Revisiting the Dynamics of CEE Capital Markets [1]

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Abstract. *This paper examines the links between capital markets from European Union, with a primary focus on the dynamics between stock markets from Central and Eastern Europe. The sample includes a pre-pandemic period (January 2016 – December 2019) and a COVID-19 pandemic period (January 2020 – December 2023). We employ two nonparametric correlation coefficients, namely Spearman's rank correlation coefficient and Kendall's tau rank correlation coefficient over the two sub-periods. To gain a better understanding of the evolving relationships, we employ a rolling window Spearman correlation over the entire sample. Second, we use a nonparametric, nonlinear causality test to explore the cause–effect relationships between stock markets from Central and Eastern Europe. Our main findings reveal a moderate correlation between capital markets from Central and Eastern Europe. Furthermore, most of these correlations have increased during the outbreak of the COVID-19 pandemic and the Russian invasion in Ukraine. Moreover, Central and Eastern European stock markets exhibit stronger connections to developed capital markets from European Union. Our findings provide a better understanding of the dynamics of selected European capital markets offering valuable insight for investors due to their implications in the diversification properties of international portfolios. Our results are also important for policymakers and regulators.*

Keywords: Dynamic Linkages, Correlation, Nonlinear causality, Central and Eastern Europe, stock markets.

Introduction

There is substantial literature that examines the co-movements of international financial markets (e.g., Levy and Sarnat, 1970; Forbes and Rigobon, 2002; Kearney and Poti, 2006; Bein and Tuna, 2015; Polanco-Martínez, 2019; Gil-Alana et al., 2023). The inter-links between capital markets could be driven by the following factors: (i) monetary integration (Walti, 2011; Virk and Javed, 2017; Joyo and Lefen, 2019), (ii) bilateral trade (Forbes and Chinn, 2004; Mukherjee and Mishra, 2010; Virk and Javed, 2017; Siriopoulos et al., 2021; Zehri, 2021), and (iii) geographical proximity (Flavin et al., 2002; Pretorius, 2002; Mukherjee and Mishra, 2010; Virk and Javed, 2017). Given these considerations, our study focuses on the CEE region. Particularly, only some of the selected countries are already part of the European monetary union, thus it could be interesting to observe if the correlations between these capital markets increased. Prior literature has documented an increase in the stock market integration following the EU accesion (Buttner and Bernd, 2009; Syllignakis and Kouretas, 2010).

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This paper aims to explore the dynamics of the relationships between the main Central and Eastern European (CEE)[2] daily stock market indices. The analysis will focus on two distinct periods: January 2016 to December 2023 (pre-COVID-19 crisis), and January 2020 to December 2023 (post-COVID-19 crisis). We propose a combined use of two advanced statistical methods. Firstly, we employ two nonparametric correlation coefficients, namely Spearman's rank correlation coefficient and Kendall's tau rank correlation coefficient over the two sub-periods. To gain a better understanding of evolving relationships, we follow the model of Polanco-Martínez (2019) and we employ a rolling window Spearman correlation over the entire sample. Second, we use a nonparametric, nonlinear causality Granger test to explore the cause–effect relationships between CEE stock markets. Our main findings reveal a moderate correlation between CEE capital markets. However, the relationships between CEE capital markets and the developed capital markets from the EU appear to be stronger. Furthermore, most of these correlations have increased during the outbreak of the COVID-19 pandemic and the Russian invasion in Ukraine.

Although our preliminary analysis includes other capital markets from the EU, our primary focus is on the stock markets from the CEE region. The CEE stock markets are becoming more appealing to the investors and they play a significant role in the international financial environment (Syllignakis and Kouretas, 2010). In particular, most of them are still characterized as emerging or frontier capital markets, making it interesting to observe how their dynamics have shifted in light of the COVID-19 pandemic and the outbreak of the Russian invasion in Ukraine. The limited available research on this topic for the selected capital markets (e.g., Oner et al., 2022; Rehman et al., 2022) underlines the importance of our results.

Our contribution to the literature is two folded. First, we aim to understand if the degree of stock market integration has increased over time and how the dynamics between the selected capital markets have shifted over time. Second, the increased levels of correlation between stock market indices after a certain event could be perceived as contagion (Forbes and Rigobon, 2002; Tilfani et al., 2020). Therefore, we could provide some valuable insight in terms of contagion of the markets for the two major events comprised in our sample, i.e. the outbreak of the COVID-19 pandemic and the Russian invasion in Ukraine.

Understanding the level of connectedness of international stock markets represents a concern for several agents. First, our results are important for investors due to their implications in the diversification properties of international portfolios (Bertero and Mayer, 1990; Kearney and Poti, 2006; Sensoy et al., 2013; Tilfani et al., 2020). Second, we provide valuable insights for policymakers and regulators given the major role of our results for the spillover effects of economic policies (Reboredo et al., 2015). For example, highly correlated stock markets heighten vulnerability to external shocks and they offer lower diversification opportunities (Buttner and Bernd, 2009; Lee and Cho, 2017). On the other hand, higher levels of correlation between different financial markets could also promote a more efficient allocation of the global capital and economic growth (Lee and Cho, 2017). The effects of financial integration have been extensively detailed in the previous literature (e.g., Kearney and Lucey, 2004; Beine et al., 2010; Doman and Doman, 2013; Tilfani et al., 2020).

The remainder of this paper is as follows. In Section 2 the existing literature is briefly reviewed. In Section 3, the methodology is presented. In Section 4 the dataset is described. The results are discussed in Section 5. Section 6 concludes.

[2] The CEE list of countries is defined by OECD as Bulgaria, Croatia, the Czech Republic, Hungary, Poland, Romania, the Slovak Republic, Slovenia, Estonia, Latvia, and Lithuania (Oner et al., 2022).

Literature review

There is extensive evidence on the dependencies between financial markets around the world (e.g. Bertero, 1990; Chesnay and Jondeau, 2001; Morana and Beltratti, 2008; Aityan et al., 2010; Kotkatvuori-Örnberg et al., 2013; Sensoy et al, 2013; Polanco-Martínez, 2019; Su et al., 2022). Recognizing geographical proximity as a driving factor of the financial integration, most researchers analyze the stock markets on different regions. Some analyze stock markets from Asia (e.g., Johnson and Soenen, 2002; Huyghebaert and Wang, 2010; Jiang et al., 2017; Das and Manoharan, 2019), while others examine Africa (e.g., Yu and Hassan, 2008; Boako and Alagidede, 2017; Siyou and Bene, 2023; Junior et al., 2024), and others scrutinize Europe (e.g., Graham and Nikkinen, 2011; Dajcman et al., 2012; Gjika and Horvath, 2013; Kiviaho et al., 2014; Trivedi et al., 2021). There are also studies that investigate the dynamics between stock markets from all around the world. For example, Junior and Franca (2012) analyse the main stock market indices from the all over the world during several crisis period and conclude that financial markets tend to behave as one during turbulent times. Later, Rehman et al. (2022) investigate the level of interconnectedness of international stock markets during the COVID-19 pandemic. Their findings show an increase in the connectedness between the capital markets from CEE and G7 countries.

The strand of literature that investigates relationships between stock market indices from CEE countries is vast (Harrison and Moore, 2010; Syllignakis and Kouretas, 2010; Reboredo et al., 2015; Tilfani et al., 2020). For most of the CEE markets the literature provides evidence regarding the increase in the dynamic correlations during the Global Financial Crisis (Savva and Aslanidis, 2010; Kenourgios and Samitas, 2011; Reboredo et al., 2015; Horvath et al., 2018). Despite the acknowledged degree of dependence between these capital markets, the strength of the relationship varies. For example, Reboredo et al. (2015) shows a stronger correlation between Hungarian, Czech and Polish stock markets. Later, Tilfani et al. (2020) using a Detrended Cross-Correlation Analysis correlation coefficient show that Croatia, Czech Republic, Hungary, Poland and Romania are the most integrated.

Methodology

We adopted a two-pronged approach to address the research questions. Firstly, we employ two nonparametric correlation coefficients, namely Spearman's rank correlation coefficient and Kendall's tau rank correlation coefficient over the two sub-periods. To gain a better understanding of the evolving relationships, we employ a rolling window Spearman correlation over the entire sample. Second, we use a nonparametric, nonlinear causality test to explore the cause–effect relationships between CEE stock markets.

First, the data concerning the stock market indices was collected. The dataset was transformed by logarithmizing the difference between the closing prices in two consecutive days, according to the existing literature (Polanco-Martínez, 2019). Subsequently, the chosen methods were employed on the series of log-returns. The subsequent section will provide a description of the mathematical concepts and hypotheses underlying the selected methods.

Pearson correlation coefficient

For comparative reasons, we also use a parametric method, namely Pearson's correlation coefficient. Equation 1 shows the formula introduced by Pearson (1896).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

Spearman's rank correlation coefficient

According to the literature (Zhang et al., 2015; Polanco-Martínez, 2019), financial data often violates the assumption of normal distribution. we employ Spearman's rank correlation, a non-parametric measure, alongside Pearson's correlation coefficient. Equation 2 shows the formula for Spearman's correlation.

$$r_S = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{R(i) - \bar{R}}{S_{n,R}}\right)\left(\frac{S(i) - \bar{S}}{S_{n,S}}\right) \quad (2)$$

Where $\bar{R}$ and $\bar{S}$ are the sample means and $S_{n,R}$ and $S_{n,S}$ are the sample standard deviations calculated with the denominator n (sample size).

To further analyze the dynamics of the markets' links, we follow Polanco-Martínez (2019) and apply a rolling window Spearman correlation. The window length is set to 125.

Kendall's tau rank correlation coefficient

Another non-parametric approach used in the literature to evaluate the relationship between variables is the Kendall's tau rank correlation coefficient. The equation described by Kendall (1955) can be observed in Eq. (3).

$$\tau = \frac{N_c - N_d}{N_c + N_d} \quad (3)$$

Where N_c is the number of concordant pairs and N_d is the number of discordant pairs computed as in Eq. (4).

$$\begin{cases} \frac{Y_j - Y_i}{X_j - X_i} > 0, \text{pair is concordant} \\ \frac{Y_j - Y_i}{X_j - X_i} < 0, \text{pair is discordant} \\ \frac{Y_j - Y_i}{X_j - X_i} = 0, \text{pair is considered a tie} \end{cases} \quad (4)$$

As stated previously, financial data often violates the assumptions of linear approaches. Thus, we employ the nonlinear Granger causality test proposed by Diks and Panchenko (2006), following the model of Polanco-Martínez (2019). We implemented this method using the freely available C program GCTtest[3].

Given two variables X and Y, which represent the log returns for the selected stock market indices, the null hypothesis of the test is "that past observations of $X_t^{l_X}$ contain no additional information—beyond that in $Y_t^{l_Y}$ —about Y_{t+1}" (Polanco-Martínez, 2019) which is mathematically described by Eq. (5)

[3] http://research.economics.unsw.edu.au/vpanchenko/software/2006_GC_JEDC_c_and_exe_code.zip.

$$H_0: Y_{t+1}\left|\left(X_t^{l_X}; Y_t^{l_Y}\right) \sim Y_{t+1}\right| Y_t^{l_Y}, \tag{5}$$

where $X_t^{l_X} = (X_{t-l_X+1}, \dots, X_t)$ and $Y_t^{l_Y} = (Y_{t-l_Y+1}, \dots, Y_t)$ are the delay vectors.

Data and sample selection

The purpose of this paper is to study the dynamics of the links between capital markets in CEE countries that are also part of the European Union. The data consist of daily returns of the main market indices from Bulgaria (**SOFIX**), Czech Republic (**PX**), Croatia (**CROBEX**), Estonia (**OMXT**), Hungary (**BUX**), Latvia (**OMXR**), Lithuania (**OMXV**), Poland (**WIG**), Romania (**BET**), Slovakia (**SAX**) and Slovenia (**SBITOP**). Furthermore, to offer a broader perspective we also include in our initial analysis all the other members of the European Union (EU). The data consist of daily returns of the main market indices from all the 27 members of EU. The rationale behind using daily data is the fact that co-movements between capital markets are more evident at high frequency levels (Aloui et al., 2013; Reboredo et al., 2015).

Local currency-based closing prices were taken from the Thomson Reuters platform[4]. In order to cope with different official holidays, we use the interpolation method. More information on the selected stock markets can be found in Table 1. Capital markets in Table 1 are categorized into three groups: Frontier, Emerging and Developed capital markets, based on the FTSE Russell report from March 2024.

Table 1. Information about EU stock markets

Country	Stock Exchange	Market Index	Market capitalization (mil. EUR)*	Stock Exchange Website
Panel A: Emerging capital markets				
Czech Republic	Prague	PX	31,334.54	https://www.pse.cz/en/
Greece	Athens	ATHEX	73,673.21	https://www.athexgroup.gr/
Hungary	Budapest	BUX	35,242.36	https://www.bse.hu/
Romania	Bucharest	BET	43,327.05	https://m.bvb.ro/
Panel B: Developed capital markets				
Austria	Vienna	ATX	125,601.94	https://www.wienerborse.at/en/
Belgium	Euronext Brussels	BEL 20	6,241,462.08	https://www.euronext.com/en/markets/brussels
Denmark	Nasdaq Nordics – Copenhagen	OMX Copenhagen 20	1,920,368.74	https://www.nasdaqomxnordic.com/
Finland	Nasdaq Nordics – Helsinki	OMX Helsinki All Share	1,920,368.74	https://www.nasdaqomxnordic.com/
France	Euronext	CAC 40	6,241,462.08	https://www.euronext.com/en/markets/paris
Germany	Frankfurt	DAX	1,973,315.58	https://www.boerse-frankfurt.de/en
Ireland	Euronext Dublin	ISEQ 20	6,241,462.08	https://www.euronext.com/en/markets/dublin

[4] The access to the Thomson Reuters platform was ensured by the Bucharest University of Economic Studies.

Country	Stock Exchange	Market Index	Market capitalization (mil. EUR)*	Stock Exchange Website
Italy	Borsa Italiana	FTSE MIB	6,241,462.08	https://www.borsaitaliana.it/homepage/homepage.en.htm
Luxembourg	Luxembourg	LUXX	48,763.61	https://www.luxse.com/
Netherlands	Euronext Amsterdam	AEX	6,241,462.08	https://www.euronext.com/en/markets/amsterdam
Poland	Warsaw	WIG	191,453.18	https://www.gpw.pl/en-home
Portugal	Euronext Lisbon	PSI 20	6,241,462.08	https://www.euronext.com/en/markets/lisbon
Spain	BME Madrid	IBEX 35	697,235.10	https://www.bolsasymercados.es/bme-exchange/en/Madrid-Stock-Exchange
Sweden	Nasdaq Nordics – Stockholm	OMX Stockholm 30	1,920,368.74	https://www.nasdaqomxnordic.com/
Frontier Capital markets				
Bulgaria	Sofia	SOFIX	7,925.53	https://www.bse-sofia.bg/en/
Croatia	Zagreb	CROBEX	22,970.83	https://zse.hr/en
Republic of Cyprus	Cyprus	CSE General Index	9,404.40	https://www.cse.com.cy/en-GB/home/
Estonia	Nasdaq Nordics – Tallinn	OMX Tallinn	1,920,368.74	https://www.nasdaqbaltic.com/
Latvia	Nasdaq Nordics - Riga	OMX Riga	1,920,368.74	https://nasdaqbaltic.com/about-us/nasdaq-riga/
Lithuania	Nasdaq Nordics – Vilnius	OMX Vilnius	1,920,368.74	https://nasdaqbaltic.com/about-us/nasdaq-vilnius/
Malta	Malta	MSE	4,669.09	https://www.borzamalta.com.mt/
Slovakia	Bratislava	SAX	1,881.99	https://www.bsse.sk/bcpb/en/
Slovenia	Ljubljana	SBITOP	46,331.27	https://ljse.si/en

*The market capitalization is available on the website of Federation of European securities exchanges.

Source: Authors' own research.

Table 2 summarizes the descriptive statistics for the stock index return series from January 2016 to December 2019. The data exhibits characteristics of non-normal distributions, particularly the presence of fat tails. This finding justifies the use of non-parametric methods.

Table 2. Descriptive statistics for the pre-COVID period

Country	Market Index	Mean	Median	SD	Skewness	Kurtosis	JB test*
Austria	ATX	0.0003	0.0006	0.0102	-0.5569	4.1714	**795.09**
Belgium	BEL 20	0.0001	0.0004	0.0088	-0.6731	4.4188	**909.90**
Bulgaria	SOFIX	0.0002	0.0000	0.0060	0.0925	7.9389	**2686.70**
Croatia	CROBEX	0.0002	0.0003	0.0054	-0.5722	5.3119	**1258.70**
Republic of Cyprus	CSE General Index	-0.0001	-0.0002	0.0115	0.4069	2.5982	**316.64**
Czech Republic	PX	0.0002	0.0006	0.0072	-0.6604	4.0936	**789.12**
Denmark	OMX Copenhagen 20	0.0001	0.0005	0.0101	-0.5183	3.7075	**632.28**
Estonia	OMX Tallinn	0.0003	0.0004	0.0047	-0.4352	5.0559	**1122.20**
Finland	OMX Helsinki All Share	0.0002	0.0004	0.0088	-0.2315	1.6845	**130.68**
France	CAC 40	0.0003	0.0004	0.0095	-0.7747	7.3577	**2408.80**

Country	Market Index	Mean	Median	SD	Skewness	Kurtosis	JB test*
Germany	DAX	0.0002	0.0008	0.0097	-0.5274	3.6098	**603.45**
Greece	ATHEX	0.0002	0.0011	0.0160	-1.4246	17.4939	**13373.00**
Hungary	BUX	0.0006	0.0008	0.0093	-0.1436	1.1251	**57.93**
Ireland	ISEQ 20	0.0001	0.0004	0.0103	-1.6132	15.4047	**10546.00**
Italy	FTSE MIB	0.0001	0.0007	0.0129	-1.0909	12.4029	**6752.90**
Latvia	OMX Riga	0.0006	0.0004	0.0095	0.3248	14.3750	**8816.10**
Lithuania	OMX Vilnius	0.0004	0.0004	0.0048	0.5004	44.9266	**85932.00**
Luxembourg	LUXX	0.0000	-0.0001	0.0130	-0.1037	1.1140	**55.19**
Malta	MSE	0.0001	0.0001	0.0044	-0.1373	2.7081	**316.55**
Netherlands	AEX	0.0003	0.0008	0.0087	-0.5044	3.7736	**650.94**
Poland	WIG 20	0.0002	-0.0002	0.0105	-0.0209	0.7244	**22.76**
Portugal	PSI 20	0.0000	0.0001	0.0092	-0.7141	5.1796	**1230.60**
Romania	BET	0.0004	0.0005	0.0090	-2.3234	35.4675	**54451.00**
Slovakia	SAX	0.0002	0.0000	0.0092	-0.3946	5.1611	**1162.20**
Slovenia	SBITOP	0.0010	0.0001	0.0225	28.7124	881.4017	**331902.00**
Spain	IBEX 35	0.0000	0.0003	0.0108	-1.8832	22.5180	**22186.00**
Sweden	OMX Stockholm 30	0.0002	0.0004	0.0095	-0.2469	2.1652	**210.89**

*Bold numbers indicate p values ≤ 0.01

Source: Authors' own results.

Table 3 summarizes the descriptive statistics for the stock index return series from January 2020 to December 2023. The data exhibits characteristics of non-normal distributions, particularly the presence of fat tails. This finding justifies the use of non-parametric methods.

Table 3. Descriptive statistics for the post-COVID period

Country	Market Index	Mean	Median	SD	Skewness	Kurtosis	JB test*
Austria	ATX	0.0001	0.0007	0.0160	-1.2719	14.2029	**8950.00**
Belgium	BEL 20	-0.0001	0.0005	0.0136	-1.6210	19.6855	**17108.00**
Bulgaria	SOFIX	0.0003	0.0004	0.0088	-2.7493	33.1009	**48383.00**
Croatia	CROBEX	0.0002	0.0005	0.0089	-3.9202	46.0934	**93931.00**
Republic of Cyprus	CSE General Index	0.0008	0.0010	0.0135	-0.5033	8.2363	**2961.80**
Czech Republic	PX	0.0002	0.0005	0.0113	-1.0373	10.1769	**4639.00**
Denmark	OMX Copenhagen 20	0.0007	0.0013	0.0128	-0.1543	3.8833	**653.84**
Estonia	OMX Tallinn	0.0003	0.0004	0.0099	-2.3009	24.8043	**27352.00**
Finland	OMX Helsinki All Share	0.0000	0.0006	0.0125	-1.0290	8.4456	**3250.10**
France	CAC 40	0.0002	0.0009	0.0139	-1.0039	12.5236	**6917.00**
Germany	DAX	0.0002	0.0007	0.0141	-0.7180	12.9726	**7324.50**
Greece	ATHEX	0.0003	0.0010	0.0172	-1.2066	15.5035	**10583.00**
Hungary	BUX	0.0003	0.0008	0.0150	-1.5284	11.8554	**6444.90**
Ireland	ISEQ 20	0.0002	0.0007	0.0151	-0.5775	5.6639	**1438.20**
Italy	FTSE MIB	0.0002	0.0013	0.0153	-2.2896	26.0523	**30070.00**
Latvia	OMX Riga	0.0002	0.0000	0.0122	-1.2272	44.2334	**84334.00**
Lithuania	OMX Vilnius	0.0003	0.0004	0.0070	-2.3295	27.3199	**33009.00**
Luxembourg	LUXX	0.0001	0.0003	0.0156	-0.5621	4.4359	**901.79**

Malta	MSE	-0.0002	-0.0003	0.0073	0.8276	7.4347	**2495.90**
Netherlands	AEX	0.0003	0.0008	0.0127	-0.8597	10.2282	**4626.20**
Poland	WIG 20	0.0001	0.0001	0.0164	-0.8776	9.0850	**3682.50**
Portugal	PSI 20	0.0002	0.0007	0.0119	-1.0121	10.5903	**4999.20**
Romania	BET	0.0004	0.0009	0.0109	-1.3289	14.9714	**9939.60**
Slovakia	SAX	-0.0001	0.0000	0.0093	-0.4713	16.2427	**11380.00**
Slovenia	SBITOP	0.0003	0.0006	0.0098	-1.9251	17.5120	**13819.00**
Spain	IBEX 35	0.0001	0.0004	0.0141	-1.3740	17.2731	**13150.00**
Sweden	OMX Stockholm 30	0.0003	0.0006	0.0129	-0.7696	7.4147	**2467.20**

*Bold numbers indicate p values ≤ 0.01

Source: Authors' own results.

Results and discussions

Figure 1 shows the Spearman correlation coefficients between stock markets indexes of EU members for the period of January 2016 – December 2019 (pre-COVID period). The results suggest that the connections are stronger between developed capital markets. This is also evident for the Polish capital market (WIG 20 index), the only developed capital market among CEE countries. These results are in line with previous literature which also observed the strong connection between Eastern and Western Europe (Gjika and Horvath, 2013). The results for Pearson's and Kendall's tau rank correlation coefficient are similar and are described in **Appendix A**.

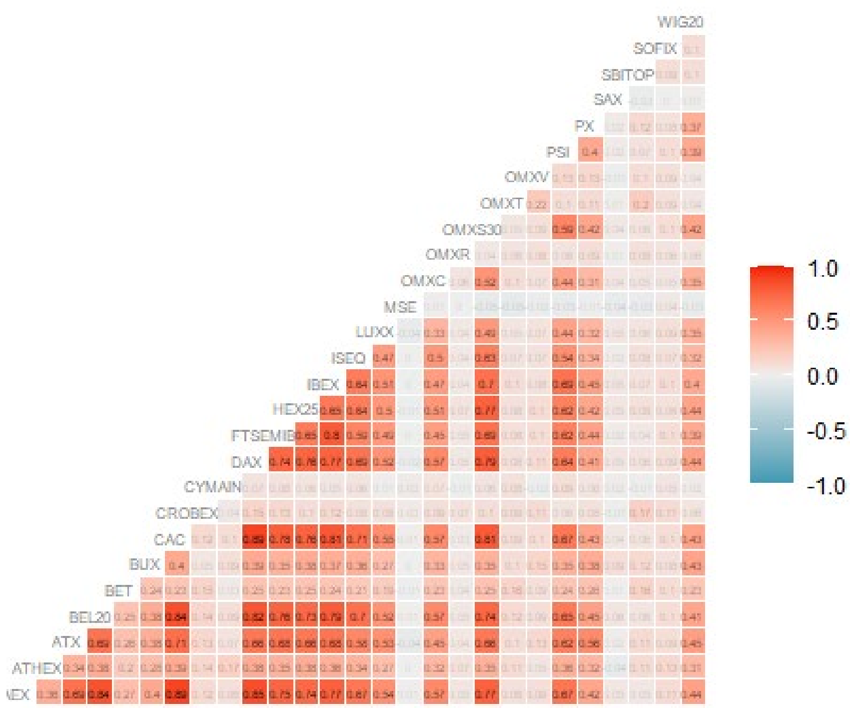

Figure 1. Spearman's rank correlation coefficient for EU countries in the pre-COVID period

Source: Authors' own contribution.

Figure 2 shows the Spearman correlation coefficients between stock markets indexes of EU members for the period of January 2020 – December 22023 (post-COVID period). During this period, our findings reveal an increase of the correlation between most of the stock market indices. These results are in line with the existing literature which have shown an increase in the comovement of the European stock market indices during turbulent periods (Savva and Aslanidis, 2010; Kenourgios and Samitas, 2011; Horvath et al., 2018). In particular, Slovakia (SAX index), Malta (MSE index) and Latvia (OMX Riga index) exhibit low correlations even after the outbreak of the COVID-19 pandemic. The low correlations observed in the cases of Slovakia and Malta could also be explained by their less developed structure (Amin and Orlowski, 2014). This is evidenced by their consistently lower market capitalization compared to the other EU capital markets included in this study (see Table 1).

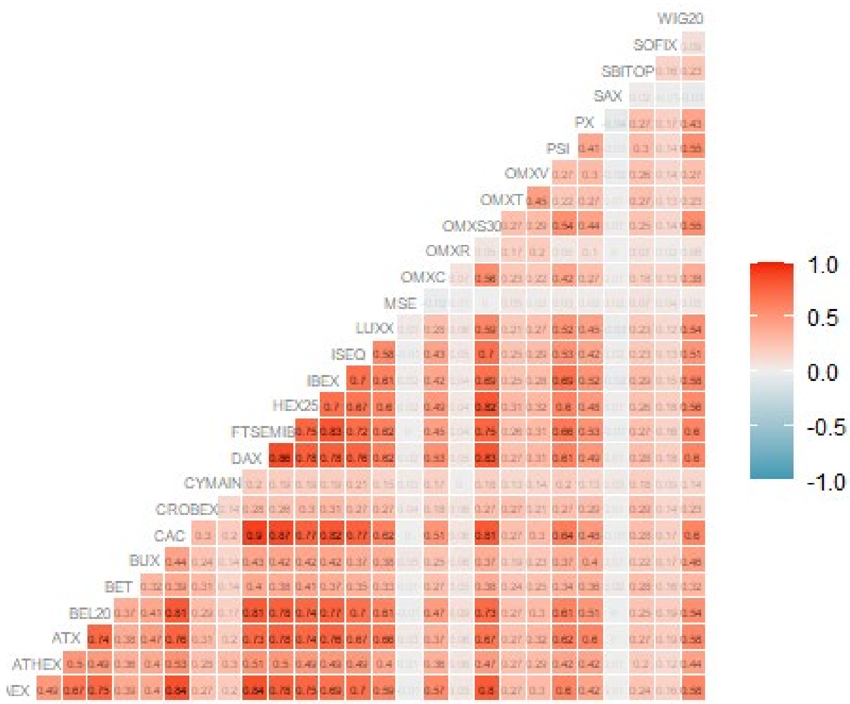

Figure 2. Spearman's rank correlation coefficient for EU countries in the post-COVID period

Source: Authors' own contribution.

The rolling window Spearman correlation results reinforce our previous findings. Most of the stock market indices exhibit spikes around the outbreak of the COVID-19 pandemic and after the beginning of the Russian invasion in Ukraine. Furthermore, none of the indicators surpass 0.6, indicating a moderate correlation. Interestingly, most of the stock market indices appear to be more correlated with the Polish market index (WIG 20). Interestingly, some of the relationships tend to be stronger than more constant over time as in Panel E and Panel I. The rest of the results are presented in **Appendix B.**

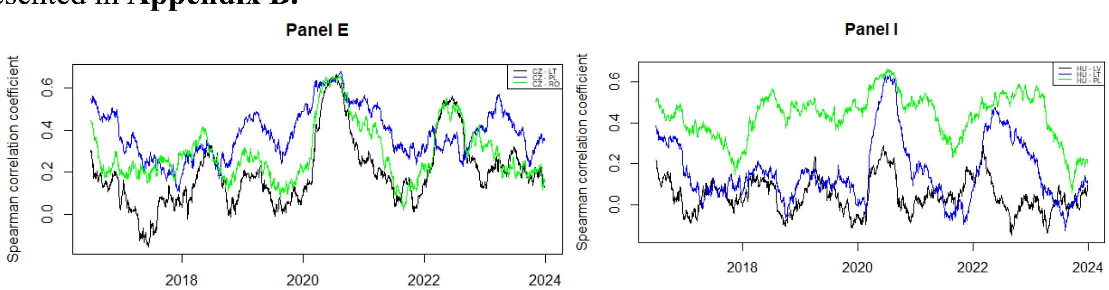

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Table 4 reports the results for the nonlinear Granger causality test. In the pre-pandemic period, statistically significant relationships between the stock market indices were scarce, and most of them are between Polish market index and other indices. In accordance with the existing literature, most capital markets exhibit stronger relationships after the occurrence of the pandemic. There are few pairs that do not exhibit a bidirectional relationship after the outbreak of the COVID-19 pandemic, namely Estonia with Latvia and Slovakia, Slovakia with Latvia, Croatia and Romania and Slovakia and Slovenia. These findings are more interesting in light of the fact that most of these countries are part of the European monetary union, while Czech Republic (which is not part of the EMU) exhibits bidirectional relationships with its peers even in the pre-pandemic period.

Table 4. Results of the nonlinear Granger causality test

	Pre Covid-19		Post Covid-19	
	Country A does not cause Country B	**Country B does not cause Country A**	**Country A does not cause Country B**	**Country B does not cause Country A**
BG – CZ	-0.4260 (0.6649)	-0.8260 (0.7956)	2.6930 (0.0035***)	2.2760 (0.0114**)
BG – EE	-0.412 (0.6597)	0.7310 (0.2325)	1.8330 (0.0334**)	2.9250 (0.0017***)
BG – HU	-1.457 (0.9275)	-0.6640 (0.7465)	2.9850 (0.0014***)	2.8380 (0.0023***)
BG – HR	1.1460 (0.1258)	0.385 (0.3502)	1.993 (0.0231**)	2.585 (0.0049***)
BG – LV	-0.7150 (0.7628)	0.0730 (0.4708)	2.4450 (0.0072***)	1.7000 (0.0445**)
BG – LT	-0.4590 (0.6767)	0.6390 (0.2616)	2.1080 (0.0175**)	2.8630 (0.0021***)
BG – PL	-0.2460 (0.1699)	0.9540 (0.1699)	2.6420 (0.0041***)	2.2580 (0.0119**)
BG – RO	-0.8870 (0.8125)	1.4620 (0.0719*)	2.2050 (0.0137**)	1.4700 (0.0707*)
BG – SK	0.2960 (0.3836)	0.5050 (0.3069)	0.8140 (0.2077)	-1.5360 (0.9377)
BG – SI	1.0010 (0.1584)	-0.6870 (0.7539)	2.2600 (0.0119**)	2.9080 (0.0018***)
CZ – EE	2.4010 (0.0081)	0.9860 (0.1621)	1.8450 (0.0324**)	1.1120 (0.1331)
CZ – HR	2.225 (0.0130**)	-2.492 (0.9936)	2.769 (0.0028***)	1.743 (0.0406**)
CZ – HU	2.2520 (0.0122**)	0.8450 (0.1989)	2.5950 (0.0047***)	2.9580 (0.0015***)
CZ – LV	0.8560 (0.8040)	0.0750 (0.4701)	1.9660 (0.0246**)	1.2160 (0.1193)
CZ – LT	1.5700 (0.0581*)	1.9410 (0.0261**)	1.5190 (0.0644*)	2.7840 (0.0027***)
CZ – PL	2.6260 (0.0043***)	2.1570 (0.0155**)	2.3750 (0.0087***)	2.7890 (0.0026***)
CZ – RO	1.8570 (0.0317**)	2.1200 (0.0170**)	2.4970 (0.0063***)	2.6630 (0.0038***)
CZ – SK	-0.3520 (0.6375)	0.7580 (0.2241)	0.9910 (0.1609)	1.1560 (0.1238)
CZ – SI	-0.4900 (0.6880)	1.0600 (0.1445)	2.6530 (0.0039***)	2.0900 (0.0182**)
EE – HR	0.835 (0.2019)	0.152 (0.4396)	2.380 (0.0086***)	1.888 (0.0295**)

	Pre Covid-19		Post Covid-19	
	Country A does not cause Country B	Country B does not cause Country A	Country A does not cause Country B	Country B does not cause Country A
EE – HU	0.8710 (0.1920)	2.4610 (0.0069*)	1.5780 (0.0573*)	2.1960 (0.0141**)
EE – LV	0.4190 (0.3375)	1.0940 (0.1371)	0.9700 (0.1660)	1.2160 (0.1119)
EE – LT	3.1490 (0.0008***)	3.3070 (0.0005***)	2.6880 (0.0036***)	2.7820 (0.0027***)
EE – PL	-0.2300 (0.5910)	-0.5940 (0.7239)	1.300 (0.0976*)	0.5740 (0.2831)
EE – RO	0.4670 (0.3200)	3.7060 (0.0001***)	1.5020 (0.0665*)	1.5480 (0.0608*)
EE – SK	-0.5100 (0.6951)	0.1410 (0.4440)	1.2100 (0.1132)	0.7120 (0.2381)
EE – SI	0.6220 (0.2268)	-1.4990 (0.9330)	2.7410 (0.0031***)	1.6160 (0.0530*)
HU – HR	0.558 (0.2883)	-0.166 (0.5658)	1.220 (0.1111)	2.431 (0.0075***)
HU – LV	1.6050 (0.0542*)	0.0560 (0.4775)	2.0230 (0.0215**)	1.6350 (0.0509*)
HU – LT	1.1760 (0.1198)	0.8920 (0.1861)	1.7340 (0.0415**)	2.2160 (0.0133**)
HU – PL	1.1870 (0.1175)	1.2230 (0.1106)	2.0750 (0.0190**)	2.3500 (0.0094***)
HU – RO	1.1920 (0.1167)	2.5330 (0.0056**)	3.7270 (0.0001***)	2.3940 (0.0083***)
HU – SK	0.1390 (0.4446)	0.4270 (0.3345)	2.6380 (0.0042***)	2.3600 (0.0091***)
HU – SI	0.3230 (0.3733)	0.8710 (0.1919)	2.8930 (0.0019***)	1.8840 (0.0298**)
LV – HR	0.490 (0.3121)	-0.688 (0.7543)	1.572 (0.0579*)	2.098 (0.0179**)
LV – LT	0.8080 (0.2097)	0.3590 (0.3599)	1.1250 (0.1304)	2.0960 (0.0180**)
LV – PL	1.9880 (0.0234**)	1.5710 (0.0580*)	2.2770 (0.0114**)	2.8330 (0.0023***)
LV – RO	0.3770 (0.3529)	0.0010 (0.4996)	2.7100 (0.0034***)	2.8010 (0.0026***)
LV – SK	0.8580 (0.1954)	0.1030 (0.4589)	0.6900 (0.2450)	-0.6420 (0.7394)
LV – SI	-1.4080 (0.9204)	0.5460 (0.2925)	1.5060 (0.0659*)	2.1990 (0.0139)
LT – HR	-0.634 (0.7368)	1.400 (0.0807*)	2.265 (0.0117**)	3.131 (0.0008***)
LT – PL	2.7250 (0.0032***)	1.8970 (0.0289**)	1.9460 (0.0259**)	1.1630 (0.1224)
LT – RO	1.8790 (0.0301**)	0.5840 (0.2795)	2.2150 (0.0134**)	0.8100 (0.2088)
LT – SK	-1.6510 (0.9506)	0.8830 (0.1886)	1.2050 (0.1141)	-0.4230 (0.6638)
LT – SI	-1.2780 (0.8995)	-1.5550 (0.9400)	2.8010 (0.0025***)	2.6190 (0.0044***)
PL – HR	1.825 (0.0340**)	-0.020 (0.5078)	2.159 (0.0154**)	2.595 (0.0047***)

	Pre Covid-19		Post Covid-19	
	Country A does not cause Country B	**Country B does not cause Country A**	**Country A does not cause Country B**	**Country B does not cause Country A**
PL – RO	1.5130 (0.0651*)	1.1280 (0.1297)	2.6710 (0.0038***)	3.5330 (0.0002***)
PL – SK	0.0230 (0.5911)	0.7140 (0.2375)	2.6400 (0.0042***)	1.5330 (0.0626*)
PL – SI	1.1840) (0.1182	-0.8480 (0.8016)	3.5250 (0.0002***)	3.2130 (0.0006***)
RO – HR	0.617 (0.2687)	-2.000 (0.9772)	2.500 (0.0062***)	2.796 (0.0025***)
RO – SK	0.1360 (0.4459)	0.6680 (0.2521)	1.4040 (0.0814*)	0.3510 (0.3629)
RO – SI	-1.5170 (0.9353)	-1.6580 (0.9514)	2.8790 (0.0019***)	2.9150 (0.0017***)
SK – HR	1.640 (0.0504*)	-1.333 (0.9086)	-0.520 (0.6984)	1.298 (0.0970*)
SK – SI	-1.2930 (0.9020)	-1.5130 (0.9349)	0.6560 (0.2560)	1.1670 (0.1216)
SI – HR	0.333 (0.3694)	-0.882 (0.8111)	2.860 (0.0021***)	2.277 (0.0114**)

Note: The symbols ***, ** , and * denote statistical significance at 1%, 5%, and 10%.

Source: Authors' own contribution

Conclusions

This paper explores the dynamics of the relationships between the main Central and Eastern European daily stock market indices. The analysis focuses on two distinct periods: January 2016 to December 2023 (pre-COVID-19 crisis), and January 2020 to December 2023 (post-COVID-19 crisis). We propose a combined use of two advanced statistical methods. Firstly, we employ two nonparametric correlation coefficients, namely Spearman's rank correlation coefficient and Kendall's tau rank correlation coefficient over the two sub-periods. To gain a better understanding of evolving relationships, we further employ a rolling window Spearman correlation over the entire sample. Second, we use a nonparametric, nonlinear causality Granger test to explore the cause–effect relationships between CEE stock markets. Our main findings reveal a moderate correlation between CEE capital markets. Furthermore, most of these correlations have increased during the outbreak of the COVID-19 pandemic and the Russian invasion in Ukraine. Moreover, the relationships between CEE capital markets and the developed capital markets from the EU appear to be stronger.

Our results are important for investors due to their implications in the diversification of international portfolios (Bertero and Mayer, 1990; Kearney and Poti, 2006; Sensoy et al., 2013; Tilfani et al., 2020). We also provide valuable insights for policymakers and regulators given the major role of our findings for the spillover effects of economic policies (Reboredo et al., 2015). In particular, acknowledging the level of connectedness between markets is important for investors in terms of risk exposure. For instance, an increase in the correlation between international stock markets could lead to a higher vulnerability to external shocks and also a lower diversification opportunity for investors (Buttner and Bernd, 2009; Lee and Cho, 2017). However, higher levels of correlation between different financial markets could also promote a more efficient allocation of the global capital and economic growth (Lee and Cho, 2017).

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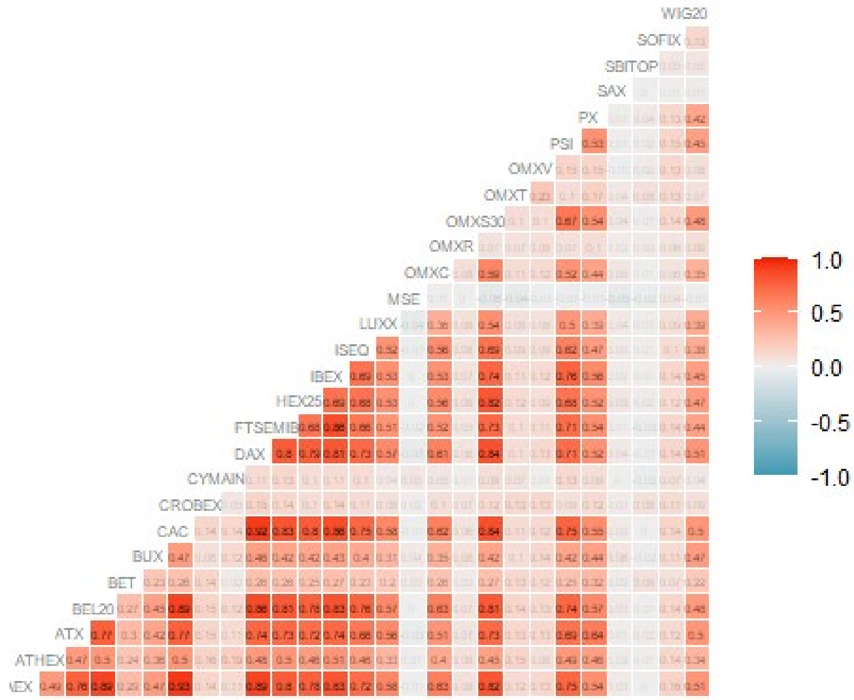
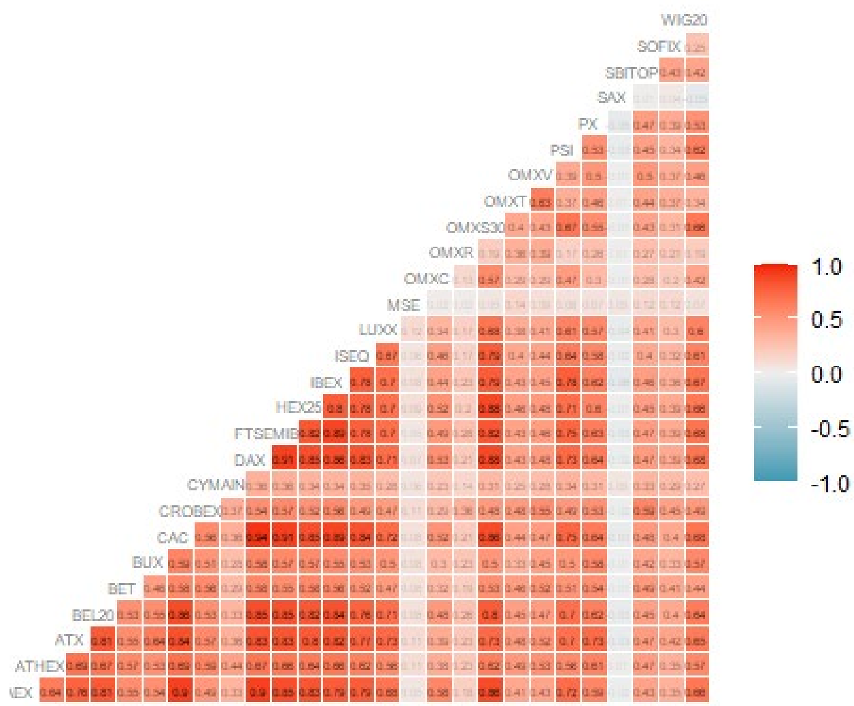
Appendix A. Pearson and Kendall's tau correlation coefficients for EU members

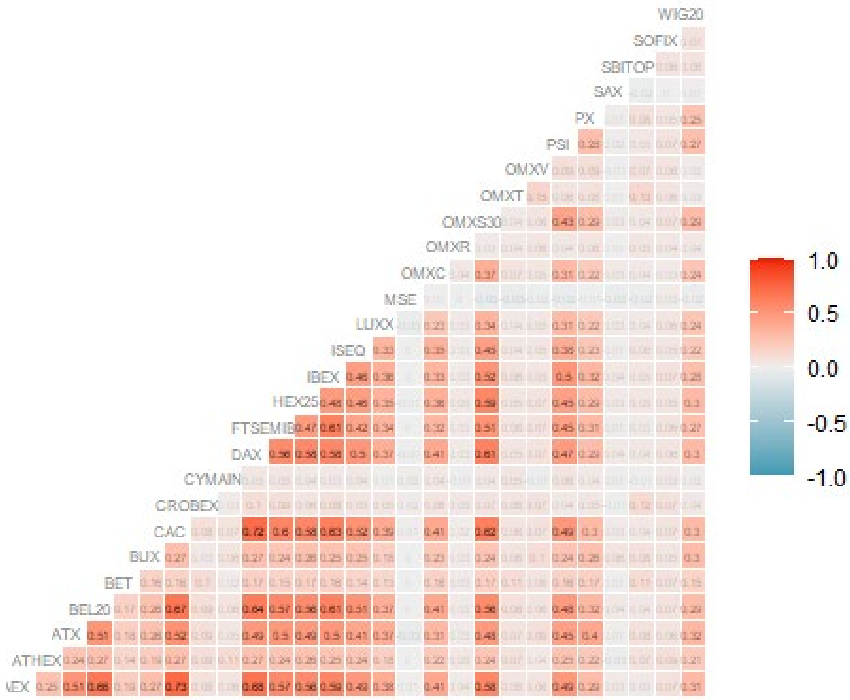
Panel A. Pearson correlation coefficients in the pre pandemic period



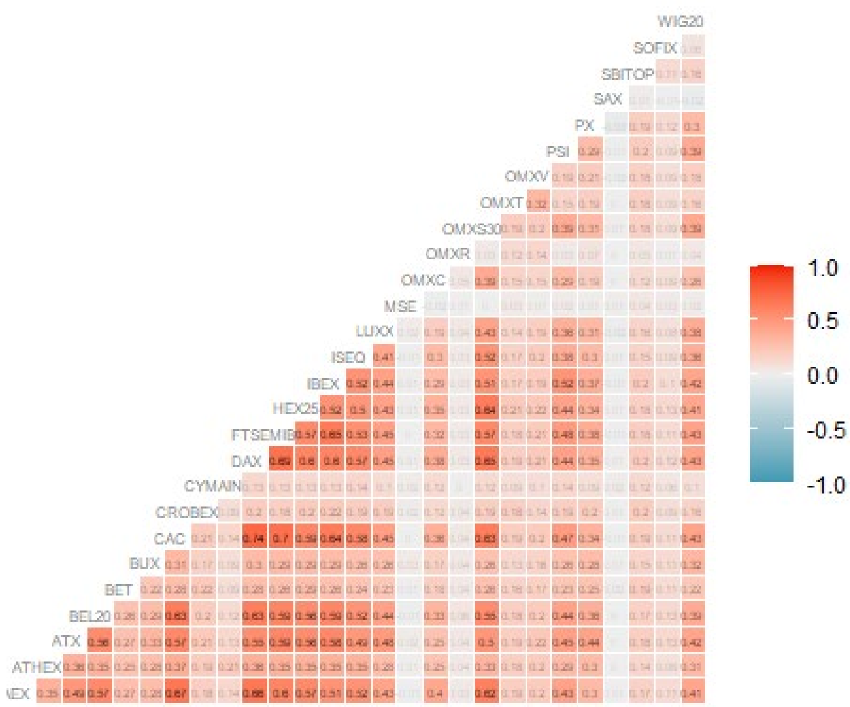
Panel B. Pearson correlation coefficient in the post pandemic period



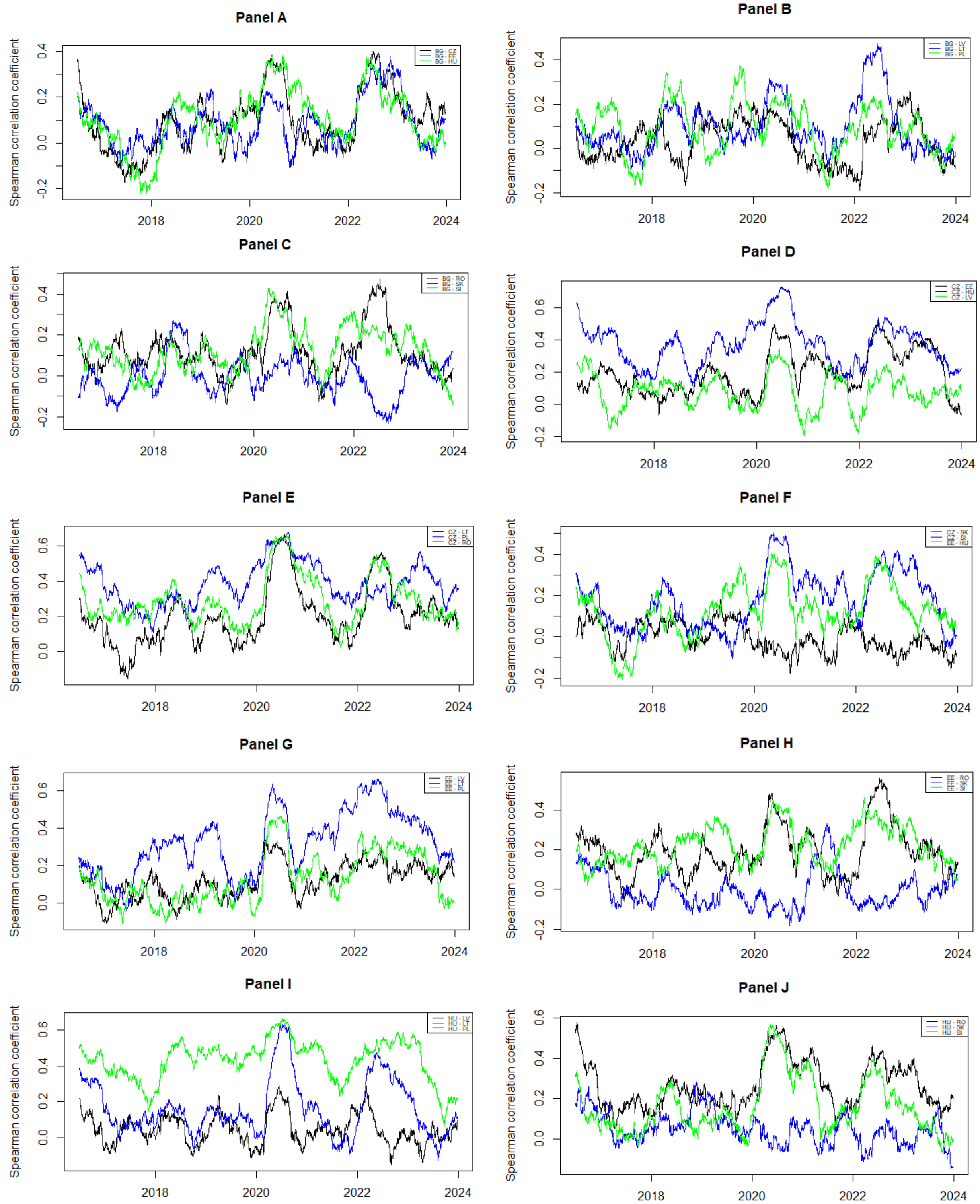
Panel C. Kendall's tau correlation coefficients in the pre pandemic period



Panel D. Kendall's tau correlation coefficient in the post pandemic period



Appendix B. Rolling window Spearman's rank correlation coefficient for CEE capital markets



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