between 15.4500 and 42.9100 percentage points suggesting a poor forecasting accuracy, in a relative sense, for the ARIMAX model for Ecuador.

[165] We did not estimate a reduced sample model for Ecuador because the period after the structural breaks are less than 39 observations.

5.5.11 Kuwait Forecast performance and evaluation

In this section, we produce forecasts for the only valid model for Kuwait, being the full sample ARIMAX specification that includes deterministic dummy variables to model structural breaks and seasonality as discussed in section 5.1 and summarised in Table 5.1.6 for Kuwait [166]. To produce out-of-sample ex post forecasts on a rolling basis, we first estimate the models over the period 1977q1 to 2012q4 and generate forecasts over the period 2013q1 to 2014q4. Second, the models are re- estimated over the period 1977q1 – 2013q1 and forecasts are produced over the period 2013q2 to 2014q4 and so on. The last estimation sample period is 1977q1 - 2014q3 and a single 1-step ahead forecast is produced for 2014q4. These forecasts are used to compute forecast error measures for each forecast horizon. The forecast performance measures for this model are given in Table 5.5.11.

Table. 5.5.11: Forecast performance of Univariate model for Kuwait

	Full sample ARIMAX model with modelling breaks		
	RMSE	**MAPE**	**U**
1-step	0.0060	22.1000	0.1040
2-step	0.0090	29.8800	0.1430
3-step	0.0130	35.3200	0.1800
4-step	0.0120	37.3600	0.1630
5-step	0.0130	38.5900	0.1650
6-step	0.0110	30.7000	0.1380
7-step	0.0080	19.1200	0.0940
8-step	0.0040	11.2100	0.0530

An asterisk indicates the model with the lowest value for any particular measure of forecasting performance for each forecasting horizon.

There is only one valid model it is the favoured univariate specification for Kuwait. However, we note that the MAPE of the favoured model is between 11.2100 and 37.7000 percentage points suggesting a poor forecasting accuracy, in a relative sense, for the univariate ARIMAX model for Kuwait.

[166] We did not estimate a reduced sample model for Kuwait because the periods after the structural breaks are less than 39 observations.

Appendix. Section 6.1

Table 6.4.1 Data availability for Russia

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1992q1 – 2014q4		IMF/IFS
Broad money in local currency unit	1994q4 -2014q4	1993 – 2014	World Bank and IMF/IFS
Money and quasi money (M2) (current LCU)		1993 - 2014	World Bank
Industrial Production	1995q1 2014q4		IMF/IFS/OECD
Lending Interest rate	1994q1 – 2014q4	1995 -2014	IMF/IFS/ world bank
Money market rate	1994q3 - 2014q4		IMF/IFS
Real interest rate		1995 - 2014	World Bank
Unemployment rate (%)	1994q1 – 2014q4		IMF/IFS
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
GDP (current) US $		1990 2014	World Bank
Real GDP	1992 2011		Penn World Table
GDP DEFLATOR (2000=100) index	1995q1- 2014q4		IMF/IFS
Real effective Exchange rate (CPI BASED)	1994q1 2014q4		IMF/IFS

The above table summarises the availability of data for Russia. For Russia we would ideally like to collect data over the period 2000q2 – 2014q4. We can implement a VAR analysis using data over this period involving the following 5 variables: consumer price index, nominal broad money supply, the money market interest rate, the real effective exchange rate and unemployment. Quarterly data on industrial production is also available over this sample period which means that the output gap can also be constructed.

Table 6.4.2. Data availability for India

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1958q1 -2014q4		IMF/IFS
Industrial Production	1960q1 2014q4		IMF/IFS/OECD
GDP deflator (%)	1998q1-2014q4		IMF/IFS
GDP (current) US $		1961 2014	World Bank
Real GDP		1993 2011	Penn World Table
Lending interest rate	1978q1 -2014q4	1975 -2012	IMF/IFS
Money market rate	1957q1 2014q4		IMF/IFS
Real interest rate		1975 -2014	World Bank
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
Broad money in current local currency)		1961 – 2014	World Bank/ IMF/IFS
Money and quasi money (M2) (current LCU)		1961 - 2014	World Bank

The above table summarises the availability of data for India. For India we would ideally like to collect data over the period 1957q1 – 2014Q4. However, for many important series data is only available from 1960q1 – 2014q4. We can implement a VAR analysis using data over this period involving the following 2 variables: consumer price index and the money market interest rate. Quarterly data on industrial production is also available over this sample period which means that the output gap can also be constructed. Annual data on the on the broad money supply and the M2 measure of money are also available over this period. We will use the EViews frequency conversion tool to generate quarterly versions of these series to consider in our VAR analysis. Annual data on unemployment is available on the reduced sample period of 1991 to 2014. We will use the EViews frequency conversion tool to generate quarterly versions of these series to consider in our VAR analysis, if on a reduced sample period.

Table 6.4.3. Data availability for China

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1982q1 – 2014q4		IMF/IFS
Broad money (current local currency		1970 – 2014	World Bank
Money and quasi money (M2) (current LCU)		1977- 2014	World bank
Foreign Exchange rate	1993q4 -2014q4		IMF/IFS
GDP (current) US $		1961 2014	World Bank
Real GDP		1992 – 2014	OCED
Industrial Production			
Treasury bill rate	1994q1-2014q4		IMF/IFS
Lending interest rate	1980q1 2014q4		IMF/IFS
Real interest rate		1980 2014	World Bank
Unemployment rate	2002q1 2014q4		IMF/IFS
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2014	World Bank
Real effective Exchange rate (CPI BASED)	1980q1 2014q4		IMF/IFS
GDP DEFLATOR (2000=100) index	2000q1 2013q4	1960 2014	IMF/IFS/World Bank

The above table summarises the availability of data for China. For China we would ideally like to collect data over the period 1989q1 – 2014Q4. We can implement a VAR analysis using data over this period involving the following 3 variables: the consumer price index, the lending interest rate and the real effective exchange rate. Annual data on the rate of unemployment, money plus quasi money (M2), the broad money supply and the world oil price are available over this period. Annual data on nominal GDP and GDP price deflator are also available over this period and can be used to construct a measure of output gap. We will use the EViews frequency conversion tool to generate quarterly versions of these series to consider in our VAR analysis.

Table 6.4.4 Data availability for South Africa

Variables	Quarterly	Observations	Source
Consumer Price Index (CPI %)	1958q1- 2014q4		IMF/ IFS
Broad Money Liabilities (Millions of national currency)	2001q3 2014q4		IMF/IFS
Broad Money Liabilities seasonal adjusted (Millions of national currency)	2001q1 2014q4		IMF/IFS
Money Supply (M1) in Million national currency	1965q1 2014q4		IMF/IFS
Money and quasi money (M2) (current LCU)		1965 2014	World Bank
GDP (current) US $		1961 2014	
Real GDP		1990 2011	Penny world Table
Treasury bill rate (%)	1957q1 – 2014q4		IMF/IFS
Real interest rate		1961 2014	World Bank
Unemployment rate%	2000q1 2014q4		IMF/IFS
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
Real effective Exchange rate (CPI BASED)	1979q1 2014q4		IMF/IFS
Lending rate	1957q1 2014q4		IMF.IFS
Manufacturer Industrial production	1980q1 2014q4		OCED
Discount rate end of period (% per annum)	1957q1 2014q4		IMF/IFS
GDP deflator		1960 2014	World Bank

The above table summarises the availability of data for South Africa. For South Africa we would ideally like to collect data over the period 1992q2 – 2014q4. We can implement a VAR analysis using data over this period involving the following 4 variables: consumer price index, the treasury bill interest rate, the money Supply (M1) and the real effective exchange rate. Industrial production data is available to construct output gap to generate quarterly versions of these series to consider in our VAR analysis.

Table 6.4.5 Data availability for Nigeria

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1960q1 2014q4		IMF/IFS
Industrial production	1970q1 2008q4		IMF/IFS
Interest rate (lending rate)	1971q1 2014q4		IMF/IFS
Real interest rate		1970 2014	World Bank
Broad Money Liabilities (Millions of national currency)	2001q4 2014q4		IMF/IFS
Broad Money Liabilities seasonal adjusted (Millions of national currency)	2001q1 2014q4		IMF/IFS
Money Supply (M1) in Million national currency	2000q1 2014q4		IMF/IFS
Money and quasi money (M2) (current LCU)		1960 2014	World Bank
GDP (current) US $		1961- 2014	World Bank
Real GDP		1992 2011	Penn World Table
Foreign Exchange rate	1961q1 – 2014q4		IMF/IFS
Treasury bill rates	1991q1 – 2014q4		IMF/IFS
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
Real effective Exchange rate (CPI BASED)	1980q1 2014q4		IMF/IFS
GDP deflator		1960 2014	World Bank

The above table summarises the availability of data for Nigeria. For Nigeria, we would ideally like to collect data over the period 1995q4 – 2014q4. We can implement a VAR analysis using data over this period involving the following 3 variables: the consumer price index, the real effective exchange rate and the treasury bill interest rate. Annual data on money plus quasi money (M2) and the rate of unemployment are also available over this period. We will use the EViews frequency conversion tool to generate quarterly versions of these series to consider in our VAR analysis.

Table 6.4.6. Data availability for Algeria

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1975q1 – 2014q4		IMF/IFS
Broad money in local currency		1965 – 2014	World Bank
Money and quasi money (M2) (current LCU)		1964 2014	World Bank
GDP (current) US $		1961 – 2014	World Bank
Real GDP		1994 2011	Penn World Table
Industrial Production	1999q1 2014q4		IMF/IFS
Foreign Exchange rate	1957q1 -2014q4		IMF/ IFS
Treasure Bill	1998q1 2014q4		IMF/IFS
Lending Interest rate	1994q1 – 2014q4		IMF/IFS
GDP deflator		1960 – 2014	World Bank
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
Real effective Exchange rate (CPI BASED)	1980q1 2014q4		IMF/IFS

The above table summarises the availability of data for Algeria. For Algeria we would ideally like to collect data over the period 1996q2 – 2014q4. We can implement a VAR analysis using data over this period involving the following 3 variables: the consumer price index, the real effective exchange rate and the lending interest rate. Annual data on money plus quasi money (M2) is also available over this period. Annual data on real GDP is also available over this period and can be used to construct a measure of output gap. We will use the EViews frequency conversion tool to generate quarterly versions of these series to consider in our VAR analysis.

Table 6.4.7 Data availability for Saudi Arabia

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1971q1 – 2014q4		IMF/IFS
Broad money in local currency		1960 – 2014	IMF/IFS
Money and quasi money (M2) (current LCU)		1960 2014	World Bank
Industrial Production	1962q1 2014q4		IMF/IFS
GDP (Current US $)		1969 – 2014	World Bank
Real GDP		1992 2011	Penn World Table
Foreign Exchange rate	1962q1 – 2014q4		IMF/IFS
GDP deflator base year		1968 -2013	World Bank
Treasury bill rates	2009q1 – 2014q4		IMF/IFS
Discount rate end of period (% per annum)	1999q2 2014q4		IMF/IFS
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
Real effective Exchange rate (CPI BASED)	1980q1 2014q4		IMF/IFS
GDP deflator		1968 2014	World Bank

The above table summarises the availability of data for Saudi Arabia. For Saudi Arabia we would ideally like to collect data over the period 1976q3 – 2014Q4. However, for many important series data is only available from 1980q1 – 2014q4. We can implement a VAR analysis using data over this period involving the following 2 variables: the consumer price index and the real effective exchange rate. Quarterly data on industrial production is available over this sample period and can be used to construct a measure of output gap. Annual data on money plus quasi money (M2) is available over this period. We will use the EViews frequency conversion tool to generate quarterly versions of these series to consider in our VAR analysis.

Table 6.4.8 Data availability for Angola

Variables	Quarterly	Annually	Source
Consumer Price Index (CPI)	1992q4 – 2014q4		IMF/ IFS
Broad money in local currency		1960 2014	World Bank
GDP (Current US $)		1986- 2014	World Bank
Broad Money Liabilities (Millions of national currency)	2001q4 2014q4		IMF/IFS
Broad Money Liabilities seasonal adjusted (Millions of national currency)	2001q1 2014q4		IMF/IFS
Money Supply (M1) in Million national currency	1999q4 2014q4		IMF/IFS
Money and quasi money (M2) (current LCU)		1995 2014	World Bank
Lending Interest rate	1995q1 2014q4	1995- 2012	IMF/IFS
Treasury Bill rate	2001Q1 2014Q4		IMF/1FS
Real interest rate		1995- 2014	World bank
Unemployment (% of total labour force) (modelled ILO estimate)		1991 -2013	World Bank
GDP deflator		1975 2014	World Bank

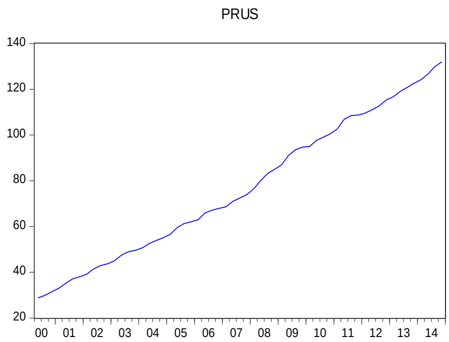
The above table summarises the availability of data for Angola. For Angola we would ideally like to collect data over the period 1997q4 – 2014Q4. However, for many important series data is only available from 1999q4 – 2014q4. We can implement a VAR analysis using data over this period involving the following 3 variables: the consumer price index, the money supply (M1) and the real lending interest rate. The annual rate real GDP is available in this period to construct a measure of output gap. will use the EViews frequency conversion tool to generate a quarterly version of this series to consider in our VAR analysis.

Appendix. Section 6.2

6.6.1 The graphical features of selected macroeconomic variables for Russia

Following the sample identified in previous section (Table 6.4.1) for Russia (2000q2-2014q4). We analyse the stationarity and seasonality characteristics of the selected macroeconomic variables to determine whether the data needs to be seasonally adjusted for our VAR analysis. The graphs below depict the following indicators. The Russian consumer price (denoted PRUS), the seasonally adjusted PRUS series (PRUS_d11) and D_PRUS = PRUS - PRUS_d11, as well as the first (nonseasonal) difference of LPRUS (DLPRUS), the seasonally adjusted LPRUS series (LPRUS_d11) and D_LPRUS = LPRUS - LPRUS_d11 (where LPRUS is the log of PRUS). The seasonally adjusted series (PRUS_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PRUS and PRUS_d11 as well as DLPRUS and DLPRUS_d11.

A



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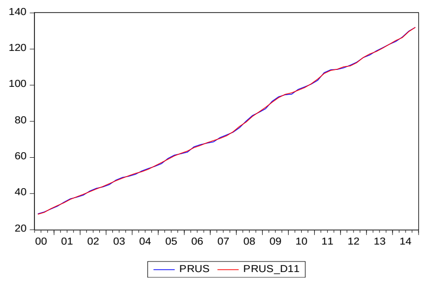
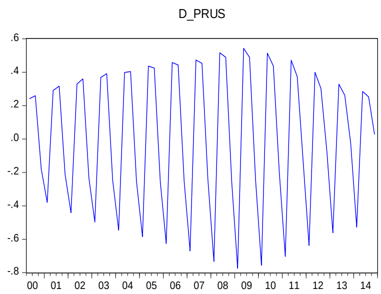


1C.

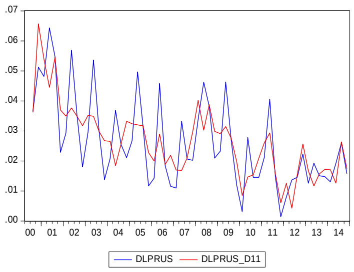


1D.

Test for equality of variance between PRUS and PRUS_D11

Method	Df	Value	Probability
F-test	(58, 58)	1.000165	0.9995
Siegel Turkey		0.005382	0.9957
Bartlett	1	3.90E-07	0.9995
Levene	(1,116)	2.08E-05	0.9964
Brown-Foresythe	(1,116)	5.55E-06	0.9981

1E.



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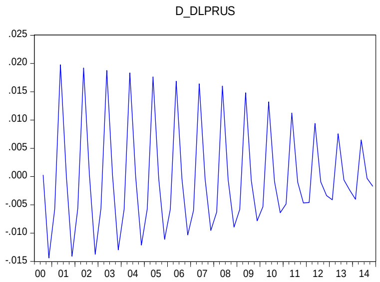


1G.

Test for equality of variance between DLPRUS and DLPRUS_D11

Method	Df	Value	Probability
F-test	(57, 57)	1.532329	0.1100
Siegel Turkey		1.631651	0.1028
Bartlett	1	2.553753	0.1100
Levene	(1,114)	3.489626	0.0643
Brown-Foresythe	(1,114)	2.074849	0.1525

1H.

Sample: 2000Q2 2014Q4
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.949	0.949	55.933	0.000
		2	0.898	-0.031	106.89	0.000
		3	0.849	-0.009	153.22	0.000
		4	0.800	-0.020	195.14	0.000
		5	0.752	-0.025	232.83	0.000
		6	0.704	-0.021	266.48	0.000
		7	0.656	-0.030	296.27	0.000
		8	0.608	-0.026	322.37	0.000
		9	0.561	-0.027	345.01	0.000
		10	0.514	-0.019	364.45	0.000
		11	0.468	-0.032	380.87	0.000
		12	0.422	-0.031	394.48	0.000
		13	0.375	-0.032	405.48	0.000
		14	0.327	-0.047	414.05	0.000
		15	0.279	-0.038	420.44	0.000
		16	0.234	-0.010	425.02	0.000
		17	0.190	-0.026	428.11	0.000
		18	0.146	-0.034	429.98	0.000
		19	0.102	-0.035	430.92	0.000
		20	0.060	-0.022	431.26	0.000

1J.

Sample: 2000Q2 2014Q4
Included observations: 58

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.441	0.441	11.895	0.001
		2	0.039	-0.193	11.992	0.002
		3	0.262	0.421	16.329	0.001
		4	0.555	0.355	36.183	0.000
		5	0.126	-0.401	37.223	0.000
		6	-0.102	0.118	37.917	0.000
		7	0.162	0.068	39.716	0.000
		8	0.432	0.170	52.692	0.000
		9	0.084	-0.092	53.189	0.000
		10	-0.150	-0.113	54.818	0.000
		11	0.042	-0.038	54.950	0.000
		12	0.361	0.259	64.795	0.000
		13	0.051	-0.171	64.996	0.000
		14	-0.195	-0.022	67.997	0.000
		15	-0.015	-0.039	68.016	0.000
		16	0.294	0.063	75.181	0.000
		17	0.001	-0.036	75.181	0.000
		18	-0.208	0.039	78.945	0.000
		19	-0.027	-0.074	79.008	0.000
		20	0.173	-0.158	81.740	0.000

As shown in Fig. 1A, the graph of the consumer price for Russia (PRUS) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing.

The time paths of PRUS and PRUS_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between PRUS and PRUS_d11 (denoted D_PRUS) is plotted in Figure 1C. The difference has revealed a cyclical fluctuation that ranges between -0.77 and 0.54. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PRUS and PRUS_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PRUS and PRUS_d11. Hence, we find that seasonality is not significant in the level of the price. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLPRUS_d11) and unadjusted (DLPRUS) data.

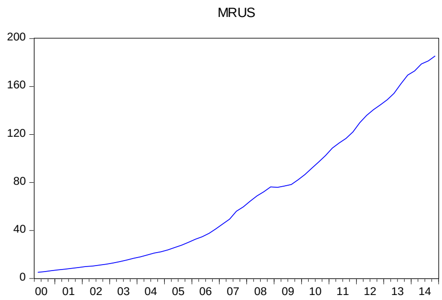
The time paths of DLPRUS and DLPRUS_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after the first differencing. The variation in DLPRUS is greater than that of LPRUS_d11 suggesting seasonality in DLPRUS while DLPRUS is smoother. This suggests that DLPRUS_d11 exhibits reduced seasonality as expected. The difference between DLPRUS and DLPRUS_d11 (denoted D_DLPRUS) is plotted in Figure 1F. The difference reveals fluctuation around a relatively constant mean that ranges between -0.0141 and 0.0198. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPRUS and DLPRUS_d11 that are reported in table 1G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLPRUS and DLPRUS_d11. Hence, we find that seasonality is not significant in the difference of the log of the price data for Russia.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of PRUS and DLPRUS in figure 1H and 1I. Shown in Fig. 1H, all autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggest nonstationary and not necessarily seasonality. The ACF for DLPRUS has significant ACs at seasonal lags 4, 8, 12 and 16 (see fig. 1I). This implies that seasonality is significant in the price data and contradicts the results of the variance equality tests. Given this result and because we believe that price data are likely seasonal we will use the seasonally adjusted data PRUS in our VAR analysis.

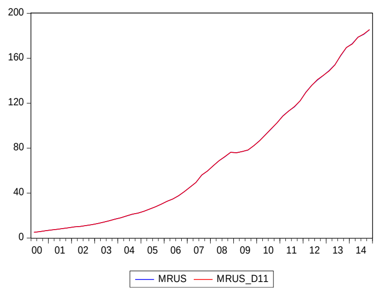
6.6.2. The seasonality features of money supply in Russia

We analyse the stationarity and seasonality characteristics of money supply variable in Russia. The graphs below depict the following indicators. The Russian money supply (denoted MRUS), the seasonally adjusted MRUS series (MRUS_d11) and D_MRUS = MRUS - MRUS_d11, as well as the first (nonseasonal) difference of LMRUS (DLMRUS), the seasonally adjusted LMRUS series (LMRUS_d11) and D_LMRUS = LMRUS - LMRUS_d11 (where LMRUS Is the log of MRUS). The seasonally adjusted series (MRUS_d11) is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for MRUS and MRUS_d11 as well as DLMRUS and DLMRUS_d11.

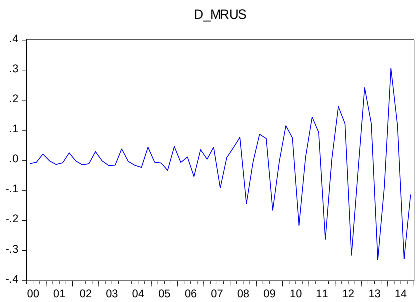
2A.



2B.



2C.

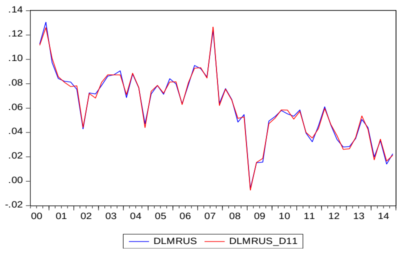


2D

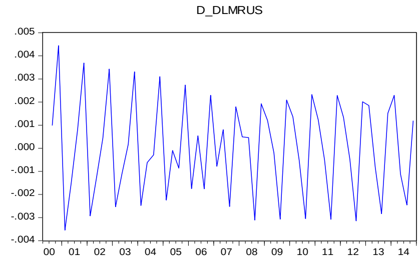
Test for equality of variance between MRUS and MRUS_D11

Method	Df	Value	Probability
F-test	(58, 58)	1.000287	0.9991
Siegel Turkey		0.086116	0.9314
Bartlett	1	1.19E-06	0.9991
Levene	(1,116)	6.78E-07	0.9993
Brown-Foresythe	(1,116)	4.15E-07	0.995

2E.



2F.



2G.

Test for equality of variance between DLMRUS and DLMRUS_D11

Method	Df	Value	Probability
F-test	(57, 57)	1.006395	0.9809
Siegel Turkey		0.002761	0.9978
Bartlett	1	0.000574	0.9809
Levene	(1,114)	5.25E-05	0.9942
Brown-Foresythe	(1,114)	6.92E-05	0.9934

2H.

Sample: 2000Q2 2014Q4
Included observations: 59

	AC	PAC	Q-Stat	Prob
1	0.950	0.950	56.041	0.000
2	0.899	-0.038	107.12	0.000
3	0.847	-0.048	153.17	0.000
4	0.794	-0.026	194.41	0.000
5	0.740	-0.042	230.89	0.000
6	0.687	-0.017	262.96	0.000
7	0.637	-0.011	291.01	0.000
8	0.586	-0.028	315.27	0.000
9	0.536	-0.036	335.93	0.000
10	0.485	-0.036	353.19	0.000
11	0.434	-0.032	367.33	0.000
12	0.385	-0.021	378.67	0.000
13	0.338	-0.010	387.61	0.000
14	0.292	-0.024	394.44	0.000
15	0.247	-0.035	399.43	0.000
16	0.202	-0.031	402.84	0.000
17	0.159	-0.016	405.01	0.000
18	0.118	-0.020	406.23	0.000
19	0.078	-0.022	406.78	0.000
20	0.041	-0.020	406.93	0.000

2I.

Sample: 2000Q2 2014Q4
Included observations: 58

	AC	PAC	Q-Stat	Prob
1	0.716	0.716	31.338	0.000
2	0.568	0.113	51.393	0.000
3	0.453	0.023	64.376	0.000
4	0.323	-0.075	71.090	0.000
5	0.286	0.099	76.458	0.000
6	0.205	-0.062	79.284	0.000
7	0.209	0.118	82.278	0.000
8	0.165	-0.063	84.162	0.000
9	0.220	0.204	87.601	0.000
10	0.227	-0.027	91.350	0.000
11	0.207	0.021	94.530	0.000
12	0.239	0.049	98.856	0.000
13	0.236	0.074	103.18	0.000
14	0.200	-0.102	106.35	0.000
15	0.191	0.081	109.31	0.000
16	0.121	-0.152	110.52	0.000
17	0.118	0.134	111.71	0.000
18	0.122	-0.026	113.01	0.000
19	0.085	-0.019	113.66	0.000
20	0.107	0.027	114.71	0.000

As shown in Fig. 2A, the graph of money supply in Russia (MRUS) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing the transformations. Although seasonality may occur in money supply it is not visible in the plot because of the dominant trend.

Hence, we plot the graph of MRUS and MRUS_d11. The time paths of MRUS and MRUS_d11 follow each other closely and it is difficult to discern whether the difference between them reflects seasonality (see Figure 2B). Therefore, the differences between MRUS and MRUS_d11 (denoted D_MRUS) is plotted in Figure 2C. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.33 and 0.31 and substantially increase over time. The variance equality tests between MRUS and MRUS_d11 are reported in table 2D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of MRUS and MRUS_d11. Hence. we find that seasonality is not significant in the level of the money supply data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLMRUS_d11) and unadjusted (DLMRUS) data.

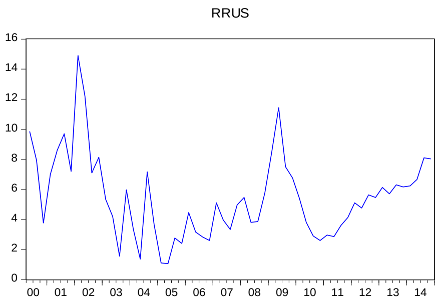
The time paths of DLMRUS and DLMRUS_d11 (see Figure 2E) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. The trend has been reduced and the series broadly fluctuates around a slight downward trend. Therefore, the difference between DLMRUS and DLMRUS_d11 (denoted D_DLMRUS) is plotted in Figure 2F. The difference has reveals a regular cyclical fluctuation that suggests time- varying seasonality. To ascertain whether this seasonality is significant we refer to variety tests for the equality of variance between DLMRUS and DLMRUS_d11 that are reported in table 2G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLMRUS and DLMRUS_d11. Hence, we find that seasonality is not significant in the difference of the log of the money supply for Russia.

As a check, we plot the autocorrelation functions (ACFs) of MRUS and DLMRUS in figure 2H and 2I. Shown in Figure 2H is the ACF for MRUS. The first 15 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not seasonality. The ACF for DLMRUS (see fig. 2I) has significant ACs for the first five lags including the first seasonal lag (lag 4) and all other ACs at seasonal lags are insignificant. This implies that seasonality is not significant in the money supply data for Russia and confirms the results of the variance equality tests. Hence, we use the unadjusted data MRUS in our VAR analysis.

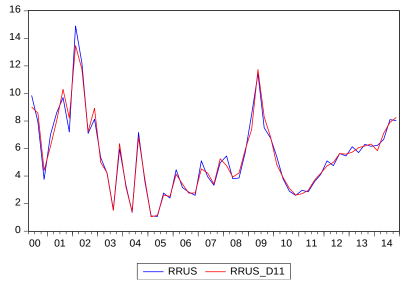
6.6.3. The seasonality features of the interest rate in Russia

We analyse the stationarity and seasonality characteristics of the interest rate variables in Russia. The graphs below depict the following indicators. The Russian interest rate (denoted RRUS), the seasonally adjusted RRUS series (RRUS_d11) and D_RRUS = RRUS - RRUS_d11, as well as the first (nonseasonal) difference of RRUS (DRRUS). The seasonally adjusted series (RRUS_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for RRUS and RRUS_d11 as well as DRRUS and DRRUS_d11.

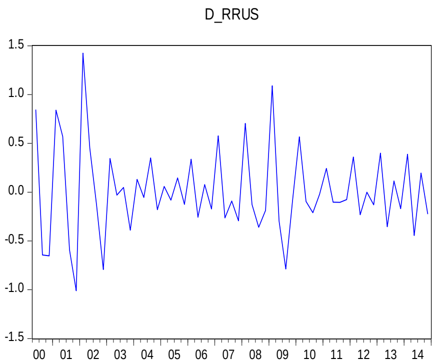
3A.



3B



3C.

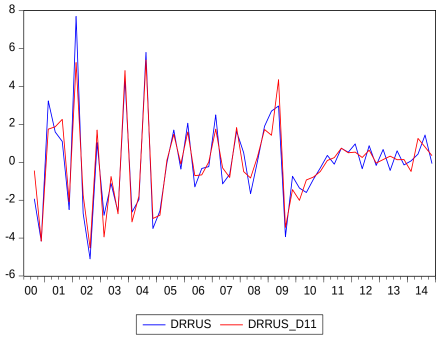


3D.

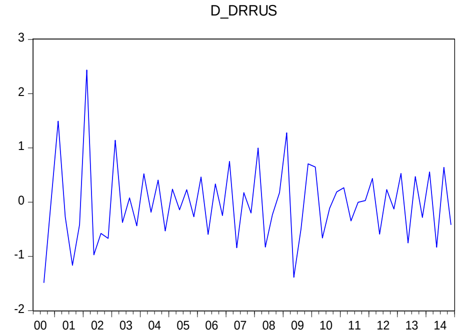
Equality of variances test between RRUS and RRUS_D11

Method	df	Value	Probability
F-test	(58, 58)	1.061942	0.8198
Siegel-Tukey		0.096882	0.9228
Bartlett	1	0.051917	0.8198
Levene	(1, 116)	0.000525	0.9818
Brown-Forsythe	(1, 116)	0.010525	0.9182

3E.



3F.



3G.

Equality variances test between DRRUS and DRRUS_D11

Method	df	Value	Probability
F-test	(58, 57)	1.190405	0.5127
Siegel-Tukey		0.400320	0.6889
Bartlett	1	0.428586	0.5127
Levene	(1, 116)	0.261044	0.6104
Brown-Forsythe	(1, 116)	0.261303	0.6102

3H.

Sample: 2000Q2 2014Q4
Included observations: 59

	AC	PAC	Q-Stat	Prob
1	0.628	0.628	24.500	0.000
2	0.430	0.058	36.170	0.000
3	0.409	0.195	46.906	0.000
4	0.259	-0.131	51.312	0.000
5	0.059	-0.187	51.542	0.000
6	0.034	0.040	51.620	0.000
7	0.123	0.202	52.662	0.000
8	-0.074	-0.288	53.046	0.000
9	-0.078	0.110	53.481	0.000
10	-0.054	-0.129	53.698	0.000
11	-0.196	-0.177	56.573	0.000
12	-0.264	0.002	61.909	0.000
13	-0.188	0.062	64.661	0.000
14	-0.201	-0.147	67.886	0.000
15	-0.288	0.008	74.692	0.000
16	-0.228	-0.104	79.048	0.000
17	-0.151	0.042	80.995	0.000
18	-0.143	0.113	82.783	0.000
19	-0.101	-0.018	83.694	0.000
20	-0.062	-0.147	84.046	0.000

3I.

Sample: 2000Q2 2014Q4
Included observations: 58

	AC	PAC	Q-Stat	Prob
1	-0.226	-0.226	3.1081	0.078
2	-0.186	-0.250	5.2573	0.072
3	0.144	0.039	6.5623	0.087
4	0.052	0.063	6.7389	0.150
5	-0.274	-0.229	11.673	0.040
6	-0.125	-0.284	12.724	0.048
7	0.301	0.117	18.897	0.009
8	-0.237	-0.189	22.806	0.004
9	0.032	0.046	22.879	0.006
10	0.233	0.130	26.809	0.003
11	-0.069	-0.062	27.166	0.004
12	-0.187	-0.133	29.802	0.003
13	0.174	0.085	32.140	0.002
14	0.051	-0.019	32.345	0.004
15	-0.179	0.055	34.936	0.003
16	0.007	-0.047	34.940	0.004
17	0.014	-0.205	34.957	0.006
18	-0.007	0.027	34.961	0.010
19	0.029	0.133	35.035	0.014
20	0.024	-0.091	35.087	0.020

As shown in Fig. 3A, the interest rate series (RRUS) has a relatively constant mean. Seasonality and the business cycle are not visible in Russia interest rate plot.

The time paths of RRUS and RRUS_d11 (see Figure 3B) follow each other closely with the largest difference between the two occurring in 2002q1 when RRUS_d11 is 13.50 and RRUS is 14.80. This suggests that RRUS_d11 is smoother than RRUS and RRUS_d11 exhibits reduced seasonality as expected.

Therefore, the differences between RRUS and RRUS_d11 (denoted D_RRUS) is plotted in Figure 3C. The difference has revealed a regular cyclical fluctuation that suggests time-varying seasonality. To ascertain whether this seasonality is significant, we refer to a variety of tests for the equality of variance between RRUS and RRUS_d11 that are reported in table 3D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RRUS and RRUS_d11. Hence, we find that seasonality is not significant in RRUS. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DRRUS_d11) and unadjusted (DRRUS) data.

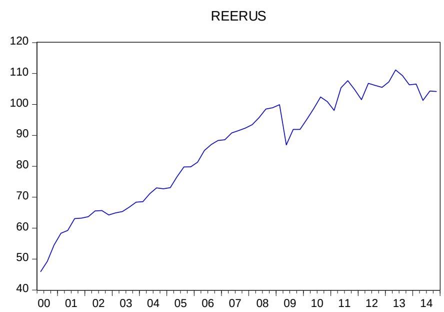
The time paths of DRRUS and DRRUS_d11 (see Figure 3E) follow each other closely. DRRUS_d11 is slightly smoother than the DRRUS and variation in DRRUS is slightly greater than that of DRRUS_d11 that suggests possible seasonality in DRRUS. Hence, the difference between DRRUS and DRRUS_d11 (denoted D_DRRUS) is plotted in Figure 3F. The difference has revealed a relatively constant mean that ranges between -1.5 and 2.4. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between DRRUS and DRRUS_d11 that are reported in table 3G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DRRUS and DRRUS_d11. Hence, we find that seasonality is not significant in the difference of interest rate for Russia.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of RRUS and DRRUS in figure 3H and 3I. Shown in Fig. 3H is the ACF for RRUS. The autocorrelation coefficients (ACs) are significant at lags 1, 2, 3 and 4 and decays exponentially suggesting that RRUS is stationary. The lack of clearly significant ACs at the seasonal lags (beyond the exponential decay in the ACF) suggests that any seasonality in the level of RRUS is not significant. The ACF for DRRUS has insignificant ACs at all the seasonal lags (see fig. 3I). This implies that seasonality is not significant in interest rates and confirms the results of the variance equality tests. Hence, we use the unadjusted data RRUS in our VAR analysis.

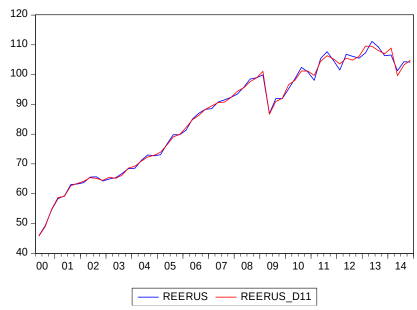
6.6.4. The seasonality features of real effective of exchange rate in Russia

We analyse the stationarity and seasonality characteristics of the real effective exchange rate variable in Russia. The graphs below depict the following indicators. The Russian real effective exchange rate (denoted REERUS), the seasonally adjusted REERUS series (REERUS_d11) and D_REERUS = REEERUS - REERUS_d11, as well as the first (nonseasonal) difference of LREERUS (DLREERUS), the seasonally adjusted LREERUS series (LREERUS_d11) and D_LREERUS = LREERUS - LREERUS_d11 (where LREERUS is the log of REERUS). The seasonally adjusted series (REERUS_d11) is obtained using the Census X13 procedure in EViews. Tables 4D and 4G report various tests of the null hypothesis of equality of variance for REERUS and REERUS_d11 as well as DLREERUS and DLREERUS_d11.

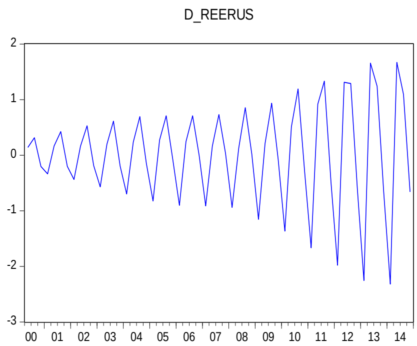
4A.



4B.



4C.

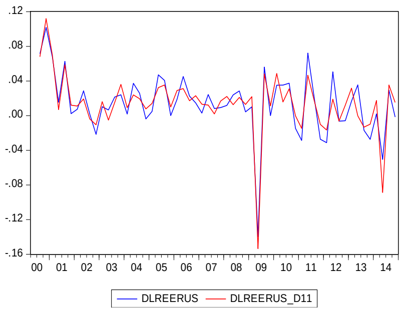


4D.

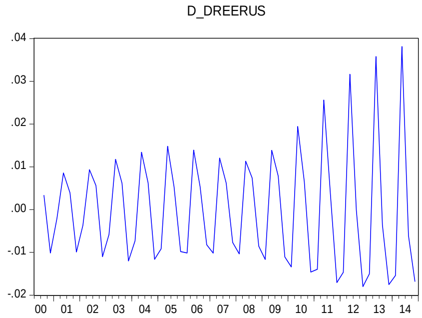
Equality of variances test between REERUS and REERUS_D11

Method	df	Value	Probability
F-test	(58, 58)	1.000484	0.9985
Siegel-Tukey		0.048440	0.9614
Bartlett	1	3.37E-06	0.9985
Levene	(1, 116)	4.36E-05	0.9947
Brown-Forsythe	(1, 116)	2.18E-05	0.9963

4E.



4F.



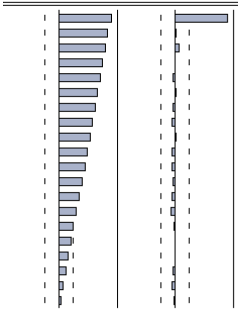
4G.

Equality of variances test between DLREERUS and DLREERUS_D11

Method	Df	Value	Probability
F-test	(57, 57)	1.016931	0.9497
Siegel-Tukey		2.205903	0.0274
Bartlett	1	0.003982	0.9497
Levene	(1, 114)	0.800453	0.3728
Brown-Forsythe	(1, 114)	0.821541	0.3666

4H.

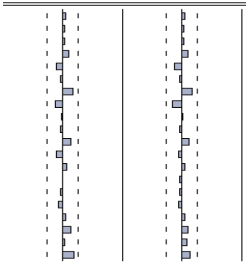
Sample: 2000Q2 2014Q4
Included observations: 59



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.933	0.933	54.068	0.000
		2	0.874	0.018	102.26	0.000
		3	0.827	0.075	146.25	0.000
		4	0.782	-0.007	186.27	0.000
		5	0.733	-0.041	222.11	0.000
		6	0.691	0.024	254.55	0.000
		7	0.646	-0.045	283.46	0.000
		8	0.597	-0.055	308.62	0.000
		9	0.555	0.023	330.81	0.000
		10	0.511	-0.050	349.99	0.000
		11	0.461	-0.060	365.95	0.000
		12	0.411	-0.045	378.90	0.000
		13	0.361	-0.051	389.08	0.000
		14	0.305	-0.074	396.54	0.000
		15	0.253	-0.022	401.78	0.000
		16	0.209	0.008	405.42	0.000
		17	0.167	-0.000	407.81	0.000
		18	0.124	-0.032	409.17	0.000
		19	0.079	-0.062	409.73	0.000
		20	0.035	-0.024	409.84	0.000

4I.

Sample: 2000Q2 2014Q4
Included observations: 58



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.042	0.042	0.1070	0.744
		2	0.029	0.028	0.1607	0.923
		3	0.035	0.033	0.2379	0.971
		4	0.114	0.111	1.0761	0.898
		5	-0.109	-0.121	1.8510	0.869
		6	-0.039	-0.037	1.9516	0.924
		7	0.173	0.181	3.9915	0.781
		8	-0.137	-0.168	5.2942	0.726
		9	-0.014	0.022	5.3075	0.807
		10	-0.044	-0.047	5.4473	0.859
		11	0.149	0.119	7.0905	0.792
		12	-0.108	-0.056	7.9674	0.788
		13	0.075	0.064	8.4003	0.817
		14	0.004	-0.042	8.4015	0.867
		15	-0.047	-0.036	8.5829	0.898
		16	-0.074	-0.053	9.0320	0.912
		17	0.048	0.063	9.2244	0.933
		18	0.146	0.106	11.086	0.891
		19	0.028	0.094	11.154	0.919
		20	0.198	0.150	14.745	0.791

From Figure 4A, the graph of real effective exchange rate for Russia (REERUS) exhibits an upward trend. Seasonality is not visible in this graph although it may be revealed once the trend is removed through differencing.

The time paths of REERUS and REERUS_d11 (see Figure 4B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between REERUS and REERUS_d11 (denoted D_REERUS) is plotted in Figure 4C. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -2.3 and 1.7 that substantially increases over time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between REERUS and REERUS_d11 that are reported in table 4D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REERUS and REERUS_d11. Hence, we find that seasonality is not significant in the level of the data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLREERUS_d11) and unadjusted (DLREERUS) data.

The time paths of DLREERUS and DLREERUS_d11 (see Figure 4E) follow each other closely with the largest difference between the two occurring in 2012q1 when (REERUS_d11) is -0.017 and (REERUS) is -0.031. This suggests that REERUS_d11 is slightly smoother than REERUS and variation DLREERUS_d11 is less than the variation of DREERUS.

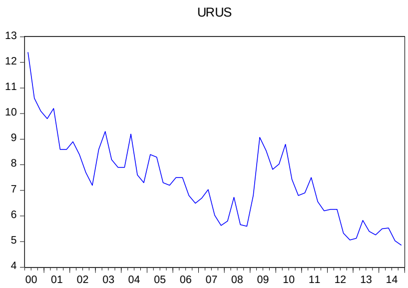
We plot the differences between DLREERUS and DLREERUS_d11 (denoted D_DLREERUS) in Figure 4F. The difference has revealed a regular fluctuation around a relatively constant mean that increases over time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREERUS and DLREERUS_d11 that are reported in table 4G. The p-values of all of our tests is greater than 0.05 except Siegel Tukey test that less than 0.05; therefore, we cannot reject the null hypothesis of equal variance for all the tests except the Siegel Tukey test. Hence, the results regarding equality of variance are ambiguous, if generally suggest equality and a lack of seasonality.

To explore the issue further we plot the ACF of REERUS and DLREERUS in figure 4H and 4I respectively. Shown in Fig.4H is the ACF for REERUS. The first 16 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLREERUS have insignificant ACs at all the seasonal lags. This provides evidence that seasonality is insignificant in real effective exchange rate for Russia. Hence, we use the unadjusted real effective exchange rate (REERUS) in our VAR analysis because the vast majority of the evidence suggests this.

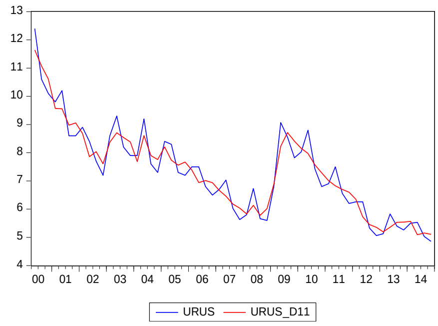
6.6.5. The seasonality features of unemployment rate in Russia

The graphs below depict the following variables. The Russian unemployment rate (denoted URUS), the seasonally adjusted URUS series (URUS_d11) and D_URUS = URUS - URUS_d11, as well as the first (nonseasonal) difference of URUS (DURUS). The seasonally adjusted series (URUS_d11) is obtained using the Census X13 procedure in EViews. Tables 5D and 5G report various tests of the null hypothesis of equality of variance for URUS and URUS_d11 as well as DURUS and DURUS_d11.

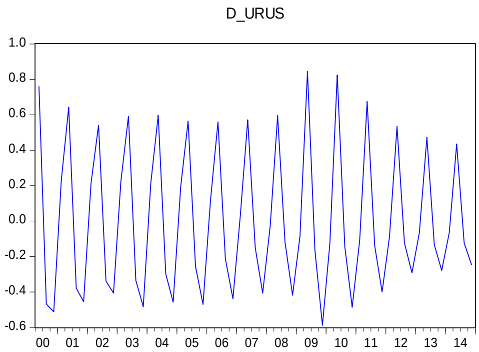
5A.



5B.



5C.

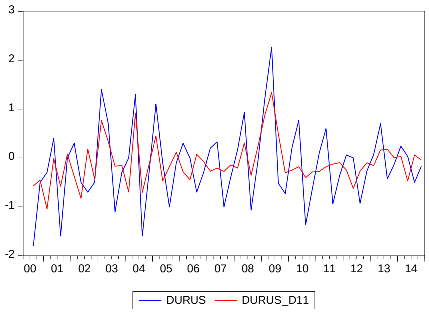


5D.

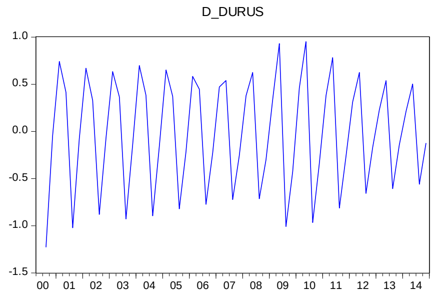
Equality of variances test between URUS and URUS_D11

Method	df	Value	Probability
F-test	(58, 58)	1.104926	0.7053
Siegel-Tukey		0.156091	0.8760
Bartlett	1	0.143065	0.7053
Levene	(1, 116)	0.06677	0.7966
Brown-Forsythe	(1, 116)	0.0626	0.8029

5E.



5F.



5G.

Equality of variances test between DURUS and DURUS_D11

Method	df	Value	Probability
F-test	(57, 57)	3.321614	0.0000
Siegel-Tukey		3.630659	0.0000
Bartlett	1	19.24045	0.0000
Levene	(1, 116)	1292584	0.0000
Brown-Forsythe	(1, 116)	1329887	0.0004

5H.

Sample: 2000Q2 2014Q4
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.772	0.772	36.965	0.000
		2	0.610	0.036	60.466	0.000
		3	0.575	0.231	81.709	0.000
		4	0.558	0.105	102.12	0.000
		5	0.374	-0.339	111.44	0.000
		6	0.252	-0.006	115.76	0.000
		7	0.259	0.128	120.40	0.000
		8	0.253	0.016	124.90	0.000
		9	0.135	-0.092	126.21	0.000
		10	0.051	-0.061	126.40	0.000
		11	0.100	0.121	127.15	0.000
		12	0.142	0.094	128.69	0.000
		13	0.037	-0.174	128.79	0.000
		14	-0.019	-0.001	128.82	0.000
		15	0.036	0.043	128.93	0.000
		16	0.114	0.164	130.02	0.000
		17	0.025	-0.125	130.08	0.000
		18	-0.010	-0.007	130.09	0.000
		19	0.061	0.056	130.43	0.000
		20	0.107	-0.008	131.48	0.000

5I.

Sample: 2000Q2 2014Q4
Included observations: 58

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.029	-0.029	0.0499	0.823
		2	-0.450	-0.451	12.637	0.002
		3	-0.056	-0.110	12.833	0.005
		4	0.622	0.520	37.773	0.000
		5	-0.039	-0.076	37.874	0.000
		6	-0.529	-0.287	56.612	0.000
		7	-0.058	-0.043	56.839	0.000
		8	0.529	0.130	76.288	0.000
		9	-0.037	-0.074	76.385	0.000
		10	-0.433	0.031	89.998	0.000
		11	-0.192	-0.312	92.733	0.000
		12	0.504	0.085	111.97	0.000
		13	-0.034	-0.091	112.07	0.000
		14	-0.374	0.001	123.12	0.000
		15	-0.150	-0.030	124.95	0.000
		16	0.499	0.114	145.57	0.000
		17	0.044	-0.064	145.73	0.000
		18	-0.320	0.096	154.63	0.000
		19	-0.116	-0.005	155.83	0.000
		20	0.426	-0.010	172.47	0.000

As shown in Fig. 5A, the graph of unemployment (URUS) follows downward trend indicating non-stationarity and a need to apply further stationarity inducing transformations. Seasonality may be expected in the unemployment series and it is visible in the unemployment plot despite the dominant downward trend; seasonality may be more clearly revealed once the trend is removed through differencing.

The time paths of URUS and URUS_d11 (see Figure 5B) follow each other closely. The variation in URUS is greater than the variation in URUS_d11 and the URUS_ d11 is smoother than the URUS. This suggests that the URUS_d11 exhibits reduced seasonality. The differences between URUS and URUS_d11 (denoted D_URUS) is plotted in Figure

5C. The difference has revealed a regular cyclical fluctuation that range between -0.059 and 0.084. Whilst this may indicate seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between URUS and URUS_d11 that are reported in table 5D. The p-value of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of URUS and URUS_d11. Hence, we find that seasonality is not significant in the level of unemployment data. However, because this result may be influenced by the trend in the data we compare the differences of the adjusted (DURUS_d11) and unadjusted (DURUS) data.

The time paths of DURUS and DURUS_d11 (see Figure 5E) follow each other closely. The downward trend has been removed and the series broadly fluctuates around a constant mean as expected after the first differencing. The variation of DURUS is greater than the variation of DURUS_ d11 suggesting seasonality in DURUS while DURUS_ d11 is smoother. This suggests that DURUS_d11 exhibits reduced seasonality as expected.

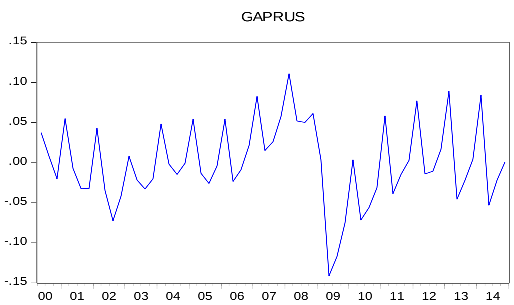
The difference between DURUS and DURUS_d11 (denoted D_DURUS) is plotted in Figure 5F. The difference has revealed cyclical fluctuations. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DURUS and DURUS_d11 that are reported in table 5G. Since the p-values of all of our tests is less than 0.05, we reject the null hypothesis and find that there is significant difference in the variances of DURUS and DURUS_d11 and hence find that seasonality is significant in the difference of the unemployment rate for Russia.

To explore this further, we plot the autocorrelation functions (ACFs) of URUS and DURUS in figure 5H and 5I. Shown in Fig. 5H is the ACF for URUS. The first 8 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not seasonality. The ACF for DURUS (see fig. 5I) has significant ACs at all seasonal lags. This implies that seasonality is significant in unemployment data and confirms the results of variance equality tests. Hence, we will use seasonally adjusted DURUS_d11 in our VAR analysis.

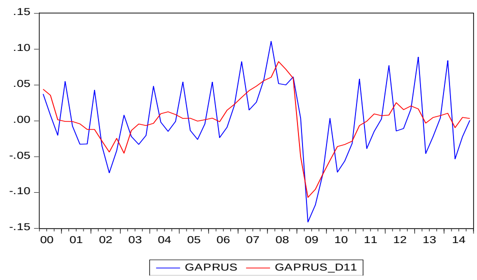
6.6.6. The seasonality features of output gap in Russia

We analyse the stationarity and seasonality characteristics of the output gap variable in Russia. The graphs below depict the following indicators. The output gap (denoted GAPRUS), the seasonally adjusted GAPRUS series (GAPRUS_d11) and D_GAPRUS = GAPRUS - GAPRUS_d11, as well as the first (nonseasonal) difference of GAPRUS (DGAPRUS). The seasonally adjusted series (GAPRUS_d11) is obtained using the Census X13 procedure in EViews. Tables 6D and 6G report various tests of the null hypothesis of equality of variance for GAPRUS and GAPRUS_d11 as well as DGAPRUS and DGAPRUS_d11.

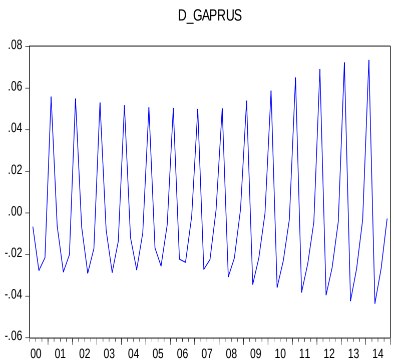
6A.



6B.



6C.

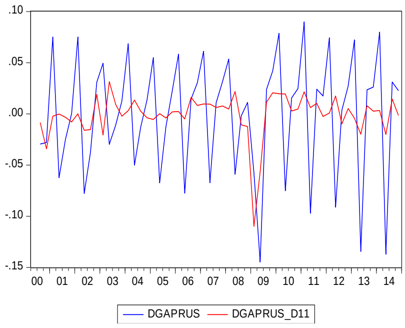


6D.

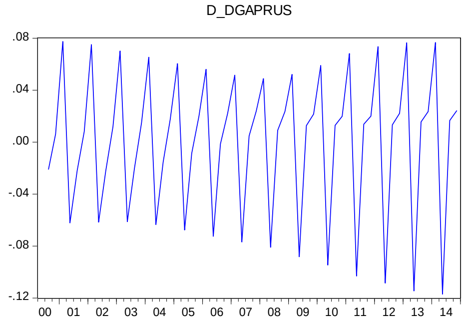
Equality of variances test between GAPRUS and GAPRUS_D11

Method	df	Value	Probability
F-test	(58, 58)	1.908671	0.0151
Siegel-Tukey		2.680368	0.0074
Bartlett	1	5.905167	0.0151
Levene	(1, 116)	6.498411	0.0121
Brown-Forsythe	(1, 116)	6.266466	0.0137

6E.



6F.

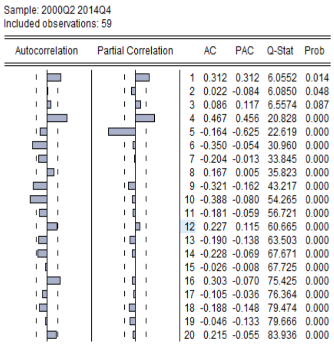


6G.

Equality of variances test between DGAPRUS and DGAPRUS_D11

Method	df	Value	Probability
F-test	(57, 57)	8.102418	0.0000
Siegel-Tukey		6.755752	0.0000
Bartlett	1	53.03630	0.0000
Levene	(1, 116)	50.24309	0.0000
Brown-Forsythe	(1, 116)	35.12867	0.0000

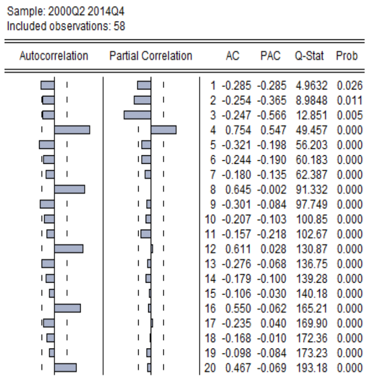
6H.



Sample: 2000Q2 2014Q4
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.312	0.312	6.0552	0.014
		2	0.022	-0.084	6.0850	0.048
		3	0.086	0.117	6.5574	0.087
		4	0.467	0.456	20.828	0.000
		5	-0.164	-0.625	22.619	0.000
		6	-0.350	-0.054	30.960	0.000
		7	-0.204	-0.013	33.845	0.000
		8	0.167	0.005	35.823	0.000
		9	-0.321	-0.162	43.217	0.000
		10	-0.388	-0.080	54.265	0.000
		11	-0.181	-0.059	56.721	0.000
		12	0.227	0.115	60.665	0.000
		13	-0.190	-0.138	63.503	0.000
		14	-0.228	-0.069	67.671	0.000
		15	-0.026	-0.008	67.725	0.000
		16	0.303	-0.070	75.425	0.000
		17	-0.105	-0.036	76.364	0.000
		18	-0.188	-0.148	79.474	0.000
		19	-0.046	-0.133	79.666	0.000
		20	0.215	-0.055	83.936	0.000

6I.



Sample: 2000Q2 2014Q4
Included observations: 58

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.285	-0.285	4.9632	0.026
		2	-0.254	-0.365	8.9848	0.011
		3	-0.247	-0.566	12.851	0.005
		4	0.754	0.547	49.457	0.000
		5	-0.321	-0.198	56.203	0.000
		6	-0.244	-0.190	60.183	0.000
		7	-0.180	-0.135	62.387	0.000
		8	0.645	-0.002	91.332	0.000
		9	-0.301	-0.084	97.749	0.000
		10	-0.207	-0.103	100.85	0.000
		11	-0.157	-0.218	102.67	0.000
		12	0.611	0.028	130.87	0.000
		13	-0.276	-0.068	136.75	0.000
		14	-0.179	-0.100	139.28	0.000
		15	-0.106	-0.030	140.18	0.000
		16	0.550	-0.062	165.21	0.000
		17	-0.235	0.040	169.90	0.000
		18	-0.168	-0.010	172.36	0.000
		19	-0.098	-0.084	173.23	0.000
		20	0.467	-0.069	193.18	0.000

From the figure 6A the series of the output gap exhibit clear cycles that appear to be of a one-year fixed length and therefore probably reflect seasonality. Therefore, GAPRUS may need to be seasonally adjusted.

The time paths of GAPRUS and GAPRUS_d11 are given in Figure 6B. Seasonality is obvious in GAPRUS and the GAPRUS_ d11 is substantially smoother than the GAPRUS. This suggests that GAPRUS_d11 exhibits reduced seasonality.

The differences between GAPRUS and GAPRUS_d11 (denoted D_GAPRUS) is plotted in Figure 6C. The difference reveals a regular cyclical fluctuation that ranges between -

0.042 and 0.073. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between GAPRUS and GAPRUS_d11 that are reported in table 6D. The p-values of all of our tests is less than 0.05, we reject the null hypothesis and find that there is a significant difference in the variances of GAPRUS and GAPRUS_d11 and hence find that seasonality is significant in the level of the output-gap data. To explore this further, we compare the differences of the adjusted (DGAPRUS_d11) and unadjusted (DGAPRUS) data.

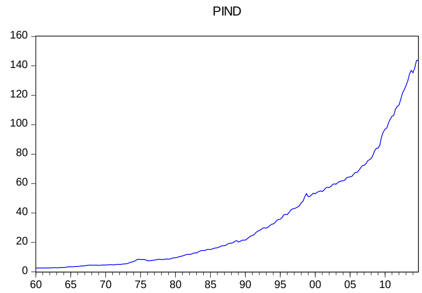
The time paths of DGAPRUS and DGAPRUS_d11 (see Figure 6E) follow each other. DGAPRUS_ d11 is notably smoother than the DGAPRUS suggesting evidence of seasonality in DGAPRUS. Hence, the difference between DGAPRUS and DGAPRUS_d11 (denoted D_DGAPRUS) is plotted in Figure 5F. The difference has revealed a regular cyclical fluctuation that ranges between -0.117and 0.077. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DGAPRUS and DGAPRUS_d11 that are reported in table 6G. Since the p-values of all of our tests is less than 0.05, we reject the null hypothesis and find that there is a significant difference in the variances of DGAPRUS and DGAPRUS_d11. Hence, we find that seasonality is significant in the difference of the output gap rate for Russia.

To explore this further, we plot the autocorrelation functions (ACFs) of GAPRUS and DGAPRUS in figure 6H and 6I. The ACF for GAPRUS has significant ACs at seasonal lags 4 and 16 (see fig. 6H). While the ACF for DGAPRUS has significant ACs at all seasonal lags (see fig. 6I). This provides additional evidence to accept the results of the variance equality tests that seasonality is significant in the output gap. Overall, we take the view that the GAPRUS is seasonal. Hence, we use the seasonally adjusted data GAPRUS_d11 in our VAR analysis.

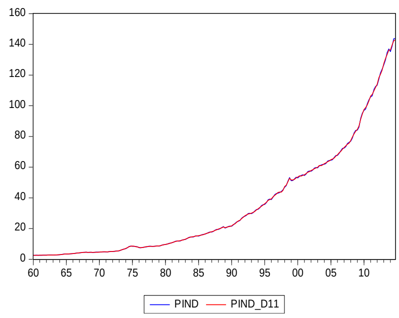
6.7.1 The graphical features of selected macroeconomic variables for India

Following the reduced sample identified in previous section (Table 6.4.2), we would ideally like to collect data over the period 1957q1 – 2014Q4. However, for many important series data is only available from 1960q1 – 2014q4. Therefore, we analyse the stationarity and seasonality characteristics of the selected macroeconomic variables over this sample (1960q1 – 2014q4). The graphs below depict the following indicators. The Indian consumer price (denoted PIND), the seasonally adjusted PIND series (PIND_d11) and D_PIND = PIND - PIND_d11, as well as the first (nonseasonal) difference of LPIND (DLPIND), the seasonally adjusted PIND series (PIND_d11) and D_LPIND = LPIND - LPIND_d11 (where LPIND is the log PIND). The seasonally adjusted series (PIND_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PIND and PIND_d11 as well as DLPIND and DLPIND_d11.

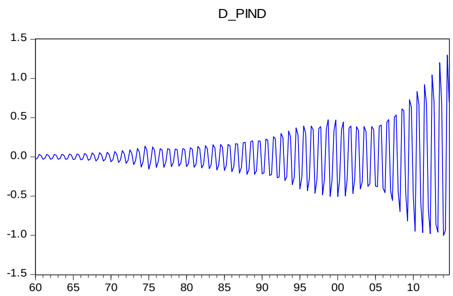
1A.



1B.



1C.



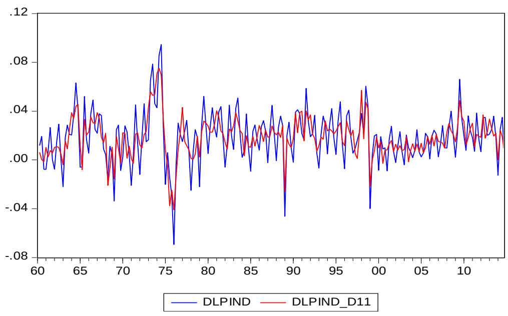
1D.

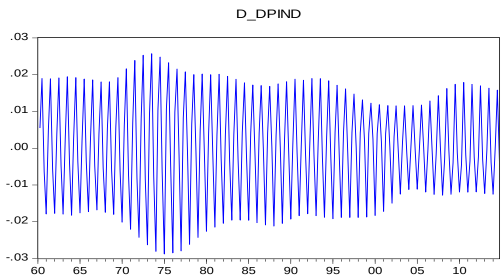
Equality of variances test between PIND and PIND_D11

Method	df	Value	Probability
F-test	(219, 219)	1.000851	0.9950
Siegel- Tukey		0.006373	0.9949
Bartlett	1	3.95E-05	0.9950
Levene	(1,438)	1.73E-05	0.9967
Brown-Forsythe	(1,438)	4.74E-06	0.9983

1E.

1F.



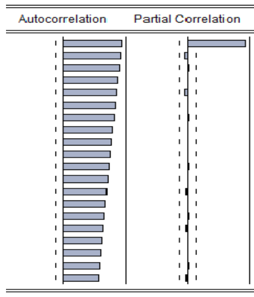


1G.

Equality of variances test between DPIND and DPIND_D11

Method	df	Value	Probability
F-test	(218, 218)	1.745616	0.0000
Siegel-Tukey		3.567107	0.0004
Bartlett	1	16.66254	0.0000
Levene	(1, 436)	11.30887	0.0008
Brown-Forsythe	(1,436)	11.02296	0.0010

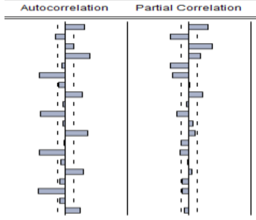
1H.



Sample: 1960Q1 2014Q4
Included observations: 220

	AC	PAC	Q-Stat	Prob
1	0.977	0.977	212.77	0.000
2	0.953	-0.026	416.20	0.000
3	0.930	0.018	611.02	0.000
4	0.908	0.000	797.63	0.000
5	0.885	-0.044	975.56	0.000
6	0.862	-0.005	1145.1	0.000
7	0.840	0.014	1306.8	0.000
8	0.819	0.000	1461.3	0.000
9	0.798	-0.005	1608.5	0.000
10	0.777	-0.003	1748.9	0.000
11	0.757	0.013	1882.9	0.000
12	0.739	0.008	2011.1	0.000
13	0.720	-0.019	2133.3	0.000
14	0.701	-0.004	2249.8	0.000
15	0.683	0.014	2361.1	0.000
16	0.666	-0.017	2467.1	0.000
17	0.648	-0.005	2568.1	0.000
18	0.630	0.002	2664.2	0.000
19	0.614	0.012	2755.9	0.000
20	0.598	-0.012	2843.2	0.000

1I.



Sample: 1960Q1 2014Q4
Included observations: 219

	AC	PAC	Q-Stat	Prob
1	0.324	0.324	23.317	0.000
2	-0.170	-0.308	29.788	0.000
3	0.153	0.402	35.064	0.000
4	0.425	0.191	75.771	0.000
5	-0.050	-0.308	76.333	0.000
6	-0.440	-0.267	120.34	0.000
7	-0.103	0.012	122.74	0.000
8	0.293	0.232	142.48	0.000
9	-0.033	-0.036	142.73	0.000
10	-0.420	-0.201	183.61	0.000
11	-0.036	0.074	183.91	0.000
12	0.374	0.113	216.54	0.000
13	-0.021	-0.138	216.65	0.000
14	-0.428	-0.155	259.91	0.000
15	-0.074	-0.009	261.23	0.000
16	0.296	0.048	282.06	0.000
17	-0.082	-0.100	283.69	0.000
18	-0.455	-0.099	333.62	0.000
19	-0.094	-0.004	335.76	0.000
20	0.255	-0.073	351.64	0.000

As shown in Fig. 1A, the graph of the consumer price for India (PIND) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing.

The time paths of PIND and PIND_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between PIND and PIND_d11 (denoted D_PIND) is plotted in Figure 1C. The difference has revealed regular cyclical fluctuation around a relatively constant mean. Whilst this may indicate seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PIND and PIND_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PIND and PIND_d11. Hence, we find that seasonality is not significant in the price level. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted DLPIND_d11 and unadjusted DLPIND data.

The time paths of DLPIND and DLPIND_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after the first differencing. The variation in DLPIND is greater than that of DLPIND_d11 suggesting seasonality in DLPIND while DLPIND_d11 is smoother. This suggests that DLPIND_d11 exhibits reduced seasonality as expected.

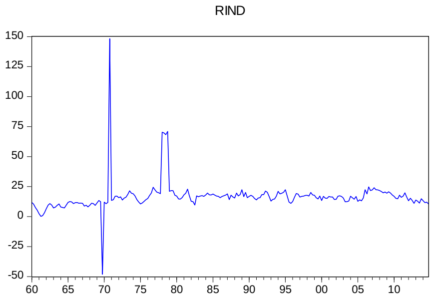
Hence, the difference between DLPIND and DLPIND_d11 (denoted D_DLPIND) is plotted in Figure 1F. The difference revealed regular cyclical fluctuations that range between -0.029 and 0.026. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPIND and DLPIND_d11 that are reported in table 1G. Since the p-values of all of our tests is less than 0.05, we reject the null hypothesis and find that there is a significant difference in the variances of DLPIND and DLPIND_d11 and hence find that seasonality is significant in the difference of the log of the price data for India.

To explore this further, we plot the autocorrelation functions (ACFs) of PIND and DLPIND in figure 1H and 1I. Shown in Fig. 1H is the ACF for PIND. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPIND (see fig. 1I) has significant ACs at all the seasonal lags. This implies that seasonality is significant in the price data and confirms the results of the variance equality tests. Hence, we will use the adjusted data PIND_d11 in our VAR analysis.

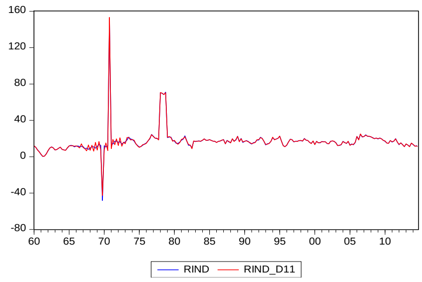
6.7.2 The seasonality features of the interest rate in India

We analyse the stationarity and seasonality characteristics of the interest rate variable in India. The graphs below depict the following indicators. The Indian interest rate (denoted RIND), the seasonally adjusted RIND series (RIND_d11) and D_RIND = RIND - RIND_d11, as well as the first (nonseasonal) difference of RIND (DRIND). The seasonally adjusted series (RIND_d11) is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for RIND and RIND_d11 as well as DRIND and DRIND_d11.

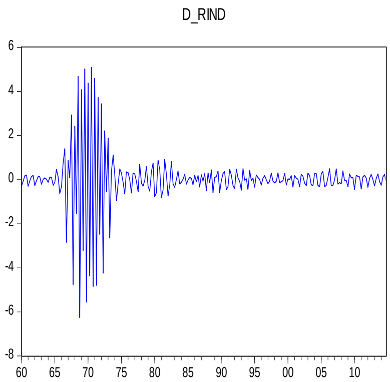
2A.



2B.



2C.

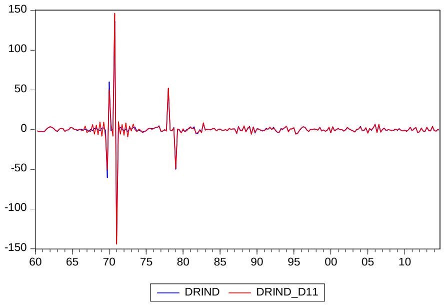


2D.

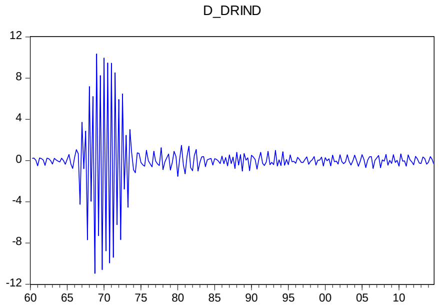
Equality of variances test between RIND and RIND_D11

Method	df	Value	Probability
F-test	(219, 219)	1.027208	0.8427
Siegel- Tukey		0.488499	0.6252
Bartlett	1	0.039362	0.8427
Levene	(1, 438)	0.014966	0.9027
Brown-Forsythe	(1,438)	0.016218	0.8987

2E.



2F.

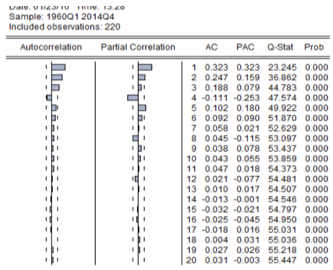


2G.

Equality of variances test between DRIND and DRIND_D11

Method	df	Value	Probability
F-test	(218, 218)	1.084339	0.5505
Siegel-Tukey		1.580098	0.1141
Bartlett	1	0.35640	0.5505
Levene	(1,436)	0.131617	0.7169
Brown-Forsythe	(1,436)	0.132314	0.7162

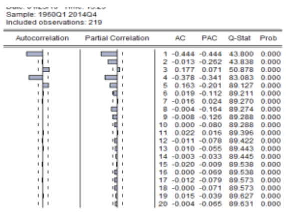
2H.



Sample: 1960Q1 2014Q4
Included observations: 220

	AC	PAC	Q-Stat	Prob
1	0.323	0.323	23.245	0.000
2	0.247	0.159	36.862	0.000
3	0.188	0.079	44.783	0.000
4	-0.111	-0.253	47.574	0.000
5	0.102	0.180	49.922	0.000
6	0.092	0.090	51.870	0.000
7	0.058	0.021	52.629	0.000
8	0.045	-0.115	53.097	0.000
9	0.038	0.078	53.437	0.000
10	0.043	0.055	53.859	0.000
11	0.047	0.018	54.373	0.000
12	0.021	-0.077	54.481	0.000
13	0.010	0.017	54.507	0.000
14	-0.013	-0.001	54.546	0.000
15	-0.032	-0.021	54.797	0.000
16	-0.025	-0.045	54.950	0.000
17	-0.018	0.016	55.031	0.000
18	0.004	0.031	55.036	0.000
19	0.027	0.026	55.218	0.000
20	0.031	-0.003	55.447	0.000

2I.



Sample: 1960Q1 2014Q4
Included observations: 219

	AC	PAC	Q-Stat	Prob
1	-0.444	-0.444	43.800	0.000
2	-0.013	-0.262	43.838	0.000
3	0.177	0.071	50.878	0.000
4	-0.378	-0.341	83.083	0.000
5	0.163	-0.201	89.127	0.000
6	0.019	-0.112	89.211	0.000
7	-0.016	0.024	89.270	0.000
8	-0.004	-0.164	89.274	0.000
9	-0.008	-0.126	89.288	0.000
10	0.000	-0.080	89.288	0.000
11	0.022	0.016	89.396	0.000
12	-0.011	-0.078	89.422	0.000
13	0.010	-0.055	89.443	0.000
14	-0.003	-0.033	89.445	0.000
15	-0.020	-0.009	89.538	0.000
16	0.000	-0.069	89.538	0.000
17	-0.012	-0.079	89.573	0.000
18	-0.000	-0.071	89.573	0.000
19	0.015	-0.039	89.627	0.000
20	-0.004	-0.065	89.631	0.000

As shown in Fig. 2A, the interest rate series (RIND) has a relatively constant mean with visible outliers around 1970 and 1978. Seasonality is not clearly visible in India's interest rate plot.

The time paths of RIND and RIND_d11 (see Figure 2B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. The differences between RIND and RIND_d11 (denoted D_RIND) is plotted in Figure 2C.

The difference has revealed multiple volatilities around a constant mean. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between RIND and RIND_d11 that are reported in table 2D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RIND and RIND_d11 and hence we find that seasonality is not significant in the level of the data. However, we compare the differences of the adjusted (DRIND_d11) and unadjusted (DRIND) data to further explore this.

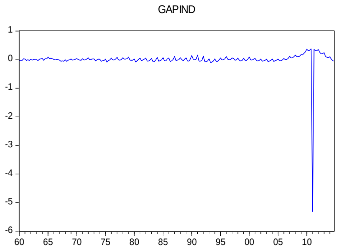
The time paths of DRIND and DRIND_d11 (see Figure 2E) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Hence, the difference between DRIND and DRIND_d11 (denoted D_DRIND) is plotted in Figure 2F. The difference may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between (DRIND) and (DRIND_d11) that are reported in table 2G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DRIND and DRIND_d11. Hence, we find that seasonality is not significant in the difference of interest rate for India.

To explore this further, we plot the autocorrelation functions (ACFs) of RIND and DRIND in figure 2H and 2I. The ACF for RIND has insignificant ACs at all the seasonal lags (see fig. 2H). While the ACF for DRIND has significant AC at seasonal lag 4 (see fig. 2I) there are no other significant ACs. Since seasonality is not expected and there is very little evidence to suggest seasonality this suggests that seasonality is not significant in the interest rate. Hence, we will use seasonally unadjusted RIND in our VAR analysis

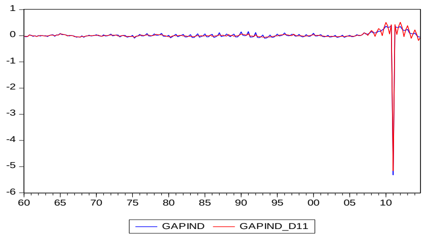
6.7.3. The seasonality features of output gap in India

We analyse the stationarity and seasonality characteristics of the output gap variable in India. The graphs below depict the following indicators. The output gap (denoted GAPIND), the seasonally adjusted GAPIND series (GAPIND_d11) and D_GAPIND = GAPIND - GAPIND_d11, as well as the first (nonseasonal) difference of GAPIND (DGAPIND). The seasonally adjusted series (GAPIND_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for GAPIND and GAPIND_d11 as well as DGAPIND and DGAPIND_d11.

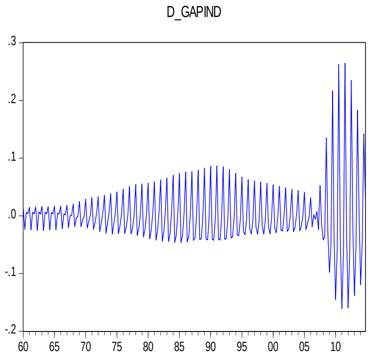
3A.



3B.



3C.

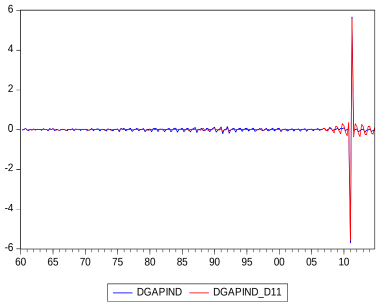


3D

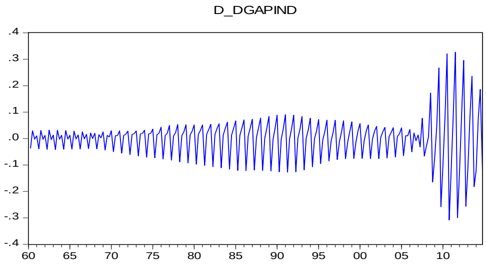
Equality of variances test between GAPIND and GAPIND_D11

Method	Df	Value	Probability
F-test	(219, 219)	1.051186	0.7122
Siegel-Tukey		4.204535	0.0000
Bartlett	1	0.136109	0.7122
Levene	(1,438)	0.090019	0.7639
Brown-Forsythe	(1, 438)	0.090019	0.7643

3E.



3F.



3G.

Equality of variances test between DGAPIND and DGAPIND_D11

Method	Df	Value	Probability
F-test	(218), 218)	1.027696	0.8403
Siegel-Tukey		5.825896	0.0000
Bartlett	1	0.040581	0.8403
Levene	(1, 436)	0.017382	0.8952
Brown-Forsythe	(1, 436)	0.012016	0.9128

3H.

Sample: 1960Q1 2014Q4
Included observations: 176

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.086	-0.086	1.3365	0.248
		2	-0.075	-0.084	2.3610	0.307
		3	-0.071	-0.086	3.2660	0.352
		4	-0.080	-0.104	4.4261	0.351
		5	-0.055	-0.090	4.9815	0.418
		6	-0.044	-0.087	5.3390	0.501
		7	-0.034	-0.083	5.5567	0.592
		8	-0.037	-0.092	5.8137	0.668
		9	-0.012	-0.073	5.8399	0.756
		10	-0.014	-0.076	5.8764	0.826
		11	-0.009	-0.074	5.8930	0.880
		12	-0.020	-0.087	5.9732	0.917
		13	-0.004	-0.075	5.9763	0.947
		14	0.006	-0.065	5.9830	0.967
		15	0.009	-0.060	5.9985	0.980
		16	-0.004	-0.071	6.0018	0.988
		17	-0.000	-0.068	6.0018	0.993
		18	0.000	-0.067	6.0018	0.996
		19	0.002	-0.065	6.0030	0.998
		20	0.003	-0.064	6.0047	0.999

3I.

Sample: 1960Q1 2014Q4
Included observations: 175

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.505	-0.505	45.407	0.000
		2	0.003	-0.339	45.409	0.000
		3	0.006	-0.246	45.416	0.000
		4	-0.016	-0.216	45.460	0.000
		5	0.006	-0.187	45.468	0.000
		6	0.001	-0.166	45.468	0.000
		7	0.006	-0.141	45.474	0.000
		8	-0.013	-0.146	45.506	0.000
		9	0.013	-0.129	45.535	0.000
		10	-0.003	-0.121	45.537	0.000
		11	0.007	-0.100	45.547	0.000
		12	-0.013	-0.107	45.578	0.000
		13	0.003	-0.109	45.579	0.000
		14	0.003	-0.105	45.581	0.000
		15	0.003	-0.096	45.583	0.000
		16	-0.003	-0.095	45.585	0.000
		17	0.002	-0.092	45.586	0.000
		18	-0.001	-0.091	45.586	0.000
		19	0.001	-0.088	45.586	0.001
		20	-0.000	-0.087	45.586	0.001

From figure 3A the series of the output gap is relatively constant with an extreme outlier around 2011 that makes all other variation difficult tom identify.

The time paths of GAPIND and GAPIND_d11 (see Figure 3B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. We refer to a variety of tests for the equality of variance between GAPIND and GAPIND_d11 that are reported in table 3D. The p-values for Levene, Brown Forsythe, F-test and Bartlett test tests are greater than 0.05 indicating equal variances while the p-values of Siegel Tukey is less than 0.05 which rejects the null hypothesis of equal variance. Hence, the results regarding equality of variance are ambiguous if they generally cannot reject the null. Hence, the evidence generally suggests no seasonality.

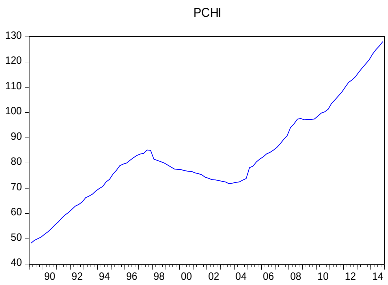
To explore the issue further, we plot the graph of DGAPIND and DGAPIND_d11 (see Figure 3E). The time paths of DGAPIND and DGAPIND_d11 follow each other closely. To ascertain whether there is any significant seasonality we refer to tests for the equality of variance between DGAPIND and DGAPIND_d11 that are reported in table 3G. The p-values for Levene, Brown Forsythe, F-test and Bartlett test tests are greater than 0.05 indicating equal variances while the p- values of Siegel Tukey is less than 0.05 which reject the null hypothesis of equal variance. Hence, the results regarding equality of variance are ambiguous if they generally cannot reject the null. Hence, the evidence generally suggests no seasonality.

To explore this further, we plot the autocorrelation functions (ACFs) of GAPIND and DGAPIND in figure 3H and 3I. The ACF for GAPIND and DGAPIND have insignificant ACs at all the seasonal lag (see fig. 3H and 31). This implies that seasonality is not significant in output gap for India. Hence, the vast majority of evidence suggests no seasonality and we will use seasonally unadjusted GAPIND in our VAR analysis

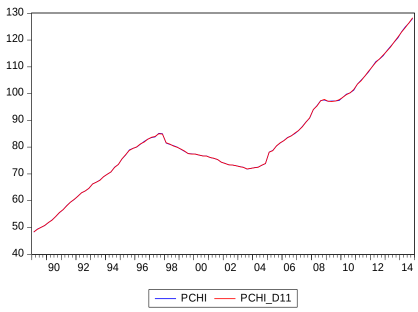
6.8.1. The graphical features of selected macroeconomic variables for China

Following the sample indicated in previous section (Table 6.4.3), we will collect data over the period 1989q1 – 2014Q4. Therefore, we analyse the stationarity and seasonality characteristics of the selected macroeconomic variables over this sample (1989q1 2014q4). The graphs below depict the following indicators. The Chinese consumer price index (denoted PCHI), the seasonally adjusted PCHI series (PCHI_d11) and D_PCHI = PCHI - PCHI_d11, as well as the first (nonseasonal) difference of LPCHI (DLPCHI), the seasonally adjusted LPCHI series (LPCHI_d11) and D_LPCHI = LPCHI - LPCHI_d11(where LPCHI is the log of PCHI). The seasonally adjusted series (PCHI_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PCHI and PCHI_d11 as well as DLPCHI and DLPCHI_d11.

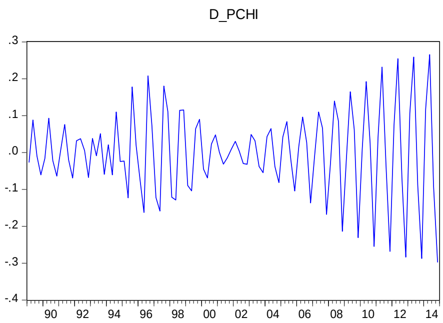
1A.



1B.



1C.

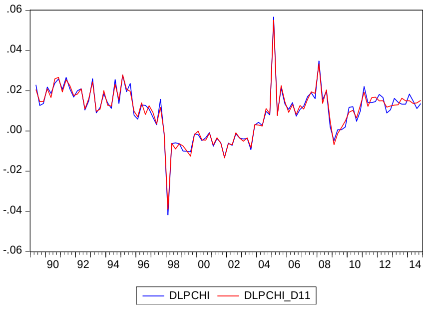


1D.

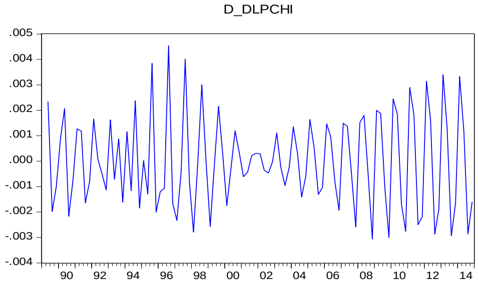
Equality of variances test between PCHI and PCHI_D11

Method	Df	Value	Probability
F-test	(103, 103)	1.000499	0.9980
Siegel-Tukey		0.012672	0.9899
Bartlett	1	6.38E-06	0.9980
Levene	(1, 206)	3.81E-09	0.9982
Brown-Forsythe	(1, 206)	5.35E-06	0.9983

1E.



1F



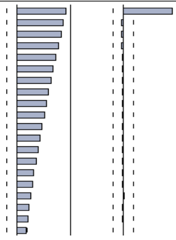
1G.

Equality of variances test between DLPCHI and DLPCHI_D11

Method	Df	Value	Probability
F-test	(102, 103)	86.43110	0.0000
Siegel-Tukey		10.77164	0.0000
Bartlett	1	314.5568	0.0000
Levene	(1, 205)	108.9892	0.0000
Brown-Forsythe	(1, 206)	108.8159	0.0000

1H.

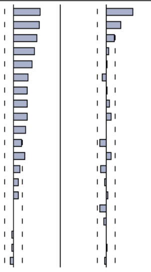
Sample: 1989Q1 2014Q4
Included observations: 104



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.952	0.952	97.102	0.00
		2	0.905	-0.026	185.58	0.00
		3	0.856	-0.035	265.60	0.00
		4	0.808	-0.027	337.49	0.00
		5	0.760	-0.015	401.79	0.00
		6	0.713	-0.024	458.92	0.00
		7	0.666	-0.018	509.36	0.00
		8	0.621	-0.015	553.64	0.00
		9	0.577	-0.014	592.29	0.00
		10	0.534	-0.020	625.72	0.00
		11	0.491	-0.024	654.32	0.00
		12	0.450	-0.012	678.58	0.00
		13	0.410	-0.010	698.98	0.00
		14	0.373	-0.010	715.98	0.00
		15	0.336	-0.017	729.93	0.00
		16	0.300	-0.013	741.22	0.00
		17	0.268	0.010	750.34	0.00
		18	0.237	-0.017	757.55	0.00
		19	0.206	-0.022	763.07	0.00
		20	0.178	-0.006	767.21	0.00

1I.

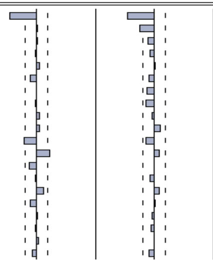
Sample: 1989Q1 2014Q4
Included observations: 103



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.599	0.599	38.052	0.000
		2	0.574	0.335	73.280	0.000
		3	0.531	0.180	103.83	0.000
		4	0.464	0.046	127.30	0.000
		5	0.414	0.010	146.17	0.000
		6	0.322	-0.085	157.72	0.000
		7	0.308	0.020	168.42	0.000
		8	0.303	0.077	178.84	0.000
		9	0.308	0.105	189.76	0.000
		10	0.268	0.002	198.14	0.000
		11	0.180	-0.145	201.93	0.000
		12	0.252	0.099	209.49	0.000
		13	0.131	-0.136	211.56	0.000
		14	0.114	-0.033	213.15	0.000
		15	0.109	0.040	214.61	0.000
		16	0.000	-0.142	214.61	0.000
		17	-0.005	-0.060	214.61	0.000
		18	-0.027	0.006	214.70	0.000
		19	-0.039	0.013	214.90	0.000
		20	-0.078	-0.037	215.69	0.000

1J.

Sample: 1989Q1 2014Q4
Included observations: 102



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.464	-0.464	22.598	0.000
		2	0.019	-0.250	22.635	0.000
		3	0.023	-0.112	22.691	0.000
		4	-0.018	-0.069	22.725	0.000
		5	0.047	0.021	22.970	0.000
		6	-0.102	-0.089	24.115	0.000
		7	-0.005	-0.130	24.118	0.001
		8	-0.019	-0.150	24.158	0.002
		9	0.064	-0.037	24.624	0.003
		10	0.064	0.113	25.099	0.005
		11	-0.208	-0.142	30.162	0.001
		12	0.245	0.096	37.245	0.000
		13	-0.120	0.004	38.966	0.000
		14	-0.020	-0.072	39.012	0.000
		15	0.116	0.094	40.659	0.000
		16	-0.108	0.024	42.104	0.000
		17	0.020	-0.034	42.152	0.001
		18	-0.023	-0.049	42.218	0.001
		19	0.039	-0.004	42.417	0.002
		20	-0.078	-0.083	43.200	0.002

As shown in Fig. 1A the graph of consumer prices for China (PCHI) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity-inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing.

The time paths of PCHI and PCHI_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between PCHI and PCHI_d11 (denoted D_PCHI) is plotted in Figure 1C. The difference has revealed cyclical fluctuations that range between -0.30 and 0.27. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PCHI and PCHI_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PCHI and PCHI_d11. Hence, we find that seasonality is not significant in the level of the consumer price. However, this result may be influenced by the nonstationarity of the data so we compare the differences of the adjusted (DLPCHI_d11) and unadjusted (DLPCHI) data.

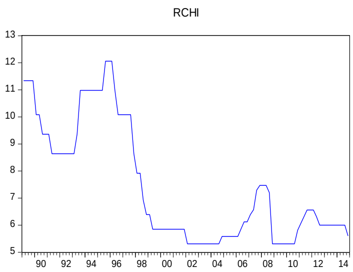
The time paths of DLPCHI and DLPCHI_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuate around a constant mean as expected after first differencing. The variation in DLPCHI is greater than that of DLPCHI_d11 suggesting seasonality in DLPCHI while DLPCHI_d11 is smoother. This suggests that DLPCHI_ d11 exhibits reduced seasonality as expected. Hence, the difference between DLPCHI and DLPCHI_d11 (denoted D_DLPCHI) is plotted in Figure 1F. The difference revealed multiple fluctuations around a constant mean that range between -0.0028 and 0. 0045. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPCHI and DLPCHI_d11 that are reported in table 1G. Since the p-values of all of our tests is less than 0.05, we reject the null hypothesis and find that there is significant difference in the variances of DLPCHI and DLPCHI_d11. Hence, we find that seasonality is significant in the difference of the log of the price data for China.

To explore further we plot the autocorrelation functions (ACFs) of PCHI and DLPCHI in figure 1H and 1I. Shown in Fig. 1H is the ACF for PCHI. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPCHI (see fig. 1I) has significant ACs for the first 12 lags, except lag 11, and not just the seasonal lags 4, 8 and 12. This implies the need to plot the ACF of the second difference of LPCHI to determine if there is seasonality. The ACF for second difference D(PCHI,2) indicates insignificant ACs at all the seasonal lag except seasonal lag 12 (see fig. 1J). This implies that seasonality is not significant in price data and we reject the results of the variance equality tests. Hence, we use the unadjusted data PCHI in our VAR analysis

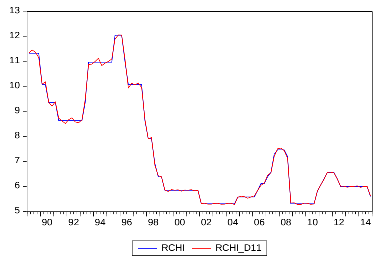
6.8.2. The seasonality features of interest rate in China

We analyse the stationarity and seasonality characteristics of the interest rate variables in China. The graphs below depict the following indicators. The Chinese interest rate (denoted RCHI), the seasonally adjusted RCHI series (RCHI_d11) and D_RCHI = RCHI - RCHI_d11, as well as the first (nonseasonal) difference of RCHI (DRCHI), the seasonally adjusted RCHI series (RCHI_d11) and D_RCHI = RCHI - RCHI_d11. The seasonally adjusted series (RCHI_d11) is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for RCHI and RCHI_d11 as well as DCHI and DRCHI_d11.

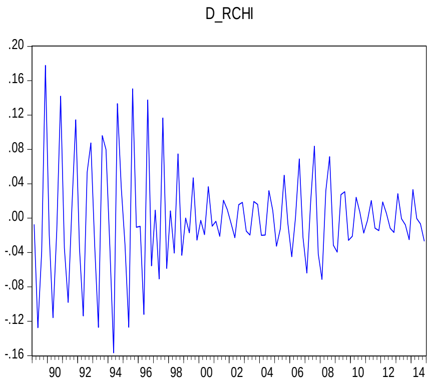
2A.



2B.



2C.

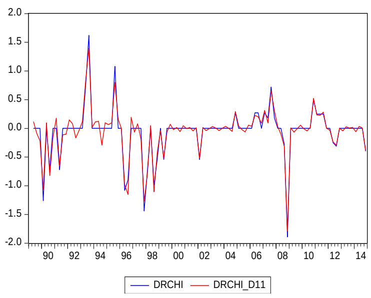


2D.

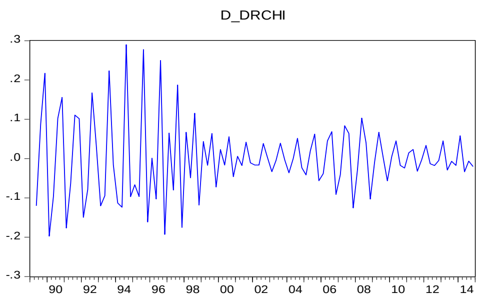
Equality of variances test between RCHI and RCHI_D11

Method	Df	Value	Probability
F-test	(103, 103)	1.000044	0.9998
Siegel-Tukey		0.121038	0.9037
Bartlett	1	4.86E-08	0.9998
Levene	(1, 206)	2.92E-07	0.9828
Brown-Forsythe	(1, 206)	2.92E-07	0.9996

2E.



2F.



2G.

Equality of variances test between DRCHI and DRCHI_D11

Method	Df	Value	Probability
F-test	(102, 102)	1.076173	0.7116
Siegel-Tukey		6.361137	0.0000
Bartlett	1	0.136723	0.7116
Levene	(1, 206)	0.078722	0.7793
Brown-Forsythe	(1, 206)	0.556538	0.4565

2H.

Sample: 1989Q1 2014Q4
Included observations: 104

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.962	0.962	99.058	0.000
		2	0.916	-0.134	189.65	0.000
		3	0.864	-0.078	271.16	0.000
		4	0.809	-0.068	343.29	0.000
		5	0.765	0.138	408.46	0.000
		6	0.718	-0.091	466.54	0.000
		7	0.673	-0.023	517.96	0.000
		8	0.626	-0.046	563.02	0.000
		9	0.578	-0.026	601.78	0.000
		10	0.538	0.079	635.73	0.000
		11	0.502	0.003	665.54	0.000
		12	0.470	0.021	692.00	0.000
		13	0.446	0.052	716.11	0.000
		14	0.425	0.031	738.29	0.000
		15	0.406	-0.033	758.66	0.000
		16	0.384	-0.039	777.14	0.000
		17	0.362	-0.013	793.70	0.000
		18	0.336	-0.058	808.17	0.000
		19	0.302	-0.129	819.99	0.000
		20	0.269	0.017	829.48	0.000

2I.

Sample: 1989Q1 2014Q4
Included observations: 103

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.253	0.253	6.7705	0.009
		2	0.114	0.054	8.1719	0.017
		3	0.086	0.048	8.9751	0.030
		4	-0.047	-0.091	9.2192	0.056
		5	0.057	0.086	9.5770	0.088
		6	0.125	0.107	11.307	0.079
		7	-0.001	-0.061	11.307	0.126
		8	0.049	0.033	11.577	0.171
		9	-0.085	-0.116	12.409	0.191
		10	-0.069	-0.006	12.957	0.226
		11	-0.116	-0.118	14.550	0.204
		12	-0.217	-0.167	20.136	0.065
		13	-0.093	0.004	21.169	0.070
		14	-0.054	-0.004	21.526	0.089
		15	0.006	0.074	21.531	0.121
		16	-0.008	-0.044	21.539	0.159
		17	-0.137	-0.101	23.901	0.122
		18	-0.136	-0.057	26.264	0.094
		19	-0.054	0.020	26.644	0.113
		20	-0.123	-0.104	28.630	0.095

As shown in Fig. 2A, the interest rate series (RCHI) exhibits a downward trend. Seasonality is not visible in the interest rate plot perhaps because of the dominant downward trend, these may be revealed once the trend is removed through differencing. This interest rate moves in a discrete manner is unlikely to be seasonal.

The time paths of RCHI and RCHI_d11 (see Figure 2B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. We plot the difference between RCHI and RCHI_d11 (denoted D_RCHI) in Figure 2C to further assess whether RCHI is seasonal. The difference indicates cycles that substantially decline. Whilst this may indicate seasonality, we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between RCHI and RCHI_d11 that are reported in table 2D. The p-values of all of our tests is greater than 0.05, thus we cannot reject the null hypothesis and find that there is no significant difference in the variances of RCHI and RCHI_d11. Hence, we find that seasonality is not significant in the level of the interest rate. However, because this result may be influenced by the trend in the data we compare the differences of the adjusted (DRCHI_d11) and unadjusted (DRCHI) data.

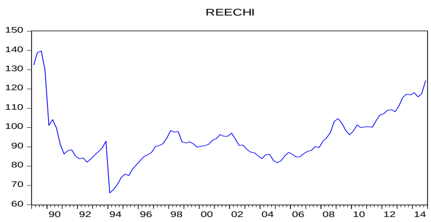
The time paths of DRCHI and DRCHI_d11 (see Figure 2E) follow each other closely. The DRCHI_d11 series is smoother than DRCHI and variation of DRCHI_d11 is less than the variation of DRCHI. Whilst this may indicate seasonality we plot the graph of the difference between DRCHI and DRCHI_d11 in Figure 2F to further assess whether RCHI is seasonal. The difference indicates time-varying cycles that dramatically decline. We refer to a variety of tests for the equality of variance between DRCHI and DRCHI_d11 that are reported in table 2G. The p-values for Levene, Brown Forsythe, F-test and Bartlett tests are greater than 0.05 indicating equal variances while the p- values of the Siegel Tukey is less than 0.05. Hence, the results regarding equality of variance are ambiguous although generally suggest equal variance and no seasonality.

To explore the issue further we plot the ACFs of RCHI and DRCHI in figure 2H and 2I, respectively. Shown in Fig. 2H is the ACF for RCHI. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DRCHI (see fig. 2I) has insignificant ACs at all the seasonal lags. This provides convincing evidence that seasonality is insignificant in the interest rate data. Hence, we use the unadjusted RCHI variable in our VAR analysis.

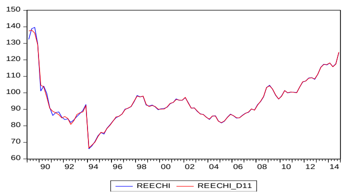
6.8.3. The seasonality features of real effective exchange rate in China

We analyse the stationarity and seasonality characteristics of the real effective exchange rate variable in China. The graphs below depict the following indicators. The Chinese real effective exchange rate (denoted REECHI), the seasonally adjusted REECHI series (REECHI_d11) and D_REECHI = REEECHI - REECHI_d11, as well as the first (nonseasonal) difference of LREECHI (DLREECHI), the seasonally adjusted LREECHI series (LREECHI_d11) and D_LREECHI = LREECHI - LREECHI_d11 (where LREECHI is the log of REECHI). The seasonally adjusted series (REECHI_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for REECHI and LREECHI_d11 as well as DLREECHI and DLREECHI_d11.

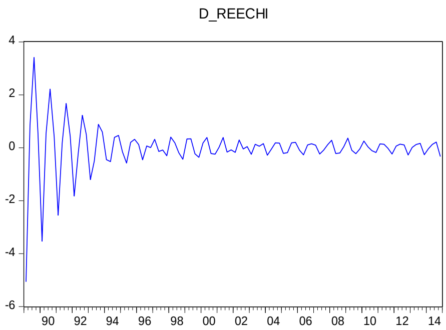
3A.



3B.



3C.

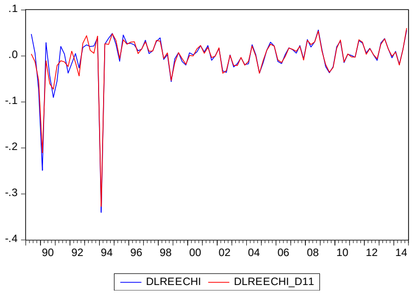


3D.

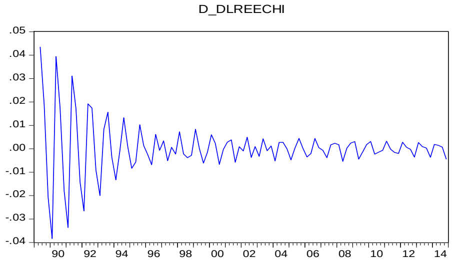
Equality of variances test between REECHI and REECHI_D11

Method	Df	Value	Probability
F-test	(103, 103)	1.000300	0.9988
Siegel-Tukey		0.051840	0.9587
Bartlett	1	2.30E-05	0.9988
Levene	(1, 206)	6.93E-05	0.9934
Brown-Forsythe	(1, 206)	5.04E-05	0.9943

3E.



3F

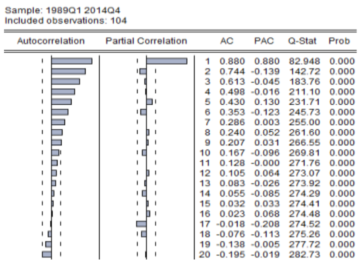


3G.

Equality of variances test between DLREECHI and DLREECHI_D11

Method	Df	Value	Probability
F-test	(102, 102)	1.169888	0.4295
Siegel-Tukey		0.247784	0.8043
Bartlett	1	0.624109	0.4295
Levene	(1, 206)	0.146815	0.7020
Brown-Forsythe	(1, 206)	0.059659	0.8073

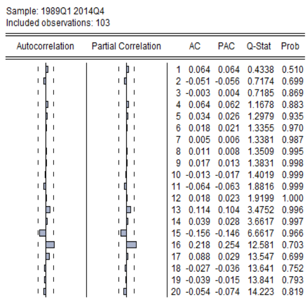
3H.



Sample: 1989Q1 2014Q4
Included observations: 104

	AC	PAC	Q-Stat	Prob
1	0.880	0.880	82.948	0.000
2	0.744	-0.139	142.72	0.000
3	0.613	-0.045	183.76	0.000
4	0.498	-0.016	211.10	0.000
5	0.430	0.130	231.71	0.000
6	0.353	-0.123	245.73	0.000
7	0.286	0.003	255.00	0.000
8	0.240	0.052	261.60	0.000
9	0.207	0.031	266.55	0.000
10	0.167	-0.096	269.81	0.000
11	0.128	-0.000	271.76	0.000
12	0.105	0.064	273.07	0.000
13	0.083	-0.026	273.92	0.000
14	0.055	-0.085	274.29	0.000
15	0.032	0.033	274.41	0.000
16	0.023	0.068	274.48	0.000
17	-0.018	-0.208	274.52	0.000
18	-0.076	-0.113	275.26	0.000
19	-0.138	-0.005	277.72	0.000
20	-0.195	-0.019	282.73	0.000

3I



Sample: 1989Q1 2014Q4
Included observations: 103

	AC	PAC	Q-Stat	Prob
1	0.064	0.064	0.4338	0.510
2	-0.051	-0.056	0.7174	0.699
3	-0.003	0.004	0.7185	0.869
4	0.064	0.062	1.1678	0.883
5	0.034	0.026	1.2979	0.935
6	0.018	0.021	1.3355	0.970
7	0.005	0.006	1.3381	0.987
8	0.011	0.008	1.3509	0.995
9	0.017	0.013	1.3831	0.998
10	-0.013	-0.017	1.4019	0.999
11	-0.064	-0.063	1.8816	0.999
12	0.018	0.023	1.9199	1.000
13	0.114	0.104	3.4752	0.996
14	0.039	0.028	3.6617	0.997
15	-0.156	-0.146	6.6617	0.966
16	0.218	0.254	12.581	0.703
17	0.088	0.029	13.547	0.699
18	-0.027	-0.036	13.641	0.752
19	-0.039	-0.015	13.841	0.793
20	-0.054	-0.074	14.223	0.819

From Figure 3A, the graph of real effective exchange rate for China (REECHI) is U-shaped without a clear trend. Seasonality is not visible in this graph however it may be revealed after differencing.

The time paths of REECHI and REECHI_d11 (see Figure 3B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between REECHI and REECHI_d11 (denoted D_REECHI) is plotted in Figure 3C. The difference has revealed cyclical fluctuations that substantially decline over time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between REECHI and REECHI_d11 that are reported in table 3D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REECHI and REECHI_d11. Hence, we find that seasonality is not significant in the level of the data. To explore this further, we compare the differences of the adjusted (DLREECHI_d11) and unadjusted (DLREECHI) data.

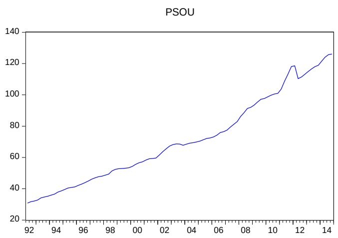
The time paths of DLREECHI and DLREECHI_d11 (see Figure 3E) follow each other closely. The first difference is a relatively constant mean process. The variation in DLREECHI is greater than that of DLREECHI_d11 suggesting possible seasonality in DLREECHI. Therefore, we plot the differences between DLREECHI and DLREECHI_d11 (denoted D_DLREECHI) in Figure 3F. The difference revealed a regular fluctuation that substantially decreases over time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREECHI and DLREECHI_d11 that are reported in table 3G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLREECHI and DLREECHI_d11. Hence, we find that seasonality is not significant in the difference of the log of the real effective exchange rate data for China.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of REECHI and DLREECHI in figure 3H and 3I. Shown in Fig. 3H is the ACF for REECHI. The first 9 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not seasonality. The ACF for DLREECHI has no significant ACs at seasonal lags (see fig. 3I). This implies that seasonality is not significant in the real effective exchange rate and confirms the results of the variance equality tests. Hence, we will use the unadjusted data REECHI our VAR analysis.

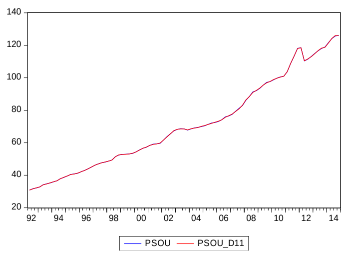
6.9.1. The graphical features of selected macroeconomic variables for South Africa

Following the sample indicated in previous section (Table 6.4.4), we will collect data over the period 1992q2 – 2014q4. Therefore, we analyse the stationarity and seasonality characteristics of the selected macroeconomic variables over this sample (1992q2 – 2014q4). The graphs below depict the following indicators. The South African consumer price (denoted PSOU), the seasonally adjusted PSOU series (SOU_d11) and D_PSOU = PSOU - PSOU_d11, as well as the first (nonseasonal) difference of LPSOU (DLPSOU), the seasonally adjusted LPSOU series (LPSOU_d11) and D_LPSOU = LPSOU - LPSOU_d11 (where LPSOU is the log of PSOU). The seasonally adjusted series (PSOU_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PSOU and PSOU_d11 as well as DLPSOU and DLPSOU_d11.

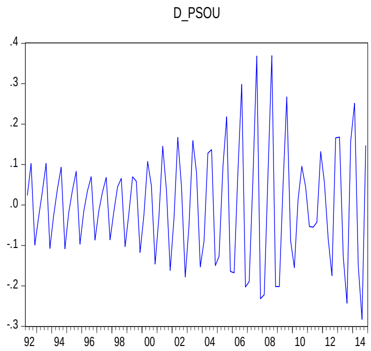
1A.



1B.



1C.

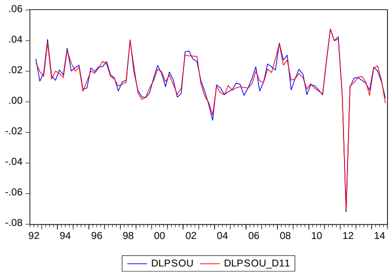


1D.

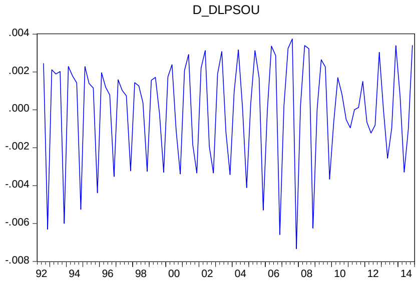
Equality of variances test between PSOU and PSOU_D11

Method	Df	Value	Probability
F-test	(90. 90)	1. 000113	0.9996
0Siegel-Tukey		0.005628	0.9955
Bartlett	1	2.85E-07	0.9996
Levene	(1, 180)	3.26E.-8	0.9999
Brown-Forsythe	(1, 180)	3.85E-06	0.9984

1E.



1F.

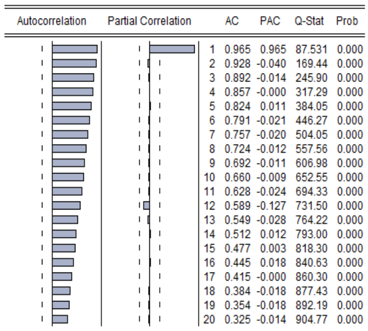


1G.

Equality of variances test between DPSOU and DPSOU_D11

Method	Df	Value	Probability
F-test	(89, 89)	1.059261	0.7866
Siegel-Tukey		0.585062	0.5585
Bartlett	1	0.073326	0.7866
Levene	(1,178	0.062764	0.8025
Brown-Forsythe	(1,178)	0.066905	0.7962

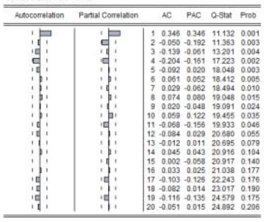
1H.



Sample: 1992Q2 2014Q4
Included observations: 91

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.965	0.965	87.531	0.000
		2	0.928	-0.040	169.44	0.000
		3	0.892	-0.014	245.90	0.000
		4	0.857	-0.000	317.29	0.000
		5	0.824	0.011	384.05	0.000
		6	0.791	-0.021	446.27	0.000
		7	0.757	-0.020	504.05	0.000
		8	0.724	-0.012	557.56	0.000
		9	0.692	-0.011	606.98	0.000
		10	0.660	-0.009	652.55	0.000
		11	0.628	-0.024	694.33	0.000
		12	0.589	-0.127	731.50	0.000
		13	0.549	-0.028	764.22	0.000
		14	0.512	0.012	793.00	0.000
		15	0.477	0.003	818.30	0.000
		16	0.445	0.018	840.63	0.000
		17	0.415	-0.000	860.30	0.000
		18	0.384	-0.018	877.43	0.000
		19	0.354	-0.018	892.19	0.000
		20	0.325	-0.014	904.77	0.000

1I



Sample: 1992Q2 2014Q4
Included observations: 90

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.346	0.346	11.132	0.001
		2	-0.050	-0.192	11.363	0.003
		3	-0.139	-0.061	13.201	0.004
		4	-0.204	-0.161	17.223	0.002
		5	-0.092	0.020	18.048	0.003
		6	0.061	0.052	18.412	0.005
		7	0.029	-0.062	18.494	0.010
		8	0.074	0.080	19.048	0.015
		9	0.020	-0.048	19.091	0.024
		10	0.059	0.122	19.455	0.035
		11	-0.068	-0.156	19.933	0.046
		12	-0.084	0.029	20.680	0.055
		13	-0.012	0.011	20.695	0.079
		14	0.045	0.043	20.916	0.104
		15	0.002	-0.058	20.917	0.140
		16	0.033	0.025	21.038	0.177
		17	-0.103	-0.126	22.243	0.176
		18	-0.082	0.014	23.017	0.190
		19	-0.116	-0.135	24.579	0.175
		20	-0.051	0.015	24.892	0.206

As shown in Fig. 1A, there is an upward trend indicating non-stationarity and a need to apply stationarity inducing transformations.

The time paths of PSOU and PSOU_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between PSOU and PSOU_d11 (denoted D_PSOU) is plotted in Figure 1C. The difference has revealed cyclical fluctuation that range between -0.23 and 0.37. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PSOU and PSOU_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PSOU and PSOU_d11. Hence, we find that seasonality is not significant in the level of the consumer price. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLPSOU_d11) and unadjusted (DLPSOU) data.

The time paths of DLPSOU and DLPSOU_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after first differencing. The variation in DLPSOU is greater than that of DLPSOU_d11 suggesting possible seasonality in DLPSOU while DLPSOU_d11 is smoother. This suggests that DLPSOU_d11 exhibits reduced seasonality as expected. The difference between DLPSOU and DLPSOU_d11 (denoted D_DLPSOU) is plotted in Figure 1F.

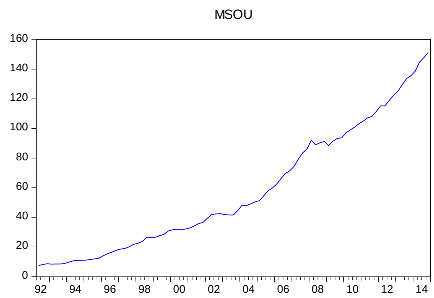
The difference reveals cyclical patterns that range between -0.0073 and 0.0037. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPSOU and DLPSOU_d11 that are reported in table 1G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLPSOU and DLPSOU_d11. Hence, we find that seasonality is not significant in the difference of the log of the price data for South Africa

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of PSOU and DLPSOU in figure 1H and 1I. Shown in Fig. 1H is the ACF for PSOU. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPSOU (see fig. 1I) has no significant ACs at seasonal lags. This implies that seasonality is not significant in the price data and confirms the results of the variance equality tests. Hence, we use the unadjusted data PSOU in our VAR analysis.

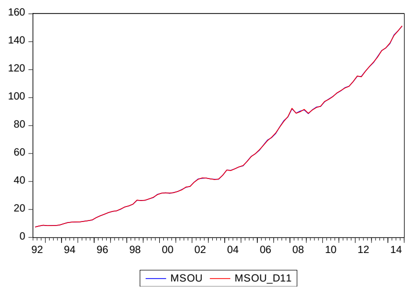
6.9. 2. The seasonality features of money supply in South Africa

We analyse the stationarity and seasonality characteristics of money supply in South Africa. The graphs below depict the following indicators. The South African money supply (denoted MSOU), the seasonally adjusted MSOU series (MSOU_d11) and D_MSOU = MSOU - MSOU_d11, as well as the first (nonseasonal) difference of LMSOU (DLMSOU), the seasonally adjusted LMSOU series (LMSOU_d11) and D_LMSOU = LMSOU - LMSOU_d11 (where LMSOU is the log of MSOU). The seasonally adjusted series (MSOU_d11) is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for MSOU and MSOU_d11 as well as DLMSOU and DLMSOU_d11.

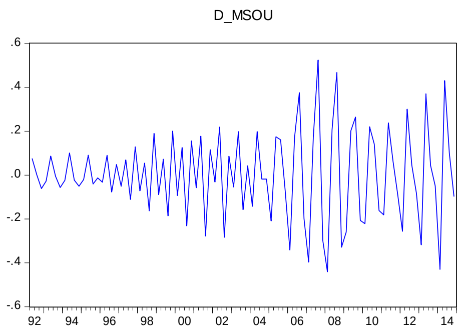
2A.



2B.



2C.

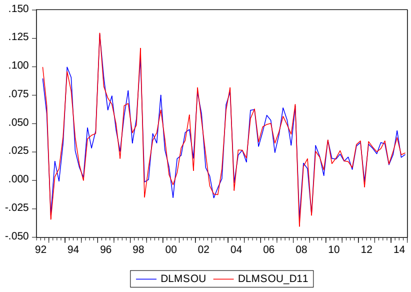


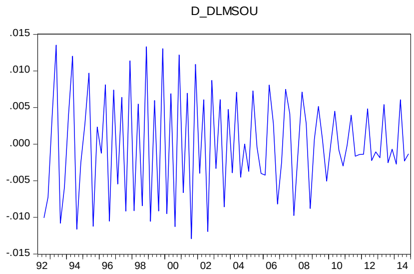
2D.

Equality of variances test between MSOU and MSOU_D11

Method	df	Value	Probability
F-test	(90, 90)	1,000062	0.9998
Siegel-Tukey		0.016884	0.9865
Bartlett	1	8.53E-08	0.9998
Levene	(1, 180	4.19E-08	0.9998
Brown-Forsythe	(1, 180)	3.92E-09	10000

2E. 2F.

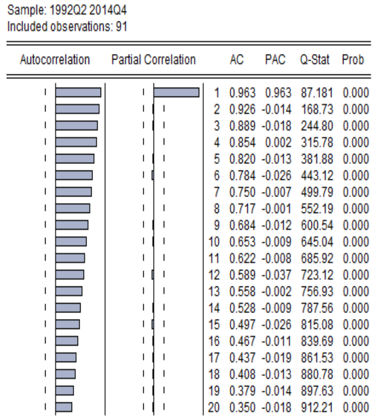




2G. 2H.

Equality of variances test between DMSOU and DMSOU_D11

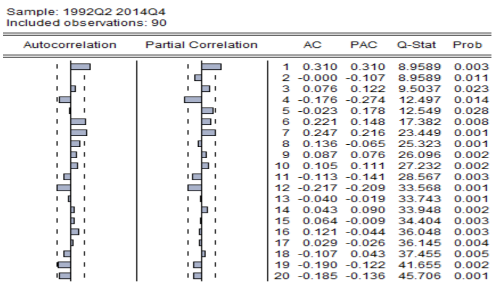
Method	df	Value	Probability
F-test	(89, 89)	1.015700	0.9416
Siegel-Tukey		0.187392	0.8514
Bartlett	1	0.005369	0.9416
Levene	(1,178)	0.006552	0.9356
Brown-Forsythe	(1, 178)	0.002292	0.9619



Sample: 1992Q2 2014Q4
Included observations: 91

	AC	PAC	Q-Stat	Prob
1	0.963	0.963	87.181	0.000
2	0.926	-0.014	168.73	0.000
3	0.889	-0.018	244.80	0.000
4	0.854	0.002	315.78	0.000
5	0.820	-0.013	381.88	0.000
6	0.784	-0.026	443.12	0.000
7	0.750	-0.007	499.79	0.000
8	0.717	-0.001	552.19	0.000
9	0.684	-0.012	600.54	0.000
10	0.653	-0.009	645.04	0.000
11	0.622	-0.008	685.92	0.000
12	0.589	-0.037	723.12	0.000
13	0.558	-0.002	756.93	0.000
14	0.528	-0.009	787.56	0.000
15	0.497	-0.026	815.08	0.000
16	0.467	-0.011	839.69	0.000
17	0.437	-0.019	861.53	0.000
18	0.408	-0.013	880.78	0.000
19	0.379	-0.014	897.63	0.000
20	0.350	-0.018	912.21	0.000

2I.



Sample: 1992Q2 2014Q4
Included observations: 90

	AC	PAC	Q-Stat	Prob
1	0.310	0.310	8.9589	0.003
2	-0.000	-0.107	8.9589	0.011
3	0.076	0.122	9.5037	0.023
4	-0.176	-0.274	12.497	0.014
5	-0.023	0.178	12.549	0.028
6	0.221	0.148	17.382	0.008
7	0.247	0.216	23.449	0.001
8	0.136	-0.065	25.323	0.001
9	0.087	0.076	26.096	0.002
10	0.105	0.111	27.232	0.002
11	-0.113	-0.141	28.567	0.003
12	-0.217	-0.209	33.568	0.001
13	-0.040	-0.019	33.743	0.001
14	0.043	0.090	33.948	0.002
15	0.064	-0.009	34.404	0.003
16	0.121	-0.044	36.048	0.003
17	0.029	-0.026	36.145	0.004
18	-0.107	0.043	37.455	0.005
19	-0.190	-0.122	41.655	0.002
20	-0.185	-0.136	45.706	0.001

As shown in Fig. 2A, the graph of money supply in South Africa (MSOU) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Seasonality is not obvious probably due to the dominant trend.

The time paths of MSOU and MSOU_d11 (see Figure 2B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between MSOU and MSOU_d11 (denoted D_MSOU) is plotted in Figure 2C. The difference has revealed a regular cyclical fluctuation that may indicate time-varying seasonality. To ascertain whether the seasonality is significant we refer to a variety of tests for the equality of variance between MSOU and MSOU_d11 that are reported in table 2D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of MSOU and MSOU_d11. Hence, we find that seasonality is not significant in the level of the data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLMSOU_d11) and unadjusted (DLMSOU) data.

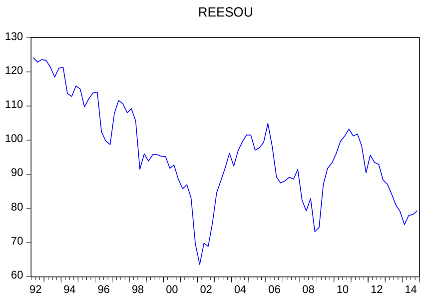
The time paths of DLMSOU and DLMSOU_d11 (see Figure 2E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after first differencing. Therefore, the difference between DLMSOU and DLMSOU_d11 (denoted D_DLMSOU) is plotted in Figure 2F. The difference reveals a regular fluctuation that has a relatively constant mean between -0.0129 and 0.0133. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLMSOU and DLMSOU_d11 that are reported in table 2G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLMSOU and DLMSOU_d11. Hence, we find that seasonality is not significant in the difference of the log of the money supply for South Africa.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of MSOU and DLMSOU in figure 2H and 2I. Shown in Fig. 2H is the ACF for MSOU. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLMSOU (see fig. 2I) has no significant ACs at seasonal lags. This implies that seasonality is not significant in the money supply and confirms the results of the variance equality tests. Hence, we will use the unadjusted data MSOU in our VAR analysis.

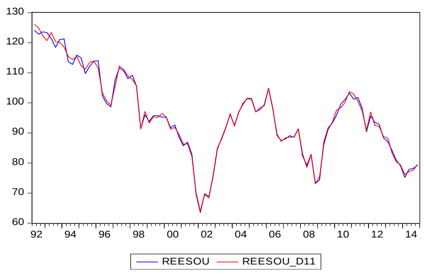
6.9.3. The seasonality features of real effective exchange rate in South Africa

We analyse the stationarity and seasonality characteristics of the real effective exchange rate variable in South Africa. The graphs below depict the following indicators. The South Africa real effective exchange rate (denoted REESOU), the seasonally adjusted REESOU series (REESOU_d11) and D_REESOU = REEESOU- REESOU_d11, as well as the first (nonseasonal) difference of LREESOU (DLREESOU), the seasonally adjusted LREESOU series (LREESOU_d11) and D_LREESOU = LREESOU - LREESOU_d11 (where LREESOU is the log of REESOU). The seasonally adjusted series (REESOU_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for REESOU and REESOU_d11 as well as DLREESOU and DLREESOU_d11.

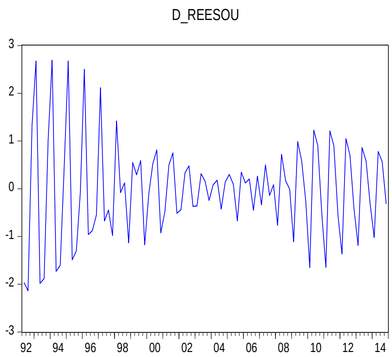
3A.



3B.



3C.

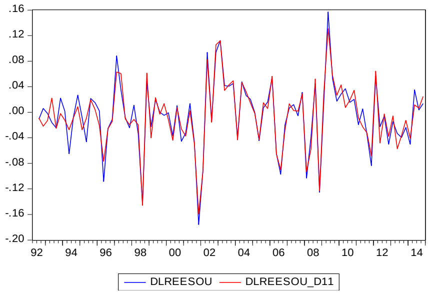


3D.

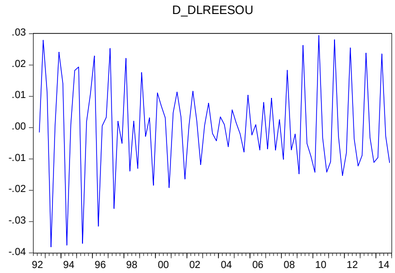
Equality of variances test between REESOU and REESOU_D11

Method	df	Value	Probability
F-test	(90,90)	1.001970	0.9926
Siegel-Tukey		0.115374	0.9081
Bartlett	1	8.67E-05	0.9926
Levene	(1,180)	0.003159	0.9552
Brown-Forsythe	(1,180	0.003634	0.9520

3E.



3F.



3G.

Equality of variances test between DLREESOU and DLREESOU_D11

Method	df	Value	Probability
F-test	(89, 89)	1.097566	0.6615
Siegel-Tukey		0.018596	0.9852
Bartlett	1	0.191688	0.6615
Levene	(1,180)	0.051050	0.8215
Brown-Forsythe	(1,180	0.038009	0.8456

3H.

Sample: 1992Q2 2014Q4
Included observations: 91

	AC	PAC	Q-Stat	Prob
1	0.916	0.916	78.830	0.000
2	0.816	-0.138	142.15	0.000
3	0.723	-0.003	192.49	0.000
4	0.623	-0.114	230.21	0.000
5	0.527	-0.017	257.54	0.000
6	0.447	0.027	277.45	0.000
7	0.373	-0.028	291.50	0.000
8	0.297	-0.071	300.53	0.000
9	0.243	0.078	306.64	0.000
10	0.184	-0.111	310.16	0.000
11	0.131	0.025	311.97	0.000
12	0.098	0.053	313.00	0.000
13	0.080	0.043	313.70	0.000
14	0.062	-0.030	314.12	0.000
15	0.039	-0.062	314.29	0.000
16	0.033	0.072	314.42	0.000
17	0.056	0.188	314.77	0.000
18	0.083	-0.001	315.57	0.000
19	0.120	0.083	317.27	0.000
20	0.136	-0.158	319.48	0.000

3I.

Sample: 1992Q2 2014Q4
Included observations: 90

	AC	PAC	Q-Stat	Prob
1	0.155	0.155	2.2260	0.136
2	-0.073	-0.099	2.7214	0.256
3	0.077	0.108	3.2804	0.350
4	-0.041	-0.083	3.4393	0.487
5	-0.127	-0.093	5.0204	0.413
6	-0.062	-0.045	5.3948	0.494
7	0.017	0.025	5.4240	0.608
8	-0.100	-0.106	6.4426	0.598
9	0.077	0.125	7.0524	0.632
10	-0.118	-0.214	8.4849	0.582
11	-0.152	-0.063	10.902	0.452
12	-0.096	-0.134	11.878	0.456
13	0.015	0.063	11.902	0.536
14	0.057	0.029	12.259	0.586
15	-0.163	-0.202	15.202	0.437
16	-0.094	-0.122	16.197	0.439
17	-0.053	-0.083	16.515	0.488
18	-0.084	-0.121	17.327	0.501
19	0.039	0.103	17.501	0.556
20	0.031	-0.105	17.615	0.613

From Figure 3A, the graph of real effective exchange rate for South Africa (REESOU) exhibits a downward trend that plateaus at the end of the sample. Seasonality is not expected in the real effective exchange rate data and is not visible in this graph, although seasonality may be revealed once the trend is removed through differencing.

The time paths of REESOU and REESOU_d11 (see Figure 3B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between REESOU and REESOU_d11 (denoted D_REESOU) is plotted in Figure 3C. The difference reveals cyclical fluctuations that may indicate time-varying seasonality. To ascertain whether this seasonality is significant we refer to a variety of tests for the equality of variance between REESOU and REESOU_d11 that are reported in table 3D. The p-value of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REESOU and REESOU_d11. Hence, we find that seasonality is not significant in the level of the data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLREESOU_d11) and unadjusted (DLREESOU) data.

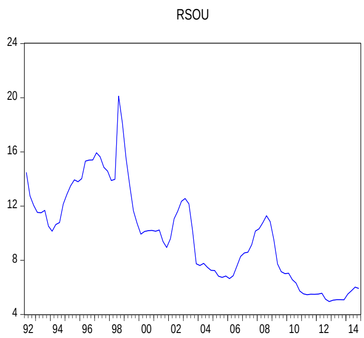
The time paths of DLREESOU and DLREESOU_d11 (see Figure 3E) follow each other closely and the difference between DLREESOU and DLREESOU_d11 (denoted D_DLREESOU) is plotted in Figure 3F. The difference has revealed fluctuations around a relatively constant mean. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREESOU and DLREESOU_d11 that are reported in table 3G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLREESOU and DLREESOU_d11 and hence find that seasonality is not significant in the difference of the log of the real effective exchange rate data for South Africa.

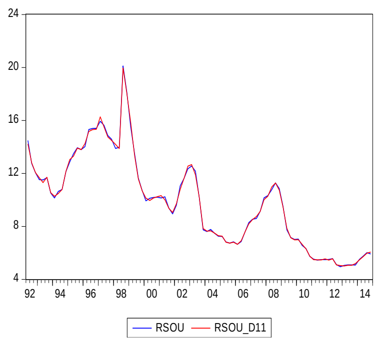
To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of REESOU and DLREESOU in figure 3H and 3I. Shown in Fig. 3H is the ACF for REESOU. The first 9 consecutive autocorrelation coefficients (ACs) lags are significant (and not just at the seasonal lags) which suggests nonstationarity and not seasonality. The ACF for DLREESOU (see fig. 3I) has no significant ACs at seasonal lags. This implies that seasonality is not significant in the real effective exchange rate and confirms the results of the variance equality tests. Hence, we use the unadjusted data REESOU in our VAR analysis.

6.9.4. The seasonality features of interest rate in South Africa

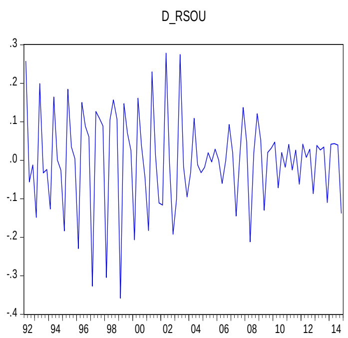
We analyse the stationarity and seasonality characteristics of the interest rate in South Africa. The graphs below depict the following indicators. The South African interest rate (denoted RSOU), the seasonally adjusted RSOU series (RSOU_d11) and D_RSOU = RSOU - RSOU_d11, as well as the first (nonseasonal) difference of RSOU (DRSOU). The seasonally adjusted series (RSOU_d11) is obtained using the Census X13 procedure in EViews. Tables 4D and 4G report various tests of the null hypothesis of equality of variance for RSOU and RSOU_d11 as well as DSOU and DRSOU_d11.

4A. **4B.**





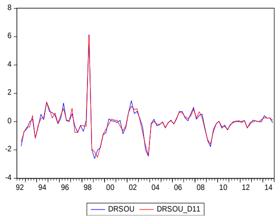
4C. **4D.**



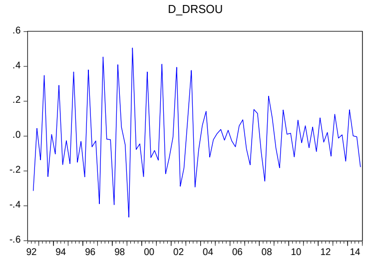
Equality of variances test between RSOU and RSOU_D11

Method	df	Value	Probability
F-test	(90, 90)	1.004577	0.9828
Siegel-Tukey		0.039396	0.9686
Bartlett	1	0.000467	0.9828
Levene	(1,180)	0.001532	0.9688
Brown-Forsythe	(1, 180)	0.000743	0.9783

4E.



4F

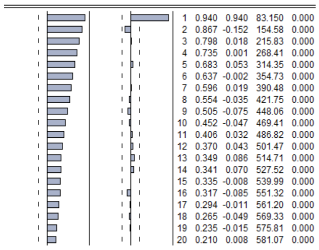


4G.

Equality of variances test between DRSOU and DRSOU_D11

Method	df	Value	Probability
F-test	(89, 89)	1.053763	0.8054
Siegel-Tukey		0.399103	0.6898
Bartlett	1	0.060669	0.8054
Levene	(1, 178)	0.003641	0.9519
Brown-Forsythe	(1,178)	0.000606	0.9804

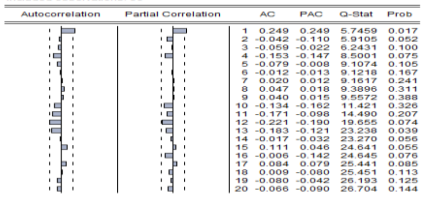
4H.



Sample: 1992Q2 2014Q4
Included observations: 91

	AC	PAC	Q-Stat	Prob
1	0.940	0.940	83.150	0.000
2	0.867	-0.152	154.58	0.000
3	0.798	0.018	215.83	0.000
4	0.735	0.001	268.41	0.000
5	0.683	0.053	314.35	0.000
6	0.637	-0.002	354.73	0.000
7	0.596	0.019	390.48	0.000
8	0.554	-0.035	421.75	0.000
9	0.505	-0.075	448.06	0.000
10	0.452	-0.047	469.41	0.000
11	0.406	0.032	486.82	0.000
12	0.370	0.043	501.47	0.000
13	0.349	0.086	514.71	0.000
14	0.341	0.070	527.52	0.000
15	0.335	-0.008	539.99	0.000
16	0.317	-0.085	551.32	0.000
17	0.294	-0.011	561.20	0.000
18	0.265	-0.049	569.33	0.000
19	0.235	-0.015	575.81	0.000
20	0.210	0.008	581.07	0.000

4I.



Sample: 1992Q2 2014Q4
Included observations: 90

	AC	PAC	Q-Stat	Prob
1	0.249	0.249	5.7459	0.017
2	-0.042	-0.110	5.9105	0.052
3	-0.059	-0.022	6.2431	0.100
4	-0.153	-0.147	8.5001	0.075
5	-0.079	-0.008	9.1074	0.105
6	-0.012	-0.013	9.1218	0.167
7	0.020	0.012	9.1617	0.241
8	0.047	0.018	9.3896	0.311
9	0.040	0.015	9.5572	0.388
10	-0.134	-0.162	11.421	0.326
11	-0.171	-0.098	14.490	0.207
12	-0.221	-0.190	19.655	0.074
13	-0.183	-0.121	23.238	0.039
14	-0.017	-0.032	23.270	0.056
15	0.111	0.046	24.641	0.055
16	-0.006	-0.142	24.645	0.076
17	0.084	0.079	25.441	0.085
18	0.009	-0.080	25.451	0.113
19	-0.080	-0.042	26.193	0.125
20	-0.066	-0.090	26.704	0.144

As shown in Fig. 4A, the interest rate series (RSOU) exhibits a downward trend. Seasonality is not visible in the interest rate plot because of the dominant trend.

The time paths of RSOU and RSOU_d11 (see Figure 4B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between RSOU and RSOU_d11 (denoted D_RSOU) is plotted in Figure 2C. The difference has revealed fluctuations around a relatively constant mean. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between RSOU and RSOU_d11 that are reported in table 4D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RSOU and RSOU_d11 and hence we find that seasonality is not significant in the level of the data. However, because this result may be influenced by the trend in the data we compare the differences of the adjusted (DRSOU_d11) and unadjusted (DRSOU) data.

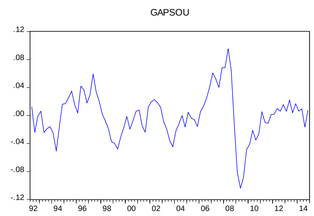
The time paths of DRSOU and DRSOU_d11 (see Figure 4E) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Hence, the difference between DRSOU and DRSOU_d11 (denoted D_DRSOU) is plotted in Figure 4F. The difference has revealed cyclical patterns. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between (DRSOU) and (DRSOU_d11) that are reported in table 4G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DRSOU and DRSOU_d11. Hence, we find that seasonality is not significant in the difference of interest rate data for South Africa.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of RSOU and DRSOU in figure 4H and 4I. Shown in Fig. 4H is the ACF for RSOU. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DRSOU (see fig. 4I) has no significant ACs at seasonal lags. This implies that seasonality is not significant in the interest rate and confirms the results of the variance equality tests. Hence, we use the unadjusted data RSOU in our VAR analysis.

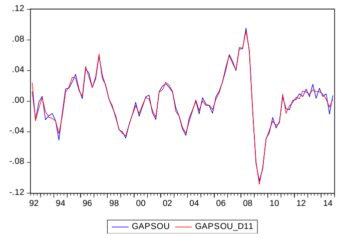
6.9.5. The seasonality features of output gap in South Africa

We analyse the stationarity and seasonality characteristics of the output gap variable in Russia. The graphs below depict the following indicators. The output gap (denoted GAPSOU), the seasonally adjusted GAPSOU series (GAPSOU_d11) and D_GAPSOU = GAPSOU - GAPSOU_d11, as well as the first (nonseasonal) difference of GAPSOU (DGAPSOU). The seasonally adjusted series (GAPSOU_d11) is obtained using the Census X13 procedure in EViews. Tables 5D and 5G report various tests of the null hypothesis of equality of variance for GAPSOU and GAPSOU_d11 as well as DGAPSOU and DGAPSOU_d11.

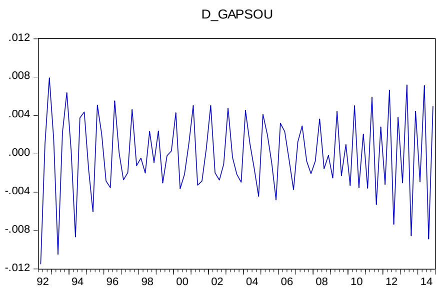
5A.



5B.



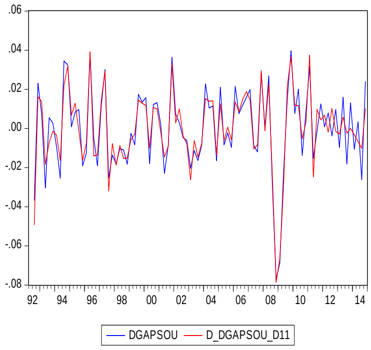
5C.



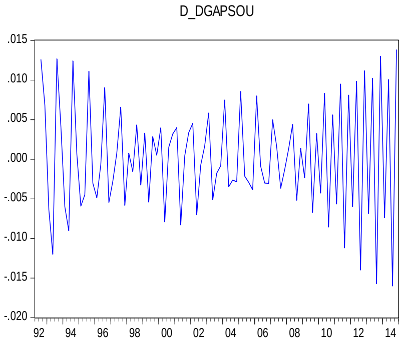
5D.

Method	Df	Value	Probability
F-test	(90, 90)	1.0153	0.9426
Siegel- Tukey		0.1603	0.8726
Bartlett	1	0.0051	0.9426
Levene	(1, 180)	0.0078	0.9299
Brown- Forythe	(1, 180)	0.0063	0.9369

5E



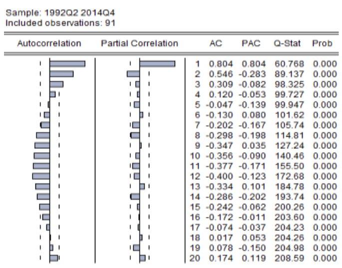
5F



5G

Method	Df	Value	Probability
F-test	(89, 89)	1.1236	0.5835
Siegel-Tukey		1.5893	0.1120
Bartlett	1	0.3007	0.5835
Levene	(1,178)	0.9395	0.3337
Brown-Forythe	(1, 178)	0.9742	0.3250

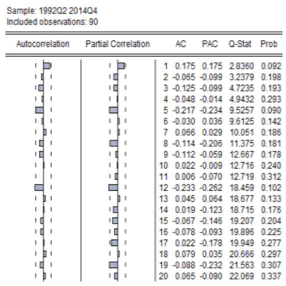
5I.



Sample: 1992Q2 2014Q4
Included observations: 91

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.804	0.804	60.768	0.000
		2	0.546	-0.283	89.137	0.000
		3	0.309	-0.082	98.325	0.000
		4	0.120	-0.053	99.727	0.000
		5	-0.047	-0.139	99.947	0.000
		6	-0.130	0.080	101.62	0.000
		7	-0.202	-0.167	105.74	0.000
		8	-0.298	-0.198	114.81	0.000
		9	-0.347	0.035	127.24	0.000
		10	-0.356	-0.090	140.46	0.000
		11	-0.377	-0.171	155.50	0.000
		12	-0.400	-0.123	172.68	0.000
		13	-0.334	0.101	184.78	0.000
		14	-0.286	-0.202	193.74	0.000
		15	-0.242	-0.062	200.26	0.000
		16	-0.172	-0.011	203.60	0.000
		17	-0.074	-0.037	204.23	0.000
		18	0.017	0.053	204.26	0.000
		19	0.078	-0.150	204.98	0.000
		20	0.174	0.119	208.59	0.000

5J.



Sample: 1992Q2 2014Q4
Included observations: 90

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.175	0.175	2.8360	0.092
		2	-0.065	-0.099	3.2379	0.198
		3	-0.125	-0.099	4.7235	0.193
		4	-0.048	-0.014	4.9432	0.293
		5	-0.217	-0.234	9.5257	0.090
		6	-0.030	0.036	9.6125	0.142
		7	0.066	0.029	10.051	0.186
		8	-0.114	-0.206	11.375	0.181
		9	-0.112	-0.059	12.667	0.178
		10	0.022	-0.009	12.716	0.240
		11	0.006	-0.070	12.719	0.312
		12	-0.233	-0.262	18.459	0.102
		13	0.045	0.064	18.677	0.133
		14	0.019	-0.123	18.715	0.176
		15	-0.067	-0.146	19.207	0.204
		16	-0.078	-0.093	19.896	0.225
		17	0.022	-0.178	19.949	0.277
		18	0.079	0.035	20.666	0.297
		19	-0.088	-0.232	21.563	0.307
		20	0.065	-0.090	22.069	0.337

From the figure 5A the series of the output gap exhibit clear cycles that appear to be of a one-year fixed length and therefore probably reflect seasonality. Therefore, GAPSOU may need to be seasonally adjusted.

The time paths of GAPSOU and GAPSOU_d11 are given in Figure 5B. Seasonality is obvious in GAPSOU and the GAPSOU_ d11 is substantially smoother than the GAPSOU. This suggests that GAPSOU_d11 exhibits reduced seasonality.

The differences between GAPSOU and GAPSOU_d11 (denoted D_GAPSOU) is plotted in Figure 5C. The difference reveals a regular cyclical fluctuation that ranges between -0.0115 and 0.0079. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between GAPSOU and GAPRSOU_d11 that are reported in table 5D. The p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of GAPSOU and GAPSOU_d11 and hence find that seasonality is not significant in the level of the output-gap data. To explore this further, we compare the differences of the adjusted (DGAPSOU_d11) and unadjusted (DGAPSOU) data.

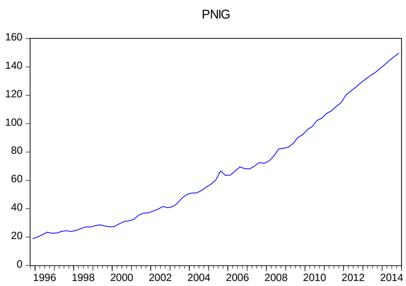
The time paths of DGAPSOU and DGAPSOU_d11 (see Figure 5E) follow each other. DGAPSOU_ d11 is notably smoother than the DGAPSOU suggesting evidence of seasonality in DGAPSOU. Hence, the difference between DGAPSOU and DGAPSOU_d11 (denoted D_DGAPSOU) is plotted in Figure 5F. The difference has revealed a regular cyclical fluctuation that ranges between -0.0160and 0.0139. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DGAPSOU and DGAPSOU_d11 that are reported in table 5G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DGAPSOU and DGAPSOU_d11. Hence, we find that seasonality is not significant in the difference of the output gap rate for South Africa

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of GAPSOU and DGAPSOU in figure 5H and 5I. Shown in Fig. 5H is the ACF for GAPSOU. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DGAPSOU (see fig. 5I) has significant ACs at seasonal lags (lag 12). This implies that seasonality is not significant in the output gap and confirms the results of the variance equality tests. Hence, we will use the unadjusted data GAPSOU in our VAR analysis.

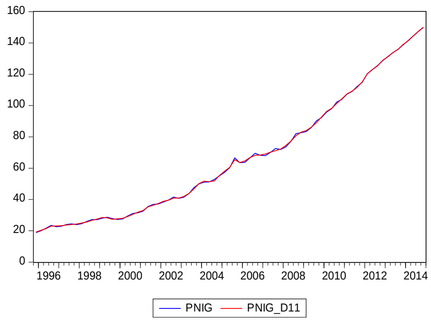
6.10.1 The graphical features of selected macroeconomic variables for Nigeria

Following the sample identified in previous section for Nigeria (Table 6.4.5) we analyse the stationarity and seasonality characteristics of the selected macroeconomic variables. The graphs below depict the following indicators. The Nigerian consumer price (denoted PNIG), the seasonally adjusted PNIG series (PNIG_d11) and D_PNIG = PNIG - PNIG_d11, as well as the first (nonseasonal) difference of LPNIG (DLPNIG), the seasonally adjusted LPNIG series (LPNIG_d11) and D_LPNIG = LPNIG - LPNIG_d11 (where LPNIG is the log of PNIG). The seasonally adjusted series (PNIG_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PNIG and PNIG_d11 as well as DLPNIG and DLPNIG_d11.

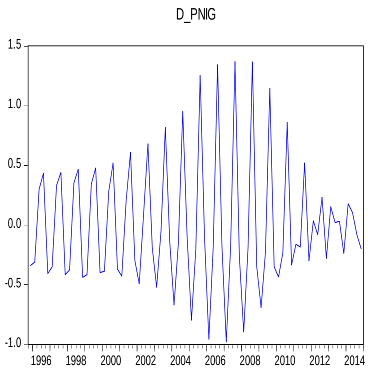
1A.



1B.



1C.

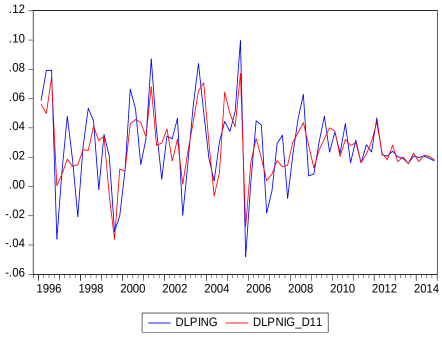


1D.

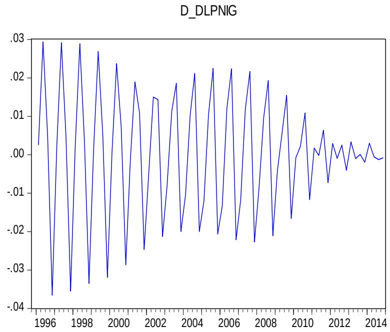
Equality of variances test between PNIG and PNIG_D11

Method	Df	Value	Probability
F-test	(76, 76)	1.000278	0.9990
Siegel- Tukey		0.028908	0.9769
Bartlett	1	1.46E-06	0.9990
Levene	(1, 152)	2.99E-05	0.9956
Brown-Forsythe	(1, 152)	2.11E-05	0.9963

1E.



1F.



1G.

Equality of variances test between DLPNIG and DLPNIG_D11

Method	Df	Value	Probability
F-test	(75, 75)	1.876686	0.0070
Siegel-Tukey		1.833261	0.0668
Bartlett	1	7.262292	0.0070
Levene	(1, 150)	4.987547	0.0270
Brown-Forsythe	(1, 150)	4.729435	0.0312

1H.

ample: 1995Q4 2014Q4
ncluded observations: 77

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.959	0.959	73.613	0.000
		2	0.918	-0.021	141.96	0.000
		3	0.878	-0.012	205.30	0.000
		4	0.838	-0.012	263.85	0.000
		5	0.798	-0.034	317.63	0.000
		6	0.757	-0.022	366.77	0.000
		7	0.717	-0.023	411.44	0.000
		8	0.676	-0.025	451.78	0.000
		9	0.635	-0.034	487.88	0.000
		10	0.594	-0.019	519.96	0.000
		11	0.554	-0.018	548.28	0.000
		12	0.515	-0.019	573.08	0.000
		13	0.477	-0.004	594.71	0.000
		14	0.440	-0.018	613.37	0.000
		15	0.403	-0.014	629.33	0.000
		16	0.366	-0.034	642.70	0.000
		17	0.329	-0.024	653.71	0.000
		18	0.292	-0.031	662.52	0.000
		19	0.258	-0.000	669.49	0.000
		20	0.224	-0.019	674.83	0.000

1I

Sample: 1995Q4 2014Q4
Included observations: 76

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.129	0.129	1.3174	0.251
		2	-0.352	-0.375	11.228	0.004
		3	-0.118	-0.008	12.353	0.006
		4	0.289	0.212	19.232	0.001
		5	-0.079	-0.257	19.748	0.001
		6	-0.286	-0.093	26.685	0.000
		7	-0.038	-0.009	26.808	0.000
		8	0.329	0.161	36.217	0.000
		9	-0.019	-0.119	36.249	0.000
		10	-0.225	-0.020	40.795	0.000
		11	-0.045	-0.024	40.984	0.000
		12	0.273	0.096	47.869	0.000
		13	-0.043	-0.096	48.043	0.000
		14	-0.274	-0.101	55.238	0.000
		15	-0.203	-0.215	59.246	0.000
		16	0.160	-0.026	61.782	0.000
		17	0.016	-0.084	61.806	0.000
		18	-0.156	-0.075	64.304	0.000
		19	0.016	0.080	64.332	0.000
		20	0.310	0.077	74.480	0.000

As shown in Fig. 1A, the graph of consumer prices for Nigeria (PNIG) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing.

The time paths of PNIG and PNIG_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between PNIG and PNIG_d11 (denoted D_PNIG) is plotted in Figure 1C. The difference has revealed cyclical fluctuations that range between -0.98 and 1.37.

Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PNIG and PNIG_d11 that are reported in table 1D. Since the p-values of all of our tests are greater than 0.05 we cannot reject the null hypothesis and find that there is no significant difference in the variances of PNIG and PNIG_d11. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the logs of the adjusted (DLPNIG_d11) and unadjusted (DLPNIG) data.

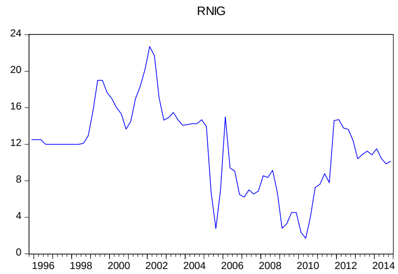
The time paths of DLPNIG and DLPNIG_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuate around a constant mean as expected after first differencing. The variation in DLPNIG is greater than that of DLPNIG_d11 suggesting seasonality in DLPNIG while DLPNIG_d11 is smoother. This suggests that DLPNIG_ d11 exhibits reduced seasonality as expected. The difference between DLPNIG and DLPNIG_d11 (denoted D_DLPNIG) is plotted in Figure 1F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.037 and 0.029. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPNIG and DLPNIG_d11 that are reported in table 1G. The p-values for Levene, Brown Forsythe, F-test and Bartlett test tests are less than 0.05 indicating unequal variances while the p-value of Siegel Tukey test is greater than 0.05 which cannot reject the null hypothesis of variance equality. Hence, the results regarding equality of variance are ambiguous, however, they generally suggest unequal variances and, hence, that the series is seasonal.

To examine this further we plot the autocorrelation functions (ACFs) of PNIG and DLPNIG in figure 1H and 1I. Shown in Fig. 1H is the ACF for PNIG. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPNIG (see fig. 1I) has significant ACs at the seasonal lags 4, 8 12 and 20 (if the AC at lag 16 is insignificant). This provides clear evidence that there is significant seasonality in the price data. Overall, the vast majority of the tests suggest that PNIG is seasonal and so we will use the adjusted data PNIG_d11 in our VAR analysis.

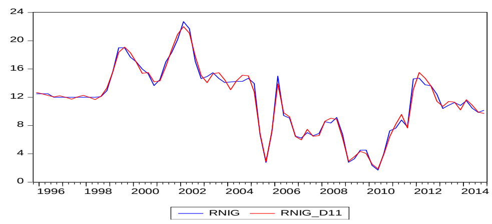
6.10. 2. The seasonality features of interest rate in Nigeria

The graphs below depict the following variables. The Nigeria interest rate (denoted RNIG), the seasonally adjusted RNIG series (RNIG_d11), D_RNIG = RNIG – RNIG_d11, and the first (nonseasonal) difference of RNIG (DRNIG). The seasonally adjusted series RNIG_d11 is obtained using the Census X13 procedure in EViews. Table 2D reports various variance equality tests for RNIG and RNIG_d11 while Table 2G reports these tests for variance equality for DRNIG and DRNIG_d11.

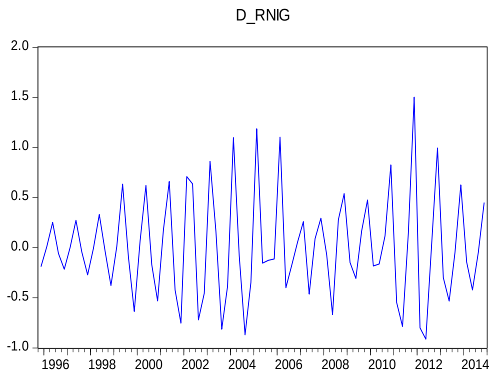
2A.



2B.



2C.

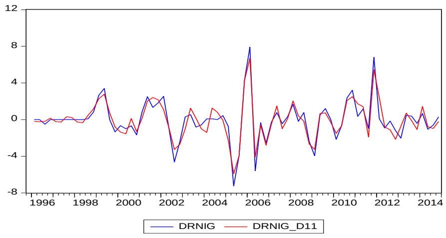


2D.

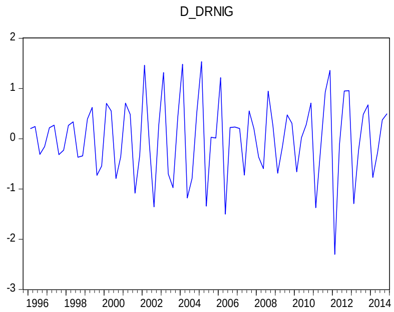
Equality of variances test between RNIG and RNIG_D11

Method	Df	Value	Probability
F-test	(76, 76)	1.006030	0.9792
Siegel-Tukey		0.090345	0.9280
Bartlett	1	0.000682	0.9792
Levene	(1, 152)	0.007945	0.9291
Brown-Forsythe	(1, 152)	0.001386	0.9704

2E.



2F.



2G.

Equality of variances test between DRNIG and DRNIG_D11

Method	Df	Value	Probability
F-test	(75, 75)	1.208488	0.4141
Siegel-Tukey		1.450302	0.1470
Bartlett	1	0.666948	0.4141
Levene	(1, 150)	0.086921	0.7685
Brown-Forsythe	(1, 150)	0.073548	0.7866

2H.

Sample: 1995Q4 2014Q4
ncluded observations: 77

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.886	0.886	62.893	0.000
		2	0.738	-0.225	107.01	0.000
		3	0.648	0.231	141.58	0.000
		4	0.613	0.112	172.93	0.000
		5	0.570	-0.073	200.39	0.000
		6	0.519	0.053	223.48	0.000
		7	0.473	0.004	242.94	0.000
		8	0.453	0.084	260.99	0.000
		9	0.428	-0.049	277.41	0.000
		10	0.396	0.013	291.66	0.000
		11	0.339	-0.122	302.25	0.000
		12	0.250	-0.183	308.12	0.000
		13	0.184	0.072	311.32	0.000
		14	0.152	-0.017	313.55	0.000
		15	0.138	0.025	315.40	0.000
		16	0.090	-0.151	316.21	0.000
		17	0.040	0.054	316.37	0.000
		18	0.012	-0.008	316.39	0.000
		19	-0.030	-0.204	316.48	0.000
		20	-0.112	-0.115	317.83	0.000

2I.

Sample: 1995Q4 2014Q4
Included observations: 76

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.155	0.155	1.9087	0.167
		2	-0.263	-0.295	7.4617	0.024
		3	-0.234	-0.152	11.917	0.008
		4	0.034	0.028	12.011	0.017
		5	0.035	-0.087	12.114	0.033
		6	-0.023	-0.043	12.160	0.058
		7	-0.114	-0.118	13.281	0.066
		8	0.023	0.031	13.328	0.101
		9	0.041	-0.043	13.473	0.142
		10	0.113	0.096	14.614	0.147
		11	0.141	0.150	16.432	0.126
		12	-0.097	-0.120	17.310	0.138
		13	-0.191	-0.062	20.745	0.078
		14	-0.082	-0.058	21.383	0.092
		15	0.143	0.085	23.366	0.077
		16	0.009	-0.110	23.373	0.104
		17	-0.107	-0.054	24.522	0.106
		18	0.054	0.140	24.825	0.130
		19	0.179	0.049	28.173	0.080
		20	-0.074	-0.147	28.751	0.093

As shown in Fig. 2A seasonality is not clearly visible in the Nigeria interest rate plot. The time paths of RNIG and RNIG_d11 (see Figure 2B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. We plot the difference between RNIG and RNIG_d11 (denoted D_RNIG) in Figure 2C to further assess whether RNIG is seasonal. The difference indicates time-varying cycles. We refer to a variety of tests for the equality of variance between RNIG and RNIG_d11 that are reported in table 2D. Since the p-values of all of our tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RNIG and RNIG_d11. Hence, we find that seasonality is not significant in the level of the data. However, because this result may be influenced by persistence in the data we compare the differences of the adjusted (DRNIG_d11) and unadjusted (DRNIG) data.

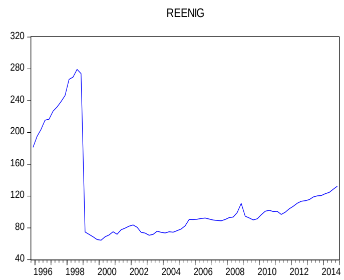
The time paths of DRNIG and DRNIG_d11 (see Figure 2E) follow each other closely. The difference between DRNIG and DRNIG_d11 (denoted D_DRNIG) is plotted in Figure 2F. The difference has revealed a cyclical pattern. Variance equality tests between DRNIG and DRNIG_d11 are reported in Table 2G. The p-values for all the tests are greater than 0.05 therefore we cannot reject the null hypothesis and find that there is no significant difference in the variances of DRNIG and DRNIG_d11. Hence, we find that seasonality is not significant in the difference of the data.

To explore the issue further we plot the ACFs of RNIG and DRNIG in figure 2H and 2I, respectively. Shown in Fig. 2H is the ACF for RNIG. The first 12 autocorrelation coefficients ACs are significant (and not just at the seasonal lags) which suggests nonstationarity and not seasonality. The ACF for DRNIG (see fig. 2I) has no significant AC at any of the seasonal lags. This implies that seasonality is not significant in the interest rate and confirms the results of the variance equality tests. Hence, we will use the unadjusted data RNIG in our VAR analysis.

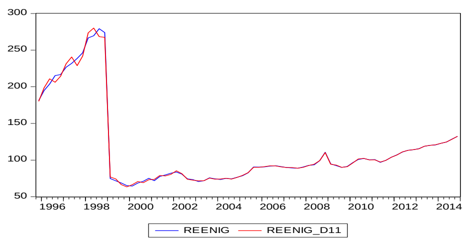
6.10.3. The seasonality features real effective exchange rate in Nigeria

The graphs below depict the following variables. The Nigerian real effective exchange (denoted REENIG), the seasonally adjusted REENIG series (REENIG_d11) and D_REENIG = REENIG - REENIG_d11, as well as the first (nonseasonal) difference of LREENIG (DLREENIG), the seasonally adjusted LREENIG series (LREENIG_d11) and D_LREENIG = LREENIG - LREENIG_d11 (where LREENIG is the log of REENIG). The seasonally adjusted series (REENIG_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for REENIG and REENIG_d11 as well as DLREENIG and DLREENIG_d11.

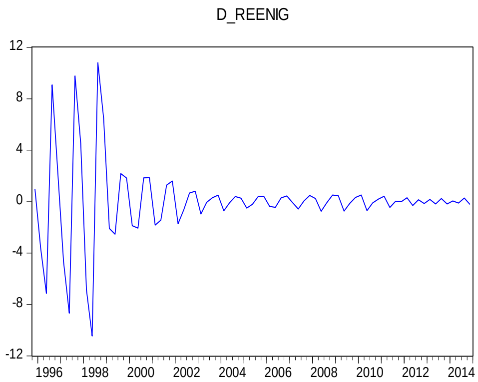
3A.



3B.



3C.

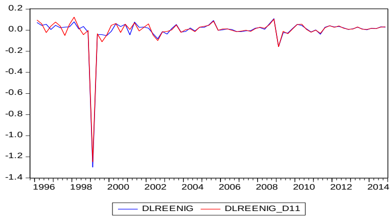


3D.

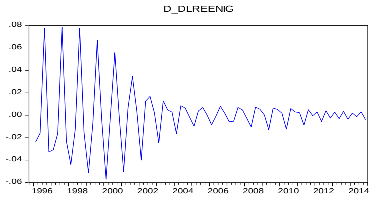
Equality of variances test between REENIG and REENIG_D11

Method	Df	Value	Probability
F-test	(76, 76)	1.003588	0.9876
Siegel-Tukey		0.007227	0.9942
Bartlett	1	0.000242	0.9876
Levene	(1, 150)	0.000112	0.9916
Brown-Forsythe	(1, 150)	5.19E-05	0.9943

3E.



3F.

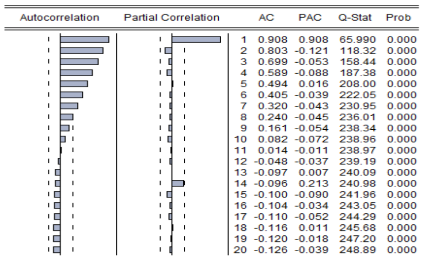


3G.

Equality of variances test between DLREENIG and DLREENIG_D11

Method	Df	Value	Probability
F-test	(75, 75)	1.057118	0.8106
Siegel-Tukey		0.738832	0.4600
Bartlett	1	0.057561	0.8106
Levene	(1, 150)	0.005465	0.9412
Brown-Forsythe	(1, 150)	0.018065	0.8933

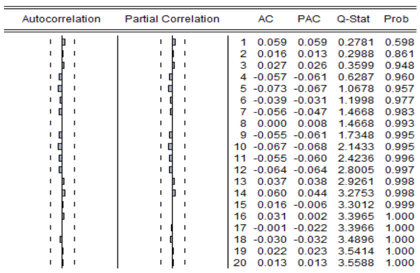
3H.



Sample: 1995Q4 2014Q4
Included observations: 77

	AC	PAC	Q-Stat	Prob
1	0.908	0.908	65.990	0.000
2	0.803	-0.121	118.32	0.000
3	0.699	-0.053	158.44	0.000
4	0.589	-0.088	187.38	0.000
5	0.494	0.016	208.00	0.000
6	0.405	-0.039	222.05	0.000
7	0.320	-0.043	230.95	0.000
8	0.240	-0.045	236.01	0.000
9	0.161	-0.054	238.34	0.000
10	0.082	-0.072	238.96	0.000
11	0.014	-0.011	238.97	0.000
12	-0.048	-0.037	239.19	0.000
13	-0.097	0.007	240.09	0.000
14	-0.096	0.213	240.98	0.000
15	-0.100	-0.090	241.96	0.000
16	-0.104	-0.034	243.05	0.000
17	-0.110	-0.052	244.29	0.000
18	-0.116	0.011	245.68	0.000
19	-0.120	-0.018	247.20	0.000
20	-0.126	-0.039	248.89	0.000

3I.



Sample: 1995Q4 2014Q4
Included observations: 76

	AC	PAC	Q-Stat	Prob
1	0.059	0.059	0.2781	0.598
2	0.016	0.013	0.2988	0.861
3	0.027	0.026	0.3599	0.948
4	-0.057	-0.061	0.6287	0.960
5	-0.073	-0.067	1.0678	0.957
6	-0.039	-0.031	1.1998	0.977
7	-0.056	-0.047	1.4668	0.983
8	0.000	0.008	1.4668	0.993
9	-0.055	-0.061	1.7348	0.995
10	-0.067	-0.068	2.1433	0.995
11	-0.055	-0.060	2.4236	0.996
12	-0.064	-0.064	2.8005	0.997
13	0.037	0.038	2.9261	0.998
14	0.060	0.044	3.2753	0.998
15	0.016	-0.006	3.3012	0.999
16	0.031	0.002	3.3965	1.000
17	-0.001	-0.022	3.3966	1.000
18	-0.030	-0.032	3.4896	1.000
19	0.022	0.023	3.5414	1.000
20	0.013	0.013	3.5588	1.000

As shown in Fig. 3A, the graph of the real effective exchange rate for Nigeria exhibits a step shift at the beginning of the sample. The time paths of REENIG and REENIG_d11 (see Figure 3B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between REENIG and REENIG_d11 (denoted D_REENIG) is plotted in Figure 3C. The difference has revealed a cyclical fluctuation that drastically declines over time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between REENIG and REENIG_d11 that are reported in table 3D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REENIG and REENIG_d11. Hence, we find that seasonality is not significant in the level of the real effective exchange rate. However, because this result may be influenced by the persistence of the data, we compare the differences of the adjusted (DLREENIG_d11) and unadjusted (DLREENIG) data.

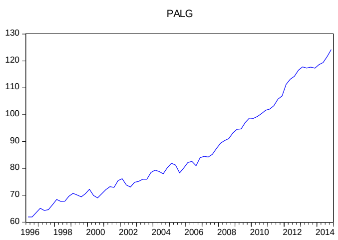
The time paths of DLREENIG and DLREENIG_d11 (see Figure 3E) follow each other closely. The first difference has removed the trend and gives a relatively constant mean process. The variation in DLREENIG is greater than that of DLREENIG_D11 suggesting seasonality in DLREENIG while DLREENIG_D11 is smoother. This suggests that DLREENIG_D11 exhibits reduced seasonality as expected. The differences between DLREENIG and DLREENIG_d11 (denoted D_DLREENIG) is plotted in Figure 3F. The difference reveals cyclical fluctuation that drastically decreases over time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREENIG and DLREENIG_d11 that are reported in table 3G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLREENIG and DLREENIG_d11. Hence, we find that seasonality is not significant in the difference of the log of the real effective exchange rate data for Nigeria.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of REENIG and DLREENIG in figure 3H and 3I. Shown in Fig. 3H is the ACF for REENIG. The first 8 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity (or persistence, possibly due to the step shift in the data) and not seasonality. The ACF for DLREENIG has no significant ACs at seasonal lags (see fig. 3I). This implies that seasonality is not significant in the real effective exchange rate and confirms the results of the variance equality tests. Hence, we will use the unadjusted data REENIG in our VAR analysis.

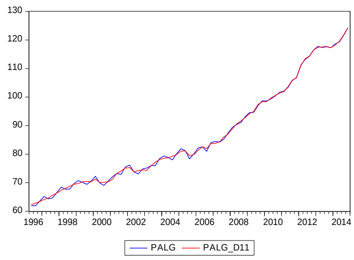
6.11.1 The graphical features of selected macroeconomic variables for Algeria

Following the sample identified in previous section (Table 6.4.6) for Algeria (1996q2 – 2014q4) we analyse the stationarity and seasonality characteristics of the selected macroeconomic variables. The graphs below depict the following indicators. The Algerian consumer price (denoted PALG), the seasonally adjusted PALG series (PALG_d11) and D_PALG = PALG - PALG_d11, as well as the first (nonseasonal) difference of LPALG (DLPALG), the seasonally adjusted LPALG series (LPALG_d11) and D_LPALG = LPALG - LPALG_d11 (where LPALG is the log of PALG). The seasonally adjusted series (PALG_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PALG and PALG_d11 as well as DLPALG and DLPALG_d11.

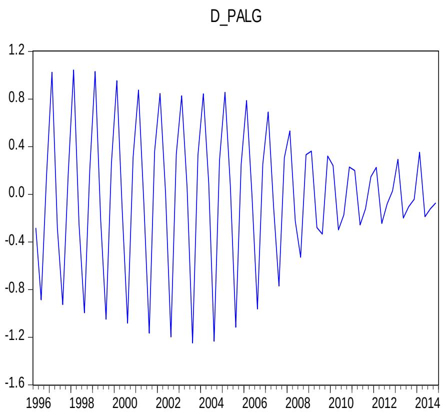
1A.



1B.



1C.

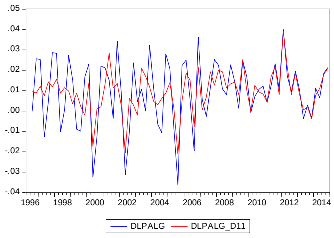


1D.

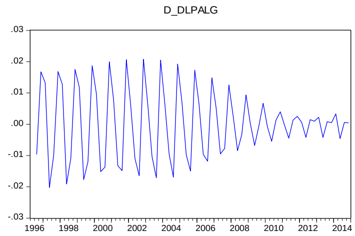
Equality of variances test between PALG and PALG_D11

Method	Df	Value	Probability
F-test	(74, 74)	1.002026	0.9931
Siegel-Tukey		0.045	0.9640
Bartlett	1	7.52E-05	0.9931
Levene	(1, 148)	0.000106	0.9918
Brown-Forsythe	(1,148)	0.000448	0.9831

1E.



1F.

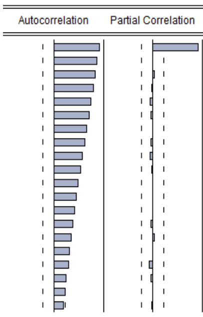


1G.

Equality of variances test between DLPALG and DLPALG_D11

Method	Df	Value	Probability
F-test	(73, 73)	2.576967	0.0001
Siegel-Tukey		3.764056	0.0002
Bartlett	1	15.6696	0.0001
Levene	(1, 146)	15.32317	0.0001
Brown-Forsythe	(1, 146)	14.04447	0.0003

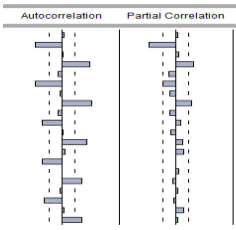
1H



Sample: 1996Q2 2014Q4
Included observations: 75

	AC	PAC	Q-Stat	Prob
1	0.952	0.952	70.793	0.000
2	0.906	-0.007	135.79	0.000
3	0.866	0.031	195.88	0.000
4	0.825	-0.015	251.27	0.000
5	0.782	-0.052	301.69	0.000
6	0.736	-0.047	347.06	0.000
7	0.693	-0.002	387.89	0.000
8	0.650	-0.036	424.28	0.000
9	0.603	-0.060	456.06	0.000
10	0.558	-0.008	483.68	0.000
11	0.516	-0.000	507.66	0.000
12	0.475	-0.004	528.38	0.000
13	0.438	0.008	546.23	0.000
14	0.399	-0.034	561.32	0.000
15	0.366	0.025	574.19	0.000
16	0.334	-0.002	585.11	0.000
17	0.297	-0.075	593.92	0.000
18	0.260	-0.033	600.79	0.000
19	0.226	-0.004	606.08	0.000
20	0.194	-0.023	610.01	0.000

1J.



Sample: 1996Q2 2014Q4
Included observations: 74

	AC	PAC	Q-Stat	Prob
1	0.027	0.027	0.0577	0.810
2	-0.492	-0.493	18.962	0.000
3	0.013	0.062	18.975	0.000
4	0.492	0.327	38.461	0.000
5	-0.080	-0.136	38.989	0.000
6	-0.497	-0.242	59.428	0.000
7	-0.026	-0.101	59.485	0.000
8	0.537	0.283	84.055	0.000
9	-0.068	-0.100	84.451	0.000
10	-0.360	0.097	95.821	0.000
11	0.018	-0.086	95.849	0.000
12	0.447	0.126	113.97	0.000
13	0.046	0.148	114.16	0.000
14	-0.355	-0.007	125.95	0.000
15	-0.006	0.047	125.96	0.000
16	0.356	-0.052	138.23	0.000
17	-0.033	0.027	138.33	0.000
18	-0.332	-0.047	149.39	0.000
19	0.029	0.140	149.47	0.000
20	0.359	0.038	162.86	0.000

As shown in Fig. 1A, the graph of consumer prices for Algeria (PALG) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not clearly visible in the price plot (there is some subtle seasonal variation) because of the dominant trend; seasonality may be more clearly revealed once the trend is removed through differencing.

The time paths of PALG and PALG_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between PALG and PALG_d11 (denoted D_PALG) is plotted in Figure 1C. The difference has revealed cyclical fluctuations that range between -1.23 and 1.04. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PALG and PALG_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PALG and PALG_d11. Hence, we find that seasonality is not significant in the price level. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the logs of the adjusted (DLPALG_d11) and unadjusted (DLPALG) data.

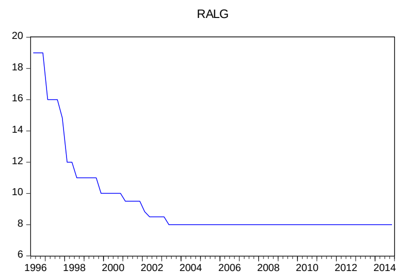
The time paths of DLPALG and DLPALG_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after first differencing. The variation in DLPALG is greater than that of DLPALG_d11 suggesting seasonality in DLPALG while DLPALG_d11 is smoother. This suggests that DLPALG_ d11 exhibits reduced seasonality as expected. The difference between DLPALG and DLPALG_d11 (denoted D_DLPALG) is plotted in Figure 1F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.020 and 0.021. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPALG and DLPALG_d11 that are reported in table 1G. Since the p-values of all of our tests are less than 0.05 we reject the null hypothesis and find that there is significant difference in the variances of DLPALG and DLPALG_d11. Hence, we find that seasonality is significant in the difference of the log of prices for Algeria.

To check this, we plot the autocorrelation functions (ACFs) of PALG and DLPALG in figure 1H and 1I. Shown in Fig. 1H is the ACF for PALG. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPALG (see fig. 1I) has significant ACs at all of the seasonal lags. This implies that seasonality is significant in the price data and confirms the results of the variance equality tests. Hence, we use the seasonally adjusted data PALG_d11 in our VAR analysis.

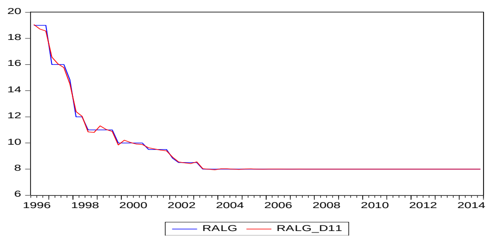
6.11.2. The seasonality features of interest rate in Algeria

The graphs below depict the following variables. The Algerian interest rate (denoted RALG), the seasonally adjusted RALG series (RALG_d11), D_RALG = RALG - R_d11, and the first (nonseasonal) difference of RALG (DRALG). The seasonally adjusted series RALG_d11 is obtained using the Census X13 procedure in EViews. Table 2D reports various variance equality tests for RALG and RALG_d11 while Table 2G reports these tests for variance equality for DRALG and DRALG_d11.

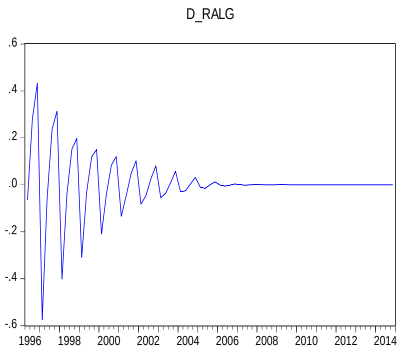
2A.



2B.



2C.

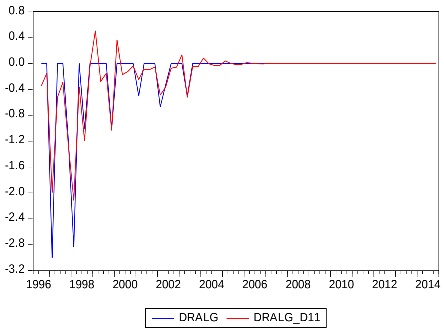


2D.

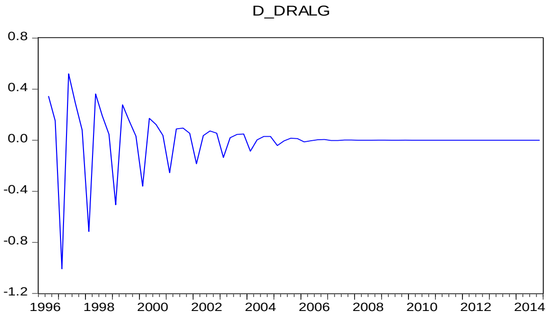
Equality of variances test between RALG and RALG_D11

Method	Df	Value	Probability
F-test	(74, 74)	1.014122	0.9521
Siegel-Tukey		1.438189	0.1504
Bartlett	(1, 148)	0.003613	0.9521
Levene	(1, 148)	0.000424	0.9521
Brown-Forsythe	(1,148)	2.18E-07	0.9996

2E.



2F.

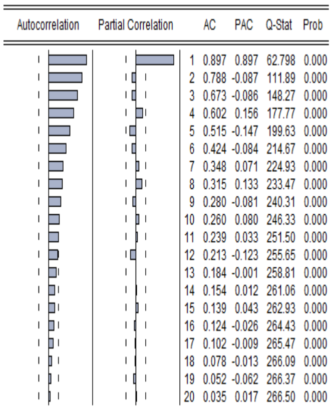


2G.

Equality of variances test between DRALG and DRALG_D11

Method	Df	Value	Probability
F-test	(73, 73)	1.553083	0.0619
Siegel-Tukey		5.224772	0.000
Bartlett	1	3.485018	0.0619
Levene	(1, 146)	0.093687	0.7600
Brown-Forsythe	(1,146)	0.176141	0.6753

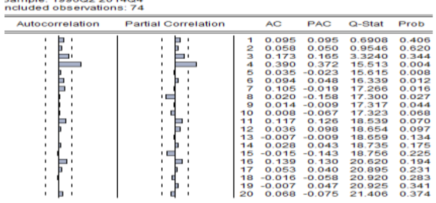
2H.



Sample: 1996Q2 2014Q4
Included observations: 75

	AC	PAC	Q-Stat	Prob
1	0.897	0.897	62.798	0.000
2	0.788	-0.087	111.89	0.000
3	0.673	-0.086	148.27	0.000
4	0.602	0.156	177.77	0.000
5	0.515	-0.147	199.63	0.000
6	0.424	-0.084	214.67	0.000
7	0.348	0.071	224.93	0.000
8	0.315	0.133	233.47	0.000
9	0.280	-0.081	240.31	0.000
10	0.260	0.080	246.33	0.000
11	0.239	0.033	251.50	0.000
12	0.213	-0.123	255.65	0.000
13	0.184	-0.001	258.81	0.000
14	0.154	0.012	261.06	0.000
15	0.139	0.043	262.93	0.000
16	0.124	-0.026	264.43	0.000
17	0.102	-0.009	265.47	0.000
18	0.078	-0.013	266.09	0.000
19	0.052	-0.062	266.37	0.000
20	0.035	0.017	266.50	0.000

2J.



Sample: 1996Q2 2014Q4
Included observations: 74

	AC	PAC	Q-Stat	Prob
1	0.095	0.095	0.6908	0.406
2	0.058	0.050	0.9546	0.620
3	0.173	0.165	3.3240	0.344
4	0.390	0.372	15.513	0.004
5	0.035	-0.023	15.615	0.008
6	0.094	0.048	16.339	0.012
7	0.105	-0.019	17.266	0.016
8	0.020	-0.158	17.300	0.027
9	0.014	-0.009	17.317	0.044
10	0.008	-0.067	17.323	0.068
11	0.117	0.126	18.539	0.070
12	0.036	0.098	18.654	0.097
13	-0.007	-0.009	18.659	0.134
14	0.028	0.043	18.735	0.175
15	-0.015	-0.143	18.756	0.225
16	0.139	0.130	20.620	0.194
17	0.053	0.040	20.895	0.231
18	-0.016	-0.058	20.920	0.283
19	-0.007	0.047	20.925	0.341
20	0.068	-0.075	21.406	0.374

As shown in Fig. 2A, the graph of RALG exhibits a downward trend (although it converges to a relatively constant mean). Seasonality is not clearly visible in the Algerian interest rate plot because of the dominant trend.

The time paths of RALG and RALG_d11 (see Figure 2B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. We plot the difference between RALG and RALG_d11 (denoted D_RALG) in Figure 2C to assess whether RALG is seasonal. The difference indicates time-varying cycles that dramatically decline. We refer to a variety of tests for the equality of variance between RALG and

RALG_d11 that are reported in table 2D. Since the p-values of all of our tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RALG and RALG_d11. Hence, we find that seasonality is not significant in the level of interest series. However, because this result may be influenced by the trend in the data, we compare the differences of the adjusted (DRALG_d11) and unadjusted (DRALG) data.

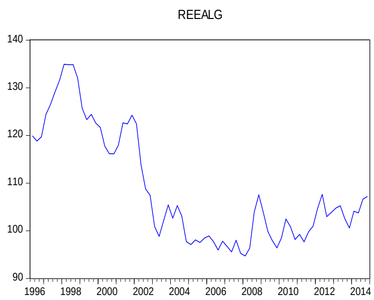
The time paths of DRALG and DRALG_d11 (see Figure 2E) follow each other closely. The difference between DRALG and DRALG_d11 (denoted D_DRALG) is plotted in Figure 2F. The difference indicates time-varying cycles that dramatically reduce through time. Variance equality tests between DRALG and DRALG_d11 are reported in Table 2G. The p-values for Levene, Brown Forsythe, F-test and Bartlett tests are greater than 0.05 indicating equal variances while the p-value for Siegel Tukey is less than 0.05. We latter rejects the null hypothesis of equal variance. Hence, the results regarding equality of variance are ambiguous, if they generally suggest equal variances and no seasonality.

To explore the issue further we plot the ACFs of RALG and DRALG in figure 2H and 2I, respectively. Shown in Fig. 2H is the ACF for RALG. The first 12 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests persistence and not seasonality. The ACF for DRALG (see fig. 2I) has a significant AC at the first seasonal lag (lag 4) and all other ACs at seasonal lags are insignificant. This provides only slight evidence that seasonality is significant in the interest rate data. Most of the evidence suggests no seasonality and because we do not expect seasonality in the interest rate data we will use the unadjusted data RALG in our VAR analysis.

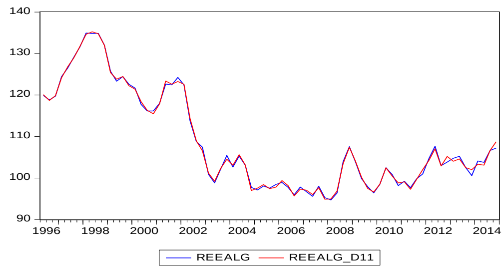
6.11.3. The seasonality features real effective exchange rate in Algeria

The graphs below depict the following variables. The Algerian real effective exchange (denoted REEALG), the seasonally adjusted REEALG series (REEALG_d11) and D_REEALG = REEALG - REEALG_d11, as well as the first (nonseasonal) difference of LREEALG (DLREEALG), the seasonally adjusted LREEALG series (LREEALG_d11) and D_LREEALG = LREEALG - LREEALG_d11 (where LREEALG is the log of REEALG). The seasonally adjusted series (REEALG_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for REEALG and REEALG_d11 as well as DLREEALG and DLREEALG_d11.

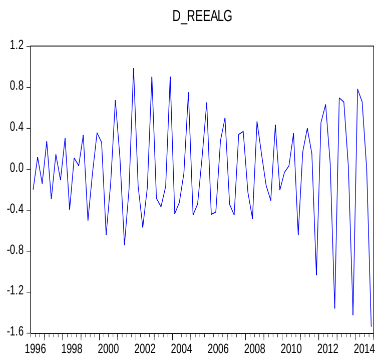
3A.



3B.



3C.

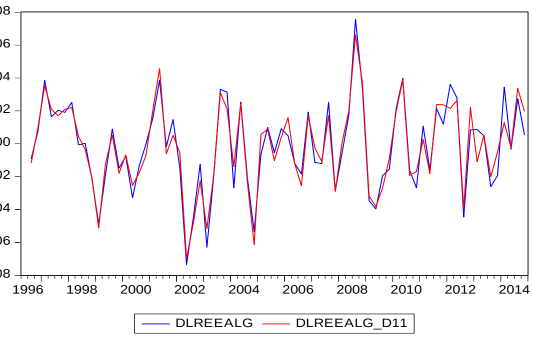


3D.

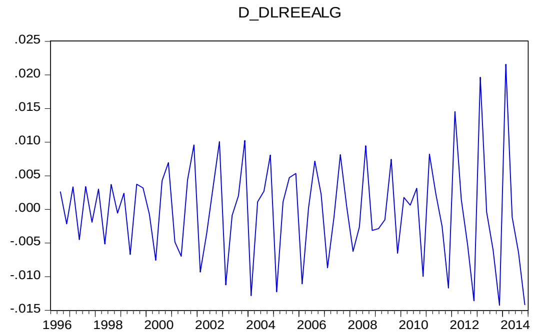
Equality of variances test between REEALG and REEALG_D11

Method	Df	Value	Probability
F-test	(74, 74)	1.001897	0.9935
Siegel-Tukey		0.018794	0.9850
Bartlett	1	6.60E-05	0.9935
Levene	(1, 148)	5.45E-05	0.9941
Brown-Forsythe	(1,148)	0.000657	0.9796

3E.



3F.



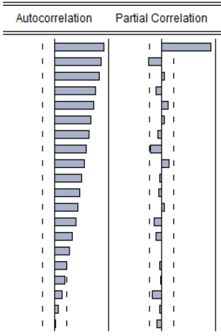
3G.

Equality of variances test between DLREEALG and DLREEALG_D11

Method	Df	Value	Probability
F-test	(73, 73)	1.085992	0.7255
Siegel-Tukey		0.347068	0.7285
Bartlett	1	0.123315	0.7255
Levene	(1, 146)	0.099302	0.7531
Brown-Forsythe	(1,146)	0.104707	0.7467

3H.

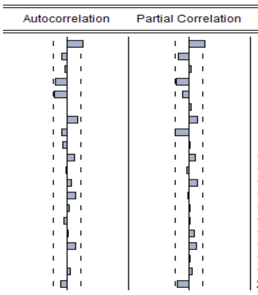
Sample: 1996Q2 2014Q4
Included observations: 75



	AC	PAC	Q-Stat	Prob
1	0.963	0.963	72.388	0.000
2	0.909	-0.262	137.70	0.000
3	0.855	0.050	196.39	0.000
4	0.798	-0.111	248.22	0.000
5	0.749	0.129	294.55	0.000
6	0.711	0.043	336.80	0.000
7	0.671	-0.071	375.03	0.000
8	0.619	-0.205	408.04	0.000
9	0.572	0.146	436.69	0.000
10	0.530	-0.027	461.61	0.000
11	0.483	-0.059	482.63	0.000
12	0.443	0.045	500.66	0.000
13	0.402	-0.143	515.71	0.000
14	0.350	-0.104	527.28	0.000
15	0.295	0.002	535.64	0.000
16	0.243	-0.033	541.40	0.000
17	0.192	-0.014	545.06	0.000
18	0.134	-0.185	546.87	0.000
19	0.077	-0.047	547.48	0.000
20	0.016	-0.087	547.50	0.000

3I.

Sample: 1996Q2 2014Q4
Included observations: 74



	AC	PAC	Q-Stat	Prob
1	0.272	0.272	5.7011	0.017
2	-0.086	-0.173	6.2822	0.043
3	-0.043	0.035	6.4313	0.092
4	-0.189	-0.224	9.3107	0.054
5	-0.207	-0.099	12.816	0.025
6	-0.003	0.041	12.817	0.046
7	0.175	0.143	15.390	0.031
8	-0.086	-0.240	16.026	0.042
9	-0.073	0.015	16.487	0.057
10	0.126	0.105	17.887	0.057
11	-0.021	-0.048	17.928	0.083
12	0.072	0.151	18.398	0.104
13	0.135	-0.010	20.072	0.093
14	0.041	0.024	20.226	0.123
15	-0.061	0.016	20.575	0.151
16	0.020	0.089	20.614	0.194
17	0.148	0.129	22.770	0.157
18	0.005	0.012	22.773	0.199
19	0.047	0.056	23.003	0.237
20	-0.102	-0.201	24.094	0.238

As shown in Fig. 3A, the graph of the real effective exchange rate for Algeria exhibits a downward trend if it converges to a constant.

The time paths of REEALG and REEALG_d11 (see Figure 3B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the difference between REEALG and REEALG_d11 (denoted D_REEALG) is plotted in Figure 3C. The difference has revealed a cyclical fluctuation. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between REEALG and REEALG_d11 that are reported in table 3D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REEALG and REEALG_d11. Hence, we find that seasonality is not significant in the level of the real effective exchange rate. However, because this result may be influenced by the trend in the data, we compare the differences of the adjusted (DLREEALG_d11) and unadjusted (DLREEALG) data.

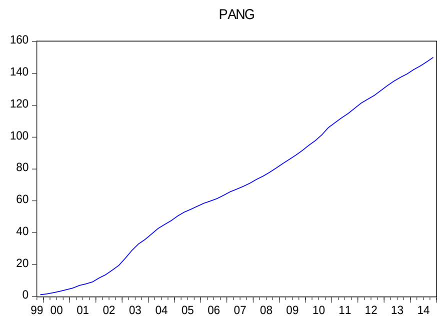
The time paths of DLREEALG and DLREEALG_d11 (see Figure 3E) follow each other closely. The first difference has removed the trend and gives a relatively constant mean process. The difference between DLREEALG and DLREEALG_d11 (denoted D_DLREEALG) is plotted in Figure 3F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.0127 and 0.0216 and substantially declines through time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREEALG and DLREEALG_d11 that are reported in table 3G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLREEALG and DLREEALG_d11. Hence, we find that seasonality is not significant in the difference of the log of the real effective exchange rate data for Algeria

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of REEALG and DLREEALG in figure 3H and 3I. Shown in Fig. 3H is the ACF for REEALG. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLREEALG has no significant ACs at seasonal lags (see fig. 3I). This implies that seasonality is not significant in real effective exchange rate and confirms the results of the variance equality tests. Hence, we will use the unadjusted data REEALG our VAR analysis.

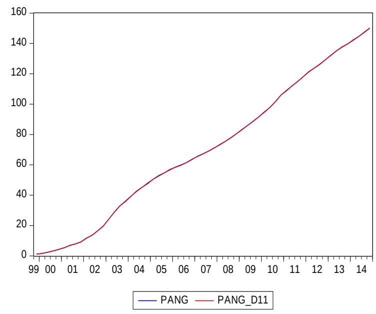
6.12.1 The graphical features of selected macroeconomic variables for Angola

In Angola, we amend the reduced sample identified in previous section (Table 6.4.8) from 1997q4 – 2014q4 to 1999q4 – 2014q4 because data is not available for many important series before 1999q4. The graphs below depict the following variables. The Angolan consumer price (denoted PANG), the seasonally adjusted PANG series (PANG_d11) and D_PANG = PANG - PANG_d11, the first (nonseasonal) difference of LPANG (DLPANG), the seasonally adjusted LPANG series (LPANG_d11) and D_LPANG = LPANG - LPANG_d11 (where LPANG is the log of PANG). The seasonally adjusted series (PANG_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PANG and PANG_d11 as well as DLPANG and DLPANG_d11.

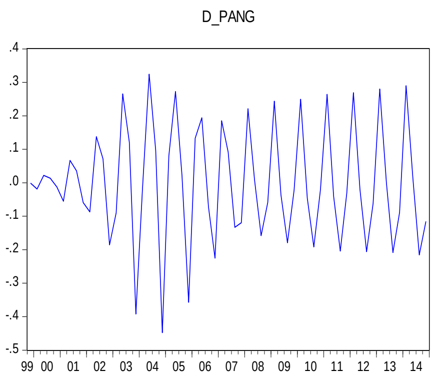
1A.



1B.



1C.

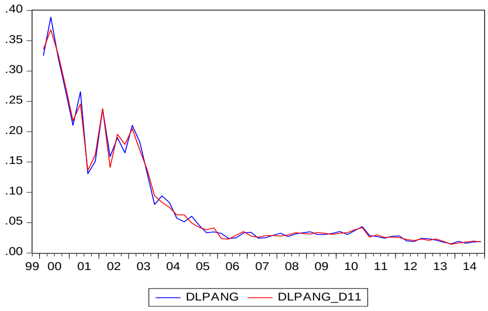


1D.

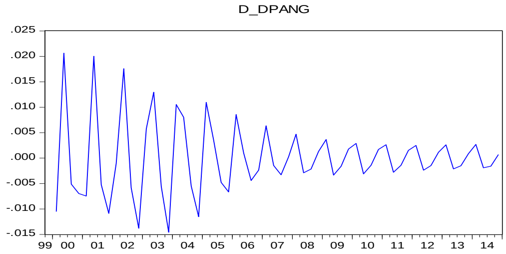
Equality of variances test between PANG and PANG_D11

Method	Df	Value	Probability
F-test	(60, 60)	1.000237	0.9993
Siegel-Tukey		0.040964	0.9673
Bartlett	1	3.77E-07	0.9993
Levene	(1, 120)	1.48E-06	0.9990
Brown-Forsythe	(1, 120)	1.48E-06	0.9990

1E.



1F.

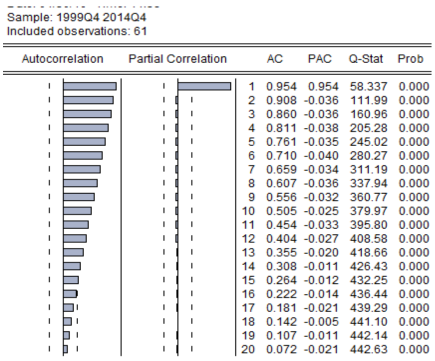


1G.

Equality of variances test between DLPANG and DLPANG_D11

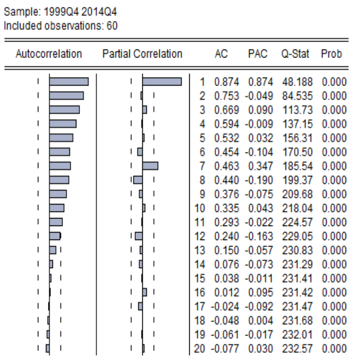
Method	Df	Value	Probability
F-test	(59, 59)	1.013802	0.9582
Siegel-Tukey		0.191575	0.8481
Bartlett	1	0.002748	0.9582
Levene	(1, 118)	0.000164	0.9898
Brown-Forsythe	(1, 118)	4.75E-05	0.9945

1H.



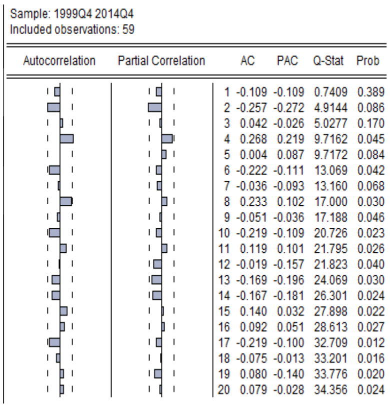
	AC	PAC	Q-Stat	Prob
1	0.954	0.954	58.337	0.000
2	0.908	-0.036	111.99	0.000
3	0.860	-0.036	160.96	0.000
4	0.811	-0.038	205.28	0.000
5	0.761	-0.035	245.02	0.000
6	0.710	-0.040	280.27	0.000
7	0.659	-0.034	311.19	0.000
8	0.607	-0.036	337.94	0.000
9	0.556	-0.032	360.77	0.000
10	0.505	-0.025	379.97	0.000
11	0.454	-0.033	395.80	0.000
12	0.404	-0.027	408.58	0.000
13	0.355	-0.020	418.66	0.000
14	0.308	-0.011	426.43	0.000
15	0.264	-0.012	432.25	0.000
16	0.222	-0.014	436.44	0.000
17	0.181	-0.021	439.29	0.000
18	0.142	-0.005	441.10	0.000
19	0.107	-0.011	442.14	0.000
20	0.072	-0.021	442.63	0.000

1I.



	AC	PAC	Q-Stat	Prob
1	0.874	0.874	48.188	0.000
2	0.753	-0.049	84.535	0.000
3	0.669	0.090	113.73	0.000
4	0.594	-0.009	137.15	0.000
5	0.532	0.032	156.31	0.000
6	0.454	-0.104	170.50	0.000
7	0.463	0.347	185.54	0.000
8	0.440	-0.190	199.37	0.000
9	0.376	-0.075	209.68	0.000
10	0.335	0.043	218.04	0.000
11	0.293	-0.022	224.57	0.000
12	0.240	-0.163	229.05	0.000
13	0.150	-0.057	230.83	0.000
14	0.076	-0.073	231.29	0.000
15	0.038	-0.011	231.41	0.000
16	0.012	0.095	231.42	0.000
17	-0.024	-0.092	231.47	0.000
18	-0.048	0.004	231.68	0.000
19	-0.061	-0.017	232.01	0.000
20	-0.077	0.030	232.57	0.000

1J



	AC	PAC	Q-Stat	Prob
1	-0.109	-0.109	0.7409	0.389
2	-0.257	-0.272	4.9144	0.086
3	0.042	-0.026	5.0277	0.170
4	0.268	0.219	9.7162	0.045
5	0.004	0.087	9.7172	0.084
6	-0.222	-0.111	13.069	0.042
7	-0.036	-0.093	13.160	0.068
8	0.233	0.102	17.000	0.030
9	-0.051	-0.036	17.188	0.046
10	-0.219	-0.109	20.726	0.023
11	0.119	0.101	21.795	0.026
12	-0.019	-0.157	21.823	0.040
13	-0.169	-0.196	24.069	0.030
14	-0.167	-0.181	26.301	0.024
15	0.140	0.032	27.898	0.022
16	0.092	0.051	28.613	0.027
17	-0.219	-0.100	32.709	0.012
18	-0.075	-0.013	33.201	0.016
19	0.080	-0.140	33.776	0.020
20	0.079	-0.028	34.356	0.024

As shown in Fig. 1A, the graph of consumer prices for Angola (PANG) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing.

The time paths of PANG and PANG_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between PANG and PANG_d11 (denoted D_PANG) is plotted in Figure 1C. The difference has revealed cyclical fluctuations that range between -0.45

and 0.32. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PANG and PANG_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PANG and PANG_d11 and hence find that seasonality is not significant in the price level. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the logs of the adjusted (DLPANG_d11) and unadjusted (DLPANG) data.

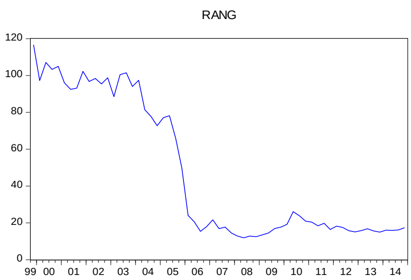
The time paths of DLPANG and DLPANG_d11 (see Figure 1E) follow each other closely. The trend has not been removed as would be expected after first differencing. The difference between DLPANG and DLPANG_d11 (denoted D_DLPANG) is plotted in Figure 1F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.0138 and 0.0206. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPANG and DLPANG_d11 that are reported in table 1G. Since the p-values of all of our tests are greater than 0.05 we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLPANG and DLPANG_d11. Hence, we find that seasonality is not significant in the difference of the log prices for Angola

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of PANG and DLPANG in figure 1H and 1I. Shown in Fig. 1H is the ACF for PANG. The first 15 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLPANG (see fig. 1I) has the first 11 significant ACs (and not just at the seasonal lags) which suggests persistence and not necessarily seasonality. This implies the need to plot the ACF of the second difference of LPANG to determine if there is seasonality. The ACF for second difference D(PANG,2) indicates insignificant ACs at all the seasonal lags except lag 4 (see fig. 1J). This implies that seasonality is not significant in price data. Hence, we use the unadjusted data PANG in our VAR analysis.

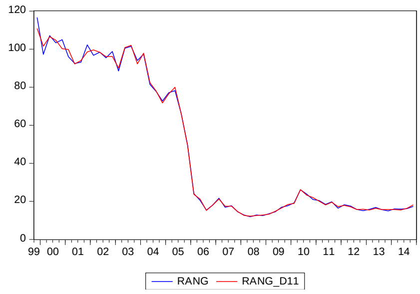
6.12. 2. The seasonality features of interest rate in Angola

We analyse the stationarity and seasonality characteristics of the interest rate variable in Angola. The graphs below depict the following indicators. The Angolan interest rate (denoted RANG), the seasonally adjusted RANG series (RANG_d11) and D_RANG = RANG - RANG_d11, as well as the first (nonseasonal) difference of RANG (DRANG). The seasonally adjusted series (RANG_d11) is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for RALG and RALG_d11 as well as DRALG and DRALG_d11.

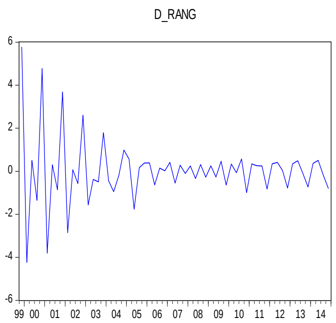
2A.



2B.



2C.

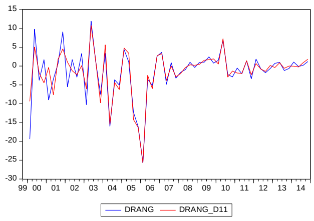


2D.

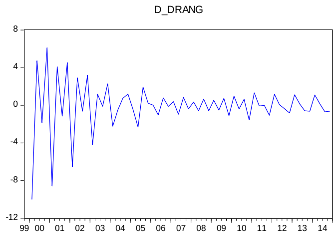
Equality of variances test between RANG and RANG_D11

Method	Df	Value	Probability
F-test	(60, 60)	1.005449	0.9833
Siegel-Tukey		0.051205	0.9592
Bartlett	1	0.000439	0.9833
Levene	(1, 120)	0.000529	0.98917
Brown-Forsythe	(1, 120)	4.96E-05	0.9944

2E.



2F.

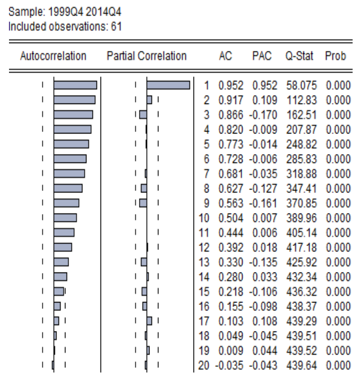


2G.

Equality of variances test between DRANG and DRANG_D11

Method	Df	Value	Probability
F-test	(59, 59)	1.2222356	0.4430
Siegel-Tukey		0.931633	0.3515
Bartlett		0.588629	0.4429
Levene	(1, 118)	0.394852	0.5310
Brown-Forsythe	(1, 118)	0.370602	0.5438

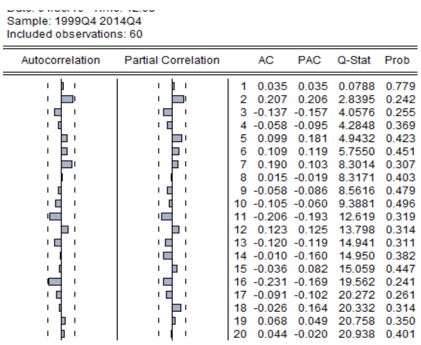
2H.



Sample: 1999Q4 2014Q4
Included observations: 61

	AC	PAC	Q-Stat	Prob
1	0.952	0.952	58.075	0.000
2	0.917	0.109	112.83	0.000
3	0.866	-0.170	162.51	0.000
4	0.820	-0.009	207.87	0.000
5	0.773	-0.014	248.82	0.000
6	0.728	-0.006	285.83	0.000
7	0.681	-0.035	318.88	0.000
8	0.627	-0.127	347.41	0.000
9	0.563	-0.161	370.85	0.000
10	0.504	0.007	389.96	0.000
11	0.444	0.006	405.14	0.000
12	0.392	0.018	417.18	0.000
13	0.330	-0.135	425.92	0.000
14	0.280	0.033	432.34	0.000
15	0.218	-0.106	436.32	0.000
16	0.155	-0.098	438.37	0.000
17	0.103	0.108	439.29	0.000
18	0.049	-0.045	439.51	0.000
19	0.009	0.044	439.52	0.000
20	-0.035	-0.043	439.64	0.000

2I.



Sample: 1999Q4 2014Q4
Included observations: 60

	AC	PAC	Q-Stat	Prob
1	0.035	0.035	0.0788	0.779
2	0.207	0.206	2.8395	0.242
3	-0.137	-0.157	4.0576	0.255
4	-0.058	-0.095	4.2848	0.369
5	0.099	0.181	4.9432	0.423
6	0.109	0.119	5.7550	0.451
7	0.190	0.103	8.3014	0.307
8	0.015	-0.019	8.3171	0.403
9	-0.058	-0.086	8.5616	0.479
10	-0.105	-0.060	9.3881	0.496
11	-0.206	-0.193	12.619	0.319
12	0.123	0.125	13.798	0.314
13	-0.120	-0.119	14.941	0.311
14	-0.010	-0.160	14.950	0.382
15	-0.036	0.082	15.059	0.447
16	-0.231	-0.169	19.562	0.241
17	-0.091	-0.102	20.272	0.261
18	-0.026	0.164	20.332	0.314
19	0.068	0.049	20.758	0.350
20	0.044	-0.020	20.938	0.401

As shown in Fig. 2A, the interest rate series (RANG) exhibits a downward trend (there may be a step shift around 2005). Seasonality and the business cycle are not visible in Angola interest rate plot.

The time paths of RANG and RANG_d11 (see Figure 2B) follow each other closely with and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between RANG and RANG_d11 (denoted D_RANG) is plotted in Figure 2C. The difference has revealed a regular cyclical fluctuation that suggests time-varying seasonality. To ascertain whether this seasonality is significant, we refer to a variety of tests for the equality of variance between RANG and RANG_d11 that are reported in table 2D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of RANG and RANG_d11. Hence, we find that seasonality is not significant in the RANG. However, because this result may be influenced by the trend (shift) in the data we compare the differences of the adjusted (DRANG_d11) and unadjusted (DRANG) data.

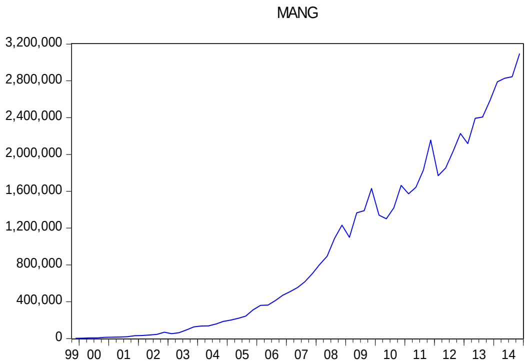
The time paths of DRANG and DRANG_d11 (see Figure 2E) follow each other closely. The difference between DRANG and DRANG_d11 (denoted D_DRANG) is plotted in Figure 2F. The difference has revealed a relatively constant mean with variations that substantially decrease. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between (DRANG) and (DRANG_d11) that are reported in table 2G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DRANG and DRANG_d11. Hence, we find that seasonality is not significant in the difference of interest rate for Angola.

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of RANG and DRANG in figure 2H and 2I. Shown in Fig. 2H is the ACF for RANG. The first 15 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DRANG (see fig. 2I) has no significant ACs at seasonal lags. This implies that seasonality is not significant in the data and confirms the results of the variance equality tests. Hence, we use the unadjusted data RANG in our VAR analysis.

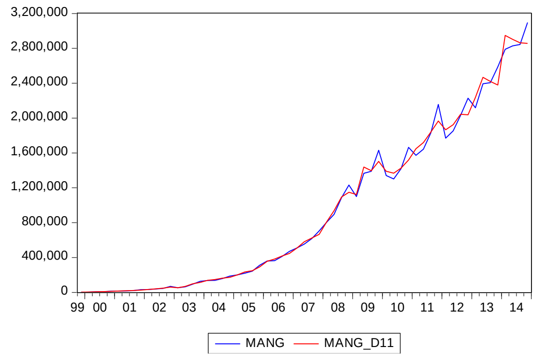
6.12.3. The seasonality features of money supply in Angola

The graphs below depict the following variables. The Angolan money supply (denoted MANG), the seasonally adjusted MANG series (MANG_d11) and D_MANG = MANG - MANG_d11, as well as the first (nonseasonal) difference of LMANG (DLMANG), the seasonally adjusted LMANG series (LMANG_d11) and D_LMANG = LMBRA - LMANG_d11 (where LMANG is the log of MANG). The seasonally adjusted series (MANG_d11) is obtained using the Census X13 procedure in EViews. Tables 3D and 3G report various tests of the null hypothesis of equality of variance for MANG and MANG_d11 as well as DLMANG and DLMANG_d11.

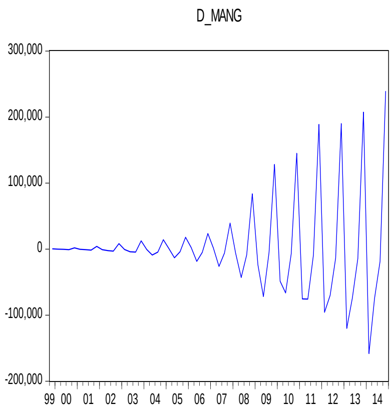
3A.



3B.



3C.

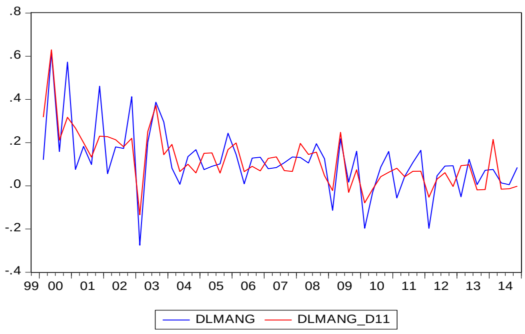


3D.

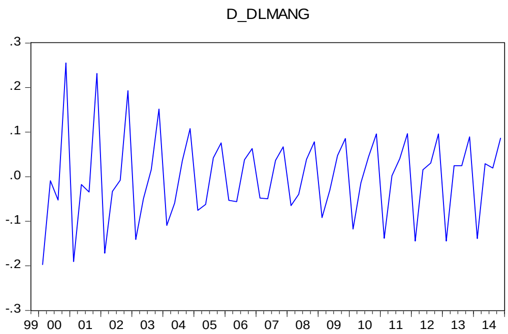
Equality of variances test between MANG and MANG_D11

Method	Df	Value	Probability
F-test	(60, 60)	1.011538	0.9647
Siegel-Tukey		0.076897	0.9388
Bartlett		0.001958	0.9647
Levene	(1, 120)	0.001661	0.9676
Brown-Forsythe	(1, 120)	0.000315	0.9859

3E.



3F.

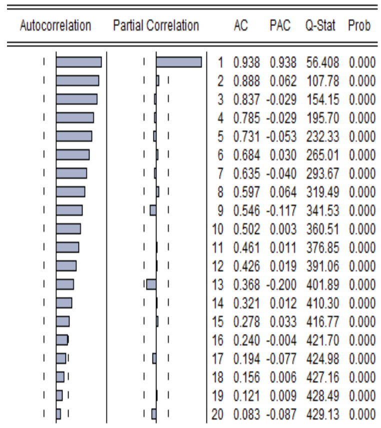


3G.

Equality of variances test between DLMANG and DLMANG_D11

Method	Df	Value	Probability
F-test	(59, 59)	1.551084	0.0945
Siegel-Tukey		1.482740	0.1381
Bartlett		2.795821	0.0945
Levene	(1, 118)	0.094022	0.7597
Brown-Forsythe	(1, 118)	0.126257	0.7230

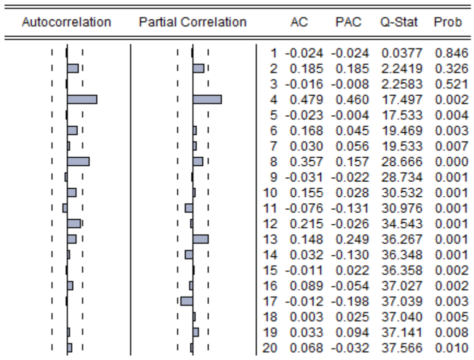
3H.



Sample: 1999Q4 2014Q4
Included observations: 61

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.938	0.938	56.408	0.000
		2	0.888	0.062	107.78	0.000
		3	0.837	-0.029	154.15	0.000
		4	0.785	-0.029	195.70	0.000
		5	0.731	-0.053	232.33	0.000
		6	0.684	0.030	265.01	0.000
		7	0.635	-0.040	293.67	0.000
		8	0.597	0.064	319.49	0.000
		9	0.546	-0.117	341.53	0.000
		10	0.502	0.003	360.51	0.000
		11	0.461	0.011	376.85	0.000
		12	0.426	0.019	391.06	0.000
		13	0.368	-0.200	401.89	0.000
		14	0.321	0.012	410.30	0.000
		15	0.278	0.033	416.77	0.000
		16	0.240	-0.004	421.70	0.000
		17	0.194	-0.077	424.98	0.000
		18	0.156	0.006	427.16	0.000
		19	0.121	0.009	428.49	0.000
		20	0.083	-0.087	429.13	0.000

3I.



Sample: 1999Q4 2014Q4
Included observations: 60

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.024	-0.024	0.0377	0.846
		2	0.185	0.185	2.2419	0.326
		3	-0.016	-0.008	2.2583	0.521
		4	0.479	0.460	17.497	0.002
		5	-0.023	-0.004	17.533	0.004
		6	0.168	0.045	19.469	0.003
		7	0.030	0.056	19.533	0.007
		8	0.357	0.157	28.666	0.000
		9	-0.031	-0.022	28.734	0.001
		10	0.155	0.028	30.532	0.001
		11	-0.076	-0.131	30.976	0.001
		12	0.215	-0.026	34.543	0.001
		13	0.148	0.249	36.267	0.001
		14	0.032	-0.130	36.348	0.001
		15	-0.011	0.022	36.358	0.002
		16	0.089	-0.054	37.027	0.002
		17	-0.012	-0.198	37.039	0.003
		18	0.003	0.025	37.040	0.005
		19	0.033	0.094	37.141	0.008
		20	0.068	-0.032	37.566	0.010

As shown in Fig. 3A, the graph of the money supply in Angola (MANG) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. There are cycles that probably reflect seasonality. Therefore, (MANG) may need to be seasonally adjusted.

The time paths of MANG and MANG_d11 (see Figure 3B) follow each other. It is obvious that the variation in MANG is greater than that of MANG_d11 and the plot of

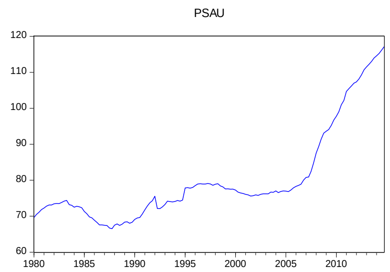
MANG_d11 is smoother than the plot of MANG most especially at the end of the sample. The difference between MANG and MANG_d11 (denoted D_MANG) is plotted in Figure 3C. The difference reveals a regular cyclical fluctuation that substantially increases through time and this could suggest time-varying seasonality. To ascertain whether the seasonality is significant we refer to a variety of tests for the equality of variance between MANG and MANG_d11 that are reported in table 3D. Since the p-values of all tests are greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of MANG and MANG_d11. Hence, we find that seasonality is not significant in the level of the data. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLMANG_d11) and unadjusted (DLMANG) data.

The time paths of DLMANG and DLMANG_d11 (see Figure 3E) follow each other closely. The trend has been removed and the series broadly fluctuates around a constant mean as expected after first differencing. The variation in DLMANG is greater than that of DLMANG_d11. Therefore, there may be seasonality in the DLMANG series. The difference between DLMANG and DLMANG_d11 (denoted D_DLMANG) is plotted in Figure 3F. The difference reveals cyclical fluctuations that range between -0.20 and 0.26. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLMANG and DLMANG_d11 that are reported in table 3G. Since the p-values of all of our tests are greater than 0.05 we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLMANG and DLMANG_d11. Hence, seasonality appears to be insignificant in the difference of the log of the money supply in Angola. As a check we plot the ACFs of MANG and DLMANG in figure 3H and 3I. Shown in Fig. 3H is the ACF for MANG. The first 15 autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLMANG (see fig. 3I) has significant ACs at seasonal lags 4 and 8. This implies that seasonality is significant in the money supply data. Hence, despite the results of the variance equality tests We infer seasonality (because we expect seasonality and it is visually apparent) and use the seasonally adjusted data MANG_d11 in our VAR analysis.

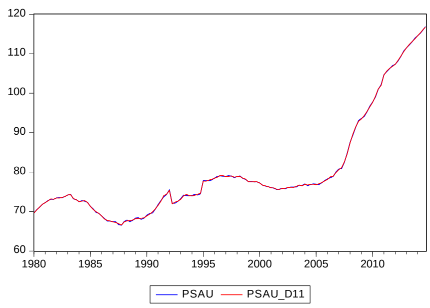
6.13.1 The graphical features of selected macroeconomic variables for Saudi Arabia

In Saudi Arabia, we amend the reduced sample identified in previous section (Table 6.4.7) from 1976q3 – 2014Q4 to 1980q1 – 2014q4 to incorporate many important variables where data is available over this reduced sample. The graphs below depict the following variables. The Saudi Arabian consumer price (denoted PSAU), the seasonally adjusted PSAU series (PSAU_d11) and D_PSAU = PSAU - PSAU_d11, the first (nonseasonal) difference of LPSAU (DLPSAU), the seasonally adjusted LPSAU series (LPSAU_d11) and D_LPSAU = LPSAU - LPSAU_d11 (where LPSAU is the log of PSAU). The seasonally adjusted series (PSAU_d11) is obtained using the Census X13 procedure in EViews. Tables 1D and 1G report various tests of the null hypothesis of equality of variance for PSAU and PSAU_d11 as well as DLPSAU and DLPSAU_d11.

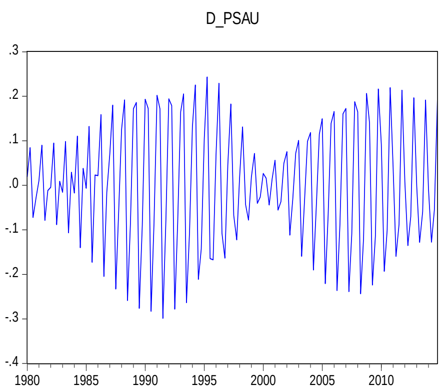
1A.



1B.



1C.

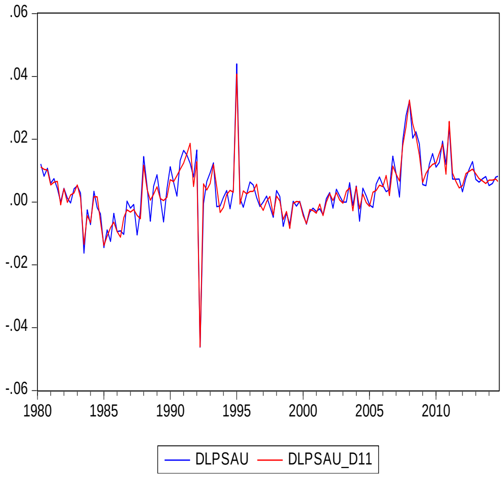


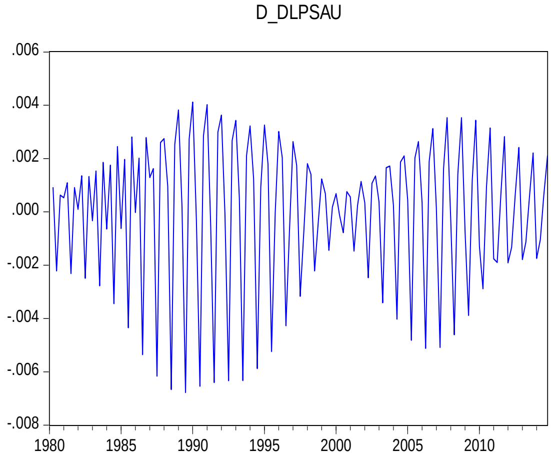
1D.

Equality of variances test between PSAU and PSAU_D11

Method	Df	Value	Probability
F-test	(139, 139)	1.000374	0.9982
Siegel-Tukey		0.008118	0.9935
Bartlett	1	4.85E-06	0.9982
Levene	(1, 278)	2.80E-07	0.9996
Brown-Forsythe	(1, 278)	1.82E-06	0.9989

1E. 1F

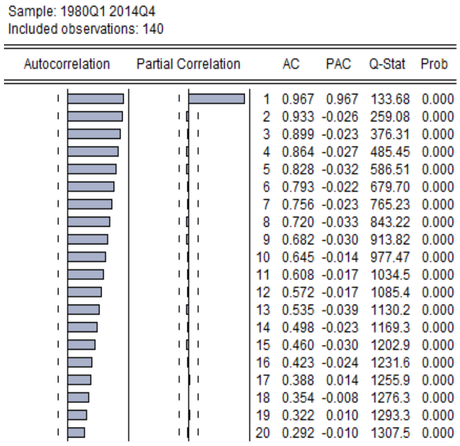




1G. 1H

Equality of variances test between DLPSAU and DLPSAU_D11

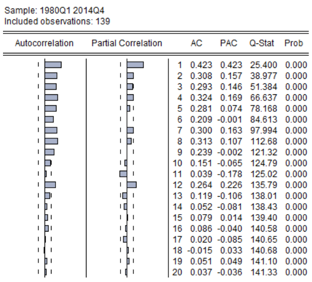
Method	Df	Value	Probability
F-test	(138, 138)	1.102046	0.5690
Siegel-Tukey		0.759438	0.4476
Bartlett	1	0.324436	0.5690
Levene	(1, 276)	0.299446	0.5847
Brown-Forsythe	(1, 276)	0.309565	0.5784



Sample: 1980Q1 2014Q4
Included observations: 140

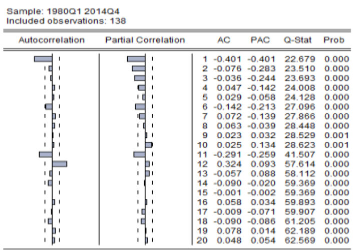
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.967	0.967	133.68	0.000
		2	0.933	-0.026	259.08	0.000
		3	0.899	-0.023	376.31	0.000
		4	0.864	-0.027	485.45	0.000
		5	0.828	-0.032	586.51	0.000
		6	0.793	-0.022	679.70	0.000
		7	0.756	-0.023	765.23	0.000
		8	0.720	-0.033	843.22	0.000
		9	0.682	-0.030	913.82	0.000
		10	0.645	-0.014	977.47	0.000
		11	0.608	-0.017	1034.5	0.000
		12	0.572	-0.017	1085.4	0.000
		13	0.535	-0.039	1130.2	0.000
		14	0.498	-0.023	1169.3	0.000
		15	0.460	-0.030	1202.9	0.000
		16	0.423	-0.024	1231.6	0.000
		17	0.388	0.014	1255.9	0.000
		18	0.354	-0.008	1276.3	0.000
		19	0.322	0.010	1293.3	0.000
		20	0.292	-0.010	1307.5	0.000

1I. 1J.



Sample: 1980Q1 2014Q4
Included observations: 139

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.423	0.423	25.400	0.000
		2	0.308	0.157	38.977	0.000
		3	0.293	0.146	51.384	0.000
		4	0.324	0.169	66.637	0.000
		5	0.281	0.074	78.168	0.000
		6	0.209	-0.001	84.613	0.000
		7	0.300	0.163	97.994	0.000
		8	0.313	0.107	112.68	0.000
		9	0.239	-0.002	121.32	0.000
		10	0.151	-0.065	124.79	0.000
		11	0.039	-0.178	125.02	0.000
		12	0.264	0.226	135.79	0.000
		13	0.119	-0.106	138.01	0.000
		14	0.052	-0.081	138.43	0.000
		15	0.079	0.014	139.40	0.000
		16	0.086	-0.040	140.58	0.000
		17	0.020	-0.085	140.65	0.000
		18	-0.015	0.033	140.68	0.000
		19	0.051	0.049	141.10	0.000
		20	0.037	-0.036	141.33	0.000



Sample: 1980Q1 2014Q4
Included observations: 138

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.401	-0.401	22.679	0.000
		2	-0.076	-0.283	23.510	0.000
		3	-0.036	-0.244	23.693	0.000
		4	0.047	-0.142	24.008	0.000
		5	0.029	-0.058	24.128	0.000
		6	-0.142	-0.213	27.096	0.000
		7	0.072	-0.139	27.866	0.000
		8	0.063	-0.039	28.448	0.000
		9	0.023	0.032	28.529	0.001
		10	0.025	0.134	28.623	0.001
		11	-0.291	-0.259	41.507	0.000
		12	0.324	0.093	57.614	0.000
		13	-0.057	0.088	58.112	0.000
		14	-0.090	-0.020	59.369	0.000
		15	-0.001	-0.002	59.369	0.000
		16	0.058	0.034	59.893	0.000
		17	-0.009	-0.071	59.907	0.000
		18	-0.090	-0.086	61.205	0.000
		19	0.078	0.014	62.189	0.000
		20	0.048	0.054	62.569	0.000

As shown in Fig. 1A, the graph of consumer prices for Saudi Arabia (PSAU) exhibits an upward trend suggesting non-stationarity and a need to apply stationarity inducing transformations. Although seasonality may be expected in price data it is not visible in the price plot because of the dominant trend; seasonality may be revealed once the trend is removed through differencing.

The time paths of PSAU and PSAU_d11 (see Figure 1B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality.

Therefore, the differences between PSAU and PSAU_d11 (denoted D_PSAU) is plotted in Figure 1C. The difference has revealed cyclical fluctuations that range between -0.30 and 0.24. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between PSAU and PSAU_d11 that are reported in table 1D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of PSAU and PSAU_d11. Hence, we find that seasonality is not significant in the price level. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the logs of the adjusted (DLPSAU_d11) and unadjusted (DLPSAU) data.

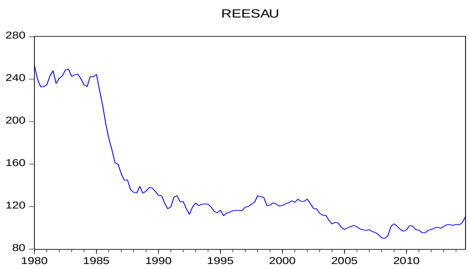
The time paths of DLPSAU and DLPSAU_d11 (see Figure 1E) follow each other closely. The trend has been removed and the series broadly fluctuates around a relatively constant mean as expected after first differencing. The variation in DLPSAU is greater than that of DLPSAU_d11 suggesting seasonality in DLPSAU while DLPSAU_d11 is smoother. This suggests that DLPSAU_ d11 exhibits reduced seasonality as expected. The difference between DLPSAU and DLPSAU_d11 (denoted D_DLPSAU) is plotted in Figure 1F. The difference has revealed a regular fluctuation around a relatively constant mean that ranges between -0.0068 and 0.0041. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLPSAU and DLPSAU_d11 that are reported in table 1G. Since the p-values of all of our tests are greater than 0.05 we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLPSAU and DLPSAU_d11. Hence, we find that seasonality is not significant in the difference of the log prices for Saudi Arabia

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of PSAU and DLPSAU in figure 1H and 1I. Shown in Fig. 1H is the ACF for PSAU. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. In the ACF for DLPSAU (see fig. 1I) the first 9 ACs are significant (and not just at seasonal lags) reflecting persistence in the data. Therefore, we plot the ACF of the second difference of LPSAU to determine if there is seasonality. The ACF for second difference D(PSAU,2) indicates insignificant ACs at all the seasonal lags except lag 12 (see fig. 1J). This implies that seasonality is not significant in price data. Hence, we use the unadjusted data PSAU in our VAR analysis.

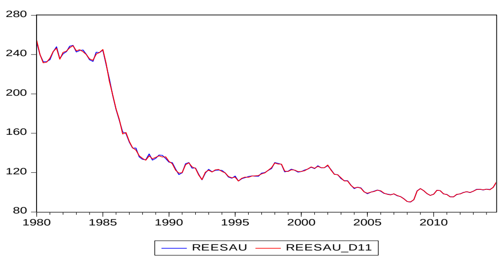
6.13.2 The seasonality features real effective exchange rate in Saudi Arabia

The graphs below depict the following variables. The Saudi Arabian real effective exchange (denoted REESAU), the seasonally adjusted REESAU series (REESAU_d11) and D_REESAU = REESAU - REESAU_d11, as well as the first (nonseasonal) difference of LREESAU (DLREESAU), the seasonally adjusted LREESAU series (LREESAU_d11) and D_LREESAU = LREESAU - LREESAU_d11 (where LREESAU is the log of REESAU). The seasonally adjusted series (REESAU_d11) is obtained using the Census X13 procedure in EViews. Tables 2D and 2G report various tests of the null hypothesis of equality of variance for REESAU and REESAU_d11 as well as DLREESAU and DLREESAU_d11.

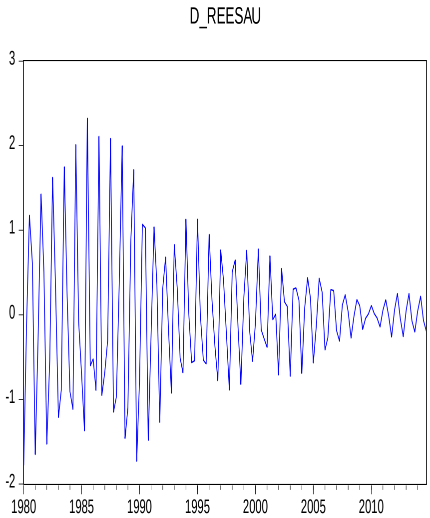
2A.



2B.



2C.

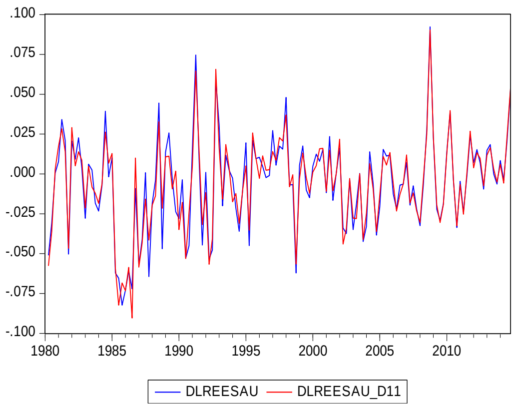


2D.

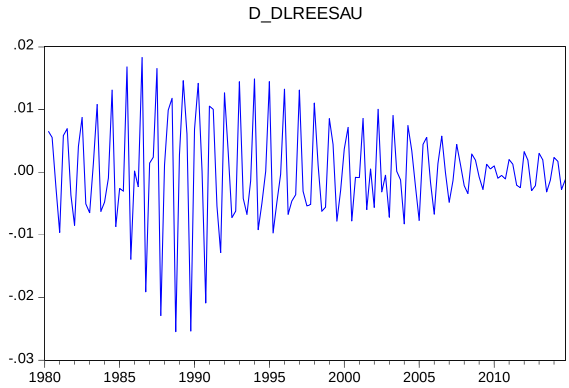
Equality of variances test between REESAU and REESAU_D11

Method	Df	Value	Probability
F-test	(139, 139)	1.000556	0.9974
Siegel-Tukey		0.033212	0.9735
Bartlett	1	1.07E-05	0.9974
Levene	(1, 278)	0.000149	0.9903
Brown-Forsythe	(1, 278)	3.33E-05	0.9954

2E.



2F.



2G.

Equality of variances test between DLREESAU and DLREESAU_D11

Method	Df	Value	Probability
F-test	(138, 138)	1.101093	0.5724
Siegel-Tukey		0.507286	0.6120
Bartlett	1	0.318685	0.5724
Levene	(1, 276)	0.362567	0.5476
Brown-Forsythe	(1, 276)	0.305904	0.5807

2H.

Sample: 1980Q1 2014Q4
Included observations: 140

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.974	0.974	135.72	0.000
		2	0.948	-0.010	265.29	0.000
		3	0.923	-0.004	388.95	0.000
		4	0.897	-0.040	506.43	0.000
		5	0.868	-0.048	617.43	0.000
		6	0.836	-0.100	721.00	0.000
		7	0.800	-0.081	816.62	0.000
		8	0.767	0.033	905.17	0.000
		9	0.731	-0.067	986.30	0.000
		10	0.694	-0.047	1059.9	0.000
		11	0.654	-0.069	1125.8	0.000
		12	0.613	-0.030	1184.2	0.000
		13	0.575	0.011	1235.9	0.000
		14	0.536	-0.020	1281.3	0.000
		15	0.496	-0.040	1320.4	0.000
		16	0.457	0.004	1353.9	0.000
		17	0.420	0.017	1382.5	0.000
		18	0.384	-0.016	1406.5	0.000
		19	0.344	-0.104	1426.0	0.000
		20	0.303	-0.043	1441.2	0.000

2I

Sample: 1980Q1 2014Q4
Included observations: 139

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.313	0.313	13.914	0.000
		2	0.043	-0.061	14.173	0.001
		3	0.062	0.075	14.727	0.002
		4	0.033	-0.008	14.889	0.005
		5	0.055	0.054	15.338	0.009
		6	0.130	0.105	17.845	0.007
		7	0.129	0.063	20.303	0.005
		8	0.022	-0.041	20.376	0.009
		9	0.015	0.016	20.410	0.016
		10	-0.056	-0.089	20.889	0.022
		11	0.009	0.055	20.902	0.034
		12	0.035	-0.007	21.091	0.049
		13	-0.108	-0.147	22.898	0.043
		14	0.100	0.204	24.478	0.040
		15	-0.017	-0.147	24.523	0.057
		16	-0.071	0.015	25.317	0.064
		17	0.059	0.099	25.868	0.077
		18	0.127	0.072	28.467	0.055
		19	0.024	-0.017	28.559	0.073
		20	-0.075	-0.098	29.494	0.078

As shown in Fig. 2A, the graph of real effective exchange rate for Saudi Arabia exhibits a downward trend (possibly a step shift in the mid-1980s) suggesting non-stationarity and a need to apply stationarity inducing transformations. Seasonality is not visible, although this may be revealed once the trend is removed through differencing.

The time paths of REESAU and REESAU_d11 (see Figure 2B) follow each other closely and it is difficult to discern whether the difference between them reflects seasonality. Therefore, the differences between REESAU and REESAU_d11 (denoted D_REESAU) is plotted in Figure 2C. The difference has revealed cyclical fluctuations that substantially decline through time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to a variety of tests for the equality of variance between REESAU and REESAU_d11 that are reported in table 2D. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of REESAU and REESAU_d11. Hence, we find that seasonality is not significant in the level of the real effective exchange rate. However, because this result may be influenced by the nonstationarity of the data we compare the differences of the adjusted (DLREESAU_d11) and unadjusted (DLREESAU) data.

The time paths of DLREESAU and DLREESAU_d11 (see Figure 2E) follow each other closely. The first difference has removed the trend and gives a relatively constant mean process. The differences between DLREESAU and DLREESAU_d11 (denoted D_DLREESAU) is plotted in Figure 2F. The difference has revealed cyclical fluctuations that substantially decline through time. Whilst this may indicate time-varying seasonality we need to ascertain whether this seasonality is significant. To do this we refer to tests for the equality of variance between DLREESAU and DLREESAU_d11 that are reported in table 2G. Since the p-values of all of our tests is greater than 0.05, we cannot reject the null hypothesis and find that there is no significant difference in the variances of DLREESAU and DLREESAU_d11. Hence, we find that seasonality is not significant in the difference of the log of the real effective exchange rate data for Saudi Arabia

To check that we have not missed any significant seasonality we plot the autocorrelation functions (ACFs) of REESAU and DLREESAU in figure 2H and 2I. Shown in Fig. 2H is the ACF for REESAU. All autocorrelation coefficients (ACs) are significant (and not just at the seasonal lags) which suggests nonstationarity and not necessarily seasonality. The ACF for DLREESAU has no significant ACs at seasonal lags (see fig. 2I). This implies that seasonality is not significant in real effective exchange rate and confirms the results of the variance equality tests. Hence, we will use the unadjusted data REESAU in our VAR analysis.

Appendix. Section 6.3

Table 6.7.1. Russia Unit root tests (the level data)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-3.6978*	-2.9136	-3.2956	-3.4907	0.2605	-1.9466	-1.0723	-3.1676
M	-2.9546*	-2.9136	-0.1664	-3.4907	0.4200	-1.9467	-0.3494	-3.1676
R	-3.6121*	-2.9126	-3.4998*	-3.4892	-2.5735*	-1.9465	-3.2216*	-3.1644
REE	-3.5466*	-2.9126	-3.0352	-3.4892	0.3029*	-1.9465	-1.2420	-3.1644
U	-1.7779	-2.9126	-2.3238	-3.4892	0.1901	-1.9465	-1.8488	-3.1644
GAP	-3.4199*	-2.9126	-3.3988	-3.4907	-2.7541*	-1.9466	-3.1639	-3.1676
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-6.1725*	-2.9126	-2.7758	-3.4893	0.9472	0.4630	0.2552	0.1460
M	-5.0755*	-2.9126	-0.3402	-3.4892	0.9402	0.4630	0.2433	0.1460
R	-3.6233*	-2.9126	-3.5077*	-3.4892	0.1716*	0.4630	0.1437*	0.1460
REE	-3.7141*	-2.9126	-3.0315	-3.4892	0.9145	0.4630	0.2523	0.1460
U	-1.8567	-2.9126	-2.6280	-3.4892	0.8369	0.4630	0.1841	0.1460
GAP	-2.6972	-2.9126	-2.6792	3.4892	0.0560*	0.4630	0.0560*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.7.1 the absolute values of all the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables (the unit root null cannot be rejected) except for the interest rate, the consumer price, the money supply, real excahnge rate and the output gap. The null is rejected for the interest rate for all 3 tests. For the consumer price and money supply for both ADF and PP tests when only the intercept is included in the test equation. For the output gap for both the ADF and DF-GLS tests when only the intercept is included in the test equation and for the real exchange rate the null is rejected when ADF, DF-GLS and PP tests included only the intercept in the test equation. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the interest rate and output gap (when both intercept and trend are included in the test equation for both variables). Hence, all Russian series are unambiguously non-stationary except for the interest rate, consumer prices, the money supply and the output gap. The interest rate is unambiguously stationary whereas the results for prices, the money supply and the output gap are ambiguous (if at least half of the tests indicate nonstationarity for all 3 variables). Therefore, we proceed to unit root tests for the first difference of the data.

Table 6.7.2 Russian unit root tests (the first difference data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.7866	-2.9135	-4.2816*	-3.49007	-2.52195*	-1.9467	-4.2728*	-3.1676
M	-2.9212*	-2.9135	-4.3181*	-3.4907	-1.1735	-1.9468	-4.2114*	-3.1676
R	-9.3901*	-2.9126	-9.3700*	-3.4901	-7.9043*	-1.9465	-9.1772*	-3.1644
REE	-7.2709*	-2.9135	-7.9079*	-3.4907	-1.1986*	-1.9465	-7.3467*	-3.1676
U	-6.3527*	-2.9136	-6.3066*	-3.4953	-5.9051*	-1.9467	-6.3141*	-3.1676
GAP	-5.3322*	-2.9135	-5.3135*	-3.4906	-5.2552*	-1.9471	-5.3899*	-3.1676
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.6265	-2.9134	-5.9121*	-3.4892	0.7877	0.4630	0.1006*	0.1460
M	-2.7522	-2.9136	-4.3653*	-3.4892	0.8346	0.4630	0.0555*	0.1460
R	-9.4962*	-2.9123	-9.7910*	-3.4907	0.1193*	0.4630	0.0359*	0.1460
REE	-7.2709*	-2.9135	-7.9926*	-3.4907	0.5732	0.4630	0.0642*	0.1460
U	-6.3701*	-2.9135	-6.3312*	-3.4906	0.0930*	0.4630	0.0754*	0.1460
GAP	-5.2259*	-2.9135	-5.1864*	-3.4907	0.0817*	0.4630	0.0650*	0.1460

As seen from Table 6.7.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables (rejecting the unit root null) except the consumer price (both ADF and PP tests when only the intercept is included in the test equation) and the money supply (DF-GLS and PP tests when only intercept is included in the tests equation). In addition, the KPSS test statistic is less than the critical value for all variables (giving non-rejection of the I(0) null) except for the consumer price, money supply and real exchange rates (when only the intercept is included in the test equation). Hence, all Russian first difference series are unambiguously stationary except for the consumer price, money supply and real exchange rate where the test results are ambiguous (if at least half of the tests indicate stationarity in all cases). That some tests indicate a nonstationary first difference for prices and the money supply may reflect low power, possibly due to structural breaks.

Table 6.7.3. Russian breakpoint unit root tests (the levels data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-5.3547*	-4.4436	-5.4428*	-4.8598	-1.2439	-4.4436	-3.3753	-4.8598
M	-3.3600	-4.4436	-1.5937	-4.8598	-0.9752	-4.4436	-1.3460	-4.8598
R	-3.9450	-4.4436	-4.2904	-4.8598	-4.1212	-4.4436	-4.7940	-4.8598
REE	-4.3638	-4.4436	-4.5700	-4.8598	-4.0913	-4.4436	-4.4572	-4.8598
U	-3.0607	-4.4436	-8.2622*	-4.8598	-3.0402	-4.4436	-4.4459	-4.8598
GAP	-4.0022	-4.4436	-8.5616*	-4.8598	-3.6935	-4.4436	-4.4188	-4.8598

Table 6.7.4. Russian breakpoint unit root test (the first difference data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-3.7799	-4.4436	-5.0135*	-4.8598	-4.0045	-4.4436	-5.1296*	-4.8598
M	-5.6844*	-4.4436	-5.5107*	-4.8498	-5.7459*	-4.4436	-5.5503*	-4.8598
R	-9.6093*	-4.4436	-9.4996*	-4.8598	-9.7767*	-4.4436	-9.7617*	-4.8598
REE	-9.2810*	-4.4437	-9.8947*	-4.8598	-9.3431*	-4.4436	-10.0043*	-4.8598
U	-7.7166*	-4.4436	-7.8445*	-4.8598	-7.8359*	-4.4437	-8.0977*	-4.8598
GAP	-8.1626*	-4.4436	-7.8874*	-4.8598	-8.1171*	-4.4436	-7.8566*	-4.8598

In Table 6.7.3 and 6.7.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.7.3., the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except prices, unemployment and the output gap. For the level of prices, the 2 of IO tests indicate stationarity around a structural break although the two AO tests suggest nonstationarity. For both unemployment and the output gap the IO test with intercept and trend indicates stationarity around a structural break if the 3 other tests suggest nonstationarity.

In Table 6.7.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the Russian first-differenced variables except for consumer prices using both IO and AO that only include the intercept – the 2 tests that include both intercept and trend suggest that this series is stationary around a structural break. However, all of the first differenced variables are unambiguously stationary without structural breaks except for the consumer prices and the money supply. Therefore, we interpret the evidence that all Russian series (except prices and the money supply) are stationary in first-differences without structural breaks. Further, because at least half of the tests indicate that the first differences of consumer prices and the money supply are stationary without structural breaks and we expect them to be stationary we will proceed with our VAR analysis as if these series are stationary in first differences. Nevertheless, the ambiguity of the results for these two series will be borne in mind if issues arise with the VAR modelling that suggests this assumption is inappropriate. Overall, despite some ambiguities in results, the unit root tests suggest that we can treat all variables for Russia as I(1) in our VAR analysis except for the interest rate that is unambiguously I(0).

Table 6.8.1. Indian unit root tests (the levels data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-0.0499	-2.8748	-2.8639	-3.4309	2.9915*	-1.9423	-2.4070	-2.9270
M	-0.2763	-2.8751	-3.1270	-3.4313	-0.8753	-1.9423	-1.5487	-2.9278
R	-5.3922*	-2.8748	-5.3859*	-3.4309	-4.6450*	-1.9423	-5.2592*	-2.9270
GAP	-16.0517*	-2.8746	-16.0147*	-3.4305	-21.2101*	-2.8746	-16.0826*	-2.9262
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	0.1841	-2.8746	-2.8855	-3.4305	1.9390	0.4630	0.14787	0.1460
M	1.4208	-2.8746	-5.1490	-3.4305	1.9360	0.4630	0.2472	0.1460
R	-10.7247*	-2.8746	-10.7516*	-3.4305	0.2317*	0.4630	0.1988	0.14600
GAP	-21.2101*	-2.8746	-21.1358*	-3.4305	0.03769*	0.4630	0.0377*	0.14600

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.8.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables in levels (the unit root null cannot be rejected) except for the interest rate, the output gap and consumer prices. For the interest rate and output gap both versions of all 3 tests unambiguously indicate that the data are stationary. For consumer prices only the DF-GLS test that includes just an intercept in the test equation indicates stationarity. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the interest rate and output gap. For the output gap both versions of the KPSS test indicate stationarity while for the interest rate only the test equation that just includes an intercept suggests stationarity. Hence, the Indian unit root tests indicate that the level of the money supply is unambiguously nonstationary and the output gap is unambiguously stationary. While the results for prices and interest rates are ambiguous, the majority of tests indicate that interest rates are stationary and prices are nonstationary (and we expect prices to be intrinsically nonstationary). Next, we proceed to unit root tests of the first difference of the data.

Table 6.8.2. Indian unit root tests (first difference)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5Critical values
P	-6.8803*	-2.8750	-6.8612*	-3.4312	-5.1288*	-1.9423	-6.3017*	-2.9270
M	-2.8663	-2.8750	-2.4616	-3.4312	-0.3552	-1.9423	-0.9674	-2.9278
R	-11.1853*	-2.8748	-11.1732*	-3.4309	-11.1970*	-1.9423	-10.8825*	-2.9270
GAP	-10.5833*	-2.8749	-10.5575*	-3.4310	-12.3042*	-1.9423	-11.3501*	-2.9272
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-7.4586*	-2.8746	-7.4395*	-3.4305	0.0532*	0.4630	0.0485*	0.1460
M	-25.1342*	-2.8746	-26.8749*	-3.4306	0.3596*	0.4630	0.1828	0.1460
R	-68.7646*	-2.8745	-70.9648*	-3.4306	0.1012*	0.4630	0.0839*	0.1460
GAP	-152.6155*	-2.8746	- 152.3218*	-3.4306	0.2136*	0.4630	0.2126	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.8.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all first differenced variables (rejecting the unit root null) except for the money supply. For the money supply all versions of both the ADF and DF-GLS tests indicate that its first difference is nonstationary. In addition, the KPSS test statistic is less than critical value for all variables (giving non-rejection of the I(0) null) except for the money supply and output gap (this rejection is for the test when both intercept and trend is included in the test equation for both variables). Hence, all Indian series are unambiguously stationary in first differences except for the money supply and output the gap. For the first difference of the output gap all except one test indicate that it is stationary which, given that the level of the output gap is unambiguously stationary, suggests that it is unlikely to have an order of integration above 1. The test results are ambiguous for the first difference of the money supply with just over half of the tests indicating nonstationarity. That the majority of tests indicate a nonstationary first difference for the money supply may reflect low power, possibly due to structural breaks.

Table 6.8.3. Indian Breakpoint Unit root test (the levels data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.1742	-4.4437	-4.1344	-4.8598	-1.1349	-4.4436	-4.3935	-4.8598
M	-1.9741	-4.4437	-3.6868	-4.8598	-1.6580	-4.4436	-3.6527	-4.8598
R	-16.5731*	-4.4436	-11.3457*	-4.8598	-11.2545*	-4.4436	-11.3512*	-4.8598
GAP	-16.2552*	-4.4436	-16.2611*	-4.8598	-22.5358*	-4.4436	-22.6431*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

Table 6.8.4. Indian Breakpoint Unit root test (the first difference data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-7.2730*	-4.4436	-7.2710*	-4.8598	-8.1278*	-4.4436	-8.1003*	-4.8598
M	-3.9409	-4.4436	-3.83750	-4.8598	-3.8815	-4.4436	-3.8998	-4.8598
R	-16.5731*	-4.4437	-16.4611*	-4.8598	-15.5884*	-4.4436	-15.5939*	-4.8598
GAP	-38.5689*	-4.4436	-40.2661*	-4.8598	-40.3315*	-4.4437	-39.7902*	-4.8590

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

In Table 6.8.3 and 6.8.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.8.3., the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except for the interest rate and output gap. The tests indicate that both the interest rate and the output gap are unambiguously stationary around a structural break.

In Table 6.8.4., the unit root null hypothesis is unambiguously rejected at the 5% level of significance for all of the first-differenced variables in India except for money supply. In contrast, the first difference of the money supply is unambiguously indicated to be nonstationary. Since the majority of unit root tests without structural breaks find the money supply to be nonstationary this suggest that the money supply data is I(2). Overall, there are some ambiguities in the results, however the unit root tests suggest that the output gap and interest rates are I(0), prices are I(1) and the money supply is probably I(2).

Table 6.9.1. Chinese unit root tests (the levels data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-0.7687	-2.8903	-1.8688	-3.4549	0.9703	-1.9440	-1.5501	-3.0290
M	-1.8682	-2.8909	-2.5115	-3.4558	0.0297	-1.9441	-1.5340	-3.0332
R	-1.8063	-2.8900	-1.9886	-3.4545	-0.4129	-1.9440	-1.8549	-3.0280
REE	-2.1837	-2.8897	-3.1444	-3.4540	-0.9647	-1.9439	-1.0443	-3.0227
GAP	-3.8917*	-2.8897	-3.8717*	-3.4540	-3.8875*	-1.9439	-3.9039*	-3.0270
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.0021	-2.8897	-1.7221	-3.4540	1.0435	0.4630	0.1499	0.1460
M	-2.3978	-2.8897	-2.2789	-3.4540	1.1298	0.4630	0.2199	0.1460
R	-1.7431	-2.8897	-1.8978	-3.4540	0.8558	0.4630	0.1570	0.1460
REE	-2.2759	-2.8897	-3.1096	-3.4540	0.3423	0.4630	0.1671	0.1460
GAP	-4.0873*	-2.8889	-4.0706*	-3.4540	0.0421*	0.4630	0.0421*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.9.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all levels variables (the unit root null cannot be rejected) except for the output gap. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the output gap. Hence, all Chinese series in levels are unambiguously non-stationary except for the output gap, which is unambiguously stationary. Next, we proceed to the first difference of the data.

Table 6.9.2. China Unit root tests (the first difference data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-3.1336*	-2.8903	-3.1065	-3.4549	-2.3977*	-1.9440	-2.9047	-3.0290
M	-1.7406	-2.8909	-2.3123	-3.4558	-1.3624	-1.9441	-1.6922	-3.0332
R	-7.6836*	-2.8900	-7.6876*	-3.4545	-7.7054*	-1.9440	-7.6494*	-3.0280
REE	-9.3562*	-2.8900	-9.8394*	-3.4545	-6.8873*	-1.9442	-8.2698*	-3.0280
GAP	-11.0676*	-2.8900	-11.0124*	-3.4545	-10.0086*	-1.9440	-10.7696*	-3.0280
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-5.3574*	-2.8900	-5.3301*	-3.4545	0.2062*	0.4630	0.2045	0.1460
M	-14.8429*	-2.8900	-16.8118*	-3.4545	0.3540*	0.4630	0.0786*	0.1460
R	-7.6692*	-2.8900	-7.6742*	-3.4545	0.11323*	0.4630	0.0613*	0.1460
REE	-9.3506*	-2.8900	-9.8394*	-3.4545	0.4564*	0.4630	0.0835*	0.1460
GAP	-11.1374*	-2.8900	-11.0791*	-3.4545	0.0289*	0.4630	0.0271*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.9.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all first differenced variables (rejecting the unit root null) except the money supply (for all versions of both ADF and DF-GLS tests) and consumer prices (for the ADF and DF-GLS tests when both intercept and trend are included in the test equation). In addition, the KPSS test statistic is less than critical value for all variables (giving non-rejection of the I(0) null) except for the consumer prices (when both intercept and trend are included in the test equation). Hence, all Chinese first differenced series are unambiguously stationary except for the money supply, consumer prices and the real exchange rate. Nevertheless, at least half of the tests indicate that the first differences of the money supply, consumer prices and the real exchange rate are stationary. That some of tests indicate a nonstationary first difference for the money supply, consumer prices and the real exchange rate may reflect low power, possibly due to structural breaks.

Table 6.9.3 China breakpoint unit root tests (the level data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-3.0010	-4.4436	-6.1896*	-4.8598	-1.9355	-4.4436	-3.0617	-4.8598
M	-3.0008	-4.4436	-4.8230	-4.8598	-1.6375	-4.4437	-2.4933	-4.8598
R	-4.9051*	-4.4436	-4.8121	-4.8598	-4.8248*	-4.4436	-4.5389	-4.8598
REE	-3.6155	-4.4436	-3.4663	-4.8598	-3.6417	-4.4436	-4.1800	-4.8598
GAP	-4.0465	-4.4436	-4.1831	-4.8598	-5.7086*	-4.4436	-5.9767*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

Table 6.9.4 China breakpoint unit root tests (First difference)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-3.8270	-4.4436	-6.9092*	-4.8598	-5.6640*	-4.4436	-7.0083*	-4.8598
M	-3.5228	-4.4436	-3.2771	-4.8598	-3.6217	-4.4436	-3.2093	-4.8598
R	-8.7299*	-4.4436	-8.8330*	-4.8598	-8.8252*	-4.4436	-4.9389*	-4.8598
REE	-12.8988*	-4.4436	-12.7519*	-4.8598	-10.6578*	-4.4436	-10.6549*	-4.8598
GAP	-11.8423*	-4.4436	-11.7887*	-4.8598	-11.9271*	-4.4436	-11.9232*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

In Table 6.9.3 and 6.9.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.9.3., the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except for consumer prices, interest rates and output gap. For consumer prices the null is rejected in 1 of the 4 tests (IO with intercept and trend), however we reject the inference of stationarity around a structural break because we believe that consumer prices are intrinsically nonstationary. The null is rejected in 2 of the 4 tests for both the interest rate (IO and AO versions with only an intercept) and the output gap (both AO versions). Since the output gap was unambiguously stationary in levels without a structural break, we simply interpret these results as confirming this variable's stationarity. With half of the test results indicating that interest rates are nonstationary in levels; we consider that this series could be nonstationary and treat it as such in our VAR analysis although we will recognise the possibility that it is stationary around a shifting intercept in our multivariate modelling.

In Table 6.9.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables except for the money supply (where the unit root null cannot be rejected for all tests). Nevertheless, since at least half of the tests without structural breaks indicate stationarity of the first difference of money supply we treat this variable as stationary in first differences in our VAR analysis although we will recognise the possibility that it is nonstationary in our multivariate analysis.

Whilst there are some ambiguities in the results the unit root tests overall suggest that all of the Chinese series are I(1) except for the output gap which is I(0).

Table 6.10.1. South African unit root tests (levels data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.0310	-2.8945	-3.2114	-3.4622	2.0643*	-1.9446	-2.2404	-3.0716
M	-2.7389	-2.8945	-1.2700	-3.4622	0.9399	-1.9447	-0.9418	-3.0716
R	-1.6625	-2.8945	-3.1730	-3.4622	-1.0405	-1.9445	-3.0644	-3.0716
REE	-1.9161	-2.8947	-2.2088	-3.4616	-0.6685	-1.9445	-2.0471	-3.0684
GAP	-3.9598*	-2.8943	-3.9365*	-3.4616	-3.8982*	-1.9445	-3.9859*	-30685
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.4087	-2.8947	-2.8308	-3.4617	1.2101	0.4630	0.1440*	0.1460
M	-2.4712	-2.8947	-1.3158	-3.4617	1.9155	0.4630	0.2515	0.1460
R	-1.6085	-2.8947	-2.6799	-3.4617	0.9188	0.4630	0.0831*	0.1460
REE	-2.0969	-2.8947	-2.4788	-3.4617	0.6494	0.4630	0.1675	0.1460
GAP	-3.0939*	-2.8939	-3.0937*	-2.8939	0.0377*	0.4630	0.0377*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.10.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables in levels (the unit root null cannot be rejected) except for the output gap and consumer prices. For the output gap all tests reject the unit root null hypothesis whereas for consumer prices only one test, DF-GLS when only the intercept is included in the test equation, rejects the null. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the consumer price, the interest rate and the output gap. For the output gap both versions of the KPSS test cannot reject the I(0) null whereas for consumer prices and the interest rate only the version of the test that includes both intercept and trend cannot reject the null. Hence, all South African series are unambiguously non-stationary except for the output gap, consumer prices and the interest rate. The output gap is unambiguously stationary whereas the majority of test results indicate that consumer prices and interest rates are nonstationary. Next, we proceed to the unit root tests of the first difference of the data.

Table 6.10.2. South African unit root tests (first difference)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-6.4352*	-2.8951	-6.4595*	-3.4622	-5.4045*	-1.9446	-6.3383*	-3.0716
M	-6.8196*	-2.8951	-7.0352*	-3.4622	-0.6505	-1.9449	-6.1250*	-3.0716
R	-7.2664*	-2.8951	-7.2261*	-3.4622	-4.5717*	-1.9446	-6.0446*	-3.0716
REE	-7.8684*	-2.8951	-7.8252*	-3.4622	-7.9100*	-1.9446	-7.8824*	-3.0716
GAP	-7.8781*	-2.8943	-7.8341*	-3.4610	-4.5795*	1.9445	-6.2040*	-3.0652
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-6.0942*	-2.8951	-6.0603*	-3.4623	0.1741	0.4630*	0.0590*	0.1460
M	-6.8547*	-2.8951	-7.0175*	-3.4622	0.4905	0.4630	0.0476*	0.1460
R	-7.2065*	-2.8951	-7.1621*	-3.4623	0.0489*	0.4630	0.0497*	0.1460
REE	-7.8795*	-2.8951	-7.8366*	-3.4622	0.0614*	0.4630	0.0528*	0.1460
GAP	-7.7779*	-2.8943	-7.7251*	-3.4612	0.0275*	0.4630	0.0258*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.10.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all first differenced variables (rejecting the unit root null) except for the money supply. Whilst the unit root null cannot be rejected for the DF-GLS test when only the intercept is included the majority of tests do reject the null. In addition, the KPSS test statistic is less than critical value for all differenced variables (giving non-rejection of the I(0) null) except for the money supply where the KPSS test rejects when only the intercept is included in the test equation. Hence, all South African series are unambiguously stationary in first differences except for the money supply. In the case of the differenced money supply the results are ambiguous; however, the majority of tests indicate stationarity.

That some of tests indicate a nonstationary first difference for the money supply may reflect low power of the unit root tests, possibly due to structural breaks.

Table 6.10.3. South African breakpoint unit root tests (level of data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.7764	-4.4436	-4.1024	-4.8598	-1.1044	-4.4437	-4.0414	-4.8598
M	-3.5732	-4.4436	-4.1069	-4.8598	-1.4944	-4.4437	-3.7147	-4.8598
R	-6.0487*	-4.4436	-5.6451*	-4.8598	-3.6484	-4.4437	-4.8929*	-4.8598
REE	-3.2460	-4.4436	-3.4831	-4.8598	-2.8203	-4.4436	-3.5192	-4.8598
GAP	-4.7447*	-44436	-4.9916*	-4.8598	-4.9899*	-4.4436	-5.1261*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

Table 6.10.4. South African breakpoint unit root tests (first difference)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-8.8063*	-4.4436	-8.7535*	-4.8598	-6.7186*	-4.4436	-6.7983*	-4.8598
M	-7.6315*	-4.4436	-7.5415*	-4.8598	-7.7096*	-4.4436	-7.6537*	-4.8598
R	-10.0762*	-4.4436	-10.5012*	-4.8598	-7.9131*	-4.4436	-7.9838*	-4.8598
REE	-8.6345*	-4.4436	-8.8668*	-4.8598	-8.7312*	-4.4436	-8.9756*	-4.8598
GAP	-8.8949*	-4.4436	-8.7963*	-4.8598	-8.8830*	-4.4436	-8.8846*	-.4.6073

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

In Table 6.10.3. and 6.10.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.10.3, the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except for the output gap and interest rate. For the output gap the unit root null is unambiguously rejected however we conclude that this series is stationary, rather than stationary around a structural break, because the unit root tests without a structural break indicated that it was unambiguously stationary. For the interest rate 3 of the 4 tests (for the exception is the AO test when only the intercept is included in the test equation) suggest that this series is stationary around a structural break. Overall we will treat interest rates as nonstationary in our VAR analysis however we will recognise that it is very possible that they are stationary around a structural break.

In Table 6.10.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables in South Africa. Whilst the alternative hypothesis is stationarity around a structural break the finding that all of the first differenced variables are stationary without structural breaks except for the money supply unambiguously indicates stationarity without a structural break for all variables except the money supply. Further, because most of the tests indicate that the first difference of the money supply is stationary without structural breaks we will proceed with our VAR analysis as if these series are stationary in first differences – although these results will be borne in mind if issues arise with the VAR modelling that suggest this assumption is inappropriate.

Whilst there are some ambiguities in the results the unit root tests overall suggest that all of the South African series can be treated as I(1) except for the output gap which is I(0). Although we note that interest rates may well be I(0) around a structural break.

Table 6.11. 1. Algerian unit root tests (the levels data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	1.4708	-2.0912	-0.7315	-3.4717	2.7518*	-1.9453	-0.7862	-3.1132
M	-1.3690	-2.0935	-1.9964	-3.4753	0.5921	-1.9455	-1.8281	-3.1260
R	-2.9229*	-2.9055	-2.4822	-3.4783	0.6514	-1.9457	-1.8927	-3.126
REE	-1.3218	-2.0912	-1.1653	-3.4717	-0.9326	-1.9453	-1.9776	-3.1164
GAP	-4.2721*	-2.9012	-4.2438*	-3.4717	-3.2241*	-1.9453	-3.8549*	-3.1132
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	1.2162	-2.9012	-0.9919	-3.4716	1.1493	0.4630	0.2689	0.1460
M	-2.3655	-2.9012	-2.6320	-3.4753	-1.1635	0.4630	0.2563	0.1460
R	-13.8906*	-2.9012	-8.2253*	-3.4716	0.7533	0.4630	0.2443	0.1460
REE	-1.3218	-2.9012	-1.4452	-3.4716	0.7886	0.4630	0.2436	0.1460
GAP	-4.4257*	-2.9035	-4.3954*	-3.4716	0.0369*	0.4630	0.0221	0.1460*

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.11.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables in levels (the unit root null cannot be rejected) except for the cosumer price, the interest rate and output gap. For the output gap all the tests unambiguously indicate that the data are stationary. For consumer prices only the DF-GLS test that includes just an intercept in the test equation rejects the null. For the interest rate the null is rejected by the ADF test that includes only an intercept in the test equation and both versions of the Phillips and Perron tests. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the output gap (for both versions of the tests). Hence, for Algeria, the unit root tests indicate that the level of the money supply and real exchange rate are unambiguously nonstationary and the output gap is unambiguously stationary. While the results for prices and interest rates are ambiguous, the majority of these tests indicate that they are nonstationary (and we expect prices to be intrinsically nonstationary). Next we proceed to unit root tests of the first difference of the data.

Table 6.11.2 Algerian unit root tests (first difference data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-6.8028*	-2.9018	-6.9890*	-3.4726	-6.8286*	-1.9453	-7.0077*	-3.1164
M	-2.9485*	-2.9018	-3.1529*	-3.4753	-1.8629	-1.9455	-2.5258	-3.1260
R	-9.3937*	-2.9055	-7.9349*	-3.4783	-9.9425*	-1.9453	-10.0189*	-3.1356
REE	-6.3732*	-2.9018	-6.3599*	-3.4726	-6.3110*	-1.9453	-6.3110*	-3.1164
GAP	-8.9941	-2.9035	-8.9186*	-3.4716	-9.0334*	-1.9455	-8.9993*	-3.1260
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-6.8641*	-2.9018	-7.0244*	-3.4726	0.2897*	0.4630	0.0643*	0.1460
M	-12.7734*	-2.9018	-20.1596*	-3.4725	0.3191*	0.4630	0.1295*	0.1460
R	-7.7177*	-2.9017	-8.9623*	-3.4725	0.7443	0.4630	0.1846	0.1460
REE	-6.2134*	-2.9018	-6.1954*	-3.4725	0.1752*	0.4630	0.0784*	0.1460
GAP	-8.5685*	-2.9018	-8.5251*	-3.4725	0.0312*	0.4630	0.0221*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.11.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all first differenced variables (rejecting the unit root null) except for the money supply (where inference is ambiguous). For the money supply the unit root null cannot be rejected for both versions of the DF-GLS test, if the null is rejected by the ADF and Phillips and Perron tests. In addition, the KPSS test statistic is less than critical value for all differenced variables (giving non-rejection of the I(0) null) except for the interest rate when only the intercept is included in the test equation. Hence, all Algerian series are unambiguously stationary in first differences except for the money supply and interest rate. For the differenced money supply and interest rate the results are ambiguous, however, the majority of these tests indicate stationarity. That some of tests indicate nonstationary of the first difference of the money supply and interest rate may reflect low power of the unit root tests, possibly due to structural breaks.

Table 6.11.3 Algerian breakpoint unit root tests (the levels data)

	Unit Root with Break Test (Innovative outliers)				Unit Root Break Test (additive outliers)			
	Intercept		Intercept & Trend		Intercept		Intercept & Trend	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.6225	-4.4437	-2.3163	-4.8598	-1.1056	-4.4436	-2.2796	-4.8598
M	-2.5766	-4.4437	-7.0223*	-4.8598	-1.1177	-4.4436	-3.4711	-4.8598
R	-10.6593*	-4.4437	-10.2772*	-4.8598	-3.6053	-4.4436	-4.2412	-4.8598
REE	-4.9030*	-4.4437	-4.1839	-4.8598	-4.8224*	-4.4436	-4.5139	-4.8598
GAP	-4.4028	-4.4436	-8.1558*	-4.8598	-7.0074*	-4.4436	-7.4426*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

Table 6.11.4. Algerian breakpoint unit root tests (first differenced data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**
P	-7.8594*	-4.4436	-7.7918*	-4.8598	-7.9658*	-4.4436	-7.7918*	-4.8598
M	-4.1415	-4.4437	-3.6799	-4.8598	-4.3539	-4.4436	-4.0155	-4.8598
R	-9.2253*	-4.4436	-8.5347*	-4.8598	-8.2809*	-4.4436	-6.4586*	-4.8598
REE	-6.7544*	-4.4436	-6.7634*	-4.8598	-6.9623*	-4.4437	-6.9524*	-4.8598
GAP	-10.3987*	-4.4436	-10.3197*	-4.8598	-9.9885*	-4.4436	-9.6005*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%.

In Table 6.11.3 and 6.11.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.11.3., the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except the money supply, interest rates, real exchange rate and output gap. For the money supply the null is rejected in 1 of the 4 tests (IO with intercept and trend). The null is rejected in 2 of the 4 tests for both the interest rate (for all versions of the IO test) and the real exchange rate (IO and AO versions with only an intercept). For the output gap the unit root null is unambiguously rejected however we conclude that this series is stationary, rather than stationary around a structural break, because the unit root tests without a structural break indicated that it was unambiguously stationary. Further, since at least half of the test results indicate that the money supply, interest rate and real exchange rate are nonstationary in levels, we consider these series as probably nonstationary and treat them as such in our VAR analysis. Nevertheless, we will recognise the possibility that they are stationary around a shifting intercept in our multivariate modelling.

In Table 6.11.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables except for the money supply (where the unit root null cannot be rejected for all tests). Nevertheless, since at least half of the tests without structural breaks indicate stationarity of the first difference of money supply we treat this variable as stationary in first differences in our VAR analysis although we will recognise the possibility that it is nonstationary in our multivariate analysis. Whilst there are some ambiguities in the results the unit root tests overall suggest that all of the Algerian series are I(1) except for the output gap which is I(0).

Table 6.12.1. Angolan unit root tests (the levels data)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.5919	-2.9187	-3.4239*	-3.4952	0.0245	-1.9472	-2.7849	-3.1836
M	-6.6402*	-2.9135	-3.8021*	-3.4907	1.0450	-1.9467	-0.4265	-3.1708
R	-1.7085	-2.9108	-1.0280	-3.4865	-0.0043	-1.9463	-1.0759	-3.1580
GAP	-2.6002	-2.9145	-2.5584	-3.4921	-2.1206*	-1.9467	-2.4918	-3.1708
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-14.5687*	-2.9109	-10.4164*	-3.4865	0.8493	0.4630	0.2226	0.1460
M	-11.3240*	-2.9109	-3.3767*	-3.4865	0.9345	0.4630	0.2516	0.1460
R	-1.7085	-2.9108	-1.0710	-3.4865	0.8205	0.4630	0.1794	0.1460
GAP	-4.6572*	-2.9108	-4.6148*	-3.4865	0.0943*	0.4630	0.0943*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.12.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables in levels (the unit root null cannot be rejected) except for the consumer price, money supply and output gap. For the consumer price both versions of Phillips and Perron tests indicate that the null hypothesis of unit root is rejected, while the ADF and DF-GLS tests suggest that the unit root null cannot be rejected. For the money supply both versions of the ADF and PP tests reject the null while the DF-GLS test cannot reject the null. For the output gap when the DF-GLS test when only an intercept is included and both versions of the Phillips Perron test reject the null while the other 3 tests do not reject the null. In addition, the KPSS test statistic is greater than the critical value for all variables (giving rejection of the I(0) null) except for the output gap for both versions of the test. Hence, the interest rate series is unambiguously non-stationary whereas the inference for the output gap, consumer prices and the money supply is ambiguous. Since at least half of the tests suggest that the levels of prices and money cannot reject the unit root null (and we believe that they are intrinsically nonstationary) we conclude that these series are nonstationary. Further, because the majority of tests reject the unit root null for the output gap (and we believe it is most likely to be stationary) we consider this series to be stationary. Next, we proceed to the unit root tests of the first difference of the data.

Table 6.12.2 Angolan unit root tests (first difference data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.6389	-2.9188	-1.4586	-3.4986	0.2032	-1.9475	-0.8002	-3.1900
M	-3.6154*	-2.9145	-6.9841*	-3.4907	-3.5061*	-1.9467	-4.9348*	-3.1708
R	-7.7986*	-2.9117	-7.7884*	-3.4878	-1.6365	-1.9475	-5.4805*	-3.1612
GAP	-2.8388	-2.9145	-2.7621	-3.4921	-2.7108*	-1.9467	-2.8792	-3.1708
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-3.3353*	-2.9117	-2.4804	-3.4878	0.7412	0.4630	0.2573	0.1460
M	-7.7449*	-2.9117	-10.7056*	-3.4878	1.2145	0.4630	0.2046	0.1460
R	-7.7785*	-2.9117	-7.78842*	-3.4878	0.2945*	0.4630	0.0904*	0.1460
GAP	-13.9089*	-2.9117	-13.7850*	-3.4878	0.0947*	0.4630	0.0919*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.12.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all first differenced variables (rejecting the unit root null) except for the consumer price , interest rates and the output gap. For the consumer price the unit root null is only rejected for 1 of the 6 tests (being the Phillips and Perron test that only includes an intercept). For interest rates the unit root is rejected for 5 of the 6 tests (the exception is the DF-GLS test that includes only an intercept). For the output gap the unit root null is rejected for 3 of the 6 tests (being both versions of the Phillips Perron test and the DF -GLS when only an intercept is included in the test equation). In addition, the KPSS test statistic is less than critical value for all variables (giving non-rejection of the I(0) null) except for the consumer price (both versions of the test) and the money supply (both versions of the test). Hence, only the first difference of the interest rate is unambiguously stationary according to the tests. Nevertheless, the majority of the tests indicate that the first differences of the money supply and the output gap are stationary and we will treat them as such. However, the majority of the tests indicate that the first difference of consumer prices is nonstationary. That some of tests indicate nonstationary for the first difference of the money supply, consumer prices and the output gap may reflect low power, possibly due to structural breaks.

Table 6.12.3 Angolan breakpoint unit root tests (the levels data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-4.4830*	-4.4436	-6.4345*	-4.8598	-3.5884	-4.4436	-3.6463	-4.8598
M	-6.5940*	-4.4436	-5.5717*	-4.8598	-0.6887	-4.4436	-3.2622	-4.8598
R	-6.3387*	-4.4436	-5.9223*	-4.8598	-5.5513*	-4.4436	-2.5587	-4.8598
GAP	-3.0154	-4.4436	-3.8360	-4.8598	-2.9252	-4.4436	-3.8802	-4.8598

Table 6.12.4. Angolan breakpoint unit root tests (first differenced data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**
P	-9.0129*	-4.4436	-11.1856*	-4.8598	-2.6915	-4.4436	-3.1451	-4.8598
M	-5.0597*	-4.4436	-7.5590*	-4.8598	-10.3314*	-4.4436	-11.2153*	-4.8598
R	-10.4385*	-4.4436	-10.1642*	-4.8598	-10.4913*	-4.4436	-10.1496*	-4.8598
GAP	-3.1479	-4.4436	-3.8884	-4.8598	-3.2192	-4.4436	-3.7013	-4.8598

In Table 6.12.3 and 6.12.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.12.3, the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected in the variables except for the consumer price, interest rate and money supply. For the interest rate the unit root null is rejected for 3 of the 4 tests (the exception is the AO test when both intercept and trend are included in the test equation). For the consumer price and money supply the null is rejected in 2 (the IO versions) of the 4 tests. Hence, at least half of these tests indicate nonstationarity for the levels of consumer prices and the money supply, which is consistent with our a priori beliefs and the unit root tests that do not account for structural breaks. The majority of tests indicate that the interest rate is stationary around a structural break. While we will treat this series as I(1) in our multivariate analysis, given the unit root tests without structural breaks, we note that this series may well be stationary around a break. Whilst the output gap is unambiguously found to be nonstationary, we suggest that it is stationary given the unit root tests that do not account for structural breaks and our prior belief that it is likely stationary.

In Table 6.12.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables in Angola except the consumer price (for all versions of the IO test) and the output gap (in all 4 tests). However, because the majority of tests that do not allow for structural breaks indicate that both the level and first difference of the the output gap are stationary and we believe this series is most likely to be stationary (given its construction) we consider this series as I(0) in our multivariate analysis. Because at least half of the tests of the first difference of consumer price indicated that it is series is stationary around a strutural break, we believe that the level of prices is not I(2). We will treat prices as I(1) although note the possibility that they are I(1) around a structural break. The results overall also suggest that money supply is I(1) and we will treat it as such. While interest rates may be stationary around a structural break, as a starting point in our multivariate analysis we will treat them as I(1). The ambiguities in these results will be borne in mind if issues arise with the VAR modelling that suggest our initial assumptions are inappropriate.

Table 6.13.1. Nigerian unit root tests (the levels data)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-0.4635	-2.9012	-2.5915	-3.4700	0.8868	-1.9454	-2.5311	-3.1068
M	-1.5984	-2.9012	-2.4285	-3.4734	-0.5703	-1.9454	-2.8092	-3.1068
R	-2.0950	-2.9001	-2.9542	-3.4708	- 2.0887*	-1.9451	-2.3653	-3.1068
REE	-1.9352	-2.9001	-1.7066	-3.4700	-1.3595	-1.9451	-1.5755	-3.1068
GAP	- 4.1425*	-2.9001	-4.1190*	-3.4700	-2.9416*	-1.9451	-3.6253*	-3.1068
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-1.1362	-2.9001	-2.7338	-3.3700	1.2054	0.4630	0.1130	0.1460
M	-1.2395	-2.9001	-1.9745	-3.3700	1.1903	0.4630	0.1208	0.1460
R	-2.0087	-2.9001	-2.3746	-3.4700	0.5045	0.4630	0.1309	0.1460
REE	-2.031	-2.9001	-1.8124	-3.4700	0.2743*	0.4630	0.2135	0.1460
GAP	-4.4322*	-2.9001	-4.4118*	-3.4700	0.0353*	0.4630	0.0353*	0.1460*

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.13.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables in levels (the unit root null cannot be rejected) except for the output gap and interest rate. For the output gap all tests reject the unit root null hypothesis indicating that this variable is unambiguously I(0). Whereas, for the interest rate only one test, the DF-GLS test when only the intercept is included in the test equation, rejects the null. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the exchange rate and the output gap. For the output gap both versions of the KPSS test cannot reject the I(0) null whereas for the exchange rate only the version of the test that includes only an intercept cannot reject the null. Hence, all Nigerian series are unambiguously non-stationary except for the output gap, real exchange rate and the interest rate. The output gap is unambiguously stationary whereas the majority of test results indicate that real exchange rate and interest rates are nonstationary. Next, we proceed to the unit root tests of the first difference of the data.

Table 6.13.2 Nigerian unit root tests (first difference data)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-8.6563*	-2.9012	-8.5999*	-3.4716	-1.7764	-1.9453	-7.2950*	-3.1132
M	-1.7039	-2.9024	-1.9765	-3.4716	-0.7200	-1.9453	-2.2358	-3.1132
R	-7.4190*	-2.9012	-7.3667*	-3.4717	-7.4686*	-1.9452	-7.4692*	-3.1132
REE	-8.0622*	-2.9007	-8.1365*	-3.4708	-7.5344*	-1.9452	-7.9091*	-3.1100
GAP	-6.9408*	-2.9024	-6.8898*	-3.4734	-0.8290	-1.9452	-5.9550*	-3.1100
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-9.5752*	-2.9007	-10.4651*	-3.4708	0.1629*	0.4630	0.0794*	0.1460
M	-12.9798*	-2.9007	-12.6507*	-3.4708	0.1975*	0.4603	0.1116*	0.1460
R	-8.0404*	-2.9006	-7.9382*	-3.4708	0.1089*	0.4630	0.1087*	0.1460
REE	-8.0615*	-2.9007	-8.1365*	-3.4709	0.1516*	0.4630	0.0431*	0.1460
GAP	-9.0774*	-2.9006	-9.0039*	-3.4708	0.0323*	0.4630	0.0252*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.13.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all first differenced variables (rejecting the unit root null) except for the consumer price, money supply and output gap. For the money supply both versions of the ADF and DF-GLS tests indicate that its first difference is nonstationary whereas the Phillips and Perron tests suggest that it is stationary in first differences. For the both the consumer price and output gap only one test, the DF-GLS test when only the intercept is included in the test equation, cannot reject the null. In addition, the KPSS test statistic is less than critical value for all variables (giving non-rejection of the I(0) null) in all the cases. Hence, all Nigerian series are unambiguously stationary in first differences except for the price, money supply and output the gap. For the first difference of the prices, money supply and the output at least half of the tests indicate that these series are stationary hence we conclude that no series is integrated of an order greater than 1. That some of the tests indicate a nonstationary first difference may reflect low power, possibly due to structural breaks.

Table 6.13.3. Nigerian breakpoint unit root tests (the levels data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.4613	-4.4436	-4.6426	-4.8598	-1.2821	-4.4436	-4.5073	-4.8598
M	-3.0670	-4.4436	-3.5112	-4.8598	-2.2920	-4.4436	-3.7271	-4.8598
R	-4.0931	-4.4436	-4.7326	-4.8598	-4.1895	-4.4436	-4.7326	-4.8598
REE	-1.9980	-4.4436	-2.4286	-4.8598	-2.0247	-4.4436	-3.6344	-4.8598
GAP	-5.8049*	-4.4436	-6.1616*	-4.8598	-8.7799*	-4.4436	-7.9681*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

Table 6.13.4. Nigerian breakpoint unit root tests (first differenced data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**
P	-9.5962*	-4.4436	-9.79984*	-4.8598	-9.1337*	-4.4436	-9.7383*	-4.8598
M	-3.2454	-4.4436	-4.4464	-4.8598	-3.4698	-4.4436	-4.0915	-4.8598
R	-8.4419*	-4.4436	-8.2927*	-4.8598	-8.3594*	-4.4436	-8.4665*	-4.8598
REE	-17.5144*	-4.4436	-19.4148*	-4.8598	-16.6100*	-4.4436	-11.4664*	-4.8598
GAP	-13.5874*	-4.4436	-13.5853*	-4.8598	-12.6258*	-4.4436	-8.4549*	-4.8598

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

In Table 6.13.3 and 6.13.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first-differences of the data, respectively. In Table 6.13.3., the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except for output gap. The output gap rejects the null for all 4 tests. Since the output gap was unambiguously stationary in levels according to unit root tests without a structural break we simply interpret these results as confirming this variable's stationarity.

In Table 6.13.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables except for the money supply (where the unit root null cannot be rejected for all tests). Nevertheless, since at least half of the tests without structural breaks indicate stationarity of the first difference of money supply we treat this variable as stationary in first differences in our VAR analysis although we will recognise the possibility that it is nonstationary in our multivariate analysis. Whilst there are some ambiguities in the results the unit root tests overall suggest that all of the Nigerian series are I(1) except for the output gap which is I(0).

Table 6.14. 1. Saudi Arabian unit root tests (the levels data)

	ADF unit root tests				**DF-GLS unit root tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	2.31179	-2.8824	-0.0019	-3.4427	3.1075*	-1.9431	-0.1430	-2.9920
M	1.6260	-2.8824	-1.2021	-3.4435	2.7716*	-1.9432	-1.6927	-2.9950
REE	-1.9950	-2.8824	-1.0510	-3.4427	0.15189	-1.9432	-0.8032	-2.9920
GAP	-4.3249*	-2.8835	-4.3329*	-3.4444	-1.8992	-1.9432	-3.3003*	-2.9920
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	2.0478	-2.8822	-0.0772	-3.4424	1.0988	0.4630	0.2544	0.1460
M	0.5115	-2.8822	-1.0833	-3.4424	1.4443	0.4630	0.4630	0.1460
REE	-2.3076	-2.8822	-1.0849	-3.4424	1.1591	0.4630	0.2465	0.1450
GAP	-6.3579*	-2.8822	-6.3300*	-3.4424	0.0376*	0.4630	0.0376*	0.1450

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.14.1 the absolute values of the test statistics are less than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables (the unit root null cannot be rejected) except for the output gap, the consumer price and the money supply. The null is rejected for the output gap by all tests except for the DF-GLS test that includes only an intercept. In contrast, the null cannot be rejected for consumer prices and the money supply for all tests except the DF-GLS test that only includes and intercept. In addition, the KPSS test statistic is greater than critical value for all variables (giving rejection of the I(0) null) except for the output gap (where the null cannot be rejected by either version of the test. Hence, the real exchange rate is unambiguously nonstationary. While there is ambiguity for the money supply and consumer prices they are regarded as nonstationary because at least half of the tests indicate non-stationarity and they are regarded as intrinsically nonstationary. The output gap is considered stationary because the majority of tests indicate this and it is expected to be stationary (given its construction as the difference from a trend). Next, we proceed to unit root tests for the first difference of the data.

Table 6.14.2 Saudi Arabian unit root tests (first difference data)

	ADF unit root tests				DF-GLS unit root tests			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-7.4382*	-2.8824	-8.1877*	-3.4427	-2.4009*	-1.9432	-4.6793*	-2.9930
M	-3.89921*	-2.8829	-4.2095*	-3.4434	-3.0724*	-1.9432	-4.4401*	-2.9930
REE	-8.2965*	-2.8824	-8.5211*	-3.4427	-2.6787*	-1.9432	-7.3434*	-2.9920
GAP	-4.6952*	-2.8835	-4.6726*	-3.4427	-1.9133	-1.9432	-3.1337*	-2.9920
	Phillips and Perron tests				**KPSS tests**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-8.1053*	-2.8822	-8.5084 *	-3.4424	0.5303	0.4630	0.1122*	0.1460
M	-14.2943 *	-2.8822	-14.3602*	-3.4427	0.2360*	0.4630	0.1575	0.1460
REE	-8.3186*	-2.8824	-8.5520*	-3.4427	0.4337*	0.4630	0.0652*	0.1460
GAP	-15.2613*	-2.8824	-15.2119*	-3.4427	0.0754*	0.4630	0.0385*	0.1460

Note* indicates rejection of the unit root null or non-rejection of the I(0) null at 5%

As seen from Table 6.14.2 the absolute values of the test statistics are greater than their corresponding 5% critical values for the ADF, DF-GLS and Phillips and Perron tests for all variables (rejecting the unit root null) except the output gap. For the output gap all tests reject the null except for the DF-GLS when only an intercept is included in the test equation. In addition, the KPSS test statistic is less than critical value for all variables (giving non-rejection of the I(0) null) except for the consumer (when only an intercept is included in the test equation) and the money supply (when both the intercept and trend are included in the test equation). Hence, for all Saudi Arabian series the majority of tests indicate that they are stationary in first differences. That some tests indicate a nonstationary first difference may reflect low power, possibly due to structural breaks.

Table 6.14.3 Saudi Arabian breakpoint unit root tests (the levels data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values	Test statistic	5% Critical values
P	-2.6198	-4.4436	-3.5362	-4.8598	-2.1398	-4.4436	-9.3501*	-4.8598
M	-2.1510	-4.4436	-3.1806	-4.8598	-0.4478	-4.4436	-0.4478	-4.8598
REE	-5.4401*	-4.4436	-5.0373*	-4.8598	-5.8316*	-4.4436	-4.9830*	-4.8598
GAP	-5.3972*	-4.4436	-5.3772*	-4.8598	-6.5355*	-4.4436	-6.6298*	-4.8598

Table 6.14.4. Saudi Arabian breakpoint unit root tests (first differenced data)

	Unit Root with Break Test (Innovative outliers)				**Unit Root Break Test (additive outliers)**			
	Intercept		**Intercept & Trend**		**Intercept**		**Intercept & Trend**	
	Test statistic	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**	**Test statistic**	**5% Critical values**
P	-9.0069*	-4.4436	-9.3109*	-4.8598	-9.0717*	-4.4436	-9.3501*	-4.8598
M	-4.9410*	-4.4436	-5.0303*	-4.8598	-4.8358*	-4.4436	-4.9403*	-4.8598
REE	-8.9608*	-4.4436	-8.9911*	-4.8598	-9.0071*	-4.4436	-9.0885*	-4.8598
GAP	-4.9893*	-4.4436	-5.0508*	-4.8598	-7.1784*	-4.4436	-7.1722*	-4.8598

In Table 6.14.3 and 6.14.4 we test the null hypothesis of a unit root against the alternative of a stationarity process around a structural break for the levels and first differences of the data, respectively. In Table 6.14.3, the null hypothesis of a unit root in the levels of the data unambiguously cannot be rejected for all of the variables except for consumer prices (in all cases except for the AO test that includes both an intercept and trend) and money supply (for all 4 test). Because the null cannot be rejected for the majority of tests for prices and the money supply, we conclude that they are nonstaionary. In contrast, all tests suggest that the real exchange rate and output gap are stationary around a structural break. Because the output gap was found to be stationary in the tests that exclude a structural break, we believe these results simply confirms its stationarity. In contrast, the real exchange was found to be nonstationary in the tests without a structural and these results therefore suggest that they may be stationary around a structural break. We treat this series as I(1) although we note that it may be stationary around a structural break.

In Table 6.14.4., the unit root null hypothesis is rejected at the 5% level of significance for all of the first-differenced variables suggesting that they are all stationary around a structural break. However, because the unit root tests without structural breaks suggested that all differenced series are stationary, we simply interpret these results as confirming this. Hence, we regard all Saudi Arabian series as I(1) except for the output gap which is I(0) without structural breaks. Although we note that the real exchange rate may be stationary around a structural break

Appendix. Section 7.1

7. 0 Box-Jenkins based ARIMAX modelling of oil prices

The reliable forecasts of the price of oil are of interest for a wide range of applications. For instance, central banks forecast oil price to achieve oil price stability, allocation of the scarce resources and assessing macroeconomic risks. A poor forecast of the oil price may lead to the poor investment decision. Therefore, how to accurately forecast the oil price is essential to policymakers and academic researchers. As a result, researchers have developed and applied different statistical and econometric models to forecast the oil price. For example, Bekiros et al. (2015) and Wang et al. (2017) applied combined methods, unrestricted VAR, Bayesian VAR, Random Walk, Autoregressive model (AR), and time-varying VAR model (TVP-VAR) as well as time-varying VAR that include Markov Switching processing model (TVP-VAP MS) to predict changes in the oil price. Whereas, Chinn et al. (2005), Agnolucci, (2009), Ahmed and Shabri (2014) applied the Box-Jenkins method to forecast the oil price. Other model explored to predict the oil price include GARCH-type models (see: Hou and Saudy, 2012 and Ahmed and Shabri, 2013).[167]

The general conclusion from many of these studies is that a valid model can be obtained (most especially ARIMA model) to forecast the oil price for the selected sample. In this study, we produce a forecast for the oil price using Box-Jenkins ARIMA method. In particular, we test whether the ARIMA model can provide a valid model that passes all the standard diagnostic test (stationarity, invertibility and autocorrelation) for the oil price between the period of 1980q1 2012q4.

7.1 ARIMA modelling for the oil price

Following the order of integration results reported in Table 6.6.5 for the oil price, we build ARIMA models to the stationary first difference of the oil price, denoted as DLOILP. We use unadjusted seasonal oil price in our modelling because seasonality is not significant in OILP (see chapter 6 Table 6.5). The quarterly oil price data available between 1980q1 – 2014q4. To allow for lags transformations and have a consistent estimation period for all models we specify an initialization period of four years and estimate all models over the period 1984q1 – 2012q4. Therefore, we regress DLOILP on a constant and use the Bai and Perron test to identify the multiple potential shifts in the series.

Table 7.1 Bai and Perron tests for structural breaks for oil price

Break Hypothesis	Scaled F-statistic	Critical Value
0 vs 1	4.0143	8.58

[167] See Cheng et. Al. (2018) for more literatures on oil price forecast.

The above table 7.1, reports the Bai and Perron scaled F-statistic with the associated 5% critical values. The test result indicates no significant breakpoint because the null hypothesis of no breaks (denoted 0 vs 1) cannot be rejected because the scaled F-statistic is less than the corresponding critical value.

Since the null hypothesis of no structural breaks cannot be rejected from this Table 7.1, we construct the autocorrelation function (ACF) and partial autocorrelation function (PACF) on the residuals of a regression of DLOILP on the intercept, which are plotted in Figure 7.1. The ACF of the non-seasonal autocorrelation coefficients (ACs) are significant at lags 1, 2 and 5 but insignificant at lags 3 and 4. This implies that there is no need for further non-seasonal differencing because no more than the first 5 non-seasonal ACs are significant. It also implies that the maximum order of non-seasonal moving average (MA) component is probably 2. Further, the seasonal ACs are insignificant at lags 4, 8, 12 and 16. This suggests that there is no need for further seasonal differencing because the first five seasonal lags are insignificant. It also indicates the maximum order of seasonal MA component is equal to 0. From the PACF the non-seasonal partial autocorrelation coefficients (PACs) are significant at lags 1 and 2 and insignificant at lags 3 and 5. This suggests the maximum order of non-seasonal autoregressive (AR) component is probably 2. The seasonal PACs are significant at lags 4 and 24 and insignificant at lags 8, 12, 16 and 20. The maximum order of seasonal AR process is 1 (because the PAC are insignificant at 8, 12, 16 and 20). Therefore, the maximum ARMA specification that we initially estimated is ARMA (2, 2) $(1,0)_{4}$.

Figure 7.1: The ACF and PACF of the residual of the constant and DLOILP

Sample: 1984Q1 2012Q4
Included observations: 116

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.206	0.206	5.0442	0.025
		2	-0.258	-0.313	13.012	0.001
		3	-0.022	0.130	13.068	0.004
		4	-0.059	-0.199	13.490	0.009
		5	-0.210	-0.133	18.920	0.002
		6	0.029	0.077	19.025	0.004
		7	0.100	-0.051	20.284	0.005
		8	-0.052	-0.031	20.629	0.008
		9	-0.077	-0.079	21.386	0.011
		10	-0.014	-0.048	21.413	0.018
		11	-0.009	-0.003	21.422	0.029
		12	0.050	0.048	21.751	0.040
		13	0.001	-0.083	21.751	0.059
		14	0.071	0.131	22.436	0.070
		15	0.072	-0.015	23.137	0.081
		16	-0.035	0.006	23.303	0.106
		17	-0.099	-0.060	24.663	0.103
		18	-0.109	-0.129	26.311	0.093
		19	0.067	0.167	26.948	0.106
		20	0.092	-0.035	28.165	0.106
		21	0.113	0.177	30.014	0.092
		22	0.068	-0.027	30.688	0.103
		23	-0.030	0.017	30.823	0.127
		24	0.037	0.173	31.026	0.153
		25	-0.003	-0.077	31.027	0.188

We report the multiplicative ARMA (2, 2) $(1,0)_{4}$ specification that includes intercept as our initial ARIMA model in the column headed 1 of Table 7.2.[168] In this model, the

[168] Note that we did not use seasonal dummy variables because seasonality is not significant in OILP (see chapter 6 Table 6.5).

intercept (C) is not significant and all the coefficients of the ARMA component are non-significant.

Table 7.2

Sample/Observations	1984q1 – 2012q4 (116)		
	1	2	3
C	0.0119 (1.0635)	0.0121 (1.085)	
AR(1)	0.4865 (1.3461)	0.5074 (1.8855)	
AR(2)	-0.0097 (-0.0251)	0.0148 (0.0421)	
SAR(4)	-0.0281 (-0.1356)		
MA(1)	-0.2096 (-0.5292)	-0.2096 (0.8483)	0.2875 (2.829)
MA(2)	-0.4141 (-1.0214)	-0.4493 (-1.4390)	-0.2249 (-2.5162)
Adj R^2	0.1225	0.1297	0.1278
SC	-0.7715	-0.8119	-0.9069
S.E	0.1468	0.1462	0.1463
AR Root	0.4998 0.3354	0.5352 -0.0278	
MA Root	0.7439 0.5566	0.7833 -0.5737	-0.6393 0.3517
P[QLB(11)]	0.8720	0.8790	0.9210

MA = the maximum order of non-seasonal moving average component, AR = the maximum order of non- seasonal autocorrelation component, SAR = the maximum order of seasonal moving average component , P[QLB(11)] = Probability value of the Ljung-Box Q-statistic at the 11th lag - based on the square root of the sample size ($\sqrt{116}$), Adj R^2 = Adjusted R – square , SC = Schwarz criterion, AR Roots = Stationary Autoregressive average and MA Roots = Stationary Moving average

For the model to be valid, we apply the standard diagnostic checks for residual autocorrelation, stationarity and invertibility. The probability value of the Ljung-Box Q-statistic at the 11th lag denoted P[QLB(11)], exceeds 0.050 indicating no evident residual autocorrelation – we choose process lag 11 based on the square root of the sample size (in this case $\sqrt{116}$). The inverse roots of the AR, denoted AR Root, are all less than one indicating that the model is consistent with a stationary process. The inverse roots of the MA process, denoted MA Root, are all less than one indicating that the model is invertible. Hence, the model is valid for forecasting in the sense that there is no evidence of misspecification according to the standard tests. However, none of the coefficient ARMA variables are significant. To improve on this model, we respecified the model reported in the column headed 1 to exclude SAR(4) term and report ARMA (2, 2) specification in the column headed 2 of the Table 7.2. This model cannot be rejected by the diagnostic checks for residual autocorrelation, stationarity and invertibility. Therefore, the model is valid to forecast. However, none of the coefficients of the ARMA terms are significant. After different experimentation, we estimate ARMA(0,2) without intercept and report this model in the column headed 3 of the Table 7.2. This model cannot be rejected according to the standard diagnostic checks for residual autocorrelation, stationarity, invertibility and all the coefficient of the MA terms are significant. Therefore, the model is valid for forecasting. We use this model (MA2, from the column 3 Table 7.2) to produce an out-sample forecast for the oil price between the period 2013q1 – 2014q4 and will also incorporate the new oil price forecast as an exogenous variable for all our multivariate models.

Appendix. A. Section 7.2

7.2 Russia Model Selection Criterion for Unrestricted VARs

In this section, we describe the process of choosing the appropriate VAR lag order for Russia. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model (as identified in chapter 6 Table 6.6.5 for Russia). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for Russia where all available variables are included as endogenous except unemployment (which is excluded). We start with the maximum possible lag-length that can be estimated for Russia (P*= 10). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, R, $\Delta InREE$, ΔGAP and $\Delta InOilp$). The results are given in Table 7.2.A column 1 and 2 where the lag length selected by the AIC and SC are 5 and 0 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 5) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.2.A. There is evidence of autocorrelation at the 5% level because all of the probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 5 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 4, 3, 2 and 1 lags and report the autocorrelation tests in columns 4, 5, 6 and 7 of Table 7.2.A, respectively. The VAR models with 4, 3, 2 and 1 lags indicate evidence of autocorrelation at the 5% level- at least one of the tests probability value is less than 0.05. However, since experimentations reveals that the VAR model cannot be estimated for Russia with more than 5 lags and estimating P*< 5 with VAR model exhibit autocorrelation. We conclude that there is no model of this form that is valid to forecast.

Table 7.2.A

Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$, ΔGAP and $\Delta InOilp$							
	1	2	3	4	5	6	7
	AIC	SC	Prob	Prob	Prob	Prob	Prob
Lags			5	4	3	2	1
0	-21.0304	-20.7744*					
1	-22.5206	-20.729	0	0.6283	0.2506	0.0303	0.0326
2	-22.6593	-19.3322	0	0.0078	0.3536	0.5358	0.0360
3	-23.7455	-18.8827	NA	0.1018	0.7219	0.1694	0.6362
4	-25.6813	-19.283	NA	0.4558	0.1915	0.0996	0.0005
5	-27.69955*	-19.7656	0	0.6769	0.6977	0.9617	0.5148
6			NA	0.1887	0.0463	0.5207	0.0111
7			0	0.0312	0.0718	0.8135	0.8536
8			0	0.6217	0.9612	0.6468	0.1913
9			0	0.8991	0.7145	0.9071	0.9951
10			NA	0.9408	0.1805	0.9299	0.2713

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for Russia where all available are included as endogenous except the output gap (which is excluded). We start with the maximum possible lag-length that can be estimated for Russia (P*= 10). The variables VAR model considered includes six stationary variables (ΔlnP, ΔlnM, R, $\Delta InREE$, ΔUN and $\Delta InOilp$). The results are given in Table 7.2.B column 1 and 2 where the lag length selected by the AIC and SC are 5 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 5) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 5 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs, as a result, we re-estimate the VAR model using a lag length of 4 (where P* = 5; P* -1 = 4) and test the validity of the model. Given a lag length of 5 is indicated by the AIC this suggests that VARs with more lags are preferred to those with less hence we consider a lag length of 4 rather than a lower lag length. The VAR model cannot reject the hypothesis of no-autocorrelation at 5% level for all of the orders of autocorrelation considered – see column 4 of Table 7.2.B. This indicates that the model is valid for forecasting Russian inflation. Hence, we choose 4 as the lag length for this Russian VAR model.

Table 7.2.B

Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$, ΔUN and $\Delta InOilp$				
	1	2	3	4
	AIC	SC	Prob.	Prob.
Lags			5	4
0	-18.8027	-18.5468		
1	-20.6522	-18.86063*	NA	0.1240
2	-20.8751	-17.548	NA	0.9222
3	-20.965	-16.1023	0	0.1217
4	-21.3397	-14.9414	0	0.3849
5	-25.21011*	-17.2762	0	0.2002
6			0	0.2156
7			NA	0.4958
8			0	0.9815
9			0	0.3587
10			NA	0.2329

The table indicates the selected lag from AIC and SC criterion by an asterisk

Third, we estimate an unrestricted VAR model for Russia where we treat oil price as exogenous and all other available variables, except the output gap (which is excluded), as endogenous. We start with the maximum possible lag-length that can be estimated for Russia (P*= 10). The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, R, $\Delta InREE$ and ΔUN). The results are given in Table 7.2.C column 1 and 2 where the lag length selected by the AIC and SC are 6 and 1. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 6 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 5 and 4 lags and report the autocorrelation tests in columns 4 and 5 of Table 7.2.C, respectively. Given a lag length of 6 is indicated by the AIC and this suggests VARs with more lags are preferred to those with less hence we select lower lags where autocorrelation is not evident, however, we do not consider lower lag length VARS than necessary. The VAR models with 5 lags indicates evidence of autocorrelation whereas the VAR with 4 lags exhibits no evident autocorrelation. Hence, we select the 4 lag VAR of this model for forecasting Russian inflation.

Table 7.2.C

Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$ and ΔUN Exogenous: $\Delta InOilp$					
	1	2	3	4	5
	AIC	SC	Prob	Prob	Prob
Lags			6	5	4
0	-14.4731	-14.0465	NA	0.0997	0.1674
1	-16.1253	-14.63236*	0	0.1471	0.9046
2	-16.6395	-14.0802	0	0.0001	0.5221
3	-16.5276	-12.9019	NA	0.0128	0.4999
4	-16.5415	-11.8494	NA	0.1896	0.2554
5	-18.83	-13.0716	NA	0.0007	0.1417
6	-21.17859*	-14.3537	NA	0.356	0.2653
			NA	0.9609	0.6599
			0	0.5229	0.3852
			NA	0.1891	0.2029

The table indicates the selected lag from AIC and SC criterion by an asterisk

Fourth, we estimate an unrestricted VAR model for Russia where we treat oil price as exogenous and all other available variables except for the unemployment (which is excluded) as endogenous. The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, R, $\Delta InREE$ and ΔGAP). The results are given in Table 7.2.D column 1 and 2 where the lag length selected by the AIC and SC are 6 and 1. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 6 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 5, 4, 3, 2 and 1 lags and report the autocorrelation tests in columns 4, 5, 6, 7 and 8 of Table 7.2.D, respectively. All the VAR models with 5, 4, 3, 2 and 1 lags indicate evidence of autocorrelation. However, since a VAR model cannot be estimated for Russia with more than 6 lags and estimating VAR model with less lags indicate evidence of autocorrelation, we conclude that we cannot find model of this form that is valid to forecast Russian inflation.

Table 7.2.D

Endogenous: ΔlnP, ΔlnM, R, $\Delta InREE$ and ΔGAP Exogenous: $\Delta InOilp$								
	1	2	3	4	5	6	7	8
Lag	AIC	SC	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
			6	5	4	3	2	1
0	-16.7008	-16.2742						
1	-18.173	-16.68009*	0	0.1082	0.0205	0.0046	0.0016	0.0142
2	-18.3038	-15.7445	0	0.0105	0.0213	0.0826	0.2497	0.5105
3	-18.7102	-15.0845	NA	0.6232	0.7006	0.7888	0.6805	0.7614
4	-18.9802	-14.2881	NA	0.2605	0.1023	0.1961	0.1142	0.0245
5	-19.9103	-14.1518	0	0.0683	0.8788	0.708	0.4325	0.269
6	-22.57834*	-15.7535	0	0.0914	0.0712	0.4700	0.5830	0.3424
7			0	0.0036	0.072	0.0168	0.763	0.3058
8			NA	0.2010	0.1157	0.5785	0.4152	0.2581
9			0	0.9634	0.9464	0.9264	0.7245	0.9804
10			0	0.9993	0.991	0.6588	0.577	0.8647

The table indicates the selected lag from AIC and SC criterion by an asterisk

7.3. India Model Selection Criterion for Unrestricted VARs

In this section, we describe the process of choosing the appropriate VAR lag order for India. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model (as identified in chapter 6 Table 6.6.5 for India). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for India where we treat all available variables as endogenous. We start with the maximum possible lag-length that can be estimated for India (P*= 10). The VAR model considered includes four stationary variables (ΔlnP, $\Delta\Delta lnM$, R and GAP). To utilise the large sample available for the core variable and other variables (1963q1 -2014q4), we did not include oil price variable in this VAR because the sample is only available between 1980-2014. The results are given in Table 7.3.A column 1 and 2 where the lag length selected by the AIC and SC are 7 and 3 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because two of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). Therefore, we re-estimate the VAR models with 8, 9, 10 and 11 lags and report the autocorrelation tests in columns 4, 5, 6 and 7 of Table 7.3.A, respectively. The VAR models with 8, 9 and 10 lags indicate evidence of autocorrelation whereas the VAR with 11 lags exhibits no evident autocorrelation. Hence, we select the 11 lag VAR of this model for forecasting Indian inflation.

Table 7.3.A

Endogenous: ΔlnP, $\Delta\Delta lnM$, R and GAP							
	1	2	3	4	5	6	7
	AIC	SC	Prob	Prob	Prob	Prob	Prob
Lag			7	8	9	10	11
0	1.997236	2.063202					
1	1.309193	1.639024	0.2620	0.2122	0.523	0.0017	0.7974
2	1.307763	1.90146	0.6003	0.3496	0.1794	0.6822	0.3419
3	-2.22753	-1.369967*	0.9597	0.4714	0.9385	0.7396	0.4270
4	-2.33151	-1.21008	0.0000	0.0002	0.0018	0.0014	0.1211
5	-2.23377	-0.84847	0.6683	0.299	0.1591	0.0706	0.3567
6	-2.15563	-0.50648	0.5717	0.6739	0.7302	0.7037	0.5615
7	-2.354716*	-0.44169	0.2227	0.3817	0.2784	0.3713	0.1912
8	-2.32205	-0.14516	0.0015	0.01	0.1632	0.1818	0.2193
9	-2.28239	0.158363	0.5796	0.7006	0.5799	0.1732	0.2187
10	-2.23377	-0.84847	0.2273	0.8695	0.9381	0.479	0.8729

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for the short period (1984q1- 2012q4) to include all available variables and the oil price that only available between 1980q1 2014q4. Therefore, we start with the initial length (P*= 10) and considered the VAR model that include all the five stationary variables (ΔlnP, $\Delta\Delta lnM$, R, GAP and $\Delta InOilp$). The results are given in Table 7.3.B column 1 and 2 where the lag length selected by the AIC and SC are both 3. We tested the maximum lag (P*= 3) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags, hence we follow the standard reaction and add lags (P**+ 1). We re-estimate the VAR models with 4, 5, 6,…..,10 lags and report the autocorrelation tests in columns 4, 5, 6,….,10 of Table 7.3.B, respectively. All the VAR models with 4, 5, 6,….,10 lags indicate evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05. Therefore, all these models cannot be valid to forecast. After different experimentation with different lags length a VAR model with 19 lags exhibits no evident autocorrelation. Hence, we select the 19 lags VAR of this model for forecasting Indian inflation.

Table 7.3.B

	Endogenous: ΔlnP, $\Delta\Delta lnM$, R, GAP and $\Delta InOilp$										
	1	2	3	4	5	6	7	8	9	10	11
	AIC	SC	Prob.		Prob.						
Lag			3	4	5	6	7	8	9	10	19
0	-1.92817	-1.80949									
1	-2.95263	-2.2405	0.0966	0.4387	0.0021	0.7926	0.0948	0.0948	0.2620	0.2122	0.7366
2	-3.22195	-1.91637	0.0130	0.7807	0.2361	0.2968	0.7041	0.7041	0.6003	0.3496	0.4693
3	-6.352927*	-4.4539*	0.1307	0.5398	0.5881	0.8587	0.3943	0.3943	0.9597	0.4714	0.5037
4	-6.29887	-3.8064	0.000	0.0015	0.012	0.0015	0.0045	0.0045	0.0000	0.0002	0.2803
5	-6.31066	-3.22474	0.6234	0.8753	0.7343	0.4585	0.3807	0.3807	0.6683	0.299	0.5704
6	-6.13277	-2.4534	0.9428	0.7929	0.862	0.7726	0.9451	0.9451	0.5717	0.6739	0.1983
7	-6.22867	-1.95586	0.9598	0.5869	0.7039	0.9591	0.9888	0.9888	0.2227	0.3817	0.4723
8	-6.25565	-1.38939	0.0008	0.0013	0.0018	0.0004	0.0094	0.0094	0.0015	0.0100	0.3484
9	-6.05206	-0.59236	0.9407	0.9803	0.9919	0.9945	0.9955	0.9955	0.5796	0.7006	0.1126
10	-5.9837	0.069455	0.4833	0.7645	0.9816	0.9105	0.908	0.908	0.2273	0.8695	0.1978

In the same sample (1984q1 2012q4), we estimate an unrestricted VAR model for India where we treat oil price as exogenous and all other available as endogenous. We start with the initial lag-length for India (P*= 10). The VAR model considered includes five stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, $\Delta\Delta lnM$, R and GAP). The results are given in Table 7.3.C column 1 and 2 where the lag length selected by the AIC and SC are 7 and 3 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.3.C. There is evidence of autocorrelation at the 5% level because 2 of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags hence, we follow the standard reaction and add lags (P**+ 1). We re-estimate the VAR models with 8, 9 and 10 lags and report the autocorrelation tests in columns 4, 5 and 6 of Table 7.3.C, respectively. All the VAR models with 8, 9 and lags indicate evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05. Therefore, all these models cannot be valid to forecast. After different experimentation with different lags length a

VAR model with 16 lags exhibits no evident autocorrelation. Hence, we select the 16 lags VAR of this model for forecasting Indian inflation.

Table 7.3.C

Endogenous: ΔlnP, $\Delta\Delta lnM$, R, GAP and $\Delta InOilp$ Exogenous: $\Delta InOilp$							
	1	2	3	4	5	6	7
	AIC	SC	Prob.	Prob.	Prob.	Prob.	Prob.
Lags			7	8	9	10	16
0	-0.595	-0.4051					
1	-1.75801	-1.1883	0.9854	0.1082	0.0205	0.0046	0.7465
2	-2.10526	-1.15574	0.4205	0.0105	0.0213	0.0826	0.6011
3	-5.35516	-4.025843*	0.9289	0.6232	0.7006	0.7888	0.7545
4	-5.33507	-3.62594	0.0039	0.2605	0.1023	0.1961	0.376
5	-5.41334	-3.32441	0.3061	0.0683	0.8788	0.708	0.5279
6	-5.35933	-2.89059	0.0995	0.0914	0.0712	0.4700	0.0690
7	-5.552335*	-2.70379	0.4337	0.0036	0.072	0.0168	0.4686
8	-5.37828	-2.14993	0.0065	0.201	0.1157	0.5785	0.2634
9	-5.25287	-1.64471	0.9954	0.9634	0.9464	0.9264	0.6848
10	-5.24779	-1.25983	0.1965	0.9993	0.991	0.6588	0.1759

7.4 China Model Selection Criterion for Unrestricted VARs

In this section, we describe the process of choosing the appropriate VAR lag order for China. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model as identified in chapter 6 Table 6.6.5 for China). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for China where all available variables are included as endogenous including the oil price. We start with the maximum possible lag-length that can be estimated for China (P*= 10). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$). The results are given in Table 7.4.A column 1 and 2 where the lag length selected by the AIC and the SC are 10 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). The probability values of the autocorrelation tests for this model are reported in column 3 of Table 7.4.A. There is evidence of autocorrelation at the 5% level because one of the probability values is less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). We re-estimate the VAR models with 11 and 12 lags (the maximum lags that can only be estimated with this VAR in China) and report the autocorrelation tests in columns 4 and 5 of Table 7.4.A., respectively. The VAR models with 11 and 12 lags indicate evidence of autocorrelation at the 5% level because at least one of the tests' probability values is less than 0.05. However, this VAR model cannot be estimated for China with more than 12 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with P*< 10 and report the autocorrelation tests in Table 7.4.A. The VAR model at 9 lags passed the test for autocorrelation at the 5% level for all lag lengths because the many the probability values are greater than 0.05 - see Table 7.4.A. Therefore, we VAR model with 9 lags for forecasting Chinese inflation.

Table 7.4.A

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$						
	1	2	3	4	5	6
Lags			10	11	12	9
	AIC	SC	Prob.	Prob.	Prob.	Prob
0	-13.0987	-12.9251				
1	-14.3939	-13.17850*	0.7875	0.0006	NA	0.2149
2	-14.5033	-12.2461	0.3040	0.4431	NA	0.9861
3	-15.2788	-11.9798	0.6064	0.6056	NA	0.1897
4	-16.6453	-12.3046	0.0034	0.0609	0	0.7853
5	-16.3778	-10.9953	0.7491	0.6695	0	0.8483
6	-16.289	-9.86471	0.9690	0.9950	NA	0.9958
7	-15.8942	-8.42812	0.5538	0.2718	NA	0.2669
8	-16.7005	-8.19268	0.5811	0.0555	NA	0.4512
9	-16.8961	-7.34648	0.7455	0.1778	0	0.9701
10	-17.52343*	-6.93202	0.4927	0.2855	NA	0.7531

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for China where we treat oil price as exogenous and all other available variables as endogenous. We start with the maximum possible lag-length that can be estimated for China (P*= 10). The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP). The results are given in Table 7.4.B column 1 and 2 where the lag length selected by the AIC and the SC are 10 and 4 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.4.B. There is evidence of autocorrelation at the 5% level because one of the tests' probability values is less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags. We re-estimate the VAR models with 11 lags and report the autocorrelation tests in columns 4 of Table 7.4.B. The VAR with 11 lags exhibits no evident autocorrelation. Hence, we select the 11 lag VAR of this model for forecasting Chinese inflation.

Table 7.4.B

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp$				
	1	2	3	4
Lags			10	11
	AIC	SC	Prob.	Prob.
0	-11.5884	-11.299		
1	-12.8744	-11.8615	0.8003	0.6336
2	-13.1413	-11.405	0.9457	0.9455
3	-13.7093	-11.2496	0.9500	0.6099
4	-15.3302	-12.1463*	0.0027	0.1814
5	-15.3512	-11.4445	0.9505	0.5816
6	-15.396	-10.7659	0.9957	0.9794
7	-15.1176	-9.76401	0.7618	0.2778
8	-15.804	-9.72694	0.1471	0.3983
9	-16.0908	-9.29032	0.2955	0.1303
10	-16.43192*	-8.90796	0.5953	0.5398

The automatic selected lag from AIC and SC are indicated by asterisk

7.5 South Africa Model Selection Criterion for Unrestricted VARs

We describe the process of choosing the appropriate VAR lag order for South Africa. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model as identified in chapter 6 Table 6.6.5 for South Africa). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for South Africa where all available variables are included as endogenous. We start with the maximum possible lag-length that can be estimated for South Africa (P*= 10). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$). The results are given in Table 7.5.A column 1 and 2 where the lag length selected by the AIC and SC are 10 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.5.A. There is evidence of autocorrelation at the 5% level because at least one of the tests' probability values is less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for South Africa with more than 10 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 9, 8 and 7 lags and report the autocorrelation tests in columns 4, 5 and 6 of Table 7.5.A, respectively. Given a lag length of 10 is indicated by the AIC this suggests VARs with more lags are preferred to those with less hence we seek to select as high a VAR lag length as possible where autocorrelation is not evident. The VAR models with 9 and 8 lags indicate evidence of autocorrelation whereas the VAR with 7 lags exhibits no evident autocorrelation. Hence, we select the 7 lag VAR of this model for forecasting South African inflation.

Table 7.5.A

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$						
	1	2	3	4	5	6
Lags			10	9	8	7
	AIC	SC	Prob	Prob	Prob	Prob
0	-15.2039	-15.0127				
1	-16.4385	-15.10002*	NA	0.0462	0.1019	0.8162
2	-16.2098	-13.7241	0	0.0002	0.1842	0.4081
3	-15.8754	-12.2424	NA	0.3334	0.6257	0.1841
4	-15.5364	-10.7561	NA	0.0781	0.002	0.3147
5	-15.0535	-9.12593	NA	0.5246	0.0569	0.0609
6	-15.0116	-7.93671	0	0.8561	0.1654	0.4019
7	-15.1486	-6.92647	0	0.1233	0.1742	0.3084
8	-15.5039	-6.13446	0	0.7896	0.0691	0.4760
9	-17.6464	-7.12967	NA	0.5244	0.2501	0.7284
10	-21.21824*	-9.55429	NA	0.4617	0.7689	0.6615

The table indicates the selected lag from AIC and SC criterion by an asterisk.

Second, we estimate an unrestricted VAR model for South Africa where we treat oil price as exogenous and all other available variables as endogenous. We start with the maximum possible lag-length that can be estimated for South Africa (P*= 10). The VAR model considered includes five stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP). The results are given in Table 7.5.B column 1 and 2 where the lag length selected by the AIC and the SC are 10 and 1. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.5.B. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values greater than 0.05 (see Table 7.5.B). Hence, we select the 10 lag VAR of this model for forecasting South African inflation.

Table 7.5.B

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp$			
	1	2	3
	AIC	SC	Prob.
Lag			10
0	-13.8132	-13.4945	
1	-15.1685	-14.05309*	0.5404
2	-14.8467	-12.9346	0.3837
3	-14.5818	-11.8729	0.4538
4	-14.2149	-10.7094	0.0799
5	-13.937	-9.63471	0.2476
6	-13.7518	-8.65284	0.3394
7	-13.5115	-7.61577	0.3884
8	-13.4836	-6.79111	0.4562
9	-13.9371	-6.44791	0.1709
10	-15.28223*	-6.99636	0.9797

The table indicates the selected lag from AIC and SC criterion by an asterisk

7.6 Algeria Model Selection Criterion for Unrestricted VARs

We describe the process of choosing the appropriate VAR lag order for Algeria. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model as identified in chapter 6 Table 6.6.5 for Algeria. We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for Algeria where all available variables are included as endogenous. We start with the maximum possible lag-length that can be estimated for Algeria (P*= 7). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$). The results are given in Table 7.6.A column 1 and 2 where the lag length selected by the AIC and SC are 7 and 0 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.6.A. There is evidence of autocorrelation at the 5% level because many of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Algeria with more than 7 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs that free from autocorrelation. As a result, we re-estimate the VAR models with 6 and 5 lags and report the autocorrelation tests in columns 4 and 5 of Table 7.6.A, respectively. Given a lag length of 7 is indicated by the AIC and this suggests VARs with more lags are preferred to those with less hence we seek to select as high a VAR lag length as possible where autocorrelation is not evident. The VAR models with 6 lags indicates evidence of autocorrelation whereas the VAR with 5 lags exhibits no evident autocorrelation. Hence, we select the 5 lag VAR of this model for forecasting Algerian inflation.

Table 7.6.A

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$					
	1	2	3	4	5
Lag	AIC	SC	Prob.	Prob.	Prob.
			7	6	5
0	-18.8407	-18.62175*			
1	-18.8231	-17.2902	0.569	0.3306	0.3489
2	-18.4766	-15.6299	0.2147	0.1137	0.3709
3	-18.4938	-14.3332	0.0005	0.4751	0.9310
4	-19.263	-13.7885	0.3766	0.0037	0.7897
5	-20.1977	-13.4093	0.003	0.2431	0.4170
6	-20.3398	-12.2375	0.0144	0.3207	0.8289
7	-21.94884*	-12.5326	0.1349	0.5196	0.6496
8			0.0389	0.2606	0.5555
9			0.0156	0.9927	0.8884
10			0.0062	0.1511	0.6451

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for Algeria where we treat oil price as exogenous and all other available variables as endogenous. We start with the maximum possible lag-length that can be estimated for Algeria (P*= 9). The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP). The results are given in Table 7.6.B column 1 and 2 where the lag length selected by the AIC and SC are 9 and 0 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC (0) and adopt the AIC (9). Therefore, we tested the maximum lag (P*= 9) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because all of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Algeria with more than 9 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 8, 7, 6 and 5 lags and report the autocorrelation tests in columns 4, 5, 7 and 6 of Table 7.6.B respectively. Given a lag length of 9 is indicated by the AIC this suggests VARs with more lags are preferred to those with less hence we seek to select as high a VAR lag length as possible where autocorrelation is not evident. The VAR models with 8, 7 and 6 lags indicate evidence of autocorrelation whereas the VAR with 5 lags exhibits no evident autocorrelation. Hence, we select the 5 lag VAR of this model for forecasting Algerian inflation.

Table 7.6.B

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp$							
	1	2	3	4	5	6	7
			9	8	7	6	5
LogL	AIC	SC	Prob	Prob	Prob	Prob	Prob
0							
1	-12.8372	-12.4723*	NA	0.528	0.2524	0.1817	0.6722
2	-12.9417	-11.6643	NA	0.5828	0.0846	0.0558	0.4905
3	-12.6627	-10.4728	NA	0.5141	0.3539	0.4106	0.4235
4	-12.7487	-9.64643	NA	0.734	0.1715	0.4298	0.0930
5	-13.3997	-9.38501	0	0.013	0.1299	0.1732	0.4211
6	-13.8048	-8.87773	NA	0.4682	0.2822	0.0281	0.0544
7	-13.5566	-7.7171	NA	0.2511	0.4201	0.1700	0.6668
8	-14.5435	-7.79154	0	0.0509	0.3429	0.0469	0.1057
9	-16.3174*	-8.65299	NA	0.1521	0.0152	0.5965	0.1832
10			0	0.5367	0.6479	0.5276	0.4370

The table indicates the selected lag from AIC and SC criterion by an asterisk

7.7 Nigeria Model Selection Criterion for Unrestricted VARs

We describe the process of choosing the appropriate VAR lag order for Nigeria. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model (as identified in chapter 6 Table 6.6.5 for Nigeria). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for Nigeria where all available variables are included as endogenous. We start with the maximum possible lag-length that can be estimated for Nigeria (P*= 8). The VAR model considered includes six stationary variables (ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$). The results are given in Table 7.7.A column 1 and 2 where the lag length selected by the AIC and SC are 8 and 0 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 8) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.7.A. There is evidence of autocorrelation at the 5% level because many of the probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Nigeria with more than 8 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs that free from autocorrelation. As a result, we re-estimate the VAR models with P*< 8., (7 and 6, lags) and report the autocorrelation tests in Table 7.7.A. The VAR estimated with 6 lags passed the test for autocorrelation at the 5% level for all lag lengths because the many the probability values are higher than 0.05 - see Table 7.7.A.

Table. 7.7.A

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$, GAP and $\Delta InOilp$					
	1	2	3	4	3
Lag	AIC	SC	Prob.	Prob.	Prob.
			8	7	6
0	1.082133	1.297191*			
1	1.286006	2.791412	NA	0.9910	0.5280
2	1.713872	4.509626	NA	0.9932	0.5828
3	1.785555	5.871658	NA	0.8489	0.5141
4	-0.87228	4.504175	NA	0.5631	0.7340
5	-0.67319	5.993612	0	0.7631	0.2130
6	-1.64262	6.314524	0	0.2897	0.4682
7	-1.91904	7.328457	NA	0.0049	0.2511
8	-4.049670*	6.488173	0	0.9252	0.0609
9			0	0.0688	0.1521
10			NA	0.5932	0.5367

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for Nigeria where we treat the oil price as exogenous and all other available variables as endogenous. We start with the maximum possible lag-length that can be estimated for Nigeria (P*= 9). The VAR model considered includes six stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP). The results are given in Table 7.7.B column 1 and 2 where the lag length selected by the AIC and SC are 9 and 0 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC (0) and adopt the AIC (9). Therefore, we tested the maximum lag (P*= 9) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because 3 of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Nigeria with more than 9 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 8, 7, 6 and 5 lags and report the autocorrelation tests in Table 7.7.B. Given a lag length of 9 is indicated by the AIC and this suggests VARs with more lags are preferred to those with less hence we seek to select as high a VAR lag length as possible where autocorrelation is not evident. The VAR model with 8, 7 and 6 lags indicate evidence of autocorrelation whereas the VAR with 5 lags exhibits no evident autocorrelation. Hence, we select the 5 lag VAR of this model for forecasting Nigerian inflation.

Table 7.7.B

Endogenous: ΔlnP, ΔlnM, ΔR, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp$					
	1	2	3	4	5
			9	8	5
Lag	AIC	SC	Prob	Prob	Prob
0	2.483251	2.84168*	0.5906	0.1685	0.9518
1	2.454515	3.70902	0.5906	0.1685	0.9518
2	2.58196	4.73254	0.9453	0.5447	0.5644
3	2.554353	5.601009	0.0051	0.3184	0.8402
4	0.432767	4.375498	0.3504	0.7955	0.7365
5	0.65671	5.495516	0.0853	0.0072	0.4657
6	0.535766	6.270646	0.0016	0.4109	0.2772
7	0.736223	7.367179	0.5393	0.7939	0.3596
8	0.257769	7.7848	0.1839	0.1144	0.6142
9	-2.46873*	5.95433	0.0795	0.6243	0.1686
10			0.0072	0.5219	0.5910

The table indicates the selected lag from AIC and SC criterion by an asterisk

7.8 Angola Model Selection Criterion for Unrestricted VARs

We describe the process of choosing the appropriate VAR lag order for Angola. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model (as identified in chapter 6 Table 6.6.5 for Angola). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate an unrestricted VAR model for Angola where all available variables are included as endogenous. We start with the maximum possible lag-length that can be estimated for Angola (P*= 6). The VAR model considered includes five stationary variables (ΔlnP, ΔlnM, ΔR, GAP and $\Delta InOilp$). The results are given in Table 7.8.A column 1 and 2 where the lag length selected by the AIC and SC are 6 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 6) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.8.A. There is evidence of autocorrelation at the 5% level because at least one of the tests' probability values is less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Angola with more than 6 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 5 and 4 lags and report the autocorrelation tests in columns 4 and 5 of Table 7.8.A, respectively. Given a lag length of 6 is indicated by the AIC and this suggests VARs with more lags are preferred to those with less hence we seek to select as high a VAR lag length as possible where autocorrelation is not evident. The VAR models with 5 lags indicate evidence of autocorrelation whereas the VAR with 4 lags exhibits no evident autocorrelation. Hence, we select the 4 lag VAR of this model for forecasting Angolans inflation.

Table 7.8.A

Endogenous: ΔlnP, ΔlnM, ΔR, GAP and $\Delta InOilp$					
	1	2	3	4	5
	AIC	SC	Prob	Prob	Prob
Lags			6	5	4
0	-3.00508	-2.79611			
1	-5.96261	-4.708772*	0.7816	0.4319	0.0653
2	-5.27633	-2.97763	0.9315	0.8565	0.1872
3	-4.93136	-1.58781	0.1394	0.5529	0.2095
4	-6.45058	-2.06216	0.9493	0.0785	0.4827
5	-8.11894	-2.68567	0.9649	0.8237	0.4929
6	-9.496350*	-3.01821	0.2182	0.6013	0.1833
7			0.2530	0.8698	0.5775
8			0.0701	0.0964	0.1268
9			0.7549	0.0228	0.3556
10			0.0004	0.4243	0.4952

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for Angola where we treat oil price as exogenous and all other available variables as endogenous. We start with the maximum possible lag-length that can be estimated for Angola (P*= 7). The VAR model considered includes five stationary variables with the oil price as exogenous ($\Delta InOilp$) and the following variables as endogenous (ΔlnP, ΔlnM, ΔR and GAP). The results are given in Table 7.8.B column 1 and 2 where the lag length selected by the AIC and SC are 7 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC (1) and adopt the AIC (7). Therefore, we tested the maximum lag (P*= 7) VAR for autocorrelation (of order 1, 2, … 10). The VAR model with 7 lags indicates no evidence of autocorrelation. Hence, we select the 7 lag VAR of this model for forecasting Angolan inflation.

Table 7.8.B

Endogenous: ΔlnP, ΔlnM, ΔR and GAP Exogenous: $\Delta InOilp$			
	1	2	3
Lag	AIC	SC	Prob
			7
0	-1.54265	-1.20829	
1	-4.66042	-3.657351*	0.0996
2	-4.23268	-2.56091	0.6011
3	-4.11943	-1.77894	0.7180
4	-5.12724	-2.11804	0.5208
5	-6.36339	-2.68548	0.9109
6	-7.31995	-2.97333	0.7966
7	-7.880953*	-2.86562	0.5492
8			0.2970
9			0.3780
10			0.6549

The table indicates the selected lag from AIC and SC criterion by an asterisk

7.9 Saudi Arabia Model Selection Criterion for Unrestricted VARs

We describe the process of choosing the appropriate VAR lag order for Angola. Note that these are the unrestricted VARs, not VECMs, and that the stationary forms of the variables are used in the model (as identified in chapter 6 Table 6.6.5 for Saudi Arabia). We use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag length. First, we estimate an unrestricted VAR model for Saudi Arabia where all available variables are included as endogenous. We start with the maximum possible lag-length that can be estimated for Saudi Arabia (P*= 10). The VAR model considered includes five stationary variables (ΔlnP, ΔlnM, ΔREE, GAP and $\Delta InOilp$). The results are given in Table 7.9.A column 1 and 2 where the lag length selected by the AIC and SC are 4 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 4) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.9.A. There is evidence of autocorrelation at the 5% level because two of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). We re-estimate the VAR models with 5, 6.,…,12 lags and report the autocorrelation tests in columns 4,5.,…,11 of Table 7.9.A., respectively. The VAR models with 4.,…,11 lags indicate evidence of autocorrelation whereas the VAR with 12 lags exhibits no evident autocorrelation. Hence, we select the 12 lag VAR of this model for forecasting Saudi Arabian Inflation (see Table 7.9.A column 11).

Table 7.9.A

Endogenous: ΔlnP, ΔlnM, $\Delta InREE$, GAP and $\Delta InOilp$											
	1	2	3	4	5	6	7	8	9	10	11
	AIC	SC	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
Lags			4	5	6	7	8	9	10	11	12
0	-20.0663	-19.9502									
1	-20.7912	-20.09437*	0.0447	0.0368	0.7932	0.0356	0.4702	0.0473	0.2996	0.4223	0.6083
2	-20.5772	-19.2996	0.7757	0.076	0.0423	0.5804	0.0944	0.5342	0.068	0.055	0.8529
3	-20.556	-18.6977	0.9836	0.5826	0.9061	0.964	0.9174	0.9413	0.811	0.7238	0.7751
4	-21.51615*	-19.0771	0.0001	0.0009	0.0216	0.1289	0.3569	0.118	0.3924	0.2961	0.3151
5	-21.4619	-18.4421	0.8993	0.6467	0.9978	0.892	0.7723	0.8845	0.7619	0.9644	0.9527
6	-21.1666	-17.5661	0.9822	0.9025	0.927	0.906	0.6869	0.9055	0.5455	0.3844	0.7942
7	-20.9327	-16.7515	0.8891	0.7758	0.4478	0.4342	0.0569	0.4559	0.0349	0.0722	0.2376
8	-21.1497	-16.3877	0.1711	0.0093	0.0208	0.0114	0.0156	0.0083	0.0088	0.0436	0.3522
9	-20.9148	-15.5721	0.9967	0.996	0.9887	0.9655	0.6948	0.9577	0.6402	0.6376	0.6293
10	-20.9404	-15.017	0.3838	0.4632	0.4052	0.5973	0.8859	0.6411	0.7853	0.5076	0.3191

The table indicates the selected lag from AIC and SC criterion by an asterisk

Second, we estimate an unrestricted VAR model for Saudi Arabia where we treat oil price as exogenous and all other available variables as endogenous. We start with the maximum possible lag-length that can be estimated for Saudi Arabia (P*= 10). The VAR model considered includes five stationary variables (ΔlnP, ΔlnM, ΔREE, GAP and $\Delta InOilp$). The results are given in Table 7.9.B column 1 and 2 where the lag length selected by the AIC and SC are 4 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 4) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.9.B. There is evidence of autocorrelation at the 5% level because two of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). We re-estimate the VAR models with 5, 6.,…,12 lags and report the autocorrelation tests in columns 4.,…,11 of Table 7.9.B., respectively. The VAR models with 5,..,11 lags indicate evidence of autocorrelation whereas the VAR with 12 lags exhibits no evident autocorrelation. Hence, we select the 12 lag VAR of this model for forecasting Saudi Arabian Inflation (see Table 7.9.B column 11).

Table 7.9.B

Endogenous: ΔlnP, ΔlnM, $\Delta InREE$ and GAP Exogenous: $\Delta InOilp$											
	1	2	3	4	5	6	7	8	9	10	11
	AIC	SC	Prob	Prob	Prob	Prob	Prob	Prob	Prob	Prob	Prob
Lags			4	5	6	7	8	9	10	11	12
0	-18.8446	-18.6617									
1	-19.8853	-19.3359*	0.0042	0.0000	0.000	0.3921	0.7932	0.0368	0.0447	0.0000	0.1135
2	-19.7849	-18.8704	0.3862	0.0000	0.0546	0.2325	0.0423	0.076	0.7757	0.0000	0.7689
3	-19.9036	-18.6233	0.9836	0.0454	0.5476	0.9053	0.9061	0.5826	0.9836	0.0044	0.9012
4	-20.4568*	-18.8215	0.0412	0.0002	0.0000	0.0000	0.0216	0.0009	0.0001	0.0000	0.3091
5	-20.3564	-18.3445	0.8723	0.8949	0.13	0.3631	0.9978	0.6467	0.8993	0.7986	0.8384
6	-20.1669	-17.7892	0.8057	0.7612	0.8802	0.2294	0.927	0.9025	0.9822	0.8222	0.7527
7	-19.9946	-17.251	0.9803	0.9131	0.2422	0.5857	0.4478	0.7758	0.8891	0.9566	0.3549
8	-20.0122	-16.9028	0.0777	0.0000	0.0000	0.0000	0.0208	0.0093	0.1711	0.0000	0.2328
9	-19.9548	-16.4796	0.9935	0.7228	0.0271	0.1941	0.9887	0.996	0.9967	0.7664	0.9433
10	-19.8771	-16.0361	0.7122	0.3421	0.6544	0.0334	0.4052	0.4632	0.3838	0.0983	0.7653

The table indicates the selected lag from AIC and SC criterion by an asterisk

Appendix. Section 7.3

7.2. Modelling Vector Error Correction Model (VECM) for Russia

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for Russia. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for Russia. The following variables are considered: lnP, lnM, $InREE$, UN, $gaprus$ and $InOilp$ (all are I(1)). First, we estimate a level VAR model for Russia where all available variables that are integrated by I(1) are included as endogenous except unemployment (which is excluded). To choose an appropriate lag length for this model, we use the Akaike (AIC) and Schwarz (SC) information criteria with the maximum possible lag-length that can be estimated (P* =6) to determine the initial lag length P^{**}. The results are given in Table 7.2.A column 1 and 2 where the lag length selected by the AIC and SC are 6 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the lower lag length identified by the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 6) VAR for autocorrelation (of order 1, 2,… 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.2.A. There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 6 lags; experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length. We consider lower lag length VARs and re-estimate the VAR model using lag lengths 5, 4,…,1 (where P* - 1;) and test the validity of each model. The VAR model reject the hypothesis of no-autocorrelation at the 5% level for all the model considered – see column 4, 5, 6,….,8 of Table 7.2.A. This indicates that there is no valid model with the appropriate lag to estimate cointegration test.

Table 7.2. A. The VECM lags order selection criteria

Endogenous: lnP, lnM, $InREE$, GAP and $InOilp$								
	1	2	3	4	5	6	7	8
Lags			6	5	4	3	2	1
	AIC	SC	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
0	-14.67211	-14.4588						
1	-26.93061	-25.65095*	0.000	0.0542	0.0258	0.289	0.5048	0.0052
2	-27.43891	-25.0929	0.000	0.065	0.0311	0.1374	0.8573	0.7726
3	-27.16896	-23.7565	0.000	0.4575	0.4153	0.8535	0.8593	0.599
4	-27.59034	-23.1115	0.000	0.5637	0.1707	0.0104	0.0095	0.000
5	-29.13809	-23.5929	0.000	0.0303	0.4009	0.9689	0.8651	0.3403
6	-32.00748*	-25.3959	0.000	0.0025	0.1785	0.6253	0.1864	0.0165
7			0.000	0.5456	0.9573	0.9157	0.7739	0.0743
8			0.000	0.9453	0.902	0.4691	0.6675	0.1941
9			0.000	0.71	0.9799	0.8773	0.8745	0.6213
10			0.000	0.3884	0.8065	0.1981	0.353	0.6755

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Second, we estimate a level VAR model for Russia where all variables that integrated by I(1) are included as endogenous except the output gap (which is excluded). We start with the maximum possible lag-length that can be estimated for Russia (P*= 6). The VAR model considered includes five non- stationary variables (lnP, lnM, $InREE$, UN and $InOilp$). The results are given in Table 7.2.B.A column 1 and 2 where the lag length selected by the AIC and SC are 6 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 6) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, a VAR model cannot be estimated for Russia with more than 6 lags, because experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs hence we do not consider the lag that less necessary. As a result, we re-estimate the VAR model using a lag length of 5, 4 and 3 and test the validity of the model – see column 4, 5 and 6 of Table 7.2.B.A respectively. The VAR models with 5 and 4 lags indicate evidence of autocorrelation whereas the VAR with 3 lags exhibits no evident autocorrelation. Hence, we select the 3 lag VAR of this model for cointegration analysis.

Table 7.2. B.A

Endogenous: $lnP, lnM, InREE, un$ and $InOilp$						
	1	2	3	4	5	6
	AIC	SC	Prob.	Prob.	Prob.	
Lag			6	5	4	3
0	-8.572662	-8.35939				
1	-20.52935	-19.24969*	0.000	0.473	0.0251	0.7201
2	-21.36295	-19.0169	0.000	0.3427	0.2151	0.4892
3	-21.0847	-17.6723	0.000	0.1679	0.9068	0.7374
4	-21.1495	-16.6707	0.000	0.8088	0.6145	0.6099
5	-22.90982	-17.3646	0.000	0.4348	0.1709	0.4551
6	-24.58742*	-17.9758	0.000	0.0327	0.3005	0.4067
7			0.000	0.1886	0.978	0.9721
8			0.000	0.7589	0.4143	0.5903
9			0.000	0.2606	0.4036	0.2595
10			0.000	0.2447	0.1946	0.1698

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 3 lagged level terms (2 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.2.B.B Based on the trace and maximum eigenvalue statistics, we reject the null hypothesis of the no cointegrating equation at the 5% level. However, the null hypothesis of one cointegrating equation cannot be rejected at 5% significance level. Therefore, our results indicate only one cointegrating equation among the five variables.

Table 7.2.B.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	84.1278	69.81889	0.0099	38.46456	33.87687	0.0041
At most 1	45.66325	47.85613	0.4123	26.67019	27.58434	0.4423
At most 2	18.99306	29.79707	0.6371	9.818529	21.13162	0.896
At most 3	9.174531	15.49471	0.3731	9.04989	14.2646	0.488
At most 4	0.124641	3.841466	0.1673	0.124641	3.841466	0.1673

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.2.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.2.B.C The Vector Error Correction Model

t-statistics in [ ]					
	DLOG(PRUS_D11)	DLOG(MRUS)	DLOG(REERUS)	D(URUS_D11)	DLOG(OILP)
DLOG(PRUS_D11(-1))	0.304561	-0.44901	0.676263	1.849259	0.63764
	[1.34907]	[-0.63459]	[1.02474]	[0.16487]	[0.56731]
DLOG(PRUS_D11(-2))	-0.19746	-0.41669	0.047485	5.216157	-0.38418
	[-0.91194]	[-0.61402]	[0.07502]	[0.48488]	[-0.35637]
DLOG(MRUS(-1))	-0.03987	0.111905	0.745683	-15.1149	0.015369
	[-0.50797]	[0.45492]	[3.25013]	[-3.87621]	[0.03933]
DLOG(MRUS(-2))	0.192625	-0.0465	0.477226	-9.1727	0.667978
	[1.71694]	[-0.13224]	[1.45514]	[-1.64564]	[1.19588]
DLOG(REERUS(-1))	-0.05981	0.200921	-0.96928	3.065071	-0.38618
	[-0.91603]	[0.98187]	[-5.07849]	[0.94489]	[-1.18800]
DLOG(REERUS(-2))	-0.05531	0.303912	-1.05027	8.776415	-0.25153
	[-0.66181]	[1.16030]	[-4.29914]	[2.11376]	[-0.60454]
D(URUS_D11(-1))	0.005707	-0.00072	0.015937	-0.59027	-0.00451
	[1.12880]	[-0.04546]	[1.07840]	[-2.35006]	[-0.17898]
D(URUS_D11(-2))	0.000378	0.006952	0.014722	-0.31082	-0.00141
	[0.10376]	[0.60900]	[1.38279]	[-1.71771]	[-0.07780]
DLOG(OILP(-1))	0.013374	0.129676	0.659381	-2.30469	-0.39915
	[0.26413]	[0.81715]	[4.45487]	[-0.91615]	[-1.58337]
DLOG(OILP(-2))	0.020982	0.028798	0.733549	-4.74827	-0.18918
	[0.35221]	[0.15424]	[4.21235]	[-1.60431]	[-0.63784]
C	0.661713	-1.4592	2.915344	-17.5692	1.211525
	[1.83696]	[-1.29248]	[2.76859]	[-0.98170]	[0.67553]
LOG(PRUS_D11(-3))	-0.1253	-0.05849	0.035183	-4.45609	-0.23437
	[-1.75137]	[-0.26082]	[0.16822]	[-1.25361]	[-0.65796]
LOG(MRUS(-3))	0.063119	-0.08031	0.138088	-0.26128	0.156222
	[2.10988]	[-0.85651]	[1.57902]	[-0.17579]	[1.04887]
LOG(REERUS(-3))	-0.08338	0.477042	-1.10993	10.97367	-0.22133
	[-0.86034]	[1.57061]	[-3.91800]	[2.27918]	[-0.45873]
URUS_D11(-3)	0.000721	0.01052	0.018106	-0.13311	0.027798
	[0.22846]	[1.06290]	[1.96139]	[-0.84840]	[1.76812]
LOG(OILP(-3))	0.009057	-0.08147	0.816275	-6.46569	-0.03614
	[0.13047]	[-0.37447]	[4.02281]	[-1.87484]	[-0.10458]
Adj. R-squared	0.480061	0.427008	0.719559	0.486229	0.027148
Akaike information criterion		-21.0847			
Schwarz criterion		-17.6723			

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.2.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Russian inflation since there is no evidence of autocorrelation.

Table 7.2.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.7201
2	0.4892
3	0.7374
4	0.6099
5	0.4551
6	0.4067
7	0.9721
8	0.5903
9	0.2595
10	0.1698

Third, we produce a VECM for Russia where we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a levels VAR using the maximum possible lag-length that can be estimated for Russia (P*= 8). The VAR model considered includes four nonstationary variables as endogenous (lnP, lnM, $InREE\ and\ gap$) and stationary log of oil price as exogenous ($\Delta lnOilp$). The results are given in Table 7.2.C.A column 1 and 2 where the lag length selected by both the AIC and SC is 8. There is evidence of autocorrelation at the 5% level in this 8-lag model because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 8 lags and because experience suggests that models with too many lags can exhibit autocorrelation, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 7, 6 and 5 lags and report the autocorrelation tests in columns 4,5 and 6 of Table 7.2.C.A, respectively. The VAR models with 7 and 6 lags indicate evidence of autocorrelation whereas the VAR with 5 lags exhibits no evident autocorrelation. Hence, we select the 5 lag VAR of this model for cointegration analysis.

Table 7.2. C.A

Endogenous: lnP, lnM, $InREE$ and gap Exogenous: $\Delta lnOilp$						
	1	2	3	4	5	6
	AIC	SC	Prob.	Prob.	Prob.	
Lag			8	7	6	5
0	-10.20365	-9.8624				
1	-21.77828	-20.7546	0.0000	0.4886	0.0174	0.0866
2	-22.54718	-20.841	0.0000	0.1277	0.2885	0.1904
3	-22.2934	-19.9047	0.0000	0.8101	0.6341	0.4435
4	-22.00025	-18.9291	0.0000	0.154	0.5089	0.5040
5	-22.49025	-18.7366	0.0000	0.287	0.1157	0.9465
6	-22.90378	-18.4676	0.0000	0.2062	0.0313	0.3139
7	-25.05141	-19.9328	0.000	0.0139	0.1911	0.3177
8	-27.80382*	-22.00268*	0.0000	0.2337	0.4777	0.2399
9			0.0000	0.4786	0.9889	0.9636
10			0.00000	0.0574	0.3537	0.4609

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 5 lagged level terms (4 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.2.C.B. Based on the trace statistics, we reject the null hypothesis of the no cointegrating equations, and at most 1,2 cointegrating equations at the 5% level. However, the null hypothesis of at most 3 cointegrating equation cannot be rejected at the 5% significance level. For the maximum eigenvalue, we reject the null hypothesis of the no cointegrating equation at the 5% level. However, the null hypothesis of one cointegrating equation cannot be rejected at 5% significance levels. Therefore, we accept the result of the trace test and assume that the system has three cointegrating equations because the trace test is more robust to departures from normally distributed residuals of the systems' equations.[169]

[169] Lutkepohi et al. (2000) observed that the trace test performs better than the maximum eigenvalue test most especially where the power is low.

Table 7.2.C.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	76.55259	47.85613	0.0050	43.8182	27.58434	0.0002
At most 1	32.73439	29.79707	0.0223	16.97035	21.13162	0.1734
At most 2	15.76403	15.49471	0.0455	14.34074	14.2646	0.0486
At most 3	1.423299	3.841466	0.2329	1.423299	3.841466	0.2329

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.2.C.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.2.C.C The Vector Error Correction Model

t-statistics in [ ]				
	DLOG(PRUS_D11)	DLOG(MRUS)	DLOG(REERUS)	D(GAPRUS_D11)
DLOG(PRUS_D11(-1))	0.173524	-0.7081	1.790761	0.888602
	[0.69512]	[-1.06957]	[1.65049]	[1.09372]
DLOG(PRUS_D11(-2))	-0.00682	-0.48637	0.261244	-1.19778
	[-0.02704]	[-0.72758]	[0.23846]	[-1.46006]
DLOG(PRUS_D11(-3))	-0.32063	0.607639	-1.23143	0.662657
	[-0.95535]	[0.68269]	[-0.84420]	[0.60666]
DLOG(PRUS_D11(-4))	-0.64232	-1.22126	1.95037	-0.49092
	[-2.09496]	[-1.50193]	[1.46357]	[-0.49196]
DLOG(MRUS(-1))	0.004297	0.019152	0.98088	0.239496
	[0.03673]	[0.06173]	[1.92898]	[0.62898]
DLOG(MRUS(-2))	0.089873	0.040638	0.130551	0.07269
	[0.90920]	[0.15502]	[0.30387]	[0.22594]
DLOG(MRUS(-3))	-0.07224	0.162927	0.152264	0.379772
	[-0.70083]	[0.59603]	[0.33988]	[1.13208]
DLOG(MRUS(-4))	0.086745	-0.41062	0.326378	0.128299
	[0.75382]	[-1.34548]	[0.65256]	[0.34257]
DLOG(REERUS(-1))	-0.06426	0.139199	-0.41937	-0.06464
	[-1.33504]	[1.09048]	[-2.00462]	[-0.41264]
DLOG(REERUS(-2))	-0.06171	0.308075	-0.37147	-0.06071
	[-1.05738]	[1.99032]	[-1.46436]	[-0.31961]
DLOG(REERUS(-3))	-0.0496	0.44396	-0.39381	0.048275
	[-0.71858]	[2.42510]	[-1.31258]	[0.21488]
DLOG(REERUS(-4))	-0.09801	0.389143	-0.51994	0.016678
	[-1.26588]	[1.89520]	[-1.54510]	[0.06619]
D(GAPRUS_D11(-1))	-0.08	0.327593	0.54279	-0.02648
	[-0.77472]	[1.19629]	[1.20946]	[-0.07881]
D(GAPRUS_D11(-2))	-0.00487	-0.27144	-0.17699	-0.42013
	[-0.05656]	[-1.19003]	[-0.47348]	[-1.50089]
D(GAPRUS_D11(-3))	0.053242	-0.50192	-0.29491	-0.65897
	[0.46744]	[-1.66159]	[-0.59572]	[-1.77761]
D(GAPRUS_D11(-4))	-0.00186	-0.05161	-0.12598	-0.57781
	-0.08955	-0.23749	-0.38921	-0.29145
	[-0.02082]	[-0.21731]	[-0.32368]	[-1.98256]
C	1.087146	-1.31401	1.132022	-1.43875
	[2.80220]	[-1.27710]	[0.67133]	[-1.13944]
LOG(PRUS_D11(-5))	-0.2175	-0.11874	0.321506	0.261745
	[-2.54301]	[-0.52348]	[0.86486]	[0.94028]
LOG(MRUS(-5))	0.098002	-0.08915	0.033172	-0.12742
	[2.74946]	[-0.94307]	[0.21412]	[-1.09834]
LOG(REERUS(-5))	-0.11014	0.507689	-0.62023	0.17087
	[-1.41049]	[2.45163]	[-1.82754]	[0.67236]
GAPRUS_D11(-5)	-0.01521	-0.30107	0.096986	-0.46135
	[-0.21773]	[-1.62561]	[0.31953]	[-2.02983]
DLOG(OILP_EXO)	0.003752	-0.03509	-0.08377	-0.03969
	[0.26713]	[-0.94198]	[-1.37210]	[-0.86822]
Adj. R-squared	0.562865	0.655065	0.478766	0.363632
Akaike information criterion		-22.4903		
Schwarz criterion		-18.7366		

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.2.C.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, his model is valid to forecast Russian inflation since there is no evidence of autocorrelation.

Table 7.2.C.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.0866
2	0.1904
3	0.4435
4	0.504
5	0.9465
6	0.3139
7	0.3177
8	0.2399
9	0.9636
10	0.4609

Fourth, we produce a VECM for Russia where unemployment is included with other variables and excludes the output gap. We treat the stationary transformation of the oil prices ($\Delta InOilp$) as exogenous and following nonstationary variables (lnP, lnM, $InREE\ and\ UN$) as endogenous. We first seek to find the appropriate lag length and start with a levels VAR using the maximum possible lag-length that can be estimated for Russia (P*= 8). The results are given in Table 7.2.D.A column 1 and 2 where the lag length selected by the AIC and SC are 8 and 2 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 8) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level in this 8-lag model because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Russia with more than 8 lags and because experience suggests that models with too many lags can exhibit autocorrelation, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 7 and 6 lags and report the autocorrelation tests in columns 4 and 5 of Table 7.2.D.A, respectively. The VAR model with 7 lag indicates evidence of autocorrelation whereas the VAR with 6 lag exhibits no evident autocorrelation. Hence, we select the 6 lag VAR of this model for cointegration analysis.

Table 7.2. D.A

Endogenous: lnP, lnM, $InREE$ and UN Exogenous: $\Delta lnOilp$					
	1	2	3	4	5
	AIC	SC	Prob.	Prob.	Prob.
Lag			8	7	6
0	2.238751	2.409373			
1	-18.86234	-18.00923	0.000	0.3441	0.3838
2	-20.04228	-18.50669*	0.000	0.1427	0.4168
3	-19.86654	-17.64846	0.000	0.034	0.4612
4	-19.29647	-16.3959	0.000	0.959	0.6915
5	-20.32674	-16.74368	0.000	0.2753	0.4255
6	-20.86821	-16.60267	0.000	0.3468	0.4808
7	-21.90786	-16.95983	0.000	0.7928	0.9376
8	-22.69874*	-17.06822	0.000	0.0788	0.4122
9			0.000	0.9022	0.9323
10			0.000	0.1654	0.0560

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 6 lagged level terms (5 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.2. D.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no cointegrating equations, and at most 1,2 cointegrating equations at the 5% level. However, the null hypothesis of at most 3 cointegrating equation cannot be rejected at the 5% significance level. Therefore, the tests indicate that there are three cointegrating equations among the five variables in this Table (7.2.D.B).

Table 7.2.D.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	91.95015	47.85613	0.0000	47.52461	27.58434	0.0000
At most 1	44.42554	29.79707	0.0005	24.20909	21.13162	0.0178
At most 2	20.21645	15.49471	0.0090	19.75729	14.2646	0.0061
At most 3	0.459156	3.841466	0.4980	0.459156	3.841466	0.4980

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.2.D.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.2.D.C The Vector Error Correction Model

t-statistics in [ ]					
	DLOG(PRUS_D11)	DLOG(MRUS)	DLOG(REERUS)	DLOG(URUS_D11)	
DLOG(PRUS_D11(-1))	0.139016	-0.78014	1.30248	1.80813	
	[0.45250]	[-0.76456]	[0.83748]	[0.82095]	
DLOG(PRUS_D11(-2))	-0.2989	-0.06443	0.710193	1.118655	
	[-1.06669]	[-0.06923]	[0.50066]	[0.55686]	
DLOG(PRUS_D11(-3))	0.046759	-0.03842	-1.93329	0.671433	
	[0.15497]	[-0.03834]	[-1.26571]	[0.31040]	
DLOG(PRUS_D11(-4))	-0.73979	-1.45129	2.197033	0.744079	
	[-2.75135]	[-1.62510]	[1.61409]	[0.38601]	
DLOG(PRUS_D11(-5))	-0.26575	0.606491	-1.25764	0.544865	
	[-0.73307]	[0.50372]	[-0.68531]	[0.20965]	
DLOG(MRUS(-1))	-0.00533	0.095625	0.815266	-2.30096	
	[-0.05320]	[0.28749]	[1.60808]	[-3.20480]	
DLOG(MRUS(-2))	0.140627	-0.21038	-0.37497	-0.88261	
	[1.48635]	[-0.66949]	[-0.78289]	[-1.30124]	
DLOG(MRUS(-3))	-0.0262	0.067581	-0.10634	0.17833	
	[-0.26905]	[0.20893]	[-0.21568]	[0.25542]	
DLOG(MRUS(-4))	0.11829	-0.1202	0.467432	-0.92786	
	[1.13857]	[-0.34835]	[0.88876]	[-1.24576]	
DLOG(MRUS(-5))	0.009503	-0.03715	-0.28135	-0.08929	
	[0.09880]	[-0.11628]	[-0.57784]	[-0.12950]	
DLOG(REERUS(-1))	-0.09687	0.097427	-0.3192	-0.23076	
	[-1.81208]	[0.54874]	[-1.17954]	[-0.60213]	
DLOG(REERUS(-2))	-0.07957	0.184105	-0.42969	0.388733	
	[-1.41216]	[0.98375]	[-1.50640]	[0.96232]	
DLOG(REERUS(-3))	-0.10364	0.465379	-0.2979	0.865327	
	[-1.56251]	[2.11242]	[-0.88716]	[1.81971]	
DLOG(REERUS(-4))	-0.13447	0.49078	-0.06407	1.053925	
	[-1.61752]	[1.77750]	[-0.15225]	[1.76840]	
DLOG(REERUS(-5))	-0.14968	0.705938	-0.06185	1.42869	
	[-1.69582]	[2.40809]	[-0.13841]	[2.25784]	
DLOG(URUS_D11(-1))	0.01136	-0.06438	-0.09531	-0.68455	
	[0.31639]	[-0.53986]	[-0.52436]	[-2.65948]	
DLOG(URUS_D11(-2))	-0.02441	0.096234	-0.00259	-0.57285	
	[-0.81731]	[0.97028]	[-0.01713]	[-2.67583]	
DLOG(URUS_D11(-3))	-0.01487	0.183991	0.066914	-0.38986	
	[-0.50117]	[1.86766]	[0.44564]	[-1.83339]	
DLOG(URUS_D11(-4))	-0.03582	0.176954	0.078232	0.041399	
	[-1.20437]	[1.79136]	[0.51960]	[0.19416]	
DLOG(URUS_D11(-5))	-0.00412	0.195832	0.210136	0.319193	
	[-0.11520]	[1.65028]	[1.16182]	[1.24616]	
C	1.739717	-3.3439	-0.84434	-2.33464	
	[3.33355]	[-1.92917]	[-0.31959]	[-0.62400]	
LOG(PRUS_D11(-6))	-0.32939	-0.14196	0.316417	-0.89449	
	[-2.48862]	[-0.32293]	[0.47224]	[-0.94267]	
LOG(MRUS(-6))	0.159836	-0.14387	-0.11196	0.012375	
	[3.00992]	[-0.81574]	[-0.41647]	[0.03251]	
LOG(REERUS(-6))	-0.20365	0.918059	-0.033	1.364076	
	[-1.91560]	[2.59999]	[-0.06131]	[1.78973]	
LOG(URUS_D11(-6))	0.004513	0.252322	0.020719	0.043739	
	[0.10611]	[1.78602]	[0.09622]	[0.14343]	
DLOG(OILP_EXO)	0.004199	-0.04744	-0.09383	0.171218	
	[0.40728]	[-1.38541]	[-1.79773]	[2.31647]	
Adj. R-squared	0.615624	0.5243	0.378256	0.575709	
Akaike information criterion		-21.2854			
Schwarz criterion		-16.8492			

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.2.D.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Russian inflation since there is no evidence of autocorrelation.

Table 7.2.D.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.4338
2	0.1485
3	0.560
4	0.6768
5	0.7973
6	0.1284
7	0.6674
8	0.5515
9	0.2979
10	0.1649

7.3 Modelling Vector Error Correction Model (VECM) for India

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for India. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for India) and use the standard Akaike (AIC) and Schwarz (SC) information criteria to identify initial lag lengths. First, we estimate a VAR model in level for India where we treat all available variables as endogenous. We start with the maximum lags length (P*= 10) to identify initial lag for India and the VAR model considered includes two nonstationary variables (lnP and lnM). To utilise the large sample available for the core variable and other variables, we estimate between 1963q1 -2014q4.[170] The results are given in Table 7.3.A column 1 and 2 where the lag length selected by the AIC and SC are 10 and 5 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because the two of the tests' probability values are less than 0.05. Since the VAR model can not be estimated more than 10 lags, we considered the lower lags. The VAR model with 9 lag exhibits no evident autocorrelation. Hence, we select the 9 lag VAR of this model for cointegration analysis.

[170] We did not include oil price variable in this VAR because the sample is only available between 1980-2014.

Table 7.3.A. A

Endogenous: lnP and lnM						
	1	2	3	4	5	6
	AIC	SC	Prob	Prob	Prob	Prob
Lag			10	11	12	13
0	2.456136	2.489119				
1	-7.96263	-7.86368	0.2620	0.2122	0.523	0.6049
2	-8.47441	-8.3095	0.6003	0.3496	0.1794	0.6768
3	-8.69151	-8.46062	0.9597	0.4714	0.9385	0.9494
4	-10.1978	-9.90096	0.0000	0.0002	0.0018	0.8138
5	-11.4847	-11.12190*	0.6683	0.299	0.1591	0.5133
6	-11.4538	-11.0251	0.5717	0.6739	0.7302	0.9404
7	-11.4411	-10.9463	0.2227	0.3817	0.2784	0.7991
8	-11.4074	-10.8466	0.0015	0.01	0.1632	0.2245
9	-11.5848	-10.9582	0.5796	0.7006	0.5799	0.7174
10	-11.60466*	-10.912	0.2273	0.8695	0.9381	0.8502

The table indicates the selected lag from AIC and SC criterion by an asterisk

Using a VECM based on 9 lagged level terms (8 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.3. A.B. Based on the trace and maximum eigenvalue results, we cannot reject the null hypothesis of the no cointegrating equations at the 5% level. Therefore, there is evidence cointegration among the two variables and the VECM can be included in this model.

Table 7.3.A.B Johansen's cointegration rank tests

Table 7.2.C.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	10.27186	15.49471	0.2604	9.683948	14.2646	0.2335
At most 1	0.587914	3.841466	0.4432	0.587914	3.841466	0.4432
At most 2	6.76403	15.49471	0.0455	6.34074	6.1649	0.0486
At most 3	2.423299	3.841466	0.2329	2.423299	3.84146	0.2329

Second, we estimate a VAR level for the short period (1984q1- 2012q4) to include all available variables and the oil price that only available between 1980q1 2014q4. Therefore, we start with the initial length (P*= 10) and considered the VAR model that include all the nonstationary variables ($lnP,\ \ and\ InOilp$). The results are given in Table 7.3.B.A column 1 and 2 where the lag length selected by the AIC and SC are both 5. We tested the maximum lag (P*= 5) VAR for autocorrelation (of order 1, 2, … 10). There is evidence of autocorrelation at the 5% level because three of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags, hence we follow the standard reaction and add lags (P**+ 1). We re-estimate the VAR models with 6,7, 8 and 9 lags and report the autocorrelation tests in columns 4, 5, 6 and 7 of Table 7.3.B, respectively. The VAR models with 6, 7 and 8 lags indicate evidence of autocorrelation whereas the VAR with 9 lags exhibits no evident autocorrelation. Hence, we select the 9 lag VAR of this model for cointegration analysis.

Table 7.3.B.A

	Endogenous: $lnP,\ lnM, and\ \ InOilp$						
	1	2	3	4	5	6	7
	AIC	SC	Prob.		Prob.	Prob.	Prob.
Lag			5	6	7	8	9
0	8.966761	9.037974					
1	-2.24817	-1.96332	0.0966	0.4387	0.0021	0.7926	0.8436
2	-2.25685	-1.75836	0.0130	0.7807	0.2361	0.2968	0.9171
3	-2.40654	-1.69441	0.1307	0.5398	0.5881	0.8587	0.9806
4	-4.37472	-3.44895	0.000	0.0015	0.012	0.0015	0.1175
5	-5.132193*	-3.992777*	0.6234	0.8753	0.7343	0.4585	0.9193
6	-5.06132	-3.70826	0.9428	0.7929	0.862	0.7726	0.9524
7	-4.98742	-3.42072	0.9598	0.5869	0.7039	0.9591	0.4079
8	-4.88913	-3.10879	0.0008	0.0013	0.0018	0.0004	0.6600
9	-5.01044	-3.01646	0.9407	0.9803	0.9919	0.9945	0.8288
10	-4.91679	-2.70917	0.4833	0.7645	0.9816	0.9105	0.9503

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 9 lagged level terms (8 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and trend (option 4 in EVIews) to determine the cointegrating rank.[171] The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.3. B.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no cointegrating equations at the 5% level. However, the null hypothesis of at most 1 and 2 cointegratings equation cannot be rejected at the 5% significance level. Therefore, there is only one cointegrating equation among the three variables.

[171] We decided to choose option 4 in the EVIew because option 3 does not specified cointegration.

Table 7.3.B.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	49.33186	42.91525	0.0101	27.68772	25.82321	0.0281
At most 1	21.64413	25.87211	0.1537	18.1756	19.38704	0.0743
At most 2	3.468532	12.51798	0.8168	3.468532	12.51798	0.8168

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.3.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.3.B.C The Vector Error Correction Model

t-statistics in [ ]			
	DLOG(PIND_D11)	DLOG(MIND)	DLOG(OILP)
DLOG(PIND_D11(-1))	0.175932	0.018916	-28.8182
	[1.65992]	[0.16223]	[-0.56974]
DLOG(PIND_D11(-2))	0.127147	-0.02575	-15.6547
	[1.19516]	[-0.22000]	[-0.30834]
DLOG(PIND_D11(-3))	0.11066	0.112219	-64.8454
	[1.05180]	[0.96952]	[-1.29148]
DLOG(PIND_D11(-4))	-0.19173	-0.00635	-47.1435
	[-1.78887]	[-0.05382]	[-0.92170]
DLOG(PIND_D11(-5))	-0.06963	-0.18893	31.38082
	[-0.64211]	[-1.58373]	[0.60641]
DLOG(PIND_D11(-6))	0.145202	-0.05518	7.508572
	[1.33227]	[-0.46021]	[0.14436]
DLOG(PIND_D11(-7))	0.119349	0.030001	0.637831
	[1.12843]	[0.25784]	[0.01264]
DLOG(PIND_D11(-8))	-0.16522	-0.05314	12.33178
	[-1.59165]	[-0.46530]	[0.24894]
DLOG(MIND(-1))	-0.0138	-0.08997	-3.25398
	[-0.15723]	[-0.93172]	[-0.07769]
DLOG(MIND(-2))	0.040502	-0.06536	-9.08417
	[0.46076]	[-0.67588]	[-0.21655]
DLOG(MIND(-3))	0.016108	-0.08976	-1.40786
	[0.18365]	[-0.93023]	[-0.03363]
DLOG(MIND(-4))	-0.01871	0.383697	44.69126
	[-0.20309]	[3.78494]	[1.01628]
DLOG(MIND(-5))	-0.00671	-0.05505	-16.3685
	[-0.07096]	[-0.52920]	[-0.36275]
DLOG(MIND(-6))	-0.03975	-0.07427	-6.25272
	[-0.42090]	[-0.71495]	[-0.13875]
DLOG(MIND(-7))	-0.00524	-0.04115	-10.4871
	[-0.05516]	[-0.39342]	[-0.23116]
DLOG(MIND(-8))	0.006111	0.47404	-30.0117
	[0.06564]	[4.62771]	[-0.67540]
DLOILP(-1)	-0.00019	-3.97E-05	-0.14665
	[-0.86443]	[-0.16537]	[-1.40842]
DLOILP(-2)	-0.00045	-8.17E-05	-0.12817
	[-2.02590]	[-0.33783]	[-1.22245]
DLOILP(-3)	-0.00012	-2.46E-05	-0.13931
	[-0.52440]	[-0.09994]	[-1.30476]
DLOILP(-4)	5.59E-05	-0.00015	-0.37122
	[0.25407]	[-0.59894]	[-3.53718]
DLOILP(-5)	0.000199	-5.21E-05	-0.18747
	[0.88224]	[-0.20977]	[-1.73898]
DLOILP(-6)	-5.21E-05	-9.27E-05	-0.18566
	[-0.22751]	[-0.36749]	[-1.69740]
DLOILP(-7)	-9.00E-05	-0.00016	-0.1516
	[-0.38929]	[-0.63971]	[-1.37438]
DLOILP(-8)	1.50E-05	-4.08E-05	-0.30512
	[0.05814]	[-0.14367]	[-2.47927]
C	-0.26166	-0.4798	-468.963
	[-0.66055]	[-1.10101]	[-2.48075]
LOG(PIND_D11(-9))	-0.02719	-0.04514	-37.1735
	[-0.79302]	[-1.19682]	[-2.27197]
LOG(MIND(-9))	0.012697	0.022883	20.8052
	[0.71259]	[1.16732]	[2.44665]
LOILP(-9)	2.49E-05	-0.0002	-0.15511
	[0.15414]	[-1.12586]	[-2.00969]
Adj. R-squared	0.036076	0.964764	0.031334
Akaike information criterion		-5.01044	
Schwarz criterion		-3.01646	

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.3.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Indian inflation since there is no evidence of autocorrelation.

Table 7.3.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.8436
2	0.9171
3	0.9806
4	0.1175
5	0.9193
6	0.9524
7	0.4079
8	0.660
9	0.8288
10	0.9503

Third, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a levels VAR using the maximum possible lag-length that can be estimated for Brazil (P*= 10). The VAR model considered includes two nonstationary variables with the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous (lnP and lnM). The results are given in Table 7.3.C. A column 1 and 2 where the lag length selected by the AIC and SC is 9 and 5 respectively. Therefore, we estimate a VAR model in level with 9 lag and report the autocorrelation tests in column 4 of Table 7.3.C.A. There is no evidence of autocorrelation at the 5% level in this model because all the tests' probability values are greater than 0.05. Therefore, we select the 9 lag VAR of this model for cointegration analysis.

Table 7.3.C.A.

Endogenous: lnP and lnM Exogenous: $\Delta InOilp$			
	1	2	3
Lags			9
	AIC	SC	Prob.
0	1.052247	1.147199	
1	-8.54135	-8.35144	0.449
2	-8.65753	-8.37267	0.2901
3	-8.85509	-8.47529	0.9768
4	-10.8315	-10.3568	0.093
5	-11.664	-11.09432*	0.6909
6	-11.6393	-10.9747	0.9092
7	-11.6346	-10.875	0.8599
8	-11.6031	-10.7485	0.2264
9	-11.75527*	-10.8058	0.2015
10	-11.7303	-10.6859	0.3168

Using a VECM based on 9 lagged level terms (8 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and trend (option 4 in EVIews) to determine the cointegrating rank.[172] The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.3. B.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no cointegrating equations at the 5% level. However, the null hypothesis of one 1 cointegrating equation cannot be rejected at the 5% significance level. Therefore, there is evidence of only one cointegrating equation among the three variables.

[172] I decided to choose option 4 in the EVIew because option 3 does not specified cointegration.

Table 7.3.C.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	29.06319	25.87211	0.0193	25.81805	19.38704	0.0051
At most 1	3.245147	12.51798	0.8462	3.245147	12.51798	0.8462

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.3.C.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.3.C.C. The Vector Error Correction Model

t-statistics in [ ]		
	DLOG(PIND_D11)	DLOG(MIND)
DLOG(PIND_D11(-1))	0.214527	2.25E-02
	[2.22454]	[0.20946]
DLOG(PIND_D11(-2))	1.37E-01	-0.02036
	[1.38878]	[-0.18540]
DLOG(PIND_D11(-3))	5.85E-02	1.07E-01
	[0.59651]	[0.97696]
DLOG(PIND_D11(-4))	-2.10E-01	-1.08E-02
	[-2.12730]	[-0.09830]
DLOG(PIND_D11(-5))	0.022004	-0.17541
	[0.22097]	[-1.57885]
DLOG(PIND_D11(-6))	1.63E-01	-0.05961
	[1.65223]	[-0.54002]
DLOG(PIND_D11(-7))	0.083132	0.041953
	[0.84112]	[0.38046]
DLOG(PIND_D11(-8))	-0.17995	-0.05
	[-1.85934]	[-0.46304]
DLOG(MIND(-1))	-0.02358	-0.08442
	[-0.28304]	[-0.90837]
DLOG(MIND(-2))	0.021679	-0.06033
	[0.25975]	[-0.64784]
DLOG(MIND(-3))	0.009652	-0.08118
	[0.11600]	[-0.87445]
DLOG(MIND(-4))	-0.00849	0.384768
	[-0.09695]	[3.94008]
DLOG(MIND(-5))	-0.00641	-0.06921
	[-0.07212]	[-0.69750]
DLOG(MIND(-6))	-0.03762	-0.09339
	[-0.42564]	[-0.94709]
DLOG(MIND(-7))	-0.01223	-0.06832
	[-0.13805]	[-0.69145]
DLOG(MIND(-8))	-0.00795	0.44989
	[-0.09110]	[4.62091]
C	-0.27282	-0.04202
	[-1.62750]	[-0.22469]
LOG(PIND_D11(-9))	-0.02781	-0.0088
	[-1.63998]	[-0.46511]
LOG(MIND(-9))	0.013209	0.003413
	[1.66909]	[0.38653]
DLOG(OILP_EXO)	-0.02502	-0.00183
	[-2.90335]	[-0.19078]
Adj. R-squared	0.123379	0.967042
Akaike information criterion		-11.7553
Schwarz criterion		-10.8058

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.3.C.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Indian inflation since there is no evidence of autocorrelation.

Table 7.3.C.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.449
2	0.2901
3	0.9768
4	0.0930
5	0.6909
6	0.9092
7	0.8599
8	0.2264
9	0.2015
10	0.3168

7.4 Modelling Vector Error Correction Model (VECM) for China

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for China. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for China). The following variables are considered: lnP, lnM, $InREE$, R and $InOilp$ (all are I(1)). First, we estimate a level VAR for China where all available variables that are integrated by I(1) are included as endogenous. To choose an appropriate lag length for this model, we use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum 9 lags (P* = 9) to determine the initial lag length P^{**}. The results are given in Table 7.4.A column 1 and 2 where the lag length selected by the AIC and SC are 9 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the lower lag length identified by the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 9) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.4.A. There is evidence of autocorrelation at the 5% level because three of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). Therefore, we re-estimate the VAR models with 10 and report the autocorrelation tests in columns 4 of Table 7.4.A. The VAR models with 10 lags indicate evidence of no autocorrelation. This model is valid for forecasting.

Table 7.4.A The VAR lags order selection criteria

Endogenous: lnP, lnM, $InREE$, R and $InOilp$				
	1	2	3	4
	AIC	SC	Prob.	
Lag			9	10
0	0.803848	0.94854		
1	-12.8803	-11.2887*	0.1130	0.7807
2	-13.0116	-10.6966	0.1772	0.5398
3	-14.0795	-11.041	0.0008	0.4555
4	-15.1153	-11.3533	0.6234	0.8753
5	-14.8158	-10.3303	0.0032	0.7929
6	-14.7245	-9.5156	0.9598	0.5869
7	-14.5404	-8.60809	0.0358	0.8993
8	-14.6128	-7.95701	0.9407	0.9803
9	-15.20700*	-7.82774	0.4833	0.7645

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Second, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a level's VAR using the maximum possible lag-length that can be estimated for China (P*= 10). The VAR model considered includes four nonstationary variables with the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous lnP, lnM, $InREE$, R and $InOilp$. The results are given in Table 7.4.B. A column 1 and 2 where the lag length selected by the AIC and SC is 10 and 5 respectively. Therefore, we estimate a VAR model in level with 10 lag and report the autocorrelation tests in column 3 of Table 7.4.B.A. There is no evidence of autocorrelation at the 5% level because one of the tests' probability values is greater than 0.05. Hence, we select the 10 lag VAR of this model for cointegration analysis.

Table 7.4. B.A

Using a VECM based on 10 lagged level terms (9 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.4.B.B. Based on the trace and maximum eigenvalue statistics, we reject the null hypothesis of the no cointegrating and at most 1 cointegrating equation at the 5% level. However, the null hypothesis of at most two cointegrating equations cannot be rejected at 5% significance level. Therefore, our results indicate 2 cointegrating equations among the variables.

Table 7.4.B.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	68.57223	47.85613	0.0002	35.72026	27.58434	0.0036
At most 1	32.85198	29.79707	0.0216	23.45235	21.13162	0.0231
At most 2	9.399627	15.49471	0.3297	9.389563	14.2646	0.2552
At most 3	0.010064	3.841466	0.9198	0.010064	3.841466	0.9198

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.4.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.4.B.C The Vector Error Correction Model

Standard errors in ( ) & t-statistics in [ ]					
	DLOG(PCHI)	DLOG(MCHI)	DLOG(REECHI)	D(RCHI)	
DLOG(PCHI(-1))	-0.21075	0.134126	0.311064	-6.11042	
	[-0.96879]	[0.28932]	[0.41614]	[-0.90422]	
DLOG(PCHI(-2))	0.065312	-0.48923	0.30593	-2.77091	
	[0.30798]	[-1.08255]	[0.41984]	[-0.42063]	
DLOG(PCHI(-3))	0.028319	0.060664	-0.69833	-2.03742	
	[0.13819]	[0.13891]	[-0.99172]	[-0.32005]	
DLOG(PCHI(-4))	-0.01125	1.200355	0.037454	2.752748	
	[-0.05627]	[2.81729]	[0.05452]	[0.44323]	
DLOG(PCHI(-5))	0.008278	-0.1243	0.761234	5.295727	
	[0.03802]	[-0.26786]	[1.01740]	[0.78291]	
DLOG(PCHI(-6))	-0.09282	0.160389	0.52045	-5.21214	
	[-0.43728]	[0.35458]	[0.71358]	[-0.79048]	
DLOG(PCHI(-7))	-0.14358	-0.28714	-0.81805	-0.59927	
	[-0.70691]	[-0.66338]	[-1.17213]	[-0.09498]	
DLOG(PCHI(-8))	-0.20222	-0.16059	2.14775	10.48074	
	[-0.94530]	[-0.35227]	[2.92187]	[1.57719]	
DLOG(PCHI(-9))	0.103753	0.930894	-0.34591	-2.88319	
	[0.41981]	[1.76748]	[-0.40734]	[-0.37555]	
DLOG(MCHI(-1))	-0.01698	-0.08107	-0.31853	0.067302	
	[-0.17165]	[-0.38469]	[-0.93739]	[0.02191]	
DLOG(MCHI(-2))	-0.09406	-0.2626	-0.17554	5.69594	
	[-0.96515]	[-1.26434]	[-0.52417]	[1.88142]	
DLOG(MCHI(-3))	-0.06664	-0.0418	0.395033	1.029775	
	[-0.69669]	[-0.20507]	[1.20195]	[0.34659]	
DLOG(MCHI(-4))	0.105303	0.458943	-1.18714	-0.24792	
	[1.10975]	[2.26957]	[-3.64095]	[-0.08411]	
DLOG(MCHI(-5))	0.027281	-0.1637	0.171911	4.939263	
	[0.20349]	[-0.57295]	[0.37318]	[1.18601]	
DLOG(MCHI(-6))	0.111433	0.108477	-0.47372	0.113497	
	[0.91675]	[0.41877]	[-1.13419]	[0.03006]	
DLOG(MCHI(-7))	0.124827	0.06695	-0.17263	4.901388	
	[1.01613]	[0.25574]	[-0.40896]	[1.28443]	
DLOG(MCHI(-8))	0.074133	0.09289	-0.32011	0.672651	
	[0.67754]	[0.39838]	[-0.85143]	[0.19791]	
DLOG(MCHI(-9))	0.034899	0.071932	0.221397	3.654016	
	[0.31634]	[0.30597]	[0.58405]	[1.06627]	
D(RCHI(-1))	0.011016	-0.02366	0.012769	0.016138	
	[1.80360]	[-1.81801]	[0.60846]	[0.08506]	
D(RCHI(-2))	0.002144	-0.02974	-0.02856	-0.19137	
	[0.34060]	[-2.21721]	[-1.32029]	[-0.97869]	
D(RCHI(-3))	-0.0005	-0.00962	-0.01591	0.061368	
	[-0.07505]	[-0.68034]	[-0.69807]	[0.29776]	
D(RCHI(-4))	-0.00091	-0.02629	0.020879	-0.11065	
	[-0.14290]	[-1.93724]	[0.95434]	[-0.55942]	
D(RCHI(-5))	0.000548	-0.01998	-0.02699	-0.43855	
	[0.07865]	[-1.34627]	[-1.12823]	[-2.02775]	
D(RCHI(-6))	0.002904	-0.01128	-0.00044	-0.15169	

	[0.42106]	[-0.76724]	[-0.01875]	[-0.70812]	
D(RCHI(-7))	0.004361	-0.03052	-0.00635	-0.16941	
	[0.65700]	[-2.15768]	[-0.27817]	[-0.82154]	
D(RCHI(-8))	0.006922	-0.00926	-0.01184	-0.26751	
	[0.98911]	[-0.62080]	[-0.49233]	[-1.23063]	
D(RCHI(-9))	0.002306	-0.01619	-0.0266	-0.36391	
	[0.33309]	[-1.09761]	[-1.11827]	[-1.69251]	
	[-0.34428]	[-2.87436]	[0.21394]	[-1.11872]	
	[0.06688]	[-0.75281]	[0.28898]	[-0.95036]	
C	-0.21572	1.354805	0.921869	12.4561	
	[-0.62412]	[1.83928]	[0.77619]	[1.16011]	
LOG(PCHI(-10))	-0.06012	0.2092	0.386001	2.469896	
	[-0.73456]	[1.19938]	[1.37250]	[0.97145]	
LOG(MCHI(-10))	0.022839	-0.05341	-0.03748	-0.31021	
	[1.36426]	[-1.49709]	[-0.65162]	[-0.59653]	
LOG(REECHI(-10))	-0.05478	-0.1004	-0.29651	-2.8809	
	[-1.04868]	[-0.90194]	[-1.65203]	[-1.77553]	
RCHI(-10)	0.003781	-0.03157	-0.01143	-0.29349	
	[0.54671]	[-2.14234]	[-0.48087]	[-1.36620]	
DLOG(OIL_EXO)	0.002833	-0.05789	-0.15271	1.227386	
	[0.20099]	[-1.92694]	[-3.15274]	[2.80288]	
Adj. R-squared	0.409834	0.939124	0.408481	0.510862	
Akaike information criterion		-14.4433			
Schwarz criterion		-7.63402			

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.4.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Chinese inflation since there is no evidence of autocorrelation.

Table 7.4.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.2256
2	0.9199
3	0.6999
4	0.0606
5	0.7985
6	0.1578
7	0.4078
8	0.3521
9	0.5845
10	0.0954

7.5 Modelling Vector Error Correction Model (VECM) for South Africa

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for South Africa. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for South Africa). The following variables are considered: lnP, lnM, $InREE$, R and $InOilp$ (all are I(1)). First, we estimate a level VAR for South Africa where all available variables integrated by I(1) are included as endogenous. To choose an appropriate lag length for this model, we use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum 10 lags (P* =10) to determine the initial lag length P^{**}. The results are given in Table 7.5.A.A column 1 and 2 where the lag length selected by both the AIC and SC is 1. We tested the maximum lag (P*= 1) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.5.A.A There is evidence of autocorrelation at the 5% level because two of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+1). Therefore, we re-estimate the VAR models with 2 lags and report the autocorrelation tests in column 4. There is no evidence of cointegration - the null hypothesis of no-autocorrelation cannot be rejected at the 5% level for this model. This indicates that the model is valid for cointegration analysis

Table 7.5.A.A The VAR lags order selection criteria

Endogenous: lnP, lnM, $InREE$, R and $InOilp$				
	1	2	3	4
	AIC	SC	Prob.	
Lag			1	2
0	1.663899	1.823242		
1	-11.32522*	-10.36916*	0.0605	0.3381
2	-11.2835	-9.53072	0.113	0.294
3	-11.1169	-8.56742	0.0372	0.4289
4	-10.9146	-7.56839	0.6238	0.8632
5	-10.8593	-6.71633	0.6234	0.3891
6	-10.6524	-5.71271	0.9428	0.1955
7	-10.7094	-4.97307	0.9598	0.9775
8	-10.8651	-4.33205	0.0008	0.1790
9	-10.9432	-3.61335	0.9407	0.8782

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 2 lagged level terms (1 lagged differenced term) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.5. A.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no cointegrating equations at the 5% level. However, the null hypothesis of at most 1 cointegrating equation cannot be rejected at the 5% significance level. Therefore, there is only one cointegrating equation among the variables.

Table 7.5.A.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	84.85363	76.97277	0.0111	45.17019	34.80587	0.0021
At most 1	39.68344	54.07904	0.4864	15.76440	28.58808	0.7608
At most 2	23.91904	35.19275	0.4680	12.92558	22.29962	0.5639
	10.99345	20.26184	0.5427	6.132251	15.8921	0.7730
	4.86120	9.164546	0.2990	4.861200	9.164546	0.2990

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.5.A.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.5.A.C. The Vector Error Correction Model

t-statistics in [ ]					
	DLOG(PSOU)	DLOG(MSOU)	DLOG(REESOU)	D(RSOU)	DLOG(OILP)
DLOG(PSOU(-1))	0.276691	-0.27808	0.155167	9.830071	0.131216
	[2.13971]	[-1.21639]	[0.30625]	[1.05898]	[0.11841]
DLOG(MSOU(-1))	-0.03519	0.236379	-0.18051	5.424197	0.119834
	[-0.51898]	[1.97206]	[-0.67948]	[1.11450]	[0.20625]
DLOG(REESOU(-1))	-0.04911	0.006507	0.04479	-0.44021	0.730674
	[-1.45271]	[0.10888]	[0.33817]	[-0.18142]	[2.52238]
D(RSOU(-1))	7.24E-05	-0.00792	0.00657	-0.00653	-0.00351
	[0.03841]	[-2.37610]	[0.88935]	[-0.04827]	[-0.21722]
DLOG(OILP(-1))	0.004872	-0.03675	-0.04408	-0.09073	-0.19954
	[0.32812]	[-1.39986]	[-0.75760]	[-0.08512]	[-1.56820]
C	0.197351	0.091318	0.184268	12.26679	-0.29901
	[1.69068]	[0.44250]	[0.40289]	[1.46394]	[-0.29891]
LOG(PSOU(-2))	-0.07646	-0.05829	0.186129	-2.73072	-0.28124
	[-2.18706]	[-0.94304]	[1.35872]	[-1.08806]	[-0.93867]
LOG(MSOU(-2))	0.027886	-0.00656	-0.07906	0.241517	0.274673
	[1.70946]	[-0.22760]	[-1.23692]	[0.20625]	[1.96481]
LOG(REESOU(-2))	0.004108	0.041662	-0.15172	-0.13893	0.284184
	[0.22331]	[1.28090]	[-2.10472]	[-0.10520]	[1.80251]
RSOU(-2)	-0.00035	-0.00235	0.002454	-0.20319	-0.01237
	[-0.37316]	[-1.43111]	[0.67347]	[-3.04362]	[-1.55187]
LOG(OILP(-2))	0.004176	0.012086	-0.00059	0.157602	-0.19181
	[0.50171]	[0.82125]	[-0.01814]	[0.26374]	[-2.68883]
Adj. R-squared	0.122145	0.29263	0.048158	0.123065	0.087632
Akaike information criterion		-11.2835			
Schwarz criterion		-9.53072			

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.5.A.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast South African inflation since there is no evidence of autocorrelation.

Table 7.5.A.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.3381
2	0.294
3	0.4289
4	0.8632
5	0.3891
6	0.1955
7	0.9775
8	0.179
9	0.8782
10	0.6252

Second, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a level's VAR using the maximum possible lag-length that can be estimated for South Afrca (P*= 10). The VAR model considered includes four nonstationary variables with the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous lnP, lnM, $InREE$ and R. The results are given in Table 7.5.B. A column 1 and 2 where the lag length selected by the AIC and SC is 2 and 1 respectively. Therefore, we estimate a level VAR with 2 lag and report the autocorrelation tests in column 3 of Table 7.5.B.A. The VAR model with 2 lag exhibits no evident autocorrelation because all the tests' probability values are greater than 0.05. Hence, we select a level VAR model with 2 lags for the cointegration analysis.

Table 7.5.A The VAR lags order selection criteria

Endogenous: lnP, lnM, $InREE$, R Exogenous: $InOilp$			
	1	2	3
	AIC	SC	Prob.
Lag			2
0	1.871293	2.126243	
1	-10.0556	-9.290710*	0.7974
2	-10.16517*	-8.89042	0.3419
3	-9.98489	-8.20024	0.4270
4	-9.85854	-7.56399	0.1211
5	-9.82273	-7.01829	0.3567
6	-9.80611	-6.49176	0.5615
7	-9.69866	-5.87441	0.1912
8	-9.46939	-5.13524	0.2193
9	-9.56327	-4.71923	0.2187
	-9.49897	-4.14503	0.8729

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 2 lagged level terms (1 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.5. B.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no cointegrating equations at the 5% level. However, the null hypothesis of 1 cointegrating equation cannot be rejected at the 5% significance level. Therefore, there is one cointegrating equation among the variables.

Table 7.5.B.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	72.70216	54.07904	0.0005	42.49636	28.58808	0.0005
At most 1	30.2058	35.19275	0.1563	15.24004	22.29962	0.3556
At most 2	14.96576	20.26184	0.2283	9.451264	15.8921	0.387
At most 3	5.514499	9.164546	0.2317	5.514499	9.164546	0.2317

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.5.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.5.B.C. The Vector Error Correction Model

Standard errors in ( ) & t-statistics in [ ]				
	DLOG(PSOU)	DLOG(MSOU)	DLOG(REESOU)	D(RSOU)
DLOG(PSOU(-1))	0.279609	-0.271	0.295878	8.793029
	[2.21966]	[-1.17738]	[0.63275]	[0.98394]
DLOG(MSOU(-1))	-0.03315	0.210275	-0.237	5.559791
	[-0.49727]	[1.72604]	[-0.95760]	[1.17543]
DLOG(REESOU(-1))	-0.04987	0.002671	0.04769	-0.51129
	[-1.49175]	[0.04373]	[0.38430]	[-0.21558]
D(RSOU(-1))	0.000198	-0.00714	0.005513	0.011631
	[0.10618]	[-2.09718]	[0.79726]	[0.08801]
C	0.180126	0.03138	0.12799	11.9637
	[1.67303]	[0.15951]	[0.32025]	[1.56634]
LOG(PSOU(-2))	-0.07514	-0.03879	0.213218	-2.7075
	[-2.21545]	[-0.62588]	[1.69365]	[-1.12532]
LOG(MSOU(-2))	0.030842	-0.00475	-0.09045	0.358444
	[2.00004]	[-0.16862]	[-1.58009]	[0.32765]
LOG(REESOU(-2))	0.007976	0.045145	-0.15847	-0.0376
	[0.47912]	[1.48410]	[-2.56430]	[-0.03184]
RSOU(-2)	-0.00051	-0.00243	0.003323	-0.21131
	[-0.57545]	[-1.49419]	[1.00521]	[-3.34431]
DLOG(OILP_EXO)	-0.01004	-0.01264	0.140987	-1.29609
	[-0.74838]	[-0.51598]	[2.83257]	[-1.36253]
Adj. R-squared	0.14048	0.260184	0.163534	0.161394
Akaike information criterion		-10.1652		
Schwarz criterion		-8.89042		

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.5.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast South African inflation since there is no evidence of autocorrelation.

Table 7.5.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.6924
2	0.4301
3	0.596
4	0.3646
5	0.9364
6	0.3009
7	0.9937
8	0.5212
9	0.9479
10	0.3618

7.6 Modelling Vector Error Correction Model (VECM) for Algeria

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for Algeria. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for Algeria). The following variables are considered: lnP, lnM, $InREE$, R and $InOilp$ (all are I(1)). First, we estimate a level VAR for Algeria where all available variables integrated by I(1) are included as endogenous. To choose an appropriate lag length for this model, we use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum lag that can be estimated (P* = 9) to determine the initial lag length P^{**}. The results are given in Table 7.6.A. A. column 1 and 2 where the lag length selected by the AIC and SC are 9 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. We tested the maximum lag (P*= 9) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.6. There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Algeria with more than 9 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 8 and 7 lags and report the autocorrelation tests in columns 4 and 5 of Table 7.6.A.A respectively. The VAR model with 8 lag indicates evidence of autocorrelation at the 5% level whereas a VAR model with 7 lag indicates no evidence of autocorrelation at the 5% level. This indicates that a VAR model with 7 lags is valid for cointegration analysis.

Table 7.5.A.A. The VAR lags order selection criteria

Endogenous: lnP, lnM, $InREE$, R and $InOilp$					
	1	2	3	4	
	AIC	SC	Prob.		
Lag			9	8	7
0	-5.66799	-5.4855			
1	-15.0512	-13.9563*	0.0000	0.3381	0.273
2	-14.8358	-12.8285	0.0000	0.294	0.6548
3	-14.5218	-11.6021	0.0000	0.0289	0.0546
4	-15.1443	-11.3121	0.0000	0.8632	0.0808
5	-16.0033	-11.2587	0.0000	0.3891	0.7247
6	-16.4435	-10.7865	0.0000	0.1955	0.4959
7	-16.5608	-9.99135	0.0000	0.9775	0.6019
8	-17.9797	-10.4978	0.0000	0.1790	0.7923
9	-23.15018*	-14.75588	0.0000	0.8782	0.5434
10	-23.5608	-15.99135	0.0000	0.9775	0.1079

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 7 lagged level terms (6 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.6. A.B. Based on the trace result, we reject the null hypothesis of the no, at most 1, 2, 3 and 4 cointegrating equations at the 5% level. For maximum eigenvalue result, we reject the null hypothesis of the no and at most 1 cointegrating equation at 5% significance level. However, the null hypothesis of at most 2 cointegrating equations cannot be rejected at the 5% significance level for maximum eigenvalue. Therefore, we accept the result of the trace test and assume that the system has 5 cointegrating equations because the trace test is more robust to departures from normally distributed residuals of the systems' equations.[173]

[173] Lutkepohi et al.(2000) observed that the trace test performs better than the maximum eigenvalue test most especially where the power is low.

Table 7.6.A.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	158.8671	69.81889	0.000	84.55229	33.87687	0.0000
At most 1	74.31483	47.85613	0.000	42.4162	27.58434	0.0003
At most 2	31.89863	29.79707	0.0282	15.34173	21.13162	0.2657
At most 3	16.5569	15.49471	0.0345	11.30465	14.2646	0.1396
At most 4	5.252249	3.841466	0.0219	5.252249	3.841466	0.0219

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.6.A.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.6.A.C. The Vector Error Correction Model

t-statistics in [ ]					
	DLOG(PALG_D11)	DLOG(M)	DLOG(REEALG)	D(RALG)	DLOG(OILP)
DLOG(PALG_D11(-1))	-0.06453	-0.20744	0.533122	0.838318	1.069698
	[-0.26306]	[-0.17794]	[0.82839]	[0.38531]	[0.46492]
DLOG(PALG_D11(-2))	-0.10818	0.267338	0.946106	2.895802	3.550871
	[-0.42154]	[0.21920]	[1.40522]	[1.27222]	[1.47520]
DLOG(PALG_D11(-3))	0.171803	-0.96045	1.707716	1.10607	1.010941
	[0.65365]	[-0.76890]	[2.47645]	[0.47444]	[0.41006]
DLOG(PALG_D11(-4))	-0.04403	1.508861	0.907346	3.636749	3.161591
	[-0.12051]	[0.86905]	[0.94664]	[1.12232]	[0.92264]
DLOG(PALG_D11(-5))	-0.16904	1.46153	0.689761	5.125925	6.231157
	[-0.49269]	[0.89635]	[0.76628]	[1.68443]	[1.93629]
DLOG(PALG_D11(-6))	-0.23225	0.816286	-0.18106	1.85196	4.132193
	[-0.61864]	[0.45752]	[-0.18383]	[0.55617]	[1.17350]
DLOG(M(-1))	0.082207	-0.39277	0.185048	-0.14136	-0.31386
	[1.60372]	[-1.61226]	[1.37596]	[-0.31091]	[-0.65278]
DLOG(M(-2))	0.072421	-0.23052	0.125553	0.280961	0.302799
	[1.31411]	[-0.88014]	[0.86835]	[0.57478]	[0.58578]
DLOG(M(-3))	0.051845	-0.26576	0.062964	-0.58788	0.154011
	[1.14295]	[-1.23282]	[0.52908]	[-1.46116]	[0.36198]
DLOG(M(-4))	0.044068	0.332997	-0.04406	-1.58619	0.496722
	[1.06509]	[1.69351]	[-0.40592]	[-4.32225]	[1.27994]
DLOG(M(-5))	-0.03123	-0.18516	-0.20839	-1.60065	0.229543
	-0.05404	-0.25681	-0.14177	-0.4793	-0.50686
	[-0.57787]	[-0.72099]	[-1.46990]	[-3.33956]	[0.45288]
DLOG(M(-6))	0.041619	-0.39823	-0.13938	-1.8952	-0.42986
	[0.65858]	[-1.32597]	[-0.84067]	[-3.38115]	[-0.72521]
DLOG(REEALG(-1))	-0.11119	-0.06398	-0.38099	-0.15622	-1.74728
	[-1.05306]	[-0.12750]	[-1.37530]	[-0.16680]	[-1.76425]
DLOG(REEALG(-2))	0.000164	-0.75467	-0.75982	-1.52841	-4.22611
	[0.00138]	[-1.33030]	[-2.42618]	[-1.44358]	[-3.77454]
DLOG(REEALG(-3))	-0.02172	-0.37437	-0.4699	-0.78356	-3.02109
	[-0.13466]	[-0.48839]	[-1.11045]	[-0.54771]	[-1.99693]
DLOG(REEALG(-4))	-0.00434	-0.78804	-0.5587	-2.14095	-5.47944
	[-0.03054]	[-1.16780]	[-1.49976]	[-1.69997]	[-4.11426]
DLOG(REEALG(-5))	0.017024	-0.39214	-0.64346	-2.34173	-3.90595
	[0.09745]	[-0.47236]	[-1.40399]	[-1.51137]	[-2.38386]
DLOG(REEALG(-6))	-0.00346	-0.32625	-0.28547	-2.77009	-5.83935
	[-0.02237]	[-0.44354]	[-0.70301]	[-2.01783]	[-4.02233]
D(RALG(-1))	0.007135	0.016866	-0.00029	-0.79341	-0.2765
	[0.47190]	[0.23473]	[-0.00737]	[-5.91644]	[-1.94973]
D(RALG(-2))	0.022468	-0.00969	0.009261	-0.81327	0.000381
	[1.44871]	[-0.13151]	[0.22760]	[-5.91216]	[0.00262]
D(RALG(-3))	-0.00011	-0.01699	-0.0013	-0.8923	-0.04025
	[-0.00839]	[-0.26981]	[-0.03742]	[-7.59106]	[-0.32376]
D(RALG(-4))	0.009042	-0.01937	-0.00792	-0.77308	0.093455
	-0.01654	-0.0786	-0.04339	-0.14669	-0.15513
	[0.54672]	[-0.24648]	[-0.18246]	[-5.27009]	[0.60245]
D(RALG(-5))	-0.00135	-0.08125	-0.00454	-0.24144	0.31116
	-0.01555	-0.07392	-0.04081	-0.13796	-0.14589
	[-0.08671]	[-1.09919]	[-0.11135]	[-1.75007]	[2.13278]
D(RALG(-6))	-0.0037	-0.06647	0.004251	-0.36319	0.310389
	[-0.22140]	[-0.83754]	[0.09703]	[-2.45192]	[1.98154]

DLOG(OILP(-1))	0.008528	-0.0462	-0.01209	0.084756	-0.4843	
	[0.35363]	[-0.40313]	[-0.19104]	[0.39627]	[-2.14119]	
DLOG(OILP(-2))	-0.03008	-0.06185	0.021239	-0.04941	-0.6375	
	[-1.52343]	[-0.65909]	[0.41000]	[-0.28214]	[-3.44217]	
DLOG(OILP(-3))	0.009925	-0.04105	0.032208	-0.05343	-0.55652	
	[0.39681]	[-0.34531]	[0.49082]	[-0.24085]	[-2.37213]	
DLOG(OILP(-4))	0.03615	0.147845	0.083393	0.331603	-0.51808	
	[1.49913]	[1.29007]	[1.31812]	[1.55037]	[-2.29053]	
DLOG(OILP(-5))	0.03092	0.070438	0.06999	0.249318	-0.60371	
	[1.12303]	[0.53831]	[0.96890]	[1.02091]	[-2.33768]	
DLOG(OILP(-6))	0.008377	0.064135	0.040645	0.22277	-0.70306	
	[0.28592]	[0.46063]	[0.52878]	[0.85728]	[-2.55847]	
C	-1.26579	12.21431	3.353084	39.90518	31.74727	
	[-0.85027]	[1.72642]	[0.85850]	[3.02215]	[2.27361]	
LOG(PALG_D11(-7))	-0.10336	1.345017	0.228561	2.966933	3.372541	
	[-0.66892]	[1.83162]	[0.56380]	[2.16482]	[2.32699]	
LOG(M(-7))	0.041209	-0.55787	-0.11043	-1.25498	-0.62369	
	[0.70181]	[-1.99916]	[-0.71684]	[-2.40966]	[-1.13242]	
LOG(REEALG(-7))	0.099677	-0.41354	-0.30324	-3.49086	-6.06495	
	[0.60102]	[-0.52469]	[-0.69692]	[-2.37312]	[-3.89885]	
RALG(-7)	0.002899	-0.06486	0.00278	-0.20954	0.225336	
	[0.23668]	[-1.11404]	[0.08649]	[-1.92840]	[1.96106]	
LOG(OILP(-7))	0.011124	0.137366	0.042599	0.313756	-0.61571	
	[0.45571]	[1.18415]	[0.66519]	[1.44920]	[-2.68928]	
Adj. R-squared	0.122065	0.583614	0.092321	0.760195	0.412006	
Akaike information criterion		-16.9495				
Schwarz criterion		-10.3800				

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.6.A.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Algerian inflation since there is no evidence of autocorrelation.

Table 7.6.A.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.273
2	0.6548
3	0.0546
4	0.0808
5	0.7247
6	0.4959
7	0.6019
8	0.7923
9	0.5434
10	0.1079

Second, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a levels VAR using the maximum possible lag-length that can be estimated for Algeria (P*= 10). The VAR model considered includes four nonstationary variables with the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous lnP, lnM, $InREE$ and R . The results are given in Table 7.6.B. A column 1 and 2 where the lag length selected by the AIC and SC are 10 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the low lag length of the SC and adopt the AIC. We tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.6.B.A. There is no evidence of autocorrelation at the 5% level because all the tests' probability values are more than 0.05. Hence, we select a level VAR model with 10 lag for the cointegration analysis.

Table 7.6.B.A The VAR lags order selection criteria

Endogenous: lnP, lnM, $InREE$, R Exogenous: $InOilp$			
	1	2	3
	AIC	SC	Prob.
Lag			10
0	2.456136	2.489119	
1	-7.96263	-7.86368*	0.6049
2	-8.47441	-8.3095	0.6768
3	-8.69151	-8.46062	0.9494
4	-10.1978	-9.90096	0.8138
5	-11.4847	-11.1219	0.5133
6	-11.4538	-11.0251	0.9404
7	-11.4411	-10.9463	0.7991
8	-11.4074	-10.8466	0.2245
9	-11.5848	-10.9582	0.7174
10	-11.60466*	-10.912	0.8502

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 10 lagged level terms (9 lagged differenced terms) we apply the standard Johansen cointegration tests with standard unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.6. B.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no, at most 1,2 and 3 cointegrating equations at the 5% level. Therefore, are 4 cointegrating equations among the variables.

Table 7.6.B.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	167.7066	47.85613	0.0000	100.6138	27.58434	0.000
At most 1	67.0927	29.79707	0.0000	45.10525	21.13162	0.000
At most 2	21.98745	15.49471	0.0046	16.73726	14.2646	0.0199
At most 3	5.250192	3.841466	0.0219	5.250192	3.841466	0.0219

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 11.6.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.6.B.C. The Vector Error Correction Model

	DLOG(PALG_D11)	DLOG(M)	DLOG(REEALG)	D(RALG)
DLOG(PALG_D11(-1))	-0.04367	0.063146	0.867071	2.914722
	[-0.15035]	[0.06436]	[1.32228]	[1.60358]
DLOG(PALG_D11(-2))	-0.23973	-0.50555	0.352565	2.502163
	[-0.79005]	[-0.49315]	[0.51460]	[1.31756]
DLOG(PALG_D11(-3))	0.263063	-0.26687	0.970531	5.288085
	[0.70697]	[-0.21228]	[1.15516]	[2.27068]
DLOG(PALG_D11(-4))	0.093694	2.480586	-0.42526	6.857665
	[0.15294]	[1.19849]	[-0.30743]	[1.78853]
DLOG(PALG_D11(-5))	-0.34096	0.42093	-0.20462	6.027108
	[-0.72322]	[0.26428]	[-0.19223]	[2.04267]
DLOG(PALG_D11(-6))	-0.32453	-0.64106	-0.54518	3.683774
	[-0.71621]	[-0.41876]	[-0.53287]	[1.29895]
DLOG(PALG_D11(-7))	-0.28512	-1.20344	0.591279	4.61351
	[-0.64826]	[-0.80989]	[0.59540]	[1.67599]
DLOG(PALG_D11(-8))	-0.315	-1.35753	-0.76266	3.568943
	[-0.77591]	[-0.98975]	[-0.83199]	[1.40460]
DLOG(PALG_D11(-9))	-0.11902	-0.32359	-0.22192	5.851181
	[-0.25213]	[-0.20290]	[-0.20821]	[1.98049]
DLOG(M(-1))	0.106506	-0.25417	0.122609	0.351643
	[1.82314]	[-1.28779]	[0.92953]	[0.96176]
DLOG(M(-2))	0.04932	-0.04127	-0.06995	0.506411
	[0.65947]	[-0.16331]	[-0.41421]	[1.08190]
DLOG(M(-3))	0.051367	-0.09842	-0.09716	0.173436
	[0.74689]	[-0.42356]	[-0.62566]	[0.40293]
DLOG(M(-4))	-0.02377	0.27946	0.085671	-1.95636
	[-0.36770]	[1.27941]	[0.58686]	[-4.83476]
DLOG(M(-5))	-0.12512	-0.523	0.100413	-2.13197
	[-0.89154]	[-1.10304]	[0.31688]	[-2.42722]
DLOG(M(-6))	0.02833	-0.4652	0.073214	-1.92183
	[0.32702]	[-1.58947]	[0.37430]	[-3.54459]
DLOG(M(-7))	0.067721	-0.25321	0.180552	-1.66773
	[0.71694]	[-0.79344]	[0.84655]	[-2.82100]
DLOG(M(-8))	0.173211	0.221308	-0.09504	-0.06081
	[1.92844]	[0.72930]	[-0.46862]	[-0.10817]
DLOG(M(-9))	0.145505	0.305916	-0.19218	-0.70619
	[1.37248]	[0.85410]	[-0.80282]	[-1.06431]
DLOG(REEALG(-1))	-0.20669	-0.67989	-0.41034	-1.09445
	[-1.49865]	[-1.45913]	[-1.31768]	[-1.26791]
DLOG(REEALG(-2))	-0.12408	-1.19234	-0.31811	-2.47516
	[-0.55446]	[-1.57705]	[-0.62956]	[-1.76720]
DLOG(REEALG(-3))	-0.05194	-0.84334	-0.29354	-1.40139
	[-0.27649]	[-1.32884]	[-0.69207]	[-1.19197]
DLOG(REEALG(-4))	0.069602	-0.17593	-0.70831	-1.76486
	[0.40874]	[-0.30581]	[-1.84222]	[-1.65597]
DLOG(REEALG(-5))	-0.12601	-0.2092	-0.65118	-3.28653
	[-0.66708]	[-0.32781]	[-1.52675]	[-2.77991]
DLOG(REEALG(-6))	-0.12721	-0.48172	-0.1473	-4.59185
	-0.25445	-0.85967	-0.57454	-1.59255

	[-0.49995]	[-0.56036]	[-0.25638]	[-2.88333]
DLOG(REEALG(-7))	-0.19899	-0.66399	-0.08752	-5.17216
	[-0.67432]	[-0.66601]	[-0.13135]	[-2.80047]
DLOG(REEALG(-8))	0.066989	-0.51117	-0.11668	-4.40743
	[0.29917]	[-0.67570]	[-0.23078]	[-3.14494]
DLOG(REEALG(-9))	-0.05872	0.220668	-0.33308	-4.99956
	[-0.24718]	[0.27496]	[-0.62099]	[-3.36273]
D(RALG(-1))	0.010852	0.117332	0.115598	-0.69099
	[0.27070]	[0.86633]	[1.27712]	[-2.75408]
D(RALG(-2))	0.018785	0.022339	0.017628	-0.82574
	[0.62095]	[0.21856]	[0.25807]	[-4.36107]
D(RALG(-3))	0.028182	0.185782	0.082637	-0.67608
	[1.27930]	[2.49625]	[1.66139]	[-4.90368]
D(RALG(-4))	0.037311	0.227831	0.066161	-0.49776
	[1.34365]	[2.42852]	[1.05522]	[-2.86406]
D(RALG(-5))	0.007726	0.037131	0.037611	-0.12942
	[0.42322]	[0.60206]	[0.91250]	[-1.13279]
D(RALG(-6))	0.008324	0.048935	0.040936	-0.22876
	[0.57625]	[1.00275]	[1.25512]	[-2.53035]
D(RALG(-7))	0.017564	0.117139	0.077798	-0.01721
	[1.05743]	[2.08735]	[2.07431]	[-0.16557]
D(RALG(-8))	0.015383	0.06551	0.026747	-0.0662
	[0.91468]	[1.15297]	[0.70436]	[-0.62894]
D(RALG(-9))	0.022154	0.116588	0.060702	-0.04329
	[1.64922]	[2.56900]	[2.00138]	[-0.51495]
C	-0.62095	2.715552	-1.12039	47.50403
	[-0.24787]	[0.32085]	[-0.19807]	[3.02982]
LOG(PALG_D11(-10))	0.032513	0.627772	-0.22224	3.835758
	[0.12371]	[0.70699]	[-0.37450]	[2.33186]
LOG(M(-10))	0.020136	-0.15478	0.07503	-1.36732
	[0.22629]	[-0.51484]	[0.37342]	[-2.45505]
LOG(REEALG(-10))	-0.04896	-0.3005	-0.09767	-5.22266
	[-0.20678]	[-0.37567]	[-0.18269]	[-3.52437]
RALG(-10)	0.015653	0.059474	0.044501	-0.09894
	[1.38307]	[1.55547]	[1.74147]	[-1.39682]
DLOG(OILP_EXO)	-0.01821	-0.16241	-0.05385	-0.14363
	[-0.80548]	[-2.12657]	[-1.05502]	[-1.01519]
Adj. R-squared	-0.06685	0.744292	0.183057	0.854907
Akaike information criterion		-17.4299		
Schwarz criterion		-11.2984		

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.6.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Algerian inflation since there is no evidence of autocorrelation.

Table 7.6.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.1812
2	0.6705
3	0.6688
4	0.221
5	0.0544
6	0.2635
7	0.7058
8	0.087
9	0.4705
10	0.5251

7.7 Modelling Vector Error Correction Model (VECM) for Angola

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for Angola. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for Angola). The following variables are considered: lnP, lnM, R and $InOilp$ (all are I(1)). First, we estimate a level VAR for Angola where all available variables integrated by I(1) are included as endogenous. To choose an appropriate lag length for this model, we use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum lag that can be estimated (P*= 8) to determine the initial lag length P^{**}. The results are given in Table 7.7.A.A column 1 and 2 where the lag length selected by both the AIC and SC is 8. We tested the maximum lag (P*= 8) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.7.A. There is evidence of autocorrelation at the 5% level because two of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Angola with more than 8 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate a level VAR model with 7 and 6 lags (where P* -1) and test the validity of the model. There is an evidence of autocorrelation with a level VAR model with 7 lag and no evidence of autocorrelation with a level VAR model with 6 lag at the 5% level. This indicates that the model with 6 lag is valid for cointegration analysis.

Table 6.7.A The VAR lags order selection criteria

	Endogenous: lnP, lnM, $InREE$, R and $InOilp$				
	1	2	3		4
	AIC	SC	Prob.		
Lag			8	7	6
0	8.231222	8.3984			
1	-1.85498	-1.01909	0.0885	0.0247	0.3381
2	-3.05872	-1.55412	0.3923	0.6548	0.2940
3	-2.7578	-0.58449	0.3296	0.0246	0.4289
4	-2.45167	0.39035	0.1217	0.0808	0.8632
5	-3.42886	0.081875	0.4075	0.7247	0.3891
6	-3.61541	0.564038	0.0078	0.4959	0.1955
7	-3.80425	1.04398	0.3144	0.6019	0.9775
8	-13.46007*	-7.274489*	0.3732	0.7923	0.1790
9			0.1175	0.5434	0.8782
10			0.0211	0.1079	0.1185

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 6 lagged level terms (5 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.7. A.B. Based on the trace and maximum eigenvalue results, we reject the null hypothesis of the no, 1 and 2 cointegrating equations at the 5% level. However, the null hypothesis of at most 3 cointegrating equation cannot be rejected at the 5% significance level. Therefore, the tests indicate that there are three cointegrating equations among the variables.

Table 7.7.A.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	97.42051	47.85613	0.0000	60.02527	27.58434	0.0000
At most 1	37.39524	29.79707	0.0055	21.63339	21.13162	0.0425
At most 2	15.76184	15.49471	0.0456	13.30501	14.2646	0.0705
At most 3	2.456835	3.841466	0.1170	2.456835	3.841466	0.1170

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.7.A.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.7.A.C. The Vector Error Correction Model

t-statistics in [ ]				
	DLOG(PANG)	DLOG(MANG_D11)	D(RANG)	DLOG(OILP)
DLOG(PANG(-1))	-0.28203	5.076529	244.3575	4.116059
	[-1.17429]	[1.81134]	[1.22316]	[0.89603]
DLOG(PANG(-2))	-0.24626	-0.32017	-15.6998	-3.68255
	[-1.80552]	[-0.20116]	[-0.13838]	[-1.41163]
DLOG(PANG(-3))	-0.52186	3.41436	174.216	-0.16731
	[-4.93349]	[2.76610]	[1.98003]	[-0.08270]
DLOG(PANG(-4))	0.268677	0.446871	36.79336	4.205962
	[2.32788]	[0.33179]	[0.38325]	[1.90528]
DLOG(PANG(-5))	0.014893	-0.68666	-41.1961	-0.91286
	[0.14631]	[-0.57805]	[-0.48652]	[-0.46885]
DLOG(MANG_D11(-1))	-0.08621	-0.20996	-14.7122	-0.00545
	[-3.89862]	[-0.81366]	[-0.79984]	[-0.01289]
DLOG(MANG_D11(-2))	-0.07987	-0.2104	13.01045	-0.3699
	[-2.55957]	[-0.57783]	[0.50128]	[-0.61980]
DLOG(MANG_D11(-3))	-0.05961	-0.12918	19.71568	-0.5095
	[-2.13725]	[-0.39694]	[0.84989]	[-0.95516]
DLOG(MANG_D11(-4))	-0.04621	-0.33967	4.119504	-1.06643
	[-1.73143]	[-1.09075]	[0.18558]	[-2.08933]
DLOG(MANG_D11(-5))	0.031999	-0.44054	17.30047	-0.20445
	[1.41679]	[-1.67153]	[0.92090]	[-0.47328]
DRANG(-1)	-0.00029	0.000118	-0.03629	-0.00423
	[-1.07449]	[0.03719]	[-0.16069]	[-0.81396]
DRANG(-2)	-5.94E-05	-0.00132	0.088764	-0.00176
	[-0.23572]	[-0.44795]	[0.42336]	[-0.36396]
DRANG(-3)	6.69E-08	-0.00116	-0.51592	-0.00639
	[0.00028]	[-0.41292]	[-2.57426]	[-1.38586]
DRANG(-4)	0.000184	-0.00252	-0.52745	0.000768
	[0.69781]	[-0.81549]	[-2.39904]	[0.15191]
DRANG(-5)	8.48E-05	-0.00139	-0.05172	-0.00176
	[0.31079]	[-0.43649]	[-0.22783]	[-0.33751]
DLOG(OILP(-1))	0.028948	-0.20547	5.684846	-0.43534
	[2.21191]	[-1.34538]	[0.52221]	[-1.73917]
DLOG(OILP(-2))	0.036968	-0.0426	-14.3573	-0.38111
	[2.56491]	[-0.25328]	[-1.19755]	[-1.38247]
DLOG(OILP(-3))	0.073763	-0.22405	-17.3695	-0.3493
	-0.01546	-0.18038	-12.858	-0.29566
	[4.77183]	[-1.24208]	[-1.35087]	[-1.18142]
DLOG(OILP(-4))	0.074483	-0.11213	-14.3382	-0.45061
	[3.77016]	[-0.48637]	[-0.87253]	[-1.19252]
DLOG(OILP(-5))	0.070582	-0.09179	-19.5442	-0.63343
	[3.59440]	[-0.40058]	[-1.19656]	[-1.68654]
C	-0.10858	3.391534	20.60417	3.130742
	[-1.29960]	[3.47872]	[0.29649]	[1.95920]
LOG(PANG(-6))	-0.27983	1.378233	48.3137	0.72159
	[-6.32659]	[2.67025]	[1.31318]	[0.85296]
LOG(MANG_D11(-6))	0.071641	-0.60734	-10.9765	-0.31877
	[5.02424]	[-3.64999]	[-0.92545]	[-1.16881]
RANG(-6)	0.000433	-0.00561	-0.31028	-0.00421
	[2.47742]	[-2.74813]	[-2.13426]	[-1.26030]
LOG(OILP(-6))	0.093859	-0.24763	-20.8271	-0.4004
	[4.02997]	[-0.91114]	[-1.07507]	[-0.89884]
Adj. R-squared	0.977698	0.3386	0.287715	-0.02226
Akaike information criterion		-3.61541		
Schwarz criterion		0.564038		

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.7.A.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Angolan inflation since there is no evidence of autocorrelation.

Table 7.7.A.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.5656
2	0.1549
3	0.0843
4	0.5726
5	0.8332
6	0.6848
7	0.5528
8	0.3655
9	0.3756
10	0.5641

Second, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a level's VAR using the maximum possible lag-length that can be estimated for Angola (P*= 10). The VAR model considered includes three nonstationary variables with the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous lnP, lnM and R . The results are given in Table 7.7.B. A column 1 and 2 where the lag length selected by both the AIC and SC is 10. Therefore, we estimate a level VAR with 10 lag and report the autocorrelation tests in column 3 of Table 7.7.B.A. There is evidence of autocorrelation at the 5% level in this 10-lag model because two of the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Angola with more than 10 lags and because experience suggests that models with too many lags can exhibit autocorrelation, we consider lower lag length VARs. As a result, we re-estimate the VAR models with 9, 8, 7 and 6 lags and report the autocorrelation tests in columns 4,5,6 and 7 of Table 7.7.B.A respectively. The VAR model with 9, 8 and 7 lags indicate evidence of autocorrelation whereas the VAR with 6 lags exhibits no evident autocorrelation. Hence, we select the 6 lag VAR of this model for cointegration analysis.

Table 6.7.B.A The VAR lags order selection criteria

Endogenous: lnP, lnM and R Exogenous: $InOilp$							
	1	2	3				
	AIC	SC	Prob.	Prob.	Prob.	Prob.	Prob.
Lag			10	9	8	7	6
0	9.453471	9.704238					
1	-0.44811	0.178811	0.7974	0.0018	0.1726	0.1059	0.1294
2	-1.72539	-0.72232	0.3419	0.4447	0.0258	0.1395	0.7229
3	-1.47203	-0.09281	0.4270	0.3020	0.0618	0.5476	0.2929
4	-1.34443	0.410936	0.0211	0.1592	0.6897	0.3654	0.5244
5	-1.81657	0.314951	0.3567	0.4186	0.2012	0.0996	0.7182
6	-1.94166	0.566011	0.0015	0.6998	0.1808	0.1289	0.1105
7	-2.34293	0.540891	0.1912	0.8537	0.8630	0.4042	0.3599
8	-3.83144	-0.57147	0.2193	0.3889	0.8666	0.0351	0.4972
9	-5.60992	-1.9738	0.2187	0.9778	0.4360	0.1125	0.3209
10	-6.277772*	-2.265506*	0.8729	0.9701	0.7357	0.0352	0.1481

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 6 lagged level terms (5 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept and no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.7.B.B. Based on the trace test result, we reject the null hypothesis of the no, 1 and 2 cointegrating equations at the 5% level. For maximum eigenvalue, we reject the null hypothesis of no cointegrating equation and failed to reject the null hypothesis of at most 1 cointegrating equation at 5% level. Therefore, we accept the result of the trace test and assume that the system has 3 cointegrating equations because the trace test is more robust to departures from normally distributed residuals of the systems' equations.

Table 7.7.B. B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	53.62932	29.79707	0.0000	31.9438	21.13162	0.001
At most 1	21.68552	15.49471	0.0051	14.17874	14.2646	0.0516
At most 2	7.506779	3.841466	0.0061	7.506779	3.841466	0.0061
At most 3	5.514499	9.164546	0.2317	5.514499	9.164546	0.2317

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.7.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.7.B.C. The Vector Error Correction Model

t-statistics in [ ]			
	DLOG(PANG)	DLOG(MANG_D11)	DRANG
DLOG(PANG(-1))	0.30112	4.74142	116.0552
	[1.33777]	[2.59837]	[0.87902]
DLOG(PANG(-2))	-0.19003	-0.14674	-77.8422
	[-1.13689]	[-0.10829]	[-0.79396]
DLOG(PANG(-3))	-0.33245	3.134788	125.5331
	[-2.66840]	[3.10372]	[1.71780]
DLOG(PANG(-4))	0.326742	0.716775	13.52784
	[2.35194]	[0.63643]	[0.16601]
DLOG(PANG(-5))	-0.20864	-0.71672	36.91432
	[-2.13912]	[-0.90644]	[0.64525]
DLOG(MANG_D11(-1))	-0.03771	-0.32496	-20.5534
	[-1.49982]	[-1.59430]	[-1.39366]
DLOG(MANG_D11(-2))	-0.00623	-0.21694	-5.03258
	[-0.19790]	[-0.84995]	[-0.27252]
DLOG(MANG_D11(-3))	0.0101	-0.19314	-5.097
	[0.35068]	[-0.82724]	[-0.30172]
DLOG(MANG_D11(-4))	0.008889	-0.40797	-5.32064
	[0.30461]	[-1.72459]	[-0.31086]
DLOG(MANG_D11(-5))	0.039093	-0.32725	9.033246
	[1.50164]	[-1.55057]	[0.59156]
DRANG(-1)	-0.00052	0.001121	0.019843
	[-1.47710]	[0.39181]	[0.09581]
DRANG(-2)	-5.84E-05	-0.00081	-0.00204
	[-0.17912]	[-0.30491]	[-0.01067]
DRANG(-3)	-2.89E-05	-0.00102	-0.45185
	[-0.08949]	[-0.38868]	[-2.38695]
DRANG(-4)	-0.00025	-1.66E-05	-0.50577
	[-0.78374]	[-0.00640]	[-2.69870]
DRANG(-5)	-0.0002	-0.00094	0.002331
	[-0.61491]	[-0.35397]	[0.01207]
C	-0.09531	3.018864	20.11886
	[-0.82162]	[3.21000]	[0.29567]
LOG(PANG(-6))	-0.16018	1.324436	13.94194
	[-3.88362]	[3.96110]	[0.57630]
LOG(MANG_D11(-6))	0.060119	-0.64247	-5.95658
	[3.49464]	[-4.60666]	[-0.59030]
RANG(-6)	0.000183	-0.00456	-0.26534
	[0.80947]	[-2.48428]	[-1.99603]
DLOG(OILP_EXO)	-0.00387	0.08572	4.885715
	[-0.24894]	[0.68077]	[0.53628]
Adj. R-squared	0.957465	0.391185	0.324468
Akaike information criterion		-1.94166	
Schwarz criterion		0.566011	

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.7.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Angolan inflation since there is no evidence of autocorrelation.

Table 7.7.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.7049
2	0.6768
3	0.9494
4	0.8138
5	0.5133
6	0.9404
7	0.7991
8	0.2245
9	0.7174
10	0.8502

7.8 Modelling Vector Error Correction Model (VECM) for Nigeria

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for Nigeria. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for Nigeria). The following variables are considered: lnP, lnM, $lnREE$, R and $InOilp$ (all are I(1)). First, we estimate a level VAR for Nigeria where all available variables integrated by I(1) are included as endogenous. To choose an appropriate lag length for this model, we use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum specified lag (P*= 10) to determine the initial lag length P^{**}. The results are given in Table 7.8.A.A column 1 and 2 where the lag length selected by both the AIC and SC is 10. We tested the maximum lag (P*= 10) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.8.A.A There is evidence of autocorrelation at the 5% level because all the tests' probability values are less than 0.05. The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Nigeria with more than 10 lags, experience suggests that models with too many lags can exhibit autocorrelation and the SC indicates a lower optimal lag length, we consider lower lag length VARs. As a result, we re-estimate a level VAR model with 9, 8, 7,….,1 lags (where P*-1) and test the validity of this model. There is an evidence of autocorrelation for this model with all the lag lengths considered (see Table 7.8.A). This indicates that the model is not valid for cointegration analyse and the VECM model cannot be considered for this model.

Table 7.8.A.A. The VAR lags order selection criteria

Endogenous: lnP, lnM, $InREE$, R and $InOilp$												
	1	2	3	4	5	6	7	8	9	10	11	12
	AIC	SC	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
Lag			10	9	8	7	6	5	4	3	2	1
0	5.715286	5.894501										
1	-4.12202	-3.04673	0.0000	0.0247	0.3381	0.0226	0.0186	0.000	0.0000	0.1059	0.9548	0.000
2	-3.7127	-1.74133	0.0000	0.6548	0.0230	0.0216	0.0674	0.8462	0.1619	0.1395	0.8282	0.0103
3	-3.50581	-0.63837	0.0000	0.0246	0.4289	0.0044	0.0251	0.1863	0.7701	0.5476	0.0324	0.9494
4	-4.91696	-1.15344	0.0000	0.0808	0.8632	0.7427	0.0031	0.2937	0.2677	0.3654	0.7639	0.8138
5	-5.66331	-1.00372	0.0000	0.7247	0.3891	0.7554	0.4309	0.0776	0.0157	0.0996	0.2865	0.0251
6	-5.81426	-0.2586	0.0000	0.4959	0.1955	0.896	0.1600	0.5311	0.1085	0.1289	0.2558	0.9404
7	-6.19898	0.252763	0.0000	0.6019	0.9775	0.4341	0.3466	0.7438	0.8627	0.4042	0.619	0.7991
8	-7.31397	0.033848	0.0000	0.7923	0.1790	0.6429	0.8513	0.6841	0.5146	0.0351	0.5152	0.2245
9	-9.4635	-1.21961	0.0000	0.5434	0.8782	0.0023	0.5223	0.8019	0.8065	0.1125	0.4665	0.7174
10	-13.59705*	-4.457085*	0.0000	0.1079	0.1185	0.4223	0.8079	0.7044	0.9192	0.0372	0.2227	0.8502

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Second, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a level's VAR using the maximum possible lag-length that can be estimated for Nigeria (P*= 10). The VAR model considered includes four nonstationary variables with the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous lnP, lnM, $lnREE$ and R. The results are given in Table 7.8.B.A column 1 and 2 where the lag length selected by the AIC and SC are 10 and 1 respectively. Therefore, we estimate a level VAR with 10 lag and report the autocorrelation tests in column 3 of Table 7.8.B.A. There is evidence of autocorrelation at the 5% level because three of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). Therefore, we re-estimate the VAR models with 11 and 12 lags - the maximum lags that can be estimated with this model and report the autocorrelation tests in columns 4 and 5 of Table 7.8.B. A, respectively. The VAR models with 11 and 12 lags indicate evidence of autocorrelation (see Table 7.8.B.A). The standard reaction would be to believe that the lag length is too short and add lags. However, because a VAR model cannot be estimated for Nigeria with more than 12 lags; experience suggests that models with too many lags can exhibit autocorrelation and the SC suggests a lower optimal lag length. We consider lower lag length VARs and re-estimate the VAR model using lag lengths 9, 8…,1 (where P* - 1) and test the validity of each model. We reject the hypothesis of no-autocorrelation at the

5% level for all the lags length considered for this model – see column 9, 8, 7,….,1 of Table 7.8.B.B. This indicates that there is no valid model with the appropriate lag for the cointegration analysis.

Table 7.8.B.A The VAR lags order selection criteria

	Endogenous: lnP, lnM, $InREE$ and R Exogenous: $lnOilp$				
	1	2	3	4	5
	AIC	SC	Prob.		Prob.
Lag			10	11	12
0	2.249858	2.536602			
1	-6.80095	-5.940714*	0.0605	0.4387	0.0021
2	-6.59106	-5.15734	0.0130	0.7807	0.2361
3	-6.51292	-4.50572	0.1772	0.5398	0.5881
4	-6.47584	-3.89514	0.0008	0.0015	0.0120
5	-8.21804	-5.06386	0.6234	0.8753	0.7343
6	-8.23473	-4.50706	0.9428	0.7929	0.8620
7	-8.60474	-4.30358	0.9598	0.5869	0.7039
8	-8.78224	-3.90759	0.0008	0.0013	0.0018
9	-8.72406	-3.27592	0.9407	0.9803	0.9919
10	-9.639221*	-3.6176	0.4833	0.7645	0.9816

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Table 7.8.B.B The VAR lags order selection criteria

	Endogenous: lnP, lnM, $InREE$ and R Exogenous: $lnOilp$								
	1	2	3	4	5	6	7	8	9
	Prob.		Prob.	Prob.	Prob.	Prob.	Prob.	Prob.	Prob.
Lag	9	8	7	6	5	4	3	2	1
0									
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0370
2	0.7061	0.0695	0.8136	0.4632	0.6626	0.0288	0.3369	0.0762	0.6882
3	0.2327	0.0553	0.2016	0.4424	0.2813	0.7492	0.7137	0.9047	0.6085
4	0.4117	0.5729	0.6333	0.7069	0.7302	0.172	0.0112	0.0049	0.0000
5	0.8234	0.3743	0.752	0.5939	0.6063	0.4688	0.7719	0.8150	0.9300
6	0.667	0.5964	0.6595	0.0672	0.0683	0.5017	0.6465	0.1625	0.3726
7	0.8926	0.8853	0.8024	0.9456	0.6551	0.6185	0.4304	0.8188	0.5452
8	0.1245	0.072	0.1461	0.3037	0.1463	0.9445	0.9431	0.7988	0.2884
9	0.8178	0.8892	0.7637	0.9619	0.927	0.5446	0.8426	0.9767	0.9765
10	0.0754	0.5964	0.6100	0.7637	0.7037	0.2147	0.7325	0.4750	0.9072

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

7.9 Modelling Vector Error Correction Model (VECM) for Saudi Arabia

In this section, we describe the process of modelling an unrestricted Vector Error Correction Model (VECM) for Saudi Arabia. We focus only on those variables that are I(1) in chapter 6 Table 6.6.5 for Saudi Arabia). The following variables are considered: lnP, lnM and $InOilp$ (all are I(1)). First, we estimate a level VAR for Saudi Arabia where all available variables integrated by I(1) are included as endogenous. To choose an appropriate lag length for this model, we use the standard Akaike (AIC) and Schwarz (SC) information criteria with the maximum (P*= 10) to determine the initial lag length P^{**}. The results are given in Table 7.9.A.A column 1 and 2 where the lag length selected by the AIC and SC are 5 and 1 respectively. To maximize the chance of selecting an appropriate lag length and minimizing the VAR exhibiting autocorrelation, we avoid selecting the lower lag length identified by the SC and adopt the AIC. Therefore, we tested the maximum lag (P*= 5) VAR for autocorrelation (of order 1, 2, … 10). The probability values of these autocorrelation tests are reported in column 3 of Table 7.9.A.A. There is evidence of autocorrelation at the 5% level because two of the tests' probability values are less than 0.05. This suggests that the lag length is too short and a VAR with more lags are preferred to those with less, hence we follow the standard reaction and add lags (P*+ 1). Therefore, we re-estimate the VAR models with 6,7,8,....,11 lags and report the autocorrelation tests in columns 4, 5, 6, 7, 8 and 9 (see Table 7.9.A.A). The VAR model with 6,7,8,....,10 lags indicate evidence of autocorrelation whereas the VAR with 11 lags exhibits no evident autocorrelation. Hence, we select the 11 lag VAR of this model for cointegration analysis.

Table 7.9.A.A The VAR lags order selection criteria

$Endogenous$: lnP, lnM and $InOilp$									
	1	2	3		4				
	AIC	SC	Prob.						
Lag			5	6	7	8	9	10	11
0	-2.05286	-1.95995	0.2488						
1	-15.6611	-15.19650*	0.4087	0.0247	0.3381	0.3701	0.9182	0.0021	0.5216
2	-15.6808	-14.8446	0.1841	0.6548	0.294	0.9333	0.7511	0.0005	0.4549
3	-15.6327	-14.4248	0.6392	0.0246	0.4289	0.1773	0.3486	0.0466	0.2645
4	-16.013	-14.4335	0.6089	0.0808	0.8632	0.005	0.0707	0.0615	0.6608
5	-16.46200*	-14.5108	0.3624	0.7247	0.3891	0.3692	0.922	0.6434	0.1095
6	-16.3017	-13.9788	0.3218	0.4959	0.1955	0.8198	0.7709	0.0301	0.1944
7	-16.1108	-13.4162	0.0268	0.6019	0.9775	0.9316	0.9194	0.0103	0.0654
8	-16.0108	-12.9446	0.1227	0.7923	0.179	0.0198	0.0081	0.0121	0.1492
9	-16.0621	-12.6242	0.4571	0.5434	0.8782	0.9426	0.9758	0.7475	0.1059
10	-16.0214	-12.2119	0.0211	0.1079	0.1185	0.9324	0.7778	0.4602	0.1302

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 11 lagged level terms (10 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted interceptand no trend (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.9.A.B. Based on the trace result, we reject the null hypothesis of the no, at most 1, 2, and 3 cointegrating equations at the 5% level. For maximum eigenvalue result, we reject the null hypothesis of the no cointegrating equation at 5% significance level. Therefore, we accept the result of the trace test and assume that the system has 4 cointegrating equations because the trace test is more robust to departures from normally distributed residuals of the systems' equations.

Table 7.9.A.B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	75.51941	47.85613	0	32.08903	27.58434	0.0123
At most 1	43.43038	29.79707	0.0008	19.34598	21.13162	0.0873
At most 2	24.0844	15.49471	0.002	18.39411	14.2646	0.0105
At most 3	5.690295	3.841466	0.0171	5.690295	3.841466	0.0171

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.9.A.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.9.A.C. The Vector Error Correction Model

Standard errors in ( ) & t-statistics in [ ]				
	DLOG(PSAU)	DLOG(MSAU)	DLOG(REESAU)	DLOG(OILP)
DLOG(PSAU(-1))	0.090769	0.043041	0.413465	0.96356
	[0.77920]	[0.13486]	[1.03866]	[0.53333]
DLOG(PSAU(-2))	-0.01642	-0.18065	-0.04929	1.211394
	[-0.14893]	[-0.59799]	[-0.13081]	[0.70840]
DLOG(PSAU(-3))	-0.04283	-0.16411	0.426317	-1.34149
	[-0.41066]	[-0.57426]	[1.19604]	[-0.82925]
DLOG(PSAU(-4))	0.052509	0.125383	0.400189	0.609839
	[0.50126]	[0.43686]	[1.11793]	[0.37536]
DLOG(PSAU(-5))	0.05879	-0.16118	0.311097	0.023075
	[0.55774]	[-0.55811]	[0.86366]	[0.01412]
DLOG(PSAU(-6))	-0.11922	0.024546	-0.31761	-0.74663
	[-1.15923]	[0.08711]	[-0.90376]	[-0.46811]
DLOG(PSAU(-7))	0.00386	-0.24971	-0.09424	0.565154
	[0.03845]	[-0.90794]	[-0.27472]	[0.36301]
DLOG(PSAU(-8))	0.021814	-0.54185	0.602272	0.607948
	[0.21674]	[-1.96495]	[1.75110]	[0.38947]
DLOG(PSAU(-9))	-0.04572	-0.22097	0.447947	-0.91732
	[-0.43978]	[-0.77586]	[1.26104]	[-0.56900]
DLOG(PSAU(-10))	-0.11354	-0.11053	0.095504	3.417539
	[-1.07919]	[-0.38345]	[0.26564]	[2.09449]
DLOG(MSAU(-1))	0.004293	-0.32696	-0.00176	0.152351
	[0.10415]	[-2.89514]	[-0.01250]	[0.23831]
DLOG(MSAU(-2))	-0.02593	-0.28348	-0.06548	0.52607
	[-0.61413]	[-2.45034]	[-0.45381]	[0.80329]
DLOG(MSAU(-3))	-0.03718	-0.25222	-0.1298	0.369677
	[-0.93409]	[-2.31257]	[-0.95414]	[0.59877]
DLOG(MSAU(-4))	-0.02691	0.277603	-0.06458	2.062807
	[-0.66556]	[2.50599]	[-0.46739]	[3.28960]
DLOG(MSAU(-5))	-0.13522	-0.14001	-0.07968	0.639553
	[-3.11881]	[-1.17867]	[-0.53781]	[0.95111]
DLOG(MSAU(-6))	-0.02412	-0.11387	0.173114	0.644003
	[-0.52689]	[-0.90802]	[1.10676]	[0.90719]
DLOG(MSAU(-7))	-0.01534	-0.06243	0.153308	1.062996
	[-0.38158]	[-0.56690]	[1.11613]	[1.70516]
DLOG(MSAU(-8))	-0.01941	0.224995	0.085476	0.050891
	[-0.51024]	[2.15888]	[0.65757]	[0.08626]
DLOG(MSAU(-9))	0.027741	0.092646	0.079003	0.722132
	[0.72581]	[0.88472]	[0.60488]	[1.21822]
DLOG(MSAU(-10))	-0.0409	0.018426	0.002334	0.524072
	[-1.09387]	[0.17989]	[0.01827]	[0.90383]
DLOG(REESAU(-1))	-0.0404	-0.20382	0.090019	-0.67221
	[-1.22318]	[-2.25220]	[0.79752]	[-1.31220]
DLOG(REESAU(-2))	-0.00148	-0.19053	-0.19384	0.058365
	[-0.04405]	[-2.07269]	[-1.69065]	[0.11216]
DLOG(REESAU(-3))	-0.01637	-0.19901	-0.08168	0.71873
	[-0.47312]	[-2.09970]	[-0.69094]	[1.33959]
DLOG(REESAU(-4))	-0.10326	-0.08986	-0.24398	0.40671
	[-2.99075]	[-0.94989]	[-2.06781]	[0.75949]
DLOG(REESAU(-5))	-0.03346	-0.0513	-0.13675	0.139147
	[-0.94887]	[-0.53094]	[-1.13481]	[0.25442]
DLOG(REESAU(-6))	-0.03746	-0.14638	-0.09316	0.459883
	[-1.07191]	[-1.52864]	[-0.77997]	[0.84840]
DLOG(REESAU(-7))	-0.00044	-0.12537	0.027784	-0.01932
	[-0.01221]	[-1.28342]	[0.22804]	[-0.03494]
DLOG(REESAU(-8))	-0.0432	0.035037	-0.1752	0.786793
	[-1.20792]	[0.35759]	[-1.43363]	[1.41854]

DLOG(REESAU(-9))	0.023593	-0.05267	-0.01227	0.925452
	[0.66605]	[-0.54273]	[-0.10139]	[1.68458]
DLOG(REESAU(-10))	-0.08402	0.055408	-0.28747	0.126856
	[-2.40803]	[0.57963]	[-2.41113]	[0.23443]
DLOG(OILP(-1))	0.008894	0.001601	0.036925	-0.13037
	[1.22357]	[0.08039]	[1.48644]	[-1.15639]
DLOG(OILP(-2))	0.015355	0.006186	0.021881	-0.11755
	[2.07006]	[0.30437]	[0.86322]	[-1.02180]
DLOG(OILP(-3))	0.003296	0.018789	0.011543	-0.13845
	[0.44173]	[0.91895]	[0.45263]	[-1.19621]
DLOG(OILP(-4))	0.004537	0.100392	0.004066	-0.31265
	[0.61543]	[4.97045]	[0.16142]	[-2.73449]
DLOG(OILP(-5))	0.010365	0.043531	0.03177	-0.22373
	[1.16424]	[1.78466]	[1.04428]	[-1.62032]
DLOG(OILP(-6))	0.019399	0.039182	0.017429	-0.28472
	[2.10094]	[1.54887]	[0.55237]	[-1.98825]
DLOG(OILP(-7))	0.019528	0.044431	0.041793	-0.25646
	[2.08989]	[1.73553]	[1.30887]	[-1.76964]
DLOG(OILP(-8))	0.008099	0.083649	0.029699	-0.46955
	[0.82809]	[3.12169]	[0.88861]	[-3.09555]
DLOG(OILP(-9))	0.016694	0.067619	0.036092	-0.33743
	[1.54768]	[2.28815]	[0.97919]	[-2.01707]
DLOG(OILP(-10))	0.026669	0.059318	-0.03348	-0.39003
	[2.39964]	[1.94808]	[-0.88154]	[-2.26283]
C	0.871178	1.239109	1.165878	-12.1839
	[2.65961]	[1.38070]	[1.04157]	[-2.39832]
LOG(PSAU(-11))	-0.00794	0.088404	0.320017	-0.74294
	[-0.23331]	[0.94843]	[2.75266]	[-1.40806]
LOG(MSAU(-11))	-0.02498	-0.04716	-0.07804	0.522419
	[-1.88144]	[-1.29636]	[-1.71982]	[2.53686]
LOG(REESAU(-11))	-0.05295	-0.10099	-0.10682	0.583607
	[-2.71446]	[-1.88953]	[-1.60237]	[1.92896]
LOG(OILP(-11))	0.026288	0.042513	-3.02E-05	-0.39995
	[2.69663]	[1.59169]	[-0.00091]	[-2.64528]
Adj. R-squared	0.360394	0.737722	0.114901	-0.03628
Akaike information criterion		-16.0202		
Schwarz criterion		-11.839		

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.9.A.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Saudi Arabian inflation since there is no evidence of autocorrelation.

Table 7.9.A.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.5216
2	0.4549
3	0.2645
4	0.6608
5	0.1095
6	0.1944
7	0.0654
8	0.1492
9	0.1059
10	0.1302

Second, we treat the stationary transformation of oil prices as exogenous and all other variables as endogenous (which are I(1)). We first seek to find the appropriate lag length and start with a levels VAR using the maximum possible lag-length that can be estimated for Saudi Arabia (P*= 10). The VAR model considered includes four nonstationary variables including the difference of the log of oil prices as exogenous ($\Delta InOilp$) and the following variables as endogenous lnP, lnM and $lnREE$. The results are given in Table 7.9.B. A column 1 and 2 where the lag length selected by both the AIC and SC is 5. Therefore, we estimate a level VAR with 5 lag and report the autocorrelation tests in column 3 of Table 7.9.B.A. There is no evidence of autocorrelation at the 5% level in this 5 lag model because all the tests' probability values are more than 0.05. Hence, we select the 5 lag VAR of this model for cointegration analysis.

Table 7.9.B.A. The VAR lags order selection criteria

Endogenous: lnP, lnM and $lnREE$ Exogenous: $InOilp$			
	1	2	3
	AIC	SC	Prob.
Lag			5
0	-1.85907	-1.71969	
1	-14.1798	-13.8313	0.9052
2	-14.3003	-13.7428	0.8121
3	-14.3339	-13.5674	0.7033
4	-14.672	-13.6964	0.0651
5	-15.14497*	-13.96028*	0.3990
6	-15.0655	-13.6717	0.7699
7	-14.9713	-13.3685	0.9630
8	-14.9239	-13.112	0.3692
9	-14.9091	-12.8882	0.8856
10	-14.9085	-12.6785	0.6457

AIC = Akaike information criteria, SC = Schwarz information criteria and Prob., is the probability value.

Using a VECM based on 5 lagged level terms (4 lagged differenced terms) we apply the standard Johansen cointegration tests with unrestricted intercept (option 3 in EVIews) to determine the cointegrating rank. The results of Johansen's trace and maximum eigenvalue tests are reported in Table 7.9.B.B. Based on the trace test result, we reject the null hypothesis of the no cointegrating equations at the 5% level and failed to reject the null hypothesis of at most 1 cointegration equation (there is one cointegrating equation). For maximum eigenvalue, we cannot reject the null hypothesis of the no, at most 1 and 2 cointegrating equation at 5% level (there is no cointegrating equation). Therefore, we accept the result of the trace test and assume that the system has 1 cointegrating equation because the trace test is more robust to departures from normally distributed residuals of the systems' equations.

Table 7.9.B. B Johansen's cointegration rank tests

	Test (Trace)			maximum eigenvalue		
Hypothesized	Trace Statistic test	Critical Value	Prob.**	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	31.71506	29.79707	0.0297	19.53573	21.13162	0.0823
At most 1	12.17933	15.49471	0.1485	11.88906	14.2646	0.1149
At most 2	0.290268	3.841466	0.59	0.290268	3.841466	0.590
At most 3	5.514499	9.164546	0.2317	5.514499	9.164546	0.2317

Because there is evidence of cointegration this suggests that long-run information should be included in our model. Hence, we will use the estimated VECM, reported in Table 7.9.B.C to forecast inflation. This specification does not impose the number or form of cointegrated equations on the model.

Table 7.9.B.C. The Vector Error Correction Model

t-statistics in [ ]			
	DLOG(PSAU)	DLOG(MSAU)	DLOG(REESAU)
DLOG(PSAU(-1))	0.225577	0.118637	0.28208
	[2.29629]	[0.43249]	[0.91392]
DLOG(PSAU(-2))	0.040793	-0.07366	-0.17899
	[0.40513]	[-0.26198]	[-0.56579]
DLOG(PSAU(-3))	-0.01002	-0.34964	0.262559
	[-0.10035]	[-1.25413]	[0.83701]
DLOG(PSAU(-4))	0.131177	-0.00307	0.284179
	[1.32533]	[-0.01111]	[0.91383]
DLOG(MSAU(-1))	-0.00627	-0.21448	0.092227
	[-0.24015]	[-2.94298]	[1.12468]
DLOG(MSAU(-2))	0.015104	-0.19574	0.084062
	[0.58549]	[-2.71729]	[1.03716]
DLOG(MSAU(-3))	0.030603	-0.18997	0.048776
	[1.18446]	[-2.63312]	[0.60085]
DLOG(MSAU(-4))	0.024928	0.661809	0.041876
	[1.04174]	[9.90450]	[0.55698]
DLOG(REESAU(-1))	-0.04351	-0.09683	0.196236
	[-1.38603]	[-1.10468]	[1.98974]
DLOG(REESAU(-2))	0.010942	-0.05321	-0.13807
	[0.33833]	[-0.58926]	[-1.35876]
DLOG(REESAU(-3))	-0.01177	-0.04243	-0.03265
	[-0.36666]	[-0.47342]	[-0.32377]
DLOG(REESAU(-4))	-0.06506	-0.02151	-0.10495
	[-2.13031]	[-0.25219]	[-1.09384]
C	0.000897	-0.42482	0.719554
	[0.00963]	[-1.63357]	[2.45911]
LOG(PSAU(-5))	-0.0065	-0.07362	0.158782
	[-0.29907]	[-1.21380]	[2.32655]
LOG(MSAU(-5))	0.002611	0.027982	-0.04141
	[0.50419]	[1.93499]	[-2.54509]
LOG(REESAU(-5))	-0.00858	0.00473	-0.06774
	[-1.28192]	[0.25296]	[-3.22011]
DLOG(OILP_EXO)	-0.00226	-0.00397	-0.03679
	[-0.33243]	[-0.20885]	[-1.72037]
Adj. R-squared	0.266868	0.687726	0.142373
Akaike information criterion		-15.145	
Schwarz criterion		-13.9603	

For the VECM to be valid to forecast, we apply the standard diagnostic check and test the model for autocorrelation (of order 1, 2, … 10). The probability values of the residual autocorrelation tests are reported in Table 7.9.B.D. There is no evidence of autocorrelation at the 5% level because all of the tests' probability values are more than 0.05. Therefore, this model is valid to forecast Saudi Arabian inflation since there is no evidence of autocorrelation.

Table 7.9.B.D. Probability value of the residual autocorrelation

Lags	Prob.
1	0.9052
2	0.8121
3	0.7033
4	0.0651
5	0.399
6	0.7699
7	0.963
8	0.3692
9	0.8856
10	0.6457

Appendix 8

Table 8.1 Summary of the best forecasting models for BRICS countries

Best forecasting Univariate model for Brazil				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1-to 2-steps	R_A _SARIMA	R_A_SARIMA	R_A_SARIMA	5.0690 – 8.0390
3 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	0.3390 -8.2540
Best forecasting univariate model for Russia				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	6.3660 – 20.6300
Best forecasting univariate model for India				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8- steps	F_SARIMA	F_SARIMA	F_SARIMA	13.5200 -63.4600
Best forecasting univariate model for China				
	RMSE	**U –statistics**	**MAPE**	
1 to 2-steps	F_TAR	F_TAR	F_TAR	5.1980 – 12.0000
Best forecasting univariate model for South Africa				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 4 –steps	R_A_SARIMA	R_A_SARIMA	R_A_SARIMA	14.2800 -20.9900
5-step	R_SARIMA	R_A_SARIMA	R_SARIMA	17.2600
6 to 7-steps	R_A_SARIMA	R_A_SARIMA	R_A_SARIMA	12.3600- 13.3600
8-step	R_SARIMA	R_SARIMA	R_SARIMA	10.2000

The best univariate forecasting model is identified by each measure (RMSE, MAPE and U) for each forecasting horizon (1, 2…, 8 steps ahead). The full sample univariate model that employs seasonal Box-Jenkins ARIMA techniques and model's structural breaks is denoted as F_SARIMAX, the full sample univariate model that employs Box-Jenkins ARIMA techniques without modelling structural breaks is denoted as F_SARIMA (this model type is exclusive to India because there were no significant structural breaks to model over the full sample). The full sample specifications that employ EViews 9's automatic seasonal and non-seasonal ARIMA model without modelling breaks are denoted as F_A_SARIMA and F_A_ARIMA respectively (these models are exclusively designed for China because the period after the structural breaks are less than 39 observations and relative step shifts for this period also appear to be small which mean that inference regarding unit roots may not be too adversely affected when using the full sample. Hence, the full sample is used for these models for this country). The reduced sample model that employs seasonal ARIMA technique's without modelling structural breaks is denoted as R_SARIMA. The reduced sample model that employs EViews 9's automatic seasonal ARIMA model selection procedure without modelling breaks is denoted as R_A_SARIMA and the reduced sample model that employs EViews 9's automatic non-seasonal ARIMA model selection method without modelling breaks is represented by R_A_ARIMA. Range gives the range of values for the MAPE for models favoured according to this forecasting measure over the specified horizon. F_TAR is denoted as full sample threshold autoregressive model and R_TAR is the reduced sample threshold autoregressive model.

Table 8.2 Summary of the best forecasting models for OPEC countries

Best forecasting univariate model for Angola				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	R_SARIMA	R_SARIMA	R_SARIMA	2.0590 – 13.3300
Best forecasting univariate model for Algeria				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 –step	F_SARIMAX	F_SARIMAX	R_A_SARIMA	61.6300
2 –step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	82.6100
3 to 7-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	27.3800- 136.0000
8-step	F_SARIMAX	R_SARIMA	F_SARIMAX	28.7700
Best forecasting univariate model for Ecuador				
	RMSE	**U- statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 8-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	15.4500 -42.9100
Best forecasting univariate model for Saudi Arabia				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 3-steps	F_TAR	F_TAR	F_TAR	5.3720 -12.6500
4 to 8-step	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	1.0100 – 15.1400
Best forecasting univariate model for Nigeria				
	RMSE	**U –statistics**	**MAPE**	
Horizon	Type	Type	Type	Range
1 to 4 steps	R_TAR	R_TAR	R_TAR	10.2400 -20.1200
5 to 8-steps	R_A_ARIMA	R_A_ARIMA	R_A_ARIMA	40.7200 – 46.5100
Best forecasting univariate model for Kuwait				
	RMSE	U-statistics	MAPE	
Horizon	Type	Type	Type	Rage
1 to 8-steps	F_SARIMAX	F_SARIMAX	F_SARIMAX	11.2100 – 38.5900

See note in the Table 5.5.2

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