Ključni pokretači volatilnosti dioničkog tržišta u Hrvatskoj

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KEY DRIVERS OF CROATIAN STOCK MARKET VOLATILITY

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Osijek, 2024.

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KEY DRIVERS OF CROATIAN STOCK MARKET VOLATILITY

Master thesis

Osijek, 2024.

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Naziv studija: Financijski menadžment

Naslov rada: Ključni pokretači volatilnosti dioničkog tržišta u Hrvatskoj

Mentor/mentorica rada: prof. dr. sc. Domagoj Sajter

U Osijeku, 11.06.2024. godine

Potpis ____________________

Ključni pokretači volatilnosti dioničkog tržišta u Hrvatskoj

SAŽETAK

Dionička tržišta važan su faktor koji pokreće svjetska gospodarstva. Zbog toga je važno razumjeti što pokreće volatilnost cijena dioničkih tržišta i njihov utjecaj na gospodarstvo. Globalizacija i integracije tržišta su istaknutije nego ikad, pa je pretpostavka da su svjetska dionička tržišta međusobno povezana. Ti odnosi utječu na odluke o ulaganju, ali i na donositelje ekonomskih politika. Ovo istraživanje koristi DCC-GARCH pristup kako bi ispitalo prisutnost efekata prelijevanja volatilnosti između hrvatskog dioničkog tržišta i globalnih tržišta dionica. Rezultati pokazuju dokaze o efektima prelijevanja i međuzavisnostima kroz vrijeme, ali ne objašnjavaju zašto ovaj odnos postoji niti smjer prelijevanja. Ovi odnosi bi mogli biti objašnjeni kulturnim, političkim, geografskim i ekonomskim sličnostima. Nadalje, rezultati ovog istraživanja mogu se koristiti za optimizaciju portfelja kroz predviđanje volatilnosti. Rezultati također sugeriraju mogućnosti zaštite i diverzifikacije na financijskim tržištima. Iako rezultati donekle objašnjavaju dinamiku volatilnosti hrvatskog tržišta dionica, važno je uzeti u obzir da drugi faktori, poput cijena roba, kriptovaluta i makroekonomskih varijabli, mogu utjecati na volatilnost hrvatskog dioničkog tržišta.

Ključne riječi: CROBEX, prelijevanje volatilnosti, DCC-GARCH, tržišna integracija

Key drivers of Croatian stock market volatility

ABSTRACT

Stock markets are an important factor driving global economies. Therefore, it is important to know what drives stock market volatility and what impact it has on the economy. Globalization and market integration are more important than ever, so it is reasonable to assume that global equity markets are interconnected. These relationships affect both investment decisions and policy makers. In this study, a DCC-GARCH approach is used to investigate the existence of volatility spillover effects between the Croatian stock market and global stock markets. The results show evidence of spillover effects and interdependencies over time, but do not explain why this relationship exists and the direction of the spillovers. These relationships could be explained by cultural, political, geographical and economic similarities. Furthermore, the results of this study could be used for portfolio optimization by predicting volatilities. The results also point to hedging and diversification opportunities in the financial markets. Although the results provide some insight into the volatility dynamics of the Croatian stock market, it is important to consider that other factors such as commodity prices, cryptocurrencies and macroeconomic variables can influence the volatility of the Croatian stock market.

Keywords: CROBEX, volatility spillovers, DCC-GARCH, market integration

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1. Introduction

The Republic of Croatia, located in Central Eastern Europe (CEE), is often characterized as a small economy. Although Croatia is a relatively young country, it has undergone significant economic changes. Key developments include joining NATO in 2009, joining the European Union in 2013, switching from the sovereign currency to the euro and integrating into the Schengen area in 2023. According to the Economic Survey of Croatia (OECD, 2023), the country has managed to maintain economic growth while effectively controlling rising prices, despite challenges such as high inflation rates and war in Europe. These factors contribute to Croatia's global market position and its attractiveness to foreign investors. (CIA, 2021)

The Croatian stock market was launched in 1989 with the establishment of Zagrebačka burza, formerly known as Zagrebačko tržište kapitala. In 1997, Zagrebačka burza introduced the first stock market index, the CROBEX (Croatian Bourse Index), which represents the Croatian stock market. (Zagrebačka burza d.d., 2021)

Volatility, one of the most important metrics in finance, can be defined as the variance between the returns of financial assets. It is used in financial and economic research, including risk management, financial modeling and forecasting, and other applications. For example, the volatility of financial markets can be related to future economic expectations. Holmes and Maghrebi (2016) analyzed the interconnectedness between US stock returns and unemployment rates. They concluded that "both positive and negative shocks to stock market returns are associated with a short-run rise in the employment rate" (Holmes & Maghrebi, 2016, p. 7). Furthermore, the authors point out that "while positive shocks can also be harmful concerning unemployment rates in the short-run, there seems to be a stronger case for stabilizing against negative stock market shocks leading to financial crises" (Holmes & Maghrebi, 2016, p. 7). These findings suggest that future volatility expectations have an impact on economic activity, which shows the importance of understanding financial market volatility. Budd (2018), who analyzed the spillover effects of cluster volatility between the US and Asia-Pacific equity markets, points to increased market integration between these regions, which is visible through positive volatility spillovers. The author assumes that the benefits of diversification are diminishing due to high market integration and linked stock price activity.

As the examples presented show, volatility can provide significant research results. Financial market volatility can also be expressed as the degree of uncertainty about future asset price movements. Bhowmik & Wang (2020) suggest that uncertainty can be characterized by variance and standard deviation. The authors give two examples of the interconnectedness between volatility and returns. The leverage effect, first documented by Black (1976), in which a negative price movement increases stock volatility due to a higher leverage ratio, and the volatility feedback hypothesis, documented by Poterba & Summers (1984), which attributes the volatility of returns to time-varying risk premia.

Due to globalization and market integration, it is important to analyze the impact of spillovers on market volatility. Singh et al. (2010) point out that “international linkage of markets has major implications for domestic economies and for international diversification” (Singh et al., 2010, p. 1). Furthermore, the authors suggest that “strong linkage reduces the insulation of domestic market for any global shock whereas weak market linkage offers potential gains from international diversification” (Singh et al., 2010, p. 1). By understanding these linkages and interdependencies between markets, investors can benefit from diversification opportunities and resilience to financial crises.

The motivation for this research stems from the importance of understanding the financial markets and the factors that influence investors' decisions. By identifying what drives the volatility of certain financial markets, investors may be able to improve their decision making, develop better risk management solutions and deepen their overall understanding of market stability and underlying risks. In addition, understanding the decision-making process of investors could have implications for future investment policy regulations.

The aim of this study is to analyze the impact of volatility of foreign stock market indices on the Croatian stock market (represented by the CROBEX index) and to investigate possible hedging and diversification opportunities. The thesis contributes to previous academic research on the volatility of the Croatian stock market by analyzing the impact of large global stock markets and local markets using a Dynamic Conditional Correlation - Generalized Autoregressive Heteroscedasticity (DCC-GARCH) approach.

The remainder of this paper is organized as follows: Section 2 presents the main results of significant studies on modeling stock market volatility at global and local levels. In addition, critical concepts from these studies are highlighted. Methodology (Section 3) defines the data used in this study and presents the models and techniques used. The results of the analysis are presented in Section 4. Discussion (Section 5), in which the results are interpreted in the context of previous research and critical concepts. Finally, the conclusion (Section 6) summarizes the results, shortcomings of the study and suggestions for further research.

2. Previous research

Financial markets encompass a wide range of topics and research opportunities. This chapter will present research on stock market volatility and its importance within stock market analysis. It will also highlight key research in this area and define key concepts related to volatility spillovers.

A comprehensive analysis of the Web of Science (WOS) database, with focus on research related to the stock market, revealed 81,656 research papers with 113,275 keywords. The bibliometric analysis (Figure 1) using VOSviewer software revealed that most of the keywords in these research papers cluster around concepts such as risk, return, market, volatility, performance and information.

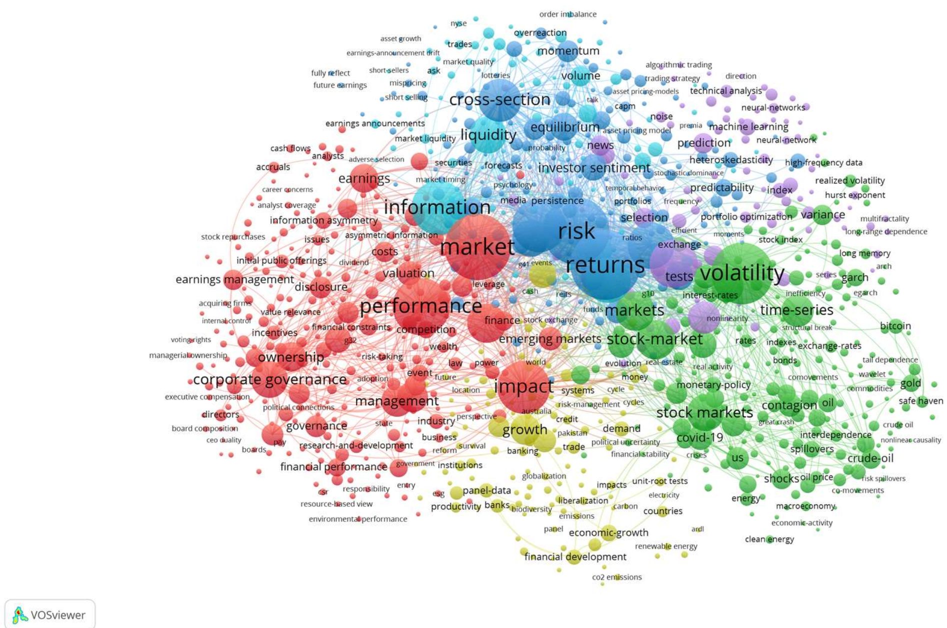

Figure 1. Bibliometric map of key concepts in stock market research.

Source: Author

The results of the analysis of the occurrence of keywords (Table 1) show the importance of volatility in stock market research, as it is one of the 5 most frequently occurring keywords. A further examination of the keywords revealed that the concept of volatility spillovers ranks in a subordinate position (80th place). Nevertheless, volatility spillovers are still an important research topic in financial market analysis.

Table 1. Rankings of keyword occurrences.

No.	Keyword	Occurrences
1	returns	8,438
2	risk	7,933
3	market	7,726
4	volatility	6,921
5	performance	6,106
6	information	5,579
7	stock returns	5,388
8	impact	5,287
9	model	4,595
10	prices	4,279
…	stock	4,084
80	volatility spillovers	909

Source: Author

The WOS database was further searched for research papers on the topic of volatility spillovers. The research papers were filtered using the keywords stock market and volatility spillover, and 3,681 academic papers were found. VOSviewer was then used to analyse the citations to identify the ten most cited papers. These papers are listed in Table 1 according to the number of citations.

Table 2. Ranking of most cited research papers regarding volatility spillover research.

No.	Research paper	Citations
1	Diebold & Yilmaz (2012)	2,531
2	Baruník & Křehlík (2018)	722
3	Sadorsky (2012)	501
4	Arouri et al. (2011)	428
5	Kang et al. (2017)	362
6	Ferrer et al. (2018)	353
7	Mensi et al. (2013)	338
8	Basher & Sadorsky (2016)	318
9	Ng (2000)	317
10	Arouri et al. (2012)	301

Source: Author

The two most cited research papers are those by Diebold & Yilmaz (2012) and Baruník & Křehlík (2018). Both papers present econometric frameworks for measuring the connectedness between financial markets.

Motivated by the existence of spillover effects in financial market volatility during crises, Diebold & Yilmaz (2009) created a framework for measuring volatility spillovers based on "forecast error variance decompositions from vector autoregressions (VARs)" (Diebold & Yilmaz, 2012, p. 2). Due to limitations of the methodology, the authors revised and updated the methodology in Diebold & Yilmaz (2012) by implementing a generalized vector autoregressive framework, which provides both "gross and net directional spillover measures that are independent of the ordering used for volatility forecast error variance decompositions" (Diebold & Yilmaz, 2012, p. 18). The authors emphasize that the methodology "produces continuously-varying indexes" and "is econometrically tractable even for very large numbers of assets." (Diebold & Yilmaz, 2012, p. 18).

Baruník & Křehlík (2018) make a further contribution to the methodology of measuring the connectedness of financial variables through a time-frequency based approach using spectral analysis. The framework is based on "the spectral representation of variance decompositions and connectedness measures", which is used for "disentangling the sources of connectedness between economic variables." (Baruník & Křehlík, 2018, p. 19). The motivation for such a framework lies in the premise that economic shocks have different effects on variables with different frequencies. Analyzing financial firms in the US, the authors found that "periods in which connectedness is created at high frequencies are periods when stock markets seem to process information rapidly and calmly, and a shock to one asset in the system will have an impact mainly in the short term. When the connectedness is created at lower frequencies, it suggests that shocks are persistent and are being transmitted for longer periods" (Baruník & Křehlík, 2018, p. 19).

The other research papers listed in the ranking use different methods to investigate volatility spillovers in different markets. As they are considered to be the most cited papers, a brief overview of these research papers is provided in the next section.

Ferrer et al. (2018) use the framework of Baruník & Křehlík (2018) to analyse the connectedness between renewable energy stocks and crude oil prices in the period from 2003 to 2017. The authors observed an "overwhelming predominance of the higher frequency band (up to 5 days) over the lower frequency band (more than 5 days) in terms of the magnitude of return and volatility connectedness." (Ferrer et al., 2018, pp. 28–29). These results indicate that information is processed quickly, suggesting a relatively fast transmission of volatility between the two markets. Also, the long-term connectedness results are consistent with the assumption that most assets are driven by their own fundamentals, unlike other assets and markets. Furthermore, the authors emphasise that crude oil prices do not affect the prices of renewable energy stocks in the short or long term over the period studied. (Ferrer et al., 2018)

Similarly, Sadorsky (2012) examined the correlations and volatility spillover effects between oil prices, clean energy stocks, and technology companies. The author's approach considers multivariate BEKK, DCC, CCC, and diagonal GARCH models from 2001 to 2010. The results show that DCC-GARCH is the preferred model, suggesting a higher DCC correlation between clean energy stocks and technology stocks than between oil prices (hedging opportunity for clean energy companies) and clean energy stocks, suggesting a closer link between technology and clean energy companies (and thus not a good hedge for clean energy companies). The authors also emphasise that the estimated DCC conditional volatilities can be used as an estimator of dynamic hedge ratios. (Sadorsky, 2012)

Further hedging opportunities were discovered in the study by Basher & Sadorsky (2016), who examined the conditional correlations between emerging market stocks, oil, VIX, gold and bond prices. Their study was conducted between 2000 and 2014 using DCC, ADCC and GO-GARCH models. The authors point out the advantages of GO-GARCH models as opposed to other GARCH models. The results indicate positive leverage effects between stock and oil prices and significant differences in the study period in terms of hedging ratios, indicating the importance of portfolio management through position changes. The authors also suggest that the oil price is the best hedge for emerging market stocks. (Basher & Sadorsky, 2016)

Arouri et al. (2011) investigated volatility spillovers between oil prices and stock markets at sectoral level. The study was conducted for the European and US stock markets using the VAR-GARCH method from 1998 to 2009. The study showed a larger volatility transmission between oil prices and stock market prices than between stocks and oil prices in Europe. In addition, the data indicate bidirectional volatility in the US. The author points to a low-cost hedging opportunity by taking a short position in the oil futures markets in Europe and the US, which outperforms traditional equity portfolios. (Arouri et al., 2011)

In addition, Arouri et al. (2012) extended the research on the impact of oil price volatility on European stock markets. By applying a VAR-GARCH approach for the period from 1998 to

2009, the authors come to a similar conclusion as Arouri et al. (2011), and point to hedging opportunities due to volatility spillovers between oil and equity markets in Europe. Furthermore, the authors emphasise that hedging opportunities vary by sector. (Arouri et al., 2012)

Further research on spillover effects was conducted by Kang et al. (2017) for gold, silver, WTI crude oil, corn, wheat and rice futures from 2002 to 2016. The study was conducted using a DECO-GARCH approach with the spillover index proposed by Diebold & Yilmaz (2012). They found "a positive equicorrelation level that jumps sharply during the recent financial crises." (Kang et al., 2017, p. 30). These results suggest diminishing benefits of international portfolio diversification. Furthermore, the diminishing benefits of diversification are also visible in times of crisis. The researchers highlight gold and silver as net transmitters of information and WTI, corn, wheat and rice as net receivers of information and explain this by the flight-to-quality effect during financial turmoil. (Kang et al., 2017)

Further evidence of volatility spillover effects can be found in the study by Mensi et al. (2013). In their study of volatility spillover effects in the S&P 500, beverage price, wheat price, gold price, WTI and European Brent from 2000 to 2011, it was found that significant correlations and volatility spillovers effects exist between commodity and equity markets. The results of the VAR-GARCH model also suggest that risk-adjusted returns improve significantly when a well-diversified equity portfolio is built with commodities. (Mensi et al., 2013)

In research on the transmission of volatility between stock markets, Ng (2000) examined the spillover effects of volatility from Japan and the US to Pacific-Basin markets between 1975 and 1996 using GARCH models. The results show that both regional and global factors influence market volatility in the Pacific Basin region. In addition, factors such as "important liberalization events (such as the introduction of country funds and changes in foreign investment restrictions), fluctuations in currency returns, number of DR listings, sizes of trade, and closed-end country fund premium" (Ng, 2000, p. 230) influence global and regional market factors. In addition, less than 10% of weekly return fluctuations in four out of six Pacific Basin countries are influenced by Japanese and US shocks. The author suggests that this may be because the local information variables are not able to capture the changing patterns of global and regional effects, that there are other variables that can better explain the effect, or that something else is related to the region. (Ng, 2000)

The next section provides a more detailed overview of the most relevant and recent research on volatility spillovers conducted in different financial markets using different methodologies. This section aims to present relevant methodologies in different markets and highlight concepts that are of interest to volatility spillover research. Both foreign and domestic research will be presented.

2.1. Effects of volatility spillovers on the Croatian stock market

Although there are only a limited number of research papers dealing with volatility spillover effects on the Croatian stock market, the existing studies include foreign markets, oil prices, foreign exchange and macroeconomic conditions and their impact on the volatility of the Croatian stock market.

Erjavec & Cota (2007) analyzed the dependence of the short-term volatility of the Croatian stock market on the information on international financial markets and the dependence on the volume of traded stocks from 2000 to 2004. First, using GARCH-type models, they concluded that the trading volume is a significant variable explaining the volatility of the CROBEX index, but they considered it irrelevant. Secondly, the authors found that the DAX30 and the FTSE100 have a significant impact on the variability of the CROBEX, suggesting co-movement effects on the same trading day. Finally, they emphasize that the movements of the US stock market indices influence the movements of the CROBEX when a one-day lag is taken into account. (Erjavec & Cota, 2007)

Further research on information from the US was conducted in the study by Sajter & Ćorić (2009), which examined spillover effects between the US and Croatian stock markets from 2005 to 2008. Using ARIMA and GARCH models, the authors found a link between the two markets in terms of investor decision making, especially during the global financial crisis in 2008. These results seem counterintuitive considering that the links between the Croatian and US economic sectors are small. They believe that this phenomenon could be explained by global factors, contagion and irrational escalation. (Sajter & Ćorić, 2009)

Jošić & Žmuk (2021) extend the literature on volatility spillovers in the Croatian stock market by using a GARCH(1,1) model with normal distribution, Student, and generalized error distribution (both with fixed degrees of freedom) for the period from 2010 to 2020. The authors confirm the evidence from Erjavec & Cota (2007) and Sajter & Ćorić (2009) that Croatian investors rely heavily on the previous day's information on the US market and that there are volatility spillovers from the European stock markets. (Jošić & Žmuk, 2021)

As the above research examines the impact of foreign stock markets and their volatility spillovers to the Croatian stock market, further research looks at the impact of other variables, such as oil prices, macroeconomic conditions and exchange rates, on volatility spillovers to the Croatian stock market.

Cipcic et al. (2017) found a non-unidirectional positive relationship between oil prices and the CROBEX using the VAR method in a study period from 2000 to 2015. The explanation for this complex, non-unidirectional relationship could lie in the dependence of oil prices on the supply and demand side. The authors emphasise that "higher oil prices, driven by an unanticipated global expansion, have positive effects on stock returns." (Cipcic et al., 2017, p. 1091).

Evidence of spillover effects between asset classes can also be found in the study by Škrinjarić et al. (2021), who found spillovers effects of exchange rates on stock returns from 2010 to 2018 by applying the methodology of Diebold & Yilmaz (2009). They emphasise that due to larger spillover effects between returns (especially between euro exchange rates and the stock market) as opposed to volatilities, this indicates diversification opportunities in the financial markets. (Škrinjarić et al., 2021)

Finally, Hsing (2011) examined a positive relationship between real GDP, the M1/GDP ratio, the German stock market index and the eurozone government bond yield with the Croatian stock market index from 1997 to 2010. Using E-GARCH models, the author also observed the negative effects of the government deficit to GDP ratio, the domestic real interest rate, the HRK/USD exchange rate and the expected inflation rate on the Croatian stock market index. (Hsing, 2011)

2.2. Volatility spillovers and international financial markets

For a deeper understanding of the impact of volatility spillovers on the Croatian stock market, the findings from research on foreign stock markets offer a valuable starting point. This can be achieved by examining different research methods, concepts and variables used in these studies. The presentation of these academic papers is organized according to the market of interest in each study.

Table 3 contains research on volatility spillovers originating from foreign stock markets. Most of the research uses GARCH-type models to determine the volatility spillovers between different stock markets and regions. Given the vast majority of papers on these spillovers and the fact that the focus of this paper is on analyzing DCC-GARCH models, only research that uses this type of model is discussed in more detail.

Table 3. International stock market volatility spillover research sorted by method and geographical association.

Research papers	Methods	Regions/Countries
Karunanayake & Valadkhani (2011)	M-GARCH	Australia, Singapore, the United States and the United Kingdom
Potharla (2014)	GJR-GARCH, P-GARCH	India and the United States
Li & Giles (2015)	VAR, GARCH-BEKK (1,1)	United States, Japan, China, India, Indonesia, Malaysia, the Philippines and Thailand
Okičić (2015)	ARCH, GARCH models	CEE
Chirila et al. (2015)	GARCH-BEKK	Eastern Europe
Alotaibi & Mishra (2015)	E-GARCH, BEKK-, CCC-, DCC-GARCH	GCC
Chow (2017)	Diebold & Yilmaz (2012)	Asia
Qian & Diaz (2017)	BEKK-, CCC-, DCC-GARCH	Malaysia
Obadiaru et al. (2018)	E-GARCH	West African region
Alfreedi (2019)	GARCH-BEKK	GCC
Spulbar et al. (2020)	E-GARCH, GJR-GARCH, GARCH (1,1)	Developed stock markets and Romania, Poland, India, China and Hungary
Zhong & Liu (2021)	BEKK-, diagonal, CCC-, DCC-GARCH	China, Singapore, Thailand, Indonesia, Malaysia and the Philippines
Chirilă & Chirilă (2022)	TVP-VAR	Germany, France and CEE markets
Sainath et al. (2023)	DCC-GARCH	India and global stock markets

Source: Author

Alotaibi and Mishra (2015) investigated volatility spillovers between global markets and Gulf Cooperation Council (GCC) markets. The study used univariate E-GARCH models as well as bivariate BEKK, DCC and CCC-GARCH models from 2005 to 2013. The authors observed significant return spillovers effects from Saudi Arabia and the United States to the GCC markets. Furthermore, they highlighted that "trade, turnover and institutional quality has significant impacts on regional volatility spillovers from Saudi Arabia to GCC markets." (Alotaibi & Mishra, 2015, p. 1)

Similarly, Qian and Diaz (2017) use the same bivariate methodology to examine volatility spillovers from global markets to the Malaysian market from 1999 to 2015. The results show such effects between European markets, while an unstable relationship is observed with the Chinese market. In addition, the authors examined cross-volatilities from other countries and found that most foreign markets have volatility spillover effects on the Malaysian market. The authors explain such effects with the market integration observed through free trade agreements, investment partnerships and political and social conflicts. They emphasize the importance of volatility transmission between markets as a way to influence investment decisions. (Qian & Diaz, 2017)

Zhong & Liu (2021) investigated volatility spillovers between the Chinese, Singaporean, Thai, Indonesian, Malaysian and Philippine stock markets. The study uses BEKK, DCC, CCC and diagonal GARCH models from 1994 to 2019. The authors emphasize that given this data, the DCC-GARCH approach is the best. They conclude that the dynamic conditional correlation between China and ASEAN markets was positive during the analysis period, with peaks during the Asian financial crisis, the US subprime crisis and the stock market crash in 2015. In addition, the data from the modeling was used to construct two equity portfolios representing hedging opportunities. (Zhong & Liu, 2021)

Finally, Sainath et al. (2023) used the DCC-GARCH model to assess the dynamic linkages and spillover effects between the Indian and global stock markets. The study covers the years 2021 to 2022 and observed significant spillover effects between the markets. In addition, the authors examined the bidirectional spillover effects between the markets in India, Japan and Hong Kong. They explain this interdependence by a high degree of interdependence in the markets, similar to the study by Qian and Diaz (2017) for the Malaysian market. Finally, the authors emphasize that "Factors such as global economic trends, geopolitical events, and investor sentiment contribute to the propagation of volatility spillovers. However, it is important to note that the economic significance of these effects may be limited due to the efficient market mechanisms, arbitrage opportunities, and risk management practices implemented by market participants and institutions." (Sainath et al., 2023, p. 8), suggesting that the results regarding the impact of global integration and market interdependence on investment decisions may not fully explain such a complex relationship.

Stock market volatility is a complex process that is influenced by many factors. To explain the impact of spillovers effects on market dynamics, it is important to analyze all factors that affect investor decision-making and to explore other financial markets that might cause similar effects.

Lamine et al. (2024) analyzed the existence of return and volatility spillover effects between the US and Chinese stock markets, the cryptocurrency market and gold over a study period from 2018 to 2021. Using the methodology of Diebold & Yilmaz (2012), the authors identified diversification and hedging opportunities in the aforementioned markets. According to them, “Bitcoin, Ether, and gold are net receivers of return and volatility shocks.” (Lamine et al., 2024, p. 37). These findings suggest that there are diversification opportunities in the US and Chinese markets by including these assets in portfolios. Furthermore, the authors point out that Stablecoins, which are considered net transmitters of shocks, do not offer hedging opportunities. (Lamine et al., 2024)

Using the same methodology, Hussain & Rehman (2022) examined the volatility spillover effects between GCC equity market returns and S&P Global Oil index returns from 2012 to 2022. They found spillover effects between markets in the GCC region and a linkage with oil prices. According to the authors, Oman's stock market receives volatility spillovers effects from the S&P Global Oil index. Furthermore, the authors point out that the results regarding the spillovers effects of the global oil market “suggest the divergent causal impact of oil price volatility on net volatility spillover in GCC stock markets.” (Hussain & Rehman, 2022, p. 14221)

From 1985 to 2017, Vardar & Aydoğan (2018) found volatility spillover effects between the real estate market and stock markets in Europe. By applying a VAR-BEKK-GARCH approach, the authors found “volatility spillover effects from real estate to stock markets in Denmark, Finland, Ireland, and Spain, whereas evidence running from stock to real estate markets is found in Spain, Sweden, and Italy. In contrast, there is no evidence of any such spillovers in Belgium.” (Vardar & Aydoğan, 2018, p. 619). This means that hedging and diversification opportunities exist considering these markets, but as the effects are not unidirectional, further research and insights are needed. (Vardar & Aydoğan, 2018)

Lee et al. (2016) found that there is a connection between interest rate swap markets and stock market volatility. The authors analyzed daily swap rates, government bond interest rates and stock market index prices of the G7 countries using the Diebold & Yilmaz (2012) approach from 1993 to 2011 and found that the German and French swap markets have an influence on the swap markets of the other countries, but only in one direction. Furthermore, they emphasize that “the long-term swap markets contain leading information to explain subsequent global stock market volatility.” (Lee et al., 2016, pp. 20–21). These findings suggest that in the case of portfolio management, considering swap markets and their impact can provide further information for the decision-making process. (Lee et al., 2016)

Endri et al. (2020) analyzed the impact of global stock indices, interest rates, inflation, and exchange rates on the dynamics of the Indonesian stock market from 2012 to 2018. The GARCH model provided mixed results, suggesting a positive impact of the US and Singapore stock markets, while the Japanese and Chinese stock markets convey negative effects on the dynamics of the Indonesian stock market. In addition, interest rates and inflation have a negative impact on stock prices, while the impact of the exchange rate is positive. (Endri et al., 2020)

Finally, Su et al. (2019) investigated the relationship between uncertainty in the US and stock market volatility in six industrialized and three emerging markets. The research method was a GARCH-MIDAS approach from 1989 to 2015, by country. The results show that news implied uncertainty (NVIX) has an impact on stock market volatility. This leads to lower stock market volatility at higher levels of NVIX. They also suggest that economic policy uncertainty (EPU) is related to stock market volatility of industrialized countries, but financial uncertainty (FU) has no effect on long-term stock market volatility. (Su et al., 2019)

3. Methodology

This study examines a database created from several time series of market price data from 12 stock market indices. The study period ranges from September 8, 2009 to February 24, 2024. All data was provided by Bloomberg Terminal.

3.1. Data

The data (Table 3) contain 12 time series representing 12 stock market indices in 1 region and 9 countries. They cover all major markets, including two local markets (Romania and Slovenia). This section provides an overview of the main variables and their calculation methods.

Table 4. Description of variables

Symbol	Representation	Region/Country
CBX	CROBEX Index	Croatia
SPX	S&P 500 Index	United States
INDU	Dow Jones Industrial Average Index	United States
CCMP	NASDAQ Composite Index	United States
SXXP	STOXX Europe 600 Index	Europe
UKX	FTSE 100 Index	United Kingdom
DAX	Deutsche Boerse DAX Index	Germany
CAC	CAC 40 Index	France
SBI	SBITOP Index	Slovenia
BET	BET Index	Romania
NKY	Nikkei 225 Index	Japan
SHCOMP	Shanghai SE Composite Index	China

Source: Author

The CROBEX Index is the stock index of the Zagreb Stock Exchange, which was introduced on March 9, 1997 and currently consists of 21 constituents representing the Croatian stock market. It is a price index compiled using the free float market capitalization weighting method, excluding dividends. The index is revised semi-annually on the third Friday in March and in

September, and its constituents can vary between 15 and 25 stocks with a maximum weighting of 10%. One of the most important requirements for selection is that a stock is listed on “the Regulated market which trades on more than 75% of the total number of trading days in the six months preceding to the revision” (Zagrebačka burza d.d., 2024, p. 1).

The S&P 500 Index is a float-adjusted market capitalization weighted index that tracks the 500 largest US companies. It was launched in 1957 by the credit agency Standard and Poor's and is used as a benchmark for assessing performance. The index is rebalanced quarterly and does not include dividends. It currently comprises 503 companies, covering around 80% of the available market capitalization. To be included in the index, companies must meet numerous requirements, such as an unadjusted market capitalization of USD 18 billion or more. (Kenton, 2023; S&P Dow Jones Indices LLC, 2024a)

The Dow Jones Industrial Average is a US stock market index that was introduced in 1896 and comprises all sectors with the exception of the transportation and utilities sector. The index is price-weighted and comprises 30 US companies (S&P Dow Jones Indices LLC, 2024b). The index is rebalanced semi-annually in March and September. The selection of stocks for the index depends on their reputation, growth and investor interest. (S&P Dow Jones Indices LLC, 2024c)

The NASDAQ Composite Index is a US stock market index that was introduced in 1985. It includes more than 3000 stocks listed on the Nasdaq Stock Market and tracks them through a market capitalization weighted index (Bajpai, 2021). To meet the criteria for inclusion in the index, a stock must be listed exclusively on the NASDAQ Stock Exchange, and its constituents and weights are rebalanced daily. (Nasdaq Inc., 2020)

The Stoxx Europe 600 Index is a free float market capitalization weighted stock market index representing the 600 largest companies in Europe. It is divided into 20 supersectors based on the ICB industry classification. The index is reviewed quarterly and serves as a benchmark for the European region. (Deutsche Boerse Group, 2024)

The FTSE 100 Index is a market index that represents the UK market. It is a market capitalization weighted index comprising the 100 largest companies traded on the London Stock Exchange. The index was launched in 1984 and is used for index-tracking funds, derivatives and benchmarking purposes (FTSE Russell, 2024). It is reviewed quarterly in March, June, September and December. (London Stock Exchange, 2024)

The DAX index is a stock market index introduced in 1988 that comprises the 40 largest companies listed on the Frankfurt Stock Exchange. It is a free float market capitalization weighted index that is reviewed on a quarterly and semi-annual basis. The index has strict requirements for its constituents, including a minimum free float of 10%, a head office in Germany and certain liquidity requirements. (Deutsche Boerse Group, 2022)

The CAC 40 index is a stock market index that reflects the Paris stock market (Euronext Paris) and was introduced in 1988. It comprises the 40 largest and most actively traded companies and is based on a free float adjusted market capitalization weighting method. The index is reviewed quarterly on the third Friday in March, June, September and December. (Euronext, 2024)

The SBITOP Index is the Slovenian blue chip index, which currently comprises nine companies. The index was introduced in 2006 and can comprise 5 to 15 ordinary shares. It is a free float market capitalization weighted index with a maximum weighting of 30% for any one component. Dividends are not included in the index and index revisions are made quarterly in February, May, August and November. (Ljubljanska borza, 2024)

The BET Index is the stock market index of the Bucharest Stock Exchange, which reflects the performance of the most traded companies, with the exception of financial investment companies. The index is a free float market capitalization weighted index that was introduced in 1997. The main criterion for inclusion in the index is liquidity, and none of the constituents may have a weighting of more than 20%. The index can comprise between 10 and 20 stocks and currently reflects the performance of 20 companies. (BVB, 2014)

The Nikkei 225 Index is the Japanese stock market index that reflects the performance of 225 stocks in the Prime Market of the Tokyo Stock Exchange. It was introduced in 1950 and is reviewed every six months in April and October (Nikkei Inc., 2024). The index is calculated as a weighted price average with a price adjustment factor or a capped price adjustment factor. (Nikkei Inc., 2023)

The Shanghai SE Composite Index is a stock market index that represents the Shanghai market and was introduced in 1991. The index is intended to reflect the development of the Chinese capital markets (Shanghai Stock Exchange, 2024b). The overall index, which is weighted by total market capitalization, is reviewed monthly. Companies must be listed on the Shanghai Stock Exchange to be included in the index. (Shanghai Stock Exchange, 2024a)

After collection, the data was loaded into R Studio for further analysis.

Before statistical tests were performed, the data was transformed into logarithmic returns (Equation 1) using:

Equation 1. Logarithmic returns equation

$$z_t = \log \frac{p_t}{p_{t-1}}$$

Source: Gundersen (2022)

where p_t represents the new price and p_{t-1} the price of the previous day. The particular choice of logarithmic returns is due to the log-normality of the returns. (Gundersen, 2022)

The descriptive characteristics of the data were also analysed. Following the study by Qian & Diaz (2017), the authors performed tests regarding normality of distribution (Jarque-Bera test) and stationarity (Augmented Dickey-Fuller test). The same methods were also used in this study. Finally, a correlation matrix was created for further analysis.

The normality of the distribution was tested using the Jarque-Bera test (Jarque & Bera, 1980). The null hypothesis of the test states that the data are normally distributed using a joint statistic with the coefficients for skewness and kurtosis. (Cromwell et al., 1994; Trapletti, 2024)

The test for stationarity was performed using the Augmented Dickey-Fuller test (Fuller, 1995), which is defined by the following equation:

Equation 2. Augmented Dickey-Fuller test specification

$$ADF = \frac{\rho.hat}{S.E(\rho.hat)}$$

Source: (Qiu, 2024)

where $\rho.hat$ and $S.E(\rho.hat)$ represent the estimation coefficient and its corresponding estimate of the standard error, respectively. The null hypothesis assumes the presence of a unit root in the univariate time series, which indicates non-stationarity. (Fuller, 1995; Qiu, 2024)

3.2. Model specifications

Before modeling the GARCH model from the data, pre-estimation tests were performed to determine the best lags of both the ARMA and GARCH models and to check for the presence of ARCH effects in the time series. Such an approach was chosen based on a similar approach by Qian & Diaz (2017).

First, the best Autoregressive Moving Average (ARMA) model is evaluated based on the Akaike Information Criterion (AIC). ARMA models are used in time series analysis to predict future values based on historical data. The model is a combination of autoregressive (AR) models and moving average (MA) models. The specifications of the ARMA model used in this study are as follows:

Equation 3. ARMA model specification

$$X_t = \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + e_t + b_1 e_{t-1} + \cdots + b_q e_{t-q}$$

Source: (R Core Team, 2024)

where X represents the value on a specific day (t), α and b as coefficients indicating which part of the specific value is relevant. p and q represent the AR and MA factors, respectively, while e represents the error term. (Mehandzhiyski, 2023)

The Akaike Information Criterion (Sakamoto et al., 1986) is a statistical test that allows comparison between fitted models by maximum likelihood estimation on the same data. The smaller the AIC statistic, the better the fit. (Pinheiro et al., 2024; Sakamoto et al., 1986) The specification of the AIC statistic is as follows:

Equation 4. AIC statistic specification

$$AIC = -2log - likelihood + kn_{par}$$

Source: (Pinheiro et al., 2024)

where n_{par} reflects the number of parameters in the model and $k = 2$. (Pinheiro et al., 2024)

Based on the AIC statistics, the best ARMA model specification is selected to fit the GARCH model. First, the data are tested for the presence of ARCH effects using the ARCH-LM test (R. F. Engle, 1982; Tsay, 2010). The null hypothesis states that there is no autoregressive conditional heteroscedasticity. (Pfaff, 2024)

ARMA-GARCH models are fitted based on the presence of ARCH effects and taking into account previous ARMA orders.

GARCH models are time series models developed by Bollerslev (1986). The models are applied to data with serial autocorrelation in the variance error. It is also assumed that the error term follows an ARMA process. The following model is used in forecasting models and in volatility research. (Bollerslev, 1986; The Investopedia Team, 2021)

Since the GARCH model consists of two equations, the conditional mean and the conditional variance equation, the conditional mean equation is represented by the ARMA model. This follows a similar approach to Okičić (2015), the only difference being the use of the ARMA model, which is in contrast to the ARIMA model. (Okičić, 2015)

In addition, the conditional variance equation is specified as follows:

Equation 5. GARCH conditional variance model specification

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_j \epsilon_{t-i}^2$$

Source: (Okičić, 2015)

where p and q are GARCH orders (lags) and w, α_i and β_j are parameters. (Okičić, 2015)

The best model is evaluated using the AIC statistic, and the Li-Mak statistic is used to evaluate the model fit.

The Li-Mak statistic is a weighted ARCH-LM test developed by Li & Mak (1994) and extended by Fisher & Gallagher (2012). Its null hypothesis states that the ARCH process is adequately fitted. (Fisher, 2023)

Since all models up to this point are univariate, methods for bivariate models using DCC-GARCH are presented in the next section.

DCC-GARCH is a mathematical model developed by Engle (2002) which is used to analyze the interconnectedness of stock markets and the presence of volatility spillover effects. Since Qian & Diaz (2017) follow a similar approach, the same methodology is used in this study in terms of DCC estimation and post-estimation techniques.

Prior to modeling DCC-GARCH, tests for multivariate ARCH effects in stock market pairs are conducted. These tests include the multivariate portmanteau tests of Hosking (1980) and Li & McLeod (1981). The null hypothesis in both tests indicates that there is no autoregressive conditional heteroscedasticity in the stock market pairs. (Qian & Diaz, 2017)

The specification of the DCC-GARCH model is based on Sainath et al. (2023) for the model pairs as follows:

Equation 6. DCC-GARCH model specification

$$R_{(t)} = D_{(t)} Q_{(t)} D_{(t)}$$

Source: Sainath et al. (2023)

where $R_{(t)}$ is the estimator of the conditional correlation, $D_{(t)} = diag\sqrt{\sigma(i,t)^\wedge 2}$ is the diagonal matrix of conditional variances. $\sigma(i,t)$ represents the conditional volatility of the return following:

Equation 7. Conditional volatility of return specification

$$\sigma_{(i,t)}{}^{\wedge 2} = \omega_{(i)} + \alpha_{(i)} \varepsilon_{(i,t-1)}{}^{\wedge 2} + \beta_{(i)} \sigma_{(i,t-1)}{}^{\wedge 2}$$

Source: Sainath et al. (2023)

$Q_{(t)}$ represents the conditional covariance matrix and is specified by equations 8 and 9:

Equation 8. Specification of the conditional covariance matrix.

$$Q_t = Q^{*1} Q_t Q^{*1}$$

Source: Sainath et al. (2023)

Equation 9. Conditional covariance matrix

$$Q_{(t)} = \{(1 - \alpha - \beta)\bar{Q}\} + \{\alpha \varepsilon_{(t-1)} \varepsilon_{(t-1)}\} + \{\beta Q_{(t-1)}\}$$

Source: Sainath et al. (2023)

where, $\bar{Q}$ is the unconditional covariance matrix and α and β are the weights given to the prior covariance matrix and the current squared residuals when updating $Q_{(t)}$. (Sainath et al., 2023)

In addition, the authors emphasize that, taking into account the methodology of Bollerslev (1986), $\alpha + \beta < 1$ is satisfied in stationary models. Qian & Diaz (2017) also highlight this as a condition for the quasi maximum likelihood estimator utilized in the modeling. The same condition is used in this model for the DCC estimates.

Based on the statistical significance of the estimates, conclusions are drawn regarding long-term and short-term volatility spillovers.

Some research explores the mixed benefits of using higher order GARCH models (Hansen & Lunde, 2005), therefore the DCC-GARCH models are run using DCC-GARCH(1,1).

The data was accessed via Bloomberg Terminal using Microsoft Excel 365 and the data preparation, statistical analysis, econometric modeling and plotting of charts were performed using R Studio software on R version 4.3.1. The R libraries used in this study include tseries, rugarch, rmgarch, FinTS, e1071, dplyr, summarytools, readxl, forecast, WeightedPortTest, fGarch, portes, corrplot, and *aTSA*.

4. Results

The following section examines the results of the univariate and bivariate econometric models, including the pre- and post-estimation tests. Table 5 categorizes the variables geographically and presents the results of the descriptive statistics and the Jaque-Bera normality test.

Table 5. Descriptive statistics

Groups of stock markets	Stock market	Observations	Mean	Std. Dev	Skewness	Kurtosis	J-Bera
Croatia	CBX	5,286	0.0001	0.0061	-1.960	50.876	573,923*** *(0.000)*
US	SPX	5,286	0.0004	0.0094	-0.784	20.354	91,866*** *(0.000)*
	INDU	5,286	0.0003	0.0092	-0.911	28.083	174,584*** *(0.000)*
	CCMP	5,286	0.0004	0.0109	-0.634	12.701	35,919*** *(0.000)*
Europe	SXXP	5,286	0.0001	0.0088	-0.881	14.623	47,826*** *(0.000)*
	UKX	5,286	0.0001	0.0093	-0.965	16.506	60,879*** *(0.000)*
	DAX	5,286	0.0002	0.0104	-0.517	11.881	31,355*** *(0.000)*
	CAC	5,286	0.0001	0.0106	0.034	12.227	33,237*** *(0.000)*
CEE	SBI	5,286	0.0001	0.0073	-1.130	16.001	57,570*** *(0.000)*
	BET	5,286	0.0002	0.0096	-1.058	25.726	146,880*** *(0.000)*
Asia	NKY	5,286	0.0002	0.0105	-0.265	7.307	11,834*** *(0.000)*
	SHCOMP	5,286	0.0000	0.0113	-1.003	10.927	27,209*** *(0.000)*

*Note: ***, **, and * are significant on a 1%, 5%, and 10% level*

Source: Author

The descriptive statistics results show that each time series examined has 5.286 observations. Most of the returns of the stock market indices are leptokurtic, indicating strong tails in the distribution during the study period. In addition, all US stock market indices and the European indices (with the exception of the CAC) appear to be slightly negatively skewed. CBX, SBI, BET and SHCOMP are strongly negatively skewed, while NKY and CAC appear symmetric.

The significance of the Jaque-Bera statistics indicates that the returns of all stock market indices are not normally distributed.

Figure 2 examines the correlation between the returns of the 12 stock market indices.

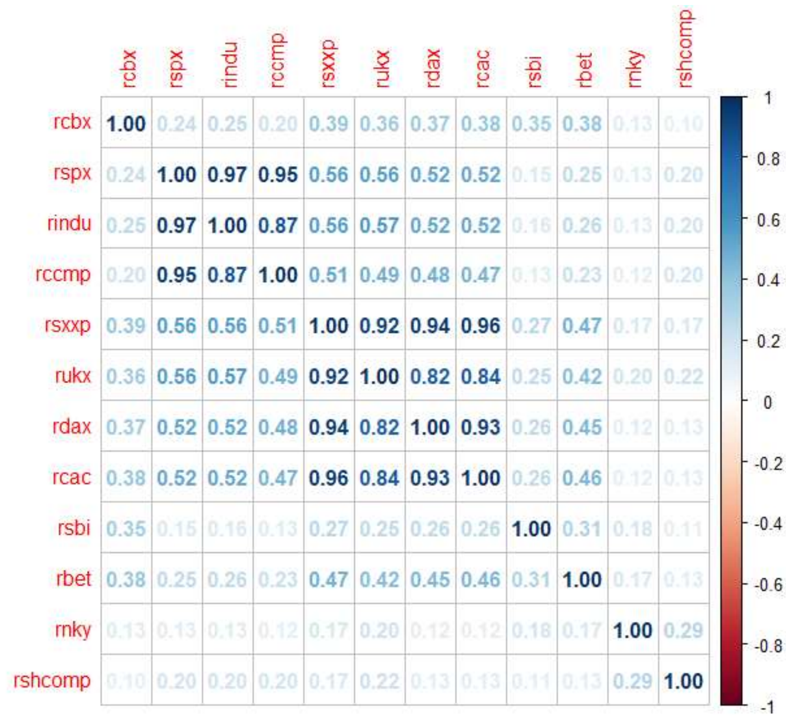

Figure 2. Correlogram of 12 stock market indices

Source: Author

The correlogram shows that the returns of all US stock market indices are correlated with each other. Similar results can be observed for the largest European stock market indices. The indices of the CEE markets appear to be moderately correlated with each other, which also applies to the returns of the Asian stock markets. Looking at the correlation between the markets and the returns of the Croatian stock market index, moderate correlations can be seen between the returns of all European and CEE stock market indices, while the returns of the US and Asian stock market indices appear to be less correlated with CBX. The highest correlation in this period is between the CBX and the SXXP.

The pre-estimation test statistics are shown in Figure 3. The results regarding the stationarity of the data indicate that all time series are stationary. The best ARMA orders were selected on the basis of the AIC statistics.

Table 6. Pre-estimation test statistics

Stock market	ADF raw	ADF	ARMA	AIC	ARCH-LM	GARCH	AIC	Li-Mak
CBX	-1.85 *(0.643)*	-14.69*** *(0.01)*	(3,3)	-39,000.60	932.12*** *(0.000)*	(2,2)	-7.694	1.694 *(0.96)*
SPX	-2.69 *(0.287)*	-16.81*** *(0.01)*	(1,0)	-34,386.64	1620.10*** *(0.000)*	(1,2)	-6.830	26.847*** *(0.000)*
INDU	-4.16*** *(0.01)*	-16.79*** *(0.01)*	(5,1)	-34,656.22	1605.80*** *(0.000)*	(1,2)	-6.914	25.325*** *(0.000)*
CCMP	-2.25 *(0.471)*	-16.87*** *(0.01)*	(1,0)	-32,860.65	1293.10*** *(0.000)*	(2,1)	-6.471	37.198*** *(0.000)*
SXXP	-4.11*** *(0.01)*	-17.20*** *(0.01)*	(0,0)	-34,995.16	675.23*** *(0.000)*	(1,2)	-6.913	22.307*** *(0.000)*
UKX	-3.62** *(0.031)*	-17.56*** *(0.01)*	(0,0)	-34,497.27	839.17*** *(0.000)*	(1,2)	-6.812	13.272** *(0.013)*
DAX	-4.11*** *(0.01)*	-16.78*** *(0.01)*	(2,2)	-33,244.89	670.24*** *(0.000)*	(1,2)	-6.532	20.056*** *(0.000)*
CAC	-3.50** *(0.042)*	-17.48*** *(0.01)*	(0,0)	-33,076.71	585.63*** *(0.000)*	(1,2)	-6.522	14.083*** *(0.009)*
SBI	-2.50 *(0.367)*	-15.61*** *(0.01)*	(5,0)	-36,321.76	528.41*** *(0.000)*	(1,2)	-7.251	14.149*** *(0.008)*
BET	-2.26 *(0.466)*	-16.16*** *(0.01)*	(2,2)	-34,139.72	503.38*** *(0.000)*	(1,2)	-6.843	1.910 *(0.939)*
NKY	-3.93** *(0.013)*	-17.48*** *(0.01)*	(0,1)	-33,213.19	679.13*** *(0.000)*	(1,2)	-6.415	20.105*** *(0.000)*
SHCOMP	-2.61 *(0.319)*	-17.38*** *(0.01)*	(0,0)	-32,398.19	454.58*** *(0.000)*	(1,2)	-6.356	16.47*** *(0.003)*

Note: ***, **, and * are significant on a 1%, 5%, and 10% level

Source: Author

The ARCH-LM statistics indicate that autoregressive conditional heteroscedasticity is present in all 12 time series. Since the presence of ARCH effects is a prerequisite for GARCH modeling, the data can be further used for GARCH modeling. Similarly, the best GARCH orders were selected based on the AIC statistics. The results indicate that the null hypothesis that the ARCH process is adequately fitted is rejected for all markets except CBX.

Table 7 shows the results of the bivariate DCC-GARCH model for stock pairs. Eleven stock pairs were constructed to reflect the dynamic conditional correlations between the Croatian and foreign stock market indices.

Table 7. Bivariate DCC-GARCH model of stock pairs

Stock market pair	Model order	AIC	Multivariate Portmanteau tests: Hosking (1980)	Multivariate Portmanteau tests: Li-McLeod (1981)	α	β	αDCC	βDCC	αDCC + βDCC	Log-Likelihood
CBX SPX	(1,1)	-14.528	260.98*** *(0.000)*	260.90*** *(0.000)*	0.0592*** *(0.000)* 0.7633*** *(0.000)*	0.9153*** *(0.000)* 0.8978*** *(0.000)*	0.0077 *(0,958)*	0.9581*** *(0.000)*	0.9657	38,407.94
CBX INDU	(1,1)	-14.615	256.00*** *(0.000)*	255.91*** *(0.000)*	0.0592*** *(0.000)* 0.7572*** *(0.000)*	0.9153*** *(0.000)* 0.8935*** *(0.000)*	0.0081** (0,015)	0.9563*** *(0.000)*	0.9644	38,638.45
CBX CCMP	(1,1)	-14.171	213.40*** *(0.000)*	213.34*** *(0.000)*	0.0592*** *(0.000)* 0.0614*** *(0.000)*	0.9153*** *(0.000)* 0.9186*** *(0.000)*	0.0079** (0,020)	0.9644*** *(0.000)*	0.9723	37,465.49
CBX SXXP	(1,1)	-14.689	83.52*** *(0.000)*	83.48*** *(0.000)*	0.0592*** *(0.000)* 0.0793*** *(0.000)*	0.9153*** *(0.000)* 0.9026*** *(0.000)*	0.0133*** *(0,000)*	0.9691*** *(0.000)*	0.9824	38,832.99
CBX UKX	(1,1)	-14.57	99.09*** *(0.000)*	99.05*** *(0.000)*	0.0592*** *(0.000)* 0.0619*** *(0.000)*	0.9153*** *(0.000)* 0.9158*** *(0.000)*	0.0117*** *(0,000)*	0.9705*** *(0.000)*	0.9822	38,520.31
CBX DAX	(1,1)	-14.306	79.52*** *(0.000)*	79.49*** *(0.000)*	0.0592*** *(0.000)* 0.0525*** *(0.206)*	0.9153*** *(0.000)* 0.9340*** *(0.000)*	0.0139*** *(0,000)*	0.9678*** *(0.000)*	0.9817	37,822.56
CBX CAC	(1,1)	-14.301	79.02*** *(0.000)*	78.99*** *(0.000)*	0.0592*** *(0.000)* 0.0742*** *(0.000)*	0.9153*** *(0.000)* 0.9096*** *(0.000)*	0.0147*** *(0,000)*	0.9683*** *(0.000)*	0.9830	37,807.77
CBX SBI	(1,1)	-15.013	105.99*** *(0.000)*	105.95*** *(0.000)*	0.0592*** *(0.000)* 0.0666*** *(0.000)*	0.9153*** *(0.000)* 0.9050*** *(0.000)*	0.0141*** *(0,000)*	0.9709*** *(0.000)*	0.9850	39,690.28
CBX BET	(1,1)	-14.602	105.98*** *(0.000)*	105.92*** *(0.000)*	0.0592*** *(0.000)* 0.0975*** *(0.000)*	0.9153*** *(0.000)* 0.8852*** *(0.000)*	0.0128** (0,016)	0.9703*** *(0.000)*	0.9831	38,605.25
CBX NKY	(1,1)	-14.093	196.93*** *(0.000)*	196.88*** *(0.000)*	0.0592*** *(0.000)* 0.0613*** *(0.000)*	0.9153*** *(0.000)* 0.8964*** *(0.000)*	0.0021 (0,269)	0.9911*** *(0.000)*	0.9932	37,259.25
CBX SHCOMP	(1,1)	-14.049	45.26*** *(0.001)*	45.25*** *(0.001)*	0.0592*** *(0.000)* 0.0336*** *(0.000)*	0.9153*** *(0.000)* 0.9592*** *(0.000)*	0.0058 (0,415)	0.8986*** *(0.000)*	0.9044	37,142.77

*Note: ***, **, and * are significant on a 1%, 5%, and 10% level*

Source: Author

The pre-estimation statistics regarding the presence of multivariate ARCH effects indicate statistical significance in both the Hosking and Li-Mcleod statistics for all stock market pairs.

These effects are further modeled using the DCC-GARCH(1,1) approach, which yielded significant results for both long-term and short-term volatilities, except for the short-term volatilities of the CBX/SPX, CBX/NKY and CBX/SHCOMP pairs. Furthermore, the results show that the condition αDCC + βDCC < 1 is fulfilled in all cases.

Figures 3 to 13 show the dynamic conditional correlations over the entire study period.

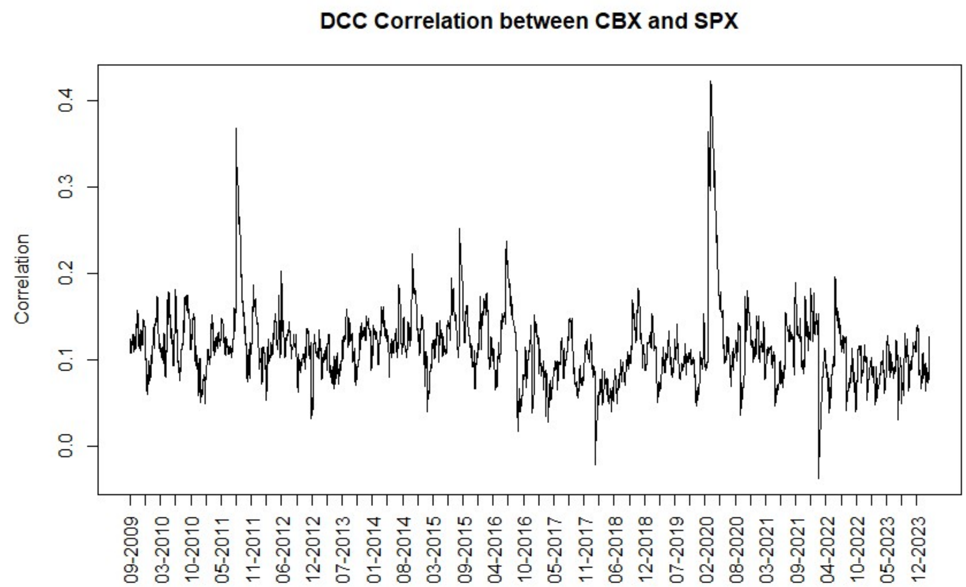

Figure 3. Dynamic Conditional Correlation between CBX and SPX

Source: Author

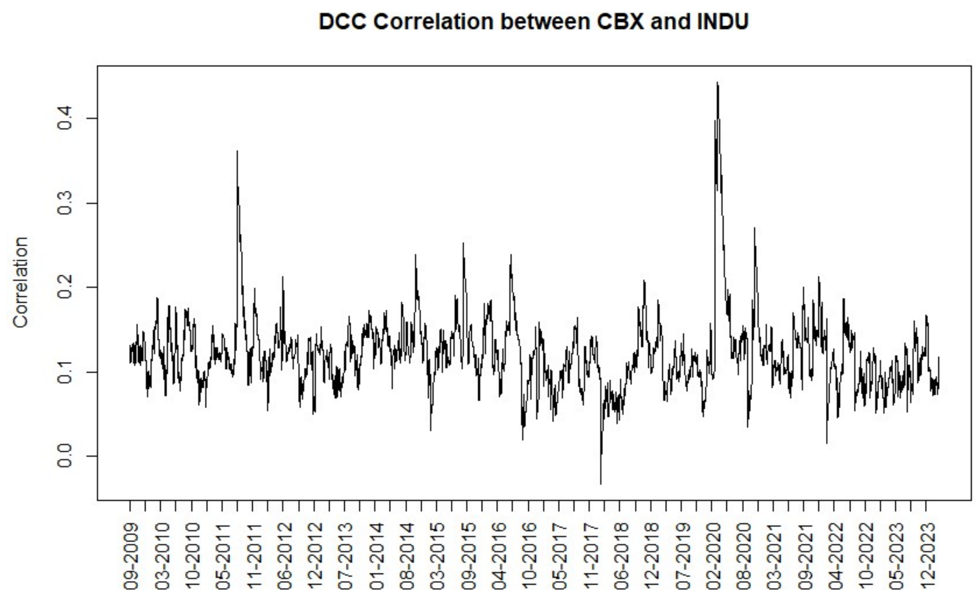

Figure 4. Dynamic Conditional Correlation between CBX and INDU

Source: Author

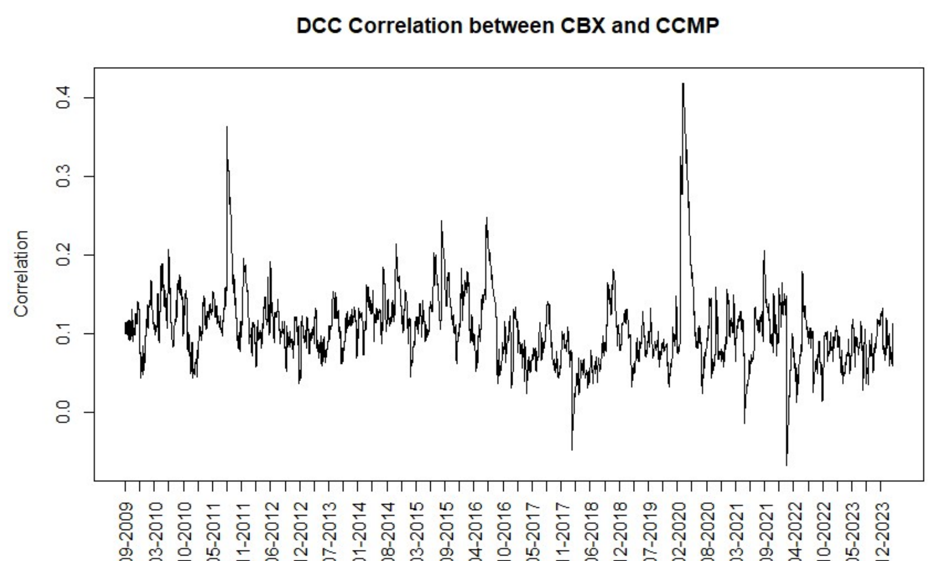

Figure 5. Dynamic Conditional Correlation between CBX and CCMP

Source: Author

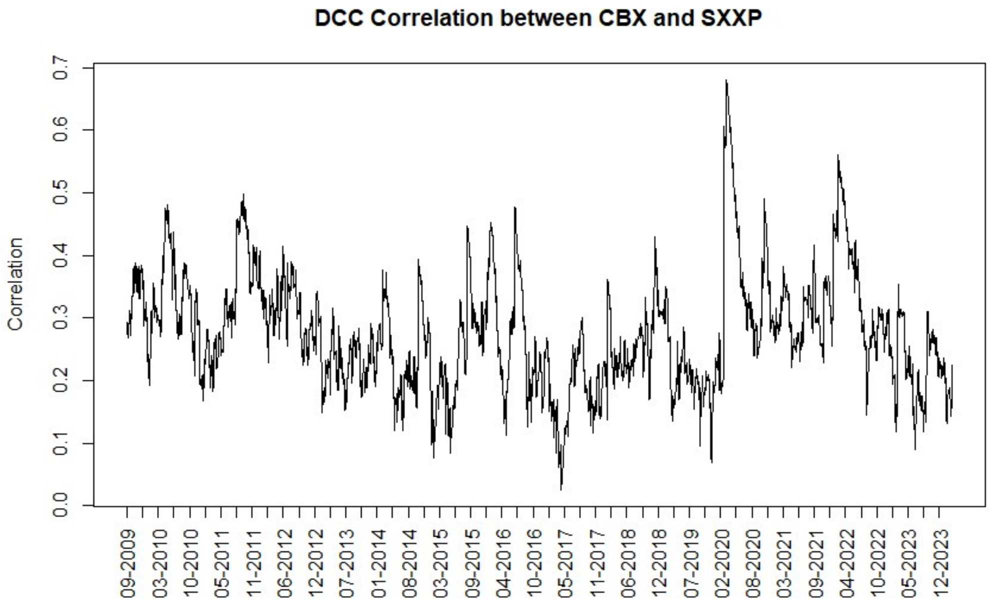

Figure 6. Dynamic Conditional Correlation between CBX and SXXP

Source: Author

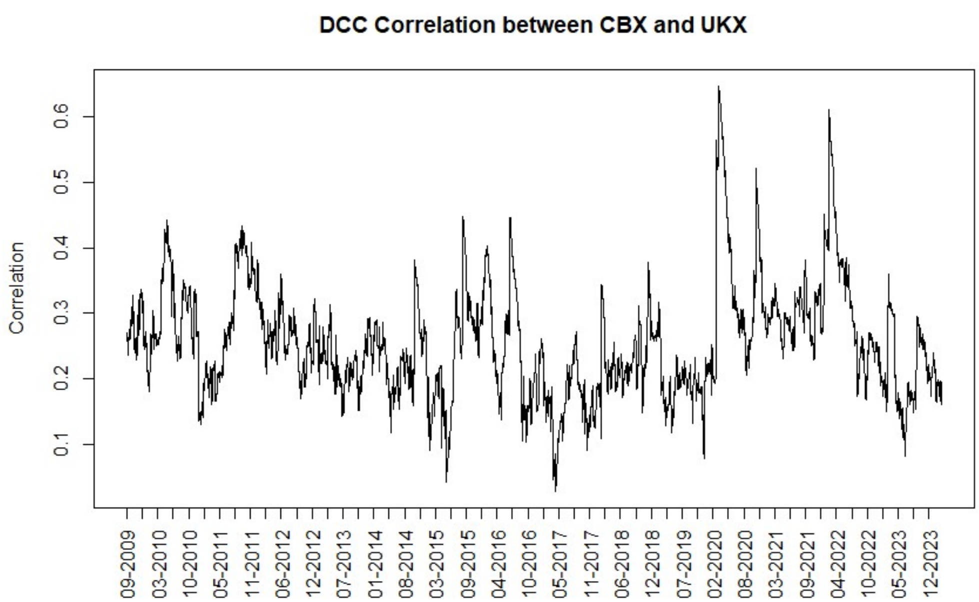

Figure 7. Dynamic Conditional Correlation between CBX and UKX

Source: Author

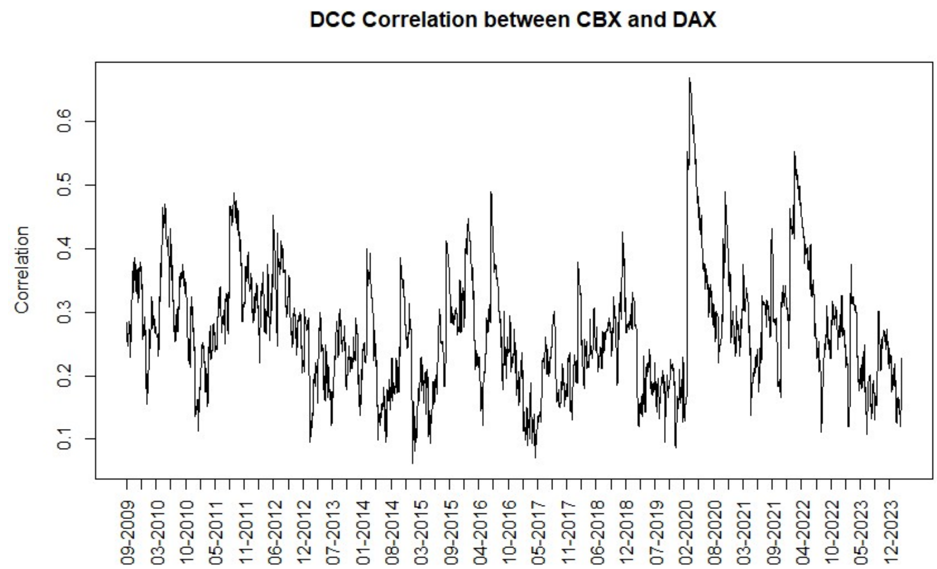

Figure 8. Dynamic Conditional Correlation between CBX and DAX

Source: Author

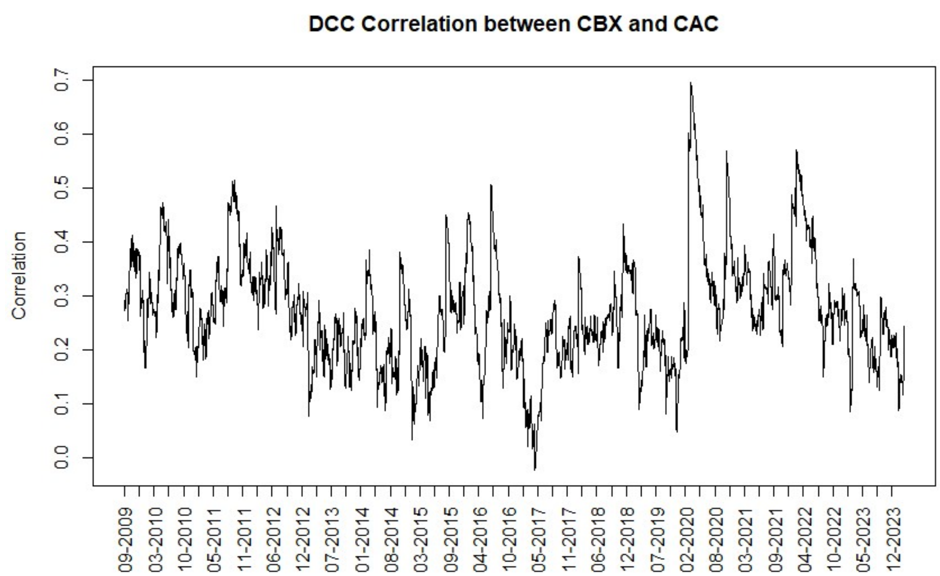

Figure 9. Dynamic Conditional Correlation between CBX and CAC

Source: Author

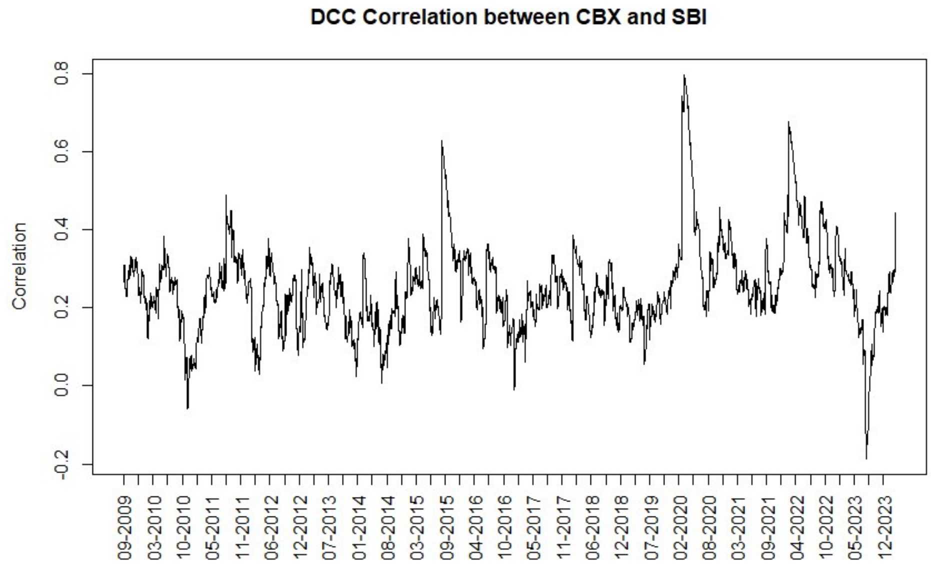

Figure 10. Dynamic Conditional Correlation between CBX and SBI

Source: Author

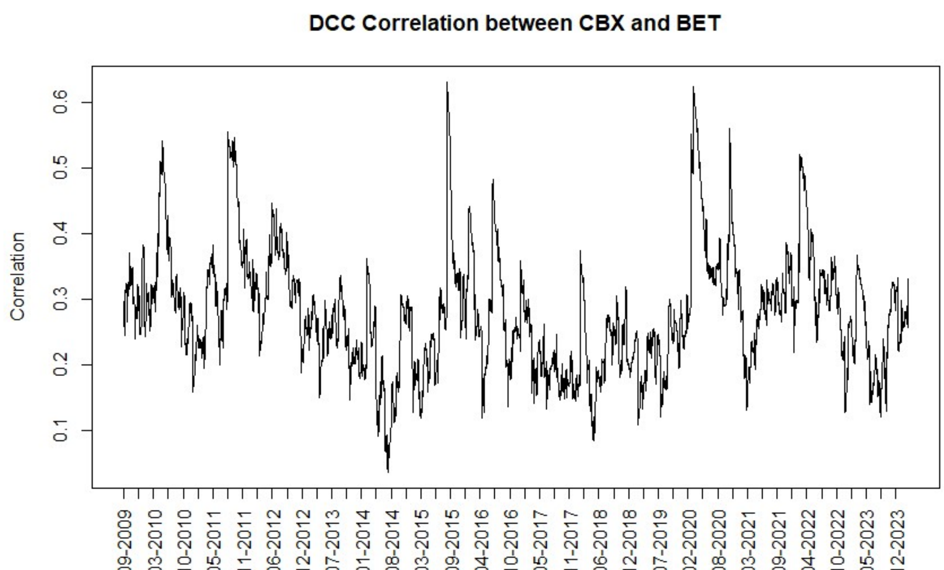

Figure 11. Dynamic Conditional Correlation between CBX and BET

Source: Author

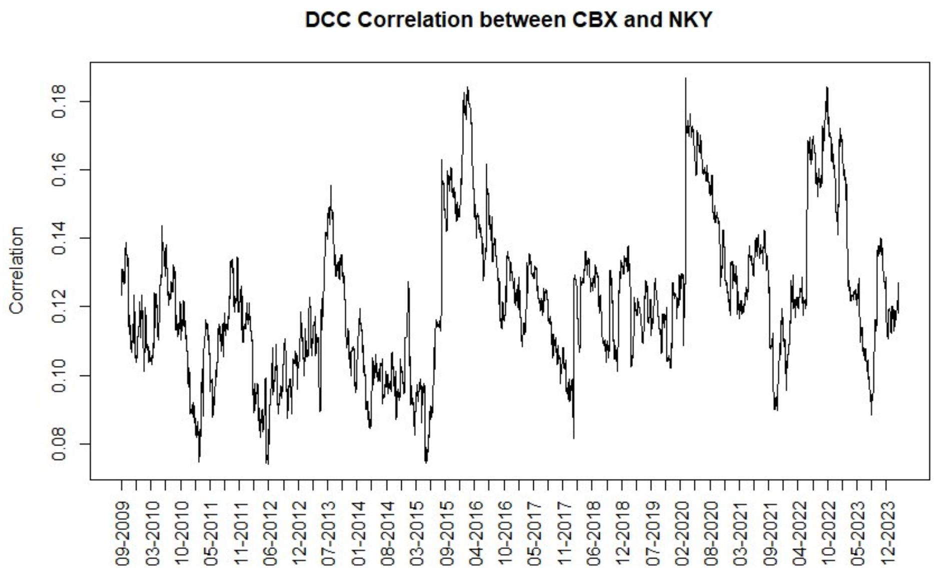

Figure 12. Dynamic Conditional Correlation between CBX and NKY

Source: Author

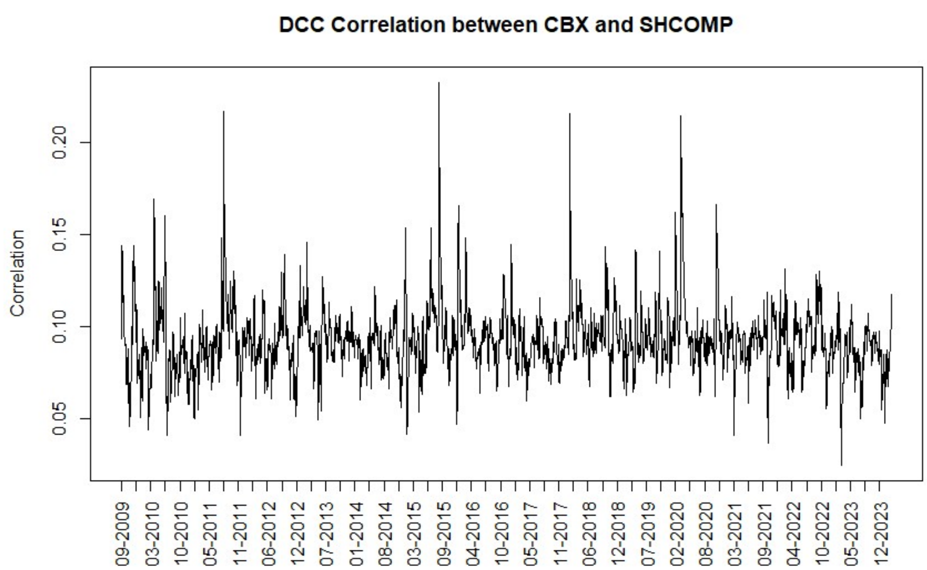

Figure 13. Dynamic Conditional Correlation between CBX and SHCOMP

Source: Author

5. Discussion

Volatility spillovers are complex processes that affect global markets in complex ways. Analyzing the volatility transmission processes between different markets shows the complexity of market dynamics and investors' decision-making processes. Taking into account the results obtained through univariate and bivariate analyses in conjunction with previous research, the impact of volatility spillovers on the Croatian stock market will be explained.

Looking first at the correlation diagram shown in Figure 2, it can be seen that there is a correlation depending on the geographical region or sub-region of the world, indicating the interconnectedness of global markets. It can be seen that most European stock markets are interdependent. These interdependencies are explained later in the text. Furthermore, the different markets show different correlations, which could be explained by the greater influence of political associations, government partnerships and the interdependence of the markets in terms of business, investment and overall dependence on the economy. The correlation analysis between foreign markets and the Croatian market has shown that there is a greater correlation between the Croatian stock market and the European markets than between the US or Asian markets. This could be logical as Croatia is an EU member. These results could become even clearer if one considers that Croatia has joined the EMU and has adopted the euro as its national currency. However, this assumption can only be verified after a longer period of time. In addition, EU membership has brought Croatia benefits such as the transition of workers, globalization, integration into international markets and greater import and export opportunities. Finally, the influence of European funding has had a major impact on the growth of the Croatian economy. This could also be confirmed considering the lower interdependence between the Asian and Croatian markets, as these markets have less in common with the Croatian economy than the European and American markets.

Since the correlations between the European nations and Croatia are moderately correlated, it is obvious that the volatility of the Croatian stock markets is not only influenced by other markets but also by other variables.

In order to explain the influence of foreign markets on the volatility of the Croatian stock market, it is important to examine the volatility dynamics over time. Figures 3 – 13 show that there is a similar dynamic conditional correlation between the European stock markets and Croatia. The same similarities can be seen when looking at the Asian markets and the US markets independently.

The European markets appear to show similar jumps in dynamic conditional correlation, and when the Europe-Croatia stock market pairs are analysed separately, it is clear that the jumps are similar. It is also interesting to note that the values for the dynamic conditional correlation are between 0 and 0.7, suggesting a strong dynamic conditional correlation. These results indicate stronger market integration during periods of high dynamic conditional correlation. This could be explained by the facts presented above, such as EU integration. The largest jumps are observed in the COVID-19 crisis period, which had the highest dynamic conditional correlation values. This is in line with the findings of Zhong & Liu (2021) and Sajter & Ćorić (2009) on greater market interdependence in times of crisis.

In addition, the dynamic correlations between the Croatian and US markets are predominantly positive and are up to 0.4, indicating less interdependence than in the European markets. Furthermore, these results indicate possible spillover effects from the US markets. These results lead to a similar conclusion regarding the interdependence and volatility spillover effects from the US markets to the Croatian stock market, which were investigated by Erjavec & Cota (2007), Sajter & Ćorić (2009) and Jošić & Žmuk (2021).

Looking at the CEE region, the dynamic conditional correlations differ significantly from the correlations evaluated with the correlogram. The DCC results might be more intuitive considering that Croatia is part of the CEE region and that more cultural, political and regional influences determine the market dynamics. The dynamic conditional correlation, which is 0.6 in the case of the Romanian market and 0.8 in the case of the Slovenian market, contributes to this fact, as Slovenia is a close neighbor of Croatia and thus exerts a greater economic influence on each other.

Finally, the data from the Asian region also provides intuitive results, considering that the Croatian and Asian markets are not directly connected. The values of up to 0.2 indicate a low dynamic correlation. In contrast to the European and American markets, which show similar correlations when considering which markets they belong to, the NKY and SHCOMP markets show different correlations, although they both belong to the Asian market. This could be due to the fact that they are different types of economies with different policies and foreign partnerships.

Looking at all markets, the interdependence of the markets is highest in times of crisis, which is particularly visible in this study due to the COVID-19 crisis.

Since most of the markets mentioned have different links to each other, the key to understanding this type of market dynamic lies in understanding the underlying political and economic drivers of country integration. As this topic is beyond the scope of this study, this is a suggestion for further research.

Looking at the αDCC and βDCC coefficients, it is clear that most of the volatility spillovers arise when considering the long-term βDCC coefficients, which appear statistically significant across all market pairs. Furthermore, markets other than the S&P 500 and Asian markets do not exhibit short-term volatility spillovers given these data. Given the coefficients, one could use them to predict volatilities for portfolio optimization and weight selection. High and low periods of dynamic conditional correlation indicate opportunities for diversification into other markets and geographical regions. In addition, such indications offer hedging opportunities in low correlation markets. Nevertheless, it is important to remember that there are other markets such as commodity markets, interest rates and other markets that could influence market dynamics, for which there is evidence from academic research. Also, it is important to consider the conclusion of Sainath et al. (2023) who questions the importance of the relationships between global integration and volatility transmission effects when efficient markets, arbitrage and similar factors are taken into account.

It is important to note that most markets are highly interconnected due to globalization. The largest stock markets that influence investors decision making globally could impact stock market pairs when considering cross-correlations between foreign markets. This could influence the results by exaggerating the impact of spillover effects in market pairs.

Suggestions for further research include exploring other methods of analysing volatility spillovers such as Diebold & Yilmaz (2012) and Baruník & Křehlík (2018) as well as other asymmetric GARCH approaches. These models could shed more light on the impact of information flowing from foreign markets to local markets and the direction of volatility transmission.

It is important to understand the market dynamics of local markets and their interdependencies, which are crucial for investors and policy makers. These outcomes can be reflected in portfolio management, optimization and risk management decisions. Furthermore, these dynamics have an impact on the economy as a whole, as demonstrated by Holmes & Maghrebi (2016) through the interlinkage of stock market returns and unemployment rates.

6. Conclusion

Research conducted in the field of volatility spillovers suggests that understanding these types of effects is of great importance. The knowledge can be used for investment purposes, portfolio management, risk assessment, governance and policy decisions.

The results show that the volatility of the Croatian stock market is influenced by volatility spillovers from all global markets, but mainly in the long term. The results also suggest a stronger interdependence of local and European markets than foreign markets. Such relationships could be explained by global integration, cultural and political similarities and economic partnerships. These results could be useful in portfolio optimization and policy making.

A shortcoming of this study is that it only tests for connectedness using one type of univariate and bivariate model. In addition, it is problematic to include only stock market indices as dependencies, as there are also dependencies in other markets, as suggested by research in different markets. Furthermore, the results do not explain the relationship in terms of the direction of spillovers and may be influenced by cross-correlations from other markets.

Recommendations for further research include the use of asymmetric GARCH models such as GJR-GARCH, E-GARCH and others. Also, an implementation of other bivariate models to explain the conditional correlation using BEKK, CCC or diagonal GARCH. Possible results regarding the effect of net receivers or transmitters of volatility on the Croatian stock market could lead to different results by using the approach of Diebold & Yilmaz (2012). Finally, the implementation of uncertainty variables such as NVIX could shed more light on this complex relationship, especially in the case of interdependence with US markets.

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