Stock market integration: A multivariate GARCH analysis on Poland and Hungary

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Abstract

This paper examines the linkages between the emerging stock markets in Warsaw and Budapest and the established markets in Frankfurt and the U.S. By using a four-variable asymmetric GARCH-BEKK model, we find evidence of return and volatility spillovers from the developed to the emerging markets. However, as the estimated time-varying conditional co-variances and the variance decompositions indicate limited interactions among the markets, the emerging markets are weakly linked to the developed markets. The implication is that foreign investors will benefit from the reduction of risk by adding the stocks in the emerging markets to their investment portfolio.

JEL classification: C32, F36, G15

Key words: stock market integration; volatility spillovers; multivariate GARCH model; asymmetric response of volatility

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1. INTRODUCTION

This paper models the stock markets in Warsaw and Budapest in a setting of regional and global influences and investigates if, and to what extent, these emerging markets are linked to the developed markets in Frankfurt and in the U.S. The extent of the global integration of the emerging markets has great implications for domestic economies and international investors. While it improves access to the international capital markets, strong market integration reduces the insulation of the emerging markets from external shocks, hence limiting the scope for independent monetary policy. From the perspective of international investors, weak market integration in the form of less than perfect correlation between returns offers potential gains from international portfolio diversification, while strong market integration or co-movement in returns eliminates the potential benefits of diversification into emerging markets.

Although stock market integration has been widely studied[1] for the developed markets and some emerging markets in Asia and South America, the research on the international linkages of the emerging markets in Central and Eastern Europe is limited. Moreover, the limited literature on the emerging markets of Central and Eastern Europe is either mainly carried out by the conventional method, co-integration analysis, or concerned with the linkage in terms of returns across markets. For example, Gilmore and McManus (2002) use the concept of co-integration to search for short and long term relationships between any pair of the three Central European markets (Czech Republic, Hungary and Poland) and the U.S. market by

[1] See Heimonen (2002) for a review of the studies on stock market integration and the methodology adopted by these studies.

using weekly data from 1995 to 2001. Although low short-run correlations were present, they do not find any evidence of a long-run relationship between the emerging markets and the U.S. Syriopoulos (2004) examines the ‘trending behaviour’ of the six daily stock indices during 1997-2003 by the Johansen approach and detects the presence of one co-integration relationship among the four major emerging Central and Eastern European stock markets (Poland, Czech Republic, Hungary and Slvakia) and the developed markets in Germany and the U.S. This result indicates a very weak integration among the six markets under study, as the necessary condition of complete integration according to Bernard and Durlauf (1995) is that there are n-1 co-integration vectors in a system of n indices. Voronkova (2004) applies the Gregory and Hansen residual-based co-integration test, allowing for a structural break, to the indices of Czech Republic, Hungary, Poland, Britain, France, Germany and the U.S. and finds six co-integration vectors in addition to those detected by the conventional co-integration tests without taking breaks into account. Voronkova (2004) concludes that the emerging markets have become increasingly integrated with the world markets. However, Lence and Falk (2005) show, in the setting of a standard dynamic general equilibrium asset-pricing model, that co-integration test results are not informative with respect to either market efficiency or market integration, in the absence of a sufficiently well-specified model. Even if such markets are not integrated in an economic sense, asset prices can be co-integrated across markets, which are subject to the same exogenous shocks.

Chelley-Steeley (2005) applies the orthogonalised variance decomposition of VAR modelling to 9 daily indices including those of Poland, Hungary, Czech Republic and Russia during 1994-1999 and finds some interactions between the four emerging markets and the five developed markets under study. She concludes that global factors influence the returns of the Polish and Hungarian stock exchanges. However, the variance decomposition approach does not provide any information about the statistical significance of the observed interactions although it can quantify the interactions. Furthermore, if markets are integrated, an unanticipated event in a market will influence not only returns but also variances of the other markets. The analysis of volatility is particularly important, because it can proxy for the risk of assets. Scheicher (2001) models on both returns and volatility of the national stock indices. It investigates the global integration of the stock markets in Hungary, Poland and the Czech Republic during 1995-1997 by using a multivariate GARCH with a constant conditional correlation. The study finds that the emerging stock exchanges are integrated with the global market, proxied by the Financial Times/Standard & Poor's Actuaries World Index, only in terms of returns. But the assumption of constant conditional correlation in Scheicher (2001) is unrealistic. Several studies have found that the correlations are time-varying. For example, Kaplanis (1988) finds that the correlation and the covariance matrix of monthly returns to numerous national equity markets are unstable over a 15-year period. Bekaert and Harvey (1995) also find that correlations between markets and, therefore, the degree of integration can vary over short periods. Longin and Solnik (1995) show that changes in the correlation between markets can be explained by changes in the conditional covariance.

Our paper will also model on both the first and second moments of the national stock indices under study. We will use a four-variable asymmetric GARCH with time-varying variance-covariance, i.e., the BEKK model (the acronym from synthesised work on multivariate models by Baba, Engle, Kraft and Kroner) proposed by Engle and Kroner (1995). Apart from the advantage of time-varying variances and co-variances, the asymmetric BEKK model to be used in this study can examine the cross-market volatility spillover effects[2] and the asymmetric responses, which are both omitted in the model used in Scheicher (2001). The cross-market effects capturing return linkage and transmission of shocks and volatility from one market to another are often used to indicate market integration in the literature. The estimated time-varying conditional co-variances by the BEKK model can measure the extent of market integration in terms of volatility. We will further use the orthogonalised and generalised variance decomposition techniques of VAR estimation to quantify the extent of integration in terms of returns, i.e., the interdependence in terms of returns, among the markets under study.

The remainder of the paper is organised as follows. Section 2 examines the features of the four indices under study. On the basis of the observations in section 2, section 3 presents the methodology to be used. Section 4 reports the empirical results and discusses their implications. Section 5 concludes.

2. DATA AND PRELIMINARY ANALYSIS

In this paper the raw data are the daily stock indices of the stock markets in Warsaw, Budapest, Frankfurt and the U.S. from1998 to 2005. We remove the data of those dates when any series has a missing value due to no trading. Thus all the data are collected on the same dates across the stock markets and there are 1898 observations

[2] The conditional variance equations of the symmetric GARCH in Scheicher (2001) only account for shock spillover effects.

for each series. The indices used in this paper are the widely accepted benchmark indices for the stock markets. The stock index of the Warsaw Stock Exchange (WIG), introduced in 1991, includes 102 large and medium companies traded on the main stock market. The construction of WIG is based on the diversification rule that aims to limit the share of the single company or market sector. It is an income index which includes prices, dividends and subscription rights. The main stock index of the Hungarian Stock Exchange (BUX), also introduced in 1991, reflects changes in the market prices of the shares, including dividends. The number of stocks in the index basket may change every half year. At the end of 2005, shares of 12 companies were included in the basket, with the share of banks being highest at 30.54%. The Frankfurt Stock Exchange is one of the biggest stock exchanges in Europe, so the index DAX generally reflects the financial situation in this part of the world. The index consists of shares of 30 large companies. The S&P 500 index tracks 500 companies in leading industries and services and is considered to be the most accurate reflection of the U.S. stock market today. The data of DAX and the S&P 500 are closing prices adjusted for dividends and splits. The data of the series used in this study are downloaded from the websites of Onet Business, the Budapest Stock Exchange and Yahoo Finance[3].

The inclusion of DAX of Germany and S&P 500 of the USA is based on the consideration that these markets serve well as proxies for the regional and global developed markets, respectively, and are expected to play an influential role in the emerging markets in Poland and Hungary, the representative markets of Central and

[3] http://www.finance.yahoo.com

http://gielda.onet.pl

http://www.bse.hu/onlinesz/index_e.html

Eastern Europe. The inclusion of DAX and S&P 500 indices, therefore, helps investigate the global integration of the emerging markets in Poland and Hungary.

[Figure 1 is about here.]

Figure 1 presents the time plots of the series, which fluctuate on a daily and longer term basis. The first impression is that the indices of the two emerging markets follow a similar movement while DAX and S&P500 have a similar trend. It can be noticed that WIG and BUX suffered from some difficulties in the mid-1998 due to the Russian crisis. The economic problems in such a large neighbouring country resulted in a fall in market indicators. While the two emerging markets started to trend upwards at mid-2001, the two developed markets were heading towards the trough of 2002. The rise in the stock indices of WIG and BUX in mid-2001 was mainly due to the increased interest of foreign investors following the announcement of the expansion of the EU towards the Central European markets.

[Figure 2 is about here.]

Figure 2 displays the returns of the share price indices, the first differences of the natural logarithm of the share price indices. The two emerging markets have very high volatility during 1998 and smaller volatility since the imposition of the price constraints in 1998. However, volatility in the emerging markets since 1998 is still higher than that of the developed markets in Frankfurt and the U.S. The feature of high volatility of WIG and BUX is consistent with the observation by Harvey

(1995).[4] Furthermore, all four indices are characterised by volatility clustering, i.e., large (small) volatility followed by large (small) volatility, and the conditional heteroscadasticity common to the financial variables. As the clusters tend to occur simultaneously, especially between the indices of the emerging markets and between the indices of the developed markets, volatility must be modelled systematically.

Table 1 reports summary statistics for the returns series. During the period under study, the performance of the shares, measured by the average returns in the two emerging markets, is better than that in the two developed markets. However, the BUX index is most volatile, as measured by the standard deviation of 1.8%, while the S&P 500 index is the least volatile with a standard deviation of 1.2%. The Jarque-Bera statistics reject the null hypothesis that the returns are normally distributed for all cases. The BUX and DAX indices have a negative skewness, indicating that large negative stock returns are more common than large positive returns. In contrast, the WIG and S&P 500 indices are slightly positively skewed. When modelling with GARCH, the non-zero skewness statistics indicate an ARCH order higher than one in the conditional variance equations. Subsequently, a GARCH(1,1) model should be preferred to an ARCH(p) model for the sake of parsimony. All the returns series are leptokurtic, having significantly fatter tails and higher peaks, as the kurtosis statistics are greater than 3. GARCH models are capable of dealing with data displaying the above features.

[Table 1 is about here.]

[4] Harvey (1995) finds that emerging markets in Europe, Latin America, Asia, the Middle East and Africa exhibit high expected returns and high volatility.

3. METHODOLOGY

The variable of interest in this study is the daily returns of the stock indices, which are computed as first differences of the natural logarithm of the four stock indices. On the basis of the features observed in the previous section, GARCH models will be appropriate. As the aim of the study is to consider the interdependence across the four stock markets, we will use a multivariate GARCH model in the style of the BEKK proposed by Engle and Kroner (1995). Specifically, the following model is used to examine the joint processes relating to the share price indices under study.

$$Y_t=\alpha +\Gamma Y_{t-1}+ \varepsilon_t, \qquad \varepsilon_t|I_{t-1} \sim N(0, H_t) \tag{1}$$

where Y_t is a 4×1 vector of daily returns at time t and Γ is a 4×4 matrix of parameters associated with the lagged returns. The diagonal elements in matrix Γ, γ_{ii}, measure the effect of own past returns while the off-diagonal elements, γ_{ij}, capture the relation in terms of returns across markets, also known as return spillover. The 4×1 vector of random errors, ε_t, is the innovation for each market at time t and has a 4×4 conditional variance-covariance matrix, H_t. The market information available at time t-1 is represented by the information set I_{t-1}. The 4×1 vector, α, represents constants.

Bollerslev et al. (1988) propose that H_t is a linear function of the lagged squared errors and cross products of errors and lagged values of the elements of H_t as follows.

$$vech(H_t) = vech(C) + \sum_{i=1}^{q} A_i vech(\varepsilon_{t-1}\varepsilon_{t-i}^{'}) + \sum_{i=1}^{p} G_i vech(H_{t-i}) \quad (2)$$

where *vech* is the operator that stacks the lower triangular portion of a symmetric matrix into a vector. The problems with this formulation are that the number of parameters to be estimated is large and restrictions on the parameters are needed to ensure that the conditional variance matrix is positive definite. Engle and Kroner (1995) propose the following new parametrisation for H_t, i.e., the BEKK model, to overcome the above two problems.

$$H_t = C'C + A'\varepsilon_{t-1}'\varepsilon_{t-1}A + G'H_{t-1}G \quad (3)$$

The BEKK model provides cross-market effects in the variance equation parsimoniously and also guarantees positive semi-definiteness by working with quadratic forms. Kroner and Ng (1998) propose to extend the BEKK model to allow for the asymmetric responses of volatility, i.e., stock volatility tends to rise more in response to negative shocks (bad news) than positive shocks (good news), in the variances and co-variances.

$$H_t = C'C + A'\varepsilon_{t-1}'\varepsilon_{t-1}A + G'H_{t-1}G + D'\xi_{t-1}^{'}\xi_{t-1}D \quad (4)$$

where ξ_t is defined as ε_t if ε_t is negative and zero otherwise. The last item on the right hand side captures the asymmetric property of the time-varying variance-covariance. The notation used in equation (4) is as follows. C is a 4×4 lower triangular matrix of constants while A, G and D are 4×4 matrices. The diagonal parameters in matrices

A and G measure the effects of own past shocks and past volatility of market i on its conditional variance, while the diagonal parameters in matrix D measure the response of market i to its own past negative shocks. The off-diagonal parameters in matrices A and G, a_{ij} and g_{ij}, measure the cross-market effects of shock and volatility, also known as volatility spillover, while the off-diagonal parameters, d_{ij}, measures the response of market i to the negative shocks, i.e., bad news, of other markets, to be called the cross-market asymmetric responses.

The above BEKK systems can be estimated efficiently and consistently using the full information maximum likelihood method. The log likelihood function of the joint distribution is the sum of all the log likelihood functions of the conditional distributions, i.e., the sum of the logs of the multivariate-normal distribution. Letting L_t be the log likelihood of observation t, n be the number of stock exchanges and L be the joint log likelihood gives

$$\begin{aligned} L &= \sum_{t=1}^{T} L_t \\ L_t &= \frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln\left|H_t\right| - \frac{1}{2}\varepsilon_t^{'} H_t^{-1}\varepsilon_t \end{aligned} \qquad (5)$$

A numerical procedure, e.g., BHHH algorithm, is used to maximise the log-likelihood function by searching for optimal estimates of the unknown parameters. In this study, we choose the first derivative method of Marquardt as the optimisation algorithm. The Marquardt algorithm is a modification of BHHH that incorporates a ‘correction’, the effect of which is to push the coefficient estimates more quickly to their optimal values. The starting values of the parameters in the mean equations and constants in the conditional variance-covariance equations are obtained from their corresponding univariate GARCH models by a two-step estimation approach. The starting values of the diagonal parameters in matrices A, G and D are approximately 0.05, 0.9 and 0.2 respectively, while the starting values of the off-diagonal elements are zero. The maximum number of iterations is 100 in this study while the convergence criterion is 1e-5.

Since the parameters estimated by the BEKK model cannot be easily interpreted, and their net effects on the variances and co-variances are not readily seen, we will use the estimated conditional co-variance to measure the extent of integration in terms of volatility. We will further use orthogonalised and generalised variance decomposition in the line of VAR estimation to help quantify the interdependence among the four returns series under study.

4. EMPIRICAL RESULTS

In this section, we report the estimated results about the market integration. We will look for any significant cross-market effects as evidence of integration and measure the extent of integration by the estimated time-varying co-variances and the decompositions of forecast error variances.

4.1 The evidence of market integration

The mean equation (1) and time-varying variance-covariance equation (4) are estimated simultaneously by the maximum log likelihood method. Note that the stock exchanges in Warsaw, Budapest, Frankfurt and the U. S. are respectively indexed as 1, 2, 3 and 4. The four-variable asymmetric GARCH model converges after 31 iterations and its results are reported in Table 2. Before we discuss the estimated results, we carry out the log likelihood ratio test to see if the four returns series should have been estimated simultaneously by the BEKK approach. As the statistic, reported in Table 3[5], from the log likelihood ratio test for the four-variable asymmetric GARCH model versus the univariate asymmetric GARCH model is 1511.8508, we can reject the null hypothesis that conditional variances of the four returns series are independent[6]. We should model the four series simultaneously.

Now we begin to discuss the results estimated by the four-variable asymmetric GARCH model as presented in Table 2. We use the conventional level of significance of 5% in the discussion. We firstly look at matrix Γ in the mean equation, equation (1), in order to see the relationship in terms of returns across the four indices. Note that the Ljung-Box Q statistics for the 12th and 24th orders in the standardised residuals indicate the appropriate specification of the mean equations. As the diagonal parameters γ_{11}, γ_{22}, and γ_{44}, are statistically insignificant, the returns of WIG, BUX and S&P500 indices do not depend on their first lags. In contrast, the effect of own past returns for DAX, γ_{33}, is significant. The cross-market return linkages are evident in the following patterns. Firstly, there are uni-directional return spillovers from S&P 500 to WIG, BUX and DAX respectively. These uni-directional return spillovers are consistent with the "global centre" hypothesis that a global centre such as the U.S. market plays a major role in the transmission of news that is

[5] Results of the restriction tests about the four-variable asymmetric GARCH model are gathered together and presented in Table 3.

[6] This hypothesis requires that all the cross products of the diagonal parameters, the coefficients in the six covariance equations, are zero, i.e., $a_{ij}a_{ji} = g_{ij}g_{ji} = d_{ij}d_{ji} = 0$ and $i \neq j$.

macroeconomic in nature. Thus the information about global economic conditions is transmitted into the pricing process of the stock exchanges in Warsaw, Budapest and Frankfurt. Secondly, there is a uni-directional spillover from DAX to BUX while there is a bi-directional return linkage between DAX and WIG. These results suggest that the regional developed market in Frankfurt is also influential in the pricing process of the emerging markets in Warsaw and Budapest, and there is a close relationship between the stock exchanges in Warsaw and Frankfurt in particular. Finally, while the pricing process of BUX is only affected by the information from the regional and global developed markets, the stock exchange in Warsaw is influenced by the neighbouring emerging market in Budapest in addition. From the above results, like Scheicher (2001), we conclude that the emerging markets are linked to the regional and global developed markets in terms of returns. The joint explanatory power of the lagged returns of DAX and S&P 500 on the returns of WIG and BUX is confirmed by the likelihood ratio test presented in Table 3. As the likelihood ratio test statistic is 324.36, we can reject the null hypothesis that $\gamma_{13}=\gamma_{14}=\gamma_{23}=\gamma_{24}=0$. The lagged returns of DAX and S&P 500 are jointly significant in explaining the returns of WIG and BUX.

[Table 2 is about here.]

Now we examine the estimated results of the time-varying variance-covariance equation (4) in the system. Note that the Ljung-Box Q statistics for the12th and 24th orders in squared standardised residuals show that there is no series dependence in the squared standardised residuals of WIG, BUX and S&P 500 at the level of significance of 5%. The squared standardised residuals of the conditional variance of DAX failed to be random.

The matrices A and G reported in Table 2 help examine the relationship in terms of volatility as stated in equation (4). The diagonal elements in matrix A capture the own ARCH effect, while the diagonal elements in matrix G measure the own GARCH effect. As shown in Table 2, the estimated diagonal parameters are all significant, indicating a strong GARCH (1, 1) process driving the conditional variances of the four indices. Own past shocks and volatility affect the conditional variance of WIG, BUX, DAX and S&P 500 indices.

The off-diagonal elements of matrix A and G capture the cross-market effects such as shock and volatility spillovers among the four stock exchanges. Firstly, we find evidence of bi-directional shock linkages between WIG and BUX. News about shocks in the Warsaw stock exchange affects volatility of BUX and past shocks of the Budapest stock exchange also affects volatility of WIG. The two-way shock spillover indicates a strong connection between the two emerging markets in Warsaw and Budapest. Secondly, there are bi-directional volatility spillovers between BUX and DAX and between DAX and S&P 500. Within these two pairs, the conditional variance of one series depends on past volatility of the other series. Thirdly, it is evident that there are uni-directional shock and volatility spillovers from S&P 500 to WIG and BUX, uni-directional volatility spillover from DAX to WIG and uni-directional shock spillover form DAX to BUX. These results suggest that the two emerging markets are linked to the regional and global developed markets in terms of volatility, contrary to the finding in Scheicher (2001). Volatility of the two emerging markets is affected by the information about risk in the regional and global developed markets. The likelihood ratio test, presented in Table 3, confirms the joint explanatory power of the past shocks and volatility of DAX and S&P 500 in the system, as we can reject the null hypothesis that past shocks and volatility of DAX and S&P 500 do not jointly affect volatility of WIG and BUX.

As far as matrix D is concerned, we find evidence of asymmetric response to negative shocks (bad news) of own market for the indices of BUX, DAX and S&P 500, as the diagonal parameters, d_{22}, d_{33} and d_{44}, are significant. The sign of the own past shocks affects the conditional variance of these three indices. In the aspect of cross market asymmetric responses, firstly we find that WIG and BUX respond asymmetrically only towards shocks of DAX. Secondly, while it does not respond to the negative shocks of WIG, DAX responds asymmetrically to the shocks of BUX and S&P 500. Thirdly, the S&P 500 index rises more in response to bad news than good news about WIG and DAX. We then use the likelihood ratio test to see if we should have included the asymmetric responses in time-varying variance-covariance equation (4). As reported in Table 3, the statistic from the log likelihood test for the four-variable asymmetric GARCH model versus the four-variable symmetric GARCH model is 295.98, suggesting that we can reject the null hypothesis that the elements in matrix D are zero simultaneously. Thus it is appropriate to include the asymmetric responses when modelling the four stock indices.

Since we find that there are returns and volatility spillovers from the developed markets in Frankfurt and the U.S. to the two emerging markets under study, we would like to test for the joint explanatory power of the lagged returns and past shocks and volatility of DAX and S&P 500 in the system. The likelihood ratio test statistic of 264.22 reported in Table 3 suggests that we can reject the null hypothesis that the effects of the lagged returns and past shocks and volatility on returns and volatility of WIG and BUX are jointly insignificant. The joint explanatory power of these variables is significant in the system. The results of the four-variable asymmetric GARCH-BEKK model are robust.

[Table 3 is about here.]

4.2 The extent of integration

By using the daily stock indices of the four markets under study from 1998 to 2005, we find that the emerging stock markets in Warsaw and Budapest are integrated both in terms of returns and volatility with the developed markets in Frankfurt and the U.S. However, the diversification benefits of investing in the emerging markets depend on the extent of integration between the emerging and the developed markets. Only when market returns are less than perfectly correlated, is risk reduction possible. From Table 4, reporting the unconditional correlation coefficients of the daily stock returns series under study, we notice that the two emerging markets are indeed correlated with the developed markets in Frankfurt and the U.S. less than perfectly. The stock index of BUX has a higher degree of contemporaneous interactions with the developed markets than the index of WIG. The less than perfect correlations are confirmed by the time-varying conditional co-variances estimated by the BEKK model in this study, presented in Figure 3, as the estimated conditional time-varying co-variances suggest limited interactions between the emerging stock exchanges in Warsaw and Budapest and the regional and global developed markets in Frankfurt and the U. S.

[Table 4 is about here.]

[Figure 3 is about here.]

We further use the decomposition of forecast error variance to quantify the interdependence in terms of returns among the four markets under study. Variance decomposition breaks down the variation in each returns series into its components. As it gives the proportion of the movements in the returns series that are due to their own shocks versus shocks due to the other series, the variance decomposition provides information about the relative importance of each random shock in affecting the series in the system. There are two ways of decomposing the variance of forecast error: the traditional and generalised methods. The traditional method uses Choleski decomposition to orthogonalise the shocks, that is, the underlying shocks to the VAR model are orthogonalised before variance decompositions are computed. By design, a variable explains almost all of its own forecast error variance at a very short horizon and a smaller proportion at a longer horizon. However, the proportions of explanation are sensitive to the order of the variables in VAR when the shocks are contemporaneously correlated. Pesaran and Shin (1998) propose the generalised decomposition method, which explicitly takes into account the contemporaneous correlation of the variables in VAR. Therefore the generalised variance decomposition is invariant to the order of variables in VAR.

In this study, we attempt both methods in order to provide robust results. By using the traditional orthogonalised method, we order the four series in the VAR of the mean equation according to the opening hour of the markets and, when opening hours are the same, market capitalisation. Thus, the order in the VAR of the mean equation is DAX, WIG, BUX and S&P500. We obtain the variance decomposition results of 1-day, 2-day, 5-day and 10-day ahead forecast error variances of each stock index from the mean equations of the four-variable asymmetric GARCH model[7]. The results of the orthogonalised variance decomposition are presented in Table 5(a).

[Table 5 is about here.]

The results in Table 5(a) quantify the return linkages among the four markets under study, although the variance decomposition does not provide any information about statistical significance of the linkages. For the stock index of WIG, the proportion of the error variance attributable to own shocks in the first step is about 90%. By 5 days ahead, the behaviour has settled down to a steady state. About 78% of the error variance in the series of WIG is attributable to own shocks. For the stock index of BUX, 73% of a 1-day-ahead forecast error variance is due to its own shock and by 5 days ahead the forecast error variance has achieved the steady state, with own shocks accounting for 68% of its variation. For both WIG and BUX, 1-day-ahead forecast error variance can be explained by shocks to DAX of the regional developed market, but not by S&P 500 of the global developed market. By 2 days ahead, both the shocks to the regional and global developed markets can explain the forecast error variances of WIG and BUX. While the regional and global developed markets exert a similar extent of influence, 11% and 10% respectively, on WIG at the steady state,

[7] According to the Akaike information criterion, the appropriate leg length is 3 in this case. As the results of variance decompositions of VAR(1) are not significantly different from those of VAR(3), we report the results of VAR(1) in Table 5(a) to be consistent with mean equation (1).

the regional developed market is more influential (15%) than the global developed market (6%) on BUX. On the basis that about 21% of the variation in the returns of WIG and BUX is caused by shocks to the regional and global developed markets, indeed the extent of influence of the developed markets on the returns of the emerging markets is small, indicating a weak integration of the emerging markets with the developed markets.

The results of the generalised variance decompositions are presented in Table 5(b). As there is no time constraint imposed on the computation of decompositions, the method provides useful information at all horizons, including the initial impacts at time t=0. The initial impact of the regional developed market, DAX, on both the emerging markets is greater than that of S&P 500 of the global developed market. By 2 days ahead, the impacts of the developed markets have achieved a steady state. The shocks to DAX and the S&P500 respectively explain about 8% and 12% of the forecast error variance of WIG while they explain about 11% and 9%, respectively, of the forecast error variance of BUX. The generalised variance decompositions confirm the finding by the orthogonalised method that about 20% of the variation in the returns of WIG and BUX can be explained by shocks to the regional and global developed markets and the extent of integration, in terms of returns, of the emerging markets with the regional and global developed markets is limited. More importantly, both the emerging markets appear to have made little progress towards integration in terms of returns, since Chelley-Steeley (2005) also estimates that about 20% of the variation in the equity returns of Poland and Hungary can be explained by shocks to the German and U.S. markets by using the traditional variance decomposition on the daily data of 1997-1999.

5. CONCLUSION

This study investigates the integration between the two emerging markets in Warsaw and Budapest and the developed markets in Frankfurt and the U.S. By applying a multivariate asymmetric GARCH approach to the daily stock indices from 1998 to 2005, we found evidence of integration, in terms of returns and volatility linkages, among the markets. There are uni-directional return spillovers from the S&P 500 index to the indices of WIG, BUX and DAX respectively, uni-directional return spillovers from DAX to BUX and from BUX to WIG and bi-directional return spillover between DAX and WIG. In the aspect of volatility, there are uni-directional spillovers from the DAX and S&P 500 indices to the indices of WIG and BUX and bi-directional spillovers between DAX and S&P 500, between BUX and DAX and between WIG and BUX. Thus, we conclude that the two emerging markets in Central and Eastern Europe are linked to the developed markets in Frankfurt and the U.S. in terms of returns and volatility. Information about the macroeconomic state of the global centre is transmitted to the pricing process of the emerging markets, while information about regional and global risk affects volatility of the emerging markets.

However, the extent of the integration is weak, as both the estimated time-varying conditional co-variances and the variance decompositions demonstrate limited interactions between any pair of the emerging and the developed markets under study. The variance decompositions by both the orthogonalised and generalised approaches indicate that about 20% of the variation in the returns to the emerging markets can be explained by the shocks to the returns of the developed markets in

Frankfurt and the U.S. The implication of the low level of the linkages is that expected returns of the investment in the emerging stock markets in Warsaw and Budapest would be determined mainly by the country-specific risk factors. Our study suggests potential benefits for international portfolio diversification into the emerging markets in Central and Eastern Europe.

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Figure 1 Stock indices

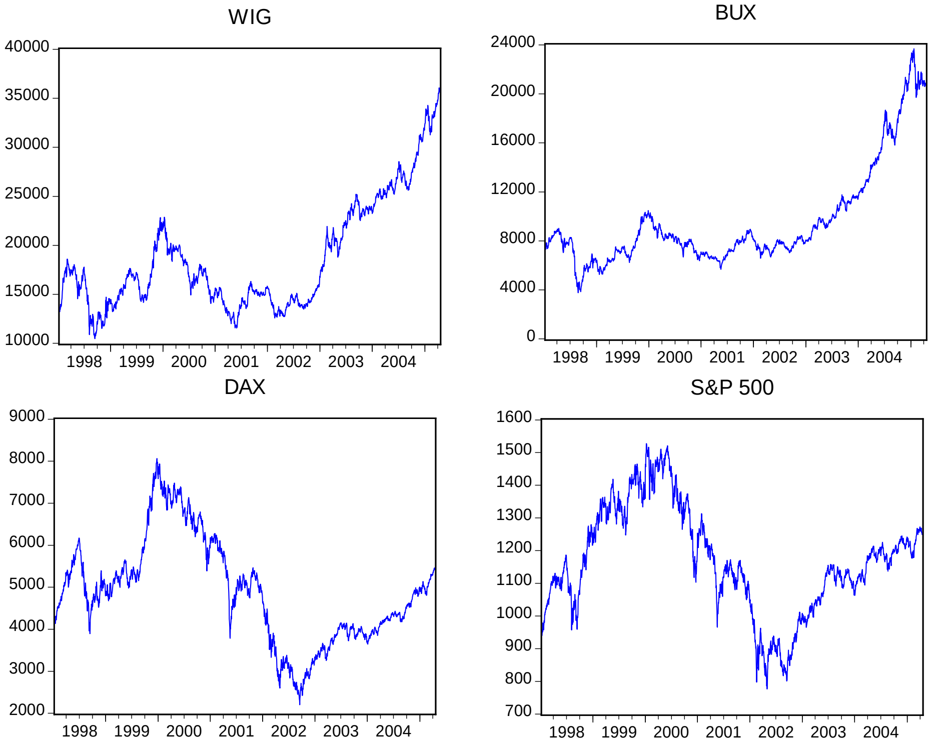

Figure 2 Returns of the stock indices

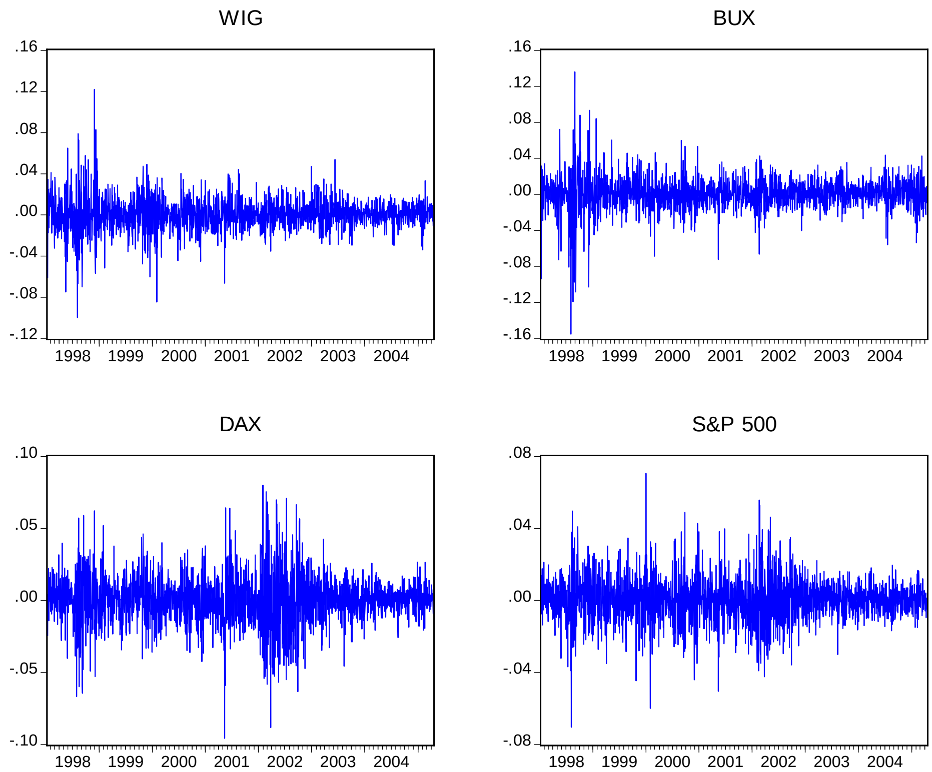

Figure 3 Estimated conditional co-variances

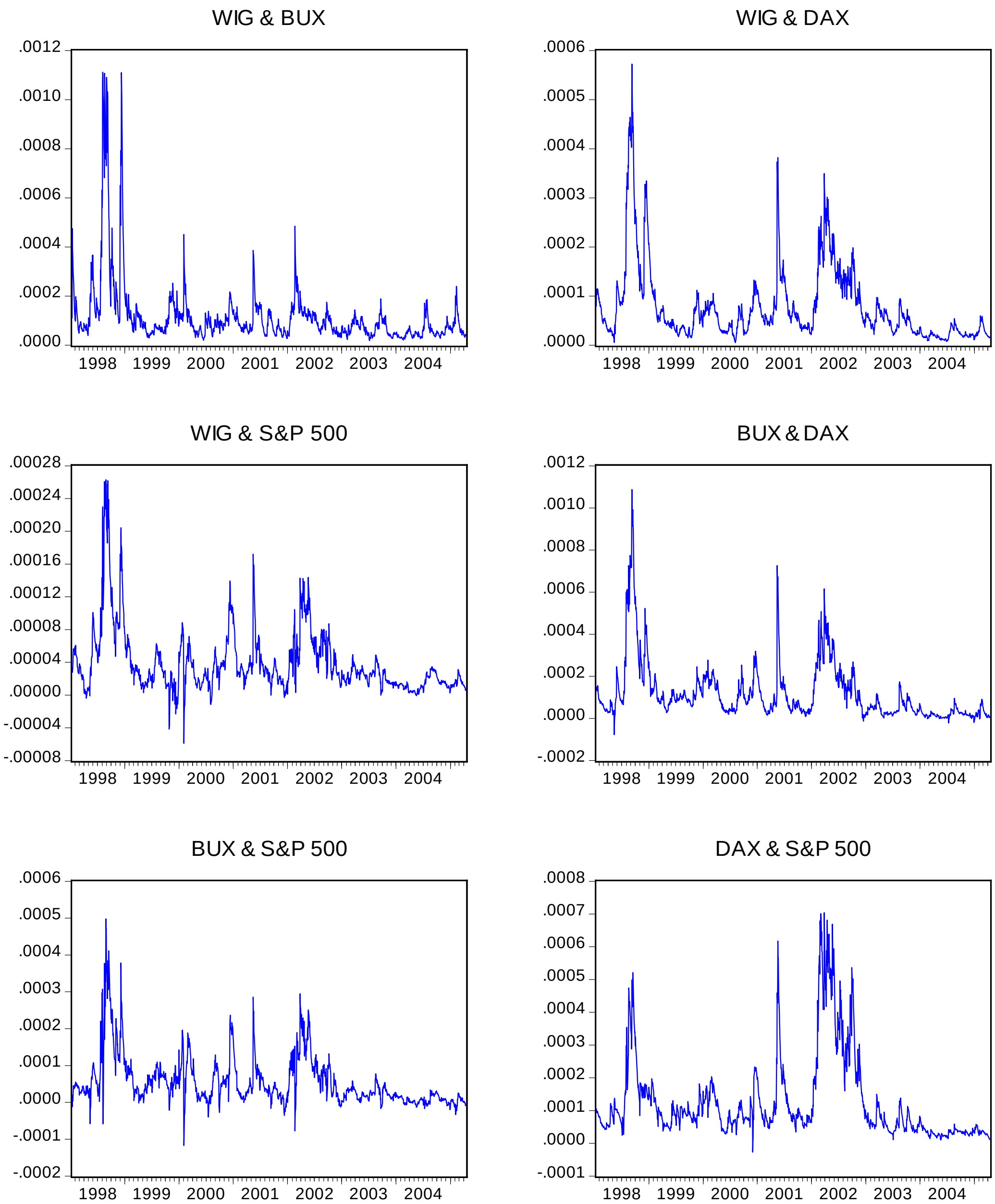

Table 1 summary statistics of the returns

	WIG	BUX	DAX	S&P 500
Mean	0.000490	0.000504	0.000129	0.000157
Std. Dev.	0.015729	0.018113	0.017452	0.012369
Skewness	0.043152	-0.589020	-0.073591	0.052801
Kurtosis	8.448472	12.18290	5.670438	5.652449
Jarque-Bera	2344.533	6767.786	564.7813	556.3908
Probability	0.000000	0.000000	0.000000	0.000000

Table 2 Estimated coefficients for the four-variable asymmetric GARCH Model

	WIG (i=1)		**BUX (i=2)**		**DAX (i=3)**		**S&P 500 (i=4)**	
γ_{i1}	0.0155	(0.0272)	0.0401	(0.0275)	0.0614**	(0.0256)	0.0330	(0.0207)
γ_{i2}	0.0523**	(0.0223)	0.0204	(0.0289)	-0.0260	(0.0237)	-0.0234	(0.0190)
γ_{i3}	-0.0935***	(0.0251)	-0.0965***	(0.0276)	-0.1445***	(0.0316)	0.0338	(0.0216)
γ_{i4}	0.3709***	(0.0333)	0.3504***	(0.0372)	0.3359***	(0.0364)	-0.0686**	(0.0282)
a_{i1}	0.1843***	(0.0157)	0.0841***	(0.0221)	-0.0065	(0.0204)	-0.0243	(0.0174)
a_{i2}	0.0457***	(0.0146)	0.2198***	(0.0244)	0.0121	(0.0188)	0.0175	(0.0144)
a_{i3}	-0.0012	(0.0173)	0.0511**	(0.0211)	0.1215***	(0.0258)	0.0317	(0.0190)
a_{i4}	-0.0780***	(0.0263)	-0.2207***	(0.0263)	-0.0363	(0.0291)	0.1171***	(0.0244)
g_{i1}	0.9859***	(0.0026)	-0.0027	(0.0052)	0.0054	(0.0044)	0.0037	(0.0033)
g_{i2}	-0.0225***	(0.0060)	0.9397***	(0.0082)	0.0138	(0.0078)	-0.0032	(0.0060)
g_{i3}	-0.0108**	(0.0042)	-0.0344***	(0.0073)	0.9393***	(0.0072)	-0.0138**	(0.0054)
g_{i4}	0.0273***	(0.0087)	0.0778***	(0.0116)	0.0443***	(0.0097)	0.9754***	(0.0066)
d_{i1}	-0.0264	(0.0313)	-0.0555	(0.0381)	0.0235	(0.0270)	-0.1218***	(0.0195)
d_{i2}	0.0091	(0.0223)	0.1781***	(0.0336)	-0.1309***	(0.0270)	-0.0140	(0.0199)
d_{i3}	0.0689***	(0.0228)	0.0596**	(0.0298)	0.3041***	(0.0275)	0.2817***	(0.0189)
d_{i4}	0.0070	(0.0340)	0.0503	(0.0482)	0.0764**	(0.0345)	-0.2422***	(0.0272)
LB-Q(12)	11.644		7.0224		10.760		13.384	
Probability	0.475		0.856		0.550		0.342	
LB-Q(24)	29.696		18.426		29.858		19.823	
Probability	0.195		0.782		0.190		0.707	
LB-Qs(12)	15.178		12.157		28.742		15.930	
Probability	0.232		0.433		0.004		0.194	
LB-Qs(24)	20.994		21.479		37.599		34.834	
Probability	0.639		0.61		0.038		0.071	
LLR	22814.71							
AIC	-23.99652							
SC	-23.76820							

Note: Constants are omitted in the above table to save space. Values in brackets are standard errors. *** and ** represent the levels of significance of 1%, and 5% respectively. LB-Q(12) and (24) stand for the Ljung-Box Q-statistic for the standardised residuals up to 12 lags and 24 lags while LB-Qs(12) and (24) for the Ljung-Box Q-statistic for the squared standardised residuals. LLR, AIC and SC represent the lag likelihood ratio, Akaike information criterion and Schwarz criterion respectively.

Table 3 Restriction tests concerning the four-variable asymmetric GARCH model

	Likelihood ratio test statistic	Degree of freedom
Asymmetric four-variable versus asymmetric univariate model H0: $a_{ij}a_{ji}=g_{ij}g_{ji}=d_{ij}d_{ji}=0,\ i\neq j$	1511.8508	284
The joint explanatory power of lagged returns of DAX and S&P 500 indices on the emerging markets H0: $\gamma_{13}=\gamma_{14}=\gamma_{23}=\gamma_{24}=0$	324.36	4
The joint explanatory power of past shocks and volatility of DAX and S&P 500 indices on the emerging markets H0: $a_{13}=a_{14}=a_{23}=a_{24}=g_{13}=g_{14}=g_{23}=g_{24}=0$	135.64	8
The joint explanatory power of lagged returns and past shocks and volatility of DAX and S&P 500 indices on the emerging markets H0: $\gamma_{13}=\gamma_{14}=\gamma_{23}=\gamma_{24}=a_{13}=a_{14}=a_{23}=a_{24}=g_{13}=g_{14}=g_{23}=g_{24}=0$	264.22	12
Four-variable asymmetric versus four-variable symmetric model H0: D=0	295.98	10

Table 4 Correlation coefficients of returns series under study

	WIG	BUX	DAX	S&P 500
WIG	1			
BUX	0.495	1		
DAX	0.359	0.422	1	
S&P 500	0.198	0.240	0.576	1

Table 5 Forecast error variance decomposition in each series

		Percentage of forecast error variance in			
Stock index	Horizon (days)	WIG	BUX	DAX	S&P 500
(a) by orthogonalised approach					
WIG	1	89.868	0	10.132	0
	2	78.083	0.771	11.395	9.750
	5	78.053	0.783	11.400	9.764
	10	78.053	0.783	11.400	9.764
BUX	1	11.555	73.166	15.278	0
	2	10.828	68.135	15.236	5.802
	5	10.823	68.107	15.230	5.840
	10	10.823	68.107	15.230	5.840
DAX	1	0	0	100	0
	2	0.203	0.0410	94.790	4.967
	5	0.203	0.0419	94.662	5.093
	10	0.203	0.0419	94.662	5.093
S&P 500	1	0.124	0.016	35.674	64.186
	2	0.141	0.152	35.600	64.108
	5	0.141	0.153	35.598	64.109
	10	0.141	0.153	35.598	64.109
(b) by generalised approach					
WIG	0	74.03	14.77	7.50	3.69
	1	64.81	14.51	8.44	12.24
	2	64.80	14.51	8.45	12.24
	5	64.80	14.51	8.45	12.23
	10	64.80	14.51	8.45	12.23
BUX	0	14.07	70.52	10.78	4.63
	1	13.48	66.68	10.87	8.97
	2	13.48	66.67	10.87	8.98
	5	13.48	66.67	10.87	8.98
	10	13.48	66.67	10.87	8.98
DAX	0	6.29	9.49	62.08	22.14
	1	6.27	9.27	60.67	23.79
	2	6.27	9.28	60.64	23.82
	5	6.27	9.26	60.64	23.82
	10	6.27	9.26	60.64	23.82
S&P 500	0	3.39	4.46	24.23	67.92
	1	3.40	4.50	24.21	67.89
	2	3.40	4.50	24.21	67.89
	5	3.40	4.50	24.21	67.89
	10	3.40	4.50	24.21	67.89