Cointegration and conditional correlations among German and Eastern Europe equity markets

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Abstract

This paper aims to examine the long term relationship between German and three Central and Eastern Europe (CEE) equity markets. Application of Johansen as well as Engle-Granger cointegration tests show that there is no long-term relationship among these markets while the Gregory-Hansen cointegration test rejects the null hypothesis of no cointegration with structural break. An additional objective is to capture the time-varying correlation among these markets through the dynamic conditional correlation models. Empirical results suggest that correlations increased after the accession of the CEE countries into the European Union.

1. Introduction

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Financial market integration among developed and emerging countries has been broadly investigated by focusing on major US and European stock markets and on emerging markets of Asia and Latin America. Less attention has been directed toward the issue of financial integration between developed and Eastern European equity markets. The aims of this paper are to investigate the integration of Eastern European markets with the developed markets. Among CEE countries, the Czech Republic, Hungary, and Poland, have made the greatest progress in terms of economic liberalization of trade and capital flows. Their accession to the EU in may 2004, pointed out their commitment towards those targets.

The main economic partner of these countries is the Germany. Euro area is the most important source of direct investment for most CEE countries; among the Euro area countries, Germany is the main contributor of direct investment towards these three countries (Lane and Milesi-Ferretti, 2007). EU enlargement to several CEE countries in May 2004 may have increased the integration of these equity markets with developed markets (Dvorak and Podpiera, 2006). The main contribution of this study is in using some techniques to test the integration of these markets with the developed markets. This study uses co-integration analysis and time varying correlation methodologies in order to understand how relationship among German and CEE equity markets change over time. Based on the political and economic changes in these countries this study assumes that correlations among these markets may not be constant over time and understanding of these changes over time may have important implications for a fund manager and/or investor. An additional contribution of our work is that we use recent data which give us the possibility to incorporate periods of financial turmoil in our analysis.

As pointed out by Bekaert and Harvey (2000), the correlation between emerging markets which open up their capital markets to foreign investors and developed markets tends to increase over time. On the other side the low correlation among developed and emerging equity markets is an indicator of advantages from investing in different markets (Eun and Resnick, 1984; Michaud et al., 1996; Gupta and Donleavy 2009). Low correlation among countries equity markets may be due to factors like lack of free trade and inadequate information of foreign securities. As pointed out by Bekaert and Harvey (2003) financial liberalization does not necessarily lead to the full integration of an emerging market into the global market[2], although the lack of financial integration among

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[2] Bekaert and Harvey (2003) define the concept of financial liberalization as the opportunity for foreign investors to purchase or sell domestic securities as well as for domestic investors to purchase or sell foreign securities

world markets seems to be one of the main characteristics which investors take into account in their investment decision given benefits deriving from diversifying internationally (Schmukler, 2004). In their recent empirical work, Gupta and Donleavy (2009) argue that the increasing integration among financial markets gradually reduces benefits derived from international diversification. However, these authors carrying out an empirical studies about cointegration among the Australia and emerging equity markets, point out that there are still benefits for Australian investors by investing into emerging equity markets.

As pointed out by Kasa (1992), benefits from international diversification indicated by low correlations may be overstated for investors with long-term investment horizons if equity markets are trending together. Studies have employed co-integration techniques to explore whether there are linkages and long-term co-movements between both emerging and developed markets (Hasan et al., 2008; Wong et al., 2004). Recent studies detected the relationships among developed and CEE emerging equity markets. Gilmore and McManus (2002) find that the Czech, Hungary and Poland are not co-integrated with the US equity market during the period spanning from 1995 to 2001. Also the correlations among returns of these markets seem to be very low. The main conclusion is that US investors can benefit from investing in these emerging markets both in the short and long time horizon. Voronkova (2004) shows evidence of long-run relationships between the German and Polish stock indices as well as German and Hungarian indices over the period between 1993 and 2002. Gilmore et al. (2005) find evidence of no cointegration relationship among German and CE equity markets for the period 1995-2005. Change of analysis period, show a stronger evidence of cointegration of CEE equity markets with UK markets rather than the German. Égert and Kočenda (2007) tests the existence of a long-run relationship among Western and Eastern Europe equity markets. This study does not find a relationship among German and Polish equity markets. However, they find co-integration between German and other two Eastern Europe equity markets (i.e. the Polish and the Czech). Li and Majerowska (2008), using a GARCH approach, find evidence that Hungarian and Polish equity markets are linked to the German stock market in terms of return and volatility: German equity market influence both the Eastern Europe markets and is not influenced by them.

Gilmore et al. (2005) using cointegration techniques do not find evidence of cointegration relationship of the German and UK markets with those of Czech Republic, Hungary, and Poland from 1995 to 2005. Égert and Kočenda (2007) using intraday stock market data from June 2003 to February 2004, do not find evidence of cointegration among German, Czech Republic, and Polish

equity indices. Li and Majerowska (2008) examined the linkages between the developed German stock market and the emerging markets in Poland and Czech Republic by using Gregory-Hansen co-integration test (Gregory and Hansen, 1996) as well as classical cointegration tests developed by Engle and Granger (1987) and Johansen (1988). Using daily stock returns from January 1998 to December 2005, they found evidence that the two emerging markets are weakly linked to the German stock market. But Syriopoulos (2007) shows that a long run relationship among German and several CEE equity markets exists both in the period before the accession of these CEE countries into EU than in the post accession period.

Another aspect the recent literature is investigating is the time-varying correlation among developed and emerging markets. The issue is relevant given that cross market linkages and correlations tend to increase over time (Marcelo et al., 2008) and are particularly relevant in the decision process for investors interested to diversify their portfolio of assets. This issue has been investigated between developed and emerging countries in Asia and Latin America (Ng, 2000; Gupta and Mollik, 2008; Gupta and Donleavy, 2009; Ratanapakorn and Sharma, 2002). Syriopoulos and Roumpis (2008), investigates time-varying linkages among Balkan and developed equity markets using either the Constant Conditional Correlation (CCC) and Asymmetric Dynamic Conditional Correlation (ADCC) models Results show that the correlations among equity markets are not constant over time, while correlations with developed markets seem to be quite modest.

The objective of this study is to examine the long-run relationship between several CEE and German equity markets and estimate time-varying correlations among these markets. We use daily closing prices of German and the CEE equity markets from 1999 to 2009. We use several co-integration methodology tests (Johansen, 1988; Gregory and Hansen, 1996), then we implement and compare the Dynamic Conditional Correlation models (Engle, 2002). The results of this study are mixed given that cointegration tests present conflicting results. On the other side, DCC model evidence that correlations coefficients between equity indices increased massively after CEE countries joined to the European Union.

The rest of the paper is organized as follows. Section 2 briefly outlines the methodologies, in section 3 the data used in this work is described and its statistical properties are explored. Section 4 discusses the empirical results, while section 5 concludes.

2. Empirical methodology

In order to detect the presence of a long run relationships among CEE and German equity indices the Johansen (1988), the Engle-Granger (1987) and the Gregory-Hansen (1986) cointegration tests are used. The Gregory-Henson takes endogenous structural breaks into account but the first two methodologies do not account for endogenous structural breaks. The aim of using different co-integration methodologies is to use different methodologies to test the robustness of our findings.

Johansen co integration test can be applied in the following way. First we evaluate the order of integration of all variables by applying the common unit root tests such as the ADF as well as Phillip-Perron test and then we proceed to estimate a vector autoregression (VAR) of order p given by the following equation:

$$y_t = \mu + A_1 y_{t-1} + ... + A_p y_{t-p} + \varepsilon_t \qquad (1)$$

Where y_t is a $n \times 1$ vector of variables that are integrated of order one, and ε_t is an $n \times 1$ vector of innovations. The second step involves to re-write the VAR(p) model as:

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum_{J=i+i}^{p} A_j$. Further, we determine the rank of the coefficient matrix Π, if this matrix has reduced rank such that $r < n$, then there exist $n \times r$ matrices with rank r such as $\Pi = \alpha \beta'$ and $\beta' y_t$ is stationary, r is the number of cointegration relationships, the elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a co-integrating vector. The Johansen methodology involves testing hypothesis about the rank of the long-run matrix Π. Two different likelihood ratio tests are used. The first one is the so-called trace test (equation 3) which tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The second one is the maximum eigenvalue test (equation 4) where the null hypothesis of r cointegrating vectors against the alternative of $r+1$ co-integrating vectors is tested.

$$\lambda_{trace} = -T \sum_{j=r+1}^{k} \log(1 - \hat{\lambda}_j) \qquad (3)$$

$$\lambda_{\max} = -T \log(1 - \hat{\lambda}_{j+1}) \qquad (4)$$

If the test statistic value exceeds the critical values it is possible to reject the null hypothesis and accept the alternative.

Engle and Granger (1987) cointegration test is based on the following regression:

$$y_t = \alpha + \beta x_t + \varepsilon_t \tag{5}$$

where y and x are two variables, and the residual ε_t from the above equation are considered to be temporary deviation from long-run equilibrium. The ADF unit root tests are then conducted on the residual ε_t obtained from the above equation based on the following linear equation:

$$\Delta \varepsilon_t = \alpha \varepsilon_{t-1} + \sum_{i=1}^{m} \beta_i \Delta_{t-i} + \omega_t \tag{6}$$

where, α and β are the estimated parameters and ω is the error term. The cointegration test is on the estimated coefficient α. If the *t-statistic* of the coefficients exceeds the critical value, the residuals ε_t from co-integration equation (5) are stationary, and thus the variables y and x are co-integrated.

Gregory et al. (1996) showed that if a model is co-integrated with a one-time regime shift in the cointegrating vector, the standard ADF test may not reject the null hypothesis of no cointegration, leading to a wrong conclusion that there is no long-run relationship. In this perspective, Gregory and Hansen (1996) suggested a modified residual-based test for cointegration in cases where the intercept and/or slope coefficients have a single break at an unknown date. The structural breakpoint is endogenously determined from the sample based on the information of the smallest t statistic. Gregory and Hansen (1996), considered three models allowing structural change in the cointegrating relationship. The first one is called Model C (level shift model), that is:

$$y_t = \mu_0 + \mu_1 \delta_t + \alpha x_t + \varepsilon_t \tag{7}$$

the second one is called Model C/T (level shift with trend), and is specified as follows:

$$y_t = \mu_0 + \mu_1 \delta_t + \beta t + \alpha x_t + \varepsilon_t \tag{8}$$

while the last one is called Model C/S (Regime shift):

$$y_t = \mu_0 + \mu_1 \delta_t + \alpha_1 x_t + \alpha_2 \delta_t x_t + \varepsilon_t \tag{9}$$

All models above permits structural change through the dummy variable δ_t which is defined as:

$$\delta_t = \begin{cases} 1 & if \quad t > \tau \\ 0 & otherwise \end{cases} \tag{10}$$

Where t denote the points at which a break occurs. The residuals obtained from the above cointegrating regressions are then employed in the following Dickey-Fuller test:

$$\Delta \hat{\varepsilon}_t = (\rho - 1)\hat{\varepsilon}_{t-1} + v_t \tag{11}$$

For all modes (C, C/T, C/S), the Dickey-Fuller test from equation (11) is estimated, with the value employed as the resulting test statistic being the minimum value obtained for the *t-ratio* for the estimated value of $(\rho - 1)$. In this perspective, the null hypothesis of no cointegration with structural breaks is tested against the alternative of cointegration by the Gregory and Hansen approach. All above cointegration tests are used to detect existence of long run relationship among return indices here considered.

We also want explore the causal relation between the German and CEE stock market indices by using a simple Granger causality test (Granger, 1969). The logic here is if the past values of a variable X can be used to predict a variable Y more accurately than simply using the past values of Y, it can be argued that X Granger cause Y. This means that if past values of X statistically improve the prediction of Y, then we can conclude that X *Granger-causes* Y. Anyway, it must be pointed out that the results from the test should be used with caution.

Past empirical research suggests that volatility of the returns of financial assets vary over time and the returns of the financial assets across markets co-move. In this environment, investors are interested in assessing the degree of equity markets linkages and volatility effects, in order to construct well-diversified portfolios. More recently, empirical financial literature has employed multivariate GARCH specification to model asset correlations. Given that this study aims to explore the interdependence across several stock market, 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 processess relating the share price indices under study:

$$Y_t = \alpha + \Gamma Y_{t-1} + \varepsilon_t \tag{12}$$

with $\varepsilon_t \mid I_{t-1} \propto N(0, H_t)$. Where Y_t is a $n \times 1$ vector of daily returns at time t and Γ is a $n \times n$ parameter associated with the lagged returns. The diagonal elements in matrix Γ, capture the

relation in terms of returns across markets, also known as returns spillover. The $n\times1$ vector of random errors, ε_t, is the innovation for each market at time t and has a $n\times n$ variance-covariance matrix H_t. The market information available at time t-1 is represented by the information set I_{t-1}. The $n\times1$ vector, α, represents constants.

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

$$vech(H_t) = \omega + \sum_{i=1}^{q} A_i vech(r_{t-1}r_{t-i}^{'}) + \sum_{i=1}^{p} B_i vech(H_{t-i}) \tag{12}$$

where *vech* is the operator that stacks the lower triangular portion of a symmetric into a vector. The problems with this formulation are that the number of parameters to be estimated is large and restrictions on 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, and which is characterized by the following equation:

$$H_t = c^{*'}c^* + \sum_{i=1}^{p} A_i^{*'} r_{t-i} r_{t-i}^{'} A_i^* + \sum_{j=1}^{q} B_j^{*?} H_{t-j} B_j^* \tag{13}$$

where c^*, A_i^* and B_j^* are $n\times n$ matrices and c^* is an upper triangular. The bivariate GARCH(1,1) model can be deduced from the above equation and we can write it as:

$$H_t = c^{*'}c^* + A_1^{*'} r_{t-1} r_{t-1}^{'} A_1^* + B_1^{*'} H_{t-1} B_1^* \tag{14}$$

Equation (14) can be re-written in matrix form as follows:

$$H_t = \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix}^{'} \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix} + \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix} \begin{bmatrix} r_{1,t-1}^2 & r_{1,t-1}\cdot r_{2,t-1} \\ r_{2,t-1}\cdot r_{1,t-1} & r_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix} + \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix} H_{t-1} \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix} \tag{15}$$

where r_x is the return of an asset x and r_y is the return of an asset y while H_t is the conditional covariance matrix which can written as follows:

$$H_t = \begin{bmatrix} \mathrm{var}(r_{1,t}) & \mathrm{cov}(r_{1,t}, r_{2,t}) \\ \mathrm{cov}(r_{2,t}, r_{1,t}) & \mathrm{var}(r_{2,t}) \end{bmatrix} = \begin{bmatrix} h_{1,t}^2 & h_{12,t}^2 \\ h_{21,t}^2 & h_{2,t}^2 \end{bmatrix} \tag{16}$$

We may note that the BEKK for a bivariate model involves 11 parameters to be estimated, but for higher-dimensional systems the extra number of parameters in the BEKK model increases. After estimate each bivariate EGARCH model, we also explore whether the conditional correlations between each pairwise of indices varies over time by using the following simple formula:

$$\rho_{xy} = \frac{h_{xy,t}^2}{h_{x,t}h_{y,t}t} \tag{17}$$

In order to check in deep the the time-varing relationship among German and CEE stock market indices we conduct a further analysis. In this perspective, the Constant Conditional Correlation (CCC) model (Bollerslev, 1990) and the Dynamic Conditional Correlation (DCC) model (Engle, 2002) are of the most widely employed multivariate GARCH specification for studying dynamic asset correlations. Both the CCC and DCC models are a two-stage estimator of conditional variances and correlations. In the first stage, a univariate GARCH model is estimated; the univariate variance estimates are subsequently introduced as inputs in the second stage of the estimation process. The DCC model (Engle, 2002) captures the dynamics of time-varying conditional correlations, contrary to the benchmark CCC model which retains the conditional correlation constant. Using the DCC model we can estimate the correlations for these markets and a plot of these correlations may indicate whether the co-movements of these markets increase over time. This last hypothesis seems to be plausible given the recent accession of the CEE countries to the EU. Following Engle (2002), the DCC-GARCH model can be formulated as follows:

$$r_t \mid \Phi_{t-1} \approx N(0, D_t R_t D_t) \tag{18}$$

$$D_t^2 = diag\{\omega_i\} + diag\{k_i\} \circ r_{t-1}r_{t-1} + diag\{\lambda_i\} \circ D_{t-1}^2 \tag{19}$$

$$\varepsilon_t = D_t^{-1}r_t \tag{20}$$

$$Q_t = S(1 - \alpha - \beta) + \alpha(\varepsilon_{t-1}\varepsilon_{t-1}') + \beta Q_{t-1} \tag{21}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \tag{22}$$

where equation (20) represents the standardized errors, S is the unconditional correlation matrix of the errors and ∘ is the Hadamard product of two matrices of the same size.. The parameters of the DCC-GARCH model can be estimated using maximum likelihood. If $(\alpha + \beta < 1)$, then equation (21) is mean reverting. The log likelihood for this estimator can be written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|D_t| + \log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t\right) \tag{23}$$

where $D_t = diag\left\{\sqrt{h_{i,t}}\right\}$ and R_t is the time varying correlation matrix.

3. Data

The data consists of daily stock market prices, which were extracted from *Financial Thomson Datastream*. For this study we use daily returns of the DAX030 Index and the Czech, Hungarian, and Polish equity markets for the period 2 January 1999 to 9 January 2009 (table 1).

Table 1– Data summary

Country	Index name	Currency	Datastream Code
Czech Republic	PX50	Czech Koruna	CZPX50(PI)
Germany	DAX30	Euro	DAXINDX(PI)
Hungary	Bux	Hungarian Forint	BUXINDX(PI)
Poland	Wig	Polish Zloty	POLWG40(PI)

Figure 1 presents the time plots of the series. While the CEE markets start to trend upwards from 2001, the German index trended downward from that time until the early 2003. The upward trend of all four indices ended in the first half of 2007 from that time these indices show a fast trend downward.

Figure 1 – Stock price indices from January 1999 to December 2008
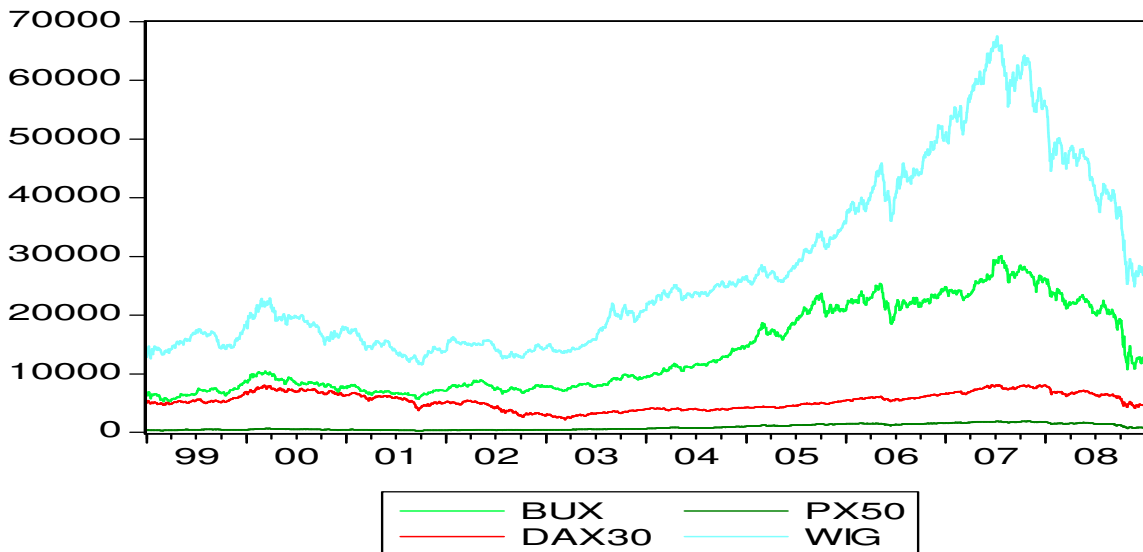
Daily stock markets log returns are calculated as $r_t = \log(p_t) - \log(p_{t-1})$, where p_t is the price index in levels. Table 2 reports summary statistics for the daily returns of the markets here considered as well as statistics testing for normality and independence. The sample means for all

markets are not different from zero. The measures for skewness and excess kurtosis show that all return series, except the DAX30 returns, are negatively skewed and highly leptokurtic.

Table 2 – Summary statistics of daily returns

Index	N. obs	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera Test	p-value
Dax30	2615	-1.71e-05	0.107	-0.088	0.016	0.046	7.792	2503.395	0.00
Bux	2615	0.0002	0.131	-0.126	0.016	-0.156	10.655	6398.74	0.00
PX50	2615	0.0003	0.123	-0.161	0.014	-0.565	17.656	23544.52	0.00
Wig	2615	0.0002	0.068	-0.084	0.014	-0.249	6.045	1037.67	0.00

Figure 2 displays the return of the price indices, the first differences of the natural logarithm of the price indices, during the period 1999-2009. The German market has very high volatility during the period 2002-2003, while all markets exhibit also high volatility during the second half of 2008. All indices are also characterized by volatility clustering, given that small (large) volatility is followed by small (large) volatility.

Figure 2 – Stock index returns during from January 1999 to December 2008
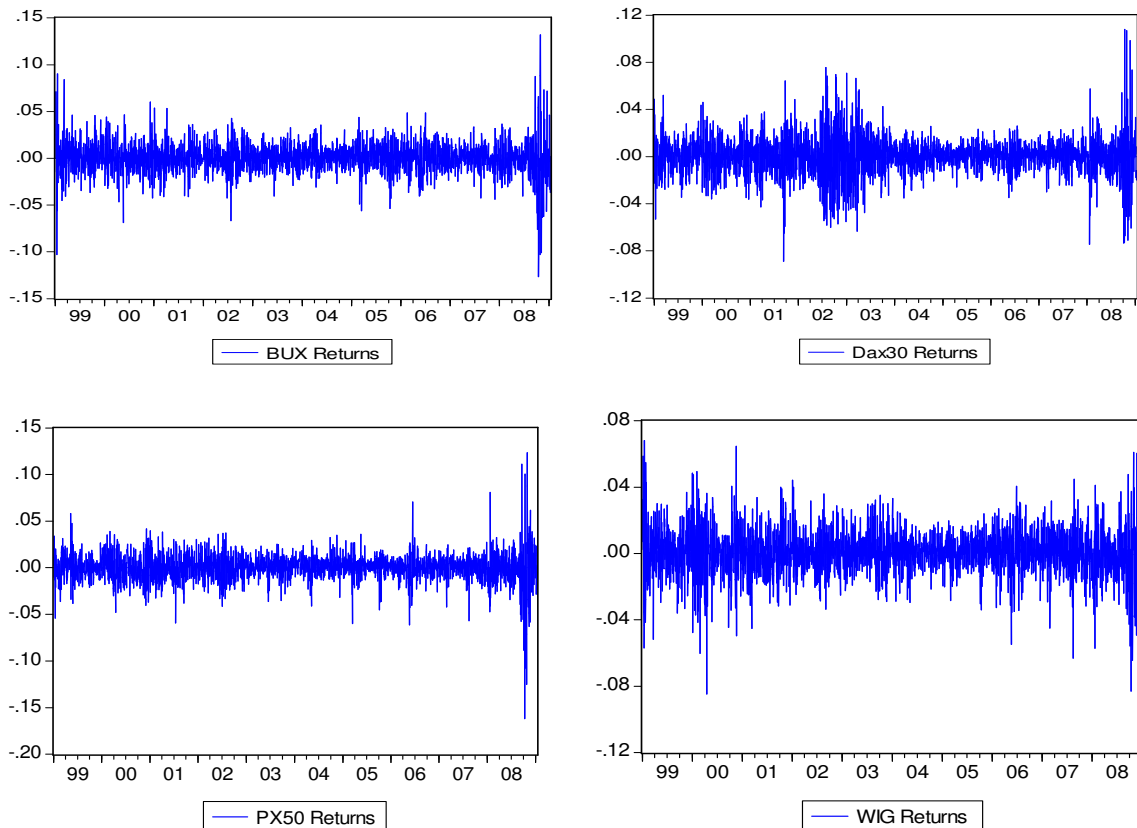
Unconditional correlation coefficients in equity market index returns (table 3) indicate significant pair-wise correlations among DAX30 index and several CEE index markets. The highest correlation is among WIG stock index returns and Bux stock index returns.

Table 3 – Unconditional market returns correlation matrix

	Dax30	Bux	Px50	Wig
Dax30	1.00	-	-	-
Bux	0.441	1.00	-	-
Px50	0.426	0.532	1.00	-
Wig	0.397	0.509	0.502	1.00

4. Results

Cointegration tests allow us to determine whether stock prices of different national markets move together over the long run. The first step in the analysis is to test each index series for the presence of unit roots, which shows whether the series are stationary. Non stationary is a precondition for cointegration; additionally, all the series must to be integrated of the same order. For this we apply both the ADF test (Dickey and Fuller, 1979; 1981) and the Phillips-Perron (PP) tests (Phillips, 1987; Phillips and Perron, 1988). Once the stationarity requirements are met, we use the Johansen cointegration test in order to determine whether the time series are co-integrated. This test determines the rank of the coefficient matrix of a vector auto-regression (VAR) of the series, with the rank indicating whether there is cointegration, as well as the number of co-integrating relationships. Table 4 and 5 report the results of the unit roots tests on the logs of the daily stock indices. Both the ADF and PP were applied to the levels and first differences of each series. Appropriate lag lengths for the ADF and PP tests were selected according to the Schwarz information criterion. For the level series, the results show that the null hypothesis of a unit root cannot be rejected at the 5% significance level. The first-differenced series reject the null hypothesis, indicating that they are stationary. Consequently, all five series are integrated I(1)

Table 4 – ADF Unit root test for daily stock market indices

Index	Index level			Index First Differences		
	Lag length p	ADF	P-value [a]	Lag length p	ADF	P-value [a]
Bux	2	-1.301	0.631	1	-37.027	0.00
Dax30	0	-1.458	0.554	0	-53.158	0.00
PX50	1	-1.250	0.654	0	-48.029	0.00
Wig	0	-1.274	0.643	0	-48.624	0.00

Notes. The lag length has been chosen using the Schwarz information criterion with, Maxlag=27 (Automatic based on SIC). [a]MacKinnon (1996) one-sided p-value

Table 5 – PP Unit root test for daily stock market indices

Index	Index level			Index First Differences		
	Bandwidth	PP	P-value [a]	Bandwidth	PP	P-value [a]
Bux	8	-1.306	0.628	9	-39.578	0.00
Dax30	7	-1.365	0.600	6	-53.246	0.00
PX50	9	-1.247	0.655	7	-47.953	0.00

| Wig | 5 | -1.284 | 0.638 | 4 | -48.627 | 0.00 |

Notes. The Bandwidth is the Newey-West using Bartlett Kernel. [a] MacKinnon (1996) one-sided p-value.

Given that the variables are integrated integrates of order 1, we may proceed to determine whether there exists a long-run relationship among CEE emerging and the German stock markets by using the Johansen procedure[3]. The first step involves determining the optimal number of lags q to apply the VAR. Two information criteria were used to determine the optimal number of lags, that is the Schwarz Information Criterion.(SIC) and the Akaike Information Criterion (SIC). Results are shown in table 6: AIC selects 6 lags while the SIC selects 8 lags. In order to estimates the more parsimonious model, we chose to follow AIC indication, so a VAR with 6 lags was chosen.

Table 6 – Selecting the optimal lags q

	2	4	6	8
AIC	-23.193	-23.206	-23.232	-23.228
SIC	-23.113	-23.053	-23.008	-22.931

Further, cointegration test was performed on the VAR(6), by using both the trace statistic (i.e. λ_{trace}) and the maximum value statistic (λ_{max}).The empirical findings (table 7) do not support the presence of cointegrating vectors in the markets under study: both trace and max-eigenvalue tests indicates no cointegration at 5% level. Our results are in contrast with that of the findings in Voronkova (2004) which show the existence of cointegration between the German and CEE markets although the examination periods in her study spans from 1993-2003. So we may suppose that our different results could be due to the different time period considered in our work. Anyway, as pointed out by Yang et al. (2005), integration among stock markets is not constant over time due to events like financial crises. If we consider the 1997 Asian crisis, some empirical studies reported that those events reduced integration among regional stock markets. For example Manning (2002), using Johansen cointegration methodology, showed that nine Asian equity markets and the US market tended to converge during the period 1988-1999. But applying the Haldane and Hall Kelman filter, only two periods of convergence are identified (that is 1988-1990 and 1992-mid-1997), while divergence occurred between 1990-1992 and in the post Asian crisis period. These results show Johansen co-integration test may not be the best methodology to detect cointegration among stock indices over periods characterized by unexpected events. For these reasons this study uses multiple techniques to get most reliable results.

Table 7 - Tests for the presence of cointegrating vectors

	λ_{trace}	Critical value	λ_{max}	Critical value

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[3] Hsueh and Kang (2007) argue that cointegration tests carried out on a system variable, must use variables with the same order of integration.

	5%			5%
r = 0	42.985	47.856	23.148	27.584
r ≤ 1	19.837	29.797	10.535	21.131
r ≤ 2	9.301	15.494	6.738	14.264
r ≤ 3	2.563	3.841	2.563	3.841

Notes. * Denotes rejection of the hypothesis at the 5% level

Table 8 presents the results of tests if there is a causal relationship among the German and each CEE equity market. Considering 2 lags, results show that Dax30 stock prices Granger-cause stock prices in all other CEE equity markets except the Czech market. And the CEE markets do not Granger-cause the Dax30 stock prices.. In other words changes in the Dax30 index cause changes in other CEE indexes with either one or two-days lags. These results seem apparently conflicting with the Johansen Co-integration Test. An explanation is based on the consideration that the Granger causality test explores the short-term relationships among variables while the Johansen Co-integration Test is used to examine long-term relationship.

Table 8 –Granger causality test between stock market prices

	Lags 1	Lags 2
Dax30 => Bux	1.879	16.959**
	(0.170)	(4.8E-08)
Bux => Dax30	0.856	1.430
	(0.354)	(0.239)
Dax30 => Px50	4.599**	14.554**
	(0.032)	(5.2E-07)
Px50 => Dax30	1.431	2.281
	(0.231)	(0.102)
Dax30 => Wig	2.299	25.551**
	(0.083)	(1.0E-11)
Wig => Dax30	1.872	1.434
	(0.171)	(0.238)

Notes: The Pairwise Granger Causality tests the null hypothesis that the series X does not Granger Causes a series Y (i.e. X=>Y). ** indicates rejection of the null hypothesis (no Granger causality) at the 5% significance level; probability values are in brackets.

Because of the variables here used are not stationary on level we use first differences of the series to make them stationary. This means that Engle-Granger method can be used in the cointegration analysis. The estimates of the long run equilibrium relationship between the variables for the model without are the following (t-statistic in parentheses):

$LogDAX30 = 0.438 + 0.272\ LogBUX\ -1.264\ LogPX50 + 1.384\ LogWIG$

$\qquad\qquad [2.09] \qquad [5.095] \qquad\qquad [-23.796] \qquad [39.165] \qquad\qquad\qquad (24)$

while for the model with trend the estimates are:

$$\text{LogDAX30} = -2.871 \quad + \quad 0.641 \text{ LogBUX} \quad + -1.107 \text{ LogPX50} + 1.311 \text{ LogWIG} \qquad (25)$$

$$[-15.760] \qquad [15.048] \qquad [-26.642] \qquad [47.528]$$

In view of the ADF unit root tests applied on error term series obtained from the second stage of the Engle-Granger procedure, it has been found (table 9) that these series are not stationary on level (this is in log form). This means that there is no co-integrating relationship between the series.

Table 9 - Results of the Engle-Granger Cointegration tests

Cointegration equation	ADF Test statistic
Model without trend	-2.966
Model with trend	-3.279

Notes. In ADF test, MacKinnon (1996) critical values are -4.98, -4.43, and -4.15 on model with trend, and -4.66, -4.10 and -3.81 on model without trend for 1%, 5%, 10% meaningfulness levels.

The traditional approach to cointegration assumes that cointegration vectors are time invariant. However, Gregory and Hansen (1996) argue that the rejection of cointegration may be to a shift in the cointegration vector during the sample period. The test developed by Gregory and Hansen (1996) (GH hereafter) accounts for one structural change that occurs at an unknown time. The three models proposed by GH shall be used here. The results for GH cointegration test are given in the following table[4]. Given that if the test statistic is below the critical value, the null hypothesis of no cointegration can be rejected in favour of the hypothesis cointegration, table 10 show that we reject the null hypothesis only for the C model. We may point out that for all cases a break is estimated to occur on August 2002. In Figure 3, 4, and 5 we graph the Gregory and Hansen statistics: clearly there is a well-defined single minimum for all three models.

Table 10 - Test for structural breaks – Gregory and Hansen (1996) cointegration test

Model specification	Breakpoint	GH Test statistic	5% Critical Value	Ho: No cointegration
Fullbreak (C/S)	2002:08:13	-5.760	-6.41	No Reject
Trend (C/T)	2002:08:13	-5.717	-5.83	No Reject
Constant (C)	2002:08:13	-5.750	-5.56	Reject

The critical values for the Gregory-Hansen tests are drawn from Gregory and Hansen (1996).

Figure 3 - Fullbreak model

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[4] We use standard Gregory and Hansen test procedure from Estima all computations were done using Rats 6.3 software.
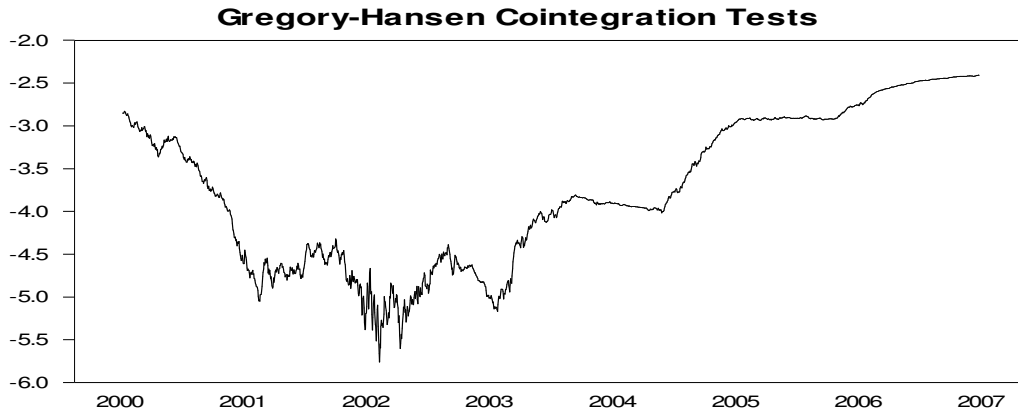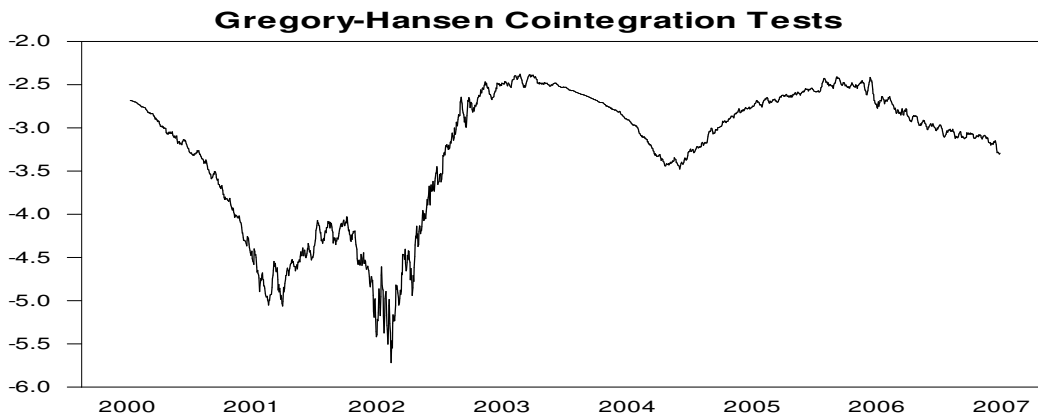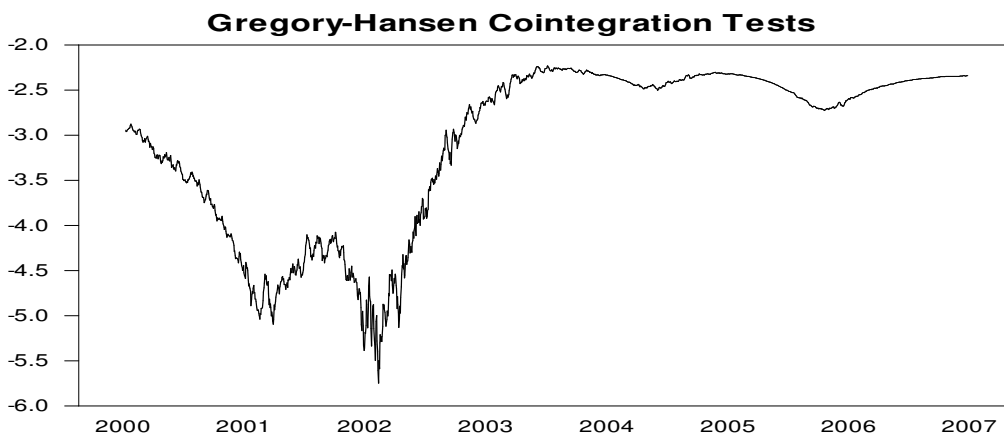
Figure 4 - Trend model

Figure 5 - Constant model

Estimation of our bivariate BEKK GARCH(1,1) were estimated with the restriction that off-diagonal terms of matrix A_1 and B_1 are zero[5]: so this specification implies that the parameters of variance covariance matrix H_t are estimated as follows:

$$H_t = \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix}' \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix} + \begin{bmatrix} a_{11}^* & 0 \\ 0 & a_{22}^* \end{bmatrix} \begin{bmatrix} r_{x,t-1}^2 & r_{x,t-1} \cdot r_{y,t-1} \\ r_{y,t-1} \cdot r_{x,t-1} & r_{y,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11}^* & 0 \\ 0 & a_{22}^* \end{bmatrix} + \begin{bmatrix} b_{11}^* & 0 \\ 0 & b_{22}^* \end{bmatrix} H_{t-1} \begin{bmatrix} 0 & b_{12}^* \\ b_{21}^* & 0 \end{bmatrix} \quad (26)$$

We can re-write the above matrix as follows:

$$\begin{cases} h_x^2 = c_{11}^2 + a_{11}^2 \cdot r_{x,t-1}^2 + b_{11}^2 \cdot h_{x,t-1}^2 \\ h_{y,t}^2 = c_{22}^2 + c_{12}^2 + a_{22}^2 r_{y,t-1}^2 + b_{22}^2 h_{y,t-1}^2 \\ h_{xy,t}^2 = c_{12} \cdot c_{11} + a_{11} \cdot a_{22} \cdot r_{x,t-1} \cdot r_{y,t-1} + b_{11} \cdot b_{22} \cdot h_{xy,t-1}^2 \end{cases} \quad (27)$$

Following the specification above, the estimates of our bivariate BEKK GARCH(1,1) models are given in table 11. As we can see, all estimated parameters are statistically significant at the 5% level.

Table 11 – Bivariate GARCH(1,1) estimates

	DAX30 and BUX	DAX30 and WIG	DAX30 and PX50
c_{11}	0.001462**	0.0015**	0.001484**
	(0.000131)	(0.00013)	(0.000217)
c_{22}	0.001092**	0.0007**	0.001022**
	(0.000191)	(0.00012)	(0.000156)
c_{12}	0.002329**	0.0014**	0.002169**
	(0.000176)	(0.0001)	(0.000147)
a_{11}	0.280589**	0.2984**	0.278534**
	(0.010827)	(0.0107)	(0.0105)
a_{22}	0.280129**	0.222**	0.315**
	(0.0188)	(0.0094)	(0.012)
b_{11}	0.955641**	0.950**	0.956**
	(0.0035)	(0.003)	(0.0032)
b_{22}	0.945435**	0.968**	0.933**
	(0.0047)	(0.0029)	(0.0120)

Notes. ** denotes statistical significance at 5% level.

Results of the table 11, allows us to calculate the conditional variance covariance matrix of the returns for each BEKK bivariate GARCH(1,1) model. The estimation of our bivariate BEKK GARCH(1,1) model relatively to the DAX30 and BUX30 indices is given in equation (18). Using the notation r_{Dax30} for the return on the German DAX30 index, and r_{Bux30} for the Hungarian stock index, equation (18) shows the intertemporal interaction between returns on the DAX30 index and the BUX index. Estimates for the coefficients on the product of the returns shocks (i.e. $r_{Dax30,t-1}^2$, $r_{Bux30,t-1}^2$, $r_{Dax30,t-1}^2 r_{Bux,t-1}^2$) appear to be larger than zero. For the estimated coefficients on

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[5] The reason is that the BEKK GARCH model have been estimated by Eviews5.1 software which include a program (called BV_GARCH) that estimates the bivariate BEKK models with the restrictions described previously.

$r^2_{Dax30,t-1}r^2_{Bux,t-1}$, this implies that two shocks of the same sign affect the conditional covariance between the return on DAX30 and the return on BUX index positively, while two shocks of opposite signs have a negative effect on the forecast covariance. Examining the coefficients on the lagged volatilities (i.e. $h^2_{Dax30,t-1}$, $h^2_{Bux30,t-1}$, $h^2_{Bux30Bux,t-1}$), we may note that these values are near 1, this means that a large part of the the information comes from the previous day forecast volatility.

$$
\begin{cases}
h^2_{Dax30,t} & = \quad 0.0000021 \quad + \quad 0.0787 \cdot r^2_{Dax30,t-1} \quad + \quad 0.913 \cdot h^2_{Dax30,t-1} \\
h^2_{Bux,t} & = \quad 0.0000062 \quad + \quad 0.0784 \cdot r^2_{Bux,t-1} \quad + \quad 0.893 \cdot h^2_{Bux,t-1} \\
h^2_{DaxBux,t} & = \quad 0.0000016 \quad + \quad 0.0786 \cdot r_{Dax30,t-1} \cdot r_{Bux,t-1} \quad + \quad 0.903 \cdot h^2_{Dax30Bux,t-1}
\end{cases}
\tag{28}
$$

Equation (19) shows the intertemporal interaction between returns on the DAX30 index and the PX50 index. The magnitude of the coefficients of equation X2 are slightly different but the conclusions are the same of the above eqaution.

$$
\begin{cases}
h^2_{Dax30,t} & = \quad 0.0000022 \quad + \quad 0.07758 \cdot r^2_{Dax30,t-1} \quad + \quad 0.914 \cdot h^2_{Dax30,t-1} \\
h^2_{Px50,t} & = \quad 0.0000057 \quad + \quad 0.09926 \cdot r^2_{Px50,t-1} \quad + \quad 0.870 \cdot h^2_{Px50,t-1} \\
h^2_{Dax30Px50,t} & = \quad 0.0000032 \quad + \quad 0.0877 \cdot r_{Dax30,t-1} \cdot r_{Px50,t-1} \quad + \quad 0.796 \cdot h^2_{Dax30Px50,t-1}
\end{cases}
\tag{29}
$$

Finally equation (20) show the interaction between DAX30 index and WIG index. Also in this case shocks of the same sign affect the conditional covariane between the return of the DAX30 and the return of the WIG positively, while shock of opposite signs have a negative effect on the forecast covariance. Lagged volatilities have a greater effect on the volatilities at time t, so new informatio have a small effect on the volatility at time *t*.

$$
\begin{cases}
h^2_{Dax30,t} & = \quad 0.0000023 \quad + \quad 0.0891 \cdot r^2_{Dax30,t-1} \quad + \quad 0.903 \cdot h^2_{Dax30,t-1} \\
h^2_{Wig,t} & = \quad 0.0000025 \quad + \quad 0.0493 \cdot r^2_{Wig,t-1} \quad + \quad 0.937 \cdot h^2_{Wig,t-1} \\
h^2_{Dax30Wig,t} & = \quad 0.0000021 \quad + \quad 0.520 \cdot r_{Dax30,t-1} \cdot r_{Wig,t-1} \quad + \quad 0.920 \cdot h^2_{Dax30Wig,t-1}
\end{cases}
\tag{30}
$$

To obtain better knowledge of our results, we can have a look at the graph of the conditional variance of returns of each bivariate BEKK GARCH(1,1) model estimates. In general, Fig.6 show that the Hungarian market seems to be more risky than the German markets especially in the second parte of the sample period.

**Figure 6 – Bivariate GARCH(1,1) model: DAX30 and BUX estimated conditional variances**
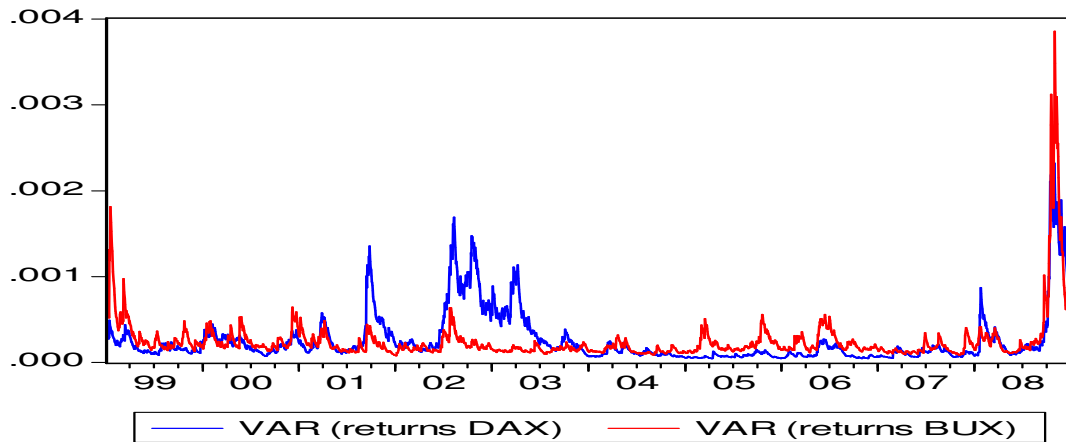
If we move to the estimated conditional variance of the DAX3 and PX50 estimates, we may see that also in this case the emerging equity market of the Czech republic is more risky than the DAX30 equity markets especially in the last part of the sample period.

Figure 7 – Bivariate GARCH(1,1) model: DAX30 and PX50 estimated conditional variances
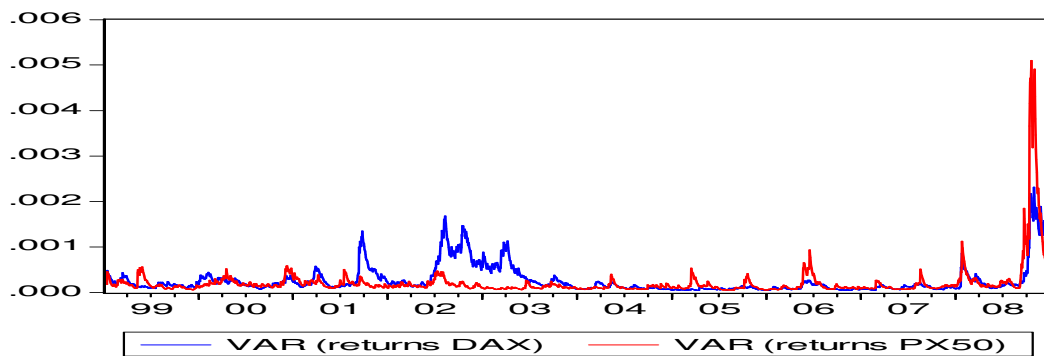
Finally, moving to the estimated conditional variance of the DAX3 and WIG returns, we may see that the DAX30 equity market seem to be more risky than the Polish WIG equity market.

Figure 8 – Bivariate GARCH(1,1) model: DAX and WIG estimated conditional variances
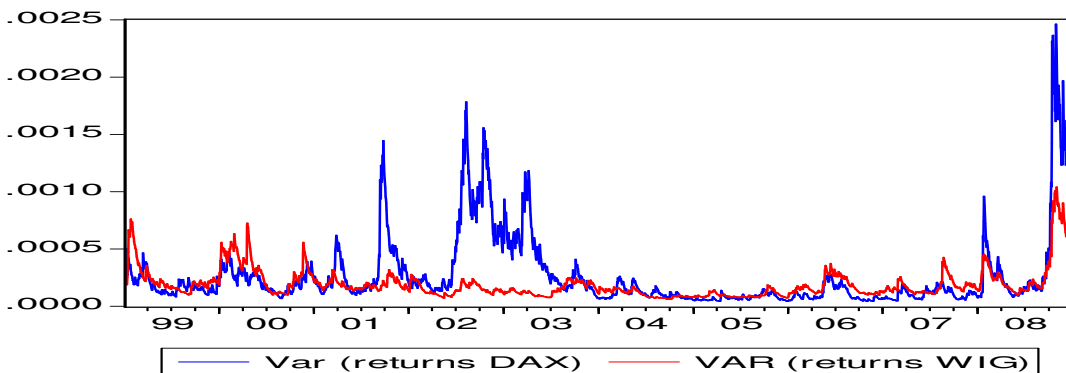
Figures 9, 10, and 11 show the conditional correlation between each pair wise of stock market returns. We see clearly that the conditional correlation is not constant over time on all cases.

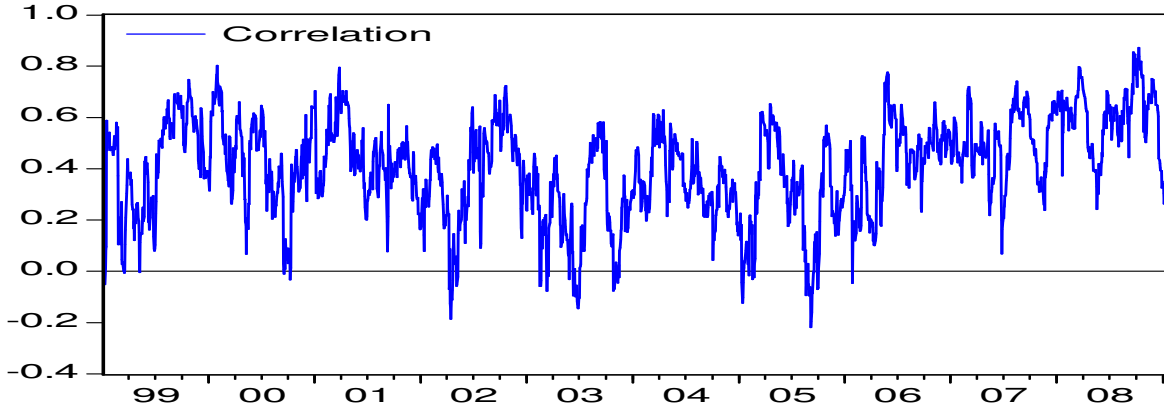**Figure 9 – Conditional correlation among Dax30 and Bux stock market returns, Bivariate BEKK model**

Figure 10 – Conditional correlation among Dax30 and Wig stock markets returns, Bivariate BEKK model
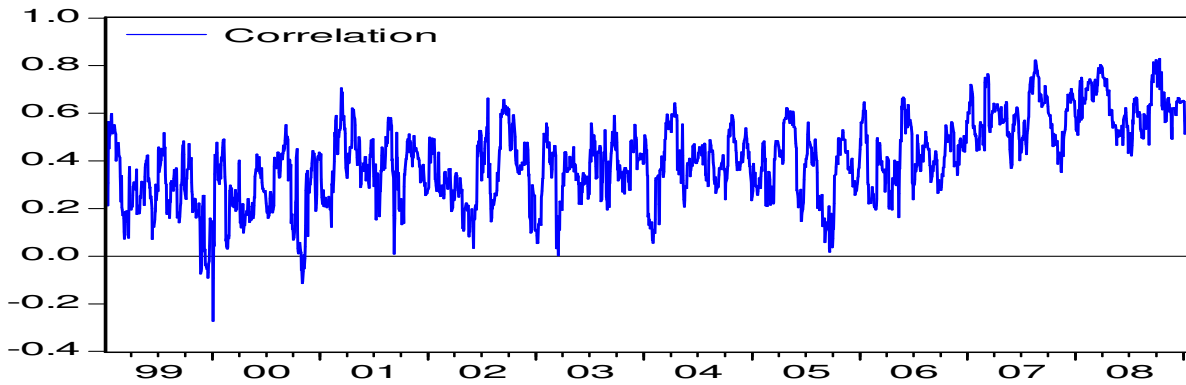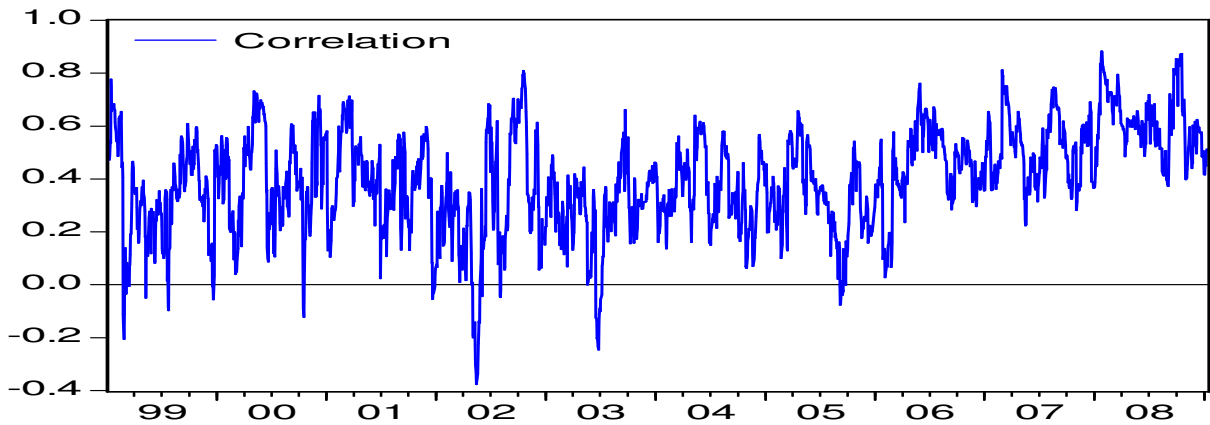

Figure 11 – Conditional correlation among Dax30 and PX50 stock market returns, Bivariate BEKK model

In order to investigate further time varying correlation across markets we estimated the DCC model. The first step of this methodology is to estimate each of the series by a univariate model. Almost all of the parameters of the GARCH (1,1) are significant at the 5% level (table 12). With respect to the persistence, our results indicate that the sum of the estimated coefficients of the variance equation (that is $\alpha + \beta$) is close to unity: this means that volatility exhibits a highly persistent behaviour.

Table 12 – DCC Full Sample model step 1: Estimation results of univariate GARCH(1,1) models

	μ	Ω	α	β	α + β
DAX30	0.066**	0.0241**	0.097**	0.894**	0.991
	(0.021)	(0.006)	(0.01)	(0.011)	
BUX	0.077**	0.069**	0.09**	0.879**	0.969
	(0.025)	(0.017)	(0.011)	(0.01)	
PX50	0.0981**	0.052**	0.118**	0.854**	0.972
	(0.021)	(0.010)	(0.013)	(0.014)	
WIG	0.065**	0.027**	0.069**	0.919**	0.988
	(0.023)	(0.008)	(0.008)	(0.010)	

Notes. The table summarizes the estimated coefficients produced by the univariate GARCH(1,1) model. The univariate variance estimates are introduced as inputs in the estimation process of the Dynamic Conditional Correlation (DCC) model. The estimated coefficient Ω denotes the constant term, α and β are the ARCH and GARCH terms, respectively, in the conditional variance equations. The sum α + β indicates volatility persistence. Figures in (.) are standard errors. ** indicates significance at 5% level.

Using the standardized residuals from the first step, we continue with the second step of the estimation procedures for DCC models by estimating the conditional correlations among the DAX30 index and the CEE equity indices returns. According to the table 13, we can say that the constant and the coefficient parameters are significant at 5%. The sum of the estimated coefficients *a* and *b* in the variance equation is close for unity, implying that volatility exhibit a highly persistent behaviour

Table 13 – DCC GARCH (1,1)

	a	b
Dax30-Bux	0.001**	0.978**
	(8.05e-10)	(2.14e-08)
Dax30-Px50	0.0174**	0.974**
	(0.005)	(0.009)
Dax30-Wig	0.006**	0.977**
	(0.003)	(0.012)

Notes. The table summarizes the estimates coefficients produced by the ADCC model in a bivariate framework for CEE and German equity markets. Figures in (.) are standard errors. ** indicate statistical significance at 5% level.

The Dynamic Conditional Correlations obtained from the DCC-GARCH models are plotted in figure 9,10, and 11. It shows varying patterns in the correlation dynamic path, which justifies the use of the DCC-GARCH modelling strategy. It clearly shows an increase in the average level of the conditional correlations among the German index and the CEE indices after the inclusion of these

countries to the EU. The German stock markets exhibit the highest correlation with the Czech and the Hungarian stock indices. We also note that the correlation between Germany and the CEE market raised dramatically during the 2008. This could be due to the recent financial turmoil however we do not specifically test the effect of financial crisis on the changes in the correlations. After the financial crisis we observe a sharp decline in the intensity of the co-movements (i.e. Germany-Hungary, Germany-Czech Republic, and Germany-Poland).
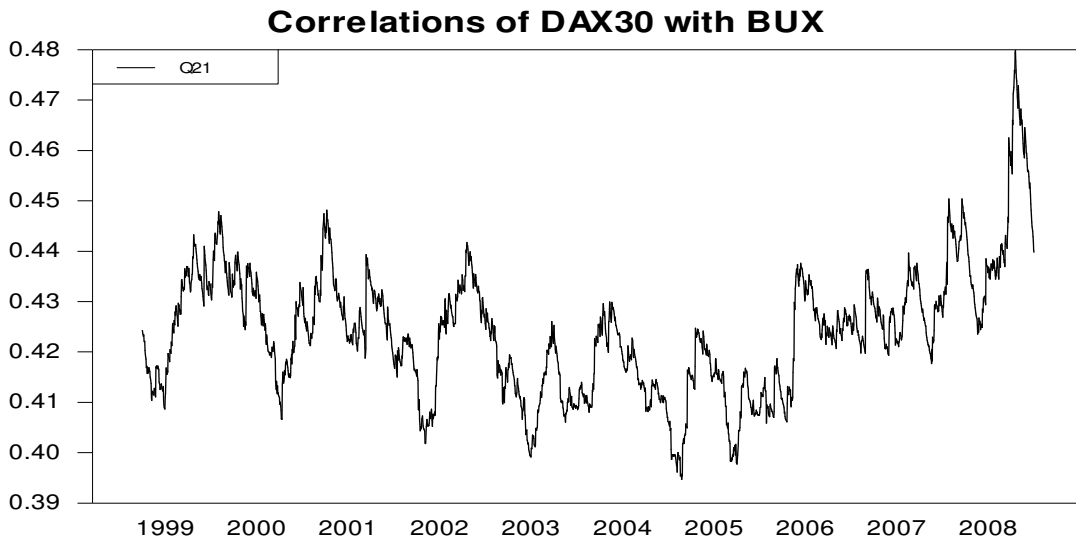
Figure 12 – Correlation of DAX30 with BUX

Figure 13 – Correlations of DAX30 with PX50
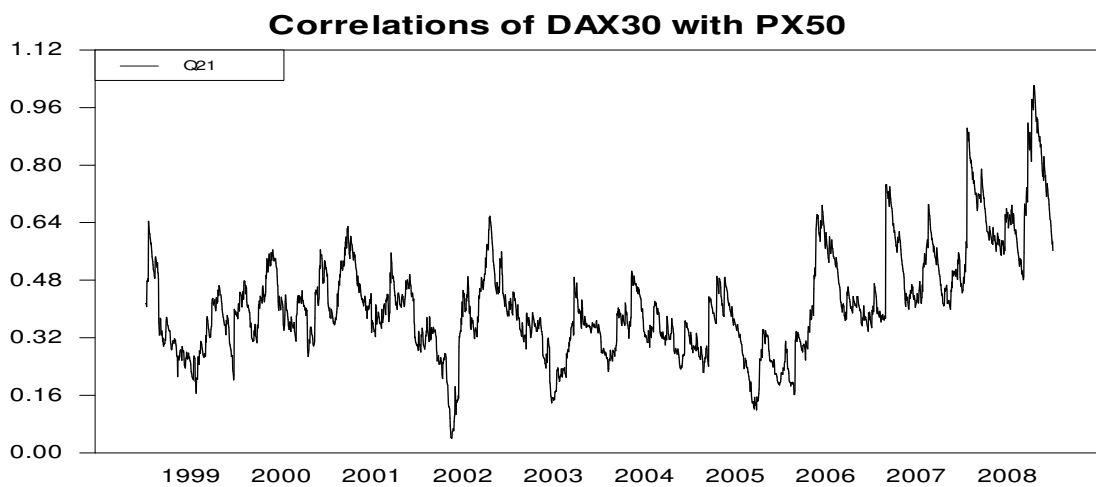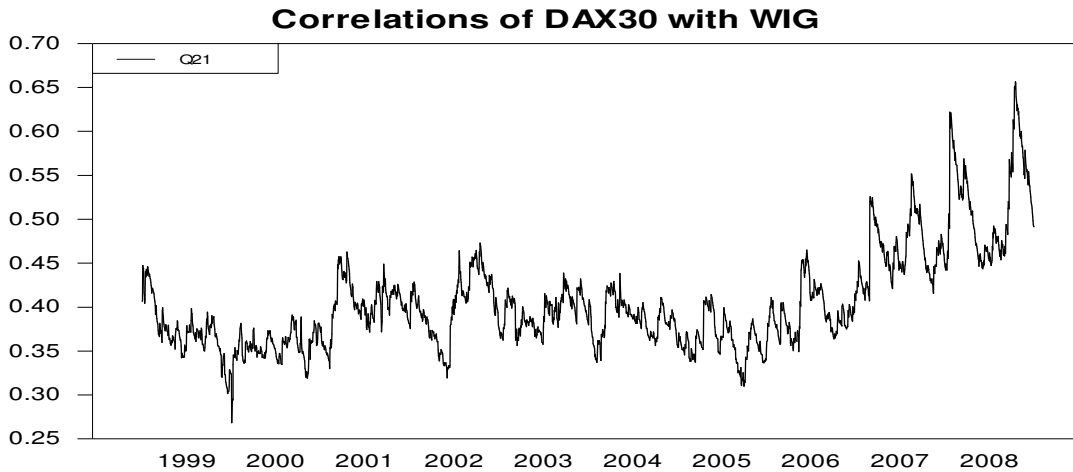

22

Figure 14 – Correlations of DAX30 with WIG

5. Conclusions

This study investigates the linkages between the German and the CEE emerging equity markets. Multivariate cointegrating methodologies are used to detect long run relationships among these markets. Results from a Granger causality tests suggest that the German market prices Granger-cause the prices on the CEE markets where as the results from the more sophisticated tests of cointegration find no co integration in these markets, while taking into account the possibility of a structural shift there are evidence of long run relationships. Moving to the BEKK GARCH(1,1) models results we may see that the conditional correlation seem to vary strongly over time, although in the last period we observe German and CEE equity markets have increased their correlation. Also the DCC analysis shows that the correlations between the German and individual CEE markets have increased since the accession of these countries into the EU confirming BEKK models results.

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