BOFIT Discussion Papers
2 • 2008

Aaron Mehrotra and José R. Sánchez-Fung

Forecasting inflation in China

EUROJÄRJESTELMÄ
EUROSYSTEMET

Bank of Finland, BOFIT
Institute for Economies in Transition

BOFIT Discussion Papers
Editor-in-Chief Iikka Korhonen

BOFIT Discussion Papers 2/2008
27.1.2008

Aaron Mehrotra and José R. Sánchez-Fung: Forecasting inflation in China

ISBN 978-952-462-895-2
ISSN 1456-5889
(online)

Suomen Pankki
Helsinki 2008

Contents

Aaron Mehrotra and José R. Sánchez-Fung

Forecasting inflation in China

Abstract

This paper forecasts inflation in China over a 12-month horizon. The analysis runs 15 alternative models and finds that only those considering many predictors via a principal component display a better relative forecasting performance than the univariate benchmark.

Keywords: inflation forecasting; data-rich environment; principal components; China.

JEL classification: C53; E31.

Acknowledgements: We thank John C. Driscoll, Iikka Korhonen, and seminar participants at the Bank of Finland (BOFIT) and Kingston University, London, for their useful comments and suggestions on previous versions of the paper. Any remaining errors are our own.

Address for correspondence: Aaron Mehrotra: Bank of Finland, Institute for Economies in Transition (BOFIT), PO Box 160, FI-00101, Helsinki, Finland. E-mail: aaron.mehrotra@bof.fi.
José R. Sánchez-Fung: School of Economics, Kingston University, Penrhyn Road, Kingston-upon-Thames, Surrey, KT1 2EE, UK.
E-mail: j.sanchez-fung@kingston.ac.uk.

Aaron Mehrotra and José R. Sánchez-Fung

Forecasting inflation in China

Tiivistelmä

Tutkimuksessa ennustetaan Kiinan inflaatiota käyttäen viittätoista erilaista mallia. Ennustehorisontti on yksi vuosi. Tulosten mukaan, jotka kokoavat informaatiota monesta ennustemuuttujasta pääkomponenttianalyysillä, ennustavat paremmin kuin yhden muuttujan autoregressiivinen malli.

Asiasanat: inflaation ennustaminen, runsas tilastoaineisto, pääkomponenttianalyysi, Kiina

1 Introduction

Economic forecasting is important for real-world decision-making. In this regard, forecasting inflation is fundamental, since expectations of inflation affect, inter alia, central bank decisions regarding the future path of monetary policy and in turn private sector consumption and investment decisions. To be sure, there is much scope for improving economic forecasts. Notably, it is striking that prevalent techniques usually employ a handful of variables in the process of forecasting economic time series, despite the fact that economic agents operate in a data-rich environment (e.g., Bernanke and Boivin, 2003; Stock and Watson, 2006).

This paper is concerned with the forecasting of inflation in China. It reports on exercises in theory-based, atheoretical, and time series forecasting. Importantly, it also seeks to advance our understanding of the usefulness of employing many predictors in forecasting inflation. In particular, the investigation tackles the following questions: Can forecasting inflation in China gain from using many predictors? How do these forecasts compare with more traditional approaches to forecasting economic time series?

Producing accurate forecasts of inflation in China is important, for example, because its government includes a target for CPI inflation among its economic and social development goals. Moreover, foreign observers have recommended a strategic focus on a well-defined inflation anchor for the monetary authority (e.g. Goodfriend and Prasad, 2006). Further, China is increasingly seen as playing a role in price developments in advanced economies and elsewhere in the world (e.g. Kamin et al., 2006).

Yet the existing literature on forecasting inflation in China is still quite limited. Gerlach and Kong (2005) and Burdekin and Siklos (2008) compute inflation forecasts using money demand. And Qin et al. (2006) compare the performance of an automatic leading indicator method with a macroeconometric structural model for forecasting GDP and inflation. This paper seeks to contribute to the existing literature. The next section describes the econometric techniques used in forecasting inflation, provides details on the economic time series feeding the empirical modelling, and reports inflation forecasts for China. Section 3 concludes.

2 Forecasting inflation

Fifteen inflation forecasting models are employed. Table 1 outlines the models, which represent time series, Phillips curves, and vector autoregression (VAR) frameworks. The time series approaches comprise an autoregressive (AR) model, an AR augmented with a principal component (e.g. Faust and Wright, 2007), an ARMA model, and a structural time series model that employs the Kalman filter (Harvey, 1989).

The theory-based modelling entails seven different Phillips curve specifications: three standard specifications applying the GMM technique, three further specifications using a dynamic general-to-specific modelling approach, and one Phillips curve with a principal component added. Regarding the latter, Stock and Watson (1999), for instance, also augment the Phillips curve by considering many predictors in forecasting US inflation. However, Atkeson and Ohanian's (2001) analysis casts doubt on the usefulness of Phillips curves for forecasting inflation (see also Stock and Watson, 2007).

The analysis also runs four VAR systems, viz. a 4-variable (benchmark) VAR, a bivariate VAR including only inflation and a principal component, and a 5-variable VAR similar to the benchmark but including a principal component. The analysis also estimates a 4-variable VAR in line with the benchmark, but with an inflation equation initially considering a data-rich set that is automatically reduced using PcGets (Hendry and Krolzig, 2005).

We employ monthly data and model the annual inflation rate, defined as $\pi_t = p_t - p_{t-12}$, where p denotes the price level in logs. The sample period runs from 1997M1 to 2007M5.[1] The data-rich set used in some of the forecasting exercises considers **34 macroeconomic indicators** available at monthly frequency for Mainland China. The data are listed in Table 2 and comprise measures of real activity, exchange rates, share prices, fiscal and monetary policy, and commodity and producer prices. The data also include the components of the OECD Composite Leading Indicator for China.

The investigation summarizes the information from the data-rich set by modelling its variance structure via principal components analysis (see Johnson and Wichern, 2002). The subsequent empirical analysis uses only the first principal component - with highest

[1] The sample period for the models with the data-rich set starts in 1998M1.

loadings on heavy industrial sales, exports, imports, and light industrial sales - and explains 33% of the total variance. Figure 1 shows the inflation rate and the principal component.

Regarding the stationarity properties of the inflation rate in China, an augmented Dickey-Fuller (ADF) test rejects the unit root hypothesis at the 1% level. Logs are also taken of the 34 macroeconomic time series whenever possible, and annual growth rates are computed. And all the variables are stationary according to ADF or KPSS tests.

Table 3 displays the root mean square forecast errors (RMSFEs) from the runs of the 15 models. These statistics are expressed relative to the univariate benchmark (AR-TS1). All forecasts are 1-step ahead for the 12-month period 2006M6-2007M5.

The lowest RMSFE corresponds to the VAR including only inflation and the principal component (VAR3). The VAR model is closely followed by the Phillips Curve (PC4) and the AR (TS2) models considering many predictors via the principal component. Thus, like other researchers (e.g. Stock and Watson, 1999), we find that considering many predictors in forecasting inflation is relevant for China. However, these models only marginally improve on the univariate benchmark AR-TS1. In fact, the AR-TS1 ranks fourth among the 15 models considered in the modelling exercises.[2] The univariate AR model's forecasting performance is consistent with, for instance, the Marcellino et al. (2003) exercises for the euro area. Finally, Figure 2 displays actual inflation and three sets of 1-step ahead forecasts computed using time series, Phillips curve and VAR models. Notably, all the models track well the increase in inflation at the end of the sample.

3 Conclusion

This paper forecasts inflation in China employing a range of alternative frameworks.
The modelling finds that only VAR, Phillips curve, and time series models considering many predictors via a principal component outperform the univariate benchmark.

[2] We also estimated TS2, PC4, VAR2 and VAR3 adding the second principal component obtaining the highest loadings for yuan-yen exchange rate, purchasing prices for raw materials, and producer prices. This component explains 15% of total variance. Only for PC4 and VAR2 are the resulting forecasts improved (marginally in the case of PC4), but they still do not outperform the benchmark (AR-TS1).

References

Atkeson, Andrews, and Lee E. Ohanian (2001) Are Phillips curves useful for forecasting inflation? Federal Reserve Bank of Minneapolis *Quarterly Review*, **25**, no. 1, 2-11.

Bernanke, Ben S., and Jean Boivin (2003) Monetary policy in a data-rich environment *Journal of Monetary Economics*, **50**, 525-546.

Burdekin, Richard and Pierre Siklos (2008) What has driven Chinese monetary policy since 1990s? Investigating the People's Bank's policy rule. Forthcoming, *Journal of International Money and Finance*.

Faust, Jon, and Jonathan H. Wright (2007) Comparing Greenbook and reduced form forecasts using a large real time dataset, NBER Working Paper No. 13397, Cambridge, MA.

Gerlach, Stefan and Janet Kong (2005) Money and inflation in China. Research Memorandum 04/2005. Hong Kong Monetary Authority.

Goodfriend, Marvin, and Eswar Prasad (2006) A framework for independent monetary policy in China, IMF Working paper No. 06/111, International Monetary Fund, Washington, DC.

Harvey, Andrew (1989) *Forecasting, structural time series models and the Kalman filter*, Cambridge University Press, Cambridge.

Hendry, David F., and Hans-Martin Krolzig (2005) The properties of automatic *GETS* modelling, *Economic Journal*, **115**, C32-C61.

Johnson, Richard A., and Dean W. Wichern (2002) *Applied multivariate statistical analysis*, Prentice Hall, New Jersey.

Kamin, Steven B., Mario Marazzi and John W. Schindler (2006) The impact of Chinese exports on global import prices, *Review of International Economics*, **14**, 179-201.

Marcellino, Massimiliano, James H. Stock, and Mark W. Watson (2003) Macroeconomic forecasting in the Euro area: Country specific versus area-wide information, *European Economic Review*, **47**, 1-18.

Qin, Duo, Marie Anne Cagas, Geoffrey Ducanes, Nedelyn Magtibay-Ramos and Pilipanas Quising (2006) Forecasting Inflation and GDP Growth: Automatic Leading Indicator (ALI) Method versus Macroeconometric Structural Models (MESMs). ERD Technical Note Series 18. Asian Development Bank, Economics and Research Department.

Scheibe, Jorg, and David Vines (2005) A Phillips curve for China, CEPR Discussion Paper No. 4957, London, UK.

Stock, James H., and Mark W. Watson (1999) Forecasting inflation, *Journal of Monetary Economics*, **44,** 293–335.

Stock, James H., and Mark W. Watson (2006) Forecasting with many predictors, Chapter 10 in G. Elliot, C. Granger, and A. Timmermann (Eds.) *Handbook of Economic Forecasting*, Vol. 1, Elsevier Science, The Netherlands.

Stock, James H., and Mark W. Watson (2007) Why has US inflation become harder to forecast? *Journal of Money, Credit, and Banking*, **39** (supplement), 3-33.

Table 1 Inflation forecasting models

	Models	Code	Model description
Time series			
1	AR	TS1	Auto regressive model starting from 12-lag specification reduced using PcGets. OLS used in estimating the final model.
2	AR with principal component	TS2	TS1 model augmented with principal component.
3	ARMA	TS3	Auto regressive moving average model of order (1,1) estimated using the ML technique; forecasts computed recursively.
4	Structural time series model	TS4	Structural time series model estimated using ML technique; forecasts computed using Kalman filter; Harvey (1989).
Phillips curves			
5	Phillips curve benchmark 1	PC1	Standard Phillips curve model, with 1-period lagged inflation and current period HP-filtered output gap as regressors, estimated using GMM.
6	Phillips curve benchmark 2	PC2	As PC1 including an AR(2) error term.
7	Open-economy Phillips curve	PC3	As PC1 including the NEER exchange rate.
8	Phillips curve with principal component	PC4	As PC1 with principal component added.
9	Phillips curve ADL backward-looking	PC5	Phillips curve model using backward looking, dynamic, specification, e.g. Scheibe and Vines (2005), and applying Hendry and Krolzig's (2005) automatic GETS technique. Includes measure of 'expected' output gap computed using STSM and Kalman filter.
10	Phillips curve ADL hybrid	PC6	As model PC5 and including a measure of expected inflation –a hybrid, e.g. Scheibe and Vines (2005). 'Expected' inflation, and output, computed using STSM and Kalman filter.
11	Phillips curve ADL hybrid-open	PC7	As model PC6 and including NEER exchange rate.
VARs			
12	VAR benchmark	VAR1	4-variable VAR including inflation, output gap, NEER exchange rate, and broad money.
13	VAR with principal component	VAR2	VAR1 including a principal component.
14	VAR with principal component	VAR3	VAR including only inflation and a principal component.
15	VAR with data-rich set	VAR4	4-variable VAR model including inflation, output gap, NEER exchange rate, and broad money. A data-rich set of 32 variables is considered and automatically reduced in the inflation equation; Hendry and Krolzig (2005).

Notes.- ML: maximum likelihood; GMM: generalised methods of moments; ADL: auto regressive distributed lag model; GETS: general-to-specific; OLS: ordinary least squares; STSM: structural time series model; VAR: vector auto regression. NEER: nominal effective exchange rate. The instrument set in models PC1-PC4 includes lags 1-2 of the inflation rate and 1-3 of the output gap. Models VAR1, VAR2 and VAR3 are reduced using the programme JMulTi, where coefficients with *t*-values below 1.67 are eliminated.

Table 2 China, 1998M1-2007M5, Data definitions and sources

No.	Data series	Source
1	CPI, China Monthly Economic Indicators, own calculations	CEIC
2	Cargo handled at ports (tonnes)	OECD
3	Enterprise deposits (CNY)	OECD
4	Exports	CEIC
5	Government expenditure	CEIC
6	Government revenues	CEIC
7	Imports from Asia (USD)	OECD
8	Imports	CEIC
9	Industrial production (real, levels), own calculations	PBoC, IFS
10	Industrial sales (value), collective ownership	CEIC
11	Industrial sales (value), heavy industry	CEIC
12	Industrial sales (value), light industry	CEIC
13	Industrial sales (value), state owned enterprises	CEIC
14	Nominal (benchmark) lending interest rate	CEIC
15	Loans, financial institutions	CEIC
16	M0	CEIC
17	M1	CEIC
18	M2	CEIC
19	NEER (nominal effective exchange rate)	IFS
20	Oil price	IFS
21	Producer prices, y-o-y	CEIC
22	Chemical fertilizer production (tonnes)	OECD
23	Production of coal	CEIC
24	Production of electricity	CEIC
25	Production of natural gas	CEIC
26	Non ferrous metal production (tonnes)	OECD
27	Production of crude oil	CEIC
28	Purchasing prices (raw materials), y-o-y	CEIC
29	REER (real effective exchange rate)	IFS
30	Retail sales	OECD
31	Savings deposits, value	CEIC
32	Shanghai Composite Index	CEIC
33	Shenzhen Composite Index	CEIC
34	Yuan-USD spot exchange rate	CEIC
35	Yuan-yen spot exchange rate	CEIC

Note: CEIC = Macroeconomic, Industry and Financial time series databases for Asia and Emerging Markets; IFS=International Financial Statistics; OECD = OECD Main economic iIndicators; PBoC = People's Bank of China Quarterly Statistical Bulletin.

Table 3 Forecasting 12-month inflation in China, 2006M6-2007M5
Relative root mean square forecast errors (RMSFEs), 1-step ahead forecasts

Models		**Relative RMSFEs**
1	**TS1**	**1.000**
2	TS2	0.994
3	TS3	1.354
4	TS4	1.143
5	PC1	1.112
6	PC2	1.121
7	PC3	1.090
8	PC4	0.992
9	PC5	1.162
10	PC6	1.207
11	PC7	1.376
12	VAR1	1.599
13	VAR2	3.570
14	VAR3	0.931
15	VAR4	1.304

Note: RMSFEs relative to AR (TS1) model.

Figure 1 China, Inflation and principal component, 1998M1-2007M5

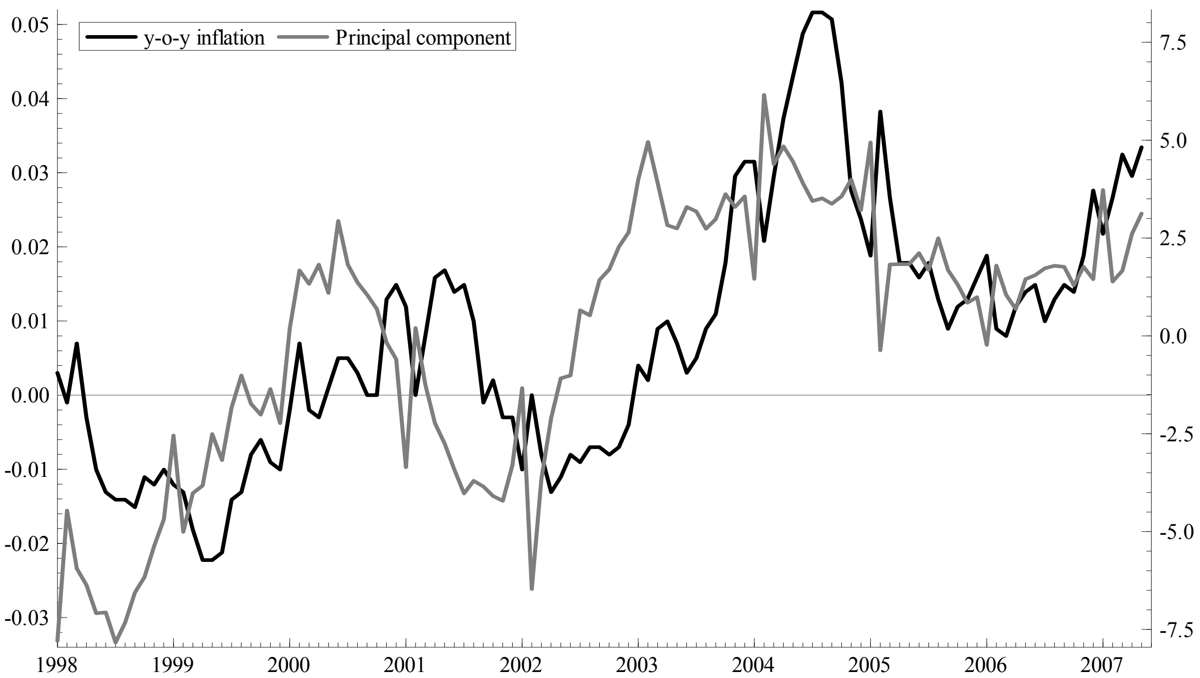
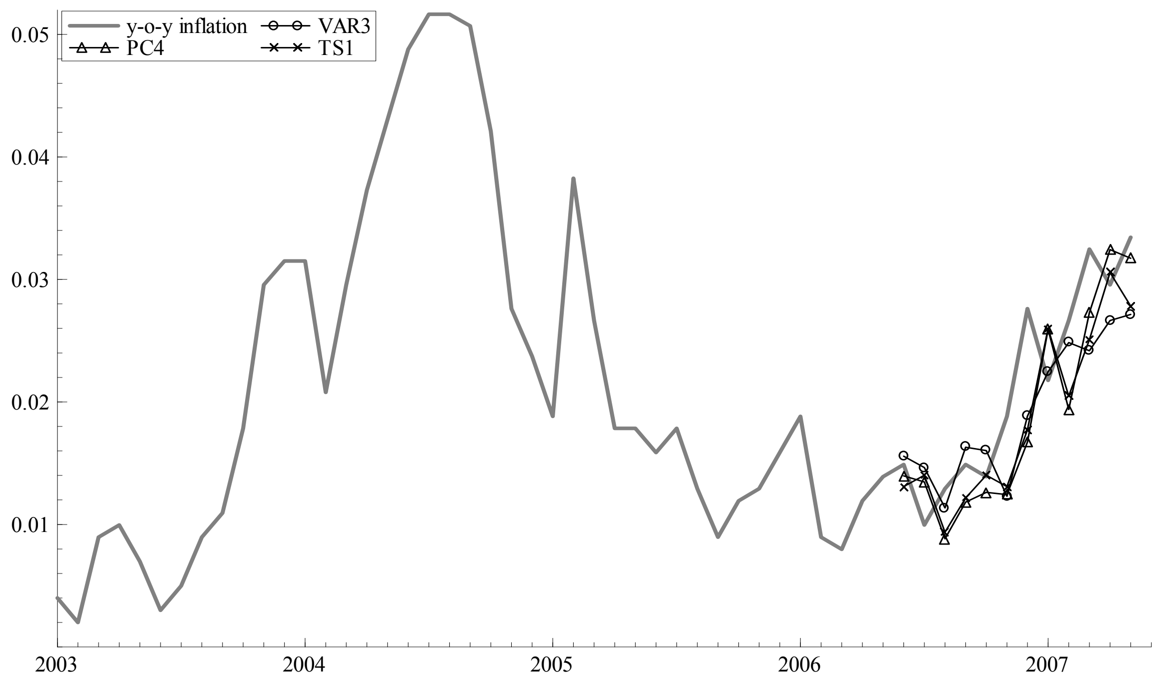


Figure 2 Forecasts of 12-month inflation in China, 2006M6-2007M5. Models VAR3, PC4 and TS1



Earlier BOFIT Discussion Papers

For a complete list of Discussion Papers published by BOFIT, see www.bof.fi/bofit

2007

No 3 Barry Harrison and Yulia Vymyatnina: Currency substitution in a de-dollarizing economy: The case of Russia
No 4 Jesús Crespo Cuaresma and Tomas Slacik: An “almost -too-late” warning mechanism for currency crises
No 5 Andrei V. Vernikov: Russia's banking sector transition: Where to?
No 6 Alicia García-Herrero and Tuuli Koivu: Can the Chinese trade surplus be reduced through exchange rate policy?
No 7 Nienke Oomes and Katerina Kalcheva: Diagnosing Dutch disease: Does Russia have the symptoms?
No 8 Iikka Korhonen and Tuuli Juurikkala: Equilibrium exchange rates in oil-dependent countries
No 9 Balázs Égert and Carol S. Leonard: Dutch disease scare in Kazakhstan: Is it real?
No 10 Mikael Mattlin: The Chinese government's new approach to ownership and financial control of strategic state-owned enterprises
No 11 Aaron Mehrotra and Jouko Rautava: Do sentiment indicators help to assess and predict actual developments of the Chinese economy?
No 12 Pertti Haaparanta and Tuuli Juurikkala: Bribes and local fiscal autonomy in Russia
No 13 Ian Babetskii and Nauro F.Campos: Does reform work? An econometric examination of the reform-growth puzzle
No 14 Iikka Korhonen and Aaron Mehrotra: Money demand in post-crisis Russia: De-dollarisation and re-monetisation
No 15 Svetlana Ledyaeva: Spatial econometric analysis of determinants and strategies of FDI in Russian re gions in pre- and post-1998 financial crisis periods
No 16 David G Mayes and Vesa Korhonen: The CIS – does the regional hegemon facilitate monetary integration?
No 17 Roberta Colavecchio and Michael Funke: Volatility dependence across Asia-pacific on-shore and off-shore U.S. dollar futures markets
No 18 William Pyle: Organized business, political regimes and property rights across the Russian Federation
No 19 Aaron Mehrotra, Tuomas Peltonen and Alvaro Santos Rivera: Modelling inflation in China – a regional perspective
No 20 Michael Funke and Marc Gronwald: The undisclosed renminbi basket: Are the markets telling us something about where the renminbi - US dollar exchange rate is going?
No 21 Declan Curran, Michael Funke and Jue Wang: Economic growth across space and time: Subprovincial evidence from mainland China
No 22 Xiaoqiang Cheng and Hans Degryse: The impact of banks and non-bank financial institutions on local economic growth in China

2008

No 1 Tuuli Koivu: Has the Chinese economy become more sensitive to interest rates? Studying credit demand in China
No 2 Aaron Mehrotra and José R. Sánchez-Fung: Forecasting inflation in China

Bank of Finland
BOFIT – Institute for Economies in Transition
PO Box 160
FIN-00101 Helsinki

☎ + 358 10 831 2268
bofit@bof.fi
http://www.bof.fi/bofit