An analysis of CEE equity market integration and their volatility spillover effects

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Abstract

Purpose – The purpose of this paper is to examine the conditional correlations and spillovers of volatilities across CEE markets, namely, Hungary, Poland, the Czech Republic, Romania and Croatia, in the post-2007 financial crisis period.

Design/methodology/approach – The authors use five-dimensional GARCH-BEKK alongside with the CCC and DCC models.

Findings – The estimation results of the three models generally demonstrate that the correlations between these markets are particularly significant. Also, own-volatility spillovers are generally lower than cross-volatility spillovers for all markets.

Practical implications – These results recommend that investors should take caution when investing in the CEE equity markets as well as diversifying their portfolios so as to minimize risk.

Originality/value – Unlike the previous studies in this field, this paper is the first study using multivariate GARCH-BEKK alongside with CCC and DCC models. The study makes an outstanding contribution to the existing literature on spillover effects and conditional correlations in the CEE financial stock markets.

Keywords Volatility spillovers, DCC, BEKK, CCC, CEE finance, Conditional correlations

Paper type Research paper

1. Introduction

The issue of financial liberalization and market integration is a central theme in international finance, and has received great attention in the financial literature, particularly after the financial market crisis in 1997–1998 (Bhar and Nikolova, 2009). Experiences to date confirm that financial integration has witnessed an increase at the end of the last century and associated with common globalization. As per Panda and Nanda (2018), the cause of driving international financial integration and volatility transmission is due to the rapid increase in the globalization of world financial markets and greater volatility transfer among the markets. More importantly, openness of financial markets not only makes substantial contribution to economic development but also makes developing countries more vulnerable to financial disruptions (Levine and Schmukler, 2007). The properties of volatilities commonly seen in equity returns consist of volatility clusters, varying over time, infinite non-divergence, varying according to price movements (Panda and Nanda, 2018). These determinants play a prominent role in the development of volatility models.

There are several kinds of methodologies to capture the volatility spillover effects. For instance, Hung (2018) employs multivariate EGARCH model to explore the volatility transmissions among foreign exchange markets in CEE countries. Kanas (2000) also uses the EGARCH model to investigate the interdependence of stock returns and exchange rates within the same economy. Prasad *et al.* (2018) use spillover index to study volatility

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spillovers among developed and emerging stock markets. Singh *et al.* (2010) highlight the price and volatility spillovers across North American, European and Asian stock markets using the VAR-GARCH model. Hung (2019) applies the ADCC model to perfectly capture the dynamic conditional correlation (DCC) between China and Southeast Asian countries. Overall, GARCH-type models are widely used to examine the volatility spillover effects and its persistence over a period of time.

In this paper, we used the sophisticated collection of volatility models for five Central and Eastern European equity markets (Hungary, Poland, the Czech Republic, Romania and Croatia), the models are based on the multivariate GARCH families as pioneered in Engle (2002). We investigate the spillover of volatility from one country to another for the system of countries after the global financial crisis. We find evidence that the structure of the conditional correlations was statistically significant. Further, modeling the spillover mechanism tremendously boosts the predictability of volatility throughout the region.

The empirical design aims at analyzing the conditional correlations and spillover effects utilizing three models, namely, multivariate GARCH-BEKK, CCC and DCC. The three models are commonly used in previous studies to investigate the volatility spillovers and its connectedness across stock markets, for example, Mohammadi and Tan (2015), Panda and Nanda (2018), Majdoub and Mansour (2014), Kim *et al.* (2015), Wong (2017), etc. These papers are closely related to this study in that we are interested in the following issues: obvious explanation of three types of spillover effects (mean-to-mean, volatility-to-mean and volatility-to-volatility) between the five CEE countries; and successful capture of DCCs in all pair countries. To address the above problems, we use MGARCH-BEKK, CCC and DCC models to estimate respectively. Overall, this paper provides a general picture of how the degree of co-movement and the conditional correlation between emerging and frontier markets in CEE region and thus contributes to the existing finance literature and research on equity market integration in CEE countries.

The rest of the paper is organized as follows: Section 2 represents a brief review of literature on the investigations of volatility spillovers across the markets. Section 3 describes the methodology and data. Section 4 reports the empirical results and discusses the findings in detail. Section 5 concludes the paper.

2. Literature review

One of the indispensable issues in stock market investments has been the all-inclusive concept of inter-market information spillovers as well as their interrelatedness. Voluminous studies have been devoted to exploring integration and spillover effects among stock markets. To the best of our knowledge, most of the studies have shed light on some common occurrences such as market liberation and market crisis on the transmission of information across borders. A collection of predominant empirical studies with regard to the interdependence among national stock markets has been brought out.

Most of the studies predominantly focus on the interdependence of developed markets such as the US, Japanese and major European markets (Koutmos and Booth, 1995; Ko and Lee, 1991; Maghyereh *et al.*, 2015). Some researchers have paid much attention to the developed Asian and emerging markets (Jebran *et al.*, 2017; Kim *et al.*, 2015). Early studies confirm that there are a slight integration and spillover effects between stock markets (Panton *et al.*, 1976; Bhar and Nikolova, 2009; Liu and Pan, 1997). However, most recent investigations applying the development of advanced technology and financial deregulation of financial markets has demonstrated strong interdependence between them (Jebran *et al.*, 2017; Okičić, 2015; Baumöhl *et al.*, 2018; Huo and Ahmed, 2017; Panda and Nanda, 2018; BenSaïda *et al.*, 2018).

More recently, there are several exciting studies under the GARCH-type frameworks. For example, Majdoub and Mansour (2014) examine the conditional correlations across the US market and a sample of five Islamic emerging markets (Turkey, Indonesia, Pakistan, Qatar and Malaysia) using multivariate GARCH-BEKK, CCC and DCC models. They state that the US and Islamic emerging markets are weakly correlated over time and the absence of volatility spillover from the US market to the Islamic emerging equity markets. At the same time, Gilenko and Fedorova (2014) focus on the mean-to-mean, volatility-to-mean and volatility-to-volatility spillover effects for the stock markets of BRIC countries. Their analysis from the four-dimensional GARCH-BEKK model reports that the impact of external spillovers from the developed stock markets of the US to Chinese market; Germany has a positive impact on Brazil and China and a negative one on Russia in the pre-crisis period. Further, the findings suggest that the linkages between the developed and the emerging BRIC stock markets have significantly changed after the crisis. In a same vein, Natarajan *et al.* (2014) provide useful insights into how information is transmitted and disseminated across stock markets. Mohammadi and Tan (2015) investigate the dynamics of daily returns and volatility in stock markets of the USA, Hong Kong and Mainland China over the period 2001–2013 by multivariate GARCH, CCC and DCC approach. The results indicate evidence of unidirectional return spillovers from the USA to the other markets, non-persistence of volatility spillover between Hong Kong and mainland China markets and there exist volatility spillovers from the USA to other three markets. Specifically, there is an increase in correlation between China and other stock markets based on the DCC model. Bissoondoyal-Bheenick *et al.* (2018) evaluate the stock market volatility spillover between three closely related countries, namely, the USA, China and Australia. Their conclusions indicate evidence of the significant bilateral causality between the countries, unidirectional volatility spillover from the USA to China, the insignificant volatility spillover from the Australian to Chinese stock markets when they take into consideration the market index level and across most of the industries for the full sample period 2007–2016. In the Asian emerging markets context, Jebran *et al.* (2017) compare the volatility spillover effects among five Asian emerging markets between pre and post-crisis period using the multivariate EGARCH model. The results highlight that the integration of emerging markets of Asia has significant implications for investors and policy makers. According to Vo and Ellis' (2018) correlation, return spillover and volatility spillover between Vietnamese stock market and other leading equity markets of the USA, Hong Kong and Japan are extremely significant employing the VAR-GARCH-BEKK frameworks. Panda and Nanda (2018) capture the return volatility and the extent of DCC between the stock markets of North America region using MGARCH-DCC. This paper reports that emerging markets are less linked to the developed market in terms of returns and weak co-movement between stock markets. More recently, Baumöhl *et al.* (2018) show the persistence of significant temporal proximity effects between markets and somewhat weaker temporal effects with regard to the US equity market, provide evidence of volatility spillovers that present a high degree of interconnectedness. The models used in this paper are ARFIMAX-GARCH. Abbas *et al.* (2019) employ Diebold and Yilmaz spillover index to investigate the interplay between return and volatility spillover effects of the stock markets and macroeconomic fundamentals for the G-7 countries, provide strong interactions between the returns and volatilities of the G-7 stock markets. Panda *et al.* (2019) explore the short-term and long-term interdependence and volatility spillovers among stock markets of Africa and Middle East region using VECM and MGARCH-BEKK models. The paper shows that the intercorrelations of stock markets are not uniform and volatility transmissions are significant across all the countries of the region.

In European countries context, Shields (1997) takes into account two emerging Eastern European markets (Hungary and Poland) to examine stock return volatility using the Tobit GARCH model. He concludes that no asymmetry exists in either emerging market. Scheicher (2001) studies the regional and global integration of stock markets in Hungary, Poland and the Czech Republic by applying VAR-GARCH approach, and finds that there is an existence of limited interaction in returns both regional and global shocks, but news to innovations to volatility have a primarily regional character. At the same time, Murinde and Poshakwale (2001) examine volatility in the six emerging stock markets including Croatia, the Czech Republic, Hungary, Poland, Russia and Slovakia. Their estimations based on ARIMA, the BDSL procedure and symmetric as well as asymmetric GARCH models pointed out that daily return volatility exhibits significant conditional heteroskedasticity and non-linear effects. Recently, estimating the behavior of stock returns in the case of stock markets from Central and Eastern Europe mainly concerned with the relationship between returns and conditional volatility was conducted by Okičić (2015). The findings provide parsimonious approximations of conditional mean and volatility dynamics in daily return series based on ARIMA and GARCH specifications, and the author presents strong evidence of the existence of a leverage effect in the selected stock markets. In these Central and Eastern European countries, based on weekly data, Melik Kamisli *et al.* (2015) also look in the structure of conditional correlations between stock markets returns as well as observed the volatility transmission between countries. By using MGARCH-CCC-DCC models, the results of this study have some key findings analogous to Okičić (2015). The findings imply that most of the conditional correlations between stock markets returns of the selected nations are constant.

Despite the wealth of finance literature in connection with equity market return and volatility spillover effects, particularly under Central and Eastern European countries – the conditional correlations-spillover effects – there remains very little in this region. The aim and the outstanding contribution of this paper are to fill this gap.

3. Data and methodology

Methodology

The dynamic connectedness among indexes is captured by employing a multivariate MGARCH model. We first take into consideration the conventional BEKK model (Engle and Kroner, 1995) in this study because it has a good property according to which the conditional covariance matrices are positive definite by construction (Majdoub and Mansour, 2014). We then use the multivariate GARCH with constant conditional correlation of Bollerslev (1990) and the multivariate GARCH model with the DCC of Engle (2002) as a benchmark to estimate time-varying conditional correlation between stock markets.

MGARCH (1,1) model. A VECH-GARCH model is proposed by Bollerslev *et al.* (1988) in which the conditional variance and covariance are a function of all lagged conditional variance and covariance. The model can be written as:

$$vech(H_t) = C_0 + \sum_{i=1}^{q} A_i vech\left(\varepsilon_{t-1}\varepsilon'_{t-1}\right) + \sum_{i=1}^{p} B_i vech(H_{t-1}), \tag{1}$$

where "*vech*" is the operator that stacks the lower triangular portion of a symmetric matrix into a vector (Majdoub and Mansour, 2014). C_0 is a $k(k+1)/2\times 1$ vector, and A_i and B_i are $k(k+1)/2\times k(k+1)/2$ matrices of parameters. The number of parameters is quite large in the formulation of multivariate GARCH model. The conventional BEKK model is utilized with multivariate GARCH (1,1) specification, whose conditional covariance matrix H_t is given by:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \tag{2}$$

where C is a $k\times k$ lower triangular matrix of constants, and A and B are $k\times k$ matrices. Note that off-diagonal elements of A and B provide information on news effect and volatility spillover effect, respectively, while diagonal elements relate to its own ARCH and GARCH effects (Kim *et al.*, 2015). For example, we explore the volatility spillover effect from stock market 1 to stock market 2; we should test whether the coefficients a_{12} and b_{12} are statistically significantly different from zero and vice versa (Kumar, 2013). The parameters of the BEKK model can be estimated by applying the maximum likelihood estimation assuming a normal distribution of errors. The following likelihood function is maximized:

$$L(\theta) = -T\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\log|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right), \tag{3}$$

where T is the number of observations and θ is the vector of parameters to be estimated. We utilize numerical maximization techniques to maximize the non-linear likelihood function. The Broyden–Fletcher–Goldfarb–Shanno algorithm is used to obtain the initial condition and the final parameter estimates of the variance-covariance matrix.

The constant conditional correlation model. We next apply the CCC model estimator (Bollerslev, 1990). The CCC-MGARCH model allows for time-varying conditional variances and covariances. The conditional variance matrix is now defined as:

$$H_t = D_t R D_t = \rho_{ij}\sqrt{h_{ii,t}h_{jj,t}}, \tag{4}$$

where D_t is the $(n\times n)$ diagonal matrix that the diagonal elements are the conditional standard deviations, and R is a $(n\times n)$ time-invariant correlation matrix.

A GARCH (1,1) specification of each conditional variance can be written as:

$$h_{ii,t} = c + a_i\varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}, \tag{5}$$

$$h_{ij,t} = \rho_{ij}\sqrt{h_{ii,t}h_{jj,t}},\ i,j = \overline{1,n}, \tag{6}$$

where c is a $n\times1$ vector, a_i and b_i are diagonal $(n\times n)$ matrices.

According to Gjika and Horvath (2013), the conditional correlations are constant may be restricted and unrealistic in many empirical applications, so Engle (2002) proposes the DCC model that is a direct generation of the CCC model of Bollerslev (1990) by making the conditional correlation matrix time dependent.

The DCC model. The DCC is employed. Engle (2002) introduced this estimator to capture the dynamic time-varying behavior of conditional covariance. The conditional covariance matrix H_t is now defined as:

$$H_t = D_t R_t D_t, \tag{7}$$

where $D_t = \mathrm{diag}\sqrt{\{H_t\}}$ is the diagonal matrix with conditional variances along the diagonal, and R_t is the time-varying correlation matrix.

Equation (7) can be re-parameterized with standardized returns as follows, $e_t = D_t'\varepsilon_t$:

$$E_{t-1}e_t e_t' = D_t^{-1}H_t D_t^{-1} = R_t = \left[\rho_{ij,t}\right]. \tag{8}$$

Engle (2002) suggests the following mean-reverting conditionals with the GARCH (1,1) specification:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}, \tag{9}$$

where:

$$q_{ij,t} = \overline{\rho}_{ij}(1-\alpha-\beta)+\alpha e_{i,t-1}e_{j,t-1}+\beta q_{ij,t-1}, \tag{10}$$

and $\overline{\rho}_{ij}$ is the unconditional correlation between $e_{i,t}$ and $e_{j,t}$. Scalar parameters α and β must satisfy:

$$\alpha \geqslant 0,\ \beta \geqslant 0,\ \text{and}\ \alpha+\beta<1.$$

The value of ($\alpha + \beta$) close to 1 reveals high persistence in the conditional variance.

In the matrix form:

$$Q_t = \overline{Q}(1-\alpha-\beta)+\alpha e_{t-1}e'_{t-1}+\beta Q_{t-1}, \tag{11}$$

where $\overline{Q} = Cov\left[e_t, e'_t\right] = E\left[e_t, e'_t\right]$ is the unconditional covariance matrix of the standardized errors $\overline{Q}$ can be estimated as:

$$\overline{Q} = \frac{1}{T}\sum_{t=1}^{T} e_t e'_t, \tag{12}$$

R_t is then obtained by:

$$R_t = \left(Q_t^*\right)^{1/2} Q_t \left(Q_t^*\right)^{1/2}, \tag{13}$$

where $Q_t^* = \text{diag}\{Q_t\}$.

To estimate the DCC model, Engle (2002) proposes a two-step approach; we have the log-likelihood function when $k = 2$ is:

$$\begin{aligned} L &= -\frac{1}{2}\sum_{t=1}^{T}\left(2\ln(2\pi)+\ln|H_t|+\varepsilon'_t H_t^{-1}\varepsilon_t\right) \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(2\ln(2\pi)+\ln|D_t R_t D_t|+\varepsilon'_t D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t\right) \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(2\ln(2\pi)+2\ln|D_t|+\ln|R_t|+\varepsilon'_t D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t\right), \end{aligned}$$

replacing with $\varepsilon'_t D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t = e'_t e_t$ to it, we rewrite the log-likelihood as the volatility component L_V and correlation L_C. Let ϕ denote a vector of parameters in D_t and φ be parameters in R_t. We have:

$$L(\phi,\varphi) = L_V(\phi)+L_C(\varphi),$$

where:

$$L_V(\phi) = -\frac{1}{2}\sum_{t=1}^{t}\sum_{i=1}^{2}\left(\ln(2\pi)+\ln\left(h_{ii,t}\right)+\frac{\varepsilon_{i,t}^2}{h_{ii,t}}\right),$$

$$L_C(\varphi) = -\frac{1}{2}\sum_{t=1}^{T}\left(e'_t R_t^{-1} e_t - e'_t e_t + \ln|R_t|\right).$$

By maximizing $L_V(\phi)$ and $L_C(\varphi)$, we may obtain the parameter ϕ and φ, respectively.

Data

In this paper, we use daily data from Bloomberg over September 2008 through September 2017 of five Central and Eastern European countries, namely, Hungary, Poland, Czech Republic, Romania and Croatia. Table I represents the main indexes we use. The number of observations across the market is 2,123, which is less than the total number of observations because the joint modeling of five markets requires matching returns. The daily return data series are calculated as $R_t = 100 \times \ln(P_t/P_{t-1})$, where P_t is the price level of the market at time t. The logarithmic stock returns are multiplied by 100 to approximate percentage changes and avoid convergence problems in estimation. The study uses R in order to estimate the aforementioned models.

Table II provides several descriptive statistics for the stock returns across markets. These statistics refer to the first five moments if the series, their normality, heteroscedasticity and stationarity. According to the standard deviation of time series, Hungary and Romania embed the higher risk. Most of the series illustrate a positive kurtosis and negative skewness, while their distributions are leptokurtic. Further evidence of non-normal distribution forms is formally confirmed by the Jarque–Bera test statistics. Similarly, the PP and ADF test for the first log differences of CEE stock markets could not accept the existence of a unit root. Finally, the ARCH test illustrates the presence of autocorrelation and heteroskedasticity issues in data, underlying the necessity of applying a time-varying volatility GARCH-type models for studying the spillover effects of financial stress among the CEE nations. Table III documents the unconditional correlation matrix across stock market returns.

Figure 1 shows the fluctuation of the daily series of indexes for the five countries during the sample period covering over 2008–2017. Overall, the index series have almost the same trend overtime. The index returns in log differences are shown in Figure 2. Daily returns vary around zero and are characterized by volatility clustering.

Stock market	Benchmark
Hungary	Budapest Stock Exchange BUX
Poland	Warsaw Stock Exchange WIG
The Czech Republic	Prague Stock Exchange PX
Romania	Bucharest Stock Exchange BET
Croatia	Zagreb Stock Exchange CRON

Table I.
Stock markets and indexes

Countries	Hungary	Poland	Czech	Romania	Croatia
Mean	0.0278	0.0218	−0.0159	0.0163	−0.0309
Median	0.0465	0.0554	0.0233	0.0504	−0.0047
Maximum	22.016	8.4639	12.364	10.564	14.778
Minimum	−14.985	−8.2888	−19.901	−14.754	−14.587
SD	1.7085	1.2903	1.5844	1.6108	1.2508
Skewness	0.3525	−0.3405	−1.2358	−1.0197	−0.6072
Kurtosis	23.391	9.5029	27.580	17.187	27.580
Jarque–Bera	36,825*	3,781.7*	53,986*	18,174*	75,053*
PP test	−45.349*	−42.929*	−44.718*	−44.696*	−43.424*
ADF test	−45.340*	−33.826*	−35.777*	−44.713*	−25.497*
ARCH test	92.763*	90.151*	360.76*	300.03*	300.45*

Notes: All returns are expressed in percentages. ADF and PP test represent the Augmented Dickey and Fuller test and Phillips–Perron test of stationarity, respectively. ARCH test is employed to test the presence of ARCH effect in the data sets. *,**,***Significance at the 1, 5 and 10 percent levels, respectively
Source: Authors' estimates; calculations of the authors

Table II.
Summary statistics for CEE daily stock returns

4. Results

Hypothesis testing

We test a diversity of hypotheses in connection with volatility spillovers among the concerned stock markets. We examine the presence of different conditional variance as follows.

Hypothesis:

H_0. $a_{ij} = b_{ij} = 0$.

Ha. $a_{ij} \neq 0$ or $b_{ij} \neq 0$ existence of volatility spillovers from the market i to the market j.

Volatility spillover

We commence the analysis of the econometric results of time-varying variance by the BEKK (1,1) model. The possibility of volatility spillovers across markets included in H_t implicates that the off-diagonal coefficients of the matrices $A(a_{ij})$ and $B(b_{ij})$ are statistically significant. The main feature of the BEKK model is that the causality relation among both variance and covariance can be explained systematically. Table V reports the results of estimated BEKK model. Throughout the empirical work, we denote the countries Hungary, Poland, Czech Republic, Romania and Croatia by 1, 2, 3, 4 and 5, respectively.

The estimation results of BEKK report that the majority of pairs are statistically significant. All diagonal elements (a_{ii}) are significant, suggesting that each conditional variance depends on its own lagged shocks, while the off-diagonal elements of the matrix A reflect the past cross innovations. For example, the coefficient $a(2,3)$ is equal to 0.165 and is statistically significant at 1 percent. It illustrates that the past cross shocks are transmitted from the Polish stock market to the Czech Republic stock market. This means

Table III. Unconditional correlation coefficients matrix of market return

	Hungary	Poland	Czech	Romania	Croatia
Hungary	1.000	0.602	0.612	0.188	0.418
Poland		1.000	0.690	0.170	0.472
Czech			1.000	0.190	0.567
Romania				1.000	0.173
Croatia					1.000

Source: Authors' estimates

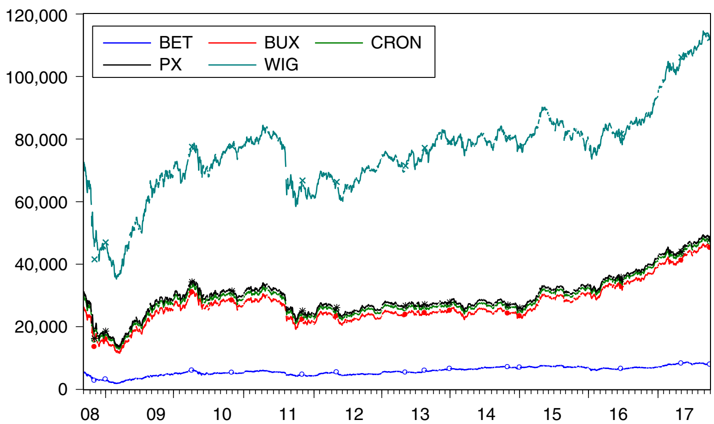

Figure 1. Daily index series

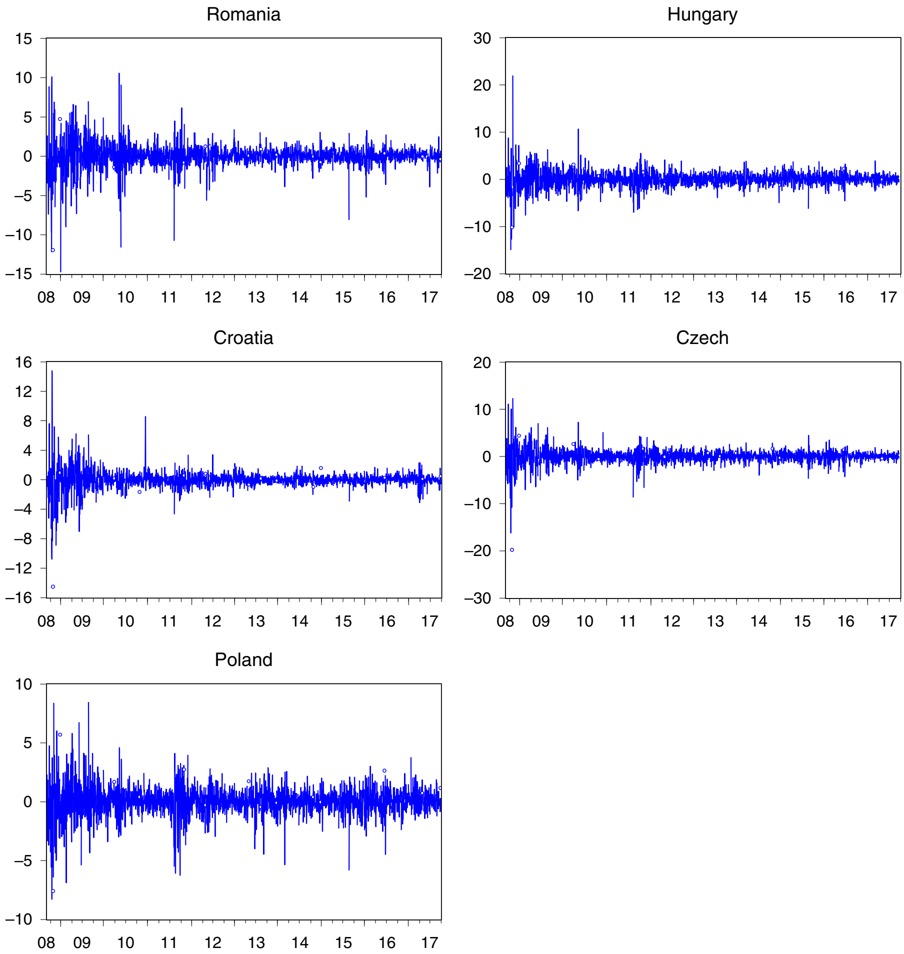

Figure 2.
Daily index returns

that, when shocks hit the Polish stock market, the Czech Republic stock market captures them. The coefficient *a*(3,2) reflects the same effects but in the opposite direction. It depicts a value (−0.046) that is statistically significant as well. Put another way, this is evidence of a bidirectional ARCH effect between the Polish and Czech Republic stock market. However, we also find evidence of non-persistence ARCH effect in cases of *a*(3,5), *a*(2,5) and *a*(5,3).

Similarly, the GARCH parameters $B(b_{ij})$ capture the responses of volatility in market *i* to past volatility in each of the five markets. For example, the coefficient of *b*(2,3) is equal to −0.13 and is statistically significant at the 1 percent significance level. This means that the Polish stock market spills over the past conditional volatility to the Czech Republic stock market. Put differently, the volatility of the Czech Republic market depends on the volatility of the Polish market. The coefficient *b*(3,2) is equal to 0.044 and is statistically significant. In other terms, there is bidirectional volatility spillover between the Polish stock market and the Czech Republic stock market during the study period. Furthermore, we also find out that the cases of *b*(2,5), *b*(3,4), *b*(5,1) and *b*(5,2) are not statistically significant. We can conclude that there is uni-bidirectional volatility spillover from Hungary to Croatia, from Romania to the Czech Republic and non-persistence volatility spillover between Croatia and Poland.

The results tally with Kamisli *et al.* (2015). All five conditional variances depend on their own history (b_{ii}) which are all statistically significant.

Consistently with previous studies, the volatility spillover effects are asymmetric, which means that the markets do not transmit innovations uniformly. This result is consistent with Bajo-Rubio *et al.* (2017), Jebran *et al.* (2017) and Bal *et al.* (2018), who found that negative shocks which have more significant impact than that of positive innovations in emerging economies. The findings also demonstrate that Romania is the main transmitter among the CEE countries. Indeed, $b(4,1)$ is highest, at 0.11. The volatility transmission from Romania to Hungary amount to 11 percent, which implies that a 1 percent increase in returns of Romania transmits 11 percent volatility to the Hungarian stock market. This result is supported by the study of Okičić (2015) for the period from October 2005 to December 2013. Table IV summarizes volatility spillovers among the stock markets under consideration; we find strong evidence in favor of the existence of conditional variance (H_a) of the spillovers in almost countries.

The results suggest a strong correlation of volatility transmission across markets in Central and Eastern European countries. Such findings give grounds for the healthy connectedness among stock markets, which constitutes a reason for international diversification and innovations spillovers between countries. Briefly, the volatility spillovers of CEE markets correlate highly with each other in both directions. This means that the stock markets are more substantially integrated after the global financial crisis. Also, it has an important connotation for both institutional and individual investors who could grasp the opportunity to invest in these markets and benefit from portfolio diversification to minimize risk.

Constant and dynamic conditional correlations

The conditional correlations of the extent of market integration are measured by the CCC and DCC models. The CCC estimates across markets are mostly high and all statistically significant at the 5 percent level. Thus, these results confirm that the innovations are correlated across markets. For instance, the highest correlation coefficient is $r(3,2)$, stand at 0.606, meaning that there is a strong interrelatedness between Poland and the Czech Republic. In contrast, the lowest CCC estimates between Croatia and Romania, $r(5,4)$ is equal to 0.13 which is the lowest value. The significant implications of the CCC estimation are consistent with very strong conditional correlations between the volatilities. Such a, somewhat surprising, result for part of professional is in accordance to latest findings of Bissoondoyal-Bheenick *et al.* (2018), Jebran *et al.* (2017) and Vo and Ellis (2018).

Nevertheless, our findings do not support the hypothesis of CCC but are in favor of dynamic conditional correlation. Note that all of the parameters of the DCC model are statistically significant, suggesting the existence of the own ARCH and GARCH effects. Specifically, the coefficient of the parameters a captures the previous shocks on the conditional correlation, while the coefficient of the parameters b captures the effects

	Hungary	Poland	Czech	Romania	Croatia
Hungary	+(H_a)	+(H_a)	+(H_a)	+(H_a)	+(H_a)
Poland	+(H_a)	+(H_a)	+(H_a)	+(H_a)	−(H_0)
Czech	+(H_a)	+(H_a)	+(H_a)	−(H_0)	+(H_a)
Romania	+(H_a)	+(H_a)	+(H_a)	+(H_a)	+(H_a)
Croatia	−(H_0)	−(H_0)	+(H_a)	+(H_a)	+(H_a)

Notes: −, (H_0): non-existence of volatility spillovers from market i to market j; +, (H_a): existence of volatility spillovers from market i to market j

Table IV.
Summarizing volatility spillovers

of the previous period's conditional correlations. For example, the Polish equity market has the following statistically significant estimates: $a_2 = 0.05$ and $b_1 = 0.91$. The sums of these parameters are fairly close to one for all nations, which means that the conditional volatility is persistent. Figure 3 gives the background information on the dynamic

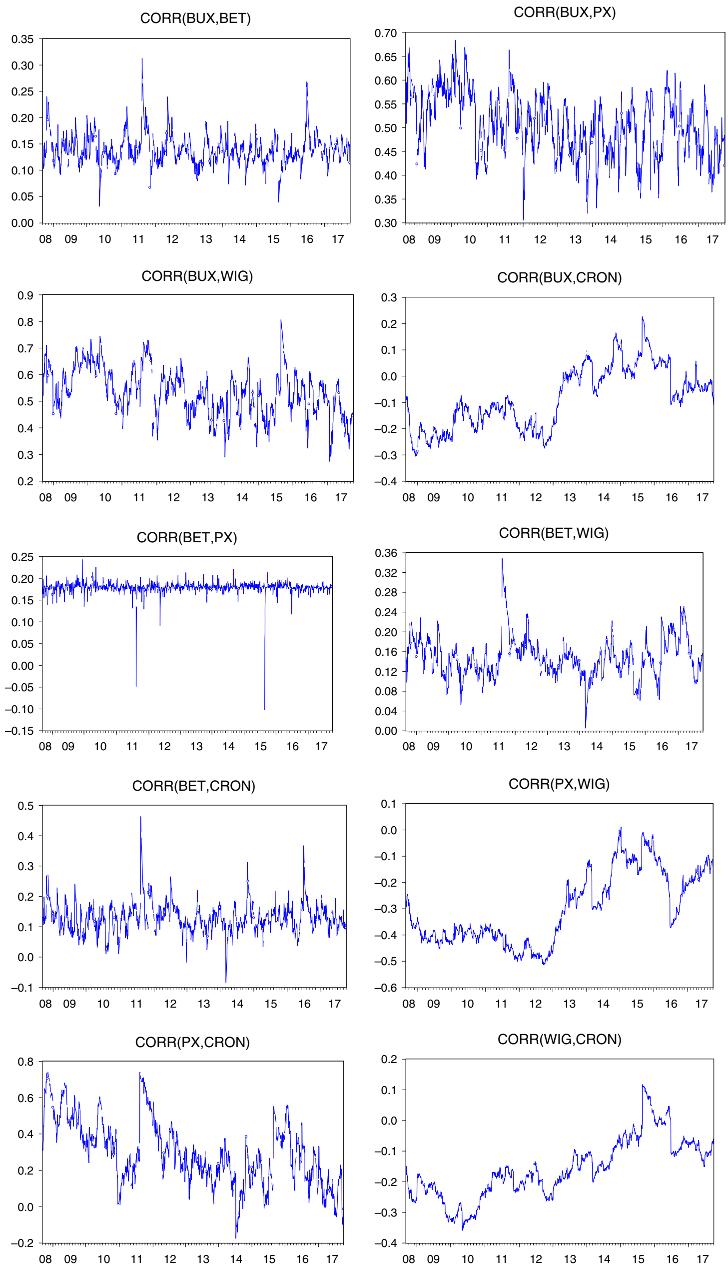

Figure 3.
Time-varying conditional correlations

conditional correlations plotted. Obviously, there are strong correlations between five stock markets. Furthermore, Table VI shows that the estimated α and β parameters associated with the dynamic conditional correlation are statistically significant at the 1 percent level, supporting the time-varying nature of the conditional correlation. The coefficient of α reflects the impact of the past shocks on current conditional correlation, while the second one captures the impact of past correlation. It is obvious that the DCC is favorable to the CCC. The sum of the parameters α and β is close to 1. This means that the process described by the model is not mean reverting. Put differently, after the innovations occurred in the stock market, the dynamic correlation will not return to the long-run unconditional level (Tables IV and V).

The stylized facts confirm previous studies. For instance, Scheicher (2001) shows innovations to volatility in equity markets of Hungary, Poland and the Czech Republic. Okičić (2015) states strong evidence of the existence of a leverage effect in CEE nations. Kamisli *et al.* (2015) maintain that markets become more integrated when the conditional correlation varies over time (Table VI).

As it may be noticed, the results of the multivariate GARCH-BEKK model alongside with the CCC and DCC models are not notable differences of volatility transmission mechanism between financial stock markets during the research period. The remarkable findings play a prominent role in terms of minimization of risk and portfolio choice. Further, the DCC model could be clarified in terms of its forecast ability relative to the unconditional correlations (Majdoub and Mansour, 2014). Finally, the integration of stock markets should be mentioned in CEE financial markets in particular, European countries in general. Our findings are consistent with Patev *et al.* (2006), Vo and Ellis (2018) and Jebran *et al.* (2017) and opposite to Panda and Nanda (2018). These results are intimately connected with some features of CEE finance industry: the screening of the CEE equity index prohibiting sectors in terms of a cause of volatility; imposing stringent restrictions on leverage ratios and interest-related dealings; and preventing purely speculative investments.

The robustness of the estimations of our study, we have used the multivariate ARCH LM test on the residuals of each model to determine whether the ARCH effect still exists in the model. As we can see from the estimates, there exist problems of ARCH effect for all selected countries during study period providing some indications of misspecification in each model. It is a limitation of this investigation. In this regard, we have read through the number of relevant articles, which are employed MGARCH models to estimate volatility across markets without diagnostic test (Vo and Ellis, 2018; Kim *et al.*, 2015; Majdoub and Mansour, 2014; Kumar, 2013; Panda and Nanda, 2018). Yet, their results had been confirmed when measuring the dynamic correlation of the economic indicators as well as its noteworthy implications. Hence, we believe that three models employed under study adequately capture volatility spillover effects and correlation processes between our variables of interest.

5. Conclusion

Our aspiration for this paper is to analyze the correlation of volatility between indexes of a sample of CEE emerging (Hungary, Poland, the Czech Republic) and frontier (Croatia, Romania) equity markets through the study of the dynamic conditional correlation based on five-dimensional GARCH-BEKK model. The persistence of volatility spillover effects is truly remarkable on the time period under study. The findings shed new light into the CEE Area's volatility transmission literature. Obviously, there is strong evidence that there exist multiple links between the CEE financial markets. Depending on the framework discussed, the main receivers and transmitters of spillover effects vary.

The analysis of interaction channels between the CEE stock markets illustrated the following. The estimates stemming from the estimation of the GARCH-BEKK model reveal that all pair countries present strong interconnection and existence of channels of shock

Parameters	Coefficient	SE	t-statistics	Prob.
μ_1	0.075345644	0.025824804	2.91757	0.00352772*
μ_2	0.065833098	0.019543558	3.36853	0.00075570*
μ_3	0.047470929	0.021133112	2.24628	0.02468595**
μ_4	0.035911485	0.021459451	1.67346	0.09423721***
μ_5	0.004079988	0.015394922	0.26502	0.79099276
c(1,1)	0.229502448	0.031241093	7.34617	0.00000000*
c(2,1)	0.109359747	0.024112911	4.53532	0.00000575*
c(2,2)	0.206119394	0.011450294	18.00123	0.00000000*
c(3,1)	0.140077111	0.028026987	4.99794	0.00000058*
c(3,2)	0.130089156	0.025066447	5.18977	0.00000021*
c(3,3)	−0.050133447	0.021776303	−2.30220	0.02132379*
c(4,1)	0.128464659	0.024017483	5.34880	0.00000009*
c(4,2)	−0.060482306	0.030969161	−1.95298	0.05082138**
c(4,3)	0.100949177	0.045293567	2.22878	0.02582887**
c(4,4)	0.091923995	0.033091132	2.77790	0.00547108*
c(5,1)	−0.046919150	0.010980810	−4.27283	0.00001930*
c(5,2)	0.023549815	0.012542412	1.87761	0.06043392**
c(5,3)	0.000773416	0.016257004	0.04757	0.96205549
c(5,4)	0.051855647	0.014455978	3.58714	0.00033432*
c(5,5)	−0.001568240	0.029834503	−0.05256	0.95807878
a(1,1)	0.044947848	0.020025045	2.24458	0.02479500**
a(1,2)	0.065982223	0.015807728	4.17405	0.00002992*
a(1,3)	−0.047176780	0.016819316	−2.80492	0.00503296*
a(1,4)	0.085967928	0.015654973	5.49141	0.00000004*
a(1,5)	0.031380032	0.009180966	3.41794	0.00063096*
a(2,1)	0.038071641	0.015855790	2.40112	0.01634501**
a(2,2)	0.129085538	0.013160646	9.80845	0.00000000*
a(2,3)	0.165386250	0.012266274	13.48301	0.00000000*
a(2,4)	0.039450365	0.019862573	1.98617	0.04701491**
a(2,5)	0.014619467	0.009264733	1.57797	0.11457261
a(3,1)	0.169276863	0.016534583	10.23775	0.00000000*
a(3,2)	−0.046464943	0.016580751	−2.80234	0.00507330*
a(3,3)	0.117908448	0.014764519	7.98593	0.00000000*
a(3,4)	0.087959104	0.018739165	4.69386	0.00000268*
a(3,5)	0.008887421	0.010841846	0.81973	0.41236821
a(4,1)	−0.211193576	0.014983040	−14.09551	0.00000000*
a(4,2)	−0.129776856	0.011963119	−10.84808	0.00000000*
a(4,3)	−0.154583318	0.012060675	−12.81714	0.00000000*
a(4,4)	0.272512838	0.016813667	16.20782	0.00000000*
a(4,5)	−0.053524886	0.008414304	−6.36118	0.00000000*
a(5,1)	0.050644088	0.014595182	3.46992	0.00052062*
a(5,2)	0.027826194	0.009745112	2.85540	0.00429826*
a(5,3)	0.015617580	0.013850870	1.12755	0.25950906
a(5,4)	0.061550069	0.017951891	3.42861	0.00060668*
a(5,5)	0.259371223	0.012874033	20.14685	0.00000000*
b(1,1)	0.967843326	0.008573333	112.88998	0.00000000*
b(1,2)	−0.026142173	0.007346966	−3.55823	0.00037337*
b(1,3)	0.069679133	0.008550430	8.14920	0.00000000*
b(1,4)	−0.057286191	0.013567246	−4.22239	0.00002417*
b(1,5)	0.009870473	0.004613127	2.13965	0.03238312**
b(2,1)	0.057952646	0.014231100	4.07225	0.00004656*
b(2,2)	0.922647933	0.008468068	108.95613	0.00000000*
b(2,3)	−0.130431483	0.009551626	−13.65542	0.00000000*
b(2,4)	−0.027482205	0.013839375	−1.98580	0.04705575**

(*continued*)

Table V. Estimates results of multivariate GARCH-BEKK model

Parameters	Coefficient	SE	t-statistics	Prob.
$b(2,5)$	−0.008396569	0.005353815	−1.56833	0.11680325
$b(3,1)$	−0.137562846	0.011358234	−12.11129	0.00000000*
$b(3,2)$	0.044021149	0.009691062	4.54245	0.00000556*
$b(3,3)$	0.954285332	0.007479993	127.57837	0.00000000*
$b(3,4)$	−0.002818504	0.010557215	−0.26697	0.78948901
$b(3,5)$	−0.019626351	0.004918574	−3.99025	0.00006600*
$b(4,1)$	0.111126812	0.013944281	7.96935	0.00000000*
$b(4,2)$	0.086215454	0.007852146	10.97986	0.00000000*
$b(4,3)$	0.081539408	0.009531739	8.55452	0.00000000*
$b(4,4)$	0.936867536	0.004656983	201.17479	0.00000000*
$b(4,5)$	0.022584372	0.004248512	5.31583	0.00000011*
$b(5,1)$	−0.004403585	0.009694522	−0.45423	0.64966017
$b(5,2)$	−0.004967523	0.007580649	−0.65529	0.51228108
$b(5,3)$	0.030150342	0.008305727	3.63007	0.00028335*
$b(5,4)$	−0.015069785	0.008409466	−1.79200	0.07313257**
$b(5,5)$	0.961145014	0.004307193	223.14882	0.00000000*
Model diagnostics				
ARCH LM		2,493.65		0.0008

Notes: This table shows the estimates of the multivariate GARCH-BEKK model. 1, 2, 3, 4 and 5 denote, respectively, Hungary, Poland, Czech Republic, Romania and Croatia. The parameters c_{ij}, a_{ij} and b_{ij} are the off-diagonal elements of the matrices C, A and B, respectively, as presented in Section 2. *,**,***Significant at 1, 5 and 10 percent levels, respectively

Table V.

propagation within CEE markets during study period. The estimates of conditional correlations are statistically significant in all most case, so the spillover of innovations among these markets is significant.

Econometrically, by utilizing time-return interaction terms based on CCC and DCC models, taking into account time-varying (heteroscedastic) volatility of the indices is appropriate. Indeed, these markets have a long memory and are strongly integrated, which can be a reason for international diversifications. Our main results do not confirm previous studies (Majdoub and Mansour, 2014; Panda and Nanda, 2018). In this scenario, the strong conditional correlations over time puts forward that the CEE stock markets are tightly integrated and the volatility transmissions among them are significant as well. Furthermore, a better forecasting of conditional correlations in CEE markets provides managers to optimize portfolio diversification.

Our main intention is to highlight the primary implications of our results for the CEE portfolio managers, investors, policy makers and corporations. The process of globalization and financial liberalization is the major factor to enhance further international linkages (Vo and Ellis, 2018). The integrations among CEE financial markets indicate low potential diversification opportunities for investors (Jebran *et al.*, 2017). Investors might aim to obtain their investment strategies by taking into account the integrations of divergent financial markets. Additionally, Singhal and Ghosh (2016) document that investors tend to diversify their investment portfolio and hedging in order to maximize returns and minimize risks. Similarly, Ahmed and Huo (2018) suggest that market integration would formally issue several new opportunities to accelerate productivity and economic growth; new economic partnership would expand the region's global competitiveness in attracting investment. Furthermore, policy makers should consider previous market condition and integration of financial markets before implementing policy on the stock market as there are dramatic influences on the financial performance of the markets from one market to other markets.

	CCC			DCC		
	Coefficient	*t*-statistic	Prob.	Coefficient	*t*-statistic	Prob.
μ_1	0.0797563776	3.20530	0.00134924*	0.0768442872	3.02707	0.00246938*
μ_2	0.0609335815	3.13862	0.00169748*	0.0601954860	2.73108	0.00631272*
μ_3	0.0363385172	1.75394	0.07944059***	0.0380149389	1.58589	0.11276425
μ_4	0.0528866556	2.73432	0.00625094*	0.0527164718	2.57050	0.01015530**
μ_5	0.0079614547	0.52138	0.60210523	0.0099456350	0.64669	0.51783052
$c(1)$	0.0546931428	4.77410	0.00000181*	0.0307128299	3.56543	0.00036325*
$c(2)$	0.0266018780	5.41338	0.00000006*	0.0148710299	4.24934	0.00002144*
$c(3)$	0.0523474363	5.59595	0.00000002*	0.0292440069	4.47998	0.00000747*
$c(4)$	0.0554420934	6.48233	0.00000000*	0.0513266053	5.48211	0.00000004*
$c(5)$	0.0147910732	5.32985	0.00000010*	0.0105073929	4.01356	0.00005981*
$a(1)$	0.0749088960	6.79133	0.00000000*	0.0776578626	6.59866	0.00000000*
$a(2)$	0.0426568511	7.59083	0.00000000*	0.0501821882	8.90060	0.00000000*
$a(3)$	0.0799602157	7.26966	0.00000000*	0.0832184317	8.29212	0.00000000*
$a(4)$	0.2402567392	16.58626	0.00000000*	0.2465209994	10.19657	0.00000000*
$a(5)$	0.1071641940	9.35041	0.00000000*	0.1141903715	9.27744	0.00000000*
$b(1)$	0.8974772593	62.91123	0.00000000*	0.9167198744	74.75856	0.00000000*
$b(2)$	0.9344069830	115.40540	0.00000000*	0.9431915321	154.39916	0.00000000*
$b(3)$	0.8816726473	59.85706	0.00000000*	0.9092090825	87.72779	0.00000000*
$b(4)$	0.7601901464	56.01244	0.00000000*	0.7665307271	40.26037	0.00000000*
$b(5)$	0.8769939544	74.86007	0.00000000*	0.8892809469	82.56190	0.00000000*
$r(2,1)$	0.5475020116	38.23011	0.00000000*	–	–	–
$r(3,1)$	0.5234915621	34.62113	0.00000000*	–	–	–
$r(3,2)$	0.6060293352	43.81264	0.00000000*	–	–	–
$r(4,1)$	0.1413728602	7.51260	0.00000000*	–	–	–
$r(4,2)$	0.1519891327	7.51281	0.00000000*	–	–	–
$r(4,3)$	0.1798502537	9.27228	0.00000000*	–	–	–
$r(5,1)$	0.2533761563	13.86171	0.00000000*	–	–	–
$r(5,2)$	0.3262800433	17.83819	0.00000000*	–	–	–
$r(5,3)$	0.3358289152	18.32144	0.00000000*	–	–	–
$r(5,4)$	0.1303644778	7.40253	0.00000000*	–	–	–
α	–	–	–	0.0126180618	6.42334	0.00000000*
β	–	–	–	0.9840458675	362.78222	0.00000000*
Model diagnostics						
ARCH LM	1,941.11		0.0078	1,941.26		0.0026

Notes: This table shows the estimates of the multivariate GARH CCC and DCC models. 1, 2, 3, 4 and 5 denote, respectively, Hungary, Poland, Czech Republic, Romania and Croatia. The parameters a_i, b_i and r_{ij} are the off-diagonal elements of the matrices A, B and R, respectively, as presented in Section 2. *,**Significant at 1 and 5 percent levels, respectively

Table VI. Estimate results of CCC and DCC models

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