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Stock market comovements in Central and Eastern Europe during the COVID-19 pandemic and the Russian war in Ukraine

Bachelors's thesis

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Abstract

We use multivariate generalized autoregressive conditional heteroskedastic models to analyze the comovements of Central and Eastern European stock markets with those of the European Union and the Russian Federation between 2013 and 2023. The thesis investigates the impacts of the COVID-19 pandemic and the Russian War in Ukraine on conditional correlations. Furthermore, we assess the progress of European market integration, quantified by changes in conditional correlations, and evaluate the relevance of the studied markets for diversification of investments. Significant asymmetries in conditional covariances are found, indicating increased interdependence during crises. Interestingly, the trend of rising correlations in the region has stalled, suggesting a slowdown in economic integration into the European Union. All analyzed countries exhibit either high correlations or extreme correlation spikes with European markets during crises, indicating the limited value of these markets as diversification vehicles.

JEL Classification	F12, F36, G15, C58, G01
Keywords	comovements, stock market, Central Europe, Eastern Europe, Baltics, volatility modelling, COVID-19, Ukraine

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Abstrakt

Používáme mnohorozměrné zobecněné autoregresivní podmíněné heteroskedastické modely k analýze ko-pohybů středoevropských a východoevropských akciových trhů s trhy Evropské unie a Ruské federace mezi lety 2013 a 2023. Tato práce zkoumá dopady pandemie COVID-19 a ruské války na Ukrajině na podmíněné korelace. Dále hodnotíme pokrok v integraci evropských trhů, který je kvantifikován změnami v podmíněných korelacích, a posuzujeme význam zkoumaných trhů pro diverzifikaci investic. Byly nalezeny významné asymetrie v podmíněných kovariancích, což naznačuje zvýšenou vzájemnou závislost během krizí. Zajímavé je, že trend rostoucích korelací v regionu se zastavil, což naznačuje zpomalení ekonomické integrace do Evropské unie. Všechny analyzované země vykazují buď vysoké korelace, nebo extrémní výkyvy korelací s evropskými trhy během krizí, což ukazuje na omezenou hodnotu těchto trhů jako prostředků pro diverzifikaci.

JEL klasifikace	F12, F36, G15, C58, G01
Klíčová slova	burza, Střední Evropa, Východní Evropa, Pobaltí, modelování volatilit, COVID-19, Ukrajina

Název	Vzájemné pohyby akciových trhů ve střední a východní Evropě během pandemie COVID-19 a ruské války na Ukrajině.

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Acronyms

EU European Union

GARCH Generalized Auto-regressive Conditional Heteroskedasticity

MPT Modern Portfolio Theory

SARS Severe acute respiratory syndrome

GDP Gross Domestic Product

EMU European Monetary Union

GFC Great Financial Crisis

ADCC Asymmetric Dynamic Conditional Correlation

DCC Dynamic Conditional Correlation

EGARCH Exponential GARCH

GJR-GARCH Glosten, Jagannathan & Runkle GARCH

TGARCH Threshold GARCH

VEC Vector GARCH

BEKK Baba, Engle, Kraft & Kroner GARCH

ARCH Auto-regressive Conditional Heteroskedasticity

CCC Constant Conditional Correlation GARCH

ADF Augmented Dickey-Fuller

BIC Bayesian Information Criterion

AIC Akaike Information Criterion

MLE Maximum Likelihood Estimation

QMLE Quasi-Maximum Likelihood Estimation

AR Auto-regressive

ARMA Auto-regressive Moving Average

CE Central European

EE Eastern European

Chapter 1

Introduction

Understanding the correlation between stock markets is invaluable for many economic agents. Using the Modern Portfolio Theory (MPT) as their basis, portfolio managers have been analyzing market correlations for decades in order to optimize their portfolio diversification, thereby maximizing their return-to-risk ratio. During the 1990s and early 2000s, investing in Central European (CE) and Eastern European (EE) stock markets had been a common way of diversifying as they were considered more segmented than the developed markets. However, the accession and increasing integration of these countries into the European Union (EU) during the 2000s has cast into doubt the effectiveness of such diversification. More generally, the efficacy of correlation-based diversification has been contested as it has been shown that market correlations increase during downturns, rendering this method ineffective during most critical moments; see Erb *et al.* (1994) and Hardouvelis *et al.* (1999).

Furthermore, market correlation has been one of the main tools for gauging market integration, which is especially relevant for European policymakers as CE and EE countries have been joining the EU. The exact nature and degree of integration of these countries are somewhat debated; see Egert & Kocenda (2007), Gilmore *et al.* (2008), Nikkinen *et al.* (2012) and Gjika & Horvath (2013), among others. However, the consensus is that the region's integration with the EU markets did increase during the 2000s. This thesis aims to assess the development of correlations between CE and EE countries and the EU and Russian markets between 2013 and 2023. The first goal is to determine whether the market integration with the EU markets continued and whether the studied countries became more distanced from the Russian market. We expect that the integration with the EU has stagnated as the EU made no significant political or economic advancements during the period. The second goal is to analyze how these market relations changed during the COVID-19 pandemic and the Russian War in Ukraine. We expect to find an increase in correlation during crises, especially at the beginning of the COVID-19 pandemic and the Ukraine war. Furthermore, we expect to observe early signs of divergence of the European economies from the Russian economy as a result of the Russian war in Ukraine. Lastly, we ascertain the relevancy of utilizing these markets for diversification in a portfolio currently made up of mostly Western stocks.

The thesis is structured in the following way: Chapter 2 discusses literature relevant to our thesis, Chapter 3 introduces the data used and specifies the methodology, Chapter 4 compares model results and further discusses the results of the better-fitted model, and Chapter 5 concludes the thesis with a summary of the findings and a discussion of limitations.

Chapter 2

Literature Review

In this chapter, we will discuss the related literature. We will go over general literature on stock market comovements. The European markets specifically will be discussed. Lastly, we will conduct an overview of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models, which we will utilize to analyze the data.

2.1 Stock Market Comovements

Minimizing risk and maximizing returns have always been at the core of investing. The most popular approach to portfolio management is the MPT, outlined by Markowitz in the 1952 essay 'Portfolio Selection,' in which he shows that it is possible to maximize the return-to-risk ratio of a portfolio by investing in different markets with low correlation (assuming one uses volatility to represent risk). As a result, the interdependence and comovement of stock markets have been of paramount interest to finance economists for decades. Periods of crises, in particular, are critical to study, as that is when adequate diversification is needed the most.

With regards to comovements, Lin *et al.* (1994) analyzed intraday data of the Tokyo and New York stock exchanges and found that daytime returns of one are correlated with overnight returns of the other, thereby implying that released information has a global effect irrespective of the hour it is released. Furthermore, it shows us that transmission between international stock markets can be nearly immediate. Moreover, Erb *et al.* (1994) studied the correlations of G7 countries' stock markets and found that correlations during bear markets tend to be higher than during bull markets. This observation can be seen repeatedly in the literature, as we will see later on. Another conclusion of the paper was that correlations are higher when countries' business cycles are in sync, perhaps a rather vacuous statement.

Another metric of interest concerning MPT and portfolio management more broadly is volatility. It has been repeatedly observed that volatility and return are negatively correlated; see Bhowmik & Wang (2020) for an overview. A common reason provided for this phenomenon is the leverage effect. As a firm loses stock value, its debt-to-equity ratio increases, thereby making the stock more risky, which causes an increase in its volatility. However, Bekaert & Wu (2000), among others, argue that the leverage effect on its own is not enough to explain the phenomenon. They propose another explanation: a 'volatility feedback loop.' It is contended that when the volatility of a stock increases, expected returns need to increase in order to compensate for the increased risk to investors. This compensation manifests in the form of a decrease in stock price.

Concerning stock movement during crises, Longin & Solnik (2001) look at monthly stock index data of five developed markets and find that the correlation of extremely positive returns between countries tends to zero the higher the returns are. However, the same can not be said about negative returns; this finding aligns with the observation made by Erb *et al.* (1994). The term contagion is often used to describe the phenomenon of increasing correlation between international markets during market downturns. However, the extent and even the existence of contagion in financial markets has been hotly debated in academic circles. Forbes & Rigobon (2002) in their contentious paper 'No Contagion, Only Interdependence' criticize the correlation studies done up to that point for not correctly accounting for heteroskedasticity in their data and that the values they used are upward biased. They show that the correlation between two variables can increase as a result of an increase in variance despite the real relationship remaining constant. Forbes & Rigobon (2002) introduce a method for calculating 'unconditional correlation' assuming no endogeneity and no omitted variable and subsequently show that many of the crises previously touted as examples of contagion were nothing but cases of simple interdependence when this metric is used. This finding, in turn, has been criticized by Corsetti *et al.* (2005), who contended that Forbes & Rigobon (2002) failed to distinguish between country-specific and global shocks and that this failure biased their test results towards the 'no contagion' conclusion. They also looked at the effects of the 1997 Hong Kong crash and concluded that contagion was likely a factor.

In recent years, contagion has been discussed in the context of the 2020 COVID-19 pandemic. For instance, using correlation analysis, Okorie & Lin (2021) found significant but short-term contagion among several world economies during the initial outbreak of COVID-19 in March 2020. He et al. (2020) conclude as well that the impact of the pandemic on stock markets has been significant but short-term. In addition, they find bidirectional spillover effects between Asian and Western economies. Furthermore, Baker *et al.* (2020) use text-based analysis of newspapers to compare the effect of the recent pandemic with the ones in 1918-1919, 1957-1958, and 1968 on the US stock market. They find that up until 2020, not a single move larger than 2.5 per cent can be reasonably attributed to a disease outbreak. However, the paper found that from February 24 to April 20, 2020, more than two dozen such jumps can be attributed to coronavirus-related developments based on newspaper headlines. The authors did not ascribe the comparatively large effect to the disease's deadliness but rather to the expected and realized government restrictions that severely hampered the service-based economies of the developed world. Lastly, Baig *et al.* (2021) found a positive link between COVID deaths and cases, and volatility and illiquidity in US stock markets.

On the other hand, one would find limited effects on the stock market when looking at the 2002-2004 SARS outbreak. Nippani & Washer (2004) analyzed stock market indices of the affected countries and found a statistically significant effect only for the Chinese and Vietnamese indices, despite the outbreak being originally thought of as a significant threat to the affected countries' economies. The most recent health crisis before COVID-19, which drew a large amount of media attention and had some limited effect on stock markets, was the Ebola outbreak. Ichev & Marinc (2018) investigate the relevance of geographic proximity with regard to the outbreak and find a statistically significant effect among companies operating in the US and West Africa. In addition, smaller companies appeared to be more vulnerable to the shock. However, unlike during the COVID outbreak, no large-scale market panic was observed during this crisis.

The last type of contagion-inducing event relevant to our research is armed conflict. Intuitively, one would expect war to have a clearly negative effect on all affected stock markets. However, the empirical research tells a more complicated story. Guidolin & La Ferrara (2010) look at 101 internal and international conflicts between 1974 and 2004 and find that the market reaction was generally mixed except for the US market, which, in fact, tended to react positively. The authors try to reason that this counter-intuitive finding results from markets generally already expecting most wars ahead of time and pricing them in. Nonetheless, investors become cautious due to heightened market uncertainty. As a result, the actual breakout of the war causes a reduction in uncertainty, which causes investors to be more willing to invest. An alternative explanation is that most conflicts during this period were not significant or close enough to affect major stock markets significantly. The researchers also found that international conflicts tend to have a more substantial impact than internal ones and commodity prices, especially oil, to be especially sensitive to conflicts in the Middle East. Unsurprisingly, the impact of wars in the Middle East, in particular, is often studied. Leigh *et al.* (2003) analyze the period before and during the Second Gulf War. Unlike the Guidolin & La Ferrara (2010) overview, they find a negative correlation between the US stock market and the probability of war. The differing results may be due to the specific threat the Iraq war posed to the US economy. Furthermore, they find a positive correlation between the probability of war and oil prices, which is consistent with Guidolin & Ferrara's work.

To this thesis, the conflict of particular interest is the ongoing Russian War in Ukraine. Boungou & Yatie (2022) present some of the earliest empirical data. They observe an adverse effect of the outbreak of the war on stock market indices worldwide, with geographically close countries and countries holding a negative stance towards Russia's invasion being affected more significantly. Closer proximity to the conflict implies stronger ties to the region, whereas a hostile stance towards Russia implies more extensive trade disruption. Federle & Sehn (2022) expand upon these findings and find that geographical proximity is relevant even within countries. They estimate that every 1000 kilometres extra distance of a country from the war equated to 1.1 fewer percentage points lost in equity value during the start of the war.

2.2 EU Market Integration

Market integration refers to the extent to which economies across different countries operate in unison, functioning almost as a single market. This phenomenon is characterized by the alignment of various economic indicators such as prices, labour costs, GDP fluctuations, and stock market volatilities across these economies. Achieving market integration involves reducing or eliminating economic, bureaucratic, and political barriers that impede the free flow of goods, services, capital, and labour. The process is thought to foster greater economic efficiency, competitiveness, and access to broader markets, thereby promoting global economic growth. As the EU project advanced, studies into the benefits and extent of market integration within the EU became increasingly relevant. Freedom of movement, unified trade policy, abolishing trade barriers, and eventually implementing a single currency and unified monetary policy were all expected to increase market integration within the EU and bring substantial economic benefits.

One of the earliest comprehensive investigations into the possible benefits of a unified EU market was the Cecchini *et al.* (1988). It outlines the costs of a fragmented European market, such as administrative costs, higher prices, and worse quality products as a result of lower competition. The report argues that the 1992 Maastricht Treaty will result in a 7 per cent GDP increase over the medium term and in the creation of 5 million jobs. Subsequent reports by the European Commission, 'The Economics of 1992' Emerson *et al.* (1988) and 'One Market One Money' Emerson *et al.* (1990) further analyze the effect of the euro's creation. The reports further reinforce the expected benefits, such as increased price stability, lower interest rates, and the euro's role as one of the world currencies. However, some difficulties are also outlined, such as the need for disciplined fiscal policy from the member states and the limited effect on labour mobility due to remaining cultural barriers.

Since the 1990s served as a preparatory period for introducing the euro, many empirical analyses of EU market integration were conducted about the period. Engel & Rogers (2004) study consumer price dispersion within the EU between 1990-2003. A significant decrease was found during the 1990s; however, no significant reduction was found after the introduction of the euro in 1999. Hardouvelis *et al.* (1999) look at the forward interest rate differential of various countries in the European Monetary Union (EMU) with Germany as a marker of EU market integration. They find that during the 1990s, EMU countries became increasingly integrated with the German market. The United Kingdom, which did not join the EMU, was used as a control to show that this integration was indeed the effect of the EMU and not caused by a wider trend of globalization.

The 2000s saw an increased focus on CE and EE countries, which joined the EU during this period. While Nikkinen *et al.* (2012) observes that the Baltic countries' stock markets remained relatively segmented from the EU ones before the Great Financial Crisis (GFC) of 2008, he also argues that this segmentation mostly disappeared during the crisis and that the behaviour of the Baltic markets could be largely predicted by the behaviour of the EUROSTOXX50 index during the crisis. Gjika & Horvath (2013) look at Czech, Polish, and Hungarian stock markets during the same period using the Asymmetric Dynamic Conditional Correlation (ADCC) model. In contrast with Nikkinen *et al.* (2012), they found an increasing correlation between CE and EU markets before the GFC and observed similar levels during the crisis. The most pronounced increase was observed during the countries' accession to the EU in 2004. Caporale & Spagnolo (2011) look at weekly data of Czech, Polish and Hungarian markets between 1996 and 2008 and find a significant correlation between these markets and both UK and Russian ones. However, the link to the UK market was found to be stronger. Additionally, the paper found one-way volatility spillover effects from the two larger markets to the smaller ones.

Nevertheless, other studies suggest that the market integration has not been so meaningful. Egert & Kocenda (2007) and Egert & Kocenda (2010) look at intraday data of certain Western European and CE markets from 2003 to 2006. Their first paper found no robust cointegration between the studied markets. In the second, which used the Dynamic Conditional Correlation (DCC) model, they found a significant intraday correlation only between the Western European markets. Furthermore, Gilmore *et al.* (2008) investigate the period between 1995 and 2005 and find only intermittent periods of cointegration caused by major political advancements like the 2004 EU accession broken up by periods of idiosyncratic volatility.

More recently, Botoc & Anton (2020) analyzed the daily market data of Central, Southeastern, and Baltic countries between 2000 and 2016. The ADCC model was employed, among others. The average long-run dynamic conditional correlation reported between the markets studied and the EU markets was 0.28. Furthermore, similar to Gilmore *et al.* (2008), they find that the cointegration process is not gradual but instead appears in surges with significant events like the 2004 EU enlargement and the 2011 EU sovereign debt crisis.

2.3 GARCH Models

In this thesis, we opt for using the class of GARCH models to study the stock market comovements. Other methods worthy of mention are cointegration techniques and Granger causality tests. We have elected to use a GARCH model as we are interested in the volatility caused by the COVID-19 pandemic and the Russian War in Ukraine, and GARCH models are most well suited for this task. Furthermore, stock market time series tend to have several problematic properties, which are addressed by various types of GARCH models. First, they are known to exhibit volatility clustering, meaning that high present volatility implies heightened future volatility and low current volatility implies lowered future volatility. GARCH models account for this phenomenon by using time-lagged variances in the model. Second, stock market data typically has time-varying volatility, which is also dealt with primarily by having time-lagged variances in the model. Moreover, because stock prices can be significantly affected by extreme events, distributions of stock returns tend to have relatively fat tails compared to normal distributions. This issue can be addressed by using a Student's t-distribution instead of a normal distribution for residuals.

GARCH models come in many different variations. Starting with the predecessor, the Auto-regressive Conditional Heteroskedasticity (ARCH) model, proposed by Engle (1982). It uses the size of the previous error terms to model current volatility. This way, it accounts for volatility clustering and time-varying volatility. This model was soon expanded upon by Bollerslev (1986), who introduced the GARCH model, which became so widely used that today we typically talk about the GARCH family of models rather than the ARCH family. It adds past volatilities into the regression of current volatility, allowing the user to quantify the degree of volatility clustering and persistence directly.

However, this practical and relatively simple model has some drawbacks. Firstly, it assumes that positive and negative shocks have the same effect on volatility, which, as we have already mentioned, is not necessarily true in the context of stock markets, see Bekaert & Wu (2000). Secondly, GARCH is limited by how many periods we use for the model. A user may leave important information out of the model by not looking farther into the past. This may cause the user to neglect a more long-term effect of volatility. Furthermore, the GARCH model assumes the relationship to be constant over the studied period. As we have already seen, stocks tend to behave differently during crises, which may lead to inaccurate results when using basic GARCH.

Several GARCH variations have been proposed to address these issues. Nelson (1991) introduced the Exponential GARCH (EGARCH). This model addresses the asymmetry by transforming the variances using the log function. Glosten *et al.* (1993) on the other hand developed the Glosten, Jagannathan & Runkle GARCH (GJR-GARCH) and Zakoian (1994) introduced the Threshold

GARCH (TGARCH). Both models deal with asymmetry by introducing a dummy variable for negative shocks.

Lastly, GARCH is univariate, meaning that it models only a single time series and is not very useful for studying the relationship between multiple time series on its own. This has led to the development of various multivariate GARCH models, which address this problem. One of the earliest multivariate GARCH models was the Vector GARCH (VEC) introduced by Bollerslev *et al.* (1988). However, the estimation of this model is computationally intensive since, as Andersen *et al.* (2009) describes, 'Every conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared returns and cross-products of returns.' leading to difficult estimation with increasing n observations. The Baba, Engle, Kraft & Kroner GARCH (BEKK) developed by Engle & Kroner (1995) simplifies the computation by building in restrictions for the estimated parameters, ensuring positive definiteness of the covariance matrix. For a more comprehensive discussion of VEC and BEKK models, see Andersen *et al.* (2009).

This thesis will utilize the branch of multivariate GARCH models known as the Conditional Correlation models. First developed by Bollerslev (1990) in the form of the Constant Conditional Correlation GARCH (CCC). As the name implies, it assumes a constant correlation between the studied variables for the sake of more straightforward estimation. The model estimation is further simplified by separating the process into two steps. First, a univariate GARCH model is applied to each series individually. Second, the conditional variance matrix H_t is estimated using the following equation: $H_t = D_t R D_t$, where R is the constant correlation matrix computed using the standardized residuals from the univariate GARCH models and D_t is a diagonal matrix with square roots of the variances σ_{it}, which represent the standard deviation of time series i at time t. However, as already discussed in this paper, the constant correlation assumption is not very realistic in the context of financial markets. Engle (2002) extends the CCC model with the introduction of the DCC with the key difference being that the correlation matrix R_t is now also dependent on t. Lastly, to address asymmetry, Cappiello *et al.* (2006) introduce a dummy for negative shocks into the DCC model, similar to the GJR-GARCH and the TGARCH. This last model is known as ADCC. The ADCC and DCC models will be discussed in more detail in the Methodology section.

Chapter 3

Data & Methodology

In this chapter, the data is introduced, data transformation is described, and the descriptive statistics are discussed. Stationarity, a requirement for the models used, is tested. Lastly, the Auto-regressive (AR), Auto-regressive Moving Average (ARMA), GARCH and ADCC models are introduced and discussed.

3.1 Data

We use the daily market data of indices made up of large-cap companies between 2013 and 2023, available at Investing.com. We will be studying the stock market indices of Bulgaria (SOFIX), Romania (BET), Czechia (PX), Hungary (BUX), Poland (WIG), Slovakia (SAX), Latvia (OMXRGI), Estonia (OMXTGI) and Lithuania (OMXVGI) and analyzing them in relation to the EU (STOXX50) and Russia (MOEX). We will be using the closing prices for our analysis. The daily log returns are calculated from these prices according to the following formula:

$$r_t = \log(P_t) - \log(P_{t-1})$$

Where:

- r_t represents the natural logarithm return on day t,
- P_t is the closing price of the index on day t, and
- P_{t-1} is the closing price of the index on the previous day.

This transformation provides several advantages over simple percentage returns.

- It allows for simple addition across time periods.
- It creates symmetry; negative values are offset with positive values of equal magnitude.
- The log transformation dampens the effect of extreme values, which are common in financial markets during panics.

Table 3.1: Unconditional Correlations

Index	STOXX50	MOEX	SOFIX	BET	PX	BUX	WIG	SAX	OMXRGI	OMXTGI	OMXVGI
STOXX50	**1**										
MOEX	0.41	**1**									
SOFIX	0.25	0.11	**1**								
BET	0.44	0.25	0.24	**1**							
PX	0.61	0.38	0.26	0.45	**1**						
BUX	0.52	0.36	0.22	0.36	0.51	**1**					
WIG	0.62	0.46	0.19	0.38	0.51	0.53	**1**				
SAX	0.01	0.00	0.02	0.00	0.00	0.01	−0.02	**1**			
OMXRGI	0.14	0.13	0.12	0.13	0.18	0.16	0.17	0.01	**1**		
OMXTGI	0.34	0.20	0.25	0.36	0.37	0.27	0.30	0.03	0.26	**1**	
OMXVGI	0.32	0.29	0.24	0.36	0.35	0.32	0.36	0.00	0.26	0.49	**1**

The Augmented Dickey-Fuller (ADF) test was applied to test for stationarity (see Table A.2), and the H_0 of a unit root was firmly rejected for all time series, implying stationarity. Looking at unconditional correlations (Table 3.1), PX and WIG appear to have the highest correlations with other indices on average, indicating stronger integration and a higher level of market development. The SAX appears to be uncorrelated with the other indices, which, considering the wider context of the Slovak economy, might imply that it is not a reliable indicator and, therefore, the index might have to be dropped.

A cursory look at Figure 3.1 suggests that a model which accounts for heteroskedasticity would be appropriate. There are clear periods of heightened volatility at the beginning of 2020 caused by the COVID-19 pandemic and at the beginning of 2022 caused by the Russian War in Ukraine. Unsurprisingly, the MOEX index saw the most drastic increase in volatility from the war. Interestingly, the 2014 annexation of Crimea is clearly visible only on the Russian (MOEX) and Bulgarian (SOFIX) graphs.

Geographically, the countries can be further subdivided into the Balkans (Bulgaria and Romania), the Visegrad Four (Czechia, Hungary, Poland and Slovakia), and the Baltic countries (Latvia, Estonia and Lithuania). All of the

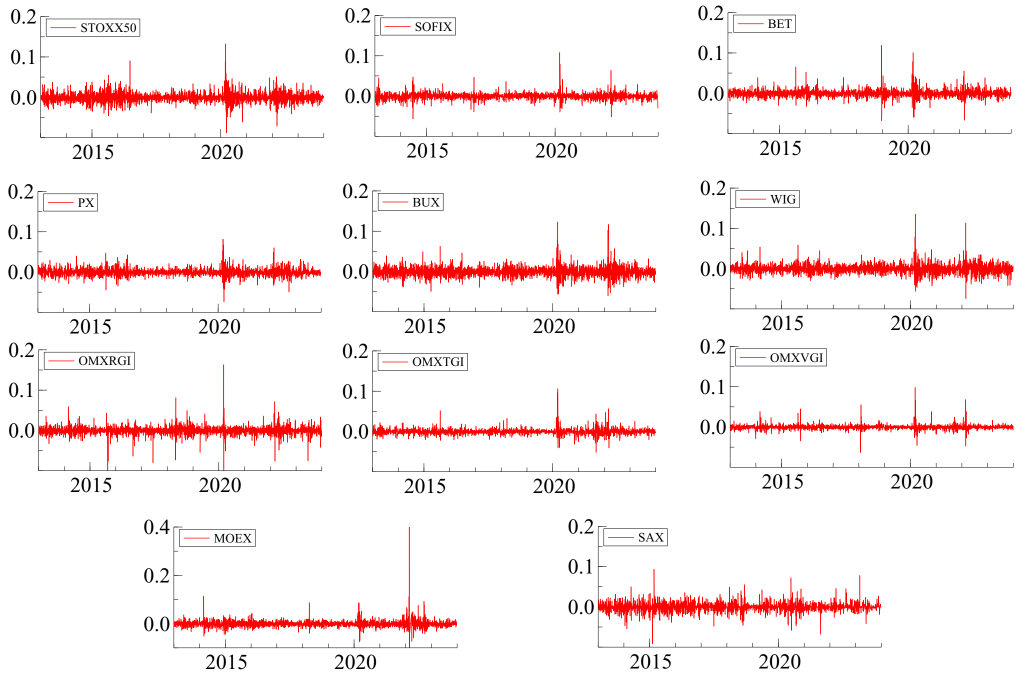

Figure 3.1: Index Log Returns

countries studied had been within the Soviet sphere of influence during the Cold War and have been gradually orienting themselves towards the West and free market economy since the fall of the Soviet Union. With relatively low standard of living compared to Western Europe and considerable growth potential, they have been categorized as ’emerging economies’; however, compared to other emerging economies such as India or China, or the earlier Tiger economies of South Korea and Japan, their growth has been tame ever since the 2007 GFC. A stagnant European economy has further hampered their growth during the 2010s. Nevertheless, the region has seen gradual economic growth (see Figure 3.2).

Today, all of the countries are part of the EU, with most of them joining as part of the 2004 enlargement except for Romania and Bulgaria, who joined in 2007. Furthermore, Estonia, Latvia, Lithuania and Slovakia have adopted the euro, whereas the rest have kept their national currencies. The region overall was significantly impacted by the Russian War in Ukraine due to its geographic proximity and social, cultural and trade ties to both Ukraine and Russia. In addition, the region as a whole and Poland and Czechia, in particular, had to absorb a large number of war refugees; it remains to be seen whether this will prove to be beneficial or detrimental to the affected countries.

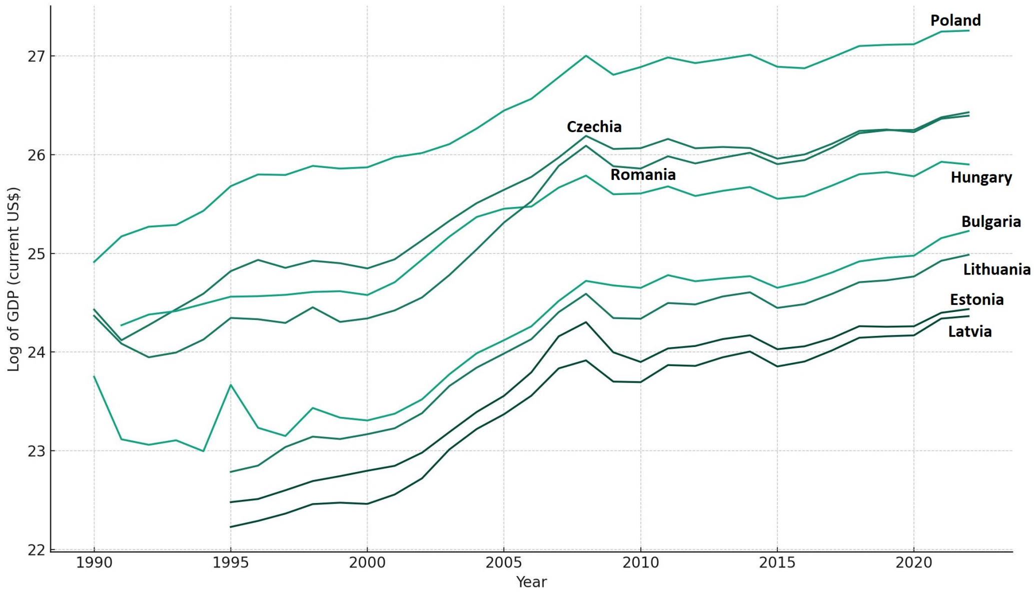

Figure 3.2: Log GDP 1990 to 2022 (Source: Worldbank)

3.2 Methodology

The ADCC model developed by Capiello et al. (2006) will be used, and its results will be compared with its simpler variant, the DCC model developed by Engle (2002), using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The basic GARCH (1,1) model introduced by Bollerslev (1986) will be used to model the individual time series.

In order to be able to estimate the GARCH model, the expected return $\mu_{t,i}$ has to be estimated first. A sample mean may be used; however, modelling the mean using an AR or ARMA model is more appropriate given the ever-changing nature of stock markets. An ARMA (p,q) model is defined as:

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

Where:

- c is a constant (intercept),
- p is the order of the autoregressive part,
- $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive parameters of the model,
- X_t is the value of the series at time t,

- $X_{t-1}, X_{t-2}, \ldots, X_{t-p}$ are the previous p values of the series,
- q is the order of the moving average part,
- $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average parameters,
- ϵ_t is the error term at time t, and
- $\epsilon_{t-1}, \epsilon_{t-2}, \ldots, \epsilon_{t-q}$ are the previous q error terms.

For $t = 1$, the recursion is started by using the sample mean and assuming the initial residuals to be equal to zero. In this thesis, we will be using the ARMA(1,0), effectively an AR(1) model. Therefore, we do not need to estimate the θ parameter. Maximum Likelihood Estimation (MLE) is used to estimate the parameter ϕ. MLE is a statistical method that estimates model parameters by maximizing the likelihood function, which represents the probability of observing the sample data under the given parameters. The function is constructed by utilizing the assumption of normal distribution of errors with a mean of 0 and variance σ^2, arriving at the following log-likelihood function for the AR (p) model:

$$L(\phi, \sigma^2) = -\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{n}(X_t - \hat{X}_t)^2$$

Where:

- σ^2 is the variance of the error terms ϵ_t,
- $\hat{X}_t$ is the predicted value from the AR model for time t, and
- n is the number of observations.

The natural logarithm transformation of the likelihood function is used since it turns the multiplication of likelihoods into a simple summation, which is significantly more straightforward to work with. The goal of MLE is to find the set of parameters $\hat{\sigma}^2$ and $\hat{\phi}$ that maximize this log-likelihood function. The estimated parameters are those that make the observed sequence of returns most probable under the assumed model. Estimating models using MLE also allows for the construction of statistical tests and confidence intervals for the parameters and for model comparison using information criteria such as the AIC and the BIC.

Using the estimated values for expected returns, we can estimate the GARCH model. A GARCH(p, q) model is defined as:

$$y_{ti} = \mu_{ti} + \epsilon_{ti}$$

$$\epsilon_{ti} = \sigma_{ti} z_{ti}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Where:

- y_{ti} is the return of an asset i at time t,
- μ_{ti} represents the expected return of asset i at time t,
- ϵ_{ti} represents the error term in the predicted return; in the context of financial markets, it represents market shocks at time t,
- z_{ti} is assumed to be an independent and identically distributed (i.i.d.) standard normal random variable, indicating that the standardized returns are normally distributed with a mean of 0 and a variance of 1,
- σ_t^2 is the conditional variance at time t,
- $\alpha_0, \alpha_1, \ldots, \alpha_p$ and $\beta_1, \ldots, \beta_q$ are parameters to be estimated,
- $\epsilon_{t-1}, \epsilon_{t-2}, \ldots, \epsilon_{t-p}$ are the lagged error terms,
- $\sigma_{t-1}^2, \sigma_{t-2}^2, \ldots, \sigma_{t-q}^2$ are the lagged conditional variances, and
- p and q are the orders of the GARCH model, indicating the number of lagged error terms and lagged variances included, respectively.

In order to start the recursion, sample variance is used and initial residual is assumed to be zero. The GARCH model parameters are also estimated using MLE. In order to construct the likelihood function, the model's residuals are assumed to be conditionally normally distributed given past information. Given that assumption, the log-likelihood function of a GARCH (p, q) model is:

$$\mathcal{L}(\alpha_0, \alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_q) = -\frac{1}{2} \sum_{t=1}^{N} \left(\log(2\pi) + \log(\sigma_t^2) + \frac{\epsilon_t^2}{\sigma_t^2} \right)$$

Where:

- N is the total number of observations,
- σ_t^2 is the conditional variance given by the GARCH model,
- $\epsilon_t = r_t - \mu_t$ is the model residual at time t, with r_t being the actual return and μ_t the expected return, and
- the parameters $\alpha_0, \alpha_1, \ldots, \alpha_p$ and $\beta_1, \ldots, \beta_q$ are to be estimated.

After modelling each time series individually using a univariate a GARCH (1,1,) model, we estimate their relationship using the ADCC model. The ADCC equation is defined as:

$$\mathbf{H}_t = (1 - a - b - c)\bar{\mathbf{H}} + a(z_{t-1}z'_{t-1}) + b\mathbf{H}_{t-1} + c(n_{t-1}n'_{t-1})$$

Where:

- H_t is the conditional covariance matrix at time t,
- $\bar{H}$ is the unconditional covariance matrix of the standardized residuals, which represents the long-term average covariance,
- z_{t-1} is the vector of standardized residuals from the univariate GARCH models at time $t - 1$,
- n_{t-1} is a vector that captures negative shocks from the standardized residuals. It is equal to z_{t-1} when z_{t-1} is negative (indicating a negative shock) and zero otherwise,
- the a parameter determines the impact of most recent shocks on the covariance,
- the b parameter determines the persistence of previous shocks and
- the c parameter determines the degree of asymmetry observed in the covariances.

The a, b, c parameters are assumed to be non-negative to ensure the covariance matrix's positive semi-definiteness. Additionally, $a + b + c$ are assumed to be smaller than 1 to ensure the model's stability.

The conditional correlation matrix $\mathbf{R}_t$ is then obtained from $\mathbf{H}_t$ by standardizing it:

$$\mathbf{R}_t = \text{diag}(\mathbf{H}_t)^{-\frac{1}{2}}\mathbf{H}_t\text{diag}(\mathbf{H}_t)^{-\frac{1}{2}}$$

Where $\text{diag}(\mathbf{H}_t)$ is the covariance matrix containing only the diagonal elements (variances). By taking their square root, we arrive at standard deviations of each time series at time t, which are used to standardize the covariance matrix. The DCC model has the same exact specification except that it does not include the asymmetry parameter.

Quasi-Maximum Likelihood Estimation (QMLE) is often chosen over MLE for the estimation of complex models like ADCC and DCC when the data are characterized by heteroskedasticity, such as in financial datasets. While both methods involve constructing a likelihood function, QMLE differs from MLE in relaxing the assumption of homoskedastic errors. This adaptation is crucial for dealing with data where the variance of errors may change over time or across observations. Furthermore, unlike MLE, which typically requires precise specification of the entire distribution of errors, QMLE focuses primarily on correctly specifying only the first and second moments (mean and variance) of the errors. This feature makes QMLE more robust to misspecifications in the error distribution.

We will be using information criteria to assess model fit. Information criteria are methods of quantifying the degree of model fitness relative to model complexity. They are a valuable and convenient tool for evaluating models. This thesis employs the AIC and BIC, the most commonly used information criteria in both econometrics and statistics more broadly.

The AIC introduced by Akaike (1974) is defined by the following equation:

$$\text{AIC} = 2k - 2\ln(L)$$

Where:

- k is the number of parameters employed by the model representing the complexity of the model and
- L is the maximum value of the likelihood function, which we obtain from MLE or QMLE. This term measures the model's goodness of fit.

The BIC, also known as the Schwarz criterion, introduced by Schwarz (1978) is defined as follows:

$$\text{BIC} = \ln(n)k - 2\ln(L)$$

The key difference from the AIC is that the 2 in the observation term is replaced by $ln(n)$, where n is the number of observations. This feature makes the BIC more strict when adding new explanatory parameters. From these definitions, it follows that the more optimal a model is, the lower its information criterion will be. There exist countless other information criteria such as the corrected AIC, which is used for dealing with small datasets, the Hannan-Quinn Information Criterion, which attempts to strike a balance between the AIC's relative laxness and the BIC's stringency, or various Cross-validation techniques, which involve partitioning data into smaller subsets and fitting the model on them and then analyzing the model's predictive power for the other data subsets.

Chapter 4

Results & Discussion

This chapter compares the results of the DCC and ADCC models and discusses in detail the observed conditional correlations with the EU and Russia and their implications.

4.1 Testing

After running the initial models, the SAX index had to be dropped from the analysis. The SAX index's correlation with all other indices was statistically insignificant. One might argue that this relative independence from other indices is caused by the Slovak Republic being a member of the eurozone and, therefore, being more tied into the Western European markets and less affected by its immediate neighbours. However, the Baltics, who have also accepted the euro, have significant correlations with other countries in the region, and the correlation between SAX and STOXX50 is also insignificant. Since all the indices had significant correlations with each other and the Slovak economy is not particularly unique within the region, we concluded that the SAX index is not a reliable enough representative of the Slovak market and, by extension, its economy. We, therefore, opted to drop the SAX index as it did not provide valuable information and only diluted the model.

As seen in Table 4.1, both of the DCC model parameters are statistically significant; however, including the asymmetry parameter c causes the short-term parameter a to become statistically insignificant, indicating that only negative shocks have a substantial impact on next period's covariances. These results support the findings of Longin & Solnik (2001) and Erb *et al.* (1994). Our results indicate that positive shocks tend to be idiosyncratic, whereas

Table 4.1: Model Results Comparison

	ADCC		DCC	
Coefficient	Value	t-prob	Value	t-prob
a	0.0028	0.299	0.0110	0.000
b	0.8839	0.000	0.8765	0.000
c	0.0180	0.002	—	—

Table 4.2: Model Information Criteria Comparison

Model	Akaike	Bayesian
ADCC	-69.477	-69.269
DCC	-69.469	-69.263

negative shocks are usually international, thereby creating asymmetry in the conditional covariances. Furthermore, the fitted ADCC has lower information criteria than the fitted DCC model, including the BIC, which should be more unforgiving towards the ADCC model. Given these results, we opted for further analyzing the ADCC results.

The standardized residuals from the individual GARCH models all exhibit significantly heavier tails than those expected under a normal distribution (see Figure 4.1). This observation suggests that the model could be better specified. One option is to use a more advanced univariate GARCH model such as the EGARCH or the GJR-GARCH. Another approach would be to assume t-distributed errors during MLE rather than normally distributed since t-distribution is better suited for dealing with heavy tails. However, these adjustments are unlikely to be able to account for the extreme outliers caused by major shocks like the ones in March 2020 or February 2022. Therefore, a certain number of outliers might be unavoidable.

Looking at Table 4.3, the null hypothesis of the Box-Pierce test, which asserts no autocorrelation in residuals, is rejected for several indices, specifically SOFIX, WIG, OMXTGI and OMXVGI. This result suggests that critical information has been left out of the model. A different specification of the GARCH and ARMA (p, q) parameters might remedy this. Conversely, the absence of autocorrelation among squared residuals indicates that the GARCH model has successfully captured volatility clustering in the data. Additionally, we applied the multivariate Hosking-Portmanteau test on the ADCC model results. The null hypothesis of no autocorrelation was consistently rejected for both lags

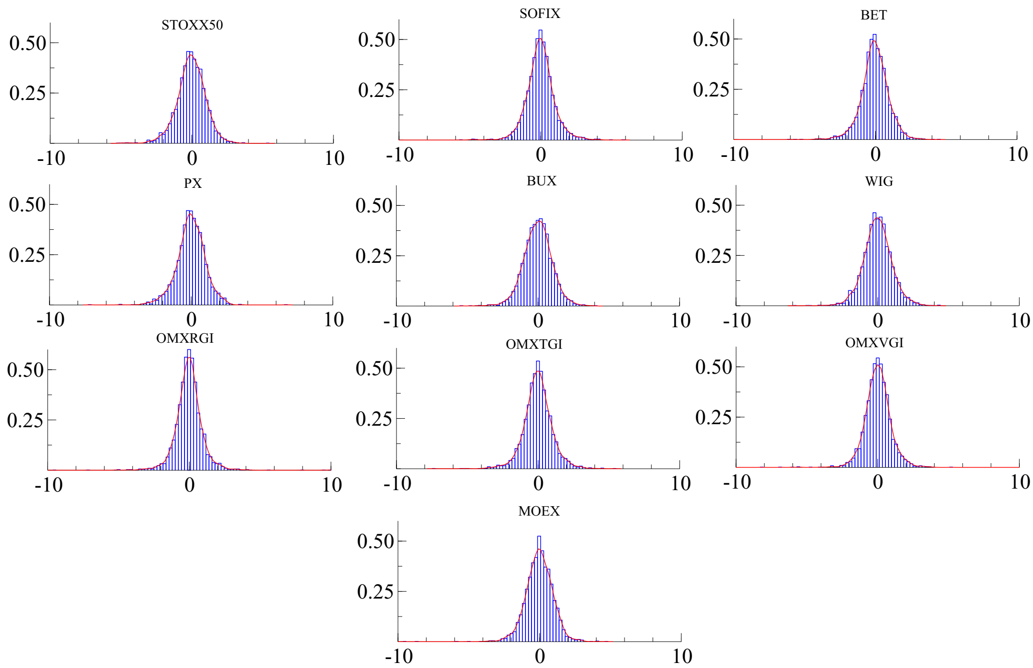

Figure 4.1: Standardized Residuals Relative to Normal Density Function

for both residuals and squared residuals, strongly suggesting that there are complex interactions between the series that the current ADCC model has not accounted for. Beyond using a different GARCH model, incorporating external economic or financial variables such as interest rates or GDP growth as exogenous inputs into the ARMA and GARCH equations might help capture these overlooked interdependencies.

4.2 Correlation Results

Overall, the correlations with MOEX are stagnant (see Figure 4.2). The initial outbreak of the Russian war in Ukraine saw a short-term correlation spike for all countries. However, the STOXX50 remained largely unaffected; if anything, the correlation slightly decreased. At the beginning of the 2020 pandemic, a sharp short-term increase in all correlations is observed, a finding which is consistent with Okorie & Lin (2021) and He et al. (2020). Lastly, for the countries bordering Russia or Ukraine, the most drastic changes in correlation can be observed in 2014 during the Crimean crisis, implying that countries closer to the conflict were more affected, which would be congruent with the findings of Federle & Sehn (2022) about proximity during the Ukraine war. However,

Table 4.3: P-values of The Box-Pierce Test on Standardized and Squared Standardized Residuals at 5 and 10 Lags

Series	**Standardized Residuals**		**Squared Standardized Residuals**	
	5 Lags	**10 Lags**	**5 Lags**	**10 Lags**
STOXX50	0.06	0.13	0.18	0.34
MOEX	0.99	0.99	0.94	0.99
SOFIX	0.00	0.00	0.70	0.96
BET	0.18	0.14	0.99	1.00
PX	0.52	0.44	0.52	0.42
BUX	0.14	0.11	0.10	0.20
WIG	0.00	0.01	0.75	0.83
OMXRGI	0.53	0.14	0.93	0.96
OMXTGI	0.04	0.22	0.42	0.54
OMXVGI	0.01	0.05	0.62	0.96

compared to the Ukraine war, the Russian neighbours' markets reacted more drastically to the Crimean crisis despite being a comparatively minor incident. The Baltic countries especially saw a drastic spike despite usually having correlations between 0.1 and 0.25 with the Russian market. Overall, the Baltic markets seem to be significantly affected by Russian-centered crises, implying that despite having relatively weak economic ties to Russia, it remains remarkably geopolitically relevant to them. The Polish, Romanian and even the STOXX50 index saw the most drastic spike in correlation during 2014. This might indicate the paradigm-shifting nature of the 2014 Crimean crisis. Whereas in 2014, the markets were caught entirely off guard by the Russian aggression, in 2022, it appears that investors were not as surprised, dampening the market reaction in 2022 relative to 2014.

The correlations with STOXX50 paint a similar picture of stagnation with regard to market integration (see Figure 4.3). Overall, the CE countries appear to be more strongly integrated, with correlations ranging from 0.4 to 0.75. On the other hand, the Balkan and Baltic countries seem to be more segmented, with correlations ranging from 0.1 up to 0.4 for the Romanian index. Interestingly, there appear to be no signs of these countries rising to the levels of their CE counterparts. Furthermore, the increase in market correlation of CE countries with the EU has also stopped since the work of Gjika & Horvath (2013). Similar to findings by Nikkinen *et al.* (2012), we observe relative segmentation of the Baltic countries from the European market, broken up by short-term spikes during the crises in 2014, 2020 and 2022. However, many

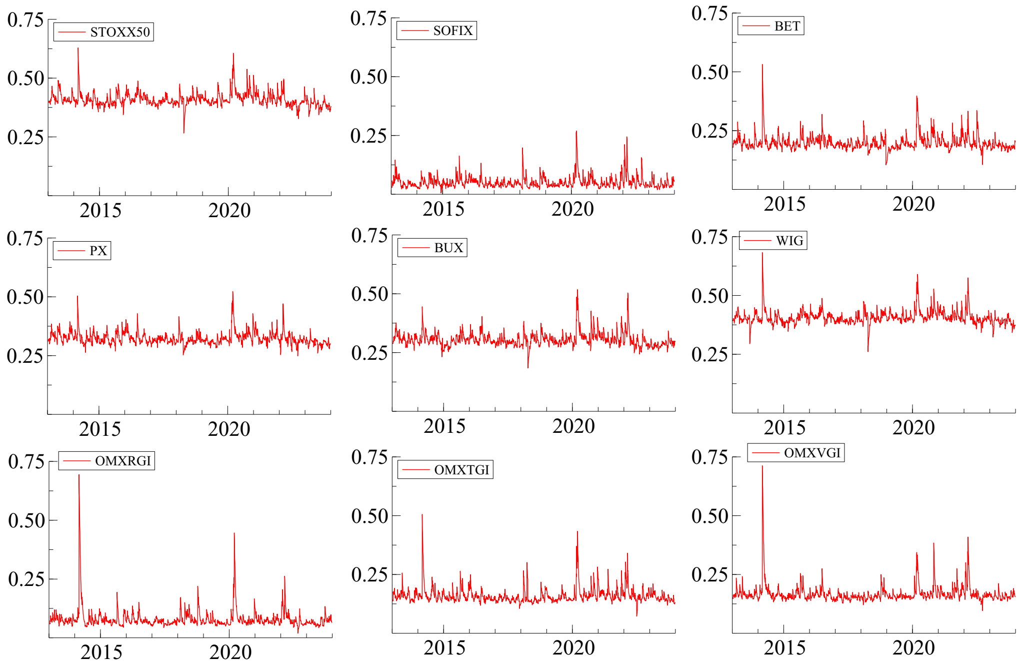

Figure 4.2: Correlations with MOEX

other spikes are also observed. The 2014 Crimean crisis is not as visible here as in the correlations with MOEX, but the Baltic countries once again appear to have been particularly affected in 2014. Furthermore, the Latvian index has a remarkably low correlation with both STOXX50 and MOEX, although it reacts to crises just as strongly as its neighbours. This might be caused by the fact that Latvia is both the smallest country by GDP and the least rich by GDP per capita of all the Baltic countries. Therefore, its stock market is likely to be underdeveloped even when compared to its Baltic counterparts. Lastly, the correlation between Russian and European markets has been slowly declining ever since the 2020 pandemic, heralding a possible process of disentanglement between the European and Russian economies.

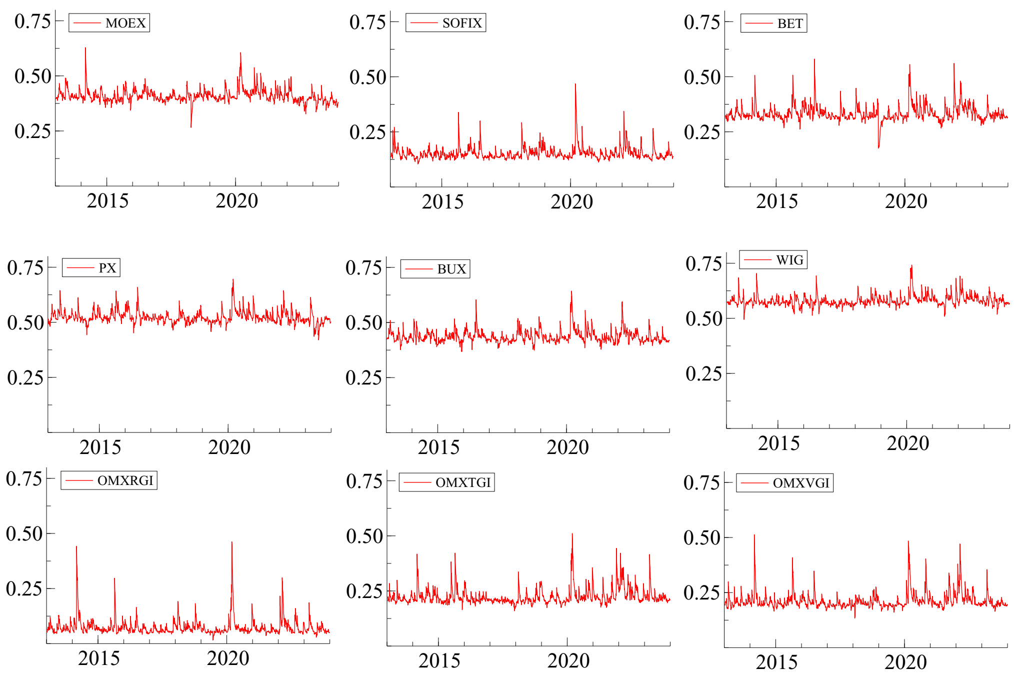

Figure 4.3: Correlations with STOXX50

Chapter 5

Conclusion

This thesis analyzed the correlation of various CE and EE countries with the Russian and EU markets using the DCC and ADCC GARCH models. Tying into the earlier work done on CE countries in the 2000s, see Gjika & Horvath (2013) and Gilmore *et al.* (2008), we observe that the market integration with the EU has stopped since then. Furthermore, none of the other studied indices exhibit an increasing correlation with either the EU or the Russian index. The only long-term change observed is a slight divergence of the EU market from the Russian one since 2020, which is further reinforced in 2022. Overall, our observations support the conclusion of Gilmore *et al.* (2008) that market integration is not gradual but rather occurs in surges caused by major political advancements. CE countries appear to be more significantly integrated with both the EU and Russian markets, with correlations ranging between 0.4 to 0.75. Similar to already established literature, see Erb *et al.* (1994), Longin & Solnik (2001) and Nikkinen *et al.* (2012), we observe short-term spikes in correlation during crises, even among markets that are more segmented during stable times, such as Bulgaria or the Baltic states. Furthermore, positive shocks appear to have little impact on conditional correlations, supporting the conclusion of Longin & Solnik (2001) that impact on correlations tends towards zero for positive shocks. In accordance with earlier work on the COVID-19 pandemic ofOkorie & Lin (2021) and et al. (2020), we find that the pandemic's impact on conditional correlations was significant but short-term. Additionally, consistent with Federle & Sehn (2022), countries bordering Russia or Ukraine were more significantly affected by the outbreak of the war. Interestingly, the 2014 Crimean crisis appears to have caused larger spikes in conditional correlations with the Russian index than the war.

With regards to investment into the region as a means of diversification, the CE countries with correlations with the STOXX50 index ranging between 0.4 and 0.75 present relatively little value in this regard. On the other hand, the Baltic countries and Bulgaria appear to be more viable, with their correlations with the STOXX50 going only rarely above 0.3. Unfortunately, it seems that the phenomenon of correlation spikes during crises, observed by, e. g. Longin & Solnik (2001) and Nikkinen *et al.* (2012) among others, is present. All three major crises of 2014, 2020 and 2022 saw spikes in correlation with the EU markets. The potential investor is then left with a choice between minor diversification benefits by investing in CE countries or investing in the Baltic and Balkan markets, where they will be able to benefit from relevant diversification only during good times. Therefore, looking into other regions for diversification or into an alternate hedging strategy like the utilization of derivatives might be more beneficial.

Any potential reader of this thesis needs to be aware of several limitations and shortcomings. First of all, several liberties have been taken in order to simplify the model. Instead of testing several different variations of the AR and ARMA models to see which would be most appropriate, a simple AR(1) model was used, which, as the autocorrelation tests of some of the residuals have shown, is most likely not optimal. Furthermore, the GARCH (1,1) model has similar shortcomings. There are countless different univariate GARCH models, some of which have been specifically designed to address the basic GARCH models issues in the context of financial data, such as the previously mentioned EGARCH, TGARCH and GJR-GARCH. If this work were to be replicated, we would recommend comparing these models and a few versions of the GARCH (p,q) model using information criteria and the Box-Pierce and Hosking-Portmanteau tests to see which model would be optimal. Additionally, given the significantly heavy tails, using the Student's t-distribution instead of a normal distribution for errors might be more appropriate.

Lastly, some limitations are inherently built into the DCC and ADCC models. They provide correlations but say nothing about causation or its direction, which could be helpful if one is interested in contagion and spillover between financial markets. In addition, quantifying the correlation overtime between time series, which include very sharp drops such as the ones during March 2020, may lead to misleading results as it takes several time periods for the model to adjust appropriately, meaning that the effect of drastic short-term volatility on correlations may be underestimated in the model.

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Appendix A

Additional Descriptive Statistics and Premodel Testing

Table A.1: Summary Statistics of Log Returns for Selected Indices

Index	**Mean**	**Median**	**Standard Deviation**	**Skewness**
MOEX	0.0003	0.0006	0.0139	−2.2517
PX	0.0001	0.0005	0.0094	−0.8419
OMXRGI	0.0004	0.0002	0.0107	−0.0689
SAX	0.0002	0.0000	0.0100	−0.1852
BET	0.0004	0.0006	0.0094	−1.6289
SOFIX	0.0003	0.0002	0.0078	−1.4513
BUX	0.0004	0.0007	0.0120	−1.1221
WIG	0.0002	0.0004	0.0113	−1.1316
STOXX50	0.0002	0.0006	0.0121	−0.7970
OMXTGI	0.0003	0.0004	0.0074	−2.2327
OMXVGI	0.0003	0.0004	0.0059	−1.5946

Table A.2: Augmented Dickey-Fuller Test Results with Two Lags

Index	**t-ADF Statistic**
MOEX	−29.24
PX	−27.52
OMXRGI	−30.52
SAX	−34.21
BET	−28.73
SOFIX	−28.25
BUX	−28.97
WIG	−29.75
STOXX50	−29.76
OMXTGI	−28.15
OMXVGI	−25.46

Appendix B

Other Correlations

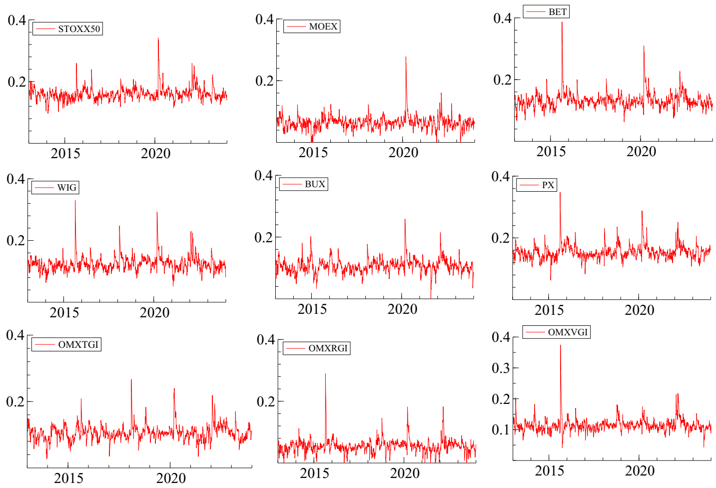

Figure B.1: Correlations with SOFIX

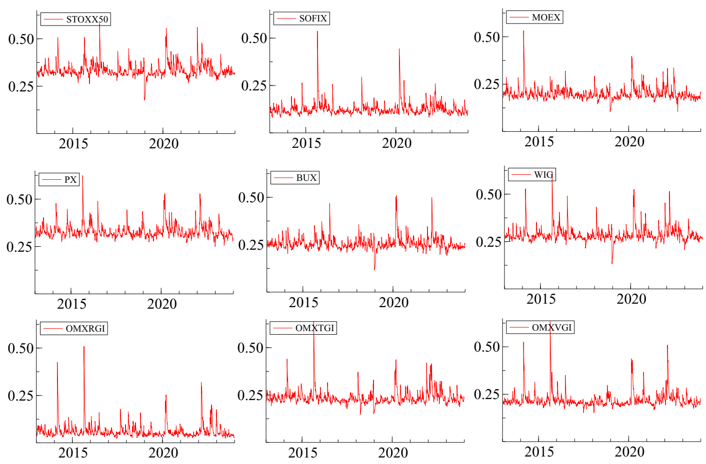

Figure B.2: Correlations with BET

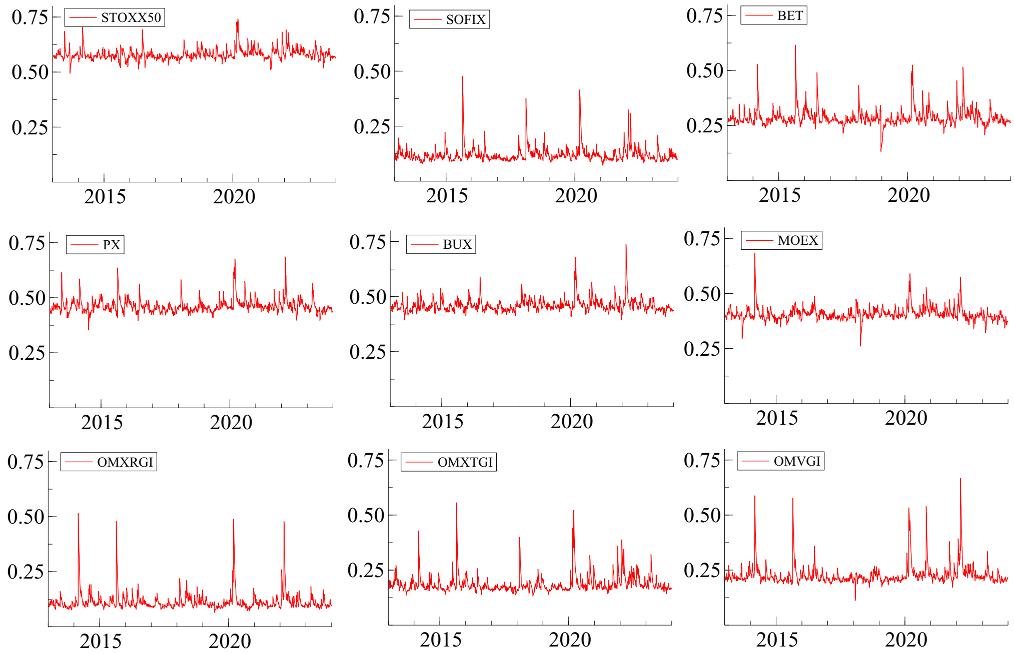

Figure B.3: Correlations with WIG

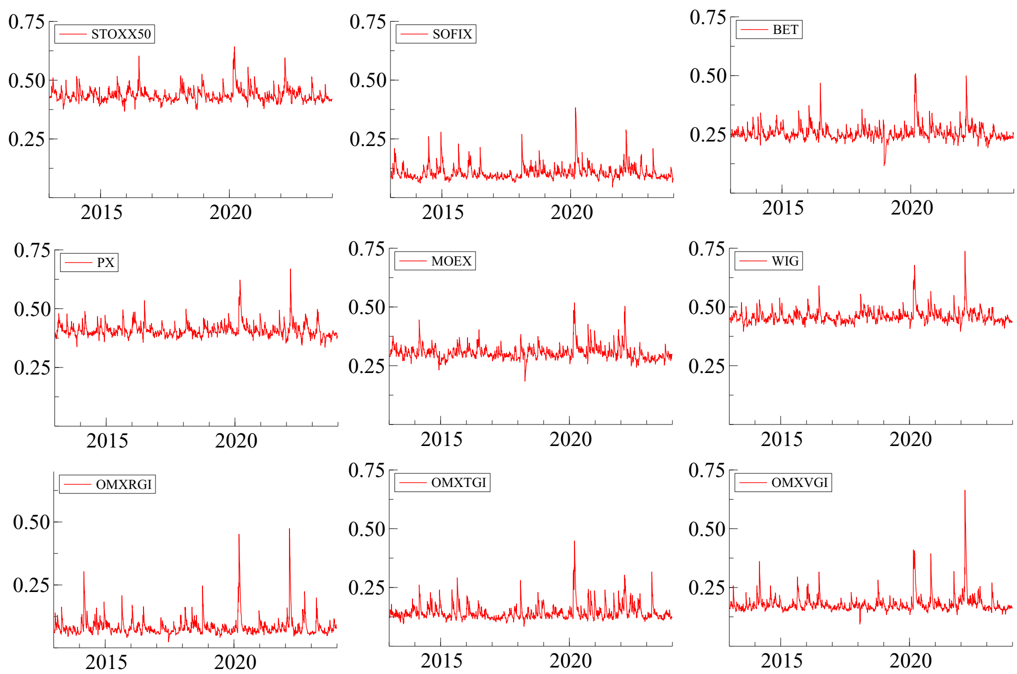

Figure B.4: Correlations with BUX

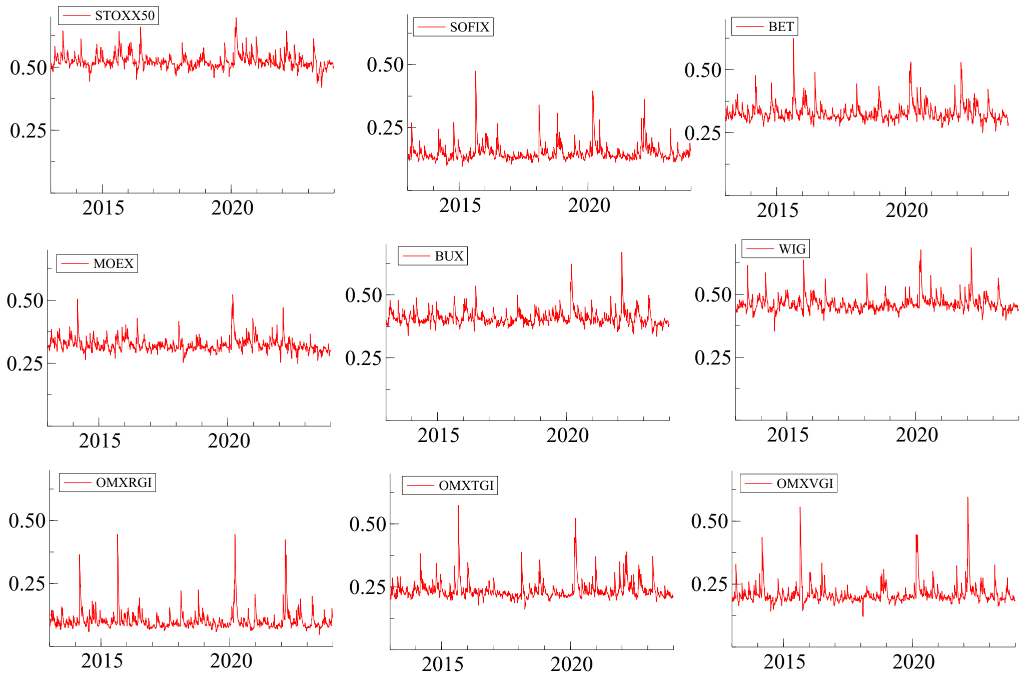

Figure B.5: Correlations with PX

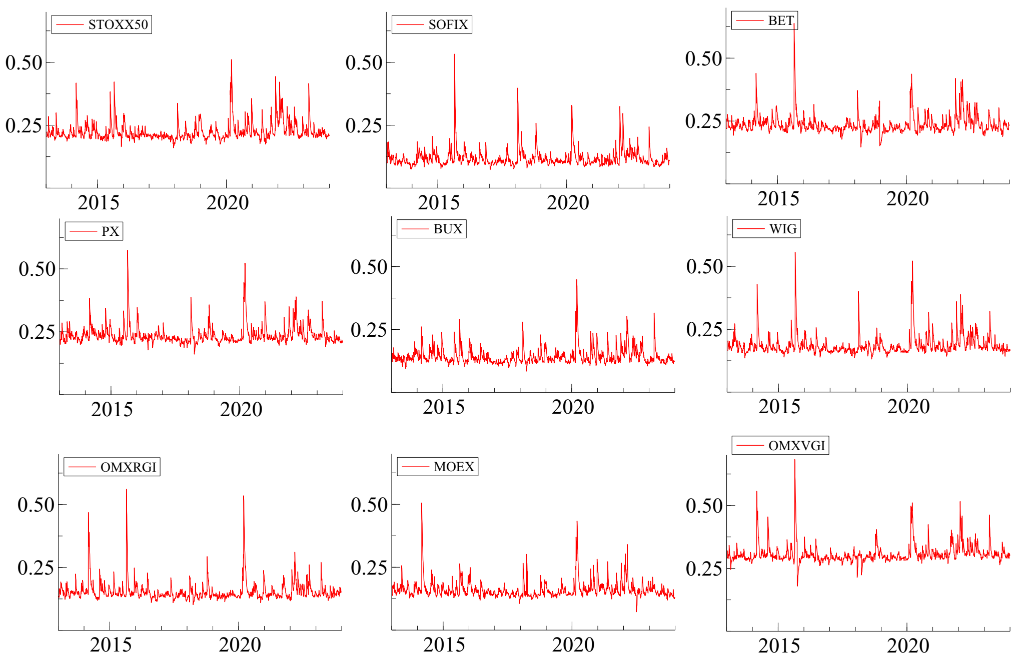

Figure B.6: Correlations with OMXTGI

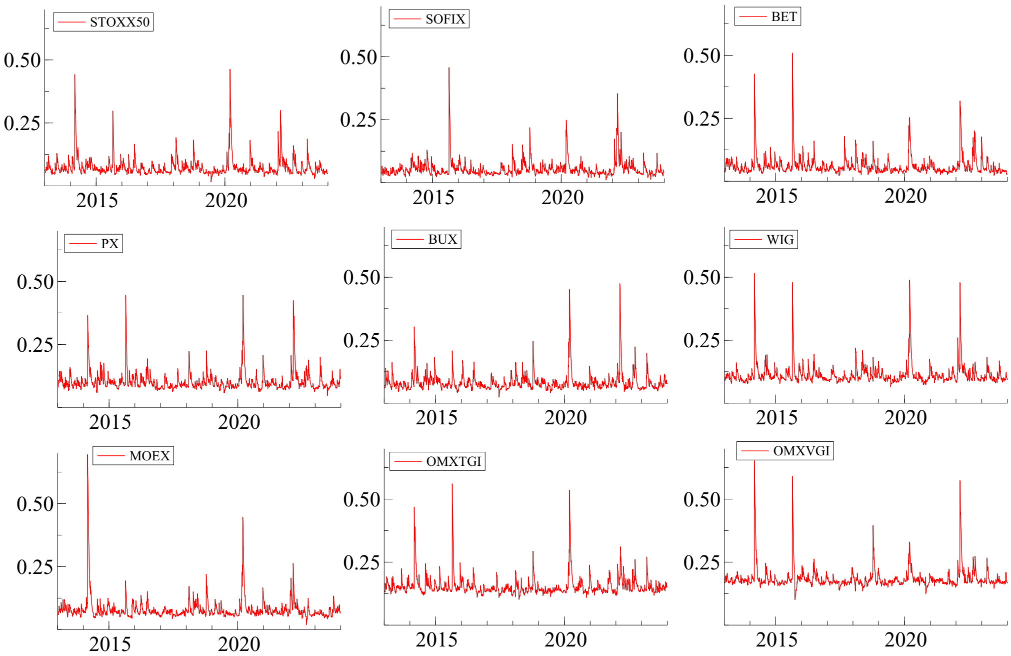

Figure B.7: Correlations with OMXRGI

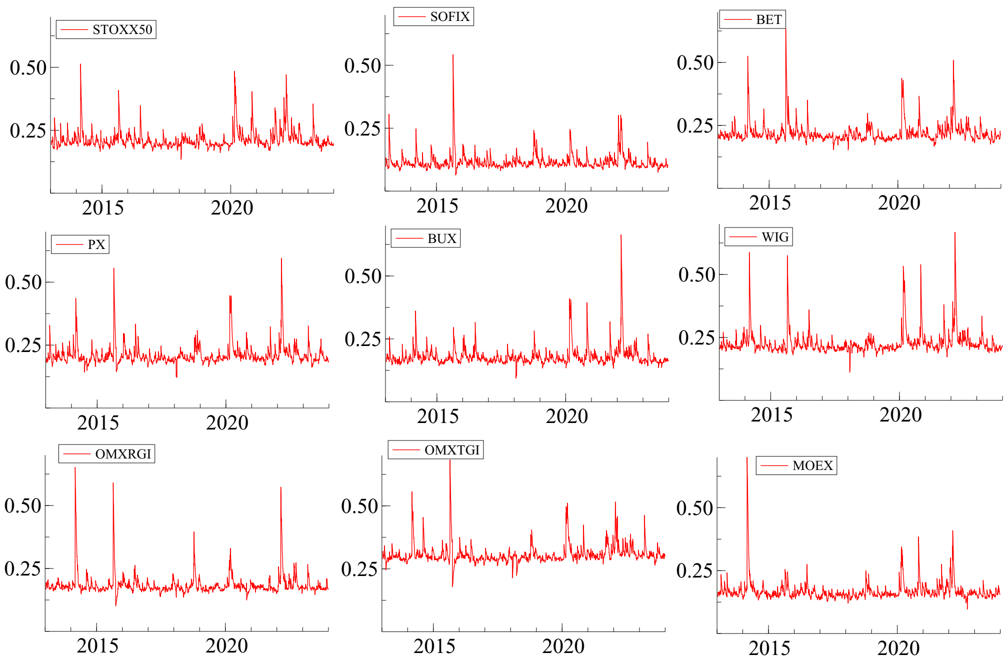

Figure B.8: Correlations with OMXVGI