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Central and Eastern European Stock Exchanges under Stress: A Range-Based Volatility Spillover Framework

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Abstract
In this paper we analyze volatility spillovers among stock markets of Central and Eastern European (CEE) countries: Poland, Hungary and the Czech Republic vis-à-vis Germany, the United States and Russia. For this, we utilize the recent and original methodology of Diebold and Yilmaz (2012) consisting in total and directional spillover analyses with a conditional autoregressive range (CARR) model. The overall results suggest that propagation of volatility exists among the CEE stock markets to a certain degree (43%) and the inclusion of the two developed markets and Russia into the analysis induces a higher level of the transmission (57.5%). We also discover that volatility spillovers are strongly responsive to episodes of extreme market stress. The results of net volatility spillovers reveal increasing volatility spillovers during the US subprime mortgage crisis and the ongoing eurozone crises, particularly from Germany and the US to Poland and Hungary. Concordantly, we provide evidence of increasing financial integration of the CEE countries with the global markets as the CEE countries eventually became more vulnerable to the shocks originating in other markets. The findings of this paper have potential implications for portfolio managers and policymakers in comprehending the nature of cross-country volatility transmission over the course of time.

1. Introduction

International investors always desire to benefit from diversification and seek alternative markets providing higher returns and new investment opportunities. Emerging equity markets have attracted noteworthy attention from investors owing to their high economic growth prospects and increasing portion of global economic output. Given the currency crises, political unrest and unfavorable macroeconomic conditions in Asian and Latin American countries in the late 1990s, international investors began to gravitate towards Central and Eastern European stock markets in order to reduce the potential losses that occur in any single market.

Following the fall of communism and socialist regimes at the beginning of the 1990s, the CEE countries progressed toward developing a market-based economy. In the first decade of the transition period, all of the countries suffered from high inflation and experienced major recessions. In the initial period of the second decade (in the early and mid-2000s), the CEE economies displayed good performance as a result of improved macroeconomic conditions, trade liberalization and large capital inflows. However, the extant financial crises, which the world economy has been witnessing since 2008, along with globalization and economic integration have made the CEE economies immensely vulnerable to external shocks originating in developed markets. For this reason, understanding the speed and scope of volatility transmission between the CEE and developed markets is of particular importance for investors, portfolio managers and policymakers in several ways. First, the existence of significant volatility transmission from one market to another implies a possibility to generate excess returns. Second, paying attention to the transmission mechanism can ameliorate risk predictions, which results in more accurate asset pricing and value-at-risk models. Third, close examination of the mechanism may help portfolio managers in tactical asset allocation and international portfolio diversification. Finally, from the policymaking perspective, comprehending the nature and causes of the risk propagation mechanism can help in formulating effective monetary policy and addressing financial stability issues.

Volatility is transmitted across stock markets through various channels. One of the main channels is trade links, which can be direct or indirect. Second, volatility propagation can arise from financial integration among countries, such as the exposure of a country's banking system to the debt of another country. Additionally, worldwide shocks, e.g. demand- or supply-side oil shocks or a rise in US interest rates, concurrently impact countries' financial markets.

Previous studies in the existing literature have extensively investigated volatility spillovers among the stock markets of developed and emerging equity markets, while little attention has been paid to the spillovers between CEE and developed markets. In the "financial economics" line of research, the most common methodologies used in the previous literature to analyze volatility transmission are multivariate GARCH models.[1] However, these models suffer from the curse of dimensionality and thus have computational complications.

Diebold and Yilmaz (2009) propose a simple yet efficient measure of volatility spillover based on forecast error variance decompositions in a vector autoregression (VAR) framework. However, this method is not robust to the ordering of the variables. To overcome this problem, Diebold and Yilmaz (2012) (hereinafter referred to as "DY") develop the model and present measures of both total and directional spillovers. Measuring the transmission across US stock, bond, foreign exchange and commodities markets, they indicate quite limited spillovers until the onset of the global financial crisis. However, after the collapse of Lehman Brothers in September 2008, they point out important spillovers from the stock market to the other markets.

Studies which measure volatility spillover effects in the context of DY methodology employ unconditional range-based estimators as underlying volatility inputs. Li and Hong (2011) assert that range-based volatility estimators (Garman and Klass, 1980; Parkinson, 1980; Rogers and Satchell, 1991; Yang and Zhang, 2000) are claimed to be 5–14 times more efficient than the historical volatility estimators. Despite the popular use of these estimators, they do not handle the time-varying evolution of the volatility process. To address this issue, Chou (2005) proposed the conditional autoregressive range (CARR) model, which is a dynamic process for

[1] See, among others Miyakoshi, 2003; Li and Majerowska, 2008; Beirne *et al.*, 2008; Horvath and Petrovski, 2013.

the high/low range of logarithmic asset prices over a fixed time interval.[2] Analyzing an out-of-sample volatility forecast of the S&P 500 index, Chou's study documents that the CARR model procures sharper volatility estimates as compared with the standard GARCH model. Furthermore, Chou and Wang (2007) conduct volatility forecasting on the UK stock market (FTSE100) with the CARR model and ascertain that the model provides simple yet efficient volatility forecasts.

This paper explores volatility spillovers among Central and Eastern stock markets *vis-à-vis* two developed markets (the US and Germany) and Russia within the context of the recent and original directional spillovers technique of Diebold and Yilmaz (2012) and contributes to the literature in several ways. First, we provide a methodological insight into the interested researchers by modeling the DY spillover framework with Chou's CARR model. This allows us to capture the dynamic evolution of range volatilities while all of the previous studies, which analyze volatility transmission across markets using the DY framework, ignore this feature and consider unconditional range-based estimators. Second, to the best of our knowledge this is the first study to measure volatility linkages among CEE and developed markets and Russia by means of the DY methodology.[3] Third, utilizing the DY technique, we investigate time-varying directional and net spillovers during both tranquil and turbulent times including the eurozone crisis, while the previous studies heavily concentrate on the impacts of the subprime mortgage crisis on the CEE stock markets.

The rest of the paper is organized as follows. Section 2 comprises the literature review part of the paper. Section 3 describes stock market characteristics of the CEE countries. Section 4 explains the methodology and preliminary data analysis. In Section 5 we present the empirical results and Section 6 concludes the paper.

2. Literature Review

2.1. Studies Using Diebold & Yilmaz Framework

A few researchers apply the DY technique to quantify the total and directional spillovers among various financial markets. Louzis (2013) analyzes price and volatility spillovers among the money, stock, foreign exchange and bond markets of the euro area. The findings of that study suggest that the stock market was the main transmitter of return and volatility spillovers during the sovereign debt crisis. Additionally, it is reported that the bonds of periphery countries transmit volatility to other markets diachronically, with the exception of the period 2011–2012. Zhou *et al.* (2012) measure volatility spillovers between the Chinese and world equity markets and posit the dominant volatility impacts of the US market on other markets, particularly during the subprime mortgage crisis. They also document that volatility spillovers among the Chinese, Hong Kong and Taiwanese stock markets are more prominent than are those among the Chinese, Western and other Asian markets, suggesting financial market integration in the Greater China region. Awartani *et al.*

[2] The model is very similar to the autoregressive conditional duration (ACD) model of Engle and Russel (1998).

[3] The US and Germany are choosen as natural global benchmarks for the CEE countries. The selection of Russia is due to features that it has in common with the CEE markets (such as a mass privatizion process) and its geographical proximity.

(2013) examine the return and volatility spillover effects from the US and Saudi markets to the Gulf Cooperation Council (GCC) stock markets. The results reveal that Saudi returns and volatilities transmit to the GCC markets and the US stock exchange was a weak return and volatility transmitter to the GCC bloc in the pre-crisis period. After the global financial meltdown in 2008, the role of the US market in volatility spillovers is more dominant.

2.2 Studies Focused on CEE Stock Markets

In the context of CEE stock markets, the previous literature can be divided into two branches. Some of the researchers apply static and dynamic cointegration techniques to examine the process of integration of the CEE markets into the global markets, while the others employ multivariate GARCH models to investigate time-varying correlations and/or volatility transmission across markets. Gilmore and McManus (2002) focus on the short- and long-term relationship between the US and CEE (the Czech Republic, Hungary and Poland) equity markets and conclude that there is no long-term relationship, but that there is unidirectional causality running from the Hungarian to the Polish market. The results imply that US investors can benefit from international diversification into these markets. Syriopoulos (2007) explores the short- and long-term behavior of four CEE (Czech Republic, Hungary, Poland and Slovakia) and two developed markets (Germany, the US) and depicts strong linkages between the CEE countries and the developed ones. He also assesses the influence of the European Monetary Union (EMU) on the linkages and finds no dramatic post-EMU impact. In a similar study, Syllignakis and Kouretas (2010) employ static cointegration and recursive testing analyses thereof to analyze links between seven CEE countries, Germany and the US. Based on the results, they document that the markets are partially integrated and the relationship between the examined markets strengthened in connection with the EU accession process. Their overall results reveal that, at least in the short run, a US or European investor can benefit from diversifying into the CEE markets.

Apart from the cointegration studies, the researchers focus on investigating the volatility (or news) spillover mechanism and dynamic correlations between CEE and developed markets in recent years.[4] Serwa and Bohl (2005) analyze contagion (a significant increase in correlations between the crisis and non-crisis markets) to European stock markets in times of financial shocks in the period from 1997 to 2002. Their results reveal that contagion to CEE markets is not more frequent than contagion to Western European stock markets, indicating possible diversification benefits of CEE stock markets. Applying the dynamic conditional correlation (DCC) model, Wang and Moore (2008) evaluate the level of co-movement between the three largest CEE stock markets and the aggregate eurozone market. The estimated DCC coefficients show a higher level of market correlation during the period following the Asian and Russian crises and the period following EU accession.

Using intraday data, Hanousek *et al.* (2009) focus on the effects of macroeconomic news announcements on the returns of three CEE stock exchanges. They report that all three markets are exposed to significant spillovers via the index returns

[4] Other papers not mentioned in the literature review include, for example, Scheicher, 2001; Savva and Aslanidis, 2010; Syllignakis and Kouretas, 2011; and Gjika and Horvath, 2013.

from the EU, US and neighboring markets. Macroeconomic news indirectly spills over to the Czech and Hungarian markets but not to the Polish market. Caporale and Spagnolo (2011) examine stock market integration between the three CEE countries, Russia and the UK. They provide evidence of spillovers from Russia and the UK that impact the conditional variance of returns in the CEE markets, but no spillovers in the reverse direction are found. Horvath and Petrovski (2013) investigate co-movements between Western Europe and and Central and Southeastern European stock exchanges from 2006 to 2011. The results demonstrate that the degree of co-movement is much higher for Central Europe in comparison with Southeastern Europe and the global financial crisis did not change the level of integration among countries.

3. Stock Markets Characteristics

As representative markets, we chose the three largest stock market indices in the CEE region: Prague (PX), Budapest (BUX) and Warsaw (WIG). The CEE countries experienced a systematic transformation and radical structural reforms after the start of the transition process in 1989. One of the main reforms was privatization of state-owned enterprises. In 2004, eight of the CEE countries, the Czech Republic, Hungary and Poland among them, were admitted to the European Union and thus gained closer economic ties to the EU. As postulated by Syllignakis and Kouratas (2011), following accession to the European Union, these countries aroused the interest of international investors, who had previously avoided investing in CEE markets due to political instability and/or corporate governance risks. Regrettably, the financial disasters that the world economy has witnessed in the last two decades caused significant harm to investors' confidence in the CEE region. *Table 1* demonstrates the characteristics of the CEE stock markets under investigation from 1998 to 2013.

According to the statistics, the highest turnover ratios (total value of stocks traded as a percentage of market capitalization) are observed for BUX, which implies lesser net returns.[5,6] *Table 1* also depicts that there were significant portfolio equity inflows to WIG during the European sovereign debt crisis (reaching its peak in 2010) when the other two markets experienced outflows. In terms of market capitalization to GDP, a key measure in assessing stock market development, Poland has the highest ratio, particularly during the last eight years. Besides that, the number of companies listed in WIG is much higher than that of PX and BUX. In the case of PX, many of the listed firms have been delisted due to the strict requirements and lack of liquidity after 2005. Briefly stated, *Table 1* shows that the Warsaw Stock Exchange is the biggest stock market in Central and Eastern Europe, which could be related to better disclosure standards, ownership transparency and an appropriate monetary and micro-prudential policy mix.

[5] The portfolio equity inflows were taken from the World Bank and the remaining statistics were obtained from the Federation of European Securities Exchanges.

[6] Easley *et al.* (2002) assert that investors demand a premium for holding illiquid stocks and thus return and turnover are inversely related.

Table 1 Market Characteristics

	1998	1999	2000	2001	2002	2003	2004	2005
Poland (WIG)								
Turnover Ratio (%)	54.7	44.6	48.1	25.9	21.3	25.8	30.6	36.3
Market Cap. (% of GDP)	11.8	17.6	18.3	13.7	14.5	17.1	28.1	30.9
Portfolio Equity (net inflows, million USD)	1734	14	447	-307	-545	-837	1660	1333
# of Listed Companies (domestic)	n/a	n/a	n/a	211	217	201	188	213
# of Listed Companies (foreign)	n/a	n/a	n/a	0	0	0	1	5
Czech Republic (PX)								
Turnover Ratio (%)	38.7	34.5	57.7	32.9	48.2	52.4	72.8	118.5
Market Cap. (% of GDP)	18.8	18.9	18.7	14.4	20.2	18.5	27.0	29.4
Portfolio Equity (net inflows, million USD)	1096	120	619	616	-265	1104	738	-1540
# of Listed Companies (domestic)	n/a	n/a	n/a	57	47	44	62	53
# of Listed Companies (foreign)	n/a	n/a	n/a	0	0	1	1	2
Hungary (BUX)								
Turnover Ratio (%)	110.6	94.8	85.7	43.0	50.6	55.6	57.2	78.0
Market Cap. (% of GDP)	29.2	33.8	25.9	19.6	19.7	20.0	28.1	29.5
Portfolio Equity (net inflows, million USD)	556	1191	-369	134	-137	269	1491	-16
# of Listed Companies (domestic)	n/a	n/a	n/a	58	53	47	49	45
# of Listed Companies (foreign)	n/a	n/a	n/a	1	1	1	1	1
	2006	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Poland (WIG)								
Turnover Ratio (%)	45.3	47.5	45.7	49.5	47.6	58.4	42.6	n/a
Market Cap. (% of GDP)	43.6	48.7	17.0	31.4	40.5	26.8	36.3	n/a
Portfolio Equity (net inflows. million US$)	-2128	-470	564	1579	7875	3079	3888	2602
# of Listed Companies (domestic)	253	269	357	443	473	581	764	846
# of Listed Companies (foreign)	7	13	23	16	16	15	20	23
Czech Republic (PX)								
Turnover Ratio (%)	75.6	68.7	70.3	40.5	29.4	38.0	27.0	n/a
Market Cap. (% of GDP)	32.7	40.6	21.6	26.7	21.6	17.7	18.9	n/a
Portfolio Equity (net inflows, million USD)	268	-268	-1124	-311	-232	-2	-148	110
# of Listed Companies (domestic)	35	26	24	17	16	16	15	17
# of Listed Companies (foreign)	4	6	8	10	10	11	11	11
Hungary (BUX)								
Turnover Ratio (%)	83.7	106.0	93.0	110.6	94.5	83.8	54.5	n/a
Market Cap. (% of GDP)	37.2	35.0	12.0	22.3	21.7	13.6	16.9	n/a
Portfolio Equity (net inflows, million USD)	912	-5010	-197	665	-206	-203	1235	25
# of Listed Companies (domestic)	44	41	39	39	42	48	51	51
# of Listed Companies (foreign)	0	0	2	3	4	3	2	1

4. Methodology and Data

4.1 Conditional Autoregressive Range (CARR) Model

Asset volatility, which is a risk measure, plays a vital role in many fields of financial economics. However, it is not directly observable and must be estimated. In volatility modeling and forecasting, most studies consider daily closing prices, yielding only squared returns and a very noisy estimate. Intraday high-frequency data can be employed to estimate daily volatility more precisely, but the availability of high-frequency financial data is limited. Daily, open, high and low prices are also available for most of the financial time assets data. Range, the difference between high and low prices, is a feasible measure of volatility and contains more information than return data. Molnar (2012) asserts that volatility models based on high and low price data might provide accuracy similar to that of models with high-frequency data.

Chou (2005) states that the range estimator performs poorly in empirical studies (see Roger, 1998; Wiggins, 1991; and Yang and Zhang, 2000). He attributes the main reason for the range estimator's poor empirical performance to its failure to capture the time-varying evolution of volatilities. For this reason, he proposed the conditional autoregressive range (CARR) model and provides a simple yet efficient framework to model volatility dynamics. The formulation introduced by Chou (2005) can be summarized as follows.

Let t, (t = 1,2,…, T), denote a discrete time index for weeks, and $\mathbf{P}_\tau$ represent the set of prices on an asset during time index t. Then, by following Chou (2005), the weekly observed range can be calculated as the logarithmic differences of the high and low asset prices of week t:

$$R_t = \log\left(\max\left\{P_\tau\right\}\right) - \log\left(\min\left\{P_\tau\right\}\right) \tag{1}$$

$$\tau = t-1, t-1+\frac{1}{n}, t-1+\frac{2}{n}, \ldots, t$$

with $\max\{P_\tau\}$ and $\min\{P_\tau\}$ denoting the highest and lowest values of the asset price during the week, whereas n stands for the number of intervals which measures the price within each range-measured interval, which is normalized to unity.

Chou (2005) proposed the conditional autoregressive range (CARR) model for the range as follows:

$$R_t = \lambda_t \varepsilon_t, \quad \varepsilon \mid \Omega_{t-1} \sim f(.) \tag{2}$$

$$\lambda_t = \omega + \sum_{i=1}^{q} \alpha_i R_{t-i} + \sum_{j=1}^{p} \beta_j \lambda_{t-j} \tag{3}$$

where $\boldsymbol{\lambda_t}$ is the conditional mean of the range based on all available information up to time t. The distribution of the error term $\boldsymbol{\varepsilon_t}$ has a density function $f(.)$ with a unit mean. The parameters ω, α_i and β_j represent the inherent uncertainty in the range and the short- and long-term impacts of shocks on the range, respectively.

Exponential distribution may be used as a choice of distribution, since $\boldsymbol{\varepsilon_t}$ is positively valued given that the range $\mathbf{R_t}$ and its expected value $\boldsymbol{\lambda_t}$ are positively valued. However, Chou (2005) asserts that even though the exponential density specification may provide consistent estimation, it is not efficient. The efficiency result can only be achieved if the conditional density is correctly specified. Thus, we estimate the CARR model with the Gumbel distribution (GCARR), which is one of the extreme value distributions (EVDs).[7]

4.2 Volatility Spillover Effects

In this section, we briefly discuss the methodology proposed by Diebold and Yilmaz (2012) for computing the volatility spillover index, in which we use the dynamic ranges generated from GCARR (1,1) as the latent volatility proxy. In their pioneering work of 2009, Diebold and Yilmaz measure the total spillover index based on the Cholesky decomposition, which is a variation of the ordering in a simple VAR system. In 2012, they developed a methodology to evaluate directional spill-overs in a generalized VAR framework. In this way, they eliminate the dependence of the results on the ordering of variables. Next, we summarize the methodology implemented for this study.

Assume a covariance stationary N-variable vector autoregressive (VAR) model at order of p:

$$y_t = \sum_{i=1}^{p} \boldsymbol{\varphi}_{\mathbf{i}} y_{t-i} + \boldsymbol{\varepsilon}_{\mathbf{t}} \quad \text{, with } \varepsilon_t \sim i.i.d. \left(0.\Sigma\right) \tag{4}$$

where $\boldsymbol{\varphi}_{\mathbf{i}}$ are N x N matrices of coefficients. $\boldsymbol{\varepsilon}_{\mathbf{t}}$ is the vector of independently and identically distributed innovations and Σ is the variance-covariance matrix.

The moving average representation of the VAR(p) model is given as:

$$y_t = \sum_{i=0}^{\infty} \mathbf{A}_{\mathbf{i}} \varepsilon_{t-i} \tag{5}$$

where $\mathbf{A}_{\mathbf{i}}$ are the N x N moving average coefficient matrices. The $\mathbf{A}_{\mathbf{i}}$ coefficient matrices obey the following recursion:

$$\mathbf{A}_{\mathbf{i}} = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_p A_{i-p} \tag{6}$$

where $\mathbf{A}_{\mathbf{0}}$ represents the N x N identity matrix and $\mathbf{A}_{\mathbf{0}} = 0$ for $i < 0$.

Given the VAR framework, h-step-ahead forecast error variance decompositions can be written as follows:

$$\theta_{ij}^{g}\left(H\right) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^T A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^T A_h \sum A_h^T e_i\right)} \tag{7}$$

where σ_{jj} represents the standard deviation of the error term for the jth equation. Σ is the variance-covariance matrix and $\mathbf{e}_{\mathbf{i}}$ is the selection vector, whose ith element is one and the other elements are zeros.

[7] In this study, we fit the model and residual densities to three types of EVDs (Gumbel, Frechet and Weibull). Our untabulated results show that the Gumbel distribution provides the best fit, with regards to Kolmogorov-Simirnov test statistics. The results are available upon request.

In the generalized VAR model, the shocks to each variable are not orthogonalized as in the Cholesky factorization. Thus, the sum of the elements in each row of the variance decomposition matrix does not add to unity. We divide each element of the decomposition matrix by the row sum, thus using the available information in the decomposition matrix to compute the spillover index as follows:

$$\tilde{\theta}_{ij}^{g}\left(H\right)=\frac{\theta_{ij}^{g}\left(H\right)}{\sum_{j=1}^{N}\theta_{ij}^{g}\left(H\right)} \tag{8}$$

with $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=N$.

The total spillover index is constructed via normalized entries of the variance decomposition matrix given in equation (8). We calculate the total spillover index based on h-step-ahead forecasts with the following equation:

$$TS^{g}(H)=\frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}x100=\frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}x100 \tag{9}$$

Equation (9) is the KPPS (Koop, Pesaran and Potter, 1996; Pesaran and Shin, 1998) analog of the Cholesky factorization, which yields robust variance decompositions to the variable ordering. The total spillover index computes the contribution of volatility spillovers across the markets to the total forecast error variance.

Even though it is important to analyze total spillovers, it is also essential to investigate the directions of spillover effects from/to a particular market. For this purpose, we resort to the generalized VAR method, which allows us to calculate directional volatility spillovers. Directional volatility spillovers from all other markets *j* to market *i* is given by:

$$DS_{i\leftarrow j}^{g}\left(H\right)=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{g}\left(H\right)}{N}x100 \tag{10}$$

The following index evaluating the spillover effects transmitted by market *i* to all other markets *j* is as follows:

$$DS_{j\leftarrow i}^{g}\left(H\right)=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{g}\left(H\right)}{N}x100 \tag{11}$$

Using equations (10) and (11), we are able to compute the net directional spillover index for market *i* as:

$$NS_{i}^{g}(H)=DS_{j\leftarrow i}^{g}(H)-DS_{i\leftarrow j}^{g}(H) \tag{12}$$

Table 2 Descriptive Statistics of the Weekly Ranges

	WIG	PX	BUX	DAX	S&P	RTSI
Mean	3.8874	3.7134	4.9433	4.5030	3.5113	6.6431
Std. Dev.	2.4310	2.7804	3.5070	2.9603	2.2652	5.0777
Skewness	2.2551	3.5309	3.9702	2.3065	3.0595	2.5211
Kurtosis	11.2817	25.1613	29.5397	11.2067	21.0214	12.3595
Jarque-Bera	3475.568[a]	21143.74[a]	29992.82[a]	3463.989[a]	14156.51[a]	4417.348[a]
	[000.0]	[000.0]	[000.0]	[000.0]	[000.0]	[000.0]
Q(12)	770.476[a]	1555.4[a]	912.357[a]	2629.67[a]	2252.51[a]	1696[a]
	[000.0]	[000.0]	[000.0]	[000.0]	[000.0]	[000.0]

Notes: (a) denotes the statistical significance at the 1% level. The values in brackets are the *p*-values of the related tests.

The net directional spillover index is the difference between the total volatility shocks transmitted to and received from all other markets. Positive values of the index indicate that there exists a spillover effect from market i to all other markets, while the negative values imply that market i is a recipient of volatility spillover.

4.3 Preliminary Data Analysis

The dataset includes weekly prices of the eight stock market indices over the period from January 12, 1996 to December 27, 2013. There are 938 observations in total.[8,9] The data were obtained from the Bloomberg database. The high and low prices of the indices are denominated in local currencies.[10] *Table 2* presents the descriptive statistics of the weekly ranges, computed by taking the logarithmic differences of the highest prices and the lowest prices throughout the week. Based on the tabulated results, the weekly ranges exhibit excess kurtosis, which implies a non-normal distribution. Jarque-Bera test statistics also confirm the non-normality by rejecting the null hypothesis of normality at the 1% significance level. The Ljung-Box Q statistics for the range series up to the 12th lag indicate a high degree of persistence. Results from the statistics show the suitability of the CARR model proposed by Chou (2005).

5. Empirical Results

5.1. Results of the Conditional Autoregressive Range (CARR) Model

In this section, we discuss and document the empirical findings of the CARR (1.1) model with the Gumbel distributed innovations, henceforth referred to as

[8] The stock exchanges are the Warsaw Stock Exchange Index (WIG), Prague Stock Exchange (PX), Budapest Stock Exchange (BUX), German Stock Exchange (DAX), S&P 500 and the Moscow Exchange (RTSI).

[9] We use weekly frequency to eliminate the non-synchronous trading problem (different trading hours of the stock markets).

[10] Choudhry (1994) and Syriopoulos (2007) state that the local currency prices reflect the domestic market's reactions to information generated in foreign markets from the perspective of local investors. Also, Voronkova (2004) asserts that expressing the stock indices in their local currencies restricts their changes to the movements solely in the stock prices, avoiding distortions induced by the numerous devaluations of the exchange rates that have taken place in the CEE region.

Table 3 GCARR (1,1) Model Results

	ω	*α*	*β*	*Q (12)*	*K-S*
WIG	0.259[b]	0.172[a]	0.682[a]	5.037	0.036
	(0.122)	(0.038)	(0.079)	[0.956]	[0.568]
PX	0.311[b]	0.260[a]	0.543[a]	9.998	0.035
	(0.126)	(0.050)	(0.098)	[0.616]	[0.607]
BUX	0.428[a]	0.204[a]	0.611[a]	17.474	0.047
	(0.159)	(0.038)	(0.077)	[0.132]	[0.230]
DAX	0.192[c]	0.286[a]	0.561[a]	13.482	0.036
	(0.098)	(0.054)	(0.085)	[0.334]	[0.568]
S&P	0.175[b]	0.253[a]	0.594[a]	6.032	0.029
	(0.089)	(0.050)	(0.085)	[0.914]	[0.797]
RTSI	0.302[b]	0.182[a]	0.697[a]	10.314	0.043
	(0.130)	(0.034)	(0.061)	[0.588]	[0.331]

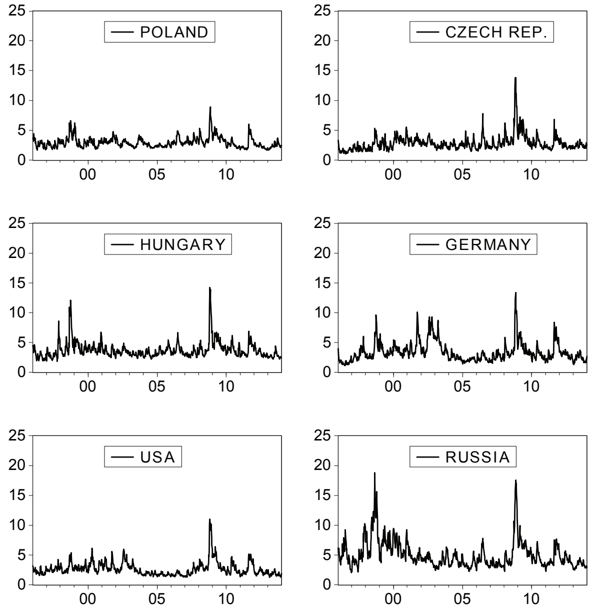
Notes: (a), (b) and (c) denotes statistical significance at the 1%, 5% and 10% levels, respectively. The values in parenthesis are standard errors and *p*-values associated with the test statistics are in brackets.

GCARR (1.1). *Table 3* demonstrates that all of the model parameters are statistically significant at the 1% level, except for the constant terms, ω. The parameters α are 0.172, 0.260, 0.204, 0.286, 0.253 and 0.182 for WIG, PX, BUX, DAX, S&P and RTSI, respectively, implying that the volatility shock impacts in the short term are the highest for the range data of DAX and the smallest for the range data of WIG. In addition, the coefficients β are 0.682, 0.543, 0.611, 0.561, 0.594 and 0.697 for WIG, PX, BUX, DAX, S&P and RTSI, respectively, which shows that the long-term effects of shocks on the range are highly persistent.

The sum of the parameters $\alpha + \beta$ is less than unity, suggesting that conditional range processes are covariance stationary. Moreover, we observe that the Ljung-Box Q (12) statistics show no serial correlations in the standardized innovations of the models. Regarding the fitness of the model residuals to the Gumbel distribution, we utilize Kolmogorov-Simirnov (KS) tests. The results of the test statistics substantiate the suitability of the distribution, providing that the models' residuals follow the Gumbel distribution. These results draw the conclusion that the dynamic structure we employ is adequate and the GCARR model is correctly specified.

Figure 1 displays time-evolution of the volatilities obtained from the fitted GCARR (1,1) model. During the late 1990s the Polish, Hungarian, German and Russian stock markets had episodes of high volatility in combination with the effects of the Asian, Latin American and Russian financial crises. We observe that all the stock markets exhibit relatively low volatility during the tranquil period from 2003 to the beginning of 2008. The subprime mortgage crisis, which turned into a global financial meltdown with the bankruptcy of Lehman Brothers in September 2008, induces higher volatility in all of the stock markets under investigation. Additionally, the European sovereign debt crisis that began with the collapse of Iceland's banking system and intensified in 2009 spread to many European countries with devastating effects. These findings motivate us to investigate the volatility transmission mechanism across the examined stock markets.

Figure 1 Time-Varying Volatilities Generated from the GCARR (1,1) Model



5.2 Results of Volatility Spillovers

To investigate the volatility transmission mechanism among stock markets, we employ the total and directional volatility spillover methodology of Diebold and Yilmaz (2012), using the estimated conditional ranges from the GCARR (1,1) model as input variables (latent volatilities).[11] In this context, the results of the total spillovers for the three CEE stock markets are presented in *Table 4*. The ij^{th} elements of the spillover in *Table 4* show the forecast error variance of market i coming from shocks to market j.[12] The variance shares of market i which represent the forecast error variance of market i resulting from its own shock, are given in the diagonal elements of *Table 4*. The off-diagonal column elements of the table denote the contribution of market i to the other market j. The spillover effects received by market i from the other market j are given in the off-diagonal row elements of the table. Moreover, the off-diagonal row and column sums show "directional spillovers from others" and "directional spillovers to others", respectively. In addition, net volatility spillovers are computed by subtracting "directional from others" from "directional to others".

[11] As suggested by a referee and to highlight the benefits of using the CARR model in the DY framework, we estimate the VAR system with an unconditional range and compare the outperformance of the two models in terms of information criteria and log-likelihood values. The Schwartz information criteria of the conditional and unconditional range-based system is 7.26 and 25.64, respectively. Besides that, the log likelihood values are found to be -3259.91 and -11737.3 for the conditional and unconditional range-based systems, respectively. These results clearly indicate the empirical outperformance of the conditional range models. Further results (the individual parameter estimates, etc.) are available upon request.

[12] Forecast error variance analysis displays the contribution of each source of shocks to the variance of the future forecast error for each endogenous variable. Hence, it splits the forecast error variance of a variable into its own shock and other variables' shocks in the system.

Table 4 Volatility Spillovers among CEE Countries

	WIG	PX	BUX	From others
WIG	54	26	20	46
PX	16	67	17	33
BUX	20.6	29.4	50	50
Contribution to others	37	55	37	129
Contribution including own	91	122	87	43.0%

In *Table 4*, we document the volatility spillovers among the CEE countries.[13] In the lower right-hand corner of the table, the volatility spillover index shows that 43% of the forecast error variance stems from volatility spillovers. This suggests that the CEE countries are interconnected at a certain level.[14] Column 4 and Row 2 of *Table 4* show that volatility spillovers from the Czech market (PX) to the other two CEE markets are larger than the spillovers in the opposite direction. The directional spillovers from PX to the others are 55%, while the transmissions from the others to PX are 33%. This indicates that the net spills from PX to the others are 22%. Examining the "contribution to others" row and the "from others" column, we find evidence that WIG and BUX are volatility recipients and more exposed to regional shocks.

In *Table 5*, we report the volatility spillovers among the CEE countries and developed countries (Germany and the United States) along with Russia. The results reveal that the inclusion of the two developed countries and Russia increases the spillover index by 14.5%. The Czech market is the main volatility transmitter for Polish, Hungarian and Russian stock markets. For the Czech and German markets, the main transmitter is the US, while the US is mostly subject to volatility from Germany. In this case, the net recipients are WIG (18%) and BUX (26%) and the net transmitters are PX (22%), DAX (8%), S&P (7%) and RTSI (7%).

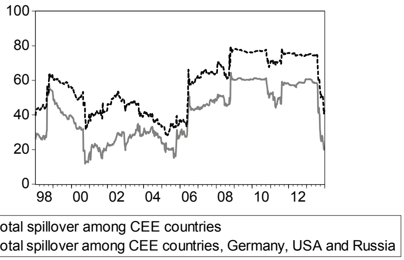
We provide a visual representation of the total volatility spillover plots in *Figure 2*. To obtain the dynamics of volatility transmission, we estimate the vector autoregression (VAR) system using a 104-week rolling window with ten-steps-ahead forecasts.[15] The black and red plots represent time-varying volatility spillovers among the CEE countries and six markets (CEE, the developed markets and Russia), respectively. Broadly speaking, the plots mostly fluctuate around 40% for the black plot

[13] We analyze the transmission mechanism among the CEE stock markets to explore and quantify the effects of regional shocks, giving insights into which CEE market transmits/receives the most among only the CEE countries. However, our main focus is the co-movement of the CEE stock markets with the two developed markets and the Russian market.

[14] To the best of our knowledge, the directional spillovers in the DY framework have not been employed for linkages between the CEE stock markets. Similar studies show results for different stock markets. For example, Zhou *et al.* (2012) compute the spillover index between the Chinese and the world equity markets (France, Germany, the UK and the US) as 59.05%. Awartani *et al.* (2013) show that the total spillover index between GCC stock markets and the US is 19.5%.

[15] For a robustness check, we reestimate the system using a 104-week rolling window with five-steps-ahead forecasts, a 104-week rolling window with 20-steps-ahead forecasts, a 52-week rolling window with five-steps-ahead forecasts, a 52-week rolling window with ten-steps-ahead forecasts, and a 52-week rolling window with 20-steps-ahead forecasts. The overall results and conclusions do not change. For the sake of brevity, we do not reproduce the results in this paper; however, they are available upon request.

Figure 2 Total Volatility Spillover Plot



Notes. Iteratively computed total spillover index—104-week rolling window with ten-steps-ahead forecasts. The solid line and dotted line plots represent time-varying volatility spillovers among the CEE countries and six markets (CEE, developed markets and Russia), respectively.

Table 5 Volatility Spillovers among CEE, the US, Russia and Germany

	WIG	PX	BUX	DAX	S&P	RTSI	From others
WIG	38.1	17.4	11.5	12.0	9.9	11.1	62
PX	10	45.9	10	10.7	14.7	8.6	54
BUX	12.2	19.1	31	11.2	10.8	15.7	69
DAX	8.5	13.2	5.7	43.1	23.7	5.8	57
S&P	7.0	15.8	5.4	23.1	40.1	8.7	60
RTSI	6.3	10.4	10	8.4	7.8	57.0	43
Contribution to others	44	76	43	65	67	50	345
Contribution including own	82	122	74	108	107	107	57.5%

and 55% for the red plot. The plots also show that interdependence between the CEE markets increases through time, which is in line with Caporale and Spagnolo (2011) and Gijka and Horvath (2013).[16]

The graphs provide evidence of significant volatility spillover upsurges in times of financial stress. Examining *Figure 2*, we note that the CEE economies were extremely exposed to external shocks due to their macroeconomic instability and fragile financial systems over the period 1998–2001. The Russian financial crisis, also known as the ruble crisis or Russian flu, significantly raises the level of volatility spillovers during 1998. The repercussions of the Asian crisis, such as the recessions of 1997–1999 in Czech Republic resulting from capital outflow, also have an effect on the rising spillovers in the same period.

The period from 2001 to mid-2006 can be identified as a relatively calm era. the global economic expansion, EU accession and gross private-capital inflows. Never-
The CEE economies experienced rapid growth during the period in conjunction with
theless, the CEE economies were subject to systemic risks stemming from exces-

[16] Gijka and Horvath (2013) utilize the Asymmetric DCC model to explore the dynamics of co-movement among the CEE markets and postulate that interdependence has increased over time. Caporale and Spagnolo (2011) find that there is significant co-movement between the CEE, Russian and UK stock markets, which is evident from VAR-GARCH in the mean models.

sive credit activities related to consumption and investment. This made the CEE economies more fragile and vulnerable.

Another significant upward movement in the spillover index plots coincides with the decision of the Federal Open Market Committee of the Federal Reserve to raise the federal funds target rate by 25 basis points on May 9, 2006. This announcement, signaling tight monetary policy in the US, triggered worries that investors would pull money out of the emerging markets, bringing a higher level of volatility transmission across the markets.

After mid-2006, the spillover plots significantly increase and remain at high levels over the next seven years in parallel with the global financial crisis and unfolding European sovereign debt crisis. The subprime mortgage meltdown and the following collapse of Lehman Brothers brought forth major chaos in the world financial markets and turned into a global crisis, causing an increase in global risk aversion. As the crisis intensified, the CEE economies were headed toward a deep recession triggered by sudden declines in foreign capital inflows, domestic demand and credit. From mid-2010 to the beginning of 2012, the spillover plots indicate a decline associated with the fragile recovery from the crisis. However, the acceleration of the eurozone crisis and its impacts, such as the output slowdown and Standard &Poor's downgrading of nine EU countries' credit ratings due to their failure to implement sufficient policy measures to fully address the systemic stress in the eurozone, increases the level of volatility spillovers to the same high extent.

Figures 3 and *4* represent the directional volatility spillovers from each of the six markets to the others ("contribution to others" row in *Table 5*) and the directional spillovers from the others to each of the markets ("contribution from others" column in *Table 5*), respectively. *Figures 3* and *4* indicate that the spillovers vary greatly over time and the directional spillovers from the Czech Republic, Germany, the US and Russia to the other countries are higher than those in the opposite direction. We also observe that the directional spillovers from each market to the other markets rise significantly during periods of turmoil, which is to some extent consistent with the findings of Beirne *et al.* (2008).[17]

In *Figure 5,* we provide net spillover plots, computed as the difference between the "contribution from" column sum and "contribution to" row sum. This analysis permits us to dynamically investigate the volatility recipient/transmitter stock markets during episodes of tranquility and turmoil.

During the Russian crisis, the main volatility recipients are the Czech, Hungarian and US stock markets. The Polish stock market is also subject to spillovers, albeit to a lesser degree. These results provide evidence that any shocks in Russia are contagious and spread to the CEE stock markets as a result of their economic and geographical proximity. As expected, Russia is the market that transmits volatility most. The second-biggest transmitter is the German stock market, although German banks had a high degree of exposure to Russia over the period.

In the boom period from 2002 to 2007, the net volatility spillover is lower compared to the crises periods, with two exceptions: the Czech and Hungarian stock

[17] Beirne *et al.* (2008) analyze volatility spillovers from mature to emerging markets (including the CEE stock markets) using BEKK-GARCH models. They document that spillovers from mature markets are present only during turbulent episodes in these markets.

Figure 3 Directional Volatility Spillovers from the Markets

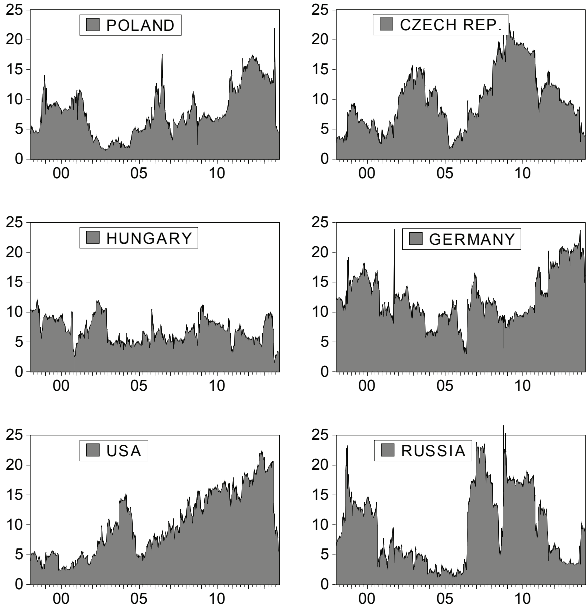
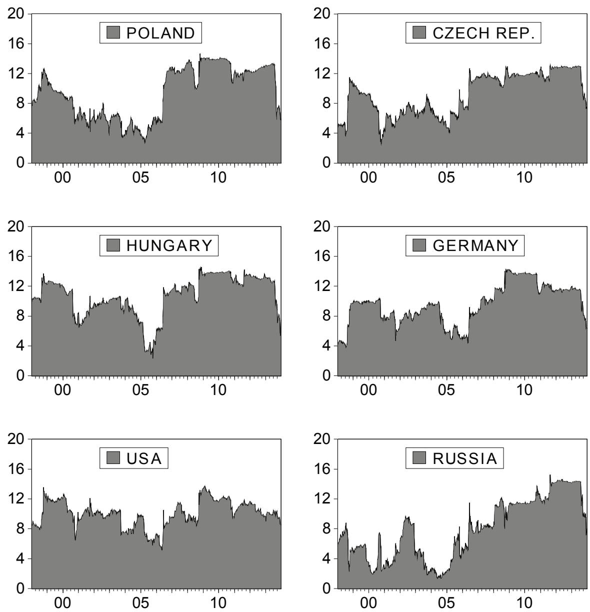
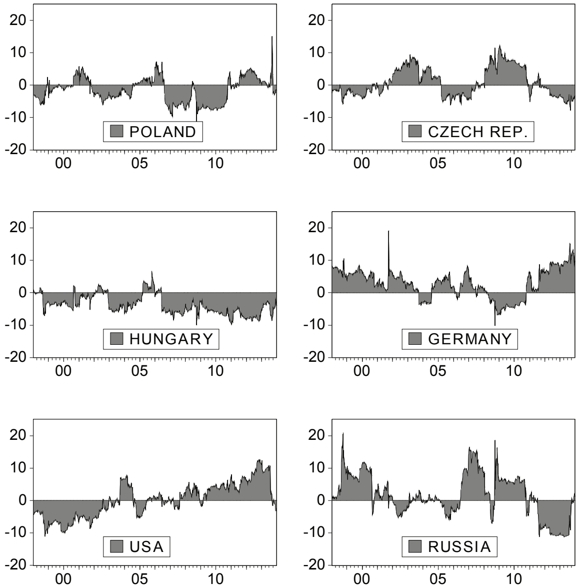


Figure 4 Directional Volatility Spillovers to the Markets



markets. The transmissions in this period likely stem from the spillover effects of idiosyncratic shocks, such as exchange rate volatility or the daily bad macro-economic news related to the domestic economy.

Figure 5 Net Volatility Spillovers



With the subprime mortgage crisis and the resulting collapse of Lehman Brothers in September 2008, the volatility spillovers become more prominent. During 2008–2009, the Polish, Hungarian and German stock markets are net volatility recipients, while the Czech Republic and the US are net transmitters. In the case of Russia, volatility is transmitted from other countries during a short period of time in late 2008. After mid-2008, Russia is a net volatility transmitter until 2011, which may be linked to insulation from the effects of shocks owing to the country's oil-related surplus and its positive impacts on the balance of payments. The findings show that Hungary receives volatility most during the global financial crisis. With high external debt and large current account deficit, the Hungarian economy was hit the hardest by the crisis. The country also experienced a currency crisis beginning in 2008 due to improper economic policies, a lack of structural reforms and speculative pressures on the forint.

During the unfolding European debt crisis, a byproduct of the US subprime mortgage crisis due to its contagion effect, the German and the US stock markets are net volatility transmitters. The Polish market also transmits volatility, though at a small magnitude. The Hungarian market is a net volatility recipient. The Czech Republic and Russia transmit volatility, though at a small magnitude at the beginning of 2011, and then receive volatility. The output and growth slowdown in the euro area and deleveraging (reduced lending and shrinking) by foreign European banks mostly contribute to the speed and dimension of risk propagation across stock markets over this period.

Overall, the results from the directional volatility spillover analyses reveal that the CEE countries were all hit during different financial crises, but to varying degrees. In the presence of external imbalances, liquidity shortages and solvency problems during turbulent periods, the level of risk propagation across the examined stock markets is much higher. Apart from the aforementioned issues, such as contagion, huge capital outflows and large budget deficits, we believe that one of the major drivers of the speed and magnitude of the spillovers is the financial integration of the CEE countries with the global markets. With deeper integration, the shocks originating in the other markets easily and quickly spill over into these markets through various channels.

6. Conclusion

Financial stability in the CEE countries is of particular importance for investors, portfolio managers and policymakers, as these countries become more vulnerable to external shocks and information flows from the global markets that have experienced downturns in recent years. This paper explores volatility spillovers between equity markets of Central and Eastern Europe and developed markets, along with Russia. For this purpose, we utilize the Diebold and Yilmaz (2012) methodology to examine both total and directional volatility spillovers. Moreover, instead of using an unconditional range as in the DY framework, we employ a conditional autoregressive range model with Gumbel distributed innovations (GCARR).

Our results shed light on a number of research questions. First, examining the conditional ranges generated from the GCARR (1,1) model, we observe that all of the stock markets under investigation are exposed to higher volatility in times of extreme market conditions. This serves as our motivation to investigate the cross-market spillovers. Second, the findings from the transmission analysis in the DY context indicate strong volatility links among the CEE countries. Besides that, the inclusion of the developed markets and Russia in the model raises volatility spillovers, providing evidence that the CEE countries are integrated with developed markets and Russia to some extent, although the financial systems of the CEE countries are largely bank-oriented. Third, we document that the CEE stock markets were affected by the different financial crises, but to varying degrees. During the US subprime mortgage crisis and the ongoing eurozone crisis, we observe a higher level of volatility spillovers than during the Asian or Russian crises, particularly for Poland and Hungary, and the role of the US and German markets is more prominent in volatility transmission.

REFERENCES

Awartani B, Maghyereh AI, Shiab MA (2013): Directional spillovers from the US and the Saudi market to equities in the Gulf Cooperation Council countries. *Journal of International Financial Markets, Institutions and Money*, 27:224–242.

Bali TG (2007): A generalized extreme value approach to financial risk measurement. *Journal of Money, Credit and Banking*, 39(7):1613–1649.

Beirne J, Caporale G, Schulze-Ghattas M, Spagnolo N (2008): Volatility spillovers and contagion from mature to emerging stock markets. *IMF Working Papers*, no 286:1–40.

Caporale GM, Spagnolo N (2011): Stock market integration between three CEECs, Russia, and the UK. *Review of International Economics*, 19(1):158–169.

Chou HC, Wang D (2007): Forecasting Volatility on the U.K. Stock Market: A Test of the Conditional Autoregressive Range Model. *International Research Journal of Finance and Economics*, 10:8–13.

Chou RY (2005): Forecasting Financial Volatilities with Extreme Values: the Conditional Autoregressive Range (CARR) Model. *Journal of Money, Credit and Banking*, 37:561–582.

Choudhry T (1994): Stochastic trends and stock prices: an international inquiry. *Applied Financial Economics*, 4(6):383–390.

Diebold FX, Yilmaz K (2009): Measuring Financial Asset Return and Volatility Spillovers with Application to Global Equity Markets. *Economic Journal*, 119:158–171.

Diebold FX, Yilmaz K (2012): Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting*, 23:57–66.

Easley D, Hvidkjaer S, O'Hara M (2002): Is information risk a determinant of asset returns? The *Journal of Finance*, 57(5):2185–2221.

Engle RF, Russell JR (1998): Autoregressive Conditional Duration: a New Model for Irregularly Spaced Transaction Data. *Econometrica*, 66:1127–1162.

Fisher RA, Tippett LHC (1928): Limiting forms of the frequency distribution of the largest or smallest member of a sample. Cambridge University Press, *Mathematical Proceedings of the Cambridge Philosophical Society*, 24(02):180–190.

Garman MB, Klass MJ (1980): On the Estimation of Security Price Volatilities from Historical Data. *Journal of Business*, 53:67–78.

Gilmore CG, McManus GM (2002): International portfolio diversification: US and Central European equity markets. *Emerging Markets Review*, 3(1):69–83.

Gjika D, Horvath R (2013): Stock market comovements in Central Europe: Evidence from the asymmetric DCC model. *Economic Modelling*, 33:55–64.

Gnedenko B (1943): Sur la distribution limite du terme maximum d'une serie aleatoire. *Annals of Mathematics*, 44:423–453.

Hanousek J, Kočenda E, Kutan AM (2009): The reaction of asset prices to macroeconomic announcements in new EU markets: Evidence from intraday data. *Journal of Financial Stability*, 5(2):199–219.

Horvath R, Petrovski D (2013): International stock market integration: Central and South Eastern Europe compared. *Economic Systems*, 37(1):81–91.

Jenkinson AF (1955): The frequency distribution of the annual maximum (or minimum) values of meteorological elements. *Quarterly Journal of the Royal Meteorological Society*, 81(348): 158–171.

Koop G, Pesaran MH, Potter SM (1996): Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Li H, Hong Y (2011): Financial Volatility Forecasting with Range-Based Autoregressive Volatility Model. *Finance Research Letters*, 8:69–76.

Li H, Majerowska E (2008): Testing stock market linkages for Poland and Hungary: A multivariate GARCH approach. *Research in International Business and Finance*, 22(3):247–266.

Louzis DP (2013): Measuring Return and Volatility Spillovers in Euro Area Financial Markets. *Bank of Greece, Working Paper*, no. 154.

Miyakoshi T (2003): Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets. Institutions and Money*, 13(4):383–399.

Molnár P (2012): Properties of range-based volatility estimators. *International Review of Financial Analysis*, 23:20–29.

Parkinson M (1980): The Extreme Value Method for Estimating the Variance of the Rate of Return. *Journal of Business*, 53:61–65.

Pesaran HH, Shin Y (1998): Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1):17–29.

Rogers LC (1998): Volatility estimation with price quanta. *Mathematical Finance*, 8(3):277–290.

Rogers LCG, Satchell SE (1991): Estimating Variances from High, Low, and Closing Prices. *Annals of Applied Probability*, 1:504–512.

Savva C S, Aslanidis N (2010): Stock market integration between new EU member states and the Eurozone. *Empirical Economics*, 39(2):337–351.

Scheicher M (2001): The comovements of stock markets in Hungary, Poland and the Czech Republic. *International Journal of Finance & Economics*, 6(1):27–39.

Serwa D, Bohl MT (2005): Financial contagion vulnerability and resistance: a comparison of European stock markets. *Economic Systems*, 29(3):344–362.

Syllignakis MN, Kouretas GP (2011): Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics & Finance*, 20(4):717–732.

Syriopoulos T (2007): Dynamic linkages between emerging European and developed stock markets: has the EMU any impact? *International Review of Financial Analysis*, 16(1):41–60.

Yang J, Hsiao C, Li Q, Wang Z (2006): The emerging market crisis and stock market linkages: further evidence. *Journal of Applied Econometrics*,21(6):727–744.

Yang D, Zhang Q (2000): Drift-independent Volatility Estimation Based on High, Low, Open, and Close Prices. *Journal of Business*, 73:477–491.

Voronkova S (2004): Equity market integration in Central European emerging markets: A co-integration analysis with shifting regimes. *International Review of Financial Analysis*, 13(5): 633–647.

Wang P, Moore T (2008): Stock Market Integration for the Transition Economies: Time-varying conditional correlation approach. The *Manchester School*, 76(s1):116–133.

Wiggins JB (1991): Empirical tests of the bias and efficiency of the extreme-value variance estimator for common stocks. *Journal of Business*, 64(3):417–432.

Zhou X, Zhang W, Zhang J (2012): Volatility spillovers between the Chinese and world equity markets. *Pacific-Basin Finance Journal*, 20(2):247–270.