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How Do Stock Indices Respond to Market Shocks? Examining Stock Market Contagion in European Countries with Minimum Spanning Trees

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ABSTRACT: This paper analyses the structural changes of the European stock markets by using a minimum spanning tree graph. The aim was to point out similarities and differences of the previous recessions, namely the Subprime crisis around 2008, the European sovereign debt crisis of the 2010s and the recent COVID-19 period. Focusing on the structural changes of the graph, we were looking for the emergence of shock-propagating hub. During each of the three examined recession periods, we could see a constant change in the stock market network, where stock market indices are connected mainly through one central index during turbulent times, while the connections became more diverse in calm periods.

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1 Introduction

Asset valuation is based on the fundamental value, especially for its expected cash flow generation capability in the future. Hence, there are internal and external components that determine the valuation: internal ones are mainly determined by productivity and financing conditions, while external ones are based on market sentiment. However, latter sentiment is embedded in the complex nature of the markets: it is irregular and seemingly unpredictable, despite the potential simplicity of the equation of its motion (Kantz et al., 2006) which causes collective effects under extreme trading days as Bonanno et al. (2001) described earlier. Therefore, market topology, which is a schematic arrangement about the physical and logical linkages of nodes in a market network, can be relevant, as with a high level of globalization, interdependence between countries became significant, including through their trade relations, and shocks in one country affect other countries, cross-market relations and can easily trigger market contagions. Economists have long been interested in examining whether and how the cross-border dependencies within the financial markets' change during periods of crisis where the well-known network theory has also been introduced as an unconventional econometric approach. In the prior literature, the usefulness of this method is proved in many cases (see Liu and Tse, 2017; Yin et al., 2017; Cupal et al., 2012; Chen et al., 2022). For this reason, it is still beneficial to apply these techniques in the research of financial markets, in terms of the phenomena observed in the case of groups of countries where it is important to assess the recent development of capital markets and financial systems.

In this study, we focused on emerging, small, and open economies and their place in the network of European stock markets, i.e., what was their importance in the region and how they connected to the other European stock markets, whether and how it changed between 2001 July and 2021 March when some serious turbulences appeared in the financial markets globally. Our sample consists of three CEE countries outside the eurozone: the Czech Republic, Poland, and Hungary. Stock markets of these countries belong to a region whose integration has increased mainly since their accession to the European Union, but their place in the network is still a puzzle in the literature.

Examining the periods following significant shocks is still vital today, as it is significant to assess past direct and indirect effects on financial markets before assessing the present situation. In addition, these days developed countries are becoming more asset-focused than before, the markets are rising, and in addition to traditional variables, new factors can be added to the determination of asset prices. For stock market analyses, for example, bond and foreign exchange markets are becoming influential explanatory variables because of shocks to the economy and economic policy measures to address them, in part due to its reliance on quantitative easing, which shape market sentiment and investor behaviour.

Section 2 summarises the influential objectives on the stock markets, the results of prior literature on market contagions, and our theoretical model. In Section 3, we present the examined database and the applied methodology. Section 4 contains the empirical results of the model testing. Finally, in Section 5, we present the main goal and economic policy conclusions of our study.

2 Theoretical background

Several studies have been published on the contexts and contagions of financial markets. In the first subsection, we summarise the definitions and the factors which influence stock price, with a longer focus on stock market transfers and the definitions of financial market networks.

2.1 Factors affecting stock markets

The capital market is of paramount importance in the economy, as it also performs financial and economic functions. This is why it is important to see what are the factors that affect the development of money and capital market instruments. When examining stock indices, it can be stated that certain company characteristics (such as profitability) greatly influence the future movement of the index, but it is also essential to mention other macroeconomic factors. Inflation has a significant negative effect on the development of stock market indices. As a result, raw material prices and production costs increase, resulting in lower yields. In contrast, exchange rate developments can have a positive effect on indices, and a similar conclusion can be drawn for oil prices (Sabilla and Kurniasih, 2020). It is necessary for investors to have a thorough knowledge of the macroeconomic environment of the capital market, as in addition to influencing the day-to-day operations of companies, their knowledge can contribute to assessing and estimating the development of stock market indices. It should also be mentioned that the capital market has an impact on the country's economy, and not just the other way around. There is mixed evidence of the causal relationship between economic growth and stock market performance in the case of developed economies.

The most relevant literature, in the US sample, showed that during the period of Great Moderation, aggregate stock market volatility explained more than 55% of real economic growth (Fornari and Mele, 2013). Moreover, they proved that the predicting power of stock market volatility has increased above to the power of traditional financial variables – but they also suggested that aggregate risk, risk-premiums and monetary policy, serves completing parts of information about future movements in real macroeconomic aggregates. In the case of OECD countries, applying panel VAR models, Pradhan et al. (2015a) found that there was unidirectional causality running from both economic growth and stock market development to inflation both in the short and in the long run. Yet in this study, it has not been substantiated that stock market development stimulate economic growth in the long run. Complementing this, in the case of G-20 countries, the study of Pradhan et al. (2015b) demonstrated a robust long-run economic relationship between economic growth, oil prices, stock market depth, real effective exchange rate, inflation rate, and real rate of interest. They showed that in the long run, real economic growth responds to any deviation in the long-run equilibrium relationship between the variable of the depth of stock market, oil prices, and other macroeconomic measures. They also found a complex network of causal relationships between the examined variables in the short run. The findings of Tekin and Yener (2019) also confirmed that the development of stock markets accelerate economic growth in the case of developed and developing countries.

The capital market is a tool for long-term capital accumulation aimed at increasing investor participation in mobilizing resources to support national development finance. In addition, the capital market is representative for assessing the state of firms in a country, as most of the local representative industries are present on stock exchanges. Rising or falling (bullish or bearish) capital markets can be detected by ups and downs in recorded stock prices, which is reflected in index movements (Nugroho et al., 2020).

Based on the efficient market hypothesis, asset prices can be fundamentally determined from factors such as the present value of expected future dividend payments. In addition, however, prices can change randomly (*random walk hypothesis*) (Fama, 1965). Stock prices indicate successful management of a company. If prices rise, investors are optimistic about the company's future performance. At the same time, fundamental indicators such as Price Earnings Ratio (PER), Earnings Per Share (EPS), Net Profit Margin (NPM) and Price-to-Book-Book Value) have a significant impact on stock prices (Astuty, 2017). According to Purnamawati (2016), stock prices are also affected by a company's capital structure as well as profitability.

Decision-making on capital markets has long been a central theme for researchers and investors. Based on the theory of efficient markets, new information is immediately incorporated into asset prices, thus forming a rational price. However, behavioural economists say this price is distorted due to several factors, including investor mistakes and responses. One such factor is herd spirit behaviour, which contributes greatly to extreme price volatility and short-term trends. This behaviour stems from the fact that investors imitate and copy the actions of other investors instead of following their own intuitions and decisions. There may be several reasons for this. For example, because of conformity, investors tend to follow market trends rather than their own intuitions. On the other hand, the results of other research, show that herd spirit behaviour is a conscious and rational act. Two groups are distinguished in general, conscious imitation, where investors purposefully copy the actions of other investors, and the other is false imitation, where indecisive investors in a similar situation act in the same way (Yao et al., 2014).

The combined movement of world stock markets is often used as a measure of economic globalization and financial integration. To put the former, financial globalization also brings benefits and risks. On the one hand, it can ensure the availability of new sources of capital at lower costs and allow for better diversification of risks, leading to a better financial infrastructure. Yet, it may increase the correlation between markets, and this could lead to the occurrence and spread of financial crisis. Greater openness to foreign investment by individual countries might reflect their integration into the world economy, thereby increasing the co-movement of stock exchanges between countries, but openness may make it more difficult to prevent a contagion (Huang, 2020). The effect of the volatility correlation itself can be explained by tail dependence. Correlation volatility and tail dependence are related when analysing the dependency structure of international stock markets. The co-movement reflects the correlation between asset returns (or returns in different markets). Therefore, when analysing international stock markets, two dependency structures need to be mentioned: the correlation within the single market and between multiple markets. Macroeconomic factors can also influence the co-movement of international markets, and investors' behaviour is similar in each market, especially their reactions to world news in each market (Sun et al., 2009).

Several methods have been used in previous research to examine the correlation of indices. Examples include the GARCH copula method, in which the degree and depth of dependence can be examined compared to a linear correlation test (e.g., Cozier and Watson, 2019) supplemented with ARMA-GARCH model copulas (e.g., Sun et al., 2009); or the risk-permeable effect of exchanges using a time-varying copula model combined with a Markov-switching model (e.g., Ji et al., 2020). The results of previous research show that capital market returns can predict business cycles and that increases in returns are accompanied by a decline in the unemployment rate. As a result, the focus needs to be on, among other things, shaping financial market volatility expectations and resolving uncertainty about future monetary policy developments in periods of financial instability (Holmes and Maghrebi, 2016). Even in a crisis, we cannot ignore the role of monetary authorities in implementing effective monetary policy in maintaining stable financial markets, given that stock markets are highly illiquid in times of crisis. Therefore, the central bank has an important role to play in maintaining the required level of liquidity, as it provides liquidity to markets and directly to large investors that hold long positions in equities (Apergis, 2015). Moreover, it should be emphasized that the flexible interest rate mechanism and the development of capital markets are the main factors influencing the change in the correlation between the money market and the capital market. Therefore, a market-oriented interest rate policy and flexible interest rate mechanisms can accelerate the transmission efficiency of monetary policy between financial markets and help the central bank to implement adjustments and day-to-day maintenance operations in times of crisis. At the same time, we can observe that bond market reforms, including interbank and stock market bond markets, also make monetary policy regulation more effective (Wang, 2019).

Regarding information asymmetry, the results suggest that managers can easily accumulate bad news. This can quickly cause the stock market to collapse if companies are forced to make the news public. Foreign investors significantly increase the risk of market failures, and the positive relationship between foreign investors and the risk of collapse is stronger in firms with higher levels of information asymmetry or effective internal control (Huang, 2020). Foreign investors increase cross-correlation between different markets. With the integration of global stock exchanges, the links between countries are becoming stronger, and such an integration process is indeed conducive to capital flows in finding the optimal investment opportunity, while stock exchanges also suffer from significant fluctuations (Xu and Li, 2020). The importance of emerging markets is evidenced by the fact that more and more foreign investors are already switching from developed, mature markets to investing in emerging markets in hopes of higher returns and a more diversified portfolio. Foreign ownership has a positive impact on the informativeness of equities, foreign investors improve the information efficiency of the stock market in emerging economies, and foreign investors operating on the Vietnamese stock market promote the information efficiency of stock prices (Vo, 2017).

2.2 Contagions and economic shocks

Since the 1990s, several crises have affected foreign exchange and capital markets. For instance, the Mexican crisis of 1994–95, which mainly affected foreign exchange markets due to the devaluation of the peso, or the Russian crisis of 1998. According to Lucey and Voronkova (2008), the Russian crisis did not have a significant impact on global capital markets, the country was segmented, and the effects were only observable in the short term. Luchtenberg and Vu (2015) found strong evidence that relationships between financial markets are increasing in many financial markets. Unlike previous crises, the post-2008 global financial crisis contagion is not limited to emerging markets. Mature financial markets receive and transmit the contagion. Domestic markets are less affected by regions than markets in other countries. Due to the globalization, an internationally diversified portfolio cannot be free of financial contagion. Finding a significant link between relative interest rates and contagion is particularly important as influencing interest rates has been a key component in many government responses to financial crises (Luchtenberg and Vu, 2015). In the context of the 2008 crisis, it was shown that almost all markets became more internationally integrated following the US financial crisis and the ensuing eurozone sovereign debt crisis (Bekiros, 2014).

Processes that affect several countries or groups of countries are called contagions, the definition of which can be distinguished at three levels. At the first level, we mean the spread of shocks between countries. At the second level, we can talk about a higher spread resulting from the system of relations between countries, while at the third level, we can talk about the level of cooperation between countries (Kiss, 2017; Csiki and Kiss, 2018). In studying these mechanisms, the phenomenon of herding behaviour should be mentioned, especially when the fundamentals do not fully explain the shocks and their spill-overs in the financial system. Along this line, economic agents over-imitate the behaviour of others, which can contribute to the persistence and even growth of established price bubbles

(Angela-Maria et al., 2015). Increased financial openness and increased liberalization of capital flows often entail a rapid reversal of short-term capital movements. This is because globalization reduces the need for country-specific information gathering, and investors themselves determine the balance between portfolio diversification and costly additional information acquisition, which also puts homogenization at the forefront.

Talking briefly about the shock's propagation in capital markets, the excessive integration of them allows shocks to spread. Addressing these is important for the health of the economic and social environment. There is a risk that investors will change the composition of their portfolio in the local capital market or move their investments to other, safer markets. The resulting panic situations and the spill-over effects of volatility have already been observed in previous shocks, such as during Black Monday 1987, the dot-com crisis of 2001, or the subprime crisis of 2008. Financial time series show different behaviours for different events, such as political or economic shocks. The emergence of the coronavirus disease has also shown that financial markets are also open to epidemic shocks, causing panic and a contagious effect on global economies (Gunay, 2020). According to the previous literature, the spread of financial contagion occurs primarily through common global shocks or direct economic relationships, such as close trade relations and financial relationships, or indirect effects such as changes in global investor attitudes (Calvo et al., 1996; Corsetti et al., 2005).

The recent events have also drawn attention to the issue of capital market contagions. Interdependence between countries, including through trade relations, one country transfers shocks to other countries. Such relationships are not contagions, but the growth of cross-market relations and co-movements after a shock to a country can be contagious. It has been found that the economic fundamentals, macro-similarities, and exposures of weak countries to certain types of financial agents and related transmission channels increase the risk of spread, and regulations in the international financial system may also play a role in the spread of the contagion. However, it is still not known what exactly makes countries vulnerable to contagions and what precise mechanisms it spreads through. While most contagions do not have to represent irrational behaviour on the part of investors, volatility will persist. Individually rational but collectively irrational changes in the international financial system can also play a role (Claessens et al., 2001).

2.3 Practical experiences of stock market contagions and correlation

There are plenty of studies on inter-stock market contagion and post-crisis speculative attacks on foreign exchange markets. Attention is drawn to research on international measurement of contagion across asset classes. Evidence from studies of contagion in international stock and foreign exchange markets is mixed, Walid et al. (2011) report the existence of infectious effects, while Boschi (2005) and Kanas (2005) deduce the absence of contagion. Empirical research, focusing on the impact of financial crises on equity and currency inflows, tends to focus on EMEs, with a limited body of literature (Dungey and Martin, 2007) devoted to examining the links between developed and EME markets. Capital market contagion can be defined as the immediate, significant, short-term transmission of shocks between financial markets in the event of a crisis (Ahlgren and Antell, 2010). According to Niţoi and Pochea (2019), there are significant differences between stock market movements that depend on economic development as well as market deepening. In addition, different phases are defined, in some phases the contagion may be temporary, while in other periods it may become more permanent, which may be due to herd spirit behaviour. Empirical evidence confirms that the country where the crisis appeared has an impact on other countries. For example, as Kenourgios et al. (2011) proved, policy responses to a crisis do not prevent the crisis from spreading across countries, as the correlation between markets is influenced by different behavioural factors.

In general, the periods following major economic shocks are characterized by declining asset prices and rising market volatility, which spread both within and across borders. During financial crises, relations between international instruments undergo drastic change and tend to collapse. This necessitates a review of hedging strategies considering changes in the correlation between assets. If shocks are transmitted internationally, a crucial question arises about the existence of portfolio diversification benefits. In times of crisis, increased market movement has a significant impact on the portfolio allocation and risk management strategy of international investors (Claessens et al., 2001; Bekaert et al., 2011).

Increasing exchange rate volatility and the resulting foreign exchange risks associated with international investment are alarming. The simultaneous collapse of markets could jeopardize institutions that hold internationally diversified portfolios and have an impact on the payment and settlement process. Nevertheless, the potential impact on the real economy could lead to severe macroeconomic fluctuations and, as a result, trigger a recession in many economies (Claessens et al., 2001). In the context of the sovereign debt crisis, we can see a shift in market pricing behaviour from the pre-August 2007 "convergence trade" model to a model driven by macroeconomic funds and subsequent international risks. The EMU debt crisis is divided into early and current crisis periods. The early crisis period, which runs from August 2007 to February 2010, and the latest crisis period, which runs from March to March 2010, in response to the Greek debt crisis. In contrast, during the latest crisis, there are many sources of contagion, most notably Greece, Ireland, Portugal, and Spain (Arghyrou and Kontonikas, 2012). The crisis of 2007–8 was special in that it started from the most developed financial markets in the world and continued to ring through the most advanced financial products to the markets of the euro area as well as emerging countries (Király et al., 2008). Based on the results of Zhang et al. (2020), it can be said that a significant spill-over effect can be observed in global capital markets, and the spread of risk is strongly visible in the case of financially smaller countries. Stock market volatility, government debt, and inflation are positively correlated with systemic risk, while the current account and macroeconomic performance are negatively correlated. Macro-prudential and financial regulatory policies can help reduce systemic risk and maintain financial stability, thus preventing the spread of risks.

Grammatikos and Vermeulen (2012) examined the impact of financial and sovereign debt crises between 2007 and 2010 in 15 countries of EMU, within which three groups of countries were distinguished: northern, southern, and smaller countries. Their results showed that the smallest countries were relatively isolated from international events between 2003 and 2010. In the case of the North and South, however, it was shown that before the crises, the appreciation of the euro coincided with the decline of the European stock market, while this relationship was reversed after the Lehman collapse. Dua and Tuteja (2016) examined stock market and foreign exchange market contagions on the sample of China, the euro area, India, Japan, and the USA. They showed that significant contagions occurred within and between asset classes, and these occurred mainly in developed country markets. In addition, it was shown that the behaviour of the euro (EUR) and Japanese yen (JPY) exchange rates differed significantly from the yuan and rupee exchange rates. Regarding contagions between different asset markets, Hung (2017) examined possible causal relationships between stock prices and foreign exchange rates in a sample of Hungary, the Czech Republic, Poland, and Romania. Using Granger causality studies and a vector autoregression method, his calculations for the period 2008–2017 showed that although stock returns and price are correlated in these countries, there is no causal relationship between them according to either method. In another study (Hung, 2022), the author also examined the further effects of the asymmetric volatility of stock and foreign exchange rates over the period 2000–2017, using the previously mentioned sample extended with Croatia. His results confirmed that the spillover effect of stock and foreign exchange market volatility had a two-way spillover in Hungary, for the whole study period, and only in the interval following the 2008 crisis. In contrast, the Croatian markets were characterized by a one-way spillover of volatility before the crisis, while in the case of the Czech Republic the effects of equity markets on the foreign exchange market were observed throughout the analysis period.

Olbrys and Majewska (2016) examined the hypothesis that there was no contagious effect between the US and CEE stock exchanges during the 2007–2009 crisis, which was rejected in the case of the Polish, Hungarian, Slovenian, and Lithuanian markets. Pappas et al. (2013) also examined these co-movements in a sample of CEE countries and the eurozone, calculating DCC-GARCH and Markov regime change models, with similar results. Onofrei et al. (2019) demonstrated that foreign monetary policy, the domestic exchange rate, and the state of the economic cycle play a key role in both short- and long-term co-movement of capital markets. In these economies, changes in foreign monetary policy amplify the effects of market shocks and increase capital market co-movements, while a stable economic environment and a strong domestic currency have the opposite effect.

2.4 Financial market networks

Before describing the features of the method that we used, we first want to introduce the basic concepts related to financial market networks. Using the simplest definition, a network is a set of nodes connected by edges and in many complex systems where these networks are built from the correlations between the dynamics of the nodes (Garas et al., 2008). Complex network theory is a well-known approach to study the interdependencies between different economic variables, and over the last decades, correlation-based estimations like dynamic conditional correlation have been extensively promoted to see financial markets as complex networks (Engle, 2002; Chen et al., 2022; Kenett and Havlin, 2015; Kenett et al., 2015; Stavroglou et al., 2017; Yin et al., 2017).

From this perspective, different financial entities – such as various markets, assets, financial institutions – identified as the nodes of a network, and the interdependencies across them are usually determined through correlation measures (Schweitzer et al., 2009). Prior studies, which deal with the links between various entities of financial markets, usually combine network theory with different econometric methods. In line with our topic, in this approach stock markets are specified as network nodes (Liu and Tse, 2017). Each pair of stock markets is connected by an edge; with its weight assigned one value calculated by one of the previously mentioned correlation measure methods – more precisely, these network links, which are the weights of the links, are specified most often by the dynamic conditional correlation (DCC) between market indices (Liu and Tse, 2017).

To sum up, the network interconnectedness framework is widely accepted as a useful tool to detect, measure, and analyse systemic risks, contagions, and spillovers between financial markets – because financial entities can be interpreted as a channel of shock transmission. For example, Liu and Tse (2017) investigated the co-movements of 67 stock market, where they tested the variation of their network parameters as time flows. Their empirical conclusion was that global stock markets had time-varying synchronization, moreover, stock markets of developed economies showed improving integration and co-movements while the markets of frontier emerging countries behaved more independently from one other. Saeedian et al. (2019) analysed the 40 biggest stock market indices and presented each market as a part of a "world-stock-market network", meaning that the correlation between two markets was not independent from the correlation between two other markets. Using Random Matrix Theory, they investigated the cross-correlation matrix of these indices. Their results demonstrated that the global financial market consists of 3 main districts each of which includes geographically close stock markets. Cupal et al. (2012) investigated the changing topological characteristics of correlation-based network of European stock markets where, on a national level, they demonstrated that the core stem of largely developed countries' stock markets is substantial over time. Moreover, on the supranational level, their finding showed that stock markets are clustered due to their economic sector, rather than country's origin. Overall, they proved that network modelling of a stock market is highly useful because the formulation of network can make the behaviour of different stock markets more understandable through their graphic representations. Examining 23 developed and 23 emerging economies, Chen et al. (2022) applied a network-based analytical framework to study the interconnectedness of their stock markets. Their outcomes confirmed that the changes in directional interconnectedness within global stock markets arise under the impact of the subprime crisis and the sovereign debt crisis. In a recent paper, Lai and Hu (2021) assessed the systemic risk of global stock markets under the COVID-19 era (from August 2019 to March 2020), where they identified risks through the comparison of the divergent aspects of the topology of a complex financial network and the centrality of the stable and volatile terms. Their outcomes suggested that the latest coronavirus epidemic enhanced the financial connectedness between countries and this effect continues to spread in a diminished area. Kumar and Deo (2013) applied Random Matrix Theory and complex network approach to analyse 20 global financial indices and how their correlation and network properties changed before and during the subprime crisis. They found a robust correlation between these indices and concluded that the clusters from these indices shaped due to their geographical location (USA, Europe, Asia). Calibrating minimum spanning tree structures, they found that its shape before the subprime crisis was more like a star figure while it became more a chain like form during the crisis period.

3 Methodology and data

3.1 Theoretical model

To model the market network (n), it is necessary to define the interactions (c) between the nodes (a), which determine the shape (sh) of the entire network. If extreme events emerge from the underlying system, the following formula should be fit to collect the most important factors behind these dynamics:

$$n(a, c, sh) \tag{1}$$

where the shape of the network (sh) can be described trough five structural properties: average path length (pa), clustering coefficient (cl), degree distribution (dd), small-world effect (sw), connectivity (cy) (Barabási and Albert, 1999; Wang and Chen, 2003; Watts and Strogatz, 1998; Alderson, 2008):

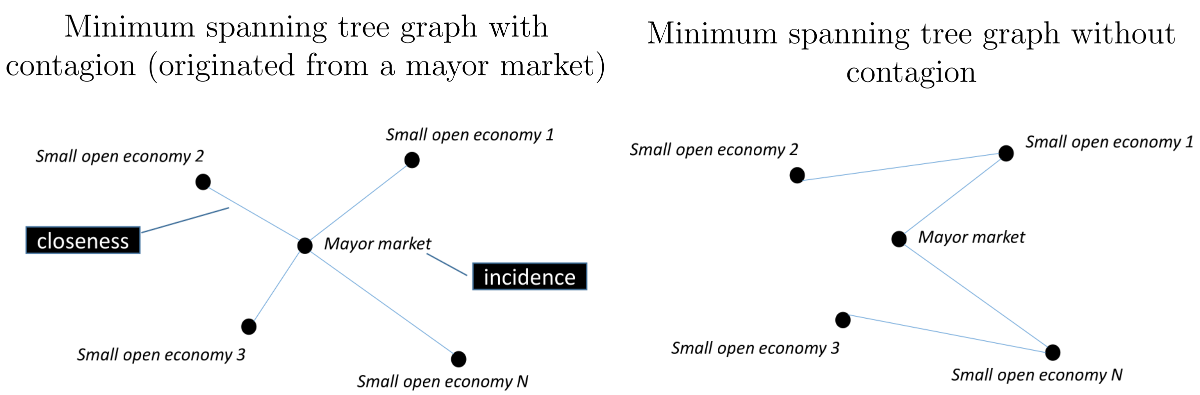
$$sh(pa, cl, dd, sw, dy) \tag{2}$$

Degree distribution (dd) describes the heterogeneity and inartistic hierarchy among the nodes. *Degree* k_i of a node i is the total number of its connections, representing the importance of this node – as larger is the degree so increased its importance in the network. The average of k_i over all i is called the *average degree* of the network, and is denoted by k.

The spread of node degrees over a network is characterized by a distribution function $P(k)$, which is the probability that a randomly selected node has exactly k edges. Average path length (pa) means the average pa_{ij} distance between the ith and jth nodes of the network – as the number of edges along the shortest path connecting them. Clustering coefficient (cl) is the average fraction of pairs of neighbours of a node that are also neighbours of each other. Suppose that a node i has k_i neighbours, then at most $k_i(k_i-1)/2$ edges can exist between them, when every neighbour of i is connected to every other neighbour of i. cl_i denotes the fraction of these allowable edges that exist. Define cl as the average of cl_i over all i. Small-world effect (sw) can be appearing due to the interaction between clustering coefficient and degree distribution. The long-range connections decrease the distance between the nodes, leading to a small-world phenomenon – if there are nodes (*hubs*) in the network with higher-than-average degree, they allow making *shortcuts* between distant nodes through the network. *Hubs* are usually responsible for the synchronisation of the network. Connectivity (cy) represents durability of the connections between nodes – its high level indicates fast recombination of the nodes, while the low-level signs stability.

The complex or even the scale-free network can describe the oligopolistic nature of the market, where key market actors are symbolized with the hubs as well as their importance with attach preferences. Statistic phenomena as fat tailness, heteroscedasticity, autocorrelation or even collective effects are the results of this market structure. Scale-free complex networks are based on the preferential attachments, causing a hub-based structure following Barabási and Albert (1999). This structure is between the two extreme statuses as regular (lattice) and random networks (Watts and Strogatz, 1998).

Figure 1: Minimum spanning tree graph with and without contagions



The *incidence* of the graph in Figure 1 describes the number of connections from one node (in our case country) to another, as *betweenness* represents the degree to which nodes stand between each other, while *closeness* describes the strength of this relation. In a minimum spanning tree design, we can assume that only the most significant edges (node-to-node connections) are represented, so an emerging hub-structure can prove the highly synchronized state of contagions. Under a fully stressed global contagion scenario, we can expect the emergence of one single hub market, which synchronizes the rest of the network due to crisis propagation. This hub will have a high incidence and betweenness value due to its relative importance in the network, while it will have a strong connection to the rest of the nodes. However, in case of country-specific stress, the network remains in an atomized (or non-centralized) state, so we will be unable to identify such a node with asymmetric properties (see Figure 1).

3.2 Data

During the research, we analysed data between 2001 July and 2021 March. We retrieved data for all European stock indices (21) for the given period and used their daily stock index price. Based on Eurostat Business Cycle Clock (see Appendix A), we examined three main periods for slowdown, i.e., July 2001-March 2005, June 2009-September 2009, and March 2013-December 2013 and three main periods for recession, i.e., March 2008-June 2009, September 2011-March 2013, and December 2019-July 2020. For the analysis, we used R program to calculate the correlations and the minimum spanning tree (MST). Based on the daily stock prices, we calculated the Pearson correlation and created the correlation matrix for the above periods – three for slowdown, three for recession and four for calm periods. After that, we created the networks for these 10 periods and calculated the MST (see Appendix B).

3.3 Method

It is important to get to know and present the concept of networks. We are surrounded by several complex systems, which we have become increasingly focused on in recent years. This focus stems in large part from the fact that, despite the obvious diversity of complex systems, the structure and development of the networks behind each system is guided by a common set of basic laws and principles. Therefore, despite the astonishing differences in the form, size, nature, age, and scope of real networks, most networks are governed by common organizational principles. Having ignored the nature of the components and the exact nature of the interactions between them, the resulting networks are more similar than different. In what follows, we discuss the forces that led to the emergence of this new area of research and its impact on science, technology, and society (Barabási, 2016).

Capital markets, such as stock market indices, are suitable for network-based analysis in terms of complexity, for which one of the most widely used methods is the minimum spanning tree (Chong et al., 2017; Zhao et al., 2018). The essence of the minimum spanning tree is to represent the relations using a graph that contains each stock index connected to at least one edge, so that the sum of the edges is minimal and that does not contain loops (Sandoval, 2014). Zhao et al. (2018) used planar maximally filtered graph (PMFG) to analyse stock market networks during crisis and they concluded that the heterogeneity index γ of the PMFG network increased significantly during the crisis.

It was also found that the US and UK markets showed similar patterns after the 2008 crisis. Sandoval (2014) constructed correlation matrices based on the time series of 79 stock indices from different countries from 2003 to 2012 and compared the results of 2003–2007 (low volatility period) to a 2008–2012 (time of high volatility) in the light of Random Matrix Theory. He found that some Central European markets were highly correlated and that two other clusters, one in the US and the other in the Asia-Pacific market, developed below lower correlation values. Chunxia et al. (2014) used a maximum spanning tree to examine stock correlations and crises. The topological structure of a maximum spanning tree first becomes compact star-like loose chain-like and then again compact star-like. Therefore, it can be concluded that the crisis is indeed changing the stock correlation, and the stock correlation becomes first from weak to strong and then weak again.

The minimum spanning tree is a clustering method that allows the acquisition of an economically significant market structure by using asset returns as input. In addition to yield, Brida and Risso (2008) also considered trading volume in their model, thereby building a multidimensional minimum spanning tree (MMST). The MST graphs show that the relationships between stock market indices are strongly influenced by the geographical location of stock exchanges, as there are well-defined clusters that are related to continents, confirming the results obtained previously with regression methods. Furthermore, cultural relations or international treaties strongly influence stock index correlations. The US capital market is relatively isolated, closely linked to other US stock exchanges, but relatively weakly linked to Europe. This is probably related to the fact that stock markets operate at different hours, so the trading hours of most European markets are less the same as the opening hours of Americans (Sandoval Jr, 2012). In addition to geographical location, other related factors, such as economic relationships, can also play a significant role. There has been a limited tendency in Central and Eastern European countries to be more closely associated with more developed EU countries (Coelho et al., 2007).

4 Results

For stock market indices to be comparable, their expected value should be zero and move on a similar scale. In this case, this is done by using logarithmic differences.

Based on Figure 2, it can be said that the expected value (average) is ≈ 0. In the case of the OMXC20 index, we did not get any interpretable values, so we will continue to analyse the basic statistics without this index. Based on the Jarque-Bera test, it can be said that the yield of the indices is not normally distributed in any case ($p > 0.05$ is not satisfied). It is therefore worth examining and filtering out extreme values. The ADF test indicates that the data set is stationary.

An efficient market cannot be autocorrelated. This can be examined using the Ljung-Box test. Since $p < 0.05$ is met for most indices, the time series is autocorrelated, i.e.,

Figure 2: Basic statistics of indices

	mean	SD	skewness	kurtosis	Jarque-Bera (p>0.05)	Ljung-Box (p>0.05)	ARCH-LM (p>0.05)	ADF (p<0.05)
GDAXHI	0.0002	0.0143	-0.2464	9.1707	0.0000	0.8944	0.9568	0.0000
FCHI	0.0000	0.0144	-0.2028	9.8395	0.0000	0.1257	0.4449	0.0000
FTMIB	-0.0001	0.0155	-0.6031	12.4043	0.0000	0.1160	0.4609	0.0000
IBEX	0.0000	0.0147	-0.2914	11.5739	0.0000	0.7673	0.9149	0.0000
AEX	0.0000	0.0141	-0.2285	10.5888	0.0000	0.8504	0.9527	0.0000
SSMI	0.0001	0.0116	-0.2938	11.0964	0.0000	0.0033	0.1596	0.0000
OMXS30	0.0002	0.0140	-0.1047	8.2115	0.0000	0.0062	0.1048	0.0000
WIG20	0.0001	0.0144	-0.3297	7.7766	0.0000	0.0056	0.0535	0.0000
BUX	0.0004	0.0145	-0.2829	10.8041	0.0000	0.0001	0.1085	0.0000
BETI	0.0006	0.0144	-0.8325	14.8349	0.0000	0.0000	0.0710	0.0000
SAX	0.0003	0.0114	-0.7297	19.8201	0.0000	0.0000	0.0000	0.0000
SOFIX	0.0003	0.0123	-0.6248	16.6915	0.0000	0.0000	0.0101	0.0000
PX	0.0002	0.0131	-0.6339	18.6849	0.0000	0.0000	0.0883	0.0000
BFX	0.0001	0.0128	-0.4541	12.7838	0.0000	0.0007	0.0922	0.0000
OBX	0.0003	0.0149	-0.6004	10.4003	0.0000	0.1649	0.6099	0.0000
ATX	0.0002	0.0145	-0.5517	12.6924	0.0000	0.0000	0.0208	0.0000
ATG	-0.0002	0.0184	-0.5065	11.2082	0.0000	0.0001	0.0147	0.0000
OMXHPI	0.0001	0.0147	-0.1840	7.8438	0.0000	0.2360	0.4721	0.0000
PSI20	-0.0001	0.0119	-0.4134	10.7526	0.0000	0.0000	0.0029	0.0000
OMXIPI	0.0001	0.0190	-40.3102	2273.3497	0.0000	0.0360	0.0318	0.0000

today's values are also affected by past values. The exceptions to this are the cells marked in green in the "Ljung-Box" column (see Figure 2), so there is no autocorrelation in those cases.

The ARCH-LM test can be used to examine homoskedasticity. In most cases, this is the case for the time series examined (see Figure 2, green cells in the "ARCH-LM" column), but in the case of indices marked in black, we can talk about heteroskedasticity, i.e., the market is uncertain about how much the asset is worth. The value of kurtosis should be close to 3, but this is not the case for any of the indices. This is, of course, since the time series does not follow a normal distribution. It can be said, then, that there is a thick tail in the evening of the time series, in which case the extreme, salient cases appear in a larger mass. After fitting a 5% VaR for the whole examined period, we can see that the time series follows the normal distribution better and kurtosis is also around the permitted value (see Figure 3).

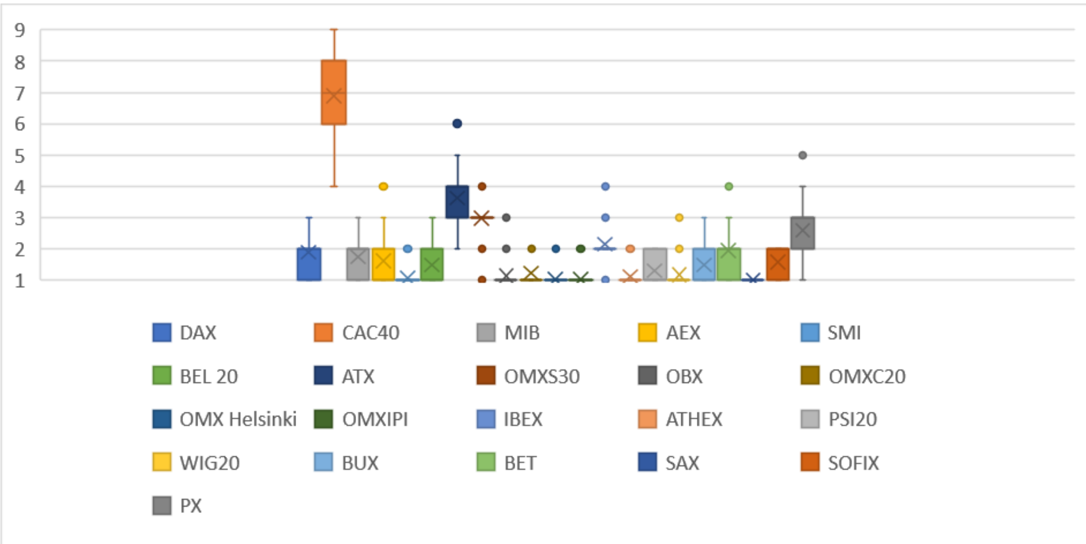
The main features of the stock market network are analysed based on incidence, betweenness and closeness. Figure 4 clearly shows that the French stock index (CAC40) had the most links during the period under review, and the Austrian index (ATX) had a larger network. Based on this, we can conclude that the French index has the greatest influence, i.e., the CAC40 index influences the development of most indices the most. The impact of the Austrian index is also strong. Betweenness is the sum of all possible shortest paths between any stocks used to analyse the flow of information within the network. Thus, the index with the highest score is considered a significant index for its role in coordinating the flow of information in the network (Lee and Djauhari, 2012).

A similar result to Figure 4 is obtained for the betweenness test (see Figure 5). As the French index takes the highest score in this case (0.043), it can be said that among

Figure 3: Basic statistics of indices with VaR (5%)

	mean	*SD*	*skewness*	*kurtosis*	*Jarque-Bera (p>0.05)*	*Ljung-Box (p>0.05)*	*ARCH-LM (p>0.05)*	*ADF (p<0.05)*
GDAXHI	0.0006	0.0090	-0.0697	3.1159	0.0000	0.1318	0.1362	0.0000
FCHI	0.0004	0.0090	-0.0587	3.0847	0.0000	0.0257	0.0328	0.0000
FTMIB	0.0003	0.0099	-0.0903	3.1126	0.0000	0.0382	0.0465	0.0000
IBEX	0.0002	0.0093	-0.0653	3.0371	0.0000	0.5035	0.5084	0.0000
AEX	0.0004	0.0085	-0.0834	3.2170	0.0000	0.6040	0.6529	0.0000
SSMI	0.0004	0.0073	-0.0580	3.0793	0.0000	0.1001	0.1182	0.0000
OMXS30	0.0004	0.0088	-0.0562	3.0421	0.0000	0.0286	0.0324	0.0000
WIG20	0.0001	0.0096	0.0221	2.9193	0.0000	0.0014	0.0012	0.0000
BUX	0.0004	0.0095	0.0023	2.8811	0.0000	0.2295	0.2544	0.0000
BETI	0.0007	0.0084	0.0557	3.4466	0.0000	0.0000	0.0000	0.0000
SAX	0.0004	0.0062	0.0770	4.2689	0.0000	0.0000	0.0000	0.0000
SOFIX	0.0004	0.0068	0.0866	3.7842	0.0000	0.0000	0.0000	0.0000
PX	0.0005	0.0081	-0.0747	3.1253	0.0000	0.0357	0.0462	0.0000
BFX	0.0004	0.0079	-0.0784	3.1355	0.0000	0.3714	0.4013	0.0000
OBX	0.0008	0.0094	-0.0448	3.0506	0.0000	0.0070	0.0114	0.0000
ATX	0.0007	0.0090	-0.0968	3.0707	0.0000	0.4212	0.4456	0.0000
ATG	0.0002	0.0114	-0.1089	3.1656	0.0000	0.0000	0.0000	0.0000
OMXHPI	0.0003	0.0091	-0.1115	3.1247	0.0000	0.5478	0.6135	0.0000
PSI20	0.0003	0.0077	-0.0402	3.0230	0.0000	0.3546	0.3900	0.0000
OMXIPI	0.0006	0.0082	-0.0839	4.5118	0.0000	0.0000	0.0000	0.0000

Figure 4: Incidence of markets



the European stock market indices, the French index is the most meaningful in terms of information flow coordination during the period under review. Closeness also includes the shortest path between all possible index pairs in the network, so the average number of shortest paths between an index and all other indexes available from it. Basically, proximity is a measure of how close an index is to all other indices. The higher the score of a given index, the faster the index disseminates the information to all others (Lee and Djauhari, 2012).

The weight of the markets considered to be central is better illustrated by the closeness (see Figure 6), in which these markets are indeed closer to all other markets on the graph

Figure 5: Betweenness of markets

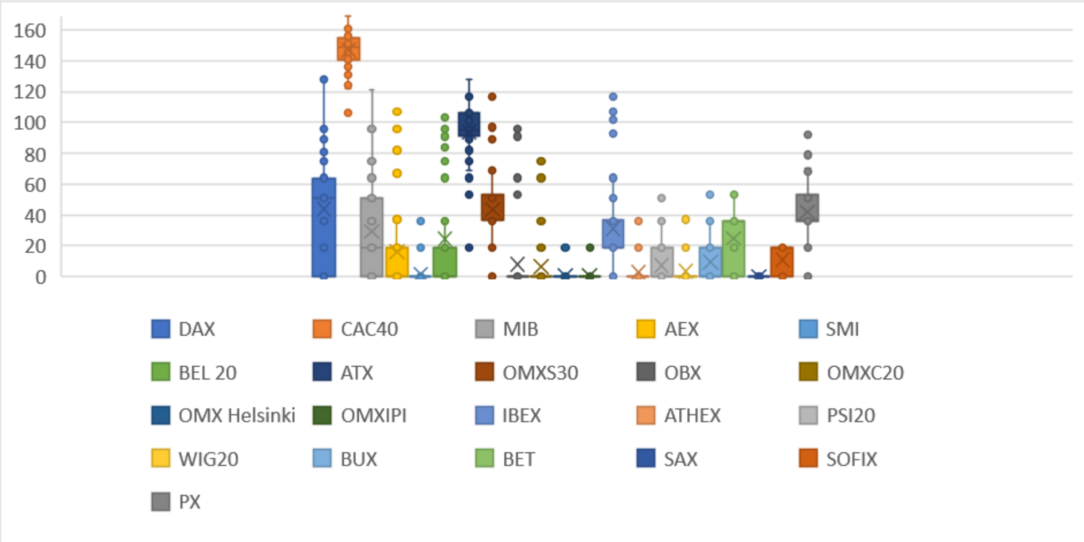
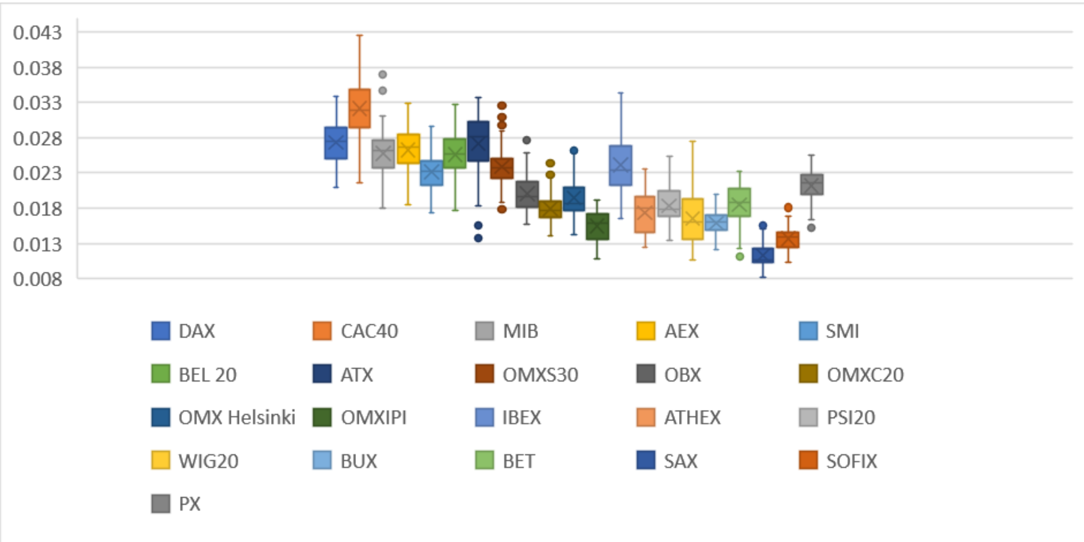


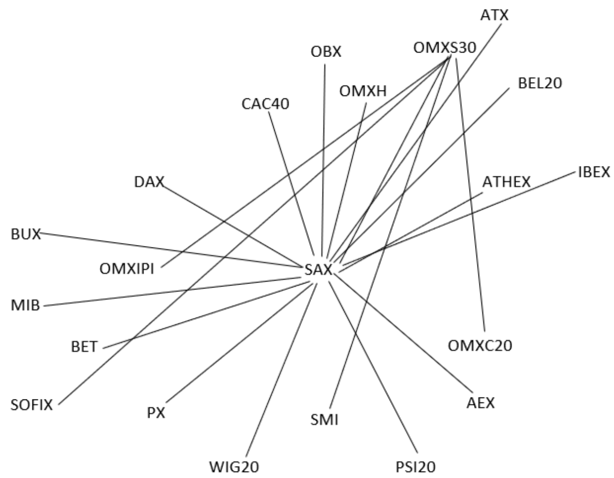
Figure 6: Closeness of markets



under which the Scandinavian (led by the Swedish OMX30 index), the Mediterranean (Spanish) led by the IBEX index) and Central and Eastern Europe (led by the Czech PX index). As in the case of proximity and the number of relationships, the French index has the highest score (169), so it can be said that this index disseminates information to the other indices the fastest. The influence of the German and Austrian indices is not negligible either (128 points). Examining the centrality metrics, our expectations have been confirmed, as the European core countries are the most dominant. If we talk about the first 20%, the German, French, Italian and Austrian stock indexes had the highest scores, so they have the greatest impact on the other European stock market indices. These results are supported by Eryiğit and Eryiğit (2009), among others. Although they conducted a comprehensive analysis, not only for European stock indices, the results of their research on European indices showed that the French index is the most decisive, while the German DAX index is more influential.

Below, we analyse the structure of stock market network in different periods.

Figure 7: Stock index network in the first recession period (March 2008 – June 2009)



In Figure 7, there was one central index, which connected most indices to each other, the SAX (Slovakian) index. The other central index is the OMXS 30 (Stockholm), which is mainly connected to other Northern-European indices, such as OMXPI (Stockholm), OMXC 20 (Copenhagen), SMI (Sweden). In the second period of recession (between September 2011 and March 2013), we could identify different connections to the European stock indices. SAX remained the central index, but as it can be seen in Figure 8, some indices separated from the central. These indices mainly are IBEX (Spain), PSI20 (Portugal). In the third period of recession, the focus remained on one central index but there has been a change in the subject of focus. OMXS 30 (Stockholm) and OMXC 20 (Copenhagen) became the most connected two indices, and SAX became a less connected one (see Figure 9).

When comparing the graphs with slowdown periods, index connections are more diverse, in most cases we cannot determine one central index (see Appendix C). In general, the observation is that in the calm periods, networks are more diverse, but a reorganisation can be seen with one, or more central indices. In the periods of recession, this centrality becomes stronger, and the network structure is more defined. In the first slowdown period AEX and BET are the central indices, and the rest connects to them. In the first calm period a more structured network can be observed with only once central index, the SAX. We can conclude that there might be a change in the nature of the period from this structure. It is followed by the first recession period discussed in depths earlier, but the structure is similar, with two main indices. In the second slowdown period, the structure is like the recession period but in the following calm period we can see a more diverse network structure where no real central index can be found. This structure is followed

Figure 8: Stock index network in the second recession period (September 2011 – March 2013)

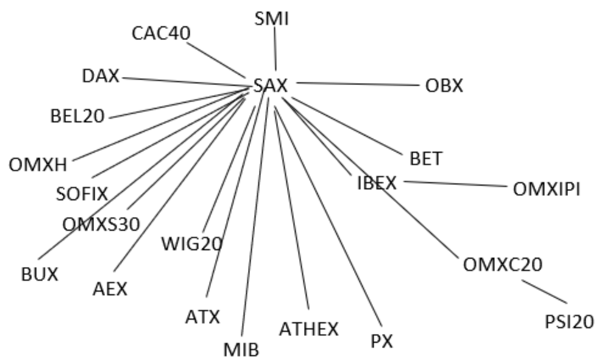
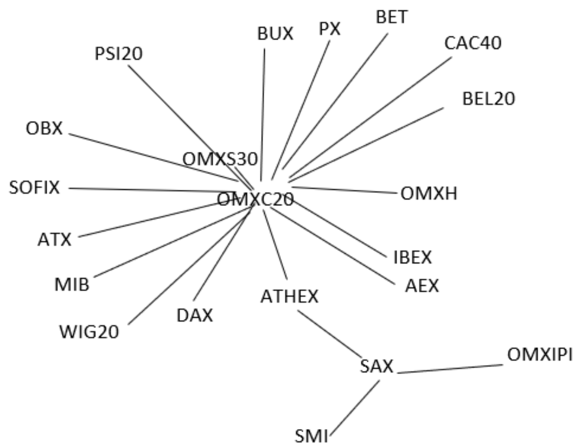


Figure 9: Stock index network in the third recession period (December 2019 – July 2020)



in the later periods as well. Our finding is that in the periods of recession the network structure is more defined whereas before and after recession the structure remains similar but transfers to a more diverse structure after it is eased.

5 Conclusion

In our research the aim was to examine the co-movement of European stock indices during various market shocks. The results show that during the three examined recession periods we could see a constant change in the stock market network. In all cases there is a central index that connects most of the other indices to each other, but the type of the index is not determined. In calm periods, we cannot state the same, the connections are more widespread and without a central element. Our conclusion is that during shocks, stock indices are connected mainly through one central index, while in calm periods the connection is more diverse. This, in turn, might mean that because of market shocks and indices becoming more concentrated a higher level of contagion spread could be expected.

As further research, examining American stock indices for the same period and comparing it to the European could provide more information on contagion spreading and co-movement of stock indices during turbulent periods.

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A Business Cycle Clock

`https://ec.europa.eu/eurostat/cache/bcc/bcc.html?fbclid=IwAR0xTmJiFCD4zELuarB27AZRsLQ-NEm3qhvJEqNVU9xvC00Pcx7CdZn80AU`

B R code used for the research

Code.txt

C MST graphs for all periods (in topological order)

Figure C1: First slowdown period (July 2001 – March 2005)

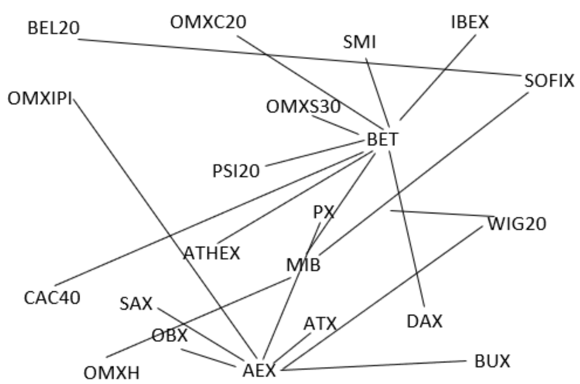

Figure C2: First calm period (April 2005 – February 2008)

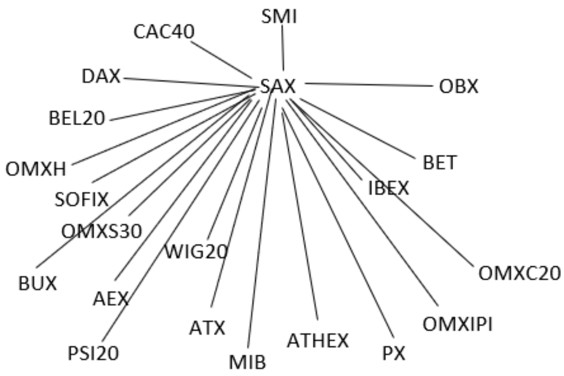

Figure C3: First recession period (March 2008 – June 2009)

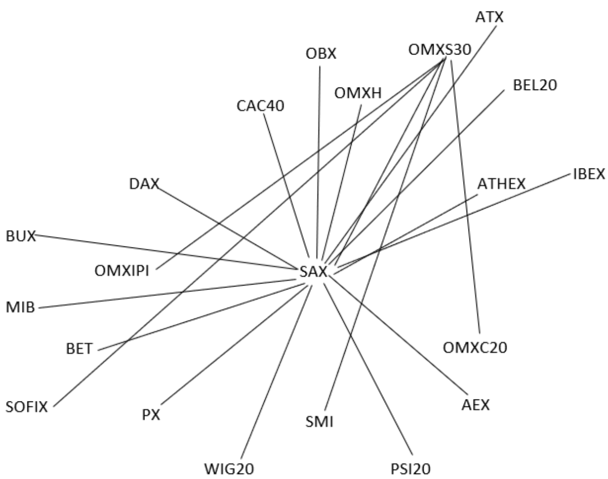

Figure C4: Second slowdown period (June 2009 – September 2009)

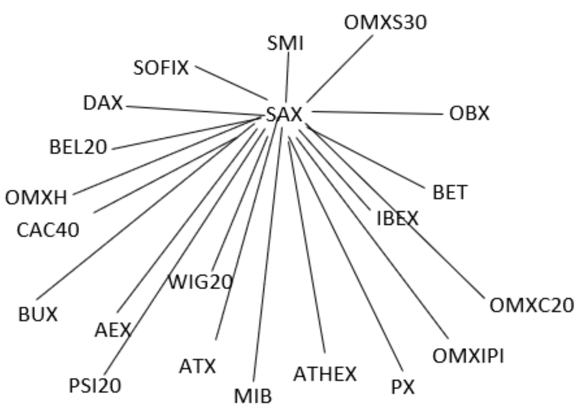

Figure C5: Second calm period (October 2009 – August 2011)

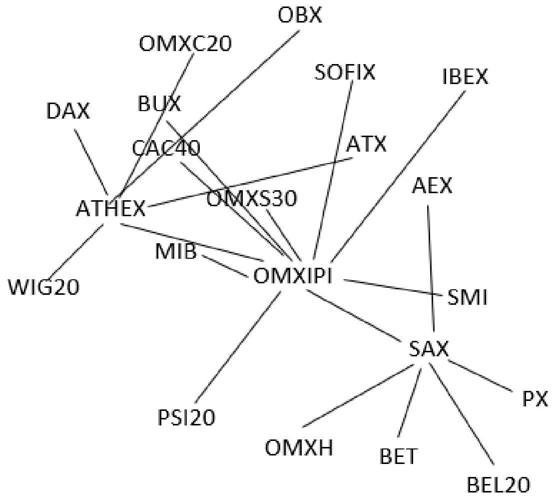

Figure C6: Second recession period (September 2011 – March 2013)

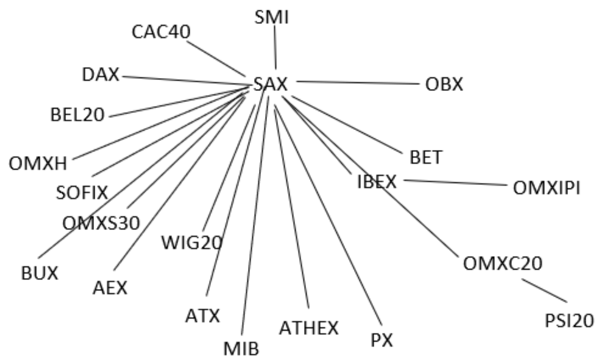

Figure C7: Third slowdown period (March 2013 – December 2013)

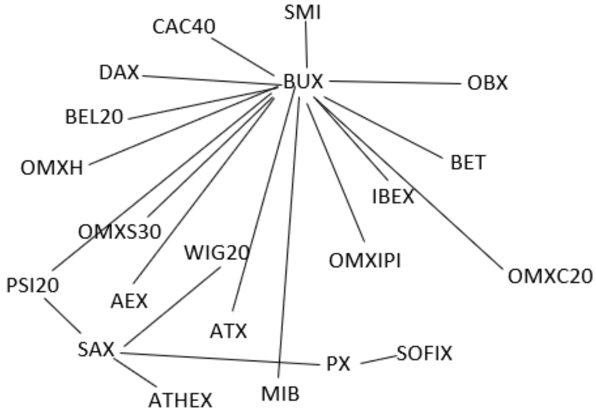

Figure C8: Third calm period (January 2014 – November 2019)

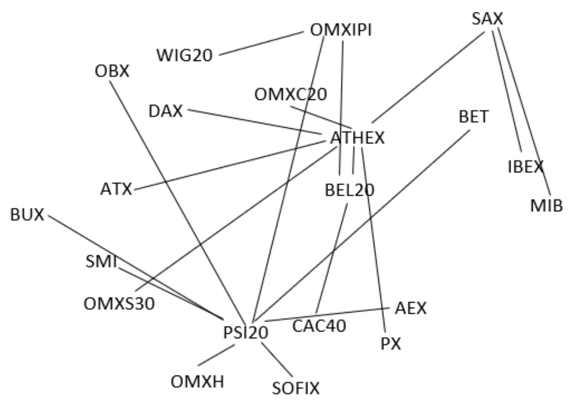

Figure C9: Third recession period (December 2019 – July 2020)

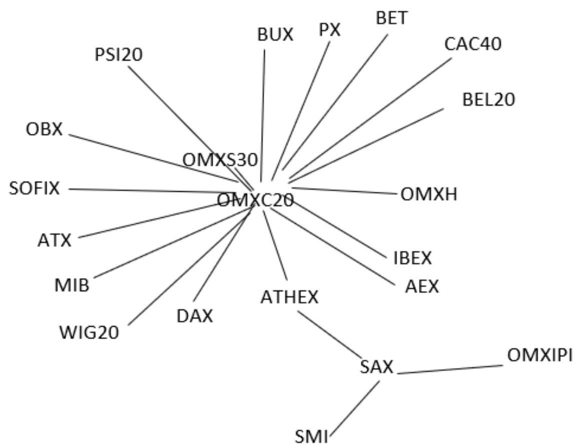

Figure C10: Fourth calm period (August 2020 – March 2021)