Professor Ioan POPA, PhD
E-mail: ioan.popa.rei@gmail.com
Associate Professor Cristiana TUDOR, PhD
E-mail: cristiana.tudor@net.ase.ro (corresponding author)
Professor Dorel PARASCHIV, PhD
E-mail: dorel.paraschiv@ase.ro
The Bucharest Academy of Economic Studies

SHOCKS SPILLOVER WITHIN EMERGING EASTERN EUROPEAN EQUITY MARKETS

Abstract. *We estimate a multivariate GARCH-BEKK model to examine the returns and volatility dynamics between post-communist CEE stock markets and two of the largest international equity markets (namely US and Germany) over the last decade (2004-2014), with an emphasizes on the credit-crunch crisis period (2007-2009). We find that Russia is the only market that does not present significant linkages with other markets in terms of return. An analysis of the crisis window reflects that the smaller CEE equity markets report much smaller GARCH coefficients, indicating that although shocks have the most important impact (highest a coefficients for Romania and Serbia), these shocks are not persistent and disappear quickly. Other findings show that past news in the Czech market persist more than shocks in the other markets, whilst the lowest persistence of shocks is encountered in Russia, thus implying it is the most stable market in terms of propagation, perhaps due to its low level of integration with the other equity markets included in the sample.*

Keywords*: diagonal GARCH-BEKK, volatility spillovers, Emerging Eastern Europe, credit-crunch.*

JEL classification: G1; G11; G12; G15; G23

1. Introduction and related literature

The study of interdependencies between markets - a traditional theme in the economic literature - is brought to attention by the spectacular developments in the recent period (crisis phenomena) and advances in research techniques in financial economics (multivariate GARCH models, etc.). Two types of approaches can be identified in this field. Firstly, a "spatial" approach, which includes researches at a global level (influenced by the trend and philosophy of globalization), centered on the metaphoric key concept of contagion (Claessens, Stijn& Forbes, Kristin J, 2001), Rigobon, 2002**;** Talbott, 2009, Kolb, 2011).

Secondly, a "phenomenal" approach using quantitative analysis techniques of volatility transmission (spillover) (Kanas,Angelos, 1998; Hol, E. (2003; Weber,2013).Even if there are differences (and even controversies) in connection with the two notions, the term contagion is generally accepted to reflect market interdependences in times of crisis and the term “volatility transmission” to reflect normal periods in the evolution of markets.

In this paper we intend to test the following hypotheses by making use of one of the newer multivariate generalized autoregressive conditionally heteroskedastic model, namely GARCH-BEKK:

- H1. -The transmission the crisis / shocks takes place primarily at a global level - as a contagion; the spreading factor is the information which is currently immediately accessible worldwide. The contagion is produced by the behavior of market actors, i.e. the radical change of short-term expectations produced by the new information. The resulting reaction is one of herd behavior, imitative.
- H2. -In normal times (and long term), the global correlations are less pronounced; the equity market depends more on regional and local factors. Second hypothesis: The stock market is less dependent on general stock market movements and more influenced by the movement of the real economy (Fundamentals).
- H3. -In the Romanian case the shock has occurred under the conditions of an economy in full growth period. This process had also a speculative component (in the case of the real estate market boom) but also had, after all data is considered, a basis in the real economy. The overlapping of the global / regional shock over the local trend led the economy in crisis.

The rationale of our study is threefold. Firstly, as the comovements of asset returns in a portfolio constitute an important element in both portfolio and risk management, a multivariate GARCH volatility model should be more dependable model than independent univariate models. Moreover, in the aftermath of the global financial crisis, it became obvious that a thorough understanding of the degree of securities markets linkages is paramount for both policymakers and investors. And finally, post-communist equity markets in Eastern Europe have attracted more and more the attention of practitioners and academic researchers during the last decade.

The remainder of this paper is organized as follows. Section 2 presents the data, discusses some descriptive statistics insisting on the evolution of equity market volatility during the credit crunch crisis period and also reflects the methodology of the BEKK models of volatility and co-volatility. Section 4 presents the empirical results and diagnosis, while Section 5 concludes.

2. Data and Method

2.1. Data

We employ daily closing values for stock market indices form a selection of seven equity markets, including smaller post-communist transition countries and developed G7 markets (Table 1 presents the markets, their respective stock indices and also serves as a correspondence table for the time series notation used throughout the paper).

Table 1. Equity markets included in the analysis - Correspondence table

Time series	Country	Equity market	Index
a	Romania	Bucharest	BET
b	Hungary	Budapest	BUX
c	Czech Republic	Prague	PX
d	Serbia	Belgrade	BELEX
e	Russia	Moscow	RTS
f	US	NYSE	Dow Jones
g	Germany	Frankfurt	DAX

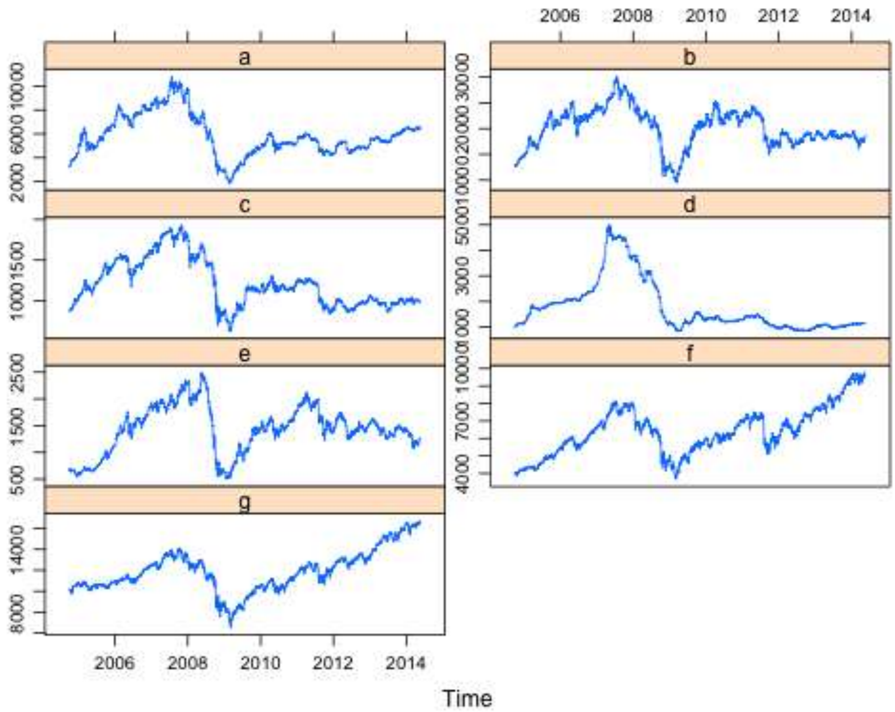
The analysis period runs from 01/10/2004 to 23/05/2014, totaling 2415 daily observations for each of the seven series. In an adjacent investigation we also subtract the credit-crunch crisis period, considered to have started on 09/08/2007 when BNP Paribas terminated withdrawals from three hedge funds citing "a complete evaporation of liquidity" and to have ended on 01/06/2009, according to the U.S. National Bureau of Economic Research. This way, the crisis period contains 471 daily observations for each market.

The indices are taken from the Quandl database and are in terms of local currency, as inEun and Shim (1989), Theodossiou and Lee (1993), and Koutmos and Booth (1995). Subsequently, continuously compounded returns are calculated as the difference in natural logarithms of the closing index value for two consecutive trading days.

We start by analyzing the dynamic behavior of each univariate series, with Figure 1 reflecting the evolution of the seven equity markets during the ten years period.

It is obvious that all markets have been harshly affected by the crisis, and also that the impact seems to have been bigger in the case of the smaller CEE countries and Russia. Actually, Russia (series e) suffered the highest decrease, with a maximum daily loss of 21.20% (Table 2). The two developed markets from Germany and US (series f and g) registered a softer impact of the crisis and also a more significant recovery in the post-crisis period as compared to the CEE markets included in the analysis.

Figure 1. Equity markets evolution: 2004-2014



2.2. Descriptive statistics

Descriptive statistics in Table 2 for daily market returns show that the smaller Eastern European stock markets included in this analysis have similar mean returns to the bigger developed markets of Germany, Russia and the U.S. Perhaps surprisingly, Germany reports the highest average daily return (0.04%), while the stocks markets from Prague and Belgrade report the smallest daily return (0.01%) within this sample.

As expected, the volatility is generally higher within the CEE group of markets.

The data suggests the most volatile market is Russia and the least volatile is Serbia. The most volatile CEE market is Romania, but also the most rewarding in terms of returns. Three of the CEE markets (all with the exception of Serbia) are skewed to the left and all the markets included in this analysis are leptokurtic with non-normal distributions. The leptokurtic behavior implies returns are likely to produce outliers, and this behavior is present, with fat tails, in every series. The Jarque—Bera (JB) statistic rejects normality at any level of statistical significance for all series.

Table 2. Descriptive statistics: Whole sample, whole period: 2004-2014

	n	mean	sd	median	trimmed	mad
BET	2509	0.03	1.72	0.01	0.06	1.11
BUX	2509	0.02	1.67	0.00	0.02	1.26
PX	2509	0.01	1.53	0.01	0.04	1.04
BELEX	2509	0.01	0.95	0.00	0.00	0.57
RTS	2509	0.03	2.18	0.05	0.09	1.37
DAX	2509	0.04	1.38	0.07	0.07	0.91
DJIA	2509	0.02	1.17	0.04	0.04	0.69
	min	max	range	skew	kurtosis	se
BET	-13.12	10.56	23.68	-0.64	7.87	0.03
BUX	-12.65	13.18	25.83	-0.09	6.65	0.03
PX	-16.19	12.36	28.55	-0.54	14.63	0.03
BELEX	-6.97	9.87	16.84	0.26	13.02	0.02
RTS	-21.20	20.20	41.40	-0.50	12.68	0.04
DAX	-7.43	10.80	18.23	0.02	7.29	0.03
DJIA	-8.20	10.51	18.71	-0.08	11.35	0.02

The unconditional correlations between the seven markets are reported in Table 3 and reflect a relatively important diversification benefit between the markets, as depicted by the relatively low pair-wise unconditional correlation between the analyzed markets. The cross-correlation of squared returns (Table 4) shows similar numbers, with the most significant relationship between the two developed markets of Germany and the US (0.67) and another important positive relation between Russia and the Czech Republic (0.55). The Serbian market seems to be the least integrated with the others.

Table 3. Cross correlations of returns

	a	b	c	d	e	f	g
a	1	0.3771524	0.5011646	0.22315961	0.4063583	0.3956402	0.23282584
b	0.3771524	1	0.5931122	0.15394143	0.5056099	0.5566252	0.37223604
c	0.5011646	0.5931122	1	0.21696226	0.62519	0.577263	0.34926931
d	0.22315	0.15394	0.21696	1	0.19194	0.13564	0.060146

	96	14	23		91	12	38
e	0.4063583	0.5056099	0.62519	0.19194914	1	0.5425482	0.32038999
f	0.3956402	0.5566252	0.577263	0.13564117	0.5425482	1	0.63015468
g	0.2328258	0.372236	0.3492693	0.06014638	0.32039	0.6301547	1

Table 4.Cross correlations of squared returns

	a	b	c	d	e	f	g
a	1	0.3285197	0.4939926	0.2606186	0.3354733	0.3128238	0.2277238
b	0.3285197	1	0.4713706	0.1870548	0.4054699	0.4458207	0.3953008
c	0.4939926	0.4713706	1	0.2241595	0.5493208	0.4525064	0.2911343
d	0.2606186	0.1870548	0.2241595	1	0.2646858	0.1406382	0.133367
e	0.3354733	0.4054699	0.5493208	0.2646858	1	0.3927116	0.2843807
f	0.3128238	0.4458207	0.4525064	0.1406382	0.3927116	1	0.6743453
g	0.2277238	0.3953008	0.2911343	0.133367	0.2843807	0.6743453	1

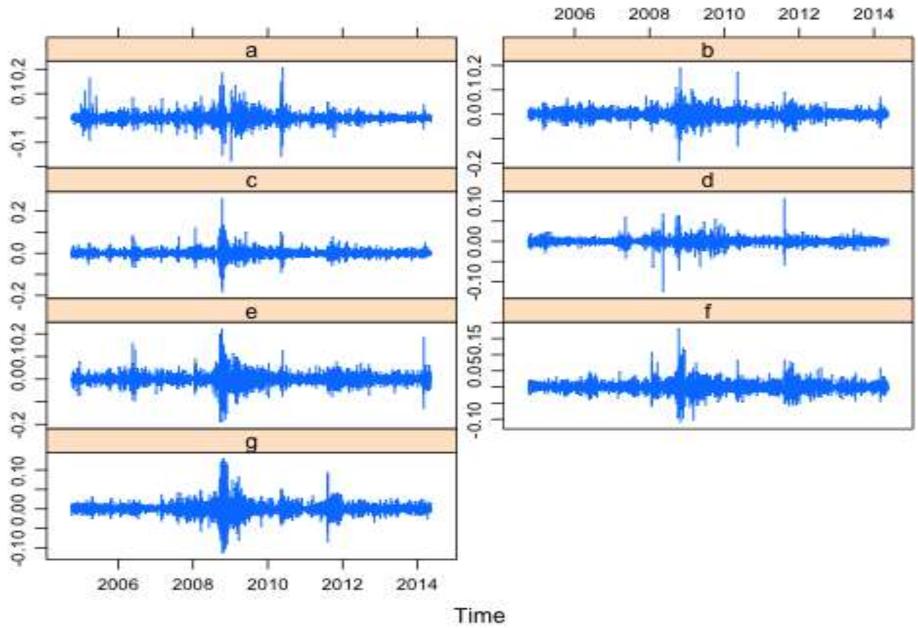
Next, the stationarity of the four series is tested by subsequently conducting the Augmented Dickey Fuller Unit Root Test, the KPSS test and also the PP test, rejecting the null hypothesis of a unit root in all cases.

We therefore conclude that the time series are stationary at level and we can proceed to model the conditional volatility with GARCH-class models.

The final step in this preliminary investigation consists in the analysis of autocorrelation within the seven time series. The Ljung—Box statistic applied both on returns and squared returns indicate that significant linear and nonlinear dependencies exist, which could reflect evidence of the presence of ARCH effects in the conditional volatility. Finally, we employ the BDS test (Brock, Dechert and Scheimkman (1996)) to investigate the presence of nonlinear dependence in the return. Results reject the null hypothesis of independent and identically distributed (IID) variables at all levels, therefore confirming the presence of nonlinear innovations in the return series.

Figure 2 presents the evolution of daily logarithmic returns of the seven time series during the entire ten years period. We observe that volatility clustering seems to be present in all cases, especially during the 2007-2009 crisis period. Volatility clustering can be thought of as clustering of the variance of the error term over time or, in other words, volatility clustering implies that the error exhibits time-varying heteroskedasticity (unconditional standard deviations are not constant).

Figure 2. Daily logarithmic returns: 2004-2014



2.3. Volatility during the credit crunch crisis period

Data in Table 5 reflect that all risk indicators are significantly higher during crisis and the squared returns evolution in Figure 3 attest that most markets are relatively calm before the crisis and quickly return to low levels of volatility after the end of the crisis. Romania, Hungary, Russia and Germany reach higher levels of volatility more frequently and maintain those elevated levels for longer time periods. The same markets seem to exhibit more evidence of volatility clustering during crisis (Figure 4).

Table 5. Descriptive statistics: Whole sample, crisis period: 2007-2009

	n	mean	sd	median	trimmed	mad
a	471	-0.23	2.63	-0.07	-0.18	1.96
b	471	-0.14	2.42	0.00	-0.15	1.68
c	471	-0.14	2.57	-0.09	-0.11	1.58
d	471	-0.29	1.43	-0.28	-0.32	0.86
e	471	-0.11	3.51	0.00	-0.04	1.92
f	471	-0.08	2.08	0.00	-0.06	1.28
g	471	-0.10	2.06	0.00	-0.08	1.44
	min	max	range	skew	kurtosis	se
a	-13.12	10.09	23.21	-0.38	2.82	0.12
b	-12.65	13.18	25.83	-0.06	5.39	0.11
c	-16.19	12.36	28.55	-0.35	7.54	0.12
d	-6.97	9.87	16.84	0.68	9.09	0.07
e	-21.20	20.20	41.40	-0.21	7.43	0.16
f	-7.43	10.80	18.23	0.35	5.27	0.10
g	-8.20	10.51	18.71	0.18	4.17	0.10

Figure 3. Squared returns: 2004-2014

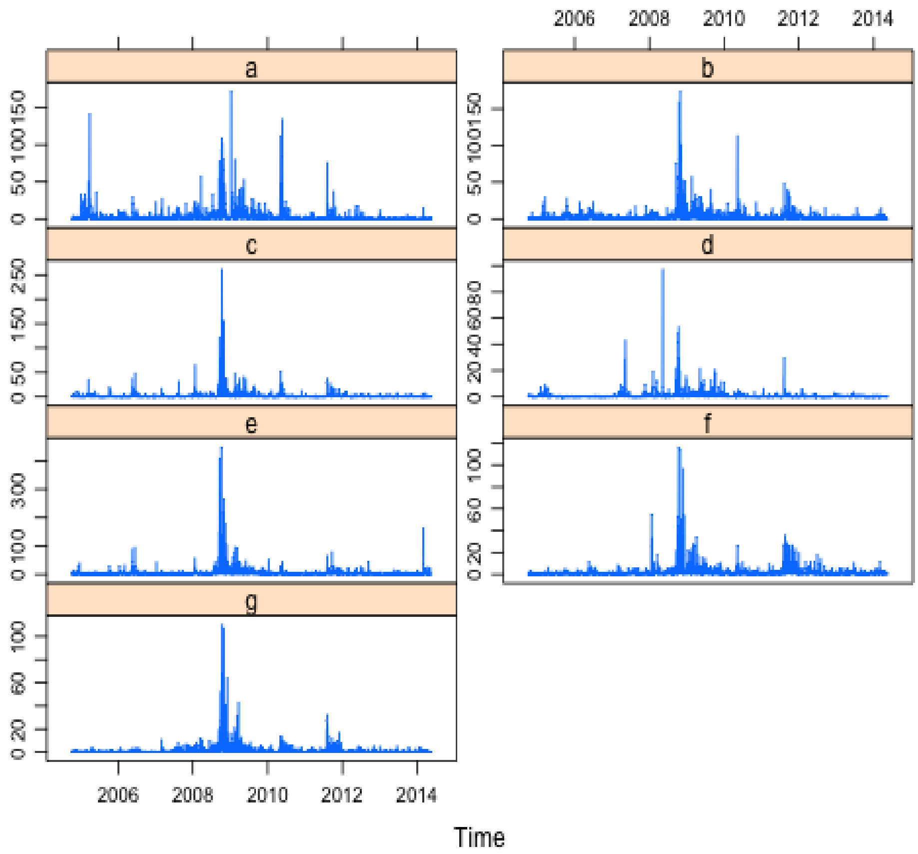
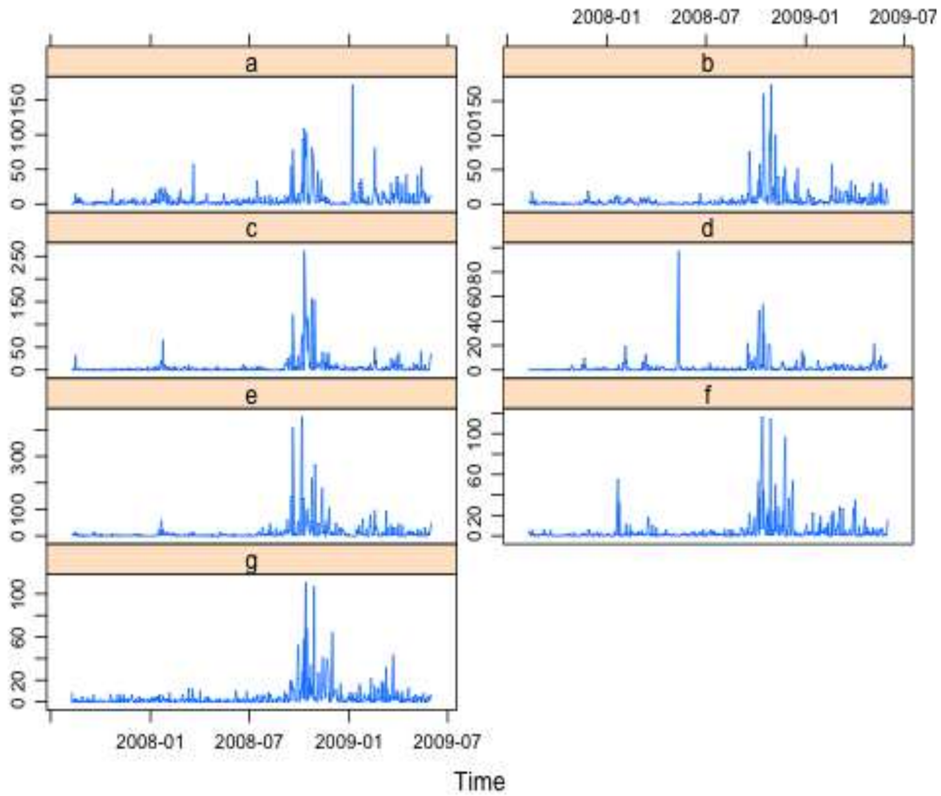


Figure 4. Squared returns: crisis period: 2007-2009



3. The Multivariate GARCH-BEKK Model and its Development

Multivariate GARCH models evolved from Engle's (1982) ARCH model, which was later extended by Bollerslev (1986) into the generalized ARCH (GARCH) model. Both ARCH and GARCH models were initially univariate, being later extended and taking multivariate forms. Among these, Baba, Engle, Kraft and Kroner (1990) and later Engle and Kroner (1995) proposed and defined the model which became known as the BEKK model by trying to explain the conditional variance matrix Ht in such a way that positive definiteness is ensured.

The model most commonly used in practice is the more restrictive first-order Diagonal BEKK GARCH(1,1) model given by:

$$H_t = CC' + A\varepsilon_{t-1}\,\varepsilon'_{t-1}A' + BH_{t-1}B' \qquad (1)$$

or, in the extended manner:

$$H_t = CC' + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \varepsilon_{t-1}\varepsilon'_{t-1} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \quad (2)$$

If the vector of residuals is ε_t and the information set at time t-1 is ω_{t-1}, then $(\varepsilon_t|\omega_{t-1}) \sim N(0, H_t)$, which means that the residuals are distributed conditionally normal with mean zero and variance (covariance) matrix H_t. In eq. (2) c is a triangular matrix, and A and B are diagonal matrices. There are a total of N(N + 5)/2 free parameters and the conditional covariance matrices are guaranteed to be stationary if:

$aii + bii < 1 \ \forall i = 1, \ldots, N$.

As mentioned earlier, the most important feature of the GARCH BEKK specification is the non-negativity of conditional variance-covariance matrix. This is guaranteed by the fact that each matrix (A, B, and C) is paired with its transpose.

For higher orders, the conditional variance-covariance matrix for GARCH BEKK (p, q), is written as:

$$H_t = CC' + \sum_{i=1}^{q} A_i \varepsilon_{t-i}\, \varepsilon'_{t-i} A'_i + \sum_{j=1}^{p} B_j H_{t-j} B'_j \quad (3)$$

The BEKK GARCH model is widely used in the literature to study volatility and contagion (see for example Kearney and Patton (2000), Worthington and Higgs (2004), Ciffarelli and Paladino (2005), Caporale, Pittis, and Spagnolo (2006), Antonakakis (2008), Erten et al. (2012), and Beirne, Caporale, Schultze-Ghattas, and Spagnolo (2013). Su and Huang (2010) estimate both the DCC and the BEKK model and conclude that BEKK parameter estimates are more accurate than the estimates given by the DCC model.

4. Empirical results and discussion

In order to examine the linkages between the seven stock markets we estimate a multivariate Diagonal-BEKK-MGARCH(1,1) for the whole decade (2004-2014), as well as the crisis (2007-2009) and post-crisis (2009-2014) windows.

The estimation is done by maximizing the quasi-likelihood assuming conditional normality. Parameter estimates for the entire period are reported in Table 6, while Table 7 report variance matrix coefficients during crisis (Panel A) and Post-Crisis (Panel B). All models seem to be well specified, as the multivariate tests Hosking (1980) and Li and McLeod (1981) show that there is no serial correlation left in the standardized and squared standardized residuals up to 50 lags.

The relationships in terms of returns among the equity markets for the entire decade are given by the parameters *cij* in Table 6. First, it is obvious that returns of all markets are highly dependent on their first lags, as all diagonal matrix C parameters *cii* are positive and statistically significant at 1%, with the highest value in the case of Russia (0.22%), suggesting that yesterday's stock market evolution has an important effect on the following trading day. Interestingly, Russia is the only market that does not present significant linkages with other markets in terms of return, as all off-diagonal elements of matrix C are insignificant when Russia (market *5* in our estimation) is included and significant otherwise.

Next we investigate the parameters of the time-varying variance-covariance by examining the coefficients of matrices A and B in Table 6. The diagonal elements of matrix A capture the own ARCH effects or the impact of past news or shocks while the diagonal elements of matrix B reflect the own GARCH effects or the persistence of past shocks within a market. All estimated diagonal elements *a11….a77* and *b11….b77* respectively are statistically significant at 1% level of significance, indicating that past news in a specific market have a great impact of the future volatility of that respective market and also that these news are persistent and decay slowly.

The highest estimated *acoefficient* is *a55,* indicating that Russian investors give a greater importance to news that affect the domestic market as compared to investors on the other stock markets, for which perhaps global news are more significant. Indeed, the ARCH effect is more than double on the stock exchange from Moscow than on each of the other markets. The smallest *a coefficient* is encountered for the Czech equity market, suggesting that investors pay little attention to domestic events and follow events on the international markets.
On the contrary, the highest estimated *b*coefficient is found in the case of the Prague's stock market (0.98)while the lowest is encountered for Russia (0.84), all others having similar values of about 0.97. This means that shocks in the Czech market persist more than shocks in the other markets (although the rate of decay is somewhat similar), but Russia stands apart again within this group of markets, its lowest persistence of shocks implying it is the most stable market in terms of propagation of shocks.

When we split up the estimation period and estimate eq. (2) separately for the crisis window (09/08/2007-01/06/2009 -471 daily observations) as well as for the post-crisis interval (02/06/2009-23/05/2014 – 1350 daily observations) many of the above relationships appear significantly different. During crisis, the diagonal elements of matrix C lose their statistical significance in the case of Germany and USA, suggesting that the previous day's evolution of the stock market doesn't still impact current day's return within a turbulent period; for the smaller CEE markets like Romania, Czech Republic, Hungary, Serbia and Russia the last trading day has consequences for current stock returns during crisis (and this consequences are even greater during turmoil for all markets, especially Romania). Post-crisis, all

*Cii*coefficients regain their significance (with the exception of Serbia), and all stock markets depend on their own past evolution. All coefficients of matrices A and B are significant after the crisis, but not during the crisis period; also, their impact is different in the two periods: *aii*coefficients are higher during crisis for Romania, Serbia, and the two developed markets Germany and USA, indicating that shocks or news received within these markets have a very significant effect for their own future volatility. Romania is the market most impacted by past shocks also in the post-crisis period, while post-crisis Serbian investors seem to have switched their attention away from domestic events and toward global news. Inversely, the GARCH coefficients are higher post-crisis than during crisis, indicating that volatility in the equity markets persists more after the crisis than during crisis. In both periods, Serbia is the market that is least affected by its own past volatility. Another interesting finding is that for Romania, Serbia and RussiaGARCH coefficients are quite small during crisis indicating that although shocks have the most important impact (highest *a* coefficients for Romania and Serbia), these shocks are not persistent and disappear quickly.

In the midst of the financial turmoil of 2007-2009, the smaller CEE equity markets report much smaller GARCH coefficients; this could be a reflection of the fact that these markets are more influenced by global risk factors during crisis. Post-crisis, the persistence of volatility within CEE markets is higher than in USA and Germany; meanwhile, for the two developed markets, the rate of decay in volatility remained constant, reaching similar levels during and post-crisis.

Table 6. Estimation results of Diagonal-BEKK-MGARCH(1,1) - whole period (2004-2014)

	Coefficient	Std.Error	t-value	t-prob
C_11	0.093982	0.011624	8.085	0
C_12	0.009729	0.011369	0.8558	0.3922
C_13	0.041885	0.012944	3.236	0.0012
C_14	0.042457	0.014223	2.985	0.0029
C_15	-0.027624	0.024439	-1.13	0.2585
C_16	0.048444	0.01547	3.131	0.0018
C_17	0.07185	0.012079	5.948	0
C_22	0.135696	0.04071	3.333	0.0009
C_23	0.029057	0.01234	2.355	0.0186
C_24	0.038424	0.014056	2.734	0.0063
C_25	0.042344	0.036956	1.146	0.252
C_26	0.050933	0.021684	2.349	0.0189
C_27	0.020466	0.0093171	2.197	0.0281

C_33	0.157829	0.028509	5.536	0
C_34	0.067833	0.014777	4.591	0
C_35	0.016449	0.02375	0.6926	0.4886
C_36	0.070739	0.017161	4.122	0
C_37	0.040911	0.0080625	5.074	0
C_44	0.132173	0.016782	7.876	0
C_45	0.011695	0.019907	0.5875	0.5569
C_46	0.053608	0.01212	4.423	0
C_47	0.029804	0.0068575	4.346	0
C_55	0.219215	0.047187	4.646	0
C_56	0.020918	0.017866	1.171	0.2418
C_57	0.012435	0.010027	1.24	0.2151
C_66	0.169984	0.026503	6.414	0
C_67	0.023151	0.0074345	3.114	0.0019
C_77	0.090556	0.011009	8.226	0
b_1.11	0.976872	0.0034428	283.7	0
b_1.22	0.97626	0.0087366	111.7	0
b_1.33	0.98031	0.0052569	186.5	0
b_1.44	0.970671	0.0049726	195.2	0
b_1.55	0.843801	0.058276	14.48	0
b_1.66	0.978552	0.0044571	219.5	0
b_1.77	0.978199	0.0033974	287.9	0
a_1.11	0.193455	0.016878	11.46	0
a_1.22	0.202984	0.034463	5.89	0
a_1.33	0.168057	0.023853	7.045	0
a_1.44	0.210502	0.02175	9.678	0
a_1.55	0.495988	0.08771	5.655	0
a_1.66	0.174655	0.020342	8.586	0
a_1.77	0.182113	0.017098	10.65	0

Table 7. Estimation results of Diagonal-BEKK-MGARCH(1,1) - Crisis and Post-Crisis

PANEL A: CRISIS					PANEL B: POST_CRISIS				
	Coefficient	Std.Error	t-value	t-prob		Coefficient	Std.Error	t-value	t-prob
C_11	1.312.976	0.35019	3.749	0.0002	C_11	0.192657	0.049933	3.858	0.0001
C_1	0.22407	0.088	2.53	0.01	C_1	0.05337	0.0209	2.55	0.01

2	7	305	8	15	2	1	04	3	08
C_13	0.419092	0.11404	3.675	0.0003	C_13	0.063522	0.019315	3.289	0.001
C_14	0.021425	0.023269	0.9207	0.3577	C_14	0.010006	0.021494	0.4655	0.6417
C_15	0.407842	0.092599	4.404	0.0000	C_15	0.097484	0.039872	2.445	0.0146
C_16	0.253229	0.088976	2.846	0.0046	C_16	0.057955	0.019927	2.908	0.0037
C_17	0.041263	0.029156	1.415	0.1577	C_17	0.029284	0.015142	1.934	0.0533
C_22	0.528200	0.24464	2.159	0.0314	C_22	0.148631	0.067121	2.214	0.027
C_23	0.466344	0.16885	2.762	0.0060	C_23	0.045967	0.01989	2.311	0.021
C_24	0.004721	0.024355	0.1938	0.8464	C_24	0.011511	0.030702	0.3749	0.7078
C_25	0.384579	0.38502	0.9989	0.3184	C_25	0.070287	0.029957	2.346	0.0191
C_26	0.139478	0.086479	1.613	0.1075	C_26	0.062527	0.025989	2.406	0.0163
C_27	0.062053	0.031134	1.993	0.0468	C_27	0.054977	0.037353	1.472	0.1413
C_33	0.605806	0.13315	4.550	0.0000	C_33	0.111767	0.026327	4.245	0
C_34	0.020841	0.023149	0.9003	0.3684	C_34	0.007224	0.027638	0.2614	0.7938
C_35	0.310987	0.10117	3.074	0.0022	C_35	0.044186	0.023489	1.881	0.0602
C_36	0.201171	0.076725	2.622	0.0090	C_36	0.04154	0.018373	2.261	0.0239
C_37	0.102858	0.037759	2.724	0.0067	C_37	0.032831	0.027467	1.195	0.2322
C_44	0.292449	0.11479	2.548	0.0112	C_44	0.163375	0.14724	1.11	0.2674
C_45	0.052906	0.063017	0.8396	0.4016	C_45	0.015962	0.019766	0.8076	0.4195
C_46	0.009365	0.027767	0.3373	0.7361	C_46	0.003923	0.011075	0.3542	0.7232
C_4	-	0.028	-	0.80	C_4	-	0.0176	-	0.50

7	0.007115	138	0.2528	05	7	0.011669	3	0.6619	82
C_55	0.754985	0.34630	2.180	0.0298	C_55	0.173258	0.049089	3.529	0.0004
C_56	0.046090	0.17709	0.2603	0.7948	C_56	0.045293	0.018664	2.427	0.0154
C_57	0.016725	0.061899	0.2702	0.7871	C_57	0.039056	0.034259	1.14	0.2545
C_66	0.043780	0.11007	0.3978	0.6910	C_66	0.112823	0.025201	4.477	0
C_67	-0.024429	0.059603	-0.4099	0.6821	C_67	0.071548	0.023301	3.071	0.0022
C_77	0.04.3034	0.394299	0.7321	0.7128	C_77	0.107405	0.028613	3.754	0.0002
b_1.11	0.614295	0.30068	2.043	0.0416	b_1.11	0.952515	0.0185	51.49	0
b_1.22	0.884291	0.10705	8.261	0.0000	b_1.22	0.982597	0.010371	94.74	0
b_1.33	0.708407	0.14335	4.942	0.0000	b_1.33	0.981158	0.0061284	160.1	0
b_1.44	0.703682	0.12781	5.506	0.0000	b_1.44	0.927663	0.10804	8.587	0
b_1.55	0.748464	0.25842	2.896	0.0040	b_1.55	0.982383	0.0067188	146.2	0
b_1.66	0.932337	0.029788	31.30	0.0000	b_1.66	0.978237	0.0075944	128.8	0
b_1.77	0.958408	0.011691	81.98	0.0000	b_1.77	0.964296	0.023072	41.79	0
a_1.11	0.268548	0.095417	2.814	0.0051	a_1.11	0.261893	0.049221	5.321	0
a_1.22	-0.093703	0.10798	-0.8678	0.3859	a_1.22	0.147241	0.040547	3.631	0.0003
a_1.33	-0.092368	0.14439	-0.6397	0.5227	a_1.33	0.148559	0.024479	6.069	0
a_1.44	0.710508	0.10232	6.944	0.0000	a_1.44	0.304331	0.19394	1.569	0.1168
a_1.55	0.013500	0.10346	0.1305	0.8962	a_1.55	0.136955	0.026463	5.175	0
a_1.	0.16953	0.069	-	0.01	a_1.	0.16260	0.0250	6.49	0

66	1	150	2.45 2	46	66	6	44	3	
a_1. 77	0.27313 6	0.036 444	- 7.49 5	0.00 00	a_1. 77	0.20124 3	0.0646 13	3.11 5	0.00 19

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