Return equicorrelation and dynamic spillovers between Central and Eastern European, and World* stock markets, 2010–2019

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Globalisation and financial development have significantly integrated stock markets worldwide. A higher degree of interrelatedness and integration provides firms with increased access to global capital markets and a reduced cost of equity. This study examines the evolution of the return and volatility spillover effects between the world stock index, and the Central and Eastern European (CEE) countries' (Croatia, the Czech Republic, Hungary, Poland, and Romania) stock markets using both the multivariate dynamic equicorrelation – generalised autoregressive conditional heteroskedasticity (DECO-GARCH) model and the spillover index. The results indicate that the average return equicorrelation across the CEE and world stock indices is positive. This impairs the benefits of CEE and world portfolio diversification. In addition, bidirectional return and volatility between the world stock index's and CEE stock markets' returns exist in the aftermath of the recent European debt crisis. Importantly, the net volatility spillover bursts in either a negative or positive direction, and its sign changes over the study period. Finally, the author employ Clark–West's (2007) test of equal mean squared prediction error, and show that the world stock index can help predict the future returns and volatility of the CEE stock markets. These findings have significant implications for portfolio investors and policymakers interested in the CEE and world stock markets in predicting portfolio market risk exposures and determining the persistence of diversification benefits in these markets.

Keywords:
CEE stock markets,
DECO,
spillover index,
financial market contagion,
world stock index

* Referring to the Morgan Stanley Capital International (MSCI) World index.

Introduction

Emerging European markets have attracted much attention from global investors because of their essential desire to seek diversification benefits (Živkov et al. 2018). Over the past two decades, domestic equity markets became more globalised. Further, the degree of synchronisation of economies and financial markets has become important for understanding business cycles and evaluating diversification opportunities (Kang–Yoon 2019). In addition, the evolution of emerging equity markets has considerably increased their market size, leverage, and interrelationships with the international financial mechanism. This increased global financial integration reveals the crucial importance of a better understanding and forecasting of stock market connectedness and volatility spillover across markets worldwide (Vo–Ellis 2018). Moreover, the degree of market co-movement is a key determinant for evaluating diversification opportunities across national financial markets. Studies have demonstrated that market co-movements are significantly impacted by the global trade channel, money integration, and financial market connectedness (Chevallier et al. 2018). Cross-sectional impacts between equity markets offer helpful information for setting up asset pricing models in the global context. An in-depth analysis of cross-market time-varying interconnectedness, in terms of both return and volatility spillover, is of particular interest to investors, fund managers, and policymakers (Hung 2019, Grabowski 2019).

Croatia, the Czech Republic, Hungary, Poland, and Romania (henceforth referred to as the Central and Eastern European countries, or CEE) joined the European Union (EU) in 2004, 2007, 2013. Therefore, their stock markets are still less developed than markets in industrialised nations. Studying the return and volatility spillovers of the CEE and world stock markets is not a coincidence. It provides a compelling case to study the transmission of return and volatility from the world to emerging stock markets, and vice versa (Özer et al. 2020). Many studies have discussed co-movements between the European and international financial markets (Voronkova 2004, Syllignakis–Kouretas 2010; Joseph et al. 2020, Miloş et al. 2020). These studies suggest that the interrelations are strongly impacted by several economic and financial determinants, as well as an increase in direct investment flows and trade with the European Union (Grabowski 2019).

This study examines the return and volatility spillovers between the world and CEE stock markets to determine how well the CEE stock markets are integrated with the global market. The CEE financial markets, known as emerging and frontier markets, are riskier than developed markets, especially in terms of price volatility (Özer et al. 2020). Therefore, this study makes a significant contribution to the financial integration literature by extending the geographical scope of present empirical studies and adding CEE nations to the portfolio with the most developed ones. Considering these crucial externalities, we examine the direction and size of spillovers from the world stock markets influencing the CEE stock markets over the period 2010-2019 using a multivariate generalised autoregressive conditional heteroscedasticity (GARCH) model with Engle–Kelly's (2012) dynamic equicorrelation (DECO) framework and Diebold–Yilmaz's (2012) spillover index.

The motivation for the specification of the empirical model is as follows: First, this study focuses on the increase in widespread economic activities among countries in our data sample. Clearly, a potential connectedness exists between the CEE and world stock markets. Hence, it is vital to estimate the correlation among CEE markets for undertaking portfolio diversification across various markets, as the performance of a portfolio relies on the correlation between its equities. Second, the increased importance of emerging markets, in general, and CEE, in particular, should be considered. The two strong points of emerging markets are their high returns and potential diversification benefits for global investors (Vo–Ellis 2018). In addition, the increased presence of international investors in the local market is expected to enhance the integration of CEE markets into global markets. To examine this integration this study uses the multivariate DECO-GARCH model along with the spillover index. A combination of these two techniques has been used to successfully capture the directional spillover effects between the Association for Southeast Asian Nations (ASEAN) and the world stock markets (Kang et al. 2019), and the dynamic spillovers among Chinese stock and commodity future markets (Kang–Yoon 2019).

Since the current literature on CEE countries is scarce, this study aims to fill the gap in the literature within this area of research. Prior empirical studies provide information only about the variance-covariance matrix and correlations; their multivariate GARCH models are unable to estimate the direction of spillovers among the dimensions of assets and markets (Bouri et al. 2020a, Kang et al. 2019, Kang–Yoon 2019). To overcome these drawbacks, Diebold–Yilmaz's (2012) spillover indices based on forecast error variance decomposition from generalised vector autoregressions can be used to measure the direction of spillover. This technique allows for the measurement of spillover in returns and volatility between the world stock market index and CEE stock markets over time. However, to the best of our knowledge, limited research has been conducted on CEE stock markets. In addition, these markets suffer from radical differences in banking conditions (Škrinjarić 2020). Consequently, inducing financing and stabilising stock markets in the CEE region may reduce the cost of financing, which offers better selections and financial innovation.

To the best of our knowledge, this is the first study using empirical analysis based on equicorrelation and directional spillover effects between the world and CEE stock markets. This helps in providing extensive insights into the stability of these stock markets. Policymakers can use these insights to adjust and enact specific policies to develop the stock market and its connections with other markets.

Further, this study enables, for the first time in the literature, a differentiation between country-specific and systematic shocks for the examined markets. This can further impact the selection of adequate economic policies.

The remainder of this study is organised as follows: undertakes a brief literature review on this topic, then comprehensively describes the methodology and the data, discusses the empirical results and finally presents the conclusions of this study.

Literature review

Interrelatedness among global stock markets has been studied in two broad contexts: interdependence in returns and in volatility (Singh et al. 2010). The majority of studies have concentrated on developed markets (Baumöhl–Lyócsa 2014, Vo–Ellis 2018, Ren et al. 2019, Sehgal et al. 2019). Many studies have also focused on developed European (Miloş et al. 2020, Égert–Kočenda 2007, Voronkova 2004, Syllignakis–Kouretas 2010, Joseph et al. 2020) and emerging markets (Kang et al. 2019, Yilmaz 2010, Kim et al. 2015, Škrinjarić 2020, Özer et al. 2020, Grabowski 2019, Arendas–Kotlebova 2019, Hajdú 2020, Hung 2020a, Fekete–Morvay 2019), and explored the intercorrelations among emerging markets (Central Eastern Europe, Latin American, the Middle East, and East Asia) and developed financial markets. Some studies have explored the integration relationships among the ASEAN region, and between the ASEAN and advanced markets (Kang et al. 2019, Vo–Ellis 2018, Kim et al. 2015, Yilmaz 2010). In the context of European countries, numerous authors investigate the influence of the introduction of the Euro on European market links, and the relationship between European and US markets (Voronkova 2004, Syllignakis–Kouretas 2010, Joseph et al. 2020, Miloş et al. 2020). This section briefly reviews several studies that examine the interrelationships across stock markets in CEE countries.

In the CEE market context, Syllignakis–Kouretas (2006) investigate the short- and long-run connectedness between Central and Eastern European (Czech Republic, Hungary, Poland, Slovenia and Slovakia) CEE-5stock markets and two developed stock markets (the German and the US). The authors find these stock markets being partially integrated. Nevertheless, based on the dynamic conditional correlation (DCC) model, they suggest that the short-run interrelatedness between the CEE and developed stock markets remarkably increased during the Asian and Russian crises. Égert–Kočenda (2007) examine independence among three stock markets in CEE (Hungary Budapest Stock Exchange (BUX), Czech Republic Prague Stock Exchange (PX), and Poland Warsaw Stock Exchange (WIG)) and find no robust cointegration connectedness for any pair of markets. However, the authors do find signs of short-run spillovers in terms of the mean and volatility of stock prices. Dajcman et al. (2012) analyse the nexus between developed (Austria, France, Germany, and the UK) and developing stock markets (Hungary, Slovenia, and the Czech Republic) in Europe based on a time-frequency domain framework. The authors report substantial co-movements between the developed and developing European stock markets, varying at different time investment horizons. Baumöhl–Lyócsa (2014) assess the stock market integration of emerging CEE stock markets (Czech, Hungarian, and Polish markets) with Dow Jones Euro Stoxx 50, MSCI Germany, and MSCI World, and report clear linkages among these markets. Živkov et al. (2018) investigate the interdependence between the German stock market and four emerging European markets, and find that a high level of integration exists between the German and these emerging markets.

Recently, Škrinjarić (2019) examines the reactions of the CEE, and South and Eastern European (SEE) stock markets to the Brexit vote in June 2016. The author finds mixed results on the abnormal cumulative return indices, while the volatilities are indeed dramatically impacted by the Brexit event. Arendas–Kotlebova (2019) examine the existence of the turn of the month's influence in the CEE stock markets and provide evidence that a significant statistical turn of the month effect exists in these markets. Hung (2019) explores the conditional correlations and volatility spillovers across CEE stock markets (Croatia, Hungary, Poland, Romania, and the Czech Republic). The author finds that the interrelationship between these markets being statistically significant, and cross-volatility spillovers are generally higher than own-volatility spillovers for all markets. Grabowski (2019) considers time-varying connectedness and volatility spillovers between the Czech, Hungarian, and Polish stock markets, and the capital markets of advanced countries (Germany and the US). The author highlights the level of relationship between stock return innovations of CEE nations rises considerably during the US subprime crisis and the euro area sovereign debt crisis. Importantly, the author reports that CEE stock markets are recipients of volatility. Živkov et al. (2019) also examine the level of correlation between the four stock markets of the Visegrad group and two advanced stock markets (*Germany and the US) via the time and frequency domains. Their results support* Grabowski's (2019) findings. Škrinjarić (2020) evaluates stock market stability in the CEE and SEE markets. The author suggests that Serbian, Hungarian, Bulgarian, Croatian, Slovenian, Romanian and Ukrainian stock markets respond more to the systematic shocks in the SEE index compared to CEE. Similarly, Özer et al. (2020) examine the return and volatility spillovers between SEE, and vis-à-vis regional and global stock markets (Europe, Japan, China, and the US). The authors find evidence of significant spillover effects between these markets. Importantly, the authors document both short- and long-run intra- and inter-regional return and volatility spillovers between the SEE and the developed stock markets.

Notably, researchers capture price and volatility spillovers among stock markets using multivariate GARCH-type models to facilitate the analysis of multi-dimensional interdependence among the markets in the European region (Hung 2018, 2019, Živkov et al. 2018, Joseph et al. 2020). Several studies have used various cointegration methods (Joseph et al. 2020, Syllignakis–Kouretas 2010, Dajcman et al. 2012, Hegerty 2018, Égert–Kočenda 2007, Voronkova 2004, Hung 2021) to highlight the level of the interrelationship between CEE and SEE stock markets. Other researchers employ the DCC GARCH model to estimate time-varying conditional correlations in these countries (Grabowski 2019, Baumöhl–Lyócsa 2014, Syllignakis–Kouretas 2006). Aboura–Chevallier (2014) employ the DECO model to analyse the volatility equicorrelation across markets (equities, bonds, foreign exchange rates, and commodities). The authors prove that this model significantly simplifies the estimation process because it reduces to two equicorrelation parameters α and β. Bouri et al. (2020a) explore market integration among 12 leading cryptocurrencies using the DECO model and confirm that the DECO model is able to deal with a large set of variables compared to the conventional GARCH-type models. Recently, Kang et al. (2019) and Kang–Yoon (2019) use Engle–Kelly's (2012) DECO-GARCH model along with Diebold–Yilmaz's (2012) spillover index to estimate the dynamic linkages among financial markets. We employ both these approaches here.

This literature review shows that empirical studies have provided evidence that the global financial crisis, Brexit, and the European debt crisis increased market integration or contagion between the CEE and SEE stock markets, and between the CEE and developed stock markets. However, these studies did not demonstrate the channels through which such adverse shocks propagated from the source market in the CEE region to other markets.

Here, we examine the direction and intensity of return and volatility spillovers between each of the CEE stock markets and a world stock market index in terms of the total, directional, and net pairwise spillover indices. We employ Engle–Kelly's (2012) multivariate DECO-GARCH model and Diebold–Yilmaz's (2012) e spillover index. In reality, the DECO model assumes that the pairs of stock series are equicorrelated at a given time, yet this correlation varies over time. This simplifies the computations of the log-likelihood of the high-dimension system of returns (Kang et al. 2019). The DECO model uses more information to compute the DCCs between each pair of stock returns than classical MGARCH models (DCC or Baba, Engle, Kraft, and Kroner BEKK models). Further, the DECO model can tackle a large set of indicators without encountering estimation issues arising from numerical problems, thereby reducing the estimation noise of the correlation (Bouri et al. 2020a). The directional spillover effects for each market are determined using the spillover index approach based on forecast error variance decomposition from a general vector autoregressive (VAR) specification. Our results of net return and volatility spillovers presented here assist in better understanding the direction of information transmission. Furthermore, they can help in classifying the net transmitters and recipients of information between the CEE and the world stock markets. Therefore, this study complements the emerging body of literature by shedding light on the direction and intensity of return and volatility spillovers between each of the CEE and world stock markets.

Methodology and data

Here, we briefly introduce our empirical methods. We first start with a multivariate GARCH model with the DECO specification to capture the equicorrelation between the world stock index and CEE stock markets. We also use Diebold–Yilmaz's (2012) spillover index approach to identify the dynamic net directional spillover effects across stock markets.

The DECO-GARCH model

Engle–Kelly (2012) propose the DECO-GARCH model, where the average of the conditional correlations is set equal to the average of all correlation pairs. We can estimate the time-varying linkages across markets over the study period. Unlike the standard DCC model proposed by Engle (2002), the DECO framework allows large-scale correlation matrices to be addressed.

We have a vector for *n* return series $r_t = [r_{1,t}, \cdots, r_{n,t}]'$. Then, the following autoregressive moving average (ARMA) (1,1) process, or ARMA (1,1), is estimated as follows:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t + \xi \varepsilon_{t-1}, \text{ with } \varepsilon_t = u_t h_t \tag{1}$$

where μ is a constant vector, and $\varepsilon_t = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]'$ is a vector of residuals. u_t is an independently and identically distributed process.

DCC is also employed here. Engle (2002) introduced this estimator to capture the dynamic time-varying behaviour of the conditional covariance. The conditional covariance matrix H_t is defined as follows:

$$\mathrm{H}_t = D_t R_t D_t \tag{2}$$

where $D_t = diag\sqrt{\{\mathrm{H}_t\}}$ is the diagonal matrix with conditional standard deviations and R_t is the time-varying correlation matrix.

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

$$h_{ii,t} = c + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1} \tag{3}$$

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}}, i, j = 1, 2, ..., n \tag{4}$$

where c is a $n \times 1$ vector, and a_i and b_i are diagonal$(n \times n)$ matrices.

Equation (2) can be re-parameterised with standardised returns as follows, $e_t = D_t^{'} \varepsilon_t$,

$$\mathrm{E}_{t-1}[e_t e_t^{'}] = D_t^{-1} H_t D_t^{-1} = R_t = \left[\rho_{ij,t}\right] \tag{5}$$

where $R_t = \left[\rho_{ij,t}\right]$ is the conditional correlation matrix.

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

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{6}$$

where,

$$q_{ij,t} = \bar{\rho}_{ij}(1-\alpha-\beta) + \alpha e_{i,t-1}e_{j,t-1} + \beta q_{ij,t-1} \tag{7}$$

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

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

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

In matrix form,

$$Q_t = \bar{Q}(1-\alpha-\beta) + \alpha e_{t-1}e_{t-1}^{'} + \beta Q_{t-1} \tag{8}$$

where $\bar{Q} = Cov\left[e_t, e_{t'}\right] = E\left[e_t, e_{t'}\right]$ is the unconditional covariance matrix of the standardised errors and can be estimated as follows:

$$\bar{Q} = \frac{1}{T}\sum_{t=1}^{T} e_t e_t^{'} \tag{9}$$

R_t is then obtained by

$$R_t = \left(Q_t^*\right)^{1/2} Q_t \left(Q_t^*\right)^{1/2} \tag{10}$$

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

Nevertheless, Aielli (2013) suggests that the estimation of the covariance matrix Q_t is inconsistent because $E[R_t] \neq E[Q_t]$. The author illustrates the following consistent model with the correlation-driving process (cDCC):

$$Q_t = (1-a-b)S^* + a\left(Q_{t-1}^{*1/2}\varepsilon_{t-1}\varepsilon_{t-1}^{'}Q_{t-1}^{*1/2}\right) + bQ_{t-1} \tag{11}$$

where S^* is the unconditional covariance matrix of $Q_t^{*1/2}\varepsilon_t$. a and b are non-negative scalars that satisfy the condition $a+b<1$.

Engle–Kelly (2012) suggest modelling ρ_t using the cDCC process to obtain the conditional correlation matrix Q_t and then taking the mean of its off-diagonal elements. The DECO specification reduces the estimation time. The scalar equicorrelation can be written as follows:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(K_n^{'}R^{cDCC}K_n - n\right) = \frac{2}{n(n-1)}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \tag{12}$$

where $q_{ij,t} = \rho_t^{DECO} + \alpha_{DECO}\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \rho_t^{DECO}\right) + \beta_{ECO}\left(q_{ij,t} - \rho_t^{DECO}\right)$, K is a vector of ones, and $q_{i,j,t}$ is the $(i,j)^{th}$ component of the matrix Q_t from the DCC model. We then apply ρ_t^{DECO} to capture the conditional correlation matrix.

$$R_t^{DECO} = (1-\rho_t)I_n + \rho_t K_n \tag{13}$$

where I_n is the n -dimensional identity matrix and K_n is the $(n \times n)$ matrix of ones.

Hence, DECO modelling is less burdensome and computationally faster to estimate. In addition, it reports the relationship between a group with a single DCC coefficient.

Spillover index approach

Consider a covariance stationary VAR model of order p and N variables, $x_i = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_i$, where $\varepsilon_i(0,\Sigma)$ is a vector of independent and identically distributed distances. We can turn the VAR into a moving average (MA) representation, that is, $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where a $N \times N$ coefficient matrix A_i is obtained by the recursive substitution, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with $A_0 = I_n$, which is an identity matrix of order n, and $A_i = 0$ for $i < 0$. The MA presentation can be employed to forecast the future with H-step-ahead.

The H-step-ahead generalised forecast error variance decomposition can be written as follows:

$$\phi_{ij}^{g}(H) = \frac{\sigma_{ij} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma e_i \right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma A_h^{'} e_i \right)} \tag{14}$$

where $\sum$ is the variance matrix of the error vector, σ_{ii} is the standard deviation of the error term for the ith equation, and e_i is the selection vector with 1 as the ith element and 0 otherwise.

According to the properties of generalised VAR, we have $\sum_{j=1}^{N} \phi_{ij}^{g}(H) \neq 1$. Each entry of the variance decomposition matrix is normalised by the row sum as follows:

$$\tilde{\theta}_{ij}^{g} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{15}$$

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

The total volatility spillover index proposed by Diebold–Yilmaz (2012) is defined as follows:

$$S^g(H) = \frac{\sum_{i,j=1,j\neq i}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{16}$$

We can measure the directional volatility spillovers received by market i from all other markets j as follows:

$$S_{.i}^g(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{17}$$

Similarly, we can calculate the directional spillovers transmitted by market i to all other markets j as follows:

$$S_{i.}^g(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ji}^g(H)}{N} \times 100 \tag{18}$$

We can also obtain the net volatility spillover for each market by calculating the difference between equations (18) and (17) as follows:

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{19}$$

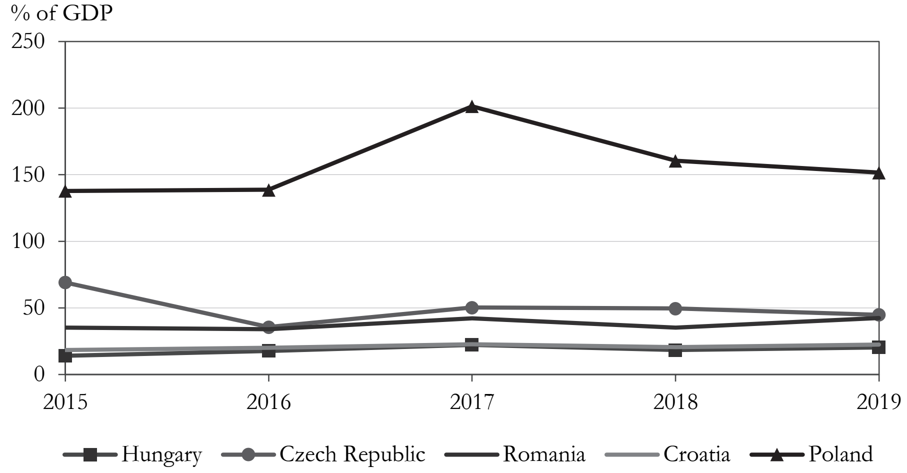
Data and descriptive statistics

The dataset we use spans from 5 January, 2010, to 31 December, 2019, which is known as a post/stable crisis period (Shehzad et al. 2020). We investigate the daily stock market indices of five emerging markets in the CEE region: Hungary Budapest Stock Exchange (BUX), Poland Warsaw Stock Exchange (WIG), Czech Republic Prague Stock Exchange (PX), Romania Bucharest Stock Exchange (BET), and Croatia Zagreb Stock Exchange (CRON). For the world (WORLD) stock market index, we use the Morgan Stanley Capital International (MSCI) World index. The MSCI World index represents large and mid-cap equity performance across all 23 developed markets countries. Compared to several studies that applied low-frequency data (e.g., weekly or monthly data), we employ daily data to adequately capture the rapidity and intensity of the time-varying interdependence among the considered variables. Note that data samples at higher frequencies are tend to contain more complicated and up-to-date information than lower frequency data (Ahmed–Huo 2020, Hung 2020b).

Our sample covers stock markets with different degrees of financial development. Figure 1 illustrates the evolution of market size between 2015 and 2019 using the World Development Indicators. The ratio of market capitalisation to gross domestic product reveals that stock markets in these nations have considerably increased their relative significance over the period studied. In other words, it is worth noting the CEE's capitalisation growth in recent years. Overall, Poland had the largest stock market in this region, while the other group members had only deficient levels of market capitalisation. In addition, these stock markets have experienced substantial development, increased in size, and enhanced institutional properties (Hung 2018, Živkov et al. 2020). We observe that market developments in emerging economies with a relatively high and stable growth rate in the CEE region are particularly remarkable. These economics are often good choices for investors seeking diversification of their portfolios globally (Hung 2019, 2020b, Williams–Bezeredi 2018).

Figure 1

Market capitalisation between 2015 and 2019



The CEE emerging markets that we consider joined the EU in 2004 (Hungary, Poland, and the Czech Republic) and 2007 (Croatia and Romania). We choose these nations because they joined the EU only in 2004 and 2007. Hence, we can explore the CEE stock market developments. Furthermore, we select the CEE markets to observe whether they have a connection with the world stock market.

The data for our empirical investigation are obtained from Bloomberg. Our dataset contains six stock indices with 2516 daily price observations. The daily returns for each stock market 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 the percentage changes and avoid convergence problems in the estimation.

Table 1

Descriptive statistics for daily returns world stock index and five CEE stock markets, 2010–2019

	World	Croatia	Czech Republic	Hungary	Poland	Romania
Mean	0.024170	–0.010023	0.023001	0.028844	–0.064202	–0.065941
SD	1.010381	0.638750	0.978240	0.638750	1.14770	4.914622
Max	5.539731	8.562884	7.248696	10.67431	5.063068	10.56451
Min	–7.653503	–4.682503	–6.134577	–6.984201	–7.543131	–24.03233
Skew.	–0.516852	0.577434	–0.394086	–0.008004	–0.344455	–46.48898
Kurt.	8.006562	18.75350	7.606236	7.915980	5.604665	22.07282
J-B	2738.647	2614.620	2288.506	2532.512	760.6697	5413.414
ADF	–53.0129***	–46.37884***	–48.86194***	–50.08192***	–37.10785***	–49.91994***
Q^2 (10)	1098.1***	56.338***	773.32***	332.45***	284.72***	43.0244***
ARCH-LM	109.7927***	4.063256*	168.9711***	117.7001***	28.78501***	720.0121***

Notes: Q^2 (10) is the Ljung-Box statistics for the squared series for the 10^{th} lag.
The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 1 presents the results of the descriptive statistics of the CEE and world daily stock market returns. The average daily stock market returns are positive for Hungary, Czech, and the world, and negative for the rest of the return series under consideration. The unconditional volatility of the stock indices is measured by standard deviations. The sample variance ranges from 0.6% (Hungary) to 4.9% (Romania). All return series are negatively skewed, except Croatia. Further, the high kurtosis ratios suggest that the distribution of stock market returns is fatter tailed. The Jarque-Bera (J-B) statistics for all concerned variables also show that the examined return series are not normally distributed.

We use the Augmented-Dickey-Fuller (ADF) test to check the stationarity of the time series for unit root testing. The results of this test show that all series are stationary at level I(0). We also use the Ljung-Box (Q^2) tests for squared returns and the ARCH-LM test to check the serial correlation and the ARCH effect. The results of these tests justify the application of multivariate GARCH-type models to measure the return and volatility of daily data series for the selected stock markets.

Figure 2 depicts the data distribution and correlation structure in terms of the data distribution, and pairwise correlations between the variables under consideration. There are significant cross-correlations between the markets, based on Pearson's methodology. WORLD is likely to have a significant linear dependence on the WIG and CRON stock markets, while CEE stock returns have a low connection with each other. This finding suggests that investors tend to reallocate their assets across stock markets.

Figure 2
Distribution and pairwise correlation plot between variables, 2010–2019

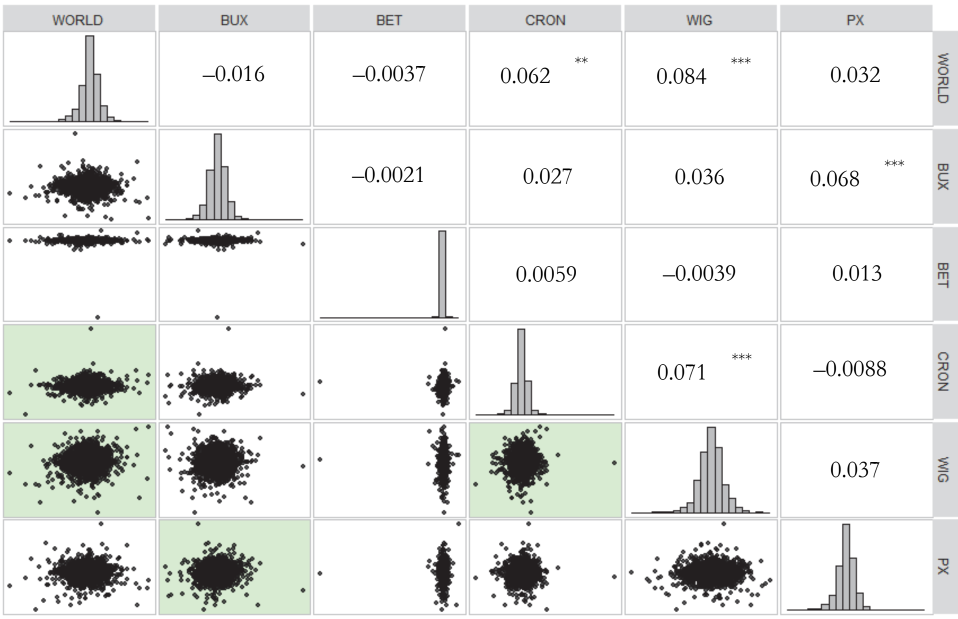
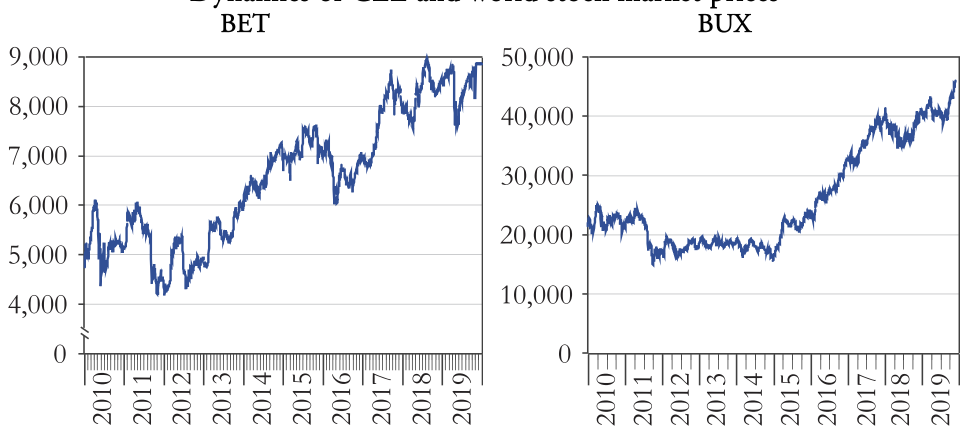


Figure 3 shows the raw series in which each CEE market and the world market fluctuate. Although the index series have almost the same trend over the study period, they clearly cross each other. Indeed, the world, BET, and BUX show positive co-movements, meaning that they exhibit a positive correlation.

Figure 3
Dynamics of CEE and world stock market prices



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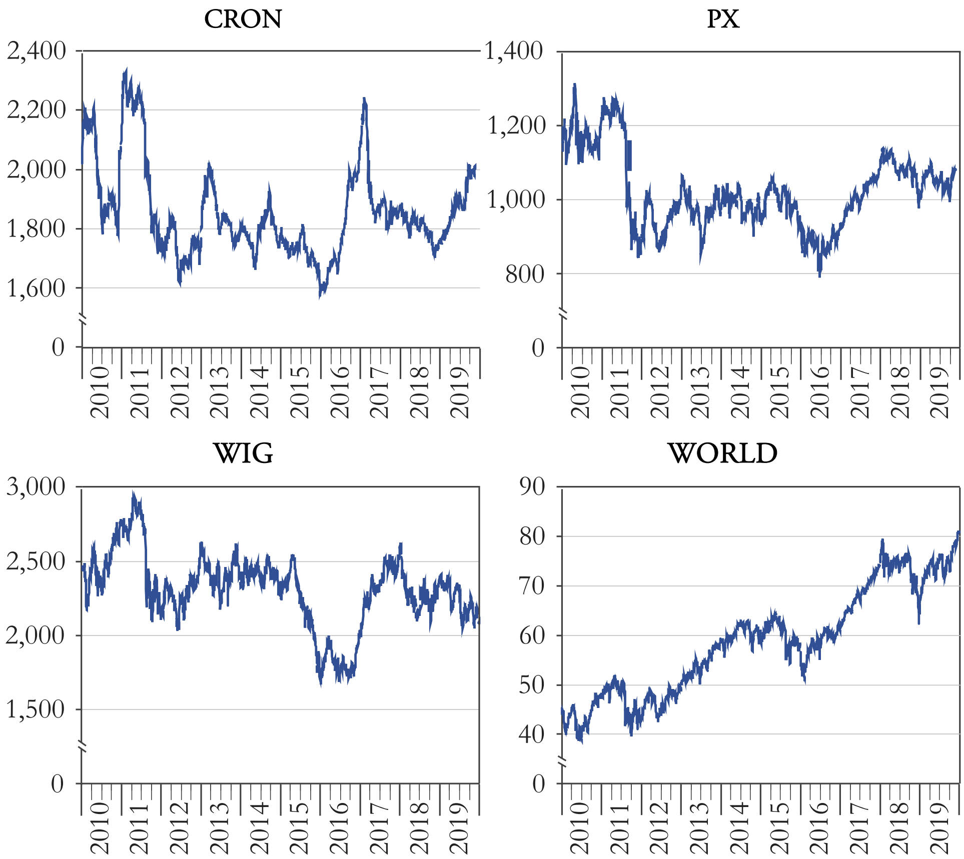


Empirical results

Results of the DECO model

We document the time-varying correlations between the world and CEE stock markets using the multivariate ARMA-GARCH model with the DECO framework in Table 2. To identify an appropriate ARMA-GARCH model, we carry out an appropriate ARMA (1,1)-GARCH (p,q) model with a lag selection of $p=1,2$ and $q=1,2$ based on the lowest values of the Akaike and Schwarz criteria. We select the univariate ARMA (1,1)-GARCH (1,1) for all combination returns. Panel A in Table 2 shows that the parameters of ARCH and GARCH for all selected variables are statistically significant at the 1% level. The sum of $(\alpha+\beta)$ for all series is close to one and statistically significant, indicating that the conditional volatility is mean-reverting.

Table 2

Estimation results of the ARMA-GARCH model with DECO specification, 2010–2019

	World	Croatia	Czech Republic	Hungary	Poland	Romania
Panel A: Estimates of the univariate ARMA (1,1) – GARCH (1,1) model						
Const (M)	0.051910***	0.003962	0.027276*	0.052054**	0.003235	–0.064323
	(0.007051)	(0.011341)	(0.015619)	(0.02132)	(0.021842)	(0.0050)
AR (1)	0.950174***	–0.108234	–0.645708	–0.358792	–0.827978***	–0.001299
	(0.013381)	(0.481885)	(0.569112)	(0.449626)	(0.110929)	(0.0004)
MA (1)	–0.977580***	0.145233	0.657765	0.382274	0.853462***	0.459164
	(0.008046)	(0.481768)	(0.560940)	(0.445527)	(0.102931)	(0.1091)
Const (V)	0.025290***	0.013737***	0.021267***	0.031723***	0.031816***	–0.06066***
	(0.003874)	(0.002082)	(0.003552)	(0.006350)	(0.007772)	(0.000)
ARCH (α)	0.155772***	0.092911***	0.110259***	0.077026***	0.053074***	0.00070***
	(0.011594)	(0.008801)	(0.008828)	(0.007359)	(0.006955)	(0.000)
GARCH (β)	0.826906***	0.876258***	0.869093***	0.901207***	0.922311***	0.902598***
	(0.012066)	(0.012683)	(0.010311)	(0.010188)	(0.010753)	(0.000)
Panel B: Estimates of the DECO model						
Average ρ_{ij}	0.021747***					
	(0.013465)					
a_{DECO}	0.0107135***					
	(0.002899)					
b_{DECO}	0.9254343***					
	(0.018470)					
Panel C: Diagnostic tests						
$Q^2(20)$	21.192	10.167	20.757	15.702	17.082	0.0803
	[0.386]	[0.965]	[0.412]	[0.735]	[0.648]	[0.9099]
ARCH-LM	0.397784	0.208647	1.081095	1.616194	1.036470	0.000250
	[0.5282]	[0.6478]	[0.2985]	[0.2036]	[0.3086]	[0.9874]
$Hosking^2$	502.4647					
	[0.6891]					
McLeod-$Li^2(20)$	526.2981					
	[0.7064]					

Notes: $Q^2(20)$ represents the Ljung-Box test statistics employed for the squared standardised residuals. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The *p*-values are in brackets and standard errors are in parentheses.

Panel B of Table 2 presents the findings of the DECO model. The DECO coefficient is statistically significant and positive with a value of 0.021747. This shows that a significant degree of integration exists across these stock markets. The parameter a_{DECO} is positive and significant, indicating the crucial importance of innovations between the world stock index and CEE stock markets. Similarly, the coefficient of b_{DECO} is statistically significant and close to one for all cases, showing the high persistence of volatility between the world stock index and CEE stock markets. In other words, equicorrelations are highly dependent on past correlations. In addition, the sum of a_{DECO} and b_{DECO} estimates is nearly equal to unity, indicating that the volatility equicorrelation is integrated. The significance of the two parameters justifies the appropriateness of the DECO-GARCH model. Moreover, we can verify that the DECO parameters lie within the range of standard estimates originating from the GARCH (1,1) models. This implies that the equicorrelations among stock markets are stable. These results are consistent with those of previous studies (Aboura–Chevallier 2014, Kang et al. 2019, Kang–Yoon 2019).

Panel C of Table 2 reports the diagnostic tests. The Ljung-Box test statistics for the standardised squared residuals do not reject the null hypothesis of no serial correlation for all cases, meaning that the residuals represent no autocorrelation. In addition, we use the multivariate autoregressive conditional heteroskedasticity - Lagrange multiplier (ARCH-LM) test on the residuals of each model to determine whether the ARCH effect still exists in the model. We find no problems for the ARCH effect for all pairs during the study period.

We find no misspecification in our model. Specifically, the Hosking, and the McLeod and Li tests' results reveal that the null hypothesis of no serial correlation in the conditional variances estimated by the DECO-GARCH model is supported. This indicates that our selected DECO-GARCH model is correctly specified.

Figure 4

Dynamic equicorrelation for returns of world stock index and CEE markets

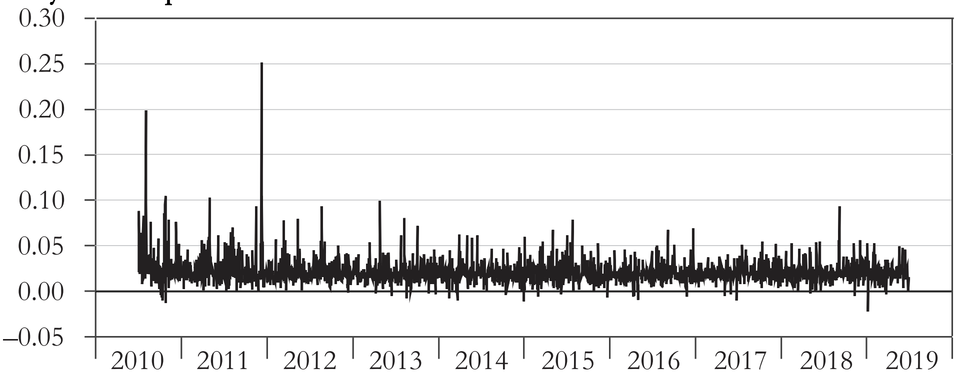
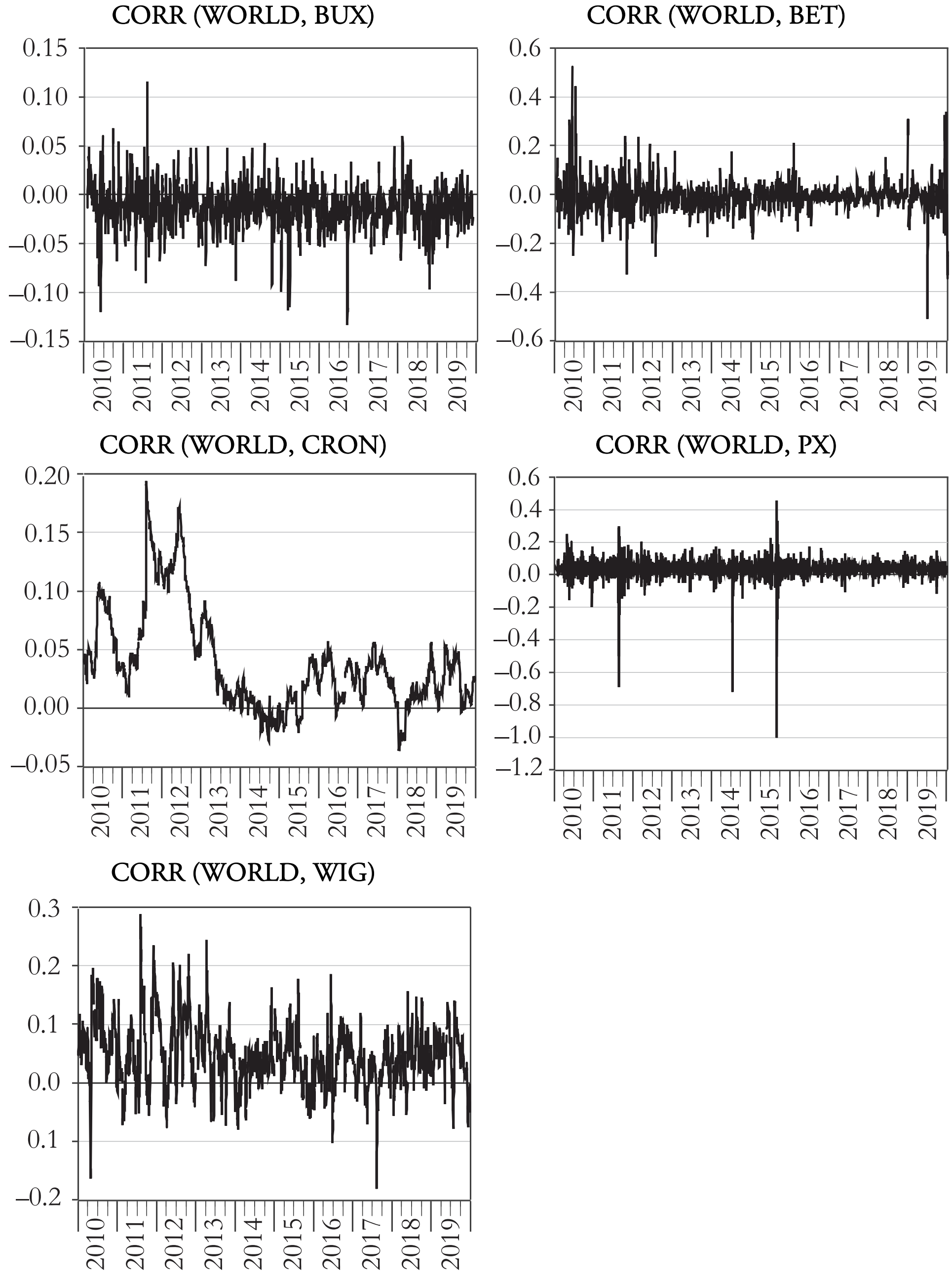


Figure 4 describes the dynamic conditional equicorrelation between the world index's and CEE stock markets' returns, which are obtained from the ARMA-GARCH model with the DECO framework. The DECO dynamics itself hold an interpretative value because the equicorrelation provides an idea of the correlation in the market. The line graph depicts a variation over time with a correlation level varying from a minimum of –2.5% to a maximum of 20%. Importantly, we observe a dramatic increase in equicorrelation levels between 2011 and 2012, corresponding to the period of the European debt crisis. Clearly, the dynamic conditional equicorrelation across stock markets fluctuated remarkably over the study period. However, an increase was also observed during 2017 and 2018. These results support the hypothesis of a contagion effect, defined as a significant rise in the correlation among stock markets in different countries during a crisis period (Hung 2019, Kang et al. 2019).

Figure 5

Dynamic conditional correlation between the returns of CEE stock markets and the world stock market index



To evaluate the robustness of the estimation results, we also estimate DCC models between the returns of each CEE country and the world stock index in Figure 5. Clearly, the pairwise DCC plots tally with the DECO estimations shown in Figure 3. The DCC level between the returns of each CEE country and the world stock index considerably increased during the European debt crisis and the 2017–2018 period, suggesting a contagion effect. Thus, the pairwise DCC results support our findings for the selected stock markets based on the DECO model.

Return and volatility spillover index

The return and volatility spillovers across the CEE and world stock markets are estimated using the spillover index method for the full sample. In essence, conditional volatilities are obtained using the ARMA-GARCH model based on the DECO specification. The total spillover index matrices of return and volatility spillover contributions to and from among the stock markets are presented in Panels A and B of Table 3, respectively. A four order VAR and generalised variance decompositions of 10-day-ahead forecast errors are employed to obtain all results. The $(i, j)^{th}$ element in each panel is the contribution to the forecast error variance of the variable i coming from shocks to the market j. Consequently, the single selected variable is connected to one of the counterpart countries' series or volatilities. The off-diagonal components $(i \neq j)$ in the spillover tables estimate cross-variable transmissions between returns and volatility within and across countries, while the diagonal components $(i = j)$ capture own-variable returns and volatility transmissions within and between countries. The total spillovers received by a given market from all other markets are shown in the last column 'From Others', while the spillover effect generated by a particular market to all other markets is shown in the row 'Contribution to Others'. Net directional spillovers, expressed as a negative value (net transmitter) and a positive value (net recipient) of return and volatility spillovers, are the disparities between 'Contribution to Others' and 'From Others'. Finally, the 'Total' in the lower right corner of each panel gives the total spillover index level in percentages.

Panel A of Table 3 reports the total and net return spillover indices between the world and CEE stock markets. The lower right corner shows that the total spillover reaches 4.7%, which indicates a low level of return spillover between the concerned variables. More precisely, the total return spillover index reveals an average of 4.7% for return forecast error variance and suggests the existence of bidirectional return transmissions between the world and CEE stock markets. Looking at the directional spillover transmitted 'to', the world stock market is the highest contributor to other markets, contributing 10.9%, followed by Croatia (6.7%), Poland (5.3%), Hungary (3.1%), the Czech Republic (2.0%), and Romania (0.3%), respectively. Croatia transmits, on average, 6.7% (2%) to (from) other markets. In contrast, the rest of the other markets (Hungary, Poland, Romania, and the Czech Republic) are net recipients because their contributions to all other markets are less than what they receive from the other markets. The Czech Republic is the highest recipients of return spillovers, with a net value of –6.2%, followed by Hungary with a net value of –3.4%.

Table 3

Directional returns and volatility spillovers, 2010–2019

	World	Croatia	Czech Republic	Hungary	Poland	Romania	From others
			Panel A: Return spillovers				
World	95.95	2.17	0.54	0.31	0.95	0.07	4.0
Croatia	0.65	98.00	0.03	0.58	0.65	0.09	2.0
Czech Republic	4.54	1.73	91.84	0.69	1.17	0.04	8.2
Hungary	2.60	0.70	0.85	93.45	2.35	0.05	6.5
Poland	2.90	1.96	0.21	1.22	93.63	0.08	6.4
Romania	0.18	0.14	0.34	0.32	0.13	98.89	1.1
Contribution to others	10.9	6.7	2.0	3.1	5.3	0.3	28.2
Contribution including own	106.8	104.7	93.8	96.6	98.9	99.2	4.7%
Net spillovers	6.8	4.7	–6.2	–3.4	–1.1	–0.8	0
			Panel B: Volatility spillovers				
World	96.04	2.10	0.52	0.30	0.97	0.08	4.0
Croatia	0.63	98.02	0.03	0.56	0.65	0.11	2.0
Czech Republic	4.48	1.67	91.93	0.71	1.16	0.05	8.1
Hungary	2.56	0.68	0.84	93.53	2.32	0.07	6.5
Poland	2.88	1.91	0.20	1.20	93.70	0.11	6.3
Romania	0.28	0.23	0.78	1.09	0.30	97.32	2.7
Contribution to others	10.8	6.6	2.4	3.9	5.4	0.4	29.5
Contribution including own	106.9	104.6	94.3	97.4	99.1	97.7	4.9%
Net spillovers	6.9	4.6	–5.7	–2.6	–0.9	–2.3	0

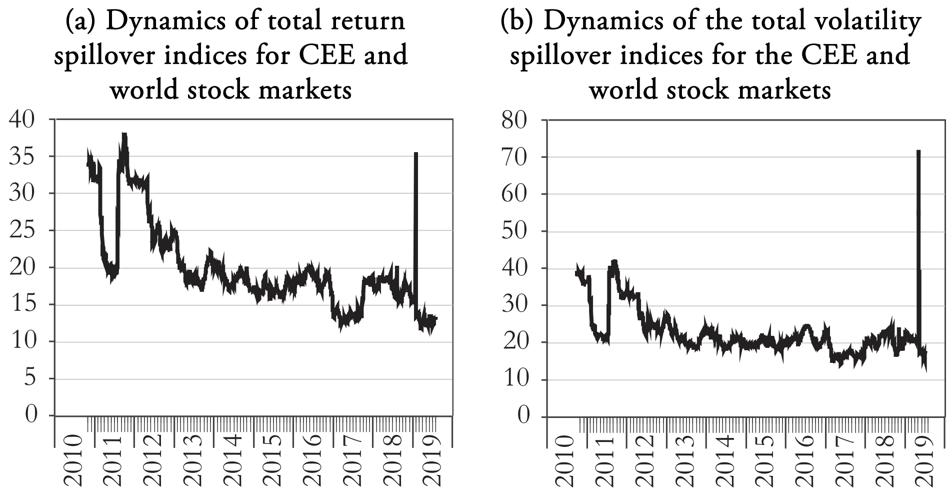
Notes: The underlying variance decomposition is based on a daily VAR system with four lags and generalised variance decompositions of 10-day-ahead volatility forecast errors.

Panel B of Table 3 reports the total and net volatility spillover indices between the CEE stock markets and the world stock index. We find no difference between the results of the volatility spillover and return spillover indices. On average, the total volatility spillover index shows that 4.9% of the volatility forecast error variance in all six markets comes from spillovers, which implies a low level of volatility spillover between the world stock index and the CEE stock markets. Regarding the directional volatility spillover effects, the world stock market is the largest contributor to other markets, with a net spillover estimated at 6.9%. The gross directional volatility spillover from the world stock market to other markets is 10.8%; meanwhile, in the opposite direction, the gross directional volatility from all five stock markets to the world stock market is only 4%. This is consistent with the findings of the return spillovers. The second largest net transmitter is Croatia at 4.6%. Nevertheless, other markets (Czech Republic, Hungary, Poland, and

Romania) are net recipients of volatility spillovers. This result suggests that the CEE stock markets provide greater diversification benefits than the world stock market. The scale of financial transmission from the international to the CEE economy, degree of trade openness, and the scale of foreign currency-denominated debt in the domestic economy are fundamental factors of market integration (Hung 2019, Grabowski 2019, Škrinjarić 2020).

Figure 6

Total return and volatility spillovers



Note: The vertical axis shows the total return spillovers.

Notes: The underlying variance decomposition is based on a daily VAR system with four lags and generalised variance decompositions of 10-day-ahead volatility forecast errors.

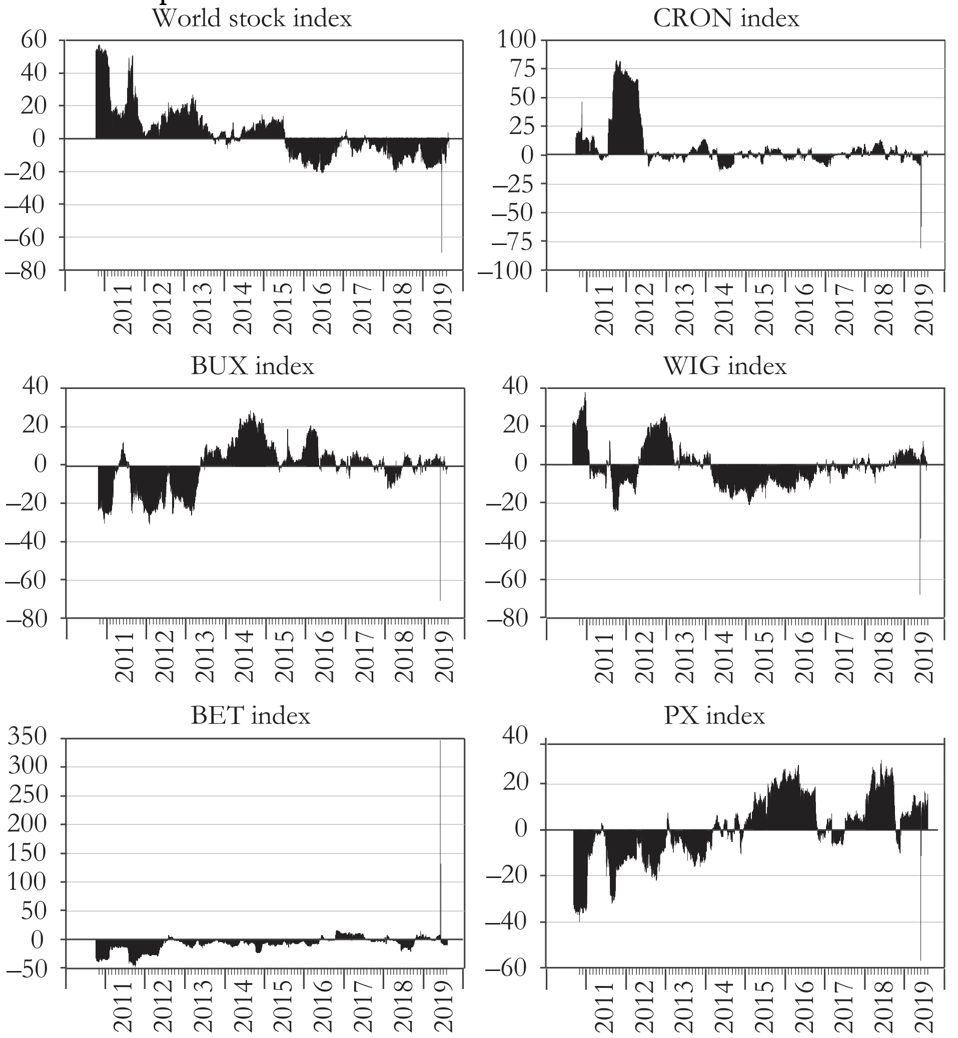
Figure 6 plots the time-varying total return and volatility spillover indices calculated based on the spillover index specification. Total spillovers are somewhat low over the research period, suggesting a small degree of relationship among stock markets over the full sample. The systemwide return and spillover indices witness a rather similar pattern, even though the magnitude of return spillovers seems to be slightly higher than that of volatility spillovers during the research period. Figure 6 shows that total spillovers vary over time and respond to economic events. The return spillovers reached a peak of nearly 40% in the 2011-2012 period, which corresponds to the slowdown in European economic activity. The average spillovers for the return and volatility of the CEE and world stock markets significantly decreased during 2012-2016, which can be interpreted as a sign of global economic recovery. The spillover index related to the return and volatility of these markets rose slightly from 15% to 35% till mid-2018 and fell gradually in 2019.

Net directional spillovers

Here, we compute the net directional spillovers that correspond to the difference in the contribution from and to others. In other words, we identify which markets are net transmitters and net recipients of spillovers. We estimate the time-varying net return and volatility spillovers based on 200-day rolling windows. Positive (negative) values indicate a transmitter (recipient) to (from) other stock markets. Figures 7a and 7b present the rolling sample net directional spillovers for return, while Figures 8a and 8b illustrate the net directional spillovers for volatility.

Figure 7a

Net return spillovers for CEE stock markets and the world stock market index



Notes: The underlying variance decomposition is based on a daily VAR system with four lags, generalised variance decompositions of 10-day-ahead volatility forecast errors, and 200-day rolling windows.

Figure 7b

Net return spillovers for CEE and world stock markets, 2010–2019

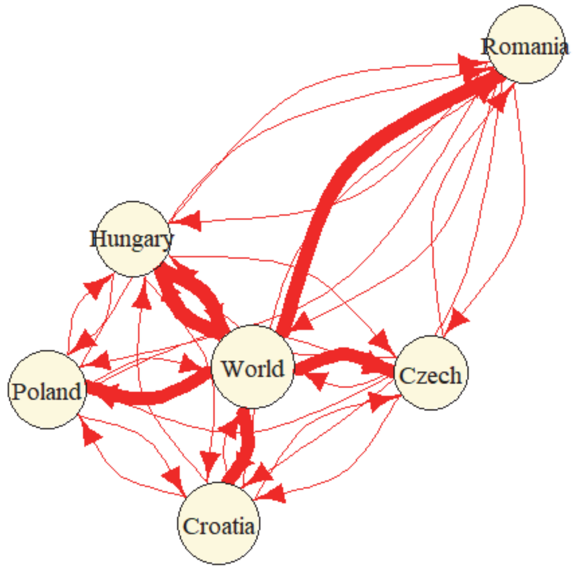
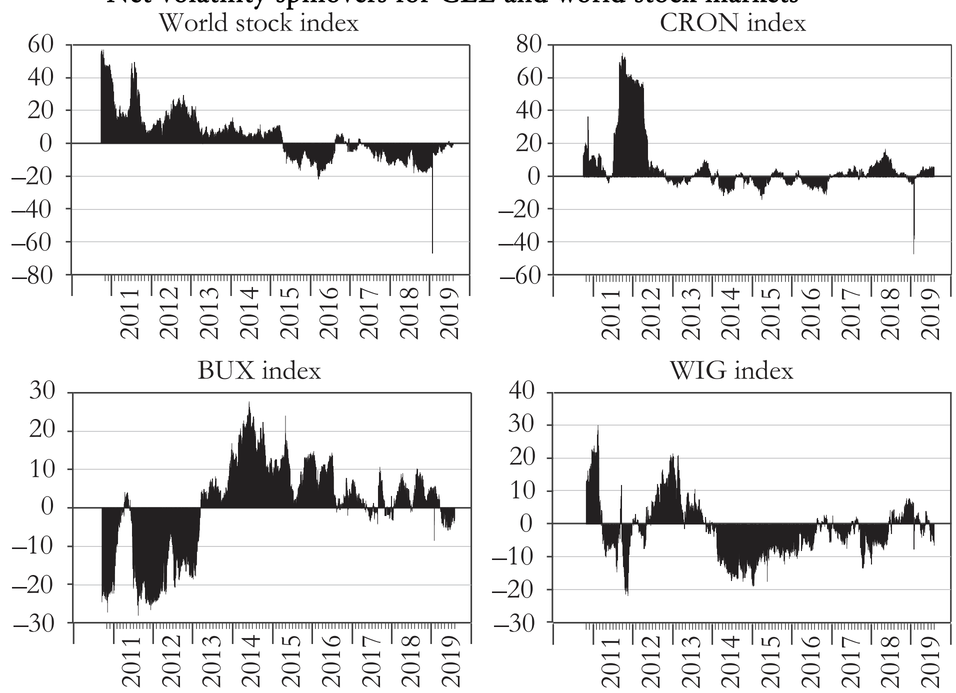


Figure 8a

Net volatility spillovers for CEE and world stock markets



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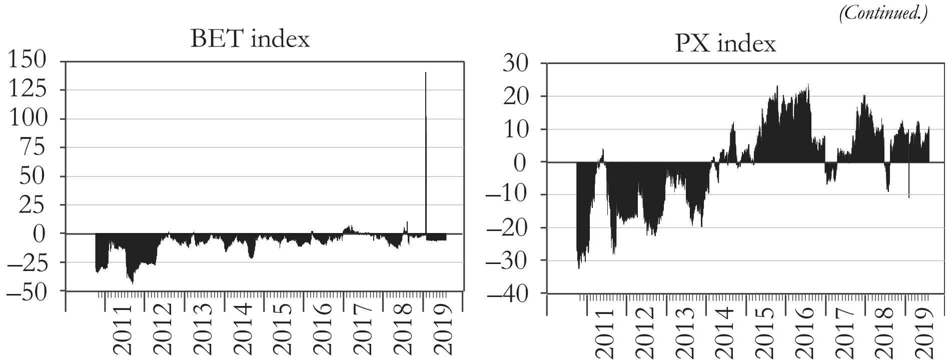
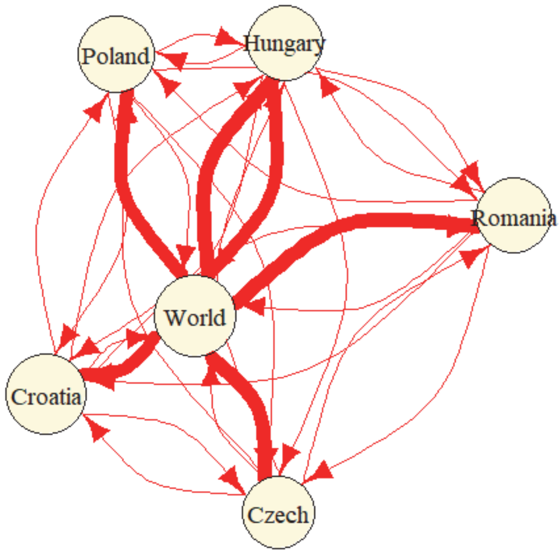


Notes: The underlying variance decomposition is based on a daily VAR system with four lags, generalised variance decompositions of 10-day-ahead volatility forecast errors, and 200-day rolling windows.

Figure 8b

Net volatility spillovers for CEE and world stock markets, 2010–2019



Figures 7 and 8 represent the sign of the temporal evolution of the net return and volatility spillovers between the CEE and world stock markets. The world stock market, Croatia, and Romania are net transmitters of risk, whereas Hungary, Poland, and the Czech Republic are net recipients of shocks during 2010–2015. However, Hungary and the Czech Republic are becoming net transmitters after 2016. This is in line with the results for the entire sample indicated in Panel A of Table 3. The volatility spillovers are bidirectional and asymmetric across CEE and world stock markets because the given graphs for each market show an asymmetric magnitude of negative and positive values over time. This result suggests the time-specific effects of the spillover direction across world and CEE stock markets, and supports Baumöhl–Lyócsa's (2014) findings.

We also evaluate net connectedness across all markets to determine which markets are net receivers and transmitters. Croatia is the greatest net transmitter of volatility spillovers, while Hungary, Poland, Romania, and the Czech Republic are net recipients of volatility spillovers. The leading role of the Croatia market in causing Central and Eastern European fluctuations is consistent with the literature (Hung 2018, 2019, 2020b). The findings for Croatian return and volatility may reflect the fact that the EU is by far the largest foreign investor in Croatia, while this market also has a higher level of market liquidity (Stoica–Diaconaşu 2011, Hung 2020b). In addition, the Croatian stock markets have a strong relationship with developed markets in the EU, such as the UK, German, and France (Joseph et al. 2020, Reininger–Walko 2020). These factors may contribute to our results on Croatia. In fact, Reininger–Walko (2020) detect both short- and long-run return and volatility spillovers between Croatian and SEE stock markets.

We also notice a remarkable rise in return and volatility spillover indices during periods of financial crises. The first jump in return and volatility spillovers between the world stock and CEE markets occurs in 2010–2011 when the European sovereign debt crisis negatively influenced the CEE stock markets. This strong magnitude of these indices continued until recent years due to the shale oil revolution, which put downward pressure on the global price of the world stock market. In general, our results reveal more significant integration across markets when there is financial turmoil, which is consistent with the studies documented in the literature (Grabowski 2019, Bouri et al. 2020a, Kang et al. 2019, Kang–Yoon 2019, Özer et al. 2020). Financial integration demonstrates a keen strategic goal at the EU level, given that a deeper financial connectedness may influence the stability of the entire financial system (Boţoc–Anton 2020). Indicators of financial integration show various tendencies. First, there was a significant deceleration trend (2010–2012) associated with the sovereign debt crisis. Second, there was a reintegration trend (2013–2015) caused by the European Central Bank's Outright Monetary Transactions framework. Third, temporary corrections were recorded between late 2015 and the end of 2016, followed by a significant increase in 2017. Based on these outcomes, one may argue that investors can benefit, at least in the short run, from diversifying into CEE equity markets.

Importantly, these findings are consistent with Živkov et al.'s (2018) explanations of co-movements between selected CEE and German stock markets during the global financial crisis and the European sovereign debt crisis. The authors point out that a high level of integration exists across these stock markets. Grabowski (2019) uncovers the high level of the interrelationship between CEE and developed stock markets during the European sovereign debt crisis. Further, the author also finds that volatility spillovers running from the advanced stock markets to Hungary, Poland, and the Czech Republic drop dramatically, and CEE countries are the recipients of volatility.

Finally, we follow the test used by Kang et al. (2019) to examine the pairwise connectedness across CEE and world stock markets using an analysis of out-of-sample predictability. We employ Clark–West's (2007) test of the equal mean squared prediction error (MSPE). To identify whether market i's returns $R_{i,t}$ and volatility $V_{i,t}$ at time t can foster the out-of-sample predictability of returns $R_{i,t+1}$ and volatility $V_{i,t+1}$, we use 1000 rolling daily out-of-sample forecasts for returns $R_{j,t+1}$ and volatility $V_{j,t+1}$, employing criteria and augmented models that consist of the returns and volatility of other stock markets. The Clark and West test can be written as:

$$H_0 : E(e_{1t}^2) = E(e_{2t}^2)$$

$$H_a : E(e_{1t}^2) > E(e_{2t}^2)$$

where e_{1t}^2 and e_{2t}^2 are the squared prediction errors of the criteria and augmented models, respectively.

This test examines the null hypothesis of equal out-of-sample MSPE between the two nested forecast models. If the null hypothesis is rejected, then we can infer that the forecast model has a smaller MSPE than the criteria model, and thus outperforms the criteria model at predicting the stock market at some level of significance. We consider the following criteria and alternative forecasting models for returns:

$$R_{j,t+1} = \alpha_1 + \alpha_2 R_{j,t} + e_{1t} \quad (20)$$

$$R_{j,t+1} = \alpha_1 + \alpha_2 R_{j,t} + \alpha_3 R_{i,t} + e_{2t} \quad (21)$$

Further, we have the MSPE of the following forecasting models for volatility:

$$V_{j,t+1} = \beta_1 + e_{1t}^* \quad (22)$$

$$V_{j,t+1} = \beta_1 + \beta_2 V_{i,t} + e_{2t}^* \quad (23)$$

Table 4

MSPE out-of-sample predictability tests to stock market returns, 2010–2019

$R_{i,t}$	Increased predictability to $R_{j,t+1}$					
	World	Croatia	Czech Republic	Hungary	Poland	Romania
World		0.0000^{***}	0.3453	0.5216	0.3832	0.6946
Croatia	0.1396		0.5668	0.2870	0.9795	0.2141
Czech Republic	0.0806^{*}	0.4162		0.0000^{***}	0.0014^{***}	0.8567
Hungary	0.0000^{***}	0.0011^{***}	0.0000^{***}		0.0001^{***}	0.7905
Poland	0.0000^{***}	0.0704^{*}	0.1943	0.0447^{**}		0.8277
Romania	0.0428^{**}	0.4070	0.2010	0.1030	0.0482^{**}	

Notes: This table documents the *p*-values of the test of equal mean squared prediction error (MSPE) developed by Clark–West (2007) for the out-of-sample predictability to $R_{j,t+1}$. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The p-values of the test for out-of-sample predictability of stock market returns are documented in Table 4. Of the five CEE countries, the Hungarian stock market's returns can forecast the future returns of the Croatian, Czech, and the Polish markets at the 1% level. Similarly, the Polish stock market's returns predict the future returns of the Croatian and Hungarian markets; the Czech stock market's returns can project the future returns of the Polish and Hungarian markets; and the Romanian stock market's return predict the Polish stock market's future returns. Moreover, the stock returns of each CEE market improve the out-of-sample predictability of the future returns of the world stock market.

Table 5

MSPE out of sample predictability tests to stock market volatility, 2010–2019

$R_{i,t}$	Increased predictability to $V_{j,t+1}$					
	World	Croatia	Czech Republic	Hungary	Poland	Romania
World		0.9258	0.6849	0.6494	0.5710	0.7859
Czech Republic	0.0292**	0.0115**		0.6845	0.6034	0.0099***
Croatia	0.0330**		0.0128**	0.0185**		0.0102**
Hungary	0.4916	0.5120	0.6498		0.5041	0.0021**
Poland	0.8478	0.7475	0.5625	0.6959		0.2059
Romania	0.0000***	0.2639	0.0000***	0.6376	0.0672*	

Notes: This table documents the p-values of the test of equal mean squared prediction error (MSPE) developed by Clark–West (2007) for the out-of-sample predictability to $R_{j,t+1}$. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 depicts the p-values of the equal MSPE test between the conditional volatility of the CEE stock markets and the world stock market index. Contrary to the findings of the returns, the volatilities of the world stock market index do not impact the future volatility of each CEE country, while the market volatilities of the Croatian, Czech, and Romanian stock markets affect the future volatility of the global stock market. This finding supports the net directional volatility spillovers described in Table 3. Apart from the markets of Hungary and Poland, the market volatilities of Croatia and Romania impact the future volatility of the markets in Hungary and the Czech Republic.

Overall, in line with the findings shown in Table 3 and Figure 2-4, we shed light on significant volatility spillovers from the world stock index to each of the CEE countries, and considerable return and volatility transmissions from the CEE stock markets to the world stock market. These results reveal that market interrelatedness exists between the world stock index and CEE stock markets. This interrelatedness may emerge due to the degree of trade integration and financial relationships based on portfolio investments with the rest of the world (Kang et al. 2019).

Hedging and diversification performance

We use the DECO-GARCH model estimates to compute hedging ratios and appropriate portfolio weights to better manage the risk of the world and CEE stock markets. According to Zhang et al. (2021), one of the most frequently utilised strategies in portfolio management is setting the hedging ratio. Here, we compute the optimal hedge ratios of WORLD required to hedge stock markets in a CEE region's exposure and minimise the variance of the position to help investors and portfolio managers make effective decisions. We define the optimal weight of holdings of the two assets (WORLD and associated assets) using the approaches of Kroner–Ng (1998) and Hammoudeh et al. (2010).

$$w_{ws,t} = \frac{h_{s,t} - h_{w,t}}{h_{w,t} - 2h_{ws,t} + h_{s,t}} \tag{24}$$

and

$$w_{ws,t} = \begin{cases} 0 & if \;\; w_{ws,t} < 0 \\ w_{ws,t} & if \; 0 \leq w_{ws,t} \leq 1 \\ 1 & if \; w_{ws,t} > 1 \end{cases} \tag{25}$$

where $w_{ws,t}$ is the weight of WORLD in a portfolio, $h_{w,t}$ is the conditional variance of WORLD, $h_{s,t}$ is the conditional variance of assets under study, and $h_{ws,t}$ is the conditional covariance between WORLD and related assets at time t. Thus, the optimal weight of related assets is $1 - w_{ws,t}$. Second, we construct the portfolio and the weights are identified by the variance minimisation hedge strategy. The hedge ratio $\beta_{ws,t}$ between the WORLD and related assets can be computed as follows:

$$\beta_{ws,t} = \frac{h_{ws,t}}{h_{s,t}} \tag{26}$$

where $h_{ws,t}$ is the conditional covariance between WORLD and related asset prices at time t, and $h_{s,t}$ is the conditional variance of other assets in the CEE region.

The average values of the optimal portfolio weights and hedging ratios computed from the results of the DECO-GARCH model for the six assets are detailed in Table 6.

Table 6

Optimal portfolio weights and average hedge ratio, 2010–2019

	Optimal $\omega_{os,t}$	Optimal $\beta_{os,t}$
WORLD – BUX	0.2282	0.0108
WORLD – WIG	0.2245	0.0410
WORLD – PX	0.0008	0.0427
WORLD – CRON	0.3443	0.0591
WORLD – BET	0.2813	0.0065

Table 6 documents the average values of the hedge ratios and optimal portfolio weights calculated from the DECO-GARCH model results for five stock markets in the CEE region and the world market index. For example, on average, the optimal weights of WORLD to minimise the volatilities of CRON and BUX portfolios are approximately 34.4% and 22.8%, respectively, but only 0.08% for PX. Thus, we can say that WORLD is a good diversifier of the stock market in Croatia. In addition, the hedge ratios are low for all portfolios, indicating that hedging effectiveness is somewhat good. For instance, the lowest average hedge ratio value is for the WORLD-BET portfolio, followed by the WORLD-BUX portfolio.

In summary, our estimates based on hedge ratios provide significant and useful information for risk management and optimal portfolio allocation decisions. These are critical goals of financial market participants who want to better understand risk over time in order to make strategic decisions.

Robustness check

Here, we evaluate the robustness of our return and volatility spillover results by addressing the issues of sensitivity to the forecasting period and the selection of the volatility estimations.

Figure 9

Sensitivity of spillover plots to the selection of the order of VAR

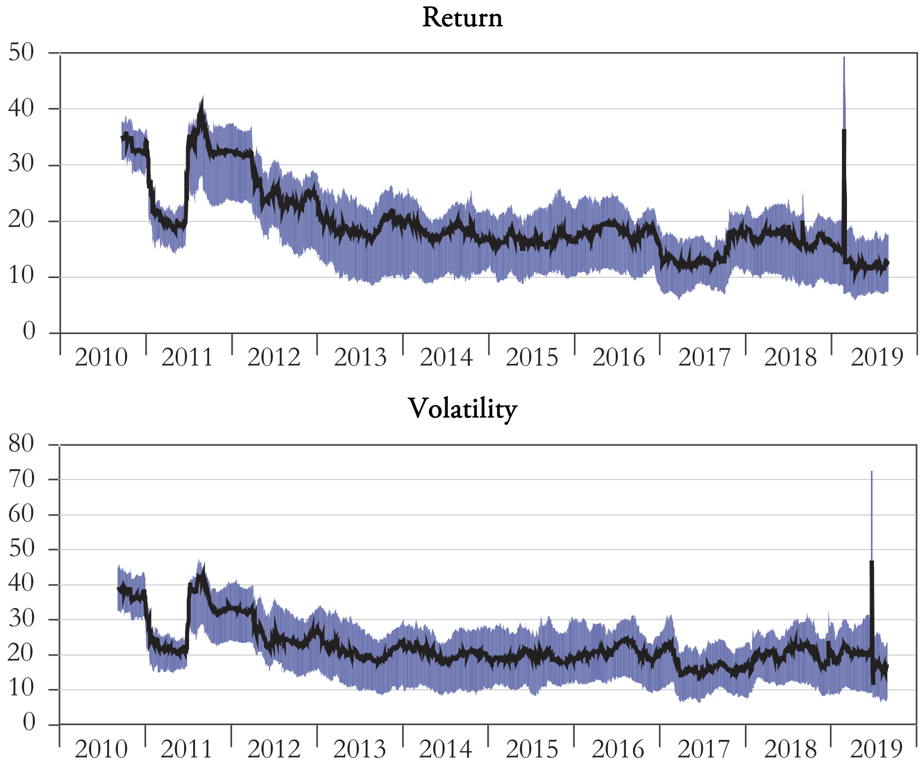
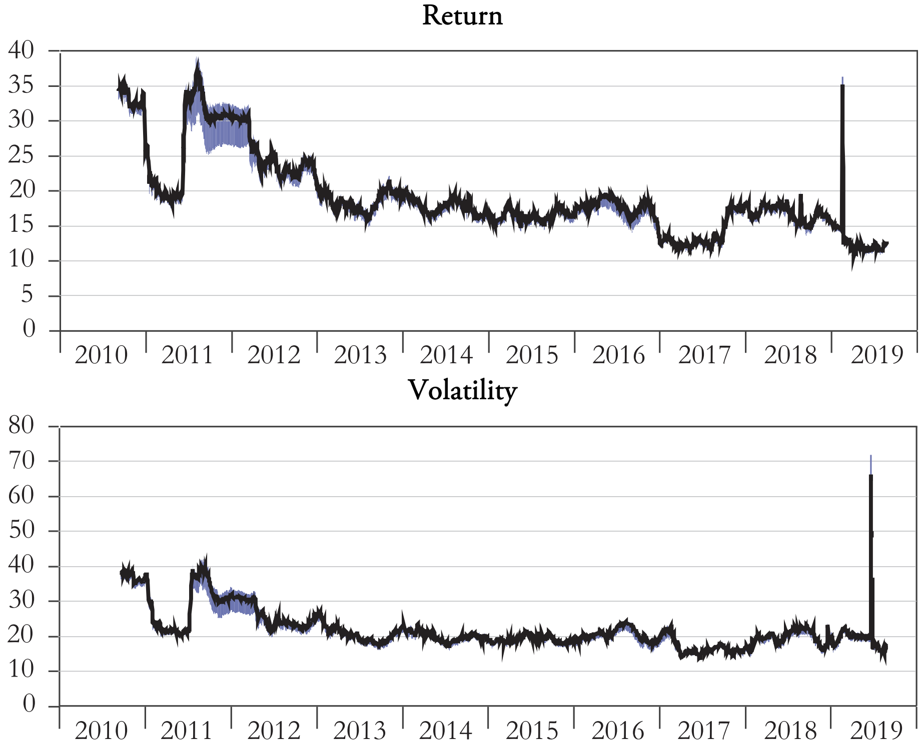


Figure 10

Sensitivity of spillover plot to the selection of the forecast horizon



We apply a slightly modified baseline model to assess the sensitivity of our time-varying return and volatility spillover results. First, we compute the dynamic indices for orders 2 through 6 of VAR, and plot the minimum, maximum, and median values of the related estimations in Figure 9. We do not detect a significant distinction among these time-varying estimation results. Second, we investigate the results for forecast horizons varying from five to ten days' rolling window VAR analysis. As shown in Figure 10, the dynamic total return and spillover plots are not sensitive to the choice of order and the forecast horizon of the VAR model. Therefore, we can conclude that our findings for directional volatility spillovers are robust to the selection of various volatility measures.

Conclusion

This study examines the evolution of the return and volatility spillover effects between the world stock index and the CEE (Croatia, Hungary, Poland, Romania, and the Czech Republic) stock markets by employing Engle–Kelly' (2012) multivariate DECO-GARCH model and the Diebold–Yilmaz's (2012) spillover index. DECO is a novel covariance matrix estimator which assumes that any pair of stock returns is equicorrelated at every period but this correlation varies over time.

The empirical results are summarised as follows. First, the average return equicorrelation across the CEE and world stock indices are positive, even though it is time-varying with a pronounced regime shift after the 2011–2012 European debt crisis. This impairs the benefits of CEE and world portfolio diversification. Second, the directional spillovers from the world stock market to CEE countries are higher than those in the opposite direction. That is, there is bidirectional return and volatility across world stock markets and CEE stock returns in the aftermath of the recent European debt crisis. Third, the net volatility spillover bursts in either a negative or positive direction, and its sign changes over the study period. Finally, we employ Clark–West's (2007) test of equal MSPE, and show that the world stock index can help predict the future returns and volatility of the CEE stock markets.

These results have significant implications for portfolio investors and policymakers interested in the CEE and world stock markets. These actors are typically interested in predicting portfolio market risk exposures and determining the persistence of diversification benefits across specific markets.

For portfolio diversification, our findings show that investors' benefits from diversifying into CEE equity markets are limited because the level of integration between the CEE stock markets and the world stock index is statistically significant. Therefore, international investors will find limited diversification benefits for portfolios allocated to these markets. Nevertheless, investors can still find diversification possibilities for investing in several stock markets in the region. To ensure efficiently diversified portfolios, investors have to constantly observe and evaluate variations in these countries' intra- and inter-regional market interconnections.

From a CEE domestic policy perspective, the outcomes suggest that policymakers must be conscious of the developed stock markets as a significant spillover source. Impartially, intraregional transmissions play a crucial role, with the CEE acting as a gateway for transmissions from globally developed markets. Moreover, policymakers should be aware of intraregional transmissions arising from Poland, Croatia, and Hungary. Overall, by understanding the nature and implications of the intra- and inter-regional linkages of CEE countries, policymakers can build better economic policies on stock markets, particularly stressing the importance of greater policy coordination among the CEE nations. Furthermore, this can help economic policymakers design proper fiscal and monetary policy solutions in reaction to external shocks in the global financial market.

Finally, these findings illustrate the nature of the interlinkages between the CEE and world stock index. These are essential for academics and investors in understanding the evolution of market integration, for constructing portfolios, and engaging in risk management. Meanwhile, these interlinkages can help policymakers in recognising how movements in global markets may have domestic influences.

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