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ESTIMATION OF CORRELATION BETWEEN CAPITAL MARKETS. ANALYSING THE IMPACT OF CRISES ON THE CENTRAL AND EASTERN EUROPEAN MARKETS

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ABSTRACT. This paper analyses the behaviour of the existing correlations between Central and Eastern Europe's markets, namely Romania, Czechia, Hungary, Poland, Slovenia, Slovakia and Bulgaria and the developed ones in Germany, France and United Kingdom. The study brings a new perspective on the subject by capturing two major stress periods – the Global Financial Crisis and the first wave of the COVID-19 pandemic. By estimating a BEKK model, as well as Spearman's rank correlation coefficient and the Diebold and Yilmaz Spillover Index, the study finds strong similarities between the analysed markets, with a general decreasing trend of the correlations' level, indicating increasing benefits of diversification.

1. INTRODUCTION

As a consequence both of the Global Financial Crisis and of the current economic environment, capital markets play an increasingly important role internationally, their primary function being to provide long-term funds to investors at a competitive cost. Moreover, as Demirguc-Kunt, Feyen and Levine (2013) state, as an economy grows, the marginal economic gain associated with the expansion of bank intermediation decreases, while the marginal impact associated with the development of capital markets increases. Their findings are further sustained by Valickova, Havranek and Horvath (2014) and Gambacorta, Hofmann and Peersman (2014). Thus, even in regions as Europe, where the banking sector has always been the key pillar of the financial system, there is a growing interest for the growth and regulation of the markets. Low short-term interest rates are a key factor in this regard, as they lead European investors to seek higher returns, which, on a long-term period, will contribute to markets' expansion.

Banks and capital markets have been considered competing funding sources for a long period, which led to the idea that only one sector can develop at the expense of the other one, as in a zero-sum game. Still, a diversified system, with interlinked and mutually beneficial banks and markets, is the most efficient in absorbing a wide range of shocks (Song and Thakor 2010). Therefore, strengthening capital markets in Europe could provide additional capital for companies, at the same time boosting the entry of foreign funds and ensuring high financial stability, especially in the context of a very challenging environment marked by the COVID-19 crisis and a continuous interest rates decrease.

Considering that correlations between markets is an important metric of risk evaluation, a further analysis on this subject is relevant. These correlations also play an important role in asset allocation and portfolio selection. As further detailed in Section 2, the literature review,

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analyses focusing on the Central and Eastern Europe capital markets are scarce. In this context, the present paper aims to bring a new perspective by providing a comprehensive analysis on these countries, regardless of their capital market status. Moreover, in terms of comparative advantage to other studies focusing on this subject, the constructed dataset of daily data spans from January 8, 2007 to August 7, 2020, capturing the early stages of development of the CEE capital markets in the EU accession context and the effects of two major turmoil events, namely the Global Financial Crisis and the COVID-19 pandemic. Therefore, the study focuses on the existing correlations between the capital markets in three frontier markets, namely Slovenia, Slovakia and Bulgaria, three emerging markets, namely Czechia and Hungary and Romania and the developed one of Poland. Nevertheless, the study also includes France, Germany and United Kingdom, aiming at analysing the evolution of the relationship between the developed markets and the CEE ones and the impact of the two structurally different crises mentioned above. Moreover, the behaviour of the correlations is a good indicator for the benefits of diversification. Including Western European countries in the analysis also contributes to the image of the worldwide transmission of shocks, as these developed economies are highly correlated to the US market.

The applied methodology is detailed in Section 3. Section 4 highlights a few qualitative and quantitative aspects of the selected series and, in this context, discusses the obtained results, identifying the latest evolutions in terms of markets' correlations and the potential sources of risk arising from the relatively uniform perception of the investors on the region. The last part of Section 4 is dedicated to the volatility spillover network, analysing the main transmitters of the shocks and the potential benefits of diversification.

2. LITERATURE REVIEW

Capital market indexes' correlation has been widely investigated over time, with interesting results. Belasri and Ellaia (2017) studied the correlation between stock prices in Moroccan stock markets, using 10 years of daily data. The authors compute the estimation using the most popular multivariate GARCH models, namely DCC and BEKK, concluding that the latter performs better in terms of variance covariance matrices. A similar approach is also used by Christoffersen, Errunza, Jacobs and Jin (2014), showing that it is possible to model comovements for many countries simultaneously using BEKK, DCC and DECO models. The authors investigate patterns and trends in correlations over time using weekly returns for developed and emerging markets, during the 1973–2012 period. The superiority of the BEKK model and it's wider utility is also proved in Caporin and McAleer (2012).

Furthermore, Siedlecki and Papla (2016) analyse the changes occurred in the links between US stock market and chosen groups of world markets. The authors define contagion in financial markets as a significant increase in cross-market linkages after a shock to one or to a group of countries, using conditional copula functions and conditional Spearman's correlation coefficient as computational tools. The same methodology is used by Shirokikh, Pastukhov, Boginski and Butenko (2013), focusing on identifying the global characteristics of the US market, between 2001 and 2011, by computing a network-based model. Interesting results regarding the impact of a crisis are also achieved by Bala and Takimoto (2017). Their paper investigates stock returns volatility spillovers in emerging and developed markets using multivariate GARCH models, focusing on the impacts of the Global Financial Crisis. The authors' main findings reveal that correlations among emerging markets are lower compared with the ones between the developed ones and that they increase during financial crises.

The study of capital markets is important from other perspectives too. Gambacorta, Hofmann and Peersman (2014) argue that during the normal downturns healthy bank system helps to cushion the shock. However, when recessions coincided with financial crises, the impact on GDP has been three times as severe for bank-oriented economies as it has for market-oriented ones. Li and Giles (2015) argue that the correlations between markets are also important from a risk diversification perspective. According to the authors, if the emerging markets are only weakly integrated with the developed ones, investors can benefit by including emerging stocks in their portfolio. The effects of the Global Financial Crisis on the behaviour of capital markets have also been investigates by Miralles-Marcelo, Miralles-Quiros and Miralles-Quiros (2013), Kenourgios and Dimitriou (2015), Coudert, Herve and Mabille (2015) and Hemche, Jawadi, Maliki and Cheffou (2016). More recently, the effect of the COVID-19 pandemic is gaining a significant interest in the literature, with a focus on the relationship between capital markets, as investigated by Ramelli and Wagner (2020a,b), Zhang, Hu and Ji (2020), Baker, Bloom, Davis, Kost, Sammon and Viratyosin (2020) and Al-Awadhi, Al-Saifi, Al-Awadhi and Alhamadi (2020).

The Diebold and Yilmaz Spillover Index approach has been widely used to examine the connectedness network across markets, such as in Diebold and Yilmaz (2009, 2012, 2014), Zhang (2017), Maghyereh, Awartani and Bouri (2016) and Shahzad, Ferrer, Ballester and Umar (2017). A more comprehensive picture of the interlinkages between economies and markets is painted in these studies using the spillover analysis, with a focus on the shocks' transmission mechanism, as well as the impact of a crisis.

Despite the numerous approaches detailed above, the literature dedicated to CEE markets is scarce. Therefore, addressing the level of correlation of the markets in Slovenia, Slovakia, Bulgaria, Czechia, Hungary, Romania and Poland with the developed ones illustrates a clear picture of the potential responses of these economies in case of a crisis and contributes to the existing literature by investigating the benefits of diversification on these markets.

3. Methodology

3.1. **Baba-Engle-Kraft-Kroner (BEKK) model.** BEKK model, as defined in Engle and Kroner (1995), has the property that the conditional covariance matrices are positive definite. This is one of the most utilized GARCH models, with great performance in capturing the time-varying nature of correlations. For the general BEKK(q, p, k) model, we consider a vector stochastic process $\{y_t\}$ of dimension $N \times 1$.

$$y_t = \mu_t + \varepsilon_t \tag{1}$$

where μ_t is the conditional mean vector and

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t, z_t \sim iid(0, I_n)$$
⁽²⁾

where $H_t^{\frac{1}{2}}$ is a $N \times N$ positive definite matrix. Furthermore, the $N \times 1$ is assumed to be a random vector z_t to have the first two moments: $E(z_t) = 0$, $Var(z_t) = I_N$, I_N being the identity matrix of order N. Moreover, the conditional variance matrix of y_t :

$$Var(y_t|I_{t-1}) = Var_{t-1}(y_t) = Var_{t-1}(\varepsilon_t) = H_t^{\frac{1}{2}}Var_{t-1}(z_t)(H_t^{\frac{1}{2}})' = H_t$$
(3)

Hence, $H_t^{\frac{1}{2}}$ is any N × N positive definite matrix such that H_t is the conditional variance matrix of y_t ,

$$H_{t} = CC' + \sum_{l=1}^{k} \sum_{i=1}^{q} A_{ik} \varepsilon_{t-i} \varepsilon'_{t-i} A'_{ik} + \sum_{l=1}^{k} \sum_{j=1}^{p} B_{jk} H_{t-j} B'_{jk}$$
(4)

where C, A_{ik} and B_{ik} are $N \times N$ parameter matrices, with C lower triangular to ensure the positive definiteness of H_t . This covariance stationary of this model is satisfied if and only if the eigenvalues denoted by $\sum_{l=1}^{k} \sum_{i=1}^{q} A_{ik} \otimes A'_{ik} + \sum_{l=1}^{k} \sum_{j=1}^{p} B_{jk} \otimes B'_{jk}$ are less than one in absolute values, where \otimes denotes the Kronecker product of two matrices. As in the univariate GARCH model case, the parameters in BEKK model are estimated by maximum likelihood (ML), optimizing numerically the Gaussian log-likelihood function:

$$\mathcal{L}(\theta) = -\frac{TN}{2}\log\left(2p\right) - \frac{1}{2}\sum_{t=1}^{T} \left(\log\left|H_t\right| + \varepsilon_t H_t^{-1}\varepsilon_t'\right)$$
(5)

where θ is the vector of parameters in a model with N variables and T observations.

The time-varying correlations are derived by dividing the conditional covariances by the product of conditional standard deviations obtained from BEKK model. In a model with N variables, there are N(N + 1)/2 variances and covariances. The computational requirements for the estimation procedure of a BEKK model are relatively high, considering that the process involves estimating $(p+q)kN^2 + \frac{N(N+1)}{2}$ parameters. Therefore, the numerical applications of the model normally assume that p=q=k=1. For p=q=k=1 and N=2, the model reduces to the following form:

$$H_{t} = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} e_{1,t-1}^{2} & e_{1,t-1}e_{2,t-1} \\ e_{1,t-1}e_{2,t-1} & e_{2,t-1}^{2} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \\ + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} h_{1,t-1}^{2} & h_{12,t-1} \\ h_{12,t-1} & h_{2,t-1}^{2} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}'$$
(6)

with 11 unknown parameters. To reduce the computational burden, the model can be constrained to diagonal–BEKK (7) or to scalar–BEKK (8):

$$H_{t} = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & 0 \\ 0 & a_{22} \end{pmatrix} \begin{pmatrix} e_{1,t-1}^{2} & e_{1,t-1}e_{2,t-1} \\ e_{1,t-1}e_{2,t-1} & e_{2,t-1}^{2} \end{pmatrix} \begin{pmatrix} a_{11} & 0 \\ 0 & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & 0 \\ 0 & b_{22} \end{pmatrix} \begin{pmatrix} h_{1,t-1}^{2} & h_{12,t-1} \\ h_{12,t-1} & h_{2,t-1}^{2} \end{pmatrix} \begin{pmatrix} b_{11} & 0 \\ 0 & b_{22} \end{pmatrix}$$
(7)

$$H_t = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} + a^2 \begin{pmatrix} e_{1,t-1}^2 & e_{1,t-1}e_{2,t-1} \\ e_{1,t-1}e_{2,t-1} & e_{2,t-1}^2 \end{pmatrix} + b^2 \begin{pmatrix} h_{1,t-1}^2 & h_{12,t-1} \\ h_{12,t-1} & h_{2,t-1}^2 \end{pmatrix}$$
(8)

This paper will further focus on the scalar–BEKK model. The estimation procedure was computed using the Oxford MFE toolbox developed by Kevin Sheppard.

3.2. **Spearman's rank correlation coefficient.** Spearman's rank correlation coefficient or Spearman's rho, named after Charles Spearman is a statistical nonparametric measure of the strength of a monotonic relationship, whether linear or not, between paired data:

$$r_s = \rho_{rg_X, rg_Y} = \frac{cov\left(rg_X, rg_Y\right)}{\sigma_{rg_X}\sigma_{rg_Y}}, \ -1 \le r_s \le 1$$
(9)

where ρ denotes the usual Pearson correlation coefficient, but applied to the rank variables, $cov(rg_X, rg_Y)$ is the covariance of the rank variables, σ_{rg_X} and σ_{rg_Y} are the standard deviations of the rank variables.

3.3. Diebold and Yilmaz Spillover Index. We start from the reduced-form VAR model defined by Sims (1981):

$$y_t = \nu + A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + u_t \tag{10}$$

where y_t is a K-dimensional vector of endogenous variables; A_p is a K-by-K matrix. The VAR(p) can be casted in the companion VAR(1) form as $Y_t = \boldsymbol{\nu} + \mathbf{A}Y_{t-1} + U_t$. Assuming it is a stable process, its MA representation can be obtained by successive substitution for Y_{t-i} :

$$y_t = A(L)^{-1}\nu + A(L)^{-1}u_t = A(L)^{-1}\nu + \sum_{i=1}^{\infty} J\mathbf{A}^i J' J U_{t-i} = \mu + \sum_{j=1}^{\infty} \Phi_i u_{t-i}$$
(11)

where $J \equiv [I_K, 0_{K \times K(p-1)}]$ is the selection matrix; $A(L)^{-1} = \sum_{i=0}^{\infty} \Phi L_i = J \mathbf{A}^i J$ for $i = 0, 1, \ldots$, so that these matrices is recursively computed as $\Phi_0 = I_K$, and $\Phi_i = \sum_{j=1}^i \Phi_{i-j} A_j$ for $i = 1, 2, \ldots$, with $A_j = 0$ for j > p. The matrix $\Phi_i \equiv [\phi_{kj, i}]_{K \times K}$ is also called the response of variable k to a unit shock $u_{jt}, j = 1, 2, \ldots, K$, i periods ago. The forecast error at the h^{th} horizon is $y_{k,t+h} - y_{k,t}(h) = \sum_{i=1}^{\infty} \Phi_i u_{t+h-i}$. If one decomposes $\Sigma_u = E(u_t u'_t) = P \Sigma_w P'$ with $\Sigma_w = I_K$ then defines $\Theta_i = \Phi_i P$ such that $\Theta_0 = \Phi_0 P = P$, and $\Theta_{i\geq 1} = \Phi_i P = J \mathbf{A}^i J'$. Thus, the forecast error variance of $y_{k,t}$ at horizon h is:

$$FEVD_{j}^{k}(h) = E(y_{k,t+h} - y_{k,t}(h))^{2} = \sum_{j=1}^{K} \left(\theta_{kj,0}^{2} + \dots + \theta_{kj,h-1}^{2}\right) = \sum_{i=0}^{h-1} \left(e_{k}^{\prime}\Theta_{i}e_{j}\right)^{2}$$
(12)

Dividing by $FEVD^k(h) = \sum_{j=1}^{K} FEVD_j^k(h)$ to give the fraction of the contribution of shock j to the forecast error variance of variable k, Diebold and Yilmaz define the Spillover Index to measure the spillover effects as:

$$Spillover \ Index = \frac{\sum_{k,j \in \{i..K\}, k \neq j} FEVD_j^k(h)}{\sum_{k,j \in \{1..K\}} FEVD_j^k(h)}$$
(13)

Furthermore, the total directional connectedness from others to country i^{th} and total directional connectedness to others from country j^{th} are defined as:

$$C_{i \leftarrow *} = \sum_{j=1, j \neq i}^{N} d_{ij}^{H}, \text{ and}$$

$$C_{* \leftarrow j} = \sum_{i=1, i \neq j}^{N} d_{ij}^{H} \qquad (14)$$

The estimation procedure was computed using the toolbox developed by Binh Pham. All the numerical computation and optimization procedures presented in Section 3 were performed in Matlab 2019a.

4. Results and discussion

4.1. General overview of the selected capital markets' characteristics. According to the FTSE Interim Classification of Markets in September 2020, there are three frontier markets among the analysed CEE countries – Slovenia, Bulgaria and Slovakia, one secondary emerging one – Romania, two advanced emerging markets – Hungary and Czechia and a developed one – Poland. The three largest countries in the CEE region, namely Poland, Hungary and Czechia have the most advanced capital markets, in terms of size, liquidity and instruments, as they were among the first countries that introduced market and macroeconomic reforms necessary during the transition period and benefited also from the early accession to the EU and continuous integration of the market. Stock markets in Romania and Bulgaria also benefited from EU membership, starting 1st of January 2007, knowing a significant development consequently.

Undoubtedly, the Global Financial Crisis has affected all markets, regardless of their level of maturity. Thus, 2008 and 2009 were dominated by decline in all major stock indexes, culminating in February 2009. Following the manifestation of mistrust and high-risk aversion, the investors withdrew their investments massively, especially from CEE, looking to rather fly to quality. As a consequence, region's indexes recorded higher losses relative to the ones in safer markets (Figure 1, percentage change of the monthly values of the main indexes in February 2009 relative to October 2007): Bulgaria –86, Romania –85, Poland –72, Hungary –69, Czechia –68, Slovenia –66 and Slovakia –26. The DAX index decreased by 52 percent, while CAC40 and FTSE dropped by 54 and 55 percent. Besides this significant decline, the CEE economies

have overcome the financial crisis with greater difficulty than the developed ones, most of them still registering much lower values of the main stock indexes in December 2019, compared to December 2007 (percentage change) – Slovenia –64, Bulgaria –71 Czechia –37, Poland –52, Slovakia –22, Romania – 30, Hungary +28, while United Kingdom recovered up to –8, France +2 and Germany +65 percent.



Figure 1. Main stock indexes in February 2009 compared to October 2007 Source: investing.com, own calculations. Note: a stronger shade means a greater decrease/ increase of the indexes



Figure 2. Main stock indexes in March 2020 compared to December 2019

Source: investing.com, own calculations. Note: a stronger shade means a greater decrease/ increase of the indexes.

In this context, the first wave of COVID-19 hit the markets at the beginning of 2020, the European stocks being destabilized once again. As expected, the lowest point was reached in March 2020, when most of the governments imposed restrictive rules in order to promote the social distancing behaviour. However, the decrease was far less significant than in 2009 – Hungary –34, Czechia –34, Poland –32, United Kingdom –28, France –26, Bulgaria –26, Germany –25, Romania –24, Slovenia –22, Slovakia –8 percent (Figure 2). On top of the lower impact, another characteristic of the COVID-19 effect is the relatively similar response of the

markets, regardless of their classification status, which, among other aspects, points out a higher degree of maturity.



Figure 3. Regional stock market indexes dynamics (reference period: July 2007) Note: grey bars marked periods represent months with VSTOXX values higher than its average value over the 2007 – 2020 period. Source: www.investing.com, own calculations.

Table I: Descriptive statistics of daily returns										
Full Sample	РX	SOFIX	BUX	WIG20	BET	FTSE	DAX	CAC40	SBITOP	SAX
Mean	0.00	-0.02	0.02	-0.01	0.01	0.01	0.04	0.02	-0.02	0.00
Standard error	0.03	0.02	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.02
Median	0.03	0.00	0.05	0.01	0.05	0.04	0.08	0.04	0.00	0.00
Standard deviation	1.53	1.17	1.83	1.75	1.58	1.35	1.41	1.46	1.10	1.15
Kurtosis	17.97	12.17	9.12	5.55	11.38	9.45	8.25	8.50	9.83	21.34
Skewness	0.07	-0.84	-0.19	-0.38	-0.42	-0.29	-0.06	0.00	-0.55	-0.76
Minimum	-14.98	-10.49	-17.40	-14.30	-12.40	-11.96	-12.24	-12.28	-8.96	-13.77
Maximum	17.60	7.57	15.58	11.60	14.26	10.34	11.40	11.18	8.72	12.61
2007 - 2014	РX	SOFIX	BUX	WIG20	BET	FTSE	DAX	CAC40	SBITOP	SAX
Mean	-0.01	-0.02	-0.01	-0.01	0.00	0.01	0.04	0.02	-0.03	-0.02
Standard error	0.04	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03
Median	0.02	0.01	0.01	0.01	0.05	0.06	0.09	0.03	0.00	0.00
Standard deviation	1.76	1.37	2.10	1.93	1.84	1.38	1.46	1.57	1.26	1.17
Kurtosis	14.39	7.67	7.31	3.91	7.98	6.85	6.27	6.84	6.61	26.44
Skewness	0.37	-0.52	0.00	-0.16	-0.13	0.14	0.20	0.41	-0.29	-1.20
Minimum	-14.98	-10.49	-17.40	-10.84	-12.40	-7.87	-7.16	-9.04	-8.09	-13.77
Maximum	17.60	7.57	15.58	11.60	14.26	9.27	11.40	11.18	8.72	12.61
2015 - 2020	РX	SOFIX	BUX	WIG20	BET	FTSE	DAX	CAC40	SBITOP	SAX
Mean	0.02	-0.02	0.06	-0.03	0.02	0.00	0.03	0.03	0.01	0.04
Standard error	0.04	0.03	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03
Median	0.05	-0.01	0.09	0.01	0.05	0.02	0.07	0.04	0.01	0.00
Standard deviation	1.09	0.78	1.33	1.45	1.08	1.29	1.33	1.29	0.82	1.11
Kurtosis	22.32	36.53	9.92	10.13	22.98	14.42	12.29	12.42	22.53	11.72
Skewness	-1.75	-2.79	-1.09	-1.12	-2.25	-1.07	-0.58	-1.07	-1.71	0.02
Minimum	-11.44	-10.31	-11.93	-14.30	-11.50	-11.96	-12.24	-12.28	-8.96	-8.91
Maximum	7.78	4.09	6.84	6.02	6.43	10.34	10.98	8.39	6.14	9.55
Source: investing.com, own calculations.										

The highlighted negative impact of the COVID-19 pandemic on the markets' evolution is in line with the findings of Liu, Manzoor, Wang, Lei Zhang and Manzoor (2020).

Overall, during the 2007 – 2020 period the main stocks in the CEE countries have fluctuated according to the Eurozone's market developments (Figure 3). Thus, the analysed indexes have decreased in the periods of tension marked by VSTOXX volatility index. The region's indexes recorded a relatively similar evolution, except for Hungary, which has risen constantly and significantly starting 2012 (Figure 3). Moreover, the similar markets' evolution indicates the existence of a contagion phenomenon between them. To capture this aspect in detail, the following sub-sections analyse the behaviour of the dynamic correlations.

4.2. Data description. Data employed in this study are daily observation of the main indexes in selected European markets, as follows: Romania – BET, Bulgaria –SOFIX, Slovakia – SAX, Slovenia – Blue-Chip SBITOP, Hungary – BUX, Czechia – PX, Poland – WIG20, Germany – DAX, France – CAC40 and United Kingdom – FTSE100. The data points sourced from the investing.com database ensure a large number of observations to adequately fit the models, starting from January 8, 2007 to August 7, 2020, providing 2984 observations for each series. All calculations were computed using Matlab 2019a software. In terms of descriptive statistics, the Kurtosis are greater than 3, indicating that the series have fat-tailed distributions, while the all the skewness are different from zero, indicating asymmetric distributions (Table I, *above*).

The initial analysis of the data is conducted in order to assess whether the series are stationary, using Augmented Dickey Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, which indicate that the index series are not stationary, but the daily returns are. Considering the significant impact of the Global Financial Crisis on the markets, the Zivot and Andrew test was also applied, to address the issue of structural breaks, which can alter the results of the aforementioned unit root tests. The previous conclusions remain mostly valid – the daily returns are stationary for all the analysed countries, while the index series are stationary for Bulgaria, Hungary, Slovakia and Slovenia (Table II).

Table II: Stationarity tests										
	ADF tes	t (intercept, no trend)	KPSS te	st (intercept, no trend)	Zivot&Andrews test (break in trend)					
Variable	Level Daily percenta change		Level	Daily percenta change	Level	Daily percent change				
РX	-2.2204	-52.5988	2.7374	0.0407	-3.9333	-15.9418				
	(0.1991)	(0.0001)	(0.0000)	(0.9957)	(0.3278)	(0.0015)				
SOFIX	-2.3166	-22.5813	1.5311	0.1395	-3.1537	-16.1455				
	(0.1667)	(0.0001)	(0.0000)	(0.2674)	(0.0013)	(0.01247)				
BUX	-1.6511	-52.6588	2.9252	0.08	-2.949	-15.5535				
	(0.4562)	(0.0001)	(0.0000)	(0.5545)	(0.0353)	(-0.0203)				
WIG20	-2.1284	-53.2239	2.1331	0.0529	-4.9138	-16.9554				
	(0.2335)	(0.0001)	(0.0000)	(0.6502)	(0.8491)	(0.0001)				
BET	-2.0724	-52.4557	0.9211	0.1518	-4.9787	-18.0204				
	(0.2561)	(0.0001)	(0.0000)	(0.7302)	(0.8079)	(0.0001)				
FTSE	-2.4006	-55.5737	1.8907	0.0705	-3.4805	-17.4946				
	(0.1416)	(0.0001)	(0.0000)	(0.7740)	(0.1529)	(0.0109)				
DAX	-1.2868	-54.9008	0.8371	0.0485	-4.0701	-17.2685				
	(0.634)	(0.0001)	(0.0000)	(0.1487)	(0.8523)	(0.0068)				
CAC40	-2.275	-56.9418	2.4729	0.0653	-4.4259	-18.2917				
	(0.1803)	(0.0001)	(0.0000)	(0.4292)	(0.5407)	(0.0062)				
SBITOP	-1.1948	-49.6777	0.8887	0.3157	-4.6498	-17.2098				
	(0.6733)	(0.0001)	(0.0000)	(0.4299)	(0.0001)	(0.0001)				
SAX	-1.5921	-59.8426	1.6396	0.392	-4.6202	-17.5206				
	(0.4865)	(0.0001)	(0.0000)	(0.9332)	(0.0001)	(0.0120)				
Note	e: the first v	value represents the test s	statistic; p-	value in brackets. Source:	investing.c	om, own calculations.				

The Johansen methodology shows that the series are cointegrated, confirming the existence of a long-term relationship between them (Table III.a). In order to ensure a dynamic analysis of the changes in the relationships between the selected indexes, a 22-day rolling window cointegration test was also computed, indicating that the level of the cointegration rank is at least one almost during the entire period. The 6M and 1Y rolling window cointegration tests are also consistent with this result, with very rare and short periods of no cointegration. The Gregory and Hansen approach was also applied, to allow for the potential structural breaks (Table III.b). The results indicate the existence of cointegration between the selected markets and identifies a breakpoint in November 2008.

Table III.a: Johansen test										
Hypothesized no. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**						
None *	0.0255	324.6657	251.2650	0.0000						
At most 1 *	0.0193	247.8682	208.4374	0.0002						
At most 2 *	0.0159	189.7028	169.5991	0.0028						
At most 3 *	0.0152	142.0936	134.6780	0.0170						
At most 4	0.0113	96.4179	103.8473	0.1401						
At most 5	0.0064	62.6709	76.9728	0.3697						
At most 6	0.0056	43.5987	54.0790	0.3041						
At most 7	0.0046	26.7652	35.1928	0.3008						
At most 8	0.0028	13.0787	20.2618	0.3576						
At most 9	0.0016	4.7215	9.1645	0.3153						
Note: Trace test	indicates 4 c	ointegrating eqn(s) at the 0.05 level.							
* denotes rejection of the hypothesis at the 0.05 level.										
** MacKinnon-Haug-Michelis (1999) p-values.										
Sou	rce: investing	.com, own calcul	ations.							

Table III.b: Gregory and Hansen test										
for cointegration with regime shift										
t-statistic Asymptotic critical values**										
	1% 5% 10%									
ADF	-13.95* -6.92 -6.41 -6.17									
Zt	-16.77* -6.92 -6.41 -6.17									
Za	-513.61* -90.35 -78.52 -72.56									
* indicates cointegration at 1% significance level.										
** values indicated by Gregory and Hansen (1996).										
5	Source: inves	sting.con	n, own ca	alculations.						

Figure 4 (*next page*) illustrates the daily stock returns' evolution for each selected market. As indicated, all markets experienced significant increased volatility episodes around and after 2008 – 2009 and at the beginning of 2020, in response to the Global Financial Crisis and to the first wave of COVID-19.

4.3. Empirical results.

4.3.1. Baba-Engle- Kraft-Kroner (BEKK) model. For the order selection of the model, the AIC and BIC selection criteria were used. For the vast majority of country pairs, the lowest values of the two indicators selected the BEKK(1,1,1) model. Therefore, for unity, this model was applied for calculating the correlations detailed hereafter. The model investigates both the correlations between the seven CEE countries and the correlations between them and the Western European developed ones. Considering the high volatility of the daily dynamic correlations, a 126-days rolling window (6 months) average was computed for all the obtained results.



Figure 4: Daily returns in selected European countries Source: www.investing.com, own calculations.

The study starts by comparing the dynamic correlations between markets with the same status (Figure 5). Poland was compared with the advanced emerging markets considering that it was promoted to developed market status only on September 24, 2018. Following the same approach, Romania was compared with the frontier markets. The results clearly indicate a very strong relationship between the developed economies, especially for the case of Germany and France, which maintained a correlation of almost 90 percent during the analysed period. The correlations with the United Kingdom are also significantly strong, but do not reach the same levels as the previously discussed one. Also, an important decrease is indicated starting 2016, as a consequence of the first steps taken on the Brexit process. However, in light of the recent context of the COVID-19 pandemic, the links between the three Western European markets returned to their highest levels, which determines investors to diversify their portfolios with assets in the emerging and frontier economies.



Figure 5: Dynamic correlations between markets with the same status Note: dynamic correlations were calculated for the period January 2007 – August 2020, using a BEKK(1,1,1) model. A 6 months (126 days) moving average was computed. Source: www.investing.com, own calculations.

The correlations decrease when moving to lower levels of markets' classification. Therefore, the emerging markets show similar evolution of their interlinkages, with a slightly decreasing trend from 2009 to 2017. The same trend is also observed for most of the frontier markets, except that for Romania and Bulgaria, the decreasing period spans from 2009 to the end of 2019, right before the first signs of the virus' spread. Most of the illustrated relationships shown increased correlations in 2012, when Europe was marked by the Sovereign Debt Crisis. The results are in line with Svilokos (2012), which highlighted the increased cointegration across the emerging European capital markets and the developed ones happening at that time, which made the portfolio diversification less effective in the EU.



Figure 6: Dynamic correlations between advanced emerging markets and the developed ones Note: dynamic correlations were calculated for the period January 2007 – August 2020, using a BEKK(1,1,1) model. A 6 months (126 days) moving average was computed. Source: www.investing.com, own calculations.

An even more important step than understanding the behaviour of the links between the same status markets is to analyse the nature of the correlations between CEE markets and the developed ones. As a general remark, both emerging and frontier markets are more correlated to the advanced markets than among themselves. Starting with Poland, Hungary and Czechia, similar patterns of the links' evolution are identified (Figure 6). However, the strongest links were identified in the case of Poland – the correlations between WIG20 and the French and German main indexes reach levels of 76 percent in 2011 and 50 percent in 2019. The same decreasing correlations' trend is present for all pairs, but the volatility is much higher, since the analysed period is marked with a lot of important events for Poland, Hungary and Czechia, triggering increased interlinkages with the mature markets in several years – the promotion to advanced emerging status in 2008 (Poland and Hungary) and 2011 (Czechia) and the promotion to advanced market status in 2018 (Poland).

The same remarks are valid for the frontier markets too (Figure 7). Romania stands out with the strongest interlinkages and the most pronounced decreasing trend. In fact, the behaviour of Romania's links with the developed economies is more similar to the ones of the emerging markets. BET index is positively correlated with the emerging and developed markets throughout the entire period under review, while the correlations with Bulgaria, Slovenia and Slovakia also have negative episodes. This is a positive indicator for Romania, which tends to respond to events rather as an emerging economy than as a frontier one, in line with FTSE decision to promote it to the emerging status, effective September 2020. Romania's main index is followed by the Bulgarian and the Slovenian ones, while the Slovak SAX shows really small signs of correlations with any of the other markets, regardless of their status.

On average, the decrease of the markets' correlations is linked to higher returns (Figure 8). Except for short periods of the analysed time frame, the returns of the selected stock markets recorded relatively high returns. A key determinant of this behaviour was the low interest rates environment, which shifted investors to riskier assets in their search for yields.



Figure 7: Dynamic correlations between frontier markets and the developed ones Note: dynamic correlations were calculated for the period January 2007 – August 2020, using a BEKK(1,1,1) model. A 6 months (126 days) moving average was computed. Source: www.investing.com, own calculations.

The decreasing trend of the correlations began in 2008 and lasted until 2019, right before the first signs of the COVID-19 pandemic. The fluctuations in 2018 are a consequence of the major negative events taking place, such as uncertainty over Brexit, the escalating trade war between the US and China, France's protests, Italy's budget proposals, which lead to the worst year on capital markets since 2008. The links mostly dominated by a decreasing pattern are the ones between the Western developed markets and Poland, Czechia, Hungary and Romania. This is a key fact, as it indicates that during normal periods, the benefits of diversification increased significantly, investors having more incentives to create mixed portfolios, mostly between developed and emerging markets in Europe. These findings are in line with Syllignakis and Kouretas (2011), which show that correlations between markets vary over time, with a tendency to increase during periods of financial turmoil. Moreover, Aslanidis and Savva (2011) highlight that even in periods of high correlations, the benefits of diversification still remain at sectoral level.



Figure 8: The relationship between European markets' correlations and main indexes' returns Source: www.investing.com, own calculations.

4.3.2. Spearman's rank correlation coefficient. The aforementioned conclusions are confirmed by the Spearman's rank correlation coefficient. In order to capture both the intensity of the links between the analysed European markets and their dynamics, the 2007 - 2020 period was split into sub-samples: 2007 - 2014, capturing the Global Financial Crisis and the recovery period and 2015 - 2020, corresponding to the years before the COVID-19 pandemic and the effects of the lockdown measures (Figures 9 and 10).

	Correlation Matrix									
20	ll.	0.21	0.57	0.62	0.47	0.52	0.59	0.61	0.17	0.01
-20									P. P	
10	0.21	d.	0.16	0.14	0.24	0.14	0.17	0.17	0.18	0.03
₩ -10					*****		in the second se			
20 ⊃ 0	0.57	0.16		0.64	0.40	0.50	0.59	0.59	0.11	0.01
± -20 20										
د م ا	0.62	0.14	0.64		0.39	0.55	0.63	0.62	0.10	-0.01
-20 20		- 2-of or								
0 0	0.47	0.24	0.40	0.39		0.38	0.41	0.42	0.29	0.02
-20	0.50			0.55			0.70		0.40	
X °	0.52	0.14	0.50	0.55	0.38	JL J	0.79	0.81	0.13	0.01
-10	0.59 **	0.17	0.59	0.63	0.41			0.02	0.15 **	-0.00 *
B 0				0.00			l de l	0.02	0.10	-0.00
10	0.61	0.17	0.59	0.62	0.42 ****	0.81	0.92		0.15	-0.00 • *
≝10	- And	1 States	and the second second	-			-	l dh		
-20 10	0.17	0.18	0.11	0.10	0.29	0.13	0.15	0.15	l.	0.01 °a
₩ 0 -10	·				1000	2.5.5.6	0	-3		
10	0.01	0.03	0.01	-0.01	0.02	0.01	-0.00	-0.00	0.01	
の -10		and the second sec	600 gr							
	-20 0 20 CZ	0 -10 0 10 BG	-20 0 20 HU	-20 0 20 PL	-20 0 20 RO	-10 0 10 UK	-10 0 10 -2 DE	e0 -10 0 10 FR	-10 0 10 SK	-10 0 10 SI

Figure 9: Spearman's correlation coefficient between European developed markets, emerging markets and frontier markets 2007 - 2014

Note: the coefficients marked in light grey indicate a statistically significant correlation between two markets. Source: www.investing.com, own calculations.



Figure 10: Spearman's correlation coefficient between European developed markets, emerging markets and frontier markets 2015 - 2020

Note: the coefficients marked in light gray indicate a statistically significant correlation between two markets. Source: www.investing.com, own calculations.

Once again, the strongest coefficients are related to the correlations between the Western European countries, followed by the coefficients of the links between the developed countries and Poland, Hungary, Czechia, Romania, Bulgaria, Slovakia and Slovenia. All coefficients are statistically significant, except for the ones of Slovenia, in both sub-samples. The only difference between the first and the second sub-sample is the rank correlations' coefficient levels, which decrease for all markets in the second period, confirming the increasing benefits of diversification.

These results also reflect the direction and intensity of the impulse transmission effects at European and global level. Clearly, global events will primarily have an impact on developed

European markets, which will forward it to the emerging markets and to the frontier ones. This fact is particularly important considering the serious impact of the COVID-19 pandemic on the US and China's markets, generating unprecedented stock market reactions, as highlighted in Baker, Bloom, Davis, Kost, Sammon and Viratyosin (2020).

Table IV: Total volatility spillovers within European capital markets (percent)											
FULL SAMPLE	UK	DE	\mathbf{FR}	CZ	PL	HU	RO	BG	SK	SI	From Others
UK	26	18	19	10	10	8	6	2	0	2	74
DE	17	24	21	10	10	9	5	1	0	2	76
FR	17	20	23	11	10	9	5	1	0	2	77
CZ	11	12	13	28	12	11	9	3	0	2	72
PL	11	13	13	13	29	13	6	2	0	1	71
HU	10	12	12	12	14	31	6	2	0	2	69
RO	9	8	9	12	8	8	36	4	0	5	64
BG	5	5	5	7	5	4	7	56	0	6	44
SK	1	1	1	1	1	1	1	1	93	0	7
SI	6	5	6	6	4	4	8	5	0	55	45
To others	87	94	99	82	74	67	53	21	1	21	60
Net	12	18	22	9	3	-2	-11	-23	-6	-24	
GFC	UK	DE	FR	CZ	PL	HU	RO	BG	SK	SI	From Others
UK	22	17	19	11	9	9	7	3	0	3	78
DE	17	22	20	10	10	10	6	2	1	3	78
FR	18	19	21	11	9	9	7	2	1	3	79
CZ	11	11	11	23	13	11	10	5	1	4	77
PL	11	12	11	14	26	12	6	3	1	2	74
HU	11	12	12	12	13	26	6	3	2	3	74
RO	10	9	9	12	9	8	29	7	1	7	71
BG	6	7	6	9	6	6	9	41	1	9	59
SK	2	2	2	2	2	3	3	3	78	2	22
SI	9	8	8	8	6	5	9	8	1	38	62
To others	94	97	100	88	78	71	64	36	9	36	67
Net	16	19	21	11	4	-2	-7	-23	-13	-26	
COVID19	UK	DE	\mathbf{FR}	CZ	PL	HU	RO	BG	SK	SI	From Others
UK	15	13	14	12	11	11	12	4	1	7	85
DE	14	15	15	12	12	9	11	3	1	7	85
FR	14	14	16	12	12	10	11	4	1	6	84
CZ	12	12	13	16	11	10	11	6	2	9	84
PL	12	13	14	11	17	11	11	3	1	6	83
HU	11	10	11	12	11	18	12	5	2	7	82
RO	11	11	11	12	9	13	19	4	1	7	81
BG	9	9	9	9	9	12	11	15	2	13	85
SK	10	9	9	6	7	9	7	4	28	7	72
SI	11	10	10	10	9	11	10	7	1	17	83
To others	104	102	107	98	90	97	97	41	13	68	82
Net	20	18	22	14	7	15	22	-44	-58	-15	
Source: investing.com, own calculations.											

Note: The (i, j)th element of the table shows the estimated contribution to the variance of the 10-day-ahead forecast error of i from innovations to variable j. The diagonal elements (i = j) are the own variance shares estimates, which indicate the fraction of the forecast error variance of market i that is the result of its own shocks.

4.3.3. Diebold and Yilmaz Spillover Index. To further investigate the transmission of shocks, the analysis is complemented with the study of the network connectedness of volatility spillovers. For a better assessment of the relationship between the markets, as well as for a complete picture of the impacts of the two turmoil events included in the paper, the spillover index was calculated for three periods: the full sample (2007 – 2020), the one related to the Global Financial Crisis (2008 – 2009) and the one related to the COVID-19 pandemic (November 2019 – August 2020) (Table IV, *above*).

Table IV presents the total spillovers across the selected European markets. In the lower right corner, the total spillover level is highlighted. When applied on the full period, the spillover index reaches a level of 60%, implying a high connectedness across markets. This strong link is further inflated when a crisis occurs – the spillover index reached a level of 67% during the period related to the Global Financial Crisis and a level of 82% in the period corresponding to the first wave of the COVID-19 pandemic. Looking at the directional spillovers transmitted To, the CAC40 is the largest transmitter to other capital markets, contributing around 100% in the full 2007 – 2020 period and during the Global Financial Crisis and 107% during the COVID-19 period. The French index is closely followed by DAX and FTSE100, both of them contributing with more than 100% in 2020. Therefore, the results suggest that these 3 markets are the main transmitters of shocks to the other markets included in the analysis. Among the CEE markets, the Czech one has a significant contribution, followed by the Polish and the Hungarian ones. However, more recently, the Romanian BET gains importance, reaching a contribution of 97% during the pandemic.

From a diversification opportunity perspective, it is also important to analyse the received From spillovers. Once again, the Western developed markets are the biggest receivers, followed by Czechia, Poland, Hungary, Romania, Slovenia, Bulgaria and Slovakia. The emerging markets receive between 64 and 72 percent of their return spillover from other markets when analysing the full time period. The numbers further decrease when moving to the frontier markets (between 7 and 45 percent), Slovakia being the smallest contributor and receiver. However, the three parts of Table IV highlight significant variation in the volatility spillover index, which is shown to be very responsive to the various financial and economic events, in line with the findings of Kang and Lee (2019). Applying a shock in the markets, significantly impacts the received spillovers, which increase across all countries regardless of their status. However, the overall hierarchy remains valid, the emerging and frontier markets being slightly less affected by the fluctuations on the developed ones, offering diversification opportunities for investors.

5. Concluding Remarks

Capital markets' development has important benefits for countries in the CEE region, whereas a more diversified financial system could reduce volatility and could mitigate systemic risks vulnerabilities. However, the expansion of local capital markets must be conducted in parallel with upgrading the existing infrastructure, the implementation of laws, regulations, governance and adequate supervisory structures. Although the 2008 financial turmoil opened the road to better market regulations, the effects of the first wave of the COVID-19 pandemic has proved that further steps in increasing the stability and maturity of the European markets are still necessary. The worldwide low interest rates environment contributes to the same argument, as it shifted investments to riskier assets, making the whole financial system more vulnerable to markets' fluctuations.

This paper studies the existing correlations between selected CEE markets, focusing on three frontier markets, namely Bulgaria, Slovakia and Slovenia, three emerging ones, Hungary, Romania and Czechia and a developed one, Poland. The dataset contains daily returns of the main indexes, spanning from January 8, 2007 to August 7, 2020 and, therefore, captures both the Global Financial Crisis and the first wave of the COVID-19 pandemic. Moreover, the study also includes the developed Western European capital markets of France, Germany and United

Kingdom, in order to analyse the relationships between markets with different status through different stages of the financial cycle.

Starting with a BEKK model, the results clearly indicate a very strong relationship between the developed markets, especially between Germany and France, the correlations with the United Kingdom being also significantly strong, but with short periods of fluctuations determined by the Brexit process. However, in light of the recent context of the COVID-19 pandemic, all links between the three developed markets returned to their highest levels, highlighting the investors' need to diversify their portfolios on other markets. Analysing the nature of the correlations between emerging and frontier markets with the developed ones, similar patterns of the interlinkages are identified among Poland, Czechia Hungary and Romania, with Poland dominating the picture. Moreover, a decreasing trend of the correlations is noticed, lasting from 2009 to 2019, before the first signs of the virus' spread.

On average, the decrease of the markets' correlations is linked to higher returns. Except for short periods of the analysed period, the returns of the selected stock markets recorded relatively high values, in response to the low interest rates environment, which shifted investors to riskier assets in their search for yields. The lowering interlinkages is a key aspect, highlighting the fact that during normal periods, the benefits of diversification increased significantly, investors having more incentives to create mixed portfolios, mostly between developed markets and the emerging CEE ones. The same conclusions are confirmed by the results of the Spearman's rank correlation coefficient model.

The results of both the BEKK model and the correlation coefficient also indicate the direction and intensity of the impulse transmission effects at European and global level. Clearly, global events will primarily have an impact on developed European markets, which will forward it to the emerging markets and to the frontier ones. For a better understanding of this phenomenon, the paper was complemented with a volatility spillovers analysis. The main findings in this regard confirm that the developed Western European markets are the main shocks transmitters, but also the most important receivers, while the emerging and frontier markets are less impacted. Both the Global Financial Crisis and the COVID-19 pandemic had a significant impact on the volatility spillovers network, the latter being notably stronger. However, the overall hierarchy of the analysed capital markets remained the same. These results emphasize the importance of constructing diversified portfolio, which would protect investors against contagion risk, even during periods of turmoil.

Considering the worldwide recent evolution of the COVID-19 pandemic, the conclusions of this study have a clear broad-brush character. Therefore, there is still space for further investigation into the effects of the unprecedented measures and restrictions aiming at diminishing the spread of the virus and also into the reactions of the CEE stock markets. Moreover, future research on this subject could further investigate the correlations of the CEE and the developed European capital markets by better distinguishing between interdependence and contagion effects. In this regard, a more granular approach would contribute to the existing study, by considering the analysis of sectoral indices of, to investigate the correlations and the shock transmission mechanism. Moreover, a dataset with higher frequency, such as intra-day data, would contribute to the study by highlighting the behaviour of the responses of the markets.

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