The relevance of network effects on the Central-Eastern European (CEE) stock market indices, 2008 Q1–2022 Q1

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This study examines the development of stock market indices in the open and small economies of Central-Eastern European (CEE) countries between 2008 Q1 and 2022 Q1. A panel vector autoregression model (PVAR) was estimated on a set of macrodata and time-variant closeness centralities to understand the role of network effects. The time variance of closeness was achieved through quarterly re-estimation of a minimum spanning tree graph, representing the entire set of European stock markets (market-network). The sample covers the major events of the Global Financial Crisis and Eurozone sovereign debt crisis of 2008 and 2012 and the Covid-19 pandemic after 2020. In this study, the authors estimated the development of stock market indices in relation to macro variables related to funding, foreign exchange, and profitability, which can affect the expectations about the discounted cash flows of publicly listed companies. However, stock market indices decrease if the European market network has a higher degree of synchronization, leading to the temporary emergence of financial contagions. The findings indicate that stock market indices primarily react to traditional macro variables in the short and medium term, but changes in the network's shape can alter this process in the short term. These results underline the occurrence of cheaper-than-fundamental entry points for value-based investors in these markets due to such contagion-driven excessive decreases in share prices.

Keywords:
stock market index,
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Introduction

The period of great moderation, which was characterized by decreasing inflation and capital market volatility beginning in 1982, presumably ended with the subprime crisis in 2008. Since then, there has been an emergent trend of erratic and turbulent times in capital markets, such as the sovereign crisis in the Eurozone after 2010 that was concluded in 2018 and the Covid-19 pandemic between 2020 and 2021, which was followed by the energy crisis related to the Russian-Ukrainian war after 2022. Meanwhile, the members of the European Union conduct most of their trade with each other, while the free movement of capital is one of the key cornerstones of the union, which leads to an increased level of stock market integration (Bley 2009). In this highly complex environment, cross-market interdependencies can also have a disruptive nature. In recent years, network science has emerged as a major tool to study such complex systems (Kenett–Havlin 2015) since stock market indices can reflect changes in macroeconomic fundamentals, corporate performance, and spillovers from other markets (Aristeidis–Elias 2018). Therefore, investors should focus not only on macroeconomic fundamentals (such as key monetary interest rates, sovereign risk premiums, inflation, and foreign exchange rates) but also on the emergent biases that come from the market network itself since markets are connected through investors' portfolios and affected by changes in their sentiment (Kekre–Lenel 2021).

Diversification could only be an efficient tool for portfolio risk management if markets have minimal to no interaction with each other. However, the concept of financial contagion states that stock market returns tend to move together at a stronger degree during turbulent times (Forbes–Rigobon 2002). Therefore, the structural shape of a market network will always reflect these contagion biases, where the relative importance of each node is estimated from the correlation-derived distance matrix. In the case of systemic shocks, cross-market correlation and therefore each market's relative importance should rise. These network effects will bias diversification as well, since it assumes cross-market correlation as low and stable (considering unsystematic risks only)[1]. Meanwhile, contagion-driven share price decreases are not combined with the decrease in expected discounted cash flows, creating a better entry point for value-based investors (a "wake-up call" by Ahnert–Bertsch 2022). Therefore, it is important to assess the relevance of such network (or contagion) biases compared to traditional macrovariables that can affect a firm's funding and profitability conditions.

This paper is intended to show what happens with the Central-Eastern European (CEE) stock market indices if we consider the changes in their relative importance within the entire European economic region. We can assume that the CEE markets

[1] To improve the efficiency of diversification, Samitas et al. (2022d) recommended the inclusion of nonsecurity-like alternative assets, such as fine art, fine wine and stamps.

have similar exposure to network biases since their nodes are located in the same branch of the network that contains all European stock markets. Therefore, the first objective of this paper is to construct a minimum spanning tree graph from quarter to quarter (2008 Q1–2022 Q1) that covers the entire European continent with 21 stock market indices[2] to identify their structural changes based on weekly dynamic conditional correlations (DCC) among the markets. To identify the changing nature (retractions and extensions) of the network, the "closeness" centrality[3] will be analyzed to describe each market's relative importance (or range of collaboration). Second, the CEE market subset[4] of closeness will be analyzed with a panel vector autoregression (PVAR) model to provide impulse responses and variance decompositions of the regional stock market indices' reactions to the generally assumed macro, monetary, and capital market shocks, extended with the network bias (closeness). If the closeness of the market has a significant negative impact on the regional stock market indices, diversification will be undermined at some levels by the forces of financial contagion among these markets (Bacsosz 2019, Samitas et al. 2022b).

The motivation behind the sample selection is that stock market development in the CEE posttransition economies followed a quite similar pattern due to their common history and capitalism model, high dependence on capital inflows from Western Europe, large-scale liberalization reforms, and privatization initiated in 1989–1990 (Farkas 2019). Increased trade, financial interlinkages and convergence with Western Europe and the lack of capital barriers due to European Union membership have spurred the stock markets of CEE posttransition economies (Iloskics et al. 2021). However, based on the MSCI Market Classification Framework, stock markets in these countries are still different: Romania is classified as a frontier market, while the Czech Republic, Hungary, and Poland are still considered emerging markets. Although over the past decade, stock market capitalization in CEE economies has increased significantly, the ratio of public listings has remained under the European Union (EU) average (Moagăr-Poladian et al. 2019).

The paper is structured as follows: relevant literature about the theoretical model variables is assessed in the theoretical background section, then the methods of minimum spanning tree and panel VAR modeling are presented, which are followed by the discussion of the results and the conclusion of the paper.

[2] Country name (index name): Germany (DAX), France (CAC40), Italy (MIB), Netherlands (AEX), Switzerland (SMI), Belgium (BEL 20), Austria (ATX), Sweden (OMXS30), Norway (OBX), Denmark (OMXC20), Finland (OMX Helsinki), Iceland (OMXIPI), Spain (IBEX), Greece (ATHEX), Portugal (PSI20), Poland (WIG20), Hungary (BUX), Romania (BET), Slovakia (SAX), Bulgaria (SOFIX), Czechia (PX).

[3] Hence, there are other centralities as well, namely, the betweenness (how many times the node connects two other nodes) and the degree (the number of connections) centralities (Samitaset al. 2020), but the quarterly changes in these variables remained close to zero in most of the cases, making them inefficient in any regression estimation.

[4] Czechia (PX), Hungary (BUX), Poland (WIG20), Romania (BETI), Bulgaria (SOFIX) (Slovakia, Croatia and Slovenia was excluded due to insufficient data for the entire time period).

Theoretical background

This paper models the changes in stock market indices in a twofold way. First, it is necessary to assess the impact of macroeconomic variables, such as inflation, which reflects the imbalance between aggregate supply and demand, overall funding conditions that guide the discounting of future cash flows, and the foreign exchange rate, which represents the external balance of the economy as it affects corporate transactional and economic exposures. The asset purchase and long-term lending programmes of the European Central Bank (ECB) and the United States Federal Reserve (US Fed) determine the extended monetary conditions. Second, it is necessary to highlight the impact of network effects on stock market pricing as well as to present the nature of their biases.

Macroeconomic variables and stock markets

Corporate stock value is supposed to represent the sum of discounted future cash flows. Monetary policy transmission channels alter valuation through the funding conditions, namely, the weighted cost of capital and the overall interest payments. Therefore, investors should re-evaluate stock prices as a response to unexpected changes in monetary policy. Revaluation of stock prices will affect the cost of capital and the financial wealth of investors and therefore the real investment (Sellin 2001). Meanwhile, foreign exchange rate changes affect corporate value directly through their trade-related margins (transaction exposure) and indirectly through the value of foreign subsidiaries (economic exposure) as the general economic environment develops (Madura 2008).

Inflation can affect price-taking and price-making companies differently, while it can trigger monetary tightening on the macro level as well. Therefore, it can be one of the main sources of stock volatility and stock market performance. Additionally, dividends and cash flows generally increase less when discount rates are increasing, while inflation leads to a further reduction in stock value and the total return of investors (Geetha et al. 2011, Barakat et al. 2016). Şükrüoğlu–Nalin (2014) estimated dynamic panel data on the period of 1995–2011 for 19 European countries and found a negative relationship between inflation and stock market development. In addition, Hsing (2011) reached the same result when he investigated the impact of the expected inflation rate on the Czech stock market index.

Studying the effectiveness of short-term interest rates for selected asset prices in the cases of the Czech Republic, Hungary, Poland, and Romania, Cocriş–Nucu (2013) found that there is a negative significant relationship between unexpected changes in the short-term interest rate and stock prices. This means that by using interest rate forecasts as an efficient instrument of intervention to correct the evolution of asset prices, investors will make their investment decisions in the capital markets of these countries. Stoica et al. (2014), using a four-variable structural vector error correction model, found that the stock market indices in the Czech Republic, Hungary, Poland, and Romania responded noticeably to international monetary policy shocks.

Stock markets negatively react to a sovereign debt rating downgrade because it signals a deteriorating ability to borrow in international markets and a sudden sharp reduction in the available credit. A sovereign debt rating can signal some information about the country's future economic health and the policies that the government will make accordingly, for example, by imposing higher corporate taxes following a downgrade, which can directly affect companies' prospects. Moreover, security prices should be expected to react negatively (positively) to a sovereign rating downgrade (upgrade) because only investment-grade instruments can be held by many institutional investors (Ferreira–Gama 2007). Coronado et al. (2012) found a significant negative correlation between the stock market returns and the sovereign spread (using the Credit Default Swaps-CDS) for eight European countries for the period between 2007 and 2010. The results showed that the link between the two markets is more significant for European countries with a higher sovereign risk premium. Ballester et al. (2021) also found that in Europe, mainly during the sovereign debt crisis, the sovereign spread (measured by the CDS spread) causes conditional stock volatility.

Understanding the development patterns and time-varying correlations between exchange rates and stock markets is important for investors and policy-makers, especially after the global financial crisis and sovereign debt crisis in Europe. A significant number of studies in finance investigate the relationship between exchange rates and stock markets but with conflicting results. There are three models that explain the nexus between exchange rates and stock markets, namely, the portfolio-based model, the flow-oriented model, and the monetary model. Based on the portfolio-based model, there is a negative relationship between the two assets, while the flow-oriented model assumes a positive relationship, and the monetary-based model proposes a weaker relationship or even no link between them (Moagăr-Poladian et al. 2019). Baroian (2014), using the identified and overidentified dynamic panel GMM models, found that among macroeconomic fundamentals, exchange rate volatility is the sole significant explanatory variable for stock market volatility in five CEE emerging markets, including the Czech Republic, Croatia, Poland, Romania, and Hungary. The results showed that when the exchange rate increases, investors delay order placement, and then the number of transactions decreases, leading to higher volatility in stock market indices. Moagăr-Poladian et al. (2019) studied the relationship between foreign exchange markets and stock markets for four CEE countries (Czech Republic, Hungary, Poland, and Romania) and found that there is an increased comovement and correlation between these two markets, especially during the European sovereign debt crisis, which can be a sign of contagion and fewer opportunities for portfolio diversification for investors.

Stock markets as networks

Network research in economics has grown exponentially over the past two decades, from a handful of publications in the late 1990s to hundreds today. First, it is important to grasp relational patterns to understand diverse economic behavior, from product acceptance dynamics to financial contagion. Ignoring network structure can lead to a misinterpretation of observed behavior and institutional response. Second, networks have increasingly understandable characteristics – how closely connected or isolated the nodes are – that have concrete and important implications for economic behavior. Ahelegbey et al. (2021) showed their network-VAR model on a global (US, Japan, Europe) sample between 2007–2015 that both Italy- and Germany-centered interbank lending (more stable) and US-centered financial markets (more volatile) act as contagion channels in the transmission of shocks arising from a country to the overall system. While countries inside the Eurozone are maintaining a substantially high correlation among their stock markets due to their shared currency, other EU member states present lower common movements even under turbulent times (Samitas et al. 2022a).

Additionally, data on interaction networks are often available along with behavior. One example of collective behavior is herding: in the case of information asymmetry, relatively uninformed investors follow the supposedly informed investors. However, a sudden increase in market participants' risk aversion fuels flight to safety, which in turn leads to an abrupt decline in riskier assets in their portfolio as they replace them with safe assets. A new model of network development and behavior based on strategic interactions was advocated by the neoclassical economic paradigm of (bounded rational) human choice (Jackson 2016). Despite its limitations, the model is powerful and gives us more to learn about how individual partnership-building choices affect emerging networks.

A complex system is one whose collective behavior is difficult to infer from knowledge of the system components. They are complex because they consist of many interconnected parts and are difficult to understand and manage. Despite differences in the shape, size, nature, age, and size of actual networks, most networks follow common organizational principles. Ignoring the nature of the components and the exact nature of the interactions between them, the resulting networks are more similar than different (Barabási 2016). While random networks have similarly important (and seemingly interchangeable) nodes where the failure of some of them does not affect connectivity, scale-free or "small-world networks" have a small subset of preferential nodes whose targeted elimination temporarily disarrays the network until the emergence of new hub nodes (Wang–Chen 2003, Watts–Strogatz 1998 Barabási–Albert 1999). These topologies can be analogous to the price-taker competitive and price-maker oligopolistic market models in microeconomics.

Global financial markets can be viewed as complex systems. This motivates us to focus on analyzing the interaction structure between markets based on global descriptions, which can be achieved by visualizing the system as a network. Correlations between stock markets play a central role in investment theory and risk management and are a key component of the Markowitz portfolio theory optimization problem. Correlation-based networks are therefore very useful in analyzing interactions between financial markets and developing optimal investment strategies. Networks have proven over the past few years to be a highly effective way to characterize and study complex financial systems such as stocks, bonds, commodities, and foreign exchange markets (Sensoy–Tabak 2014, Moghadam et al. 2019).

One of the most important methods related to stock exchange networks is the minimum spanning tree, a standard technique for extracting networks from correlation matrices. This approach uses single exchanges as nodes to study relationships between stock markets. The results confirm the increasing interdependence between markets over the past two decades. There can be problems when using correlation analysis to examine interdependencies between two stocks (or stock markets). For example, correlation coefficients tend to be skewed when volatility increases. This is especially important when studying stock market behavior during periods of high volatility (such as crises). Performing correlation analysis on subsamples with high volatility skews the correlation coefficient estimates upward, leading to misleading results. The consequences of this bias are even more pronounced in the context of contagion (Lyócsa et al. 2012).

When markets are hit by significant shocks (such as the subprime crisis or the Covid-19 pandemic), correlations between stock markets are amplified, and market risk is continuously transferred between stock markets, resulting in a contagion effect. A sharp shift in financial market volatility caused by a surge in stock returns due to a large-scale emergency can also lead to rapid stock selling due to panic and risk aversion. Such fire sales increase short-term liquidity pressures on equity markets and lead to higher systemic market risks. Anomalies in market liquidity happen if trade turnover increases significantly, which biases prices dramatically. Similarly, disturbances in the secondary markets of collateralizable assets will immediately affect their derivatives' trade, as the concept of funding liquidity suggests (Landau 2011). This supports the very strict definition of contagion, which "occurs when cross-country correlations increase during crisis times relative to correlations during tranquil times". Contagion spreads through financial (markets are connected through the international financial system, investors' portfolios, and leveraged institutions' balance sheets), real (international trade), and political (club of countries concept) links (Radev 2022).

The network approach used in this study has its own advantages. Previous studies have typically used conditional volatility spillover techniques to estimate the impact of severe emergencies on underlying assets (Angelidis–Koulakiotis 2022, Hung 2022). However, the application of network theory goes one step further by analyzing the conditional variance–covariance matrix and constructing conditional distance matrices on this basis. An advantage of the minimum spanning tree is that it can be used to characterize the behavior of the entire stock market through the relevant connections. It captures the important static structural features of the stock exchange network in the event of a large-scale disaster while also showing the dynamic features of the evolution of the stock exchange network structure (He et al. 2022). While the degree distribution in the network would just describe the distribution of connection numbers for each node, centralities in a minimum spanning tree can provide more details about each node's relevance by the number of their connections (incidence), their relative importance (closeness), or the number of shortcuts (betweenness). Since VAR models (especially variance decompositions) do not perform well with conditional variance data inputs, closeness centralities can be a workaround for this problem since they are based on the conditional variance–covariance matrix, but they also provide information about its structural impact on the network.

Theoretical model

Stock market indices (1a) represent the weighted average ($W_{j,t}$) of share prices ($P_{j,t}$) of the most important publicly traded enterprises, in which companies' fundamental value is linked to their ability to generate cash flows in the future ($CF_{j,t+z}$) with their tangible and intangible assets (Lippai-Makra et al. 2019), as it can be expressed in a discounted cash-flow model (Damodaran 2012). The expected cash flows can depend on the expectations about future growth, profit margins, and foreign exchange exposure, as well as on the funding conditions. Funding conditions can be estimated with a weighted average cost of capital model, where the corporate-specific debt (D) and the equity-related (E) capital expenditures can be decomposed to the interactions between the market return ($\Delta SI_{i,t}$) and the risk-free interest rate ($r_{f,t}$) if we are employing a capital asset pricing model (CAPM). However, there is an additional endogenous interaction between the variance of the stock market index ($\sigma^2_{SI,t}$) and the covariance between the share price and the stock market index ($\sigma_{j,SI,t}$), as captured by the CAPM's beta[5]: $\beta_{j,SI,t} = \frac{\sigma_{j,SI,t}}{\sigma^2_{SI,t}}$.

$$SI_{i,t} = \sum_{j=1}^{N}(W_{j,t} * P_{j,t}), \text{ where } P_{j,t} \cong \sum_{z=1}^{T}\left(\frac{E(CF_{j,t+z})}{\frac{D}{E+D} * r_{d,t} + \frac{E}{E+D} * (r_{f,t} + (\Delta SI_{i,t} - r_{f,t})\frac{\sigma_{j,SI,t}}{\sigma^2_{SI,t}})}\right) \quad (1a)$$

Financial contagion occurs if stock market returns between the ith and the $i+1$th markets have stronger common movement (ρ) during turbulent times with decreasing

[5] Meanwhile, the beta variable is highlighting the importance of the dynamic interactions between the market's variance–covariance matrix. Since the minimum spanning tree graph, which will describe the direction of the spillovers of shocks among the European stock market indices is also based on a conditional variance–covariance matrix, this analog will be important in the theoretical model formation.

share prices (α), as Forbes–Rigobon (2002) defined: $\rho_{SI_{i,t},SI_{i+1,t},turbulent} \gg \rho_{SI_{i,t},SI_{i+1,t},normal} \rightarrow (1-\alpha_{j,t}) * P_{j,t}, \alpha < 0$. Since minimum spanning tree graphs and their centralities are based on the changes in such time-variant correlations, closeness centrality will inherit the ability to describe contagions since it captures the range of collaborations among the markets, as will be described in the methodology section. Our theoretical Model (2) is intended to assess the relevance of different funding and profitability conditions as well as the market network's price-alteration effect due to the contagions (1b). The expected cash flow can depend on the changes in the domestic economic environment, while funding can be determined by the global and local monetary environment, and contagion has an emergent nature:

$$SI_{i,t} = \sum_{j=1}^{N}(W_{j,t} * P_{j,t} * (1-\alpha_{j,t})),$$

$$\text{where } P_{j,t} \cong (1-\alpha_{j,t}) * \sum_{z=1}^{T}\left(\frac{E(CF_{j,t+z})}{\frac{D}{E+D}*r_{d,t}+\frac{E}{E+D}*(r_{f,t}+(\Delta SI_{i,t}-r_{f,t})\frac{\sigma_{j,SI,t}}{\sigma_{SI,t}^{2}})}\right) \tag{1b}$$

Open and small economies rely heavily on foreign trade and capital imports to renew and acquire debt and equity-like sources. Global funding conditions are heavily influenced by key central banks such as the US Fed and the ECB due to their interest and balance sheet policies. Changes in both instruments can be expressed by the shadow federal fund rates according to Lombardi and Zhu (2014), which are estimated as the difference between the level of the federal fund rate when it reached the ZLB and the level of the federal fund rate suggested by Taylor rules. While the changes in the US Fed's shadow rate ($\Delta r_{Sh,US,t}$) can be used as a proxy variable for global funding conditions, the ECB's shadow rate ($\Delta r_{Sh,ECB,t}$) has a much more direct influence on the Eurozone and its neighboring economies (Sági–Ferkelt 2020).

Global liquidity flows are synchronized by investors' cross-border portfolios, meaning that losses on one market shall be covered by asset sales on other markets – meaning that spillover effects have a network-property. The direction of this spillover can be described with a minimum spanning tree graph, which is estimated from the dynamic common movement of the stock market indices. Closeness centrality ($\Delta Cl_{i,t}$) describes the importance of each stock market index relative to others in the network; therefore, its quarterly changes can capture the structural changes in the European stock market (Aslam et al. 2020).

Changes in the price level ($\pi_{i,t}$) respond to imbalances between domestic aggregate demand and supply, while being affected in part by imported goods and services. Companies can be assumed to be price takers or makers and therefore later have the chance to partially profit from moderate inflation. Therefore, inflation can affect future cash-flow generation as well.

The country-specific sovereign spread is measured by the risk premium between the country's 10-year sovereign bond yield and the German 10-year sovereign bond yield ($r_{10Y,i,t} - r_{10Y,DE,t}$), since it is a good indicator of the country-specific funding conditions. Therefore, the sovereign spread affects the WACC discount rate of future cash flows.

Foreign exchange rates ($FX_{i,t}$) mirror the external balance, providing a prompt indicator of investors' sentiment about their willingness to maintain positions in local currency, while corporate exposures affect their trade revenues and the value of their foreign investments[6] (Kincses et al. 2014, Salsecci–Pesce 2008). This approach suggests that cash-flow growth is not based on currency depreciation (which decreases the value of the investment from a foreign perspective as well) but is due to the improvement in productivity and therefore better cash flow generation in the future.

The exogenous shocks are represented by the dummy variables, namely, the recession in the Eurozone (based on the European Commission Business Cycle Clock, $d_{rec,EZ,t}$) and in the US (based on the NBER business cycle database, $d_{rec,US,t}$), while Eurozone membership was also highlighted ($d_{EZ,i,t}$).

$$\Delta lnSI_{i,t} = \omega + \beta_1 \Delta r_{Sh,US,t} + \beta_2 \Delta r_{Sh,ECB,t} + \beta_3 \Delta Cl_{i,t} + \beta_4 \Delta \pi_{i,t} + \beta_5 \Delta\left(r_{10Y,i,t} - r_{10Y,DE,t}\right) + \beta_6 \Delta lnFX_{i,t} + d_{rec,EZ,t} + d_{rec,US,t} + d_{EZ,i,t} \quad (2)$$

For robustness test purposes, a truncated model without the closeness ($\beta_3 \Delta Cl_{i,t}$) variable was used to check its impact on the impulse responses and variance decompositions. The model represents each of the *i*th ($i = \{1:5\}$) countries in *t* quarter (Q) of years from 2008 Q1 until 2022 Q1.

Intuitively, we can anticipate the following findings: stock market indices can increase if global funding conditions are accommodative ($\beta_{1,2} \leq 0$); however, increasing key policy rates can signal the lack of a deflationary spiral ($\beta_{1,2} \geq 0$). Financial contagion is present if the market network is more integrated under decreasing index values ($\beta_3 < 0$). If publicly listed blue chip companies are considered price makers, inflation should have a weak or moderate effect on their profitability, but for price-taking companies, this is bad news ($\beta_4 \leq 0$). Similarly, an increasing sovereign spread and depreciating currency can both cause decreasing share prices ($\beta_5 < 0, \beta_6 < 0$).

Data and methods

Data

This study analyzed the quarterly data of 6 EU member states between 2008 Q1 and 2022 Q1. The Eurostat and the Refinitiv Eikon databases were mainly used to acquire the quarterly data for further analysis. Table 1 presents the list of explanatory variables, their abbreviations, their source, and their anticipated impact on the model, based on previous literature. Business cycles were acquired from the European Commission and the NBER databases.

[6] Currencies can also be considered as net senders of shocks, based on Samitas et al. (2022c).

Table 1

Data sources

Variable (2008 Q1–2022 Q1)	Notation	Source	Anticipated impact by the literature
Stock market index	$SI_{i,t}$	[6]	
Shadow rate in the US Fed	$r_{Sh,US,t}$	[4]	
Shadow rate in the ECB	$r_{Sh,ECB,t}$	[4]	"–" Stoica et al. (2014), Cocriş–Nucu (2013)
Closeness in the minimum spanning tree market graph	$Cl_{i,t}$	Authors' calculation	"–"contagion: Lyócsa et al. (2012)
Inflation (customer price index)	$\pi_{i,t}$	[3]	"–" Şükrüoğlu–Nalin (2014), Geetha et al. (2011), Hsing (2011), Barakat et al. (2016)
Sovereign spread: 10-year sovereign bond yield of the ith country – DE 10-year sovereign bond yield	$r_{10Y,i,t} - r_{10Y,DE,t}$	[6]	"–" (but with CDS) Coronado et al. (2012), Ballester et al. (2021)
Local exchange rate in EUR	$FX_{i,t}$	[6]	"–"Moagăr-Poladian et al. (2019), Baroian (2014)
Recession in the US (1: recession in the US)	$d_{rec,US,t}$	[5]	
Recession in the Eurozone (1: recession in the Eurozone)	$d_{rec,EZ,t}$	[2]	
Eurozone membership (1: member in the Eurozone)	$d_{EZ,i,t}$	[1]	

All the variables were *I(1)* according to the unit-root tests, as highlighted in Table A1 in the Annex; therefore, we used their first differential during model estimation to describe each variable's shock's impact on the change in the stock market index.

Closeness

While multiple papers utilized the changing nature of the dynamic conditional correlation (DCC-GJR GARCH) during the estimation of market-graph centralities (see Samitas–Kampouris 2019 or Samitas et al. 2022b), the novelty of this paper is partially in its quarterly approach. Therefore, based on the weekly stock market DCC-GJR-GARCH data, we can write up a minimum spanning tree graph for each quarter of years – making the closeness centrality a dynamic variable.

A minimum spanning tree is a subgraph that contains all the nodes of the network but with fewer edges, where the topological properties determine the most important nodes in the network[7]. There are multiple ways to describe the structure of the network: betweenness centrality (which measures the "bridge-making" nature for each node), degree centrality (which measures the number of links to other nodes) or

[7] This paper used Kruskal's algorithm. This algorithm sorts all of the edges by weight, and then adds them to the tree if they do not create a cycle.

closeness centrality (which captures the range of collaboration among the nodes) (Samitas et al. 2020).

Since the panel VAR model used later will require dynamically changing input variables, only the closeness centrality (3) could be used, since it reflects the importance of the specific node relative to other nodes in the network of *N* with a changing value from quarter to quarter. This is estimated as the average shortest distance ($d(V_iV_j)$) from node V (stock market) *i* to all the other *j* nodes.

$$C(V_i) = \frac{(N-1)}{\sum_{j=1}^{n} d(V_iV_j)} \tag{3}$$

The graph is estimated from the distance matrix ($D = \frac{[\sqrt{2(1-P)}]+[\sqrt{2(1-P)}]'}{2}, P_t = [\rho_{i,j,t}]$), which is based on the quarterly DCC-GJR-GARCH matrix (H_t), estimated by a DCC-GJR-GARCH model (4).

$H_t = diag\{\sqrt{h_{i,t}}\}\{\rho_{i,j,t}\}diag\{\sqrt{h_{i,t}}\}$, where the ($\{\rho_{i,j,t}\}$) correlation matrix under the asymmetric DCC model has the following form:
$\{\rho_{i,j,t}\} = (Q_t^*)^{-1}Q_t(Q_t^*)^{-1}$, based on the ($Q_t$) model estimated elements of the conditional correlation matrix and its square-rooted *i*th diagonal (Q_t^*) positions, with (α, β) scalar parameters, (g) asymmetry coefficient, and unconditional correlation matrices ($\bar{Q}, \bar{N}, q_t, n_t$) (Samitas–Kampouris 2019):

$$Q_t = (1-\alpha-\beta)\bar{Q} - q\bar{N} + \alpha q_{t-1}q_{t-1}' + \beta Q_{t-1} + g n_{t-1}n_{t-1}' \tag{4}$$

Since both the network closeness centrality, the stock market index and the macro variables are in an endogenous relationship with autoregressive behavior, it was necessary to use panel VAR models for further analysis.

Panel VAR model

Using a VAR model is reasonable since it can separate systematic risk (common market factors) from idiosyncratic (direct institutional interconnections) elements (Ahelegbey et al. 2021). Following Canova–Ciccarelli (2013), panel VAR models (5) are appropriate to estimate spillovers from idiosyncratic interdependencies existing across sectors, markets, and countries to identify shocks among endogenous variables (Jouida 2018). In this model, we can consider all variables as endogenous and interdependent, both in a dynamic and a static sense, with a set of predetermined or exogenous variables – but with a cross-sectional dimension as well. If y_t is the vector of *G* endogenous variables in time *t* ($t = 1, \ldots, T$), its stacked version for the *i*th ($i = 1, \ldots, N$) generic unit (country, sector, market, etc.) is y_{it}.

$$y_{it} = A_{0i}(t) + A_i(\ell)y_{it-1} + Z_i(\ell)W_t + \varepsilon_{it} \tag{5}$$

where $A_i(\ell)$ is a polynomial in the lag operator, where restrictions are imposed on the coefficient matrices A_i to make the variance of the y_{it} bounded. The predetermined or exogenous *M* variables are represented by the W_t vector, common to all *i* units. The existence of $A(\ell)^{-1}$ is secured by the fact that there are no roots of $A(e^{-\omega})^{-1}$ on or inside the unit circle. Then, the standardized condition for stability is tested to see if modulus values are smaller than the one which implies the invertible interpretations and the interpretations of infinite order-vector moving averages (Lütkepohl 2005). The optimal lag length of the model will be selected by the minimum of Bayesian information criteria (BIC), Akaike information criteria (AIC) or Hannan-Quinn information criteria (HQ). The impulse response functions can be considered as the effects of a unit shock on a given model variable, where the shock of variable *i* to variable *j* is determined under 68% (1 standard error) and 95% (2 standard errors) confidence intervals. The variance decomposition makes it possible to determine which shocks are decisive in the short- and long-term evolution of certain variables, i.e., the proportion of the uncertainty of variable *i* that can be attributed to the *j*th shock after period *h*.

Panel VAR models have three characteristic features according to Canova–Ciccarelli (2013): first is the "dynamic interdependence" of all units' endogenous variables entering the model for unit *i*. Second is the "static interdependence", where error terms are generally correlated with unit *i*. Third is the "cross-sectional heterogeneity", where the intercept, the slope, and the variance of the error terms may be unit specific. Shock identification assumes Σ_ε to be block diagonal to have symmetric short- or long-term restrictions across the units. The structural form of (4) is defined as (6) (Lütkepohl 2005):

$$Ay_{it} = \sum A_p^s y_{it-p} + F_i W_t + Bu_{it}, \text{ where } \varepsilon_{it} = A^{-1}Bu_{it} \text{ and } S = A^{-1}B. \qquad (6)$$

where F_i is the matrix for (*NxN*) autoregression coefficients and $\varepsilon_t = (u_{1t}, \ldots, u_{Kt})'$ is the unobserved error term vector with a (Nx1) Gaussian distribution, where $\varepsilon_t \sim (0, E(u_t, u_t'))$ is a positive definite covariance matrix. In the long-term restriction of Blanchard and Quah (1989) (7), the shock is represented in the row of the F-matrix where the variable appears, and the cumulative long-term effect of the shock is zero and Ψ; the long-term multiplier ($F = \Psi S$) is:

$$\left(I - A_1 - \cdots - A_p\right)^{-1} \varepsilon_t = \Psi \varepsilon_t = F u_t. \qquad (7)$$

The structure of the F-matrix describes long-term effects, assuming that there will be a shock that will affect each variable, while the last item of the sequence will be the one that affects itself only. The structure of the F-matrix (Table 2) was determined by our theoretical model, which provided the highest global influence for the US Fed's shadow rate as a general growth proxy variable and the smallest local influence for the stock market index.

Table 2

Structure of the F-matrix of the long-term effects

Variable	Shock						
	$\Delta r_{Sh,US,t}$	$\Delta r_{Sh,ECB,t}$	$\Delta Cl_{i,t}$	$\Delta \pi_{i,t}$	$\Delta(r_{10Y,i,t} - r_{10Y,DE,t})$	$FX_{i,t}$	$\Delta lnSI_{i,t}$
$\Delta r_{Sh,US,t}$	f11	0	0	0	0	0	0
$\Delta r_{Sh,ECB,t}$	f21	f22	0	0	0	0	0
$\Delta Cl_{i,t}$	f31	f32	f33	0	0	0	0
$\Delta \pi_{i,t}$	f41	f42	f43	f44	0	0	0
$\Delta(r_{10Y,i,t} - r_{10Y,DE,t})$	f51	f52	f53	f54	f55	0	0
$FX_{i,t}$	f61	f62	f63	f64	f65	f66	0
$\Delta lnSI_{i,t}$	f71	f72	f73	f74	f75	f76	f77

Source: Authors' calculation in EViews 11.

Impulse-response functions (IRFs) describe the effect of a one-unit change in the explanatory variables on the dependent variable as a graph, with confidence bands around the IRFs. The "bands that correspond to the 68% posterior probability (one standard error) are often more useful than 95% bands (two standard errors), and confidence intervals with such low coverage probabilities do not generally have posterior probabilities close to their coverage probabilities", as Sims–Zha (1998: p. 6) suggested. Even though the results within the 68% band are not elegant enough to be referred to as "statistically significant", as Murphy (2015) highlighted, they are widely used in the macro financial literature (such as Blanchard–Galí 2010: p. 385, Boivin–Giannoni 2008: p. 453, Galí–Gambetti 2009: p. 45). Therefore, this paper applies both confidence bands and distinguishes them accordingly.

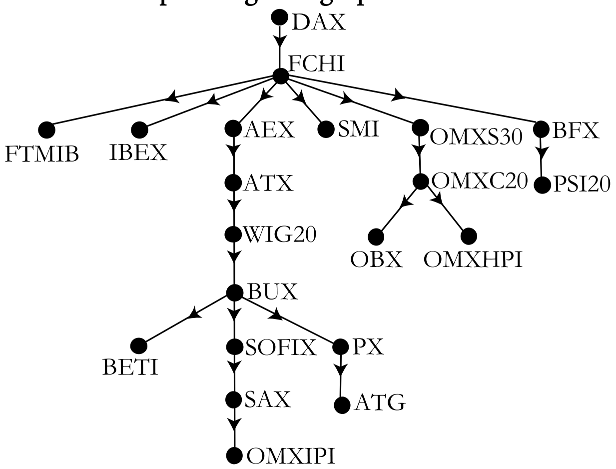
Results

Closeness

By focusing on the hierarchical structure of the entire European market network throughout the entire period, the selected CEE markets were positioned within a single branch, beneath the Austrian Wiener Börse (ATX). In the broader graph, the German DAX and the French FCHI indices dominated (Figure 1). Similar regional clustering was observed among the Nordic indices, including the Swedish SMXS30, Danish OMXC20, Finnish OMXHPI, and Norwegian OBX. The fact that the CEE subset resides on a distinct branch of the tree graph affirmed its suitability for panel analysis. This structural layout motivated an exploration of the time-variant quarterly nature of closeness centrality, aiming to understand how changes in this hierarchical graph could influence stock market pricing.

Figure 1

Minimum spanning tree graph of the entire time

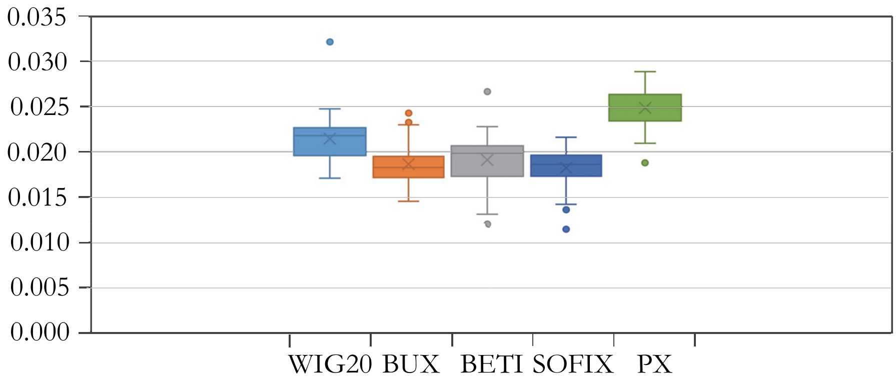


Notes: AEX (Netherlands), ATG (Auction Technology Group), ATX (Austria), BETI (Romania), BFX (first complete crypto derivatives exchange), BUX (Hungary), DAX (Germany), FCHI (France), FTMIB (Milano Italia Borsa Index), IBEX (Spain), OBX (Norway), OMXC20 (Denmark), OMXHPI (Finland),OMXIPI (Iceland), OMXS30 (Sweden), PSI20 (Portugal), PX (Czechia), SAX (Slovakia), SOFIX (Bulgaria), SMI (Switzerland), WIG20 (Poland).

Source: Authors' calculations in MATLAB.

Figure 2

Quarterly values of closeness centrality (2008 Q1–2022 Q1)



Source: Authors' calculations in MATLAB.

Closeness centrality captures the relative importance of each market. Since our analysis estimated this variable for each quarter, the contractions and expansions could be captured and added to the theoretical model. Interestingly, the Czech PX index showed the highest closeness, followed by the Polish WIG20, the Hungarian BUX, the Romanian BETI, and the Bulgarian SOFIX indices at the end (Figure 2).

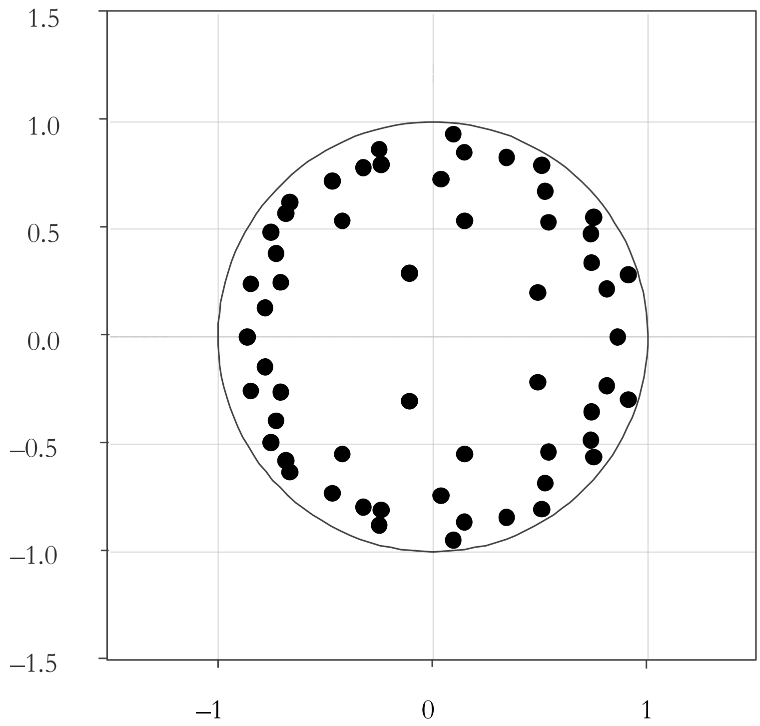
However, these results both show similar but dynamic changes in the sample markets' relative importance in the whole European stock market network.[8]

Panel VAR

The Akaike information criteria (AIC) recommended employing eight lags (see Annex Table 2), which generated characteristic polynomial roots within the unit circle, indicating model stability (Figure 3).

Figure 3

Inverse Roots of an Autoregressive Characteristic Polynomial



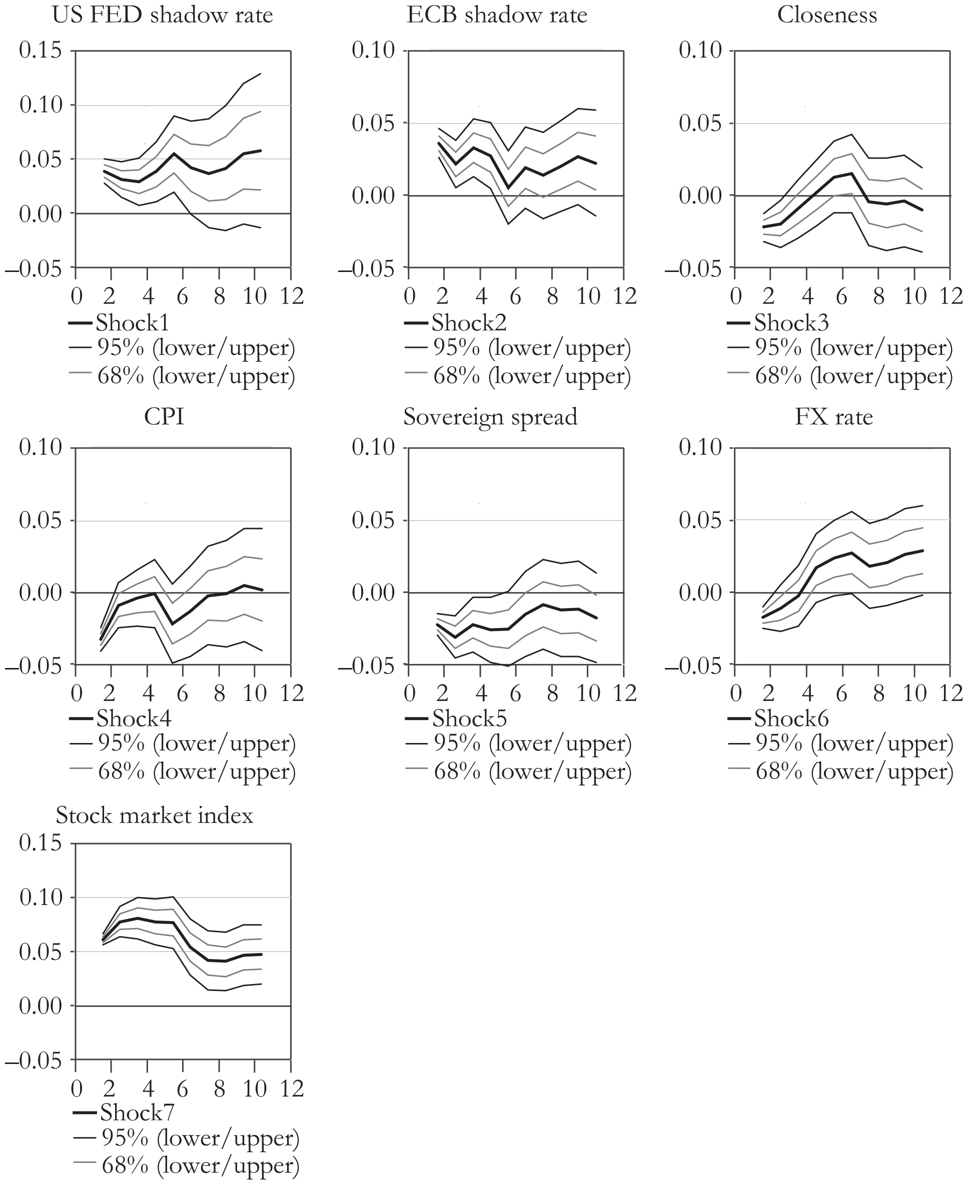
Source: Authors' calculation in EViews 13.

The panel VAR model yielded cumulative response functions of the stock market indices, yielding the subsequent findings (Figure 4). Initially, major central bank actions exerted a positive influence: both US Fed and ECB decisions regarding monetary tightening were well received in the region during the short and medium terms (0-4 quarters). This possibly signaled an economic recovery, given that much of the sample period was characterized by proximity to deflation and near-zero policy rates.

[8] The development of the closeness and the stock market indices are presented as a Figure A1 in the Annex.

Figure 4

Accumulated response functions of the stock market indices, based on the long-term structural equation (1-10 quarters of years)
(95%, 68) CIs using Monte Carlo S.Es with 999 replications



Source: Authors' calculation in EViews 13.

Greater market integration (closeness) immediately signaled stock market distress in the short term (0-2 quarters), aligning with prior literature suggesting contagions in CEE stock markets. The shifts in specific stock market indices were influenced by the overall structural expansion or contraction of the European market network. This implies that network effects bias diversification only in the short run, and observing closeness centrality proves valuable for analysts and policy-makers in detecting such anomalies.

The short-term negative impact (0-1 quarters) of increased local inflation might be interpreted as unfavorable news, as indexed companies are not recognized as price setters due to competitiveness or monopolistic positioning. However, such price shocks fall within the horizon of monetary policy focusing on the medium term (4-8 quarters), rendering them relevant primarily to investors rather than policy-makers.

An increase in the sovereign spread had an immediate and negative influence in the short and medium terms (0-5 quarters). This reinforces the earlier impression that funding costs are crucial; when the gap widens between global and country-specific interest rates, the discounted value of expected future cash flows (and hence stock market indices) begins to decline. This validates the mainstream assumptions of Damodaran (2012) for the region. The short-term reaction to the sovereign spread underscores the significance of bond market convergence, which can falter under stressed periods as per Bearce (2002).

Conversely, currency depreciation had a pronounced immediate negative impact (0-1 quarters). This suggests that foreign investors are deterred from retaining investments during currency depreciation, as their euro-denominated portfolios lose value even if the profitability of some exporting companies rises.

Variance decomposition highlights the contribution of each shock to the changes in the stock market indices (Table 3). Overall funding conditions both in the US and in the Eurozone (the US Fed's and ECB's shadow rates) contributed to nearly one-third of the shocks (15-15%), while country-specific sovereign spread added an additional 6%. This result underscores the extent of openness and limited monetary autonomy of the CEE economies.

Foreign exchange-related shocks accounted for an additional 3-6% since they influence not only export and import conditions but also funding, particularly when companies employ foreign currency-denominated debt. Domestic price levels can also impact cash-flow generation, especially when the company is considered a price-taker, which explains the 14-17% importance of these shocks.

The changes in the network structure had a modest 6-9% relevance, meaning that while stock market indices are guided mainly by the changes in profitability (inflation, foreign exchange rate) or funding (shadow rates, sovereign premium, foreign exchange rate) conditions, higher common movement among European stock markets will generate negative shocks for the CEE indices. Contagion has a dynamic, time-variant nature, but its temporary appearance can even have a long-run impact on asset prices.

Table 3

Variance decomposition of sovereign spread using structural VAR factors

t	$\Delta r_{Sh,US,t}$	$\Delta r_{Sh,ECB,t}$	$\Delta Cl_{i,t}$	$\Delta \pi_{i,t}$	$\Delta(r_{10Y,i,t} - r_{10Y,DE,t})$	$FX_{i,t}$	$\Delta lnSI_{i,t}$
1	16.60	12.63	6.23	14.09	5.86	2.80	41.80
2	15.22	13.09	5.54	17.94	5.96	2.85	39.41
3	14.66	13.71	6.39	17.45	6.46	3.38	37.96
4	14.62	13.20	7.05	16.56	6.23	6.36	35.98
5	15.20	15.54	7.25	18.14	5.58	6.04	32.24
6	15.23	15.71	6.75	17.31	5.95	5.67	33.38
7	14.56	15.02	8.93	17.13	5.93	5.92	32.52
8	14.63	15.20	8.90	17.04	5.98	5.93	32.33
9	15.50	15.15	8.74	16.89	5.85	5.99	31.87
10	15.42	15.16	8.93	16.82	6.08	5.99	31.61

Source: Authors' calculation in EViews 13.

The truncated model provided similar output (Table A3 in the Annex), with an even higher importance for the key central banks' shadow rates and foreign exchange rates – which underlines the importance of the external shocks for the CEE stock markets. Meanwhile, country-specific variables such as the sovereign spread or inflation remained at a similar level. This means that the inclusion of closeness gained importance in the model partially relative to the representation of the external variables only.

Conclusion

This study focuses on the CEE subbranch of the European stock market network, analyzing the pricing impact of quarterly changes in the relative importance of these 5 markets within a 21-market network. These markets existed as a separate branch since they primarily interacted with each other, yet they were highly affected by shocks originating from the German, French, Dutch, and Austrian stock market indices. Modeling the development of these indices was reasonable using a panel VAR model to capture their endogenous and dynamic interactions.

Our objective was to verify the biasing effect of changes in their relative importance (closeness centrality) on the index. This was accomplished through quarterly estimations of a minimum spanning tree model, with the distance matrix estimated using a DCC-GJR-GARCH model (fitted on weekly data). This approach uniquely allowed us to detect contagions in the stock market and assess their significance alongside the traditional macro variables that influence the funding and profitability conditions of publicly listed companies.

The sample period was notable, encompassing at least three distinct crises (specifically, the subprime crisis of 2008, the Eurozone sovereign crisis after 2011, and the Covid-19 pandemic after 2020) with robust institutional responses to mitigate downward pressure on aggregate demand and pricing of riskier asset classes. As a result, the likelihood of observing contagious effects was higher.

Given the dynamic nature of asset valuation, it is unsurprising that most of our variables had short-to-medium-term impacts. This paper explored a set of macroeconomic variables relevant to the expected discounted cash flows of publicly listed companies. Future cash flow generation could be influenced by the degree of price-taking behavior by specific enterprises. Our results indicated that an increase in country-specific inflation immediately exerted downward pressure on stock market indices with moderate significance. Meanwhile, country-specific funding conditions (approximated through the sovereign spread) had a similar but less impactful influence. Currency depreciations could affect both profitability (via export revenues and import costs) and funding conditions (through foreign exchange-denominated debt and foreign investors' portfolios) with potentially opposing effects, but in this case, a weakening currency led to an immediate contraction of the stock market index.

Given that the sample period witnessed the implementation of unconventional monetary policy instruments to restore functioning capital markets and prevent deflationary spirals, external funding conditions were represented by both the US Fed's and the ECB's shadow rates. This representation demonstrated that a reduced need for monetary accommodation positively influenced CEE stock market indices with high relevance.

However, stock market pricing could be biased by financial contagion, where a temporary and dynamic increase in the closeness centrality coefficient could trigger plummeting stock prices. Diversification in this environment can be challenging but not impossible if investors rebalance their portfolios frequently enough to mitigate contagion effects. However, such actions might be restricted by transactional cost factors. A practical implication of this study is that biases in the market network during turbulent times could offer cheaper entry points for value-oriented investors, as share prices come under deeper pressure due to contagion effects in the market.

Annex

Table A1

Basic statistics of the panel data

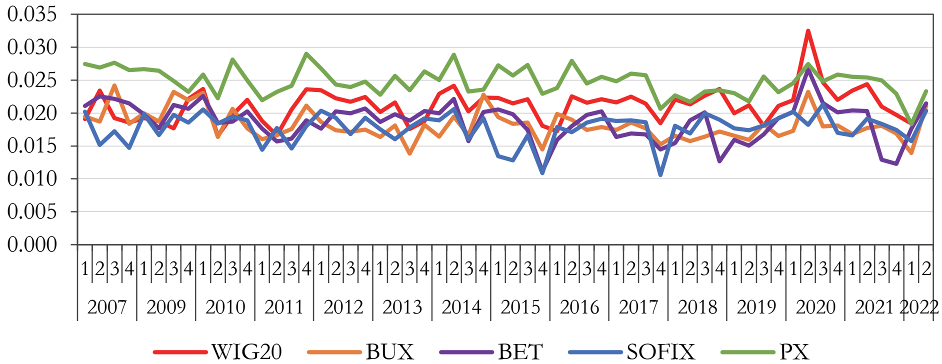
Denomination	$\Delta r_{Sh.US.t}$	$\Delta r_{Sh.ECB.t}$	$\Delta Cl_{i.t}$	$\Delta \pi_{i.t}$	$\Delta\ FX_{i,t}$	$\Delta lnFX_{i.t}$	$\Delta lnSI_{i.t}$
Mean	2.0097	2.8764	–2.6282	13.4579	7.9597	1.2030	–0.1708
Median	1.9728	2.7193	–2.3402	13.4622	7.7305	1.0270	–0.2877
Std. Dev.	0.3592	2.6793	3.2682	0.1323	1.4230	2.2392	1.4695
Skewness	0.3012	0.9789	0.0969	–0.0573	0.3732	0.4403	0.1279
Kurtosis	3.0943	5.1249	1.9147	2.0336	1.9975	4.1736	1.9866
Jarque-Bera	4.4143	99.1327	14.4334	11.2472	18.5491	36.1505	12.9733
Probability	0.1100	0.0000	0.0007	0.0036	0.0001	0.0000	0.0015
Observations	285	285	285	285	285	403	285
Im. Pesaran and Shin W-stat	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF – Fisher Chi-square	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PP – Fisher Chi-square	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Authors' calculation in EViews 13.

Figure A1

Closeness and stock market index performance

Level of closeness in the European minimum spanning tree graph



Stock market index (2005 Q1=100%)

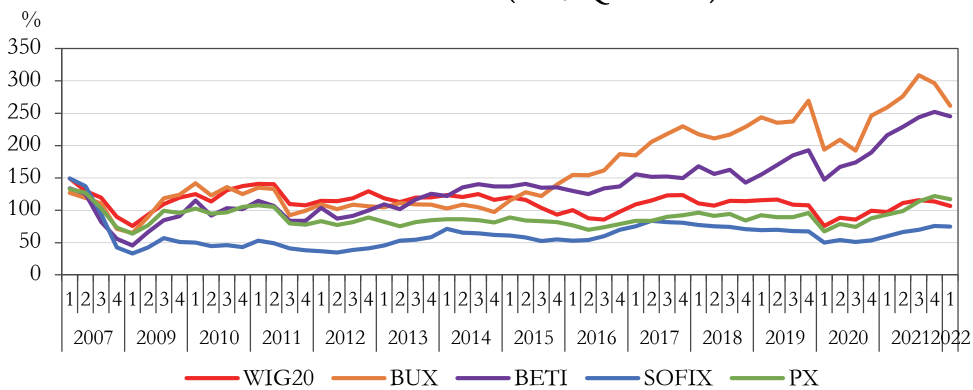


Table A2

Optimal lag number (*) according to Akaike and Bayesian information criteria

Lag	AIC	BIC
0	3,7049	3,8876
1	2,9505	3,7725*
2	2,8593	4,3207
3	2,5592	4,6601
4	1,9255	4,6658
5	1,8978	5,2775
6	1,5809	5,6000
7	1,1994	5,8579
8	0,9157*	6,2136

Table A3

The variance decomposition of the truncated models

	$\Delta r_{Sh.US.t}$	$\Delta r_{Sh.ECB.t}$	$\Delta \pi_{i.t}$	$\Delta(r_{10Y.i.t} - r_{10Y.DE.t})$	$\Delta FX_{i,t}$	$\Delta lnSI_{i.t}$
1	18.30	17.42	10.90	5.18	5.93	42.27
2	16.55	17.98	14.06	5.67	5.62	40.12
3	15.88	18.22	13.71	6.42	7.39	38.39
4	15.59	17.92	12.97	6.25	10.75	36.52
5	15.16	20.04	15.91	5.63	10.34	32.92
6	14.96	20.12	15.10	6.45	9.63	33.75
7	14.39	19.40	15.44	6.46	11.29	33.00
8	14.37	19.72	15.32	6.66	11.21	32.72
9	15.17	19.47	15.26	6.57	11.17	32.37
10	15.11	19.63	15.18	6.85	11.09	32.14

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