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Short-Term Shocks Between Central European Stock Markets: An Approach During The 2020 and 2022 Events

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ABSTRACT

Stock indexes are used as a barometer of economic health, and fluctuations in these markets can have a substantial influence on the economy. For example, the Covid-19 pandemic caused severe economic disruption, as reflected in stock market indexes. Similarly, Russia's invasion of Ukraine has geopolitical implications that might undermine global trade and economic stability, impacting stock market indexes. Considering these developments, the purpose of this article is to examine the co-movements of the stock markets of Austria (ATX), Poland (WIG), the Czech Republic (PX Prague), Hungary (BUX), Croatia (CROBEX), Serbia (BELEX 15), Romania (BET), and Slovenia (SBI TOP) from February 16, 2018, to February 15, 2023. To achieve the research objectives, the aim is to answer the following research question: i) Have the events of 2020 and 2022 accentuated the co-movements between the stock markets in Central Europe? The results show the presence of 21 shocks between markets (out of a potential 56) during the Tranquil subperiod, with the WIG stock index having a greater predictive influence on the behavior of its peers (4 shocks out of 7 possible). During the Stress subperiod, 45 shocks were confirmed (out of 56 possible). The markets that triggered the most market shocks (7 out of 7 possibilities) were BET, BUX, CROBEX, and SBI TOP. The research question was validated based on the conclusion supplied, as all markets increased their movements, showing a considerable effect of the 2020 and 2022 events on these markets.

KEYWORDS

Events of 2020 and 2022; Stock markets; Co-movements; Portfolio diversification

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1. Introduction

The globalization phenomenon has increased economic interdependence among countries, resulting in higher correlations between international financial markets, particularly in developed markets. The increased speed of communication is one factor contributing to this phenomenon. Information on market movements has spread quickly throughout the world because to technological improvements that have made it simpler for investors to transact in financial assets across borders. Furthermore, the trend toward financial market deregulation and liberalization in many nations has resulted in the elimination of barriers to cross-border investment and increased capital flows. This has allowed investors to diversify their portfolios by investing in a broader range of assets and markets, enhancing market correlation. For a better understanding, see the works of the authors Dias et al. (2019) and Dias and Carvalho (2020).

A higher correlation between international financial markets has important implications for investors, according to the authors Dias, Alexandre, et al. (2020), Dias, Pardal, et al., 2020) as well as Dias, Alexandre, et al., (2020), Dias, Pardal, et al. (2020), because it means that risks and opportunities in one market are more likely to affect other markets as well. They also emphasize the need for policymakers and regulators to work together to promote stability and reduce the likelihood of cross-border financial crises.

An essential step in successful risk management related to the possible adverse impact of global capital markets is the identification of international linkages across markets and the analysis of their variability over time (Pietrzak et al., 2017). According to Markowitz (1952) non-systemic risk can be mitigated through diversification. In fact, diversifying a portfolio entails more than just selecting various assets; it also entails looking for alternatives to assets that have risks that are decorrelated or negatively correlated. In light of this, even under identical circumstances, they will act differently. It is known as decorrelation when outcomes and price changes are unrelated. When there is a negative correlation, the assets move in opposing directions. As one asset is valued, the other decreases in value (Bhattacharyya, 2019; Kotu and Deshpande, 2019).

Financial markets are dynamic and complex, driven by a wide variety of participants who have varying levels of information. Investors can be guided to make better judgments and given prescriptive evidence for their analysis trough causal knowledge between stock markets. This essay will analyze the co-movements between the stock market indexes of Austria (ATX), Poland (WIG), the Czech Republic (PX Prague), Hungary (BUX), Croatia (CROBEX), Serbia (BELEX 15), Romania (BET), and Slovenia (SBI TOP) in the period from February 16, 2018, to February 15, 2023. To achieve these aims, the following research question should be answered: i) Have the events of 2020 and 2022 accentuated the co-movements between the stock markets in Central Europe? To answer the research question, we will use the VAR Granger Causality/Block Exogeneity Wald Test. Granger causality is a measurable concept of directed impact or causality for time series data, derived from temporal precedence and predictability.

As far as the authors know, this study is innovative because, first, it investigates the causal relationship between the stock markets of Central European countries using a newer panel data set that covers the period from 2018 to 2023, which includes the occurrence of events such as the COVID-19 pandemic in 2020 and the military conflict between Russia and Ukraine in 2022; second, it implements a Granger causality model that has proven to be superior to conventional panel data analysis approaches.

The information from the research is intended to assist investors and regulators in making decisions as they deal with the challenges of the present economic environment. These findings may be used by policymakers to modify and implement specific policies to expand the stock market and its ties to other markets, particularly in the current era of uncertainty.

This essay is divided into five sections in terms of structure. In addition to the present introduction, Section 2 presents an analysis of the state of the art in terms of publications on the upheaval in international financial markets; Section 3 outlines the methodology; and Section 4 contains the data and results. Lastly, Section 5 outlines the work's overall conclusions.

2. Literature Review

During the middle of the 2000s, there were several major crises in the international financial markets. These included the subprime crisis in the US in 2008 and the European sovereign debt crisis in 2010.
Using the Dynamic Conditional Correlation (DCC) method, Wong and Li (2010) examined the interactions between 11 major economies (United Kingdom, Canada, Germany, Japan, Hong Kong, China, Korea, and Taiwan) from January 1990 to December 2008, but for China from June 1994 to December 1994. Evidence shows that sharp and rapid changes in conditional correlation occurred during the two financial crises. The evidence also suggests that these crises started in developed economies and had a major influence on those economies but had a less pronounced impact on emerging economies.

Coeurdacier and Guibaud (2011) investigated the benefits of portfolio diversification in the Southeast Asian conventional and Islamic stock markets (Turkey, Malaysia, Singapore, Indonesia, and Thailand) at various investment horizons using Multivariate-Generalized Autoregressive Conditional Heteroscedastic (MGARCH-DCC) and wavelet approaches. The study analyzed the period from 1 June 2007 to 30 October 2018 in order to capture the fluctuations in correlations among the indexes during the 2008–2009 global financial crisis and post–crisis eras. The findings of this study point to limited long-term diversification benefits for foreign investors in Southeast Asian stock markets relative to short-term ones.

In order to investigate the changes between the stock markets of the Czech Republic and Hungary, Poland, and Turkey's foreign exchange markets between July 30, 2002, and July 28, 2011, Koseoglu and Cevik (2013) used the Causality-in mean/variance test. The authors found that the stock markets caused both the average and the variance of the exchange markets. As a result, the stock market can be regarded as playing an essential role in the process of price discovery for the foreign exchange markets of the countries analyzed.

Yarovaya and Lau (2016) using the Granger Causality test, looked at the co-movements between stock markets and the advantages of global portfolio diversification for UK investors with investments in emerging markets (including Brazil, Russia, India, China, South Africa, Mexico, Indonesia, South Korea, and Turkey) between October 10, 2005, and October 3, 2014. The overall findings indicate a lack of benefits from diversification and further indicate that the markets for assets exhibit more dependence when driven by market crashes.
Ferreira et al. (2017) used 48 stock markets from developed and emerging economies, taking the period from January 1995 to February 2014 into consideration. According to the findings, co-movements are considerable in 170 peer stock markets, and Granger's causality demonstrates that developing and border markets have strong connections with emerging economies.

The DCC-GARCH model was used by Pietrzak et al. (2017) to analyze the long-term interdependence between the stock markets of Austria, the Czech Republic, Hungary, Poland, and Germany from July 1, 1997, to September 30, 2015. The authors highlight shocks between the markets analyzed, which are concentrated on the dominant German market.

Moreover, Yang et al. (2017) investigated the co-movements and contagion in the stock markets of China, Japan, South Korea, and Taiwan, which are geographically and economically related in terms of short-term and long-term prospects. According to the findings of the investigation, which covered the period from January 4, 1996, to December 30, 2014, the authors propose that China should be treated as an isolated or segmented market because there is no significant association between it and the other markets. In East Asian countries, the impact of the financial crisis differs by country. Regardless of where the crisis began, the markets of Korea and Taiwan are more exposed to external shocks compared to China and Japan. In terms of the nature of the crisis, the 2011 financial crises in East Asia and Southern Europe were classified as local shocks because they only affected a few countries, whereas the 2008 global crisis was classified as a global shock because it caused significant short-, medium-, and long-term volatility in the markets studied.

The co-movements of the stock markets in Poland, the Czech Republic, Hungary, and developed-country stock markets (DAX, S&P 500, and IBEX) during stable and crisis periods were later studied by the author Grabowski (2019) using the Vector Autoregressive- Asymmetric Generalized Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity (VAR-AGDCC-GARCH) model. Evidence reveals that during the period of financial turbulence, the level of correlation between shocks in central and eastern European stock returns rose dramatically. It was especially strong during the US subprime crisis and the eurozone sovereign debt crisis.

In more recent studies, Hung (2022) examined the evolution of the co-movements between the global stock index and the stock markets in Central and Eastern Europe (Croatia, the Czech Republic, Hungary, Poland, and Romania) between January 5, 2010, and December 31, 2019, using the Multivariate Dynamic Equicorrelation Generalized Autoregressive Conditional Heteroscedasticity (DECO-GARCH) model. The findings reveal that co-movements between the CEE and global stock indexes are positive, which may undermine the benefits of diversifying the global and CEE portfolios. Furthermore, during the European financial crisis in 2010, there was a bidirectional return and volatility between global stock index returns and EEC stock market returns.

Harkmann (2022) examined the interdependence between Baltic stock markets (Estonia, Latvia and Lithuania) and selected European-developed stock markets. Empirical evidence for the Baltic stock markets and the main European market indexes from 2005 to 2015 shows that the Baltic stock market is integrated with the Swedish stock market and that this co-integration relationship implies the transmission of shocks from Sweden to the Baltic States. Co-integration analysis is also performed for sliding windows over consistent sub-samples, which simply evaluates the robustness of the integration between the stock markets of the Baltic States and Sweden.

Additionally, Stoupos and Kiohos (2022) applied the Fractionally Cointegrated Vector Autoregression (FCVAR) model to examine the degree of integration of the eurozone (EZ) stock markets following the end of the 2010 debt crisis. The findings show that stock market integration is strong between Germany and the major eurozone member countries but diverges on the periphery. In contrast, there are only indications of the Eurozone's integration of the Eastern Mediterranean and Baltic stock markets with the German stock index (DAX 30).

Finding causal relationships is extremely challenging because of how quickly markets assimilate new information. Several studies have been developed in order to contribute to the literature on the dynamic and causal links between financial markets, and it is possible to identify some studies that specifically focus on the central European stock markets; however, among these, their research objects have primarily gone through understanding the existing links between the Central European stock markets with other types of assets (Koseoglu and Cevik (2013); or understanding the connections between the markets of emerging and developed economies (Grabowski, 2019; Hung, 2022; Stoupos and Kiohos, 2022). Although these studies evaluate the evolution of these connections through time and account for the effects of situations like the U.S. subprime crisis and the euro area sovereign debt crisis, they do not provide evidence for the most recent events of 2020 and 2022. As a result, it is crucial to create new studies that provide current data so that decisions can be made that are appropriate for the current political, economic, and financial environment.

3. Methodology

3.1. Data

The data are the prices index of the stock markets of Warsaw Stock Exchange WIG (Poland), Prague Stock Exchange PX (the Czech Republic), Budapest Stock Exchange BUX (Hungary), Vienna Stock Exchange ATX (Austria), Zagreb Stock Exchange CROBEX (Croatia), Belgrade Stock Exchange BELEX15 (Serbia), Bucharest Stock Exchange

BET (Romania), Ljubljana Stock Exchange SBI TOP (Slovenia), from February 16, 2018, to February 15, 2023. To increase the research's robustness, we divided the sample into two subperiods: the first, called Tranquil, includes the period from February 16, 2018, to December 31, 2019; the second, which contains the events of 2020 and 2022 and is named Stress, spans the period from January 2, 2020, to February 15, 2023. The quotations are daily and were obtained through the Thomson Reuters Eikon platform, in local currency to avoid currency-related distortions.

Table 1. The name of countries and their indexes used in this paper.

Country	Index
Poland	Warsaw Stock Exchange (WIG)
Czech Republic	Prague Stock Exchange (PX)
Hungary	Budapest Stock Exchange (BUX)
Austria	Vienna Stock Exchange (ATX)
Croatia	Zagreb Stock Exchange (CROBEX)
Serbia	Belgrade Stock Exchange (BELEX 15)
Romania	Bucharest Stock Exchange (BET)
Slovenia	Ljubljana Stock Exchange (SBI TOP)

Source: Own elaboration.

3.2. Methodology

The study was conducted in stages. Initially, descriptive statistics were used to characterize the study's sample, including the Jarque and Bera (1980) adherence test. Quantile graphs were also analyzed to verify the time series residues. The Breitung (2000) and Hadri (2000) panel roots tests were used to validate the stationarity of a chronological series. It is worth noting that the two tests are based on opposing hypotheses. The intersection of the results of both tests provides greater robustness to the findings of the study. To answer the research question, we will use the VAR Granger Causality model or the Block Exogeneity Wald Test to evaluate the impact of events in 2020 and 2022 on the shocks between the stock markets under consideration. The Granger Causality concept is based on the notion of time precedence between variables. In other words, if two variables, X_t and Y_t, are taken into consideration, X_t is told to Granger cause Y_t if the past values of X_t help predict future values for Y_t. The Granger test evaluates whether the predictive capacity of the X_t values in relation to Y_t is statistically significant, i.e., it defends the null hypothesis that the exogenous coefficients lag from the causality variable and are therefore zero and do not cause the dependent variable in the Grangerian sense. On the other hand, the alternative hypothesis postulates the existence of causality between variables (Sims, 1980).

To analyze the causality relationship between the financial markets under analysis, the VAR Granger Causality model or Block Exogenety Wald Test will be estimated, which uses Wald statistics to assess whether the independent (or exogenous) variables contain information that helps explain the behavior of the dependent variable.

The model can be expressed as follows:

$$X_t = A_1 X_{t-1} + \cdots + A_p X_{t-p} + C y_t + \epsilon_t \tag{1}$$

Where X_t is an endogenous variable vector $(k \times 1)$, and y_t is an exogenous variable vector $(d \times 1)$, A_1 to Ap represent the matrices of the lags coefficients to be estimated, and C corresponds to a matrix of exogenous variable coefficients. ϵ_t denotes a white noise process, commonly referred to as an innovation or shock term, with normal and average distributions of zero.

According to Parzen (1982) statistical modeling proposes methods that are often applied automatically without adjustment. However, an important aspect to consider in estimating a robust self-regressive model is related to the specification of the number of lags considered in the model. According to the author, Lütkepohl (1993), the sensitivity of the VAR in relation to the number of lags and the specification of a length of lags of greater order may cause an increase in prediction errors, or an insufficient adjustment may lead to the origin of autocorrelated error terms and consequently to the inefficiency of the estimators of the model VAR. To address this issue, the author used the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria from among the standard selection procedures for the number of lags presented in the literature. In addition to these traditional criteria for choosing a model, the FPE (Final Prediction Error) or the LR (Likelihood Ratio) test can be used to determine the number of lags to include in the model. Finally, it is crucial to test the autocorrelation in terms of error of a regression model since its dependence results in estimating an enviable model. For decades, correlation diagnosis of error terms (or residuals) has been recognized as crucial to ensuring the robustness and suitability of the regression model.

4. Results

4.1. Descriptive Statistics

Figure 1 shows the evolution, in returns, of the stock markets of Austria (ATX), Poland (WIG), the Czech Republic (PX Prague), Hungary (BUX), Croatia (CROBEX), Serbia (BELEX 15), Romania (BET), and Slovenia (SBI TOP), in the period from February 16, 2018, to February 15, 2023. Through graphic observation, we can see significant volatility over certain periods, in early 2020 due to the Covid-19 pandemic and the oil price war between Russia and Saudi Arabia, and in the first and second quarters of 2022 due to the Russian invasion of Ukraine and concerns about rising inflation. These fluctuations suggest breakdowns in the market structure. Globally, the analysis suggests that the stock market has experienced significant volatility in recent years, with structural crashes coinciding with major geopolitical and economic events. It is important to remember that the stock market is only one aspect of the economy, and market fluctuations do not necessarily reflect the health of the overall economy. These facts are also described in the studies of the authors Pardal, P., Dias, R., Teixeira, N. and Horta (2022) and Teixeira et al. (2022).

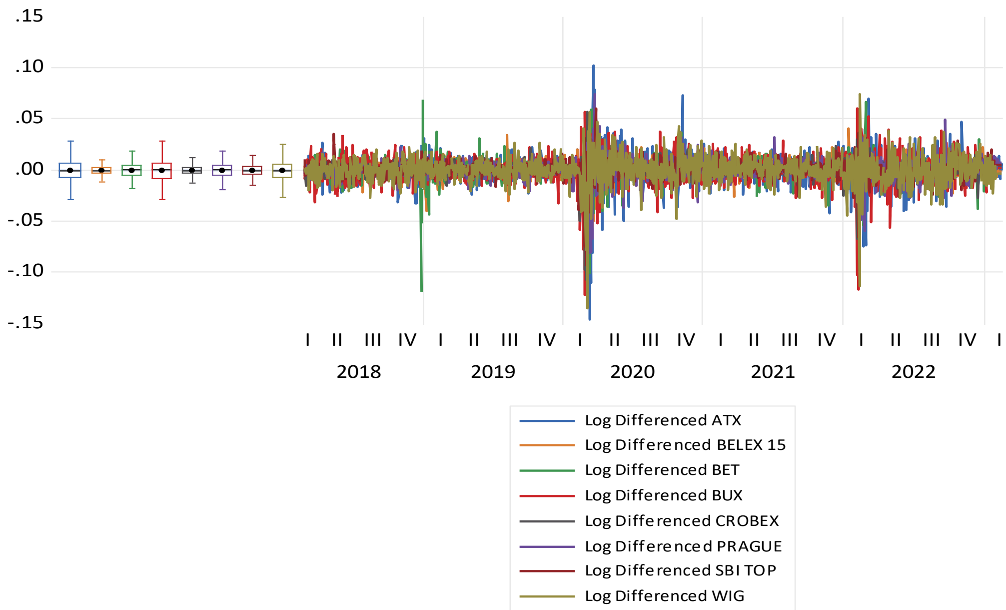

Figure 1. Evolution, in return, of the financial markets under consideration, from February 16, 2018, to February 15, 2023.

In Table 2, we can see the summary of the main statistics describing, in returns, the time series relating to the stock indexes of Austria (ATX), Poland (WIG), the Czech Republic (PX Prague), Hungary (BUX), Croatia (CROBEX), Serbia (BELEX 15), Romania (BET), and Slovenia (SBI TOP). In relation to the average return, we see that the markets present positive values, with the exception being the stock market of Polonia (-6.76E-05), in relation to standard deviation we realize that the stock index BUX (0.014293) presents the highest value, i.e., a greater dispersion over the average. To see if we were facing a normal distribution, we calculated asymmetry and kurtoses and verified that they had distinct values of 0 and 3, respectively. To validate, we used the Jarque and Bera (1980) test, which revealed that H_0 is rejected at a 1% significance level.

Table 2. Summary table of the descriptive statistics, in returns, of the stock markets under consideration for the period from February 16, 2018, to February 15, 2023.

	ATX	BELEX 15	BET	BUX	CROBEX	PRAGUE	SBI TOP	WIG
Mean	1.15E-05	9.71E-05	0.000323	0.000161	0.000181	0.000243	0.000356	-6.76E-05
Std. Dev.	0.014923	0.007040	0.011431	0.014293	0.008237	0.010466	0.009180	0.013503
Skewness	-1.204209	-1.041144	-1.746042	-1.424042	-3.961425	-1.034033	-1.876232	-1.294956
Kurtosis	18.23537	14.70699	23.20574	14.86453	53.72062	14.36294	22.27107	16.84349
Jarque-Bera	12500.56	7428.836	22092.01	7822.327	138465.8	7008.713	20252.45	10421.63
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1261	1261	1261	1261	1261	1261	1261	1261

Source: Own elaboration.

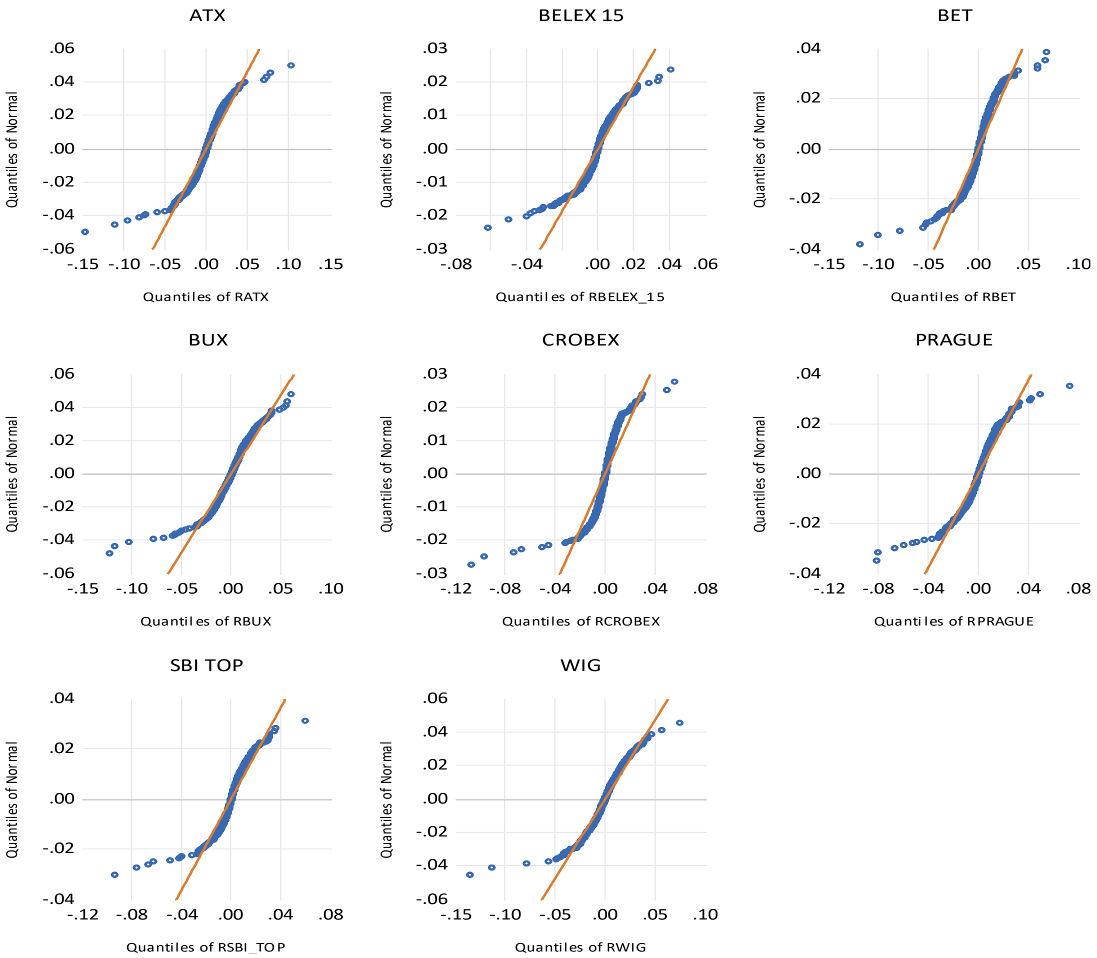

Figure 2. Q-Q Plots, in returns, of the eight stock markets under review for the period from February 16, 2018, to February 15, 2023.

Through the graphical observation of the quantile plot illustrated in Figure 3, one can also infer about the normality of the data of the time series under consideration. The orange color is represented graphically as the straight line of the normal distribution, and the blue is the distribution of the data for each time series. Comparing the dispersion of the data of the time series relative to the normal distribution, it appears that none of the series is completely overlapping, and there is a certain asymmetry. However, by incorporating a sufficiently large number of observations into the sample, it can be concluded that the data from the time series of the central European stock markets under examination follow an approximately normal distribution, thus confirming the assumption of normality.

4.2. Stationarity Time Series Analysis

Stationarity is an important property of chronological series data because it lets us use statistical models and techniques that assume a stationary chronological sequence. When a chronological sequence is not stationary, it can be difficult to make accurate predictions or draw meaningful conclusions from the data. To give robustness to our results, we conducted the panel unit root tests in Hadri (2000) and Breitung (2000) that postulate the opposite hypotheses.

In Table 3, we can see the results of the Breitung (2000) test in a set of chronological series of data. It is a statistical test used to determine whether a chronological series is stationary or contains a unit root, which indicates that the variance of the chronologic series is unstable. The results show the rejection of the null hypothesis at a level of significance of 1%. In this sense, the null hypothesis of both tests that postulates the existence of a unit root (or inconstant variance) was rejected for the period under study in the first differences.

Table 3. Breitung (2000) test for the eight stock markets under consideration, from February 16, 2018, to February 15, 2023.

Null Hypothesis: Unit root (common unit root process)				
Method			Statistic	Prob.**
Breitung t-stat			-45.8915	0.0000
Intermediate regression results on UNTITLED				
Series	S.E. of Regression	Lag	Max Lag	Obs
ATX	0.01545	6	22	1254
BELEX 15	0.00830	1	22	1259
BET	0.01337	1	22	1259
BUX	0.01603	2	22	1258
CROBEX	0.00859	2	22	1258
PRAGUE	0.01215	1	22	1259
SBI TOP	0.01008	2	22	1258
WIG	0.01909	0	22	1260
	Coefficient	t-Stat	SE Reg	Obs
Pooled	-0.60290	-45.892	0.013	10057

Source: Own elaboration.

Based on the results provided by Table 4, the null hypothesis of the Hadri (2000) test, which presupposes stationarity, was not rejected at a level of 1% significance due to the logarithmic transformation in the first differences from the original price series. This suggests that the panel data set is stationary, which validates previous evidence obtained through the Breitung (2000) test.

4.3. Granger Causality Test Results

Vectorial autoregression models (VAR) are systems of simultaneous equations that capture interdependent

Table 4. Hadri (2000) test for the eight stock markets under consideration, from February 16, 2018, to February 15, 2023.

Null Hypothesis: Stationarity				
Method			Statistic	Prob.**
Hadri Z-stat			-1.36264	0.9135
Heteroscedastic Consistent Z-stat			-1.51205	0.9347
Intermediate results on UNTITLED				
Series	LM	HAC	Bandwidth	Obs
ATX	0.0500	0.000334	12.0	1261
BELEX 15	0.0271	6.91E-05	13.0	1261
BET	0.0473	0.000153	6.0	1261
BUX	0.0440	0.000216	4.0	1261
CROBEX	0.0398	0.000119	19.0	1261
PRAGUE	0.0501	0.000161	12.0	1261
SBI TOP	0.0447	0.000144	14.0	1261
WIG	0.0517	0.000217	10.0	1261

*Source: Own elaboration. Note: * High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null. ** Probabilities are computed assuming asymptotic normality.*

relationships between multiple variables. These models allow the analysis of the impact of stochastic shocks on the variables within the system. VAR models are typically used in time series analysis and are especially useful for modeling the dynamics of multiple variables that influence each other over time. A VAR model is based on the idea that each variable in the system can be described as a function of its own past values and the past values of all other variables in the system. The model also assumes that the disturbances or errors in each equation are mutually correlated and follow a multivariate normal distribution (Granger, 1969).

The Granger (1969) test is sensitive to the number of phases. The choice of the number of lags for the two subperiods can be made from the information criteria in Tables 5 and 6, respectively. Based on the results obtained, the LR criterion was selected for the Tranquil subperiod, which suggests a model with 2 lags, and for the Stress subperiod, the information criteria LR, FPE, and AIC suggest a model that has a number of lags equal to 10.

To assess whether the number of lags selected for each model in each subperiod was estimated by the waste autocorrelation test, namely the VAR Residual Serial Correlation LM Tests, whose null hypothesis postulates the absence of waste autocorrelation. By observing Tables 7 and 8, we can exclude the possibility of autocorrelation from the residual terms of the time series under study. This ensures that the models estimated for the two subperiods are robust and valid.

The results of the Granger Causility/Block Exogeneity Wald Test for the Tranquil subperiod are presented in Table 9. These tests were conducted over the stock markets of Austria (ATX), Poland (WIG), the Czech Republic (PX Prague), Hungary (BUX), Croatia (CROBEX), Serbia (BELEX 15), Romania (BET), and Slovenia (SBI TOP). While the ATX, BET, BUX, CROBEX, and PRAGUE indices have triggered shocks in 3 markets, the WIG index has the best predictive power over the movements of its peers (4 shocks out of a potential 7). Only one market (out of a potential seven) was influenced by the BELEX 15 and the SBI TOP index. Additionally, we observe that the markets that experience the greatest shocks from other markets are the BELEX 15 index and the PRAGUE index.

During the Tranquil subperiod, we have globally observed the presence of 21 market movements (out of 56 possibilities). We can observe the existence of 15 unidirectional causal movements between ATX→BET, ATX→PRAGUE, ATX→WIG, BET→CROBEX, BET→SBI TOP, BUX→BELEX 15, BUX→WIG, CROBEX→BUX, CROBEX→PRAGUE, PRAGUE→BELEX 15, PRAGUE→BET, SBI TOP →BUX, WIG→BELEX 15, WIG→PRAGUE and WIG →SBI TOP. Additionally, 3 bidirectional links between BUX PRAGUE, CROBEX WIG, and BELEX 15 WIG may be found. These findings are in line with the findings of the authors, Pardal et al. (2021), which highlight insignificant co-movements during periods of calm in international financial markets."

Table 5. VAR Lag Order Selection Criteria, from February 16, 2018, to December 31, 2019.

Lag	LogL	LR	FPE	AIC	SC	HQ
1	12891.31	159.6123	5.27e-35	-56.22505	-55.57413	-55.96864
2	12969.86	151.2441*	4.95e-35*	-56.28887*	-55.05935	-55.80453
3	13014.04	83.51818	5.40e-35	-56.20194	-54.39383	-55.48969
4	13044.66	56.79911	6.26e-35	-56.05552	-53.66881	-55.11534
5	13084.06	71.71915	6.98e-35	-55.94763	-52.98233	-54.77954
6	13129.18	80.53907	7.61e-35	-55.86482	-52.32092	-54.46880
7	13159.65	53.31900	8.85e-35	-55.71775	-51.59525	-54.09381
8	13194.99	60.61513	1.01e-34	-55.59207	-50.89098	-53.74021
9	13228.87	56.91554	1.16e-34	-55.45997	-50.18029	-53.38019
10	13265.85	60.81891	1.32e-34	-55.34145	-49.48318	-53.03375

Source: Own elaboration.

Table 6. VAR Lag Order Selection Criteria, from January 2, 2020, to February 15, 2023.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	18867.08	NA	1.87e-31	-48.04862	-48.00108	-48.03034
1	19092.42	445.5061	1.24e-31	-48.45967	-48.03174	-48.29513
2	19343.48	491.2451	7.72e-32	-48.93626	-48.12793*	-48.62546
3	19538.23	377.0911	5.53e-32	-49.26937	-48.08066	-48.81232
4	19669.26	251.0494	4.66e-32	-49.44016	-47.87106	-48.83684
5	19802.27	252.1167	3.91e-32	-49.61597	-47.66648	-48.86639*
6	19912.16	206.0622	3.48e-32	-49.73289	-47.40302	-48.83706
7	20032.44	223.0898	3.02e-32	-49.87627	-47.16601	-48.83418
8	20113.77	149.2008	2.89e-32	-49.92044	-46.82979	-48.73209
9	20196.97	150.9288	2.76e-32	-49.96936	-46.49833	-48.63475
10	20266.61	124.9031*	2.72e-32*	-49.98372*	-46.13230	-48.50286

Source: Own elaboration.

Table 7. VAR Residual Serial Correlation LM Tests, from February 16, 2018, to December 31, 2019.

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	74.23513	64	0.1791	1.162686	(64, 2498.2)	0.1792
2	73.78861	64	0.1886	1.155591	(64, 2498.2)	0.1887
3	76.34123	64	0.1388	1.196173	(64, 2498.2)	0.1389

Source: Own elaboration.

Table 8. VAR Residual Serial Correlation LM Tests, from January 2, 2020, to February 15, 2023.

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	80.90476	64	0.0753	1.267102	(64, 3980.6)	0.0753
2	101.3105	64	0.0021	1.590746	(64, 3980.6)	0.0021
3	88.06504	64	0.0247	1.380480	(64, 3980.6)	0.0248
4	105.4795	64	0.0008	1.657072	(64, 3980.6)	0.0008
5	90.23988	64	0.0171	1.414957	(64, 3980.6)	0.0171
6	75.25015	64	0.1588	1.177709	(64, 3980.6)	0.1588
7	90.54550	64	0.0162	1.419804	(64, 3980.6)	0.0162
8	112.7890	64	0.0002	1.773525	(64, 3980.6)	0.0002
9	65.84699	64	0.4127	1.029333	(64, 3980.6)	0.4128
10	62.13464	64	0.5428	0.970851	(64, 3980.6)	0.5428
11	70.68982	64	0.2642	1.105706	(64, 3980.6)	0.2643

Source: Own elaboration.

Table 10 shows the results of the VAR Granger Causality test during the stress period. The markets that triggered the most market shocks (7 out of 7 possibilities) were BET, BUX, CROBEX, and SBI TOP, followed by the ATX index and the PRAGUE index, which caused shocks in 5 markets each. The BELEX 15, ATX, and PRAGUE indices experienced 7 shocks from their peers during the Stress subperiod, making them the most predictive or caused markets. As we can see, globally, 45 of the total 56 shocks have happened during the stress subperiod. Among these movements, it is observed that during the subperiod of stress, there are 11 unidirectional movements (BET→BELEX 15, BUX→BELEX 15, BUX→ATX, BUX→WIG, CROBEX→BELEX 15, CROBEX→ATX, CROBEX→PRAGUE, CROBEX→WIG, SBI TOP→WIG, SBI TOP→PRAGUE and WIG→BELEX 15). There were also 17 bidirectional movements during this subperiod (BELEX 15↔ATX, BELEX 15↔PRAGUE, BELEX 15↔SBI TOP, ATX↔BET, ATX↔PRAGUE, ATX↔SBI TOP, ATX↔WIG, BET↔BUX, BET↔CROBEX, BET↔PRAGUE, BET↔SBI TOP, BET↔WIG, BUX↔CROBEX, BUX↔PRAGUE, BUX↔SBI TOP, CROBEX↔SBI TOP and PRAGUE↔WIG).

We may examine how the market responded to the events of 2020 (the COVID-19 pandemic) and 2022 (the Russian invasion of Ukraine) using the results of the Stress subperiod. Similar to what happened when past crises occurred as demonstrated by Yarovaya and Lau (2016) and Grabowski (2019), the number of comovements rose significantly during the shocks brought on by the events of 2020 and 2022. The findings of this research cast doubt on the possibility of portfolio diversification to a wider number of stock market pairs in these regional financial markets.

Table 9. Granger/Block Exogeneity Wald Causality Tests, of the financial markets in analysis, during the Tranquil subperiod.

	BELEX 15	ATX	BET	BUX	CROBEX	PRAGUE	SBI TOP	WIG
BELEX 15		0,65628	3,74800**	8,09596***	0,16075	5,13508***	0,42040	2,33833*
ATX	0,10773		1,74312	0,69873	0,01443	0,82168	0,18278	1,11735
BET	6,37380***	10,3290***		1,98995	0,90047	3,73547**	0,83000	0,82421
BUX	0,13645	0,57877	0,14525		2,78865*	4,56985**	3,45779**	0,30161
CROBEX	0,72962	1,87281	3,57872**	1,10762		0,46212	1,43061	2,71418*
PRAGUE	2,10740	45,4212***	1,96656	2,63647*	3,56295**		0,98588	11,2952***
SBI TOP	0,97253	0,98930	2,42367*	1,42541	0,10337	0,10201		4,11765**
WIG	1,22614	18,7123***	1,03742	5,27099***	2,89947*	1,78559	1,54772	

*Note: ***, **, * represents 1%, 5% and 10% level of significance, respectively. Source: Own elaboration.*

Table 10. Granger/Block Exogeneity Wald Causality Tests, of the financial markets in analysis, during the Stress subperiod.

	BELEX 15	ATX	BET	BUX	CROBEX	PRAGUE	SBI TOP	WIG
BELEX 15		9,67799***	13,0980***	13,4142***	15,3499***	5,97270***	17,9016***	20,6561***
ATX	1,69125*		9,58209***	2,63114***	10,7963***	10,2432***	6,51952***	6,11460***
BET	0,68753	6,23136***		14,3174***	29,2524***	3,68171***	17,4741***	18,5957***
BUX	1,29604	1,16817	2,49164***		2,47172***	1,82478*	3,35047***	0,95435
CROBEX	1,52435	1,14561	2,15287**	13,5988***		1,44358	15,0472***	1,05798
PRAGUE	1,75317*	2,62064***	10,0491***	17,1369***	17,9723***		12,9450***	17,4176***
SBI TOP	1,69276*	3,30205***	2,03489**	12,2319***	7,69052***	1,54192		1,35821
WIG	0,91472	2,50497***	3,07698***	24,5859***	23,5700***	3,10687***	15,9812***	

*Note: ***, **, * represents 1%, 5% and 10% level of significance, respectively. Source: Own elaboration.*

Particularly for investors who use trading tactics like technical analysis, causal comprehension of their dynamic interactions has the potential to be extremely profitable. With technical analysis, the investor looks to uncover patterns in the previous movements of data series returns that may be used to predict how they will fluctuate going forward. The authors suggest that technical analysis might be used to predict the variables that influence unidirectional or bidirectional stock market movements. However, some care should be taken in applying technical analysis, as through the Granger causality test, it is not possible to identify the positive or negative direction in which these movements occur. In particular, during times of financial turmoil, the authors advise investors to remain out of stock markets with causal relationships in their portfolios because there is a chance that they will move in the same direction, which would mean that if one of their investments failed, it would also cause the other to fail, resulting in significant losses.

5. Conclusions

This study examined the co-movements of Austria's (ATX), Poland's (WIG), the Czech Republic's (PX Prague), Hungary's (BUX), Croatia's (CROBEX), Serbia's (BELEX 15), Romania's (BET), and Slovenia's (SBI TOP) stock markets from February 16, 2018, to February 15, 2023. The aim of the survey was to answer the following research question: i) Have the events of 2020 and 2022 accentuated the co-movements between the stock markets in Central Europe?

The research focuses on the exploration of short-term relationships between Central European stock markets and the influence of events that occurred on those markets between 2020 and 2022. Out of 56 possible market movements over the Tranquil subperiod, we have seen 21 market movements, including 15 unidirectional causal movements and 3 bidirectional linkages between the data series under investigation. During the stress subperiod, there were 45 comovements, specifically 11 unidirectional and 17 bidirectional movements. Based on the provided data, the study question was supported since all markets showed greater movement during the stress subperiod (21 to 45 comovements), demonstrating a significant impact of these events on these regional stock markets. These results question the possibility of risk diversification in the Central European markets, as they tend to increase their number of comovements, especially during periods of greater financial turmoil.

Financial markets are complicated and dynamic, driven by a wide range of players with various degrees of information. Causal information between stock markets can help investors make better decisions and provide prescriptive evidence for their analyses. The investor uses technical analysis to seek out patterns in the past movements of data series returns that may be utilized to anticipate future fluctuations. The authors suggest that for markets that show unidirectional or bidirectional movements, technical analysis can be used to predict what drives stock market fluctuations. The Granger causality test does not show whether these movements occur in a positive or negative direction, therefore, using technical analysis requires some caution.

In order to determine whether or not they will be appealing to markets for diversification, it is crucial to determine the direction in which they move together. This is because opposing movements may imply that when one market is down, the gains of the other market may compensate for those losses. In this way, future research should employ methods that allow for a more intuitive understanding of the links over the long term but also allow for inference about the direction of the causal relationship, which will help investors define more specialized strategies. This will help to further justify the results produced in our study through the Granger causality test.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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