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MASTER THESIS

CEE stock market comovements: An asymmetric DCC analysis

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Acknowledgments

Abstract

We investigate the interdependence among three CEE stock markets and between CEEs vis–à–vis euro area, using daily data from 2001–2011. Initially, we estimate bivariate ADCC models. Then, OLS regressions are employed to understand the evolution of correlations in time and during the recent financial crises. Finally, we examine the relationship between correlations and volatilities using the simple OLS model and the rolling stepwise regression methodology. Our results indicate that 3 out of 4 series exhibit asymmetries in conditional variances, while only 1 pair out of 6 exhibit asymmetries in correlations. We found that correlations are increased over time and during the recent financial crises for both pairs (CEEs–CEEs and CEEs–eurozone). However, the highest increase is observed for CEEs–eurozone. Mainly, we found a positive relationship between correlations and volatilities, even though this relationship is niether constant in time nor strictly positive or negative during all the sample period, but rather time–varying with periods of being higher or lower than zero.

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Acronyms

ADF Augmented Dickey–Fuller test

ACF Autocorrelation Function

ADCC Asymmetric Dynamic Conditional Correlation

AIC Akaike Information Criterion

ARMA Autoregressive Moving Average

ARCH Autoregressive Conditional Heteroskedasticity

AVGARCH Absolute Value Generalized Autoregressive Conditional Heteroskedasticity

BIC Bayesian Information Criterion

BSE Budapest Stock Exchange

CCC Constant Conditional Correlation

CEE Central Eastern Europe

DCC Dynamic Conditional Correlation

FESE Federation of European Securities Exchanges

GARCH Generalized Autoregressive Conditional Heteroskedasticity

IPOs Initial Public Offerings

MVGARCH Multivariate Generalized Autoregressive Conditional Heteroskedasticity

OLS Ordinary Least Squares

PACF Partial Autocorrelation Function

PSE Prague Stock Exchange

SEE South Eastern Europe

STCC Smooth Transition Constant Correlation

TGARCH Threshold Generalized Autoregressive Conditional Heteroskedasticity

WSE Warsaw Stock Exchange

Chapter 1

Introduction

The investigation of international stock market linkages represents an interesting and important topic not only for researchers in this field, but also for international portfolio managers, policy makers etc. For e.g. in a monetary union, such as the European Union, understanding the linkages between financial markets plays a crucial role in implementing an effective common monetary policy. Also, in order to compose an optimal diversified portfolio, international investors should have a good knowledge of market comovements. If comovements are strengthened, diversification benefits are reduced and investors would try to recompose their portfolios. These and many other examples emphasize the importance of studying interdependeces among stock markets.

In this respect, a huge amount of research is conducted for U.S., developed European, Asian and Latin American stock markets. Recently, a lot of attention is paid to the Central Eastern European (CEE) stock markets. After the fall of communism, CEE countries undertook different reforms to adapt their economies to the new market conditions. The transition from centrally–planned economies to market economies was associated with a large-scale privatization process, where state–owned companies were transferred to the private sector. This process made necessary the establishment of stock exchanges, where the ownership rights could be traded.

The growing importance of CEE markets in the region, especially after the CEE countries joined the EU in May 2004, led to a large body of literature devoted to the study of interdependencies among different CEE markets (see e.g. Kasch-Haroutounian & Price (2001), Scheicher (2001)) and between CEEs vis–à–vis developed European, U.S. and Russian markets (see e.g. Babetskii et al. (2007), Gilmore & McManus (2002), Horvath & Petrovski (2012), Voronkova

(2004), Egert & Kocenda (2005), Cappiello et al. (2006a), Syllignakis & Kouretas (2006), Patev et al. (2006), Syriopoulos (2007), Wang & Moore (2008),
Savva & Aslanidis (2010), Egert & Kocenda (2011), Syllignakis & Kouretas
(2011), Tudor (2011)). Generally, the research methodology found in the literature is divided in two groups. One group of authors use cointegration and
causality tests, while the other uses various multivariate GARCH techniques.
The latter, substantially improved the way we measure the dergee of integration between markets. All the above–mentioned studies reveal low short–term
comovements among CEE markets and between CEEs vis–à–vis developed ones,
which probably during the recent years have been strengthened. Also, during
the different crisis (emerging market crisis, recent financial crisis etc.) increased
comovements were reported. There is a discrepancy between different studies
on the existence of a long–term relationship between these markets. Some studies detect the presence of a long–term relationship, while others conclude that
such long–term relationships do not exist.

My research will be focused on the largest CEE markets (namely Czech,
Polish and Hungarian stock markets). Besides the interlinkages among these
markets, we will study the interdependece between them vis–à–vis the aggregate eurozone market. We will use daily closing price indices of three CEE
countries and eurozone, for the period from December 20, 2001 to October
31, 2011. Specifically, we will use PX index (Czech Republic), BUX (Hungary), WIG (Poland) and STOXX50 (eurozone). Among the large number of
econometric techniques suitable for this purpose, we have found the dynamic
conditional correlation model of Engle (2002) as the most appropriate one. This
model allows for time–varying dependence and gives a more realistic approach
compared to VAR–CCC model applied by Scheicher (2001), or the STCC[1] model
applied by Savva & Aslanidis (2010). In addition, the asymmetric DCC model
of Capiello et al. (2006b) will be employed and to my best knowledge is not yet
applied to CEE stock markets. Different authors have investigated the presence of asymmetric effects in conditional variances of CEE markets, while this
study will also investigate the presence of asymmetric effects in the correlation
dynamics. In the aforesaid literature, researchers usually use a GARCH(1,1)
specification or an assymetric GARCH specification (e.g. EGARCH(1,1)) to
model all the return series. Our model will be flexible enough to allow each
conditional variance to be given as one of the four possible GARCH specifications (GARCH, GJR–GARCH, AVGARCH, TGARCH). The best model fitting

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[1]STCC stands for smooth transition constant correlation.

the data will be chosen using Bayesian information criterion (BIC). Hence, the usage of four univariate GARCH specifications and the application of the asymmetric DCC model will differentiate our study from the previous literature. Even though visual inspection sometimes proves to be enough to draw meaningful conclusions, we will run supplementary OLS regressions to better understand the evolution of correlations in time and during the recent financial crises. Of a great importance is also the relationship between conditional correlations and conditional volatilities. If correlations and volatilities move in the same direction, then long–run risks are higher than they appear in the short–run (Capiello et al. 2006b). To estimate this relationship a simple OLS model on the whole sample data and the rolling "stepwise" regression methodology will be employed. In this context, we will try to answer the following questions: Are correlations among CEE stock markets and between CEEs vis–à–vis euro-zone high or low? Are they increased over time or during the recent financial crises? Are correlations and volatilities positively or negatively related? Are there asymmetric effects present in the correlation dynamics? Are there any good possibilities for risk diversification in CEE region? Are these diversification benefits reduced in time as a result of increased integration between the markets?

Our results indicate that 3 out of 4 series (BUX, PX and WIG) exhibited asymmetries in conditional variances while only 1 pair out of 6 (BUX–WIG) exhibited asymmetries in correlations. This implies that asymmetries in conditional correlations are not as widespread as in conditional variances in CEE markets. We found that correlations are increased over time and during the recent financial crises for both pairs (CEEs–CEEs and CEEs–eurozone). However, the highest increase is observed for CEEs–eurozone pairs. Mainly, we found a positive relationship between correlations (CEEs–eurozone) and volatilities (eurozone), even though there exist short time periods when this relationship becomes negative.

The rest of the thesis is structured as follows. Chapter 2 reviews the relevant literature, chapter 3 gives a brief description of the CEE markets, chapter 4 presents the research questions we are trying to answer, chapter 5 describes the methodology (theoretical framework), chapter 6 presents the empirical results and finally chapter 7 summarizes the main findings of the thesis.

Chapter 2

Literature review

The focus of my thesis is to investigate the interdependence among three major CEE stock markets (the Czech Republic, Poland and Hungary) and between CEEs vis–à–vis the aggregate eurozone market, using multivariate GARCH (MVGARCH) modeling. Consequently, literature review will be concentrated on different studies analyzing stock market linkages in CEE countries. In this context, numerous research papers make use of cointegration (Engle–Granger, Gragory–Hansen and Johansen methodology) and causality tests to measure short– and long–term linkages between financial markets. In addition to conventional econometric methods, MVGARCH models (CCC, STCC, BEKK, DCC) are also extensively used as a powerful tool in quantifying market comovements. Below we will synthetize the most important workings on this topic and then summarize the key facts.

Gilmore & McManus (2002) examined short– and long–term linkages between three CEE stock markets (the Czech Republic, Poland and Hungary) and the US stock market, using weekly data from 1995–2001. They argued that no long–run relationships exist between CEE markets and the US market (employing Johansen cointegration tests). Granger causality tests reveal only one causal relationship among the CEE markets, with the Hungarian market Granger causing the Polish market. While, Czech market is neither Granger caused by the other markets nor influencing them. Also, no causality effect is observed in either direction between the CEE markets and the US market. Overall, these results indicate the presence of good diversification benefits in CEE stock markets, from the point of view of a US investor.

In a similar vein, Patev et al. (2006) explored short– and long–run stock market comovements between four CEE stock markets (the Czech Republic,

Poland, Hungary and Russia) vis–à–vis the US market, for the period from 1996–2001. They divided the sample into three sub–periods: before, during and after the emerging markets crises. Similar to Gilmore & McManus (2002) cointegration analysis (Johansen methodology) indicated no long–run relationships among CEE stock markets and between CEEs and the US stock market. Using causality tests and variance decompositions, they documented an increase in markets interdependence during the crisis. This led to a temporary reduction in diversification benefits. A weaken in comovements was observed after the crisis, even though not reaching the pre–crisis levels.

Tudor (2011) studied causal relationships between six CEE stock markets (the Czech Republic, Poland, Hungary, Romania, Bulgaria and Russia) and the US stock market, using Granger causality tests. The data set were split into two sub–periods, before and during the recent financial crises. The results showed limited unilateral causal relationships among the CEE markets before the crises, followed by an intensified interaction in the crisis period. Furthermore, unidirectional causal relationships between the US market and the CEE markets in the pre–crisis period (with the US market Granger causing all the CEE markets) turned out to be bidirectional during the crisis.

Unlike Gilmore & McManus (2002) and Patev et al. (2006), there are a number of authors who claim the presence of a long–term relationship between the CEEs and developed markets. Among which we can distinguish Voronkova (2004), Syriopoulos (2007) and Syllignakis & Kouretas (2006).

Syriopoulos (2007) studied the interdependeces between four Central European stock markets (the Czech Republic, Hungary, Poland and Slovakia) and two developed ones (Germany and the US). A long–run relationship is found between the markets under study, attested by the existence of a one cointegrated vector (using Johansen methodology). In addition, both German and the US stock markets had a substantial influence on CEE stock markets and not vice–versa. This is well documented by Granger causality tests and forecast error variance decompositions. Among the CEE countries, Slovakia appears to be less related to other CEE markets and developed markets. Furthermore, a stronger dependence is observed among CEE stock markets than between CEEs and developed ones.

By the use of conventional cointegration tests and cointegration tests with shifting in regimes, Voronkova (2004) investigated the interlinkages between three emerging markets (the Czech Republic, Poland and Hungary) and four developed ones (Germany, France, the UK and the US). Conventional cointegra-

tion techniques (Engle–Granger tests) reveal long–run links between Polish and Hungarian markets, and between Czech and Hungarian markets. Also, long–run relationships exist between Polish and Czech markets vis–à–vis German, the UK and the US markets. When using cointegration tests with shifting in regimes (Gregory–Hansen tests), long–run linkages between Czech and Polish markets, and between Hungarian market vis–à–vis German, French and the US markets not detected by Engle–Granger procedure emerge. In general, there exist certain long–run links among developing markets and between developing markets and developed ones, but the number of cointegrating relationships is increased when taking into account structural breaks either in the intercept or in the slope of cointegrating vector.

Syllignakis & Kouretas (2006) analyzed comovements between seven CEE stock markets (the Czech Republic, Poland, Hungary, Slovakia, Slovenia, Estonia and Romania) and two major stock markets (Germany and the US), for the period from 1995–2005. Their results indicate a high degree of integration between five CEE markets (the Czech Republic, Poland, Hungary, Slovakia and Slovenia) vis–à–vis developed ones, supported by the evidence of increased conditional correlations over time. Correlations of developed markets with respect to Estonia and Romania were found to be quite low, except for the Russian crisis period. Long–term relationships were established only between the five CEE markets mentioned above and developed ones, whereas for Estonia and Romania such relationships were not present. As such, they suggest the Romanian and Estonian markets as good diversification possibilities in CEE region.

In addition to cointegration analysis and causality tests, a lot of papers (e.g. Kasch-Haroutounian & Price (2001), Scheicher (2001), Savva & Aslanidis (2010) etc) use MVGARCH modeling to study the dependence among stock markets. Kasch-Haroutounian & Price (2001) investigated the interdependence among four CEE stock markets (the Czech Republic, Poland, Hungary and Slovakia) employing two different multivariate GARCH approaches, such as constant conditional correlation (CCC) and BEKK. Their sample covers the period from 1994–1998 and consists of daily data. Using CCC model, they found a positive and statistically significant correlation coefficient between Czech and Hungarian stock markets (0.22), and between Hungarian and Polish stock markets (0.13). For the other pairs, correlations were very small and statistically insignificant. Moreover, applying the BEKK model, they detected only one unidirectional volatility spillover from Budapest stock market to Warsaw stock market. Both squared lagged innovation and conditional volatility of Budapest

stock market influencing Warsaw stock market volatility.

Also, Scheicher (2001) studied comovements between three European emerging markets (the Czech Republic, Poland and Hungary), for the period from 1995–1997, using a vector autoregression (VAR)–CCC model. They found both regional and global spillovers in returns, while observing only regional spillovers in volatilities. Hence, international shocks are transmitted in CEE stock markets through return shocks rather than volatility shocks. Another important finding which is in line with Kasch-Haroutounian & Price (2001) is that the most interconnected markets are Budapest and Warsaw stock market, with shocks generated in Budapest stock market influenced both the returns and volatilities in Warsaw stock market.

Although CCC model can be a good approximation, assuming constant correlations among stock returns is too restrictive. A more realistic approach can be the smooth transition CC model or the dynamic conditional correlation model. The former allows for a smooth switch between two correlation regimes, whereas the latter allows for time–varying correlations.

Savva & Aslanidis (2010) investigated the degree of stock market integration between 5 CEE countries (the Czech republic, Poland, Hungary, Slovakia and Slovenia) via–à–vis aggregate eurozone market, for the period from 1997–2008. Their methodology comprises CCC model and smooth transition CC (STCC) model. The largest CEE markets (namely the Czech Republic, Poland and Hungary) exhibit higher correlations vis–à–vis eurozone compared to Slovenia and Slovakia, and are also found to be the most interconnected markets in the region. Furthermore, they found increasing correlations among the CEE markets, and between Polish, Slovenian and Czech markets vis–à–vis eurozone. While, for the remaining pairs correlations were constant in time. The strengthen in correlations between CEEs and eurozone occurs much earlier than among the CEE markets itself, suggesting the influence of eurozone in inducing correlation shifts among CEEs. Accordingly, this evolution in correlations structure is mainly attributed to EU developments (all these CEE countries joined the EU in May 2004), rather than being a broad–based phenomenon.

Using a DCC model, Wang & Moore (2008) examined the interdependence between three major emerging markets (the Czech Republic, Poland and Hungary) vis–à–vis the aggregate eurozone market. Moreover, their efforts were concentrated in uncovering the factors that influenced the correlation dynamics. The main findings are: financial crisis and the EU enlargement had a substantial impact in increasing correlations between CEE markets and the eu-

rozone market. The detrimental factor in shifting correlations upward seems to be the stock market development measured by financial depth. On the contrary, macroeconomic and monetary convergence did not explain the increased interdependence between CEE markets and the EU market.

Syllignakis & Kouretas (2011) using a DCC model and employing weekly data from 1997–2009, investigated stock market correlations between three major stock markets (the US, Germany and Russia) and those of the Central Eastern Europe (the Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia and Slovenia). They argue a reduction in the diversification benefits in CEE markets, supported by the evidence of increasing correlations over time. The shift in the correlation coefficients can be mainly explained by a greater degree of financial openness, followed by an increased presence of foreign investors in the region, and finally the entry in EU. In contrast to Wang & Moore (2008), they emphasized the role of macroeconomic fundamentals in explaining the increased correlations during the recent financial crises.

So far, we have described different studies employing weekly or daily data. Yet, there exist a number of authors which make use of ultra high frequency data, among which Egert & Kocenda (2005) and Egert & Kocenda (2011). Using various conventional econometric techniques, Egert & Kocenda (2005) found no long–run relationships among the CEE markets (the Czech Republic, Poland and Hungary) and between CEE markets and developed ones (Germany, France and the UK). However, significant short–term spillover effects were present, more pronounced from volatility–to–volatility than from returns–to–returns.

Egert & Kocenda (2011) using a DCC model, examined comovements between three developed (France, Germany and the United Kingdom) and three emerging stock markets (the Czech Republic, Poland and Hungary). They found extremely low correlations among the developing markets (ranging from 0.02–0.05), and between developing markets and developed ones (ranging from 0.01–0.03). On the other hand, correlations among the developed markets appear to be large, indicating the high degree of integration of these markets. Also, they observed an increase in correlations in CEE markets beginning in the second half of 2004, which may be a consequence of those three countries joining the European Union.

Cappiello et al. (2006a) and Babetskii et al. (2007) studied stock market integration using alternative econometric techniques. Cappiello et al. (2006a) investigated the degree of integration between 7 new EU member states (the

Czech Republic, Poland, Hungary, Cyprus, Estonia, Latvia and Slovenia) and euro area, using a factor model of market returns. They emphasized the existence of strong comovements among the biggest CEE stock markets (the Czech Republic, Poland and Hungary), and between these markets vis–à–vis euro-zone. On the other hand, the degree of integration among the smaller stock markets (Cyprus, Estonia, Latvia and Slovenia) was assessed as low.

Babetskii et al. (2007) investigated the degree of integration between four CEE stock markets (the Czech Republic, Poland, Hungary and Slovakia) and the euro area, both at national and sectorial levels. They used two concepts, β–convergence (as a measure of the speed of convergence) and σ–convergence (as a measure of the degree of financial integration), usually found in the growth literature. They affirm the presence of a β–convergence, both at the national and sectorial levels. In addition, neither the EU enlargement nor the announcement of it did have any influence on β–convergence. They also detected a σ–convergence for the period from 1995–2005, followed by a divergence from the euro area after 2005. To summarize, the degree of integration between CEEs and euro area is increased over time.

Different authors have studied the interdependence between CEE stock markets and developed European markets, while there is a lack of literature in investigating comovements between South Eastern Europe (SEE) and Eurozone. Horvath & Petrovski (2012) fill this gap by examining both Central (the Czech Republic, Hungary and Poland) and South Eastern Europe (Croatia, Macedonia and Serbia). Using the BEKK–GARCH model, they analyze the linkages between CEE and SEE stock markets vis–à–vis euro area. Their results indicate a high degree of integration between CEEs and euro area (correlations fluctuate around 0.6) and a low degree of integration between SEEs and euro area (correlations fluctuate around 0). Among the SEE markets, Croatia exhibits the highest degree of integration. Also, they do not identify a change in market comovements during the recent financial crises.

In summary, all the above–mentioned studies reveal low short–term comovements among CEE markets and between CEEs vis–à–vis developed ones, which probably during the recent years have been strengthened. Also, during the different crisis (emerging market crisis, recent financial crisis etc.) increased comovements were reported. There is a discrepancy between different studies on the existence of a long–term relationship between these markets. Some studies detect the presence of a long–term relationship, while others conclude that such long–term relationships do not exist.

Chapter 3

Market description

3.1 A short history

Budapest Stock Exchange (BSE) was established in 1864 as the Hungarian Stock Exchange. After four years it changed to Budapest Stock and Commodity Exchange, trading not only securities but also commodities and mainly grain. In 1889, stocks quoted on BSE were also listed on Vienna, Frankfurt, London and Paris, while in 1890s government bonds issued by the Hungarian authorities were traded on Amsterdam, Berlin, London and Paris Stock Exchanges. Like other stock exchanges in Central and Eastern Europe, BSE stopped operating after WWII, reopening again on June 21, 1990.

Prague stock exchange (PSE) was established in 1871. In the beginning, securities and commodities were traded in PSE. After WWI, commodity transactions seized to exit. Between WWI and WWII, PSE experienced a prosperity period and performed even better than Vienna stock exchange. During communism it stopped operating, reopening again on November 24, 1992. The first trading session was held after 5 months on April 6, 1993 with only 7 securities listed.

Polish capital market was established in 1817 under the name of Warsaw Mercantile Exchange. During the communist era it stopped operating, reopening again on April 12, 1991 as the Warsaw Stock Exchange (WSE). The first trading session took place on April 16 and the number of listed companies was 5. In 2007, a new market, called NewConnect, devoted to small and medium enterprises was created. In 2009, another market segment dedicated to bond[1] trading was launched.

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[1]Corporate, mortgage-backed, treasury and municipal bonds.

In 2004, these CEE countries became part of EU and their stock exchanges became a full member of Federation of European Securities Exchanges (FESE).

3.2   Market segments

In this section we will describe the market's segments and financial instruments traded on Prague, Budapest and Warsaw stock exchanges. In this way, we can give a complete picture of the structure of these markets.
BSE market structure is given as below:

- Equities section – securities such as equities and investment fund shares are traded on this market. In addition to these instruments, also structured products and special securities are traded.

- Debt securities section – instruments such as government bonds, treasury bills, corporate bonds and mortgage bonds are traded in this market.

- Derivatives section – two types of contracts are traded on this market, futures and options contracts.

- Commodities section – commodities, spot and derivative commodity instruments are traded in this market.

- BETa market was established in November 2011 and serves as an alternative market for European companies with a good reputation.

The WSE market structure is given as below:

- Main list – is the first market that has been operating since 1991. Different securities are traded on this market such as equities, bonds, future contracts, options etc.

- New connect – is a special market devoted to start ups and developing companies, in particular to companies investing in innovations and new technologies. Traded securities include equities and equity–based securities.

- Catalyst – is a recently established market (2009) for debt instrument trading. Debt instruments traded on catalyst include corporate bonds, municipality bonds and treasury bonds.

PSE market structure is given as below:

- Main market – is a regulated market devoted to large issues and is subject to strict regulations.

- Free market – is also a regulated market, but in contrast to the main market is not subject to high requirements.

- MFT market – is a non regulated market, much more flexible than the regulated markets and with less strict requirements.

Instruments traded in these markets include bonds, shares, investment certificates, futures and warrants.

3.3   Market statistics

This section will cover some simple market statistics such as market capitalization, equity trading volume and the number of IPOs. Initially, we will give a brief definition of the terms and stress their importance[2].

Market capitalization – market capitalization (or market cap) of a company is defined as the total number of shares multiplied by the price of one share. Whereas, market capitalization of an exchange is the sum of market capitalisations of all domestic and foreign companies listed in that exchange. Market capitalization serves as a good measure of the market size.

Equity trading volume – is equal to the number of traded shares multiplied by their relevant prices. We can refer to this indicator as a liquidity measure.

IPOs – initial public offerings, the first time sale of stocks from an unlisted company.

Figure 3.1 below presents market capitalization of PSE, BSE and WSE, from 2001 to 2011. We can easily observe that WSE has the highest market capitalization, far from PSE and BSE. Market cap of WSE is 2.2–4.5 times higher than market cap of PSE and 2.2–7.3 times higher than market cap of BSE. This makes WSE the biggest market in the region. Until 2003, the second biggest market was BSE, followed by PSE. After 2003, PSE became the second largest market. For the period from 2001–2003, we notice a fairly constant market cap for the three markets under study, then we can observe an increasing trend until 2007. This prosperity period was disrupted by the recent financial crises, with market cap figures reaching half their values in 2008. Afterwards, PSE

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[2]For the definitions we refer to FESE statistics methodology.

and BSE experienced a small increase, whereas WSE followed a sharp raise. In 2011, all the exchanges experienced a decrease in market capitalization.

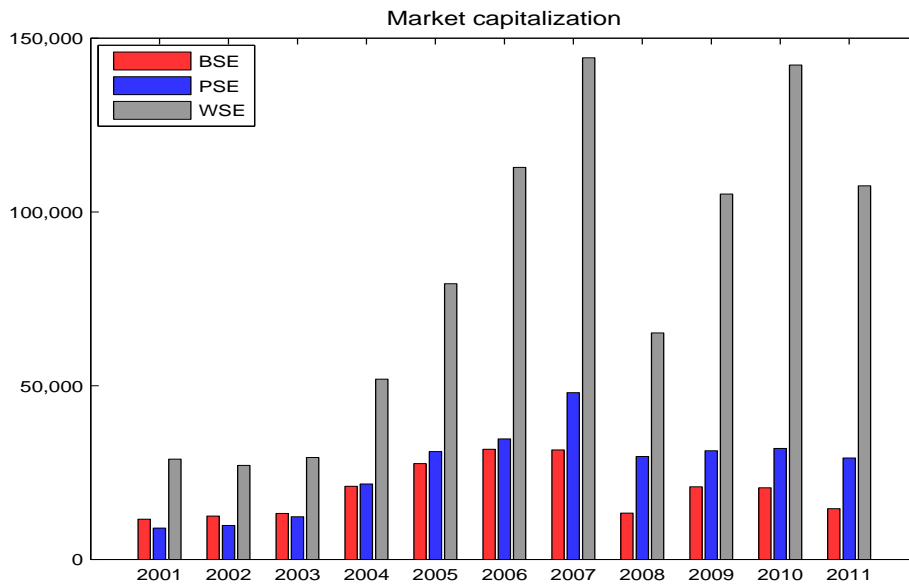Figure 3.1: Market capitalisation. Year–end values in million Euro. Data retrieved from Federation of Europen Securities Exchanges.
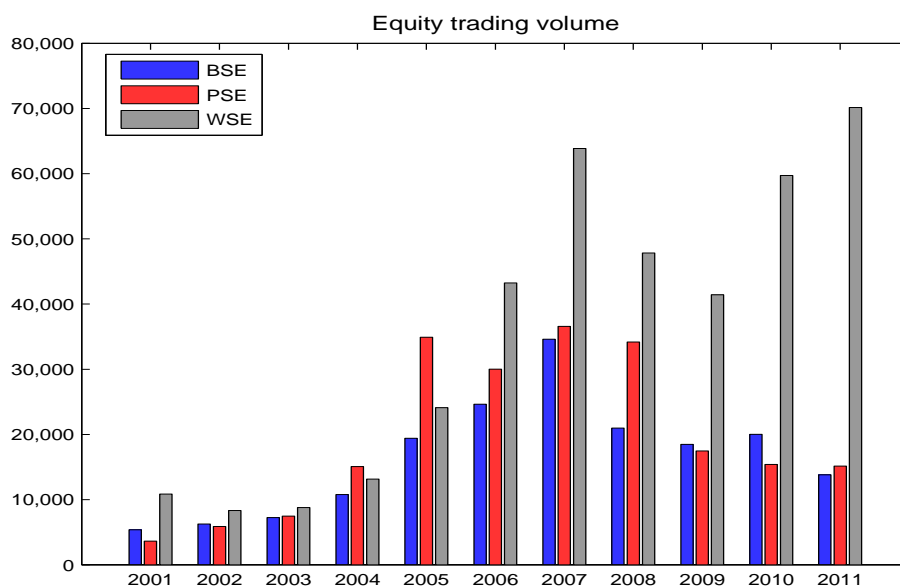
Figure 3.2: Equity trading volume. It includes electronic order book, off–electronic order book and dark pool transactions (in million Euro). Data retrieved from Federation of Europen Securities Exchanges.

WSE has the highest trading volume of shares (see figure 3.2), which makes

it the most liquid market in the region. In 2011, trading volume of WSE was 5.1 times higher than trading volume of BSE and 4.6 times higher than trading volume of PSE. Only in 2004–2005, WSE was ranked as the second market in terms of trading volume. In 2001–2002, BSE was the second most liquid market. While, after 2002 PSE surpassed BSE. Similar to market capitalization, trading volume follows approximately the same pattern.

Regarding the number of IPOs, still WSE is ranked first and we can compare it to developed European stock markets. It is very active in IPOs, with 204 IPOs only in 2011.

The wide range of securities traded in WSE (debt instruments, equity instruments, derivatives & structured products etc.), the high number of IPOs, the equity trading volume and market capitalisation make WSE a leader in Central and Eastern Europe.

	Budapest	Prague	Warsaw
2001	1	0	0
2002	0	0	0
2003	0	0	0
2004	0	0	1
2005	0	0	0
2006	0	0	27
2007	1	2	105
2008	2	1	93
2009	0	0	38
2010	0	1	110
2011	0	1	204

Table 3.1: Nr. of IPOs

Chapter 4

Hypotheses

In our study, we will address different research questions regarding stock market integration in CEE region. As mentioned, we will be concentrated on the major stock markets of Central Europe such as Czech, Polish and Hungarian markets. As these countries joined the EU in May 2004, it is also of great interest to explore the degree of integration between these markets and eurozone. Cappiello et al. (2006a) associate the degree of stock market integration to the strengthen of linkages between these markets, and the empirical strategy is based on investigating comovements of financial asset returns across different countries. The appropriate methodology, despite the existence of a wide range of techniques, consists in estimating dynamic conditional correlation model of Engle (2002) and its asymmetric version of Capiello et al. (2006b). By the use of the above–mentioned models and of supplementary OLS regressions we will try to answer the following questions:

1. *Are correlations among CEE stock markets and between CEEs vis–à–vis eurozone high or low?*

2. *Are correlations increased over time?*
   As stock markets are becoming increasingly integrated and CEE countries are now part of EU, we expect an increase in conditional correlations over time.

3. *Are correlations increased during the recent financial crises?*
   We should observe an increase in correlations compared to the pre–crises period in case of a contagion effect due to the recent financial crises.

4. *Do correlations and volatilities move in the same direction (i.e. correlations are strengthened when the level of risk is increased)?*

5. *Are there asymmetric effects present in the correlation dynamics?*
   We will test whether there is a tendency of the conditional correlations
   to increase more when both markets experience bad news[1].

6. *Are there any good possibilities for risk diversification in CEE region[2]?*
   It is very important for international portfolio managers seeking to invest
   in CEE countries to have a good knowledge of time–varying correlations
   among CEE stock markets and between their national or regional stock
   market vis–à–vis CEEs. This information plays a vital role in composing
   optimal diversified portfolios.

7. *Are these diversification benefits reduced in time as a result of increased
   integration between the markets?*

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[1]i.e. when both index returns happen to be negative.
[2]From the point of view of a European investor.

Chapter 5

Methodology

In order to investigate changes in comovements among CEE stock markets (the Czech Republic, Poland and Hungary), and between CEE markets vis–à–vis the aggregate eurozone market we will make use of DCC model of Engle (2002) and asymmetric DCC model of Capiello et al. (2006b). As it is too restrictive to estimate an A/DCC model for all return series at once, we will use bivariate versions of it[1]. Our estimation strategy will be based on the following steps:

1. Transform prices into returns by initially taking the logarithm and then first–differencing the data.

   - Test returns for unit roots using augmented Dickey–Fuller (ADF) test with automated lag selection. The optimal lag length will be determined using Akaike information criterion (AIC). Generally, financial data are integrated of order one ($I(1)$) and turn out to be covariance–stationary after log first–differencing.

2. Estimate an AR(1) model for each return series in order to remove the dependence in returns and produce the *i.i.d.* zero mean residuals (see Engle & Sheppard 2001).

3. Estimate a GARCH model for each residual series obtained from the AR(1) specification. For this purpose, four univariate GARCH specifications (GARCH, GJR–GARCH, TGARCH, AVGARCH) will be employed and the best model will be selected using BIC. Specifications up to 2 lags will be considered.

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[1] i.e. pair-wise conditional correlations will be calculated.

- Test the standardized residuals (i.e. residuals divided by their conditional standard deviations) for any remaining serial correlation using Ljung–Box Q test.

- Test the squared standardized residuals for any remaining ARCH effects using ARCH–LM test of Engle (1982).

4. Estimate DCC and ADCC models using standardized residuals.

5. Perform OLS regressions[2] of dynamic correlations on a time trend and a dummy variable for the recent financial crises. In this way, we can understand whether correlations are increased over time and during the crises.

6. Perform OLS regressions of conditional correlations on conditional volatilities. In addition, we will employ a rolling "stepwise" regression methodology to study the time–varying nature of the coefficients. If volatilities and correlations move in the same direction (i.e. correlations are strengthened when the level of risk is increased), then long run risks are higher than they appear in the short run.

To estimate all the models (OLS, ARMA, GARCH and DCC), MFE Toolbox© made available by Kevin Sheppard will be utilized. Below we will describe the models in details and the structure is as follows. Section 5.1.1 covers ARMA models, section 5.1.2 GARCH models and section 5.1.3 DCC models.

5.1 Theoretical framework

5.1.1 ARMA models

Before proceeding with the description of ARMA models, it is necessary to define the concept of covariance stationarity (or week stationarity). A stochastic process $\{r_t\}$ is said to be covariance stationary if:

- $\mathrm{E}\left[r_t\right] = \mu$ for $t = 1, 2, \ldots$

- $\mathrm{Var}\left[r_t\right] = \sigma^2$ for $t = 1, 2, \ldots$

- $\mathrm{Cov}\left[r_t, r_{t-s}\right] = \gamma_s$ for $t = 1, 2, \ldots$ and $s \neq 0$

---

[2]Newey–West covariance estimator, which is robust to both heteroskedasticity and autocorrelation, will be used.

Simply put, covariance stationarity means that the unconditional first and second moments of a stochastic process are finite and constant in time. So, stationarity imposes some regularities, which are important for estimating the model parameters.

The simplest process, upon which ARMA models are built, is the white noise process. A sequence $\{\epsilon_t\}$ is said to be a white noise process if the following properties hold:

- $\mathrm{E}\left[\epsilon_t\right] = 0$ for $t = 1, 2, \ldots$

- $\mathrm{Var}\left[\epsilon_t\right] = \sigma^2$ for $t = 1, 2, \ldots$

- $\mathrm{Cov}\left[\epsilon_t, \epsilon_{t-s}\right] = 0$ for $t = 1, 2, \ldots$ and $s \neq 0$

or equivalently expressed $\epsilon_t \overset{i.i.d.}{\sim} \mathcal{D}\left(0, \sigma^2\right)$ where $\mathcal{D}$ indicates the distribution. If $\mathcal{D}$ were a normal distribution, then we would have a Gaussian white noise process.

Basically, ARMA model is composed of the autoregressive (AR) and moving average (MA) parts. The AR(P) model has the following form:

$$r_t = \phi_0 + \sum_{p=1}^{P} \phi_p r_{t-p} + \epsilon_t \tag{5.1}$$

where ϵ_t is a white noise process.
Certain conditions have to be met for the AR(P) process to be covariance stationary. In order to define the stationarity condition, we first have to express the AR(P) model by means of lag operators[3]:

$$\left(1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_P L^P\right) r_t = \phi_0 + \epsilon_t \tag{5.2}$$

Thus, for the AR(P) process to be covariance stationary, the roots of the AR polynomial $\left(1 - \phi_1 z - \phi_2 z^2 - \ldots - \phi_P z^P\right)$ must lie outside the unit circle. Whereas, the MA(Q) process is given as:

$$r_t = \phi_0 + \sum_{q=1}^{Q} \theta_q \epsilon_{t-q} + \epsilon_t \tag{5.3}$$

or in terms of lag operators:

$$r_t - \phi_0 = \left(1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_Q L^Q\right) \epsilon_t \tag{5.4}$$

---

[3]We can define a lag operator L as $L^i r_t = r_{t-i}$. If $r_t = c$, where c is a constant, then $Lc = c$.

Unlike the AR(P) process, MA(Q) process is always stationary. Invertibility is a crucial requirement for uniquely identifying the MA process. For an MA(Q) process to be invertible the roots of the MA polynomial $\left(1 + \theta_1 z + \theta_2 z^2 + \ldots + \theta_Q z^Q\right)$ must lie outside the unit circle.

The mixture of the above mentioned models yields the ARMA(P,Q) process:

$$r_t = \phi_0 + \sum_{p=1}^{P} \phi_p r_{t-p} + \sum_{q=1}^{Q} \theta_q \epsilon_{t-q} + \epsilon_t \tag{5.5}$$

The polynomials $\left(1 - \phi_1 z - \phi_2 z^2 - \ldots - \phi_P z^P\right)$ and $\left(1 + \theta_1 z + \theta_2 z^2 + \ldots + \theta_Q z^Q\right)$ must not have any roots in common, otherwise we can reduce the model orders.

The ARMA(P,Q) model can be extended to ARIMA(P,d,Q), where I holds for the integrated and d is the order of integration. If $\nabla^d r_t$ is an ARMA(P,Q) process, then r_t is an ARIMA(P,d,Q) process. When $d = 1$, which is the case for most financial time series, we have an ARIMA(P,1,Q) process. Specifically, if $r_t = \log\left(P_t\right) - \log\left(P_{t-1}\right)$ follows an ARMA(P,Q) process, then $\log\left(P_t\right)$ follows an ARIMA(P,1,Q) process.

5.1.2 GARCH models

Volatility modeling has been one of the most promising and important areas of study over the last decades. A vast amount of literature is devoted to modeling and forecasting the second moments of asset returns. As it was difficult to find an asset whose volatility was constant over time, historical volatility became irrelevant and econometricians tried to develop models which allowed for time–varying volatility. Engle (1982) was the first to introduce the autoregressive conditional heteroskedasticity (ARCH) model, which specifies the conditional variance as a function of lagged squared errors.

The ARCH(P) process is given as:

$$r_t = \mu_t + \epsilon_t \tag{5.6}$$

$$\sigma_t^2 = \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-p}^2 \tag{5.7}$$

with parameter restrictions:

1. $\sum_{p=1}^{P} \alpha_p < 1$

2. $\omega > 0$

3. $\alpha_p \geq 0$ for $p = 1, 2, \ldots, P$

where equation 5.6 represents the model of the conditional mean. The error term ϵ_t can be decomposed as $\epsilon_t = v_t \sigma_t$, where v_t is an *i.i.d.* normal innovation with mean 0 and variance 1. Restriction 1 ensures a covariance stationary ARCH process, while restrictions 2 and 3 guarantee a positive conditional variance at each point in time.

A drawback of the ARCH specification is the high number of lags needed to properly model the conditional variance. Bollerslev's (1986) generalized ARCH (GARCH) model solved this shortcoming, by allowing the conditional variance to depend not only on lagged squared errors but also on lagged conditional variances. The GARCH(P,Q) process is given as:

$$\sigma_t^2 = \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-p}^2 + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \tag{5.8}$$

with parameter restrictions:

1. $\sum_{p=1}^{P} \alpha_p + \sum_{q=1}^{Q} \beta_q < 1$

2. $\omega > 0$

3. $\alpha_p \geq 0$ for $p = 1, 2, \ldots, P$

4. $\beta_q \geq 0$ for $q = 1, 2, \ldots, Q$

In general, the GARCH(1,1) model sufficiently explains the conditional heteroscedasticity present in the data and usually every financial time series is best described by this model. Also, it represents a parsimonious specification since it includes estimating only three parameters and performs as good as a high-order ARCH model (Bollerslev 1986).

The aforementioned models assume a symmetric response of the conditional variance to both positive and negative shocks of the same magnitude. Empirically, it is observed that conditional variance increases more after a negative shock rather than a positive shock (the so called "leverage" effect). To account for this effect different models have been developed, among which the GJR–GARCH specification of Glosten et al. (1993). The GJR–GARCH(P,O,Q) specification is given as:

$$\sigma_t^2 = \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-p}^2 + \sum_{o=1}^{O} \gamma_o \epsilon_{t-o}^2 I_{[\epsilon_{t-o}<0]} + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \tag{5.9}$$

with parameter restrictions:

1. $\sum_{p=1}^{P} \alpha_p + \frac{1}{2} \sum_{o=1}^{O} \gamma_o + \sum_{q=1}^{Q} \beta_q < 1$

2. $\omega > 0$

3. $\alpha_p \geq 0$ for $p = 1, 2, \ldots, P$

4. $\beta_q \geq 0$ for $q = 1, 2, \ldots, Q$

5. $\alpha_q + \gamma_o \geq 0$ for $q = 1, 2, \ldots, Q$ and $o = 1, 2, \ldots, O$

where $I_{[\epsilon_{t-o} < 0]}$ is an indicator function which takes on the value 1 when $\epsilon_{t-o} < 0$ and 0 otherwise.

All the GARCH models mentioned above parameterize the conditional variance. In addition, specifications of the conditional standard deviation will be employed. Among this class of models we can distinguish the absolute value GARCH (AVGARCH) model of Taylor (1986) and threshold GARCH (TGARCH) model of Zakoian (1994). TGARCH(P,O,Q) model is given as:

$$\sigma_t = \omega + \sum_{p=1}^{P} \alpha_p |\epsilon_{t-p}| + \sum_{o=1}^{O} \gamma_o |\epsilon_{t-o}| I_{[\epsilon_{t-o} < 0]} + \sum_{q=1}^{Q} \beta_q \sigma_{t-q} \tag{5.10}$$

AVGARCH model is a special case of TGARCH model when no asymmetric terms are included (i.e. $O = 0$). The AVGARCH(P,Q) specification is given as:

$$\sigma_t = \omega + \sum_{p=1}^{P} \alpha_p |\epsilon_{t-p}| + \sum_{q=1}^{Q} \beta_q \sigma_{t-q} \tag{5.11}$$

Parameter restrictions applied to AVGARCH and TGARCH models are basically the same as parameter restrictions of GARCH and GJR–GARCH models, respectively.

Estimation

GARCH models are estimated using maximum likelihood, assuming the errors are conditionally *i.i.d.* normal. The likelihood function is given as:

$$\mathcal{L}(\boldsymbol{\theta}; \boldsymbol{r}_t) = \prod_{t=1}^{T} \left(2\pi\sigma_t^2\right)^{-\frac{1}{2}} \exp\left(-\frac{(r_t - \mu_t)^2}{2\sigma_t^2}\right) \tag{5.12}$$

and the log–likelihood function takes the form:

$$\ell(\boldsymbol{\theta}; \boldsymbol{r}_t) = -\frac{1}{2} \sum_{t=1}^{T} \log(2\pi) + \log\left(\sigma_t^2\right) + \frac{(r_t - \mu_t)^2}{\sigma_t^2} \tag{5.13}$$

Parameters are estimated by maximizing the log–likelihood function:

$$\widehat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \, \ell(\boldsymbol{\theta}; \boldsymbol{r}_t)$$

For this purpose, quasi–Newton methods such as the BFGS algorithm of Boyden, Fletcher, Goldfarb and Shannon will be used. When the distribution is misspecified, $\widehat{\boldsymbol{\theta}}$ is interpreted as a quasi–maximum likelihood estimator.

Asymptotic theory

Parameters estimated through maximum likelihood are asymptotically normally distributed.

$$\sqrt{T}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\right) \xrightarrow{d} N\left(0, \mathcal{I}^{-1}\right) \tag{5.14}$$

where $\mathcal{I}$ is -1 times the expected value of the Hessian matrix[4]:

$$\mathcal{I} = -\mathrm{E}\left[\frac{\partial^2 \ell\left(\boldsymbol{\theta}_0; \boldsymbol{r}_t\right)}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}'}\right] \tag{5.15}$$

and can be estimated using the sample analogue:

$$\widehat{\mathcal{I}} = T^{-1} \sum_{t=1}^{T} \frac{\partial^2 \ell\left(\widehat{\boldsymbol{\theta}}; \boldsymbol{r}_t\right)}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}'} \tag{5.16}$$

In general, information matrix equality ($\mathcal{I} = \mathcal{J}$) holds for maximum likelihood estimators, where $\mathcal{J}$ is the outer product of scores and is given as:

$$J = \mathrm{E}\left[\frac{\partial \ell\left(\boldsymbol{\theta}_0; \boldsymbol{r}_t\right)}{\partial \boldsymbol{\theta}} \frac{\partial \ell\left(\boldsymbol{\theta}_0; \boldsymbol{r}_t\right)}{\partial \boldsymbol{\theta}'}\right] \tag{5.17}$$

Also, it can be estimated using the sample analogue:

$$\widehat{\mathcal{J}} = T^{-1} \sum_{t=1}^{T} \frac{\partial \ell\left(\widehat{\boldsymbol{\theta}}; \boldsymbol{r}_t\right)}{\partial \boldsymbol{\theta}} \frac{\partial \ell\left(\widehat{\boldsymbol{\theta}}; \boldsymbol{r}_t\right)}{\partial \boldsymbol{\theta}'} \tag{5.18}$$

If the distribution is misspecified (i.e. if we assume normal distribution but the data come from another distribution[5]) information matrix equality does not hold anymore. In this case, we should use the robust (or "sandwich") covariance estimator.

$$\sqrt{T}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\right) \xrightarrow{d} N\left(0, \mathcal{I}^{-1}\mathcal{J}\mathcal{I}^{-1}\right) \tag{5.19}$$

Both gradients and hessians are computed through numerical approximations. Specifically, we will use centered difference approximation in order to achieve a higher precision.

---

[4]Hessian matrix is the matrix of second–order derivatives.

[5]The distribution of the errors in GARCH models usually exhibit excees kurtosis and negativ skewness and thus is non–normal.

5.1.3   DCC models

Engle (2002) proposed the dynamic conditional correlation (DCC) model that is a direct generalization of the constant conditional correlation (CCC) model of Bollerslev (1990). This specification assumes that the $1 \times k$ vector of returns[6] is conditionally normally distributed with zero mean and variance–covariance matrix $\boldsymbol{H}_t$.

$$\boldsymbol{r}_t | \mathcal{F}_{t-1} \sim N\left(\boldsymbol{0}, \boldsymbol{H}_t\right) \ \ \text{where } \mathcal{F}_{t-1} \text{ is the information set at time } t-1$$

The variance–covariance matrix $\boldsymbol{H}_t$ can be decomposed as $\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t$, where $\boldsymbol{D}_t$ is a diagonal matrix with the *ith* diagonal element corresponding to the conditional standard deviation of the *ith* asset and $\boldsymbol{R}_t$ is the time–varying correlation matrix.

$$\boldsymbol{D}_t = \text{diag}\left\{\sigma_{it}\right\} \ \ \text{where } \sigma_{it} = \sqrt{\sigma_{it}^2}$$

$$\boldsymbol{R}_t = \{\rho_{ij,t}\} \text{ where } \begin{cases} \rho_{ij,t} = 1 & \text{for} \quad i = j \\ \rho_{ij,t} \le |1| & \text{for} \quad i \ne j \end{cases}$$

Our model will be flexible enough to allow each conditional variance to be given as one of the four possible GARCH specifications mentioned in section 5.1.2. Also, it will be possible for different return series to have different ARCH, TARCH[7] and GARCH lag lengths. The best model between the four specifications will be selected using BIC. All the GARCH specifications can be expressed in nested form as:

$$\sigma_{it}^\delta = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} |r_{it-p}|^\delta + \sum_{o=1}^{O_i} \gamma_{io} |r_{it-o}|^\delta I_{[r_{it-o}<0]} + \sum_{q=1}^{Q_i} \beta_{iq} \sigma_{it-q}^\delta \tag{5.20}$$

where $\delta = 1, 2$ depending on whether we parameterize the conditional standard deviation or the conditional variance.

The correlation dynamics is given by:

$$\boldsymbol{Q}_t = \left(1 - \sum_{m=1}^{M} \theta_m - \sum_{n=1}^{N} \varphi_n\right) \overline{\boldsymbol{Q}} + \sum_{m=1}^{M} \theta_m \left(\boldsymbol{\epsilon}_{t-m} \boldsymbol{\epsilon}_{t-m}'\right) + \sum_{n=1}^{N} \varphi_n \boldsymbol{Q}_{t-n} \tag{5.21}$$

and

$$\boldsymbol{R}_t = \boldsymbol{Q}_t^{\star-1} \boldsymbol{Q}_t \boldsymbol{Q}_t^{\star-1} \tag{5.22}$$

---

[6]Either demeaned returns or residuals obtained after applying ARMA filtering.

[7]TARCH refers to asymmetric inovation term.

where $\boldsymbol{\epsilon}_t = \boldsymbol{D}_t^{-1} \boldsymbol{r}_t$ (or equivalently $\boldsymbol{\epsilon}_t = \boldsymbol{r}_t \oslash \boldsymbol{\sigma}_t$[8]) are the standardized returns. $\overline{\boldsymbol{Q}} = \mathrm{E}\left[\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t'\right]$ is the unconditional correlation of the standardized returns and since the expectation is infeasible, we can estimate it using the sample analogue $T^{-1} \sum_{t=1}^{T} \boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t'$. Multiplication by $\boldsymbol{Q}_t^{\star} = (\boldsymbol{Q}_t \odot \boldsymbol{I}_k)^{-1/2}$[9] matrix guarantees that $\boldsymbol{R}_t$ is a well–defined correlation matrix with ones along the main diagonal and each off-diagonal element being less or equal to one in absolute value.

The variance–covariance matrix $\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t$ will be positive definite as long as $\boldsymbol{R}_t$ is positive definite and the univariate GARCH models are correctly specified. A necessary and sufficient condition for $\boldsymbol{R}_t$ to be positive definite is that $\boldsymbol{Q}_t$ must be positive definite (see Engle & Sheppard 2001). Parameter restrictions which ensure a positive definite $\boldsymbol{Q}_t$ matrix are:

1. $\sum_{m=1}^{M} \theta_m + \sum_{n=1}^{N} \varphi_n < 1$

2. $\theta_m \geq 0$ for $m = 1, 2, \ldots, M$

3. $\varphi_n \geq 0$ for $n = 1, 2, \ldots, N$

Beside DCC model, the asymmetric DCC (ADCC) specification of Capiello et al. (2006b) will be considered. ADCC model introduces asymmetries in the correlation dynamics.

The dynamic correlation structure is given as:

$$\boldsymbol{Q}_t = \left(1 - \sum_{m=1}^{M} \theta_m - \sum_{n=1}^{N} \varphi_n\right) \overline{\boldsymbol{Q}} - \sum_{k=1}^{K} \tau_k \overline{\boldsymbol{N}} + \sum_{m=1}^{M} \theta_m \left(\boldsymbol{\epsilon}_{t-m} \boldsymbol{\epsilon}_{t-m}'\right) +$$
$$+ \sum_{k=1}^{K} \tau_k \left(\boldsymbol{n}_{t-k} \boldsymbol{n}_{t-k}'\right) + \sum_{n=1}^{N} \varphi_n \boldsymbol{Q}_{t-n} \quad (5.23)$$

where $\boldsymbol{\epsilon}_t$ and $\overline{\boldsymbol{Q}}$ are expressed exactly as in the DCC case. $\boldsymbol{n}_t = \boldsymbol{I}_{[\boldsymbol{\epsilon}_t < 0]} \odot \boldsymbol{\epsilon}_t$, with $\boldsymbol{I}_{[\boldsymbol{\epsilon}_t < 0]}$ being a $1 \times k$ indicator function which takes on the value 1 when $\boldsymbol{\epsilon}_t < 0$ and 0 otherwise. In this case, unlike in the univariate processes, the asymmetric term is applicable when both indicators $I_{[\epsilon_{it} < 0]}$ and $I_{[\epsilon_{jt} < 0]}$[10] are equal to 1 or in other words when both returns happen to be negative. $\overline{\boldsymbol{N}} = \mathrm{E}\left[\boldsymbol{n}_t \boldsymbol{n}_t'\right]$ can be estimated using the sample analogue $\overline{\boldsymbol{N}} = T^{-1} \sum_{t=1}^{T} \boldsymbol{n}_t \boldsymbol{n}_t'$. Positive definiteness of $\boldsymbol{Q}_t$ is ensured by imposing the following restrictions:

1. $\sum_{m=1}^{M} \theta_m + \delta \sum_{k=1}^{K} \tau_k + \sum_{n=1}^{N} \varphi_n < 1$

2. $\theta_m \geq 0$ for $m = 1, 2, \ldots, M$

---

[8] $\oslash$ denotes Hadamard devision (element–by–element division).

[9] $\odot$ denotes the Hadamard product (element–by–element multiplication).

[10] $I_{[\epsilon_{it} < 0]}$ and $I_{[\epsilon_{jt} < 0]}$ where $i \neq j$ are elements of $\boldsymbol{I}_{[\boldsymbol{\epsilon}_t < 0]}$.

3. $\tau_k \geq 0$ for $k = 1, 2, \ldots, K$

4. $\varphi_n \geq 0$ for $n = 1, 2, \ldots, N$

where $\delta = \overline{\boldsymbol{Q}}^{-\frac{1}{2}} \overline{\boldsymbol{N}} \overline{\boldsymbol{Q}}^{-\frac{1}{2}}$ can be estimated on sample data.

Estimation

The A/DCC model will be estimated via maximum likelihood assuming conditional multivariate normality. Estimation of the model is done using a three step procedure (see e.g. Engle & Sheppard 2001, Engle 2002). In the first step we fit k univariate GARCH–type models for each return series. Then, the unconditional correlation matrix $\overline{\boldsymbol{Q}}$ (and the unconditional covariance matrix $\overline{\boldsymbol{N}}$ in case of ADCC) is estimated using the standardized returns (asymmetric standardized returns) and finally we estimate the parameters which govern the correlation dynamics. Although the conditional distribution is usually misspecified, there still exist quasi–maximum likelihood estimators which are consistent and asymptotically normal (Engle & Sheppard 2001).
The joint log–likelihood function is:

$$
\begin{aligned}
\mathcal{L}\left(\boldsymbol{\theta}\right) &= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log\left(2\pi\right) + \log\left(|\boldsymbol{H}_t|\right) + \boldsymbol{r}_t' \boldsymbol{H}_t \boldsymbol{r}_t \right) \\
&= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log\left(2\pi\right) + \log\left(|\boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t|\right) + \boldsymbol{r}_t' \boldsymbol{D}_t^{-1} \boldsymbol{R}_t^{-1} \boldsymbol{D}_t^{-1} \boldsymbol{r}_t \right) \\
&= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log\left(2\pi\right) + 2\log\left(|\boldsymbol{D}_t|\right) + \log\left(|\boldsymbol{R}_t|\right) + \boldsymbol{\epsilon}_t' \boldsymbol{R}_t^{-1} \boldsymbol{\epsilon}_t \right)
\end{aligned}
$$

and we can split it into a volatility and a correlation part. For this purpose parameters are divided in two groups, one corresponding to univariate GARCH parameters and the other corresponding to dynamic correlation parameters.

GARCH: $\boldsymbol{\phi} = (\phi_1, \phi_2, \ldots, \phi_k)$ where $\phi_i = (\omega_i, \alpha_{i1}, \ldots, \alpha_{iP_i}, \gamma_{i1}, \ldots, \gamma_{iO_i}, \beta_{i1}, \ldots, \beta_{iQ_i})$
DCC: $\quad \boldsymbol{\psi} = (\theta_1, \ldots, \theta_m, \tau_1, \ldots, \tau_k, \varphi_1, \ldots, \varphi_n)$

In the first step $\boldsymbol{R}_t$ is replaced with $\boldsymbol{I}_k$, an identity matrix of dimension k. Thus, the first stage quasi–likelihood becomes:

$$
\begin{aligned}
Q\mathcal{L}_1\left(\boldsymbol{\phi}|\boldsymbol{r}_t\right) &= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log\left(2\pi\right) + 2\log\left(|\boldsymbol{D}_t|\right) + \underbrace{\log\left(|\boldsymbol{I}_k|\right)}_{0} + \boldsymbol{r}_t' \boldsymbol{D}_t^{-1} \boldsymbol{I}_k \boldsymbol{D}_t^{-1} \boldsymbol{r}_t \right) \\
&= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log\left(2\pi\right) + 2\log\left(|\boldsymbol{D}_t|\right) + \boldsymbol{r}_t' \boldsymbol{D}_t^{-2} \boldsymbol{r}_t \right)
\end{aligned}
$$

$$= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log (2\pi) + \sum_{i=1}^{k} \left(\log \left(\sigma_{it}^2 \right) + \frac{r_{it}^2}{\sigma_{it}^2} \right) \right)$$

$$= -\frac{1}{2} \sum_{i=1}^{k} \sum_{t=1}^{T} \left(\log (2\pi) + \log \left(\sigma_{it}^2 \right) + \frac{r_{it}^2}{\sigma_{it}^2} \right)$$

Indeed, the first stage quasi–likelihood is the sum of individual GARCH likelihoods and maximizing the joint likelihood is equivalent to maximizing each univariate GARCH likelihood individually.

The second stage quasi–likelihood is estimated conditioning on first stage parameters:

$$Q\mathcal{L}_2 \left(\boldsymbol{\psi} | \hat{\boldsymbol{\phi}}, \boldsymbol{r}_t \right) = -\frac{1}{2} \sum_{t=1}^{T} \left(k \log (2\pi) + 2 \log (|\boldsymbol{D}_t|) + \log (|\boldsymbol{R}_t|) + \boldsymbol{r}_t' \boldsymbol{D}_t^{-1} \boldsymbol{R}_t \boldsymbol{D}_t^{-1} \boldsymbol{r}_t \right)$$

$$= -\frac{1}{2} \sum_{t=1}^{T} \left(k \log (2\pi) + 2 \log (|\boldsymbol{D}_t|) + \log (|\boldsymbol{R}_t|) + \boldsymbol{\epsilon}_t' \boldsymbol{R}_t \boldsymbol{\epsilon}_t \right)$$

Given that we are conditioning on first stage parameters and after excluding the constant term as its first–derivative with respect to correlation parameters is zero, the second step quasi–likelihood becomes:

$$Q\mathcal{L}_2^* \left(\boldsymbol{\psi} | \hat{\boldsymbol{\phi}}, \boldsymbol{r}_t \right) = -\frac{1}{2} \sum_{t=1}^{T} \left(\log (|\boldsymbol{R}_t|) + \boldsymbol{\epsilon}_t' \boldsymbol{R}_t \boldsymbol{\epsilon}_t \right)$$

The second step parameters are retrieved by maximizing $Q\mathcal{L}_2^*$ as:

$$\widehat{\boldsymbol{\psi}} = \operatorname*{argmax}_{\boldsymbol{\psi}} Q\mathcal{L}_2^*$$

As in the univariate case, BFGS algorithm will be used for the maximization problem.

Asymptotic theory

Parameters of DCC–MVGARCH model are asymptotically normally distributed as:

$$\sqrt{T} \left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0 \right) \xrightarrow{d} N \left(0, \boldsymbol{A}_0^{-1} \boldsymbol{B}_0 \boldsymbol{A}_0'^{-1} \right) \tag{5.24}$$

with

$$\boldsymbol{A}_0 = \begin{bmatrix} \boldsymbol{\nabla}_{\phi\phi} Q\mathcal{L}_1 (\boldsymbol{\phi}_0) & \boldsymbol{0} \\ \boldsymbol{\nabla}_{\phi\psi} Q\mathcal{L}_2 (\boldsymbol{\theta}_0) & \boldsymbol{\nabla}_{\psi\psi} Q\mathcal{L}_2 (\boldsymbol{\theta}_0) \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_{11} & \boldsymbol{0} \\ \boldsymbol{A}_{12} & \boldsymbol{A}_{22} \end{bmatrix} \tag{5.25}$$

and

$$\boldsymbol{B}_0 = var\left[\sum_{t=1}^{T}\left\{T^{-1/2}\boldsymbol{\nabla}'_{\phi}Q\mathcal{L}_1\left(\boldsymbol{r}_t,\boldsymbol{\phi}_0\right), T^{-1/2}\boldsymbol{\nabla}'_{\psi}Q\mathcal{L}_2\left(\boldsymbol{r}_t,\boldsymbol{\phi}_0,\boldsymbol{\psi}_0\right)\right\}\right] =$$

$$= \begin{bmatrix} \boldsymbol{B}_{11} & \boldsymbol{B}_{12} \\ \boldsymbol{B}_{12} & \boldsymbol{B}_{22} \end{bmatrix} \quad (5.26)$$

The asymptotic covariance matrix of the estimated parameters $\widehat{\boldsymbol{\theta}}$ is given as $\boldsymbol{A}_0^{-1}\boldsymbol{B}_0\boldsymbol{A}_0'^{-1}$. The asymptotic covariance of GARCH parameters $\widehat{\boldsymbol{\phi}}$ is given by $\boldsymbol{A}_{11}^{-1}\boldsymbol{B}_{11}\boldsymbol{A}_{11}'^{-1}$ and is basically a block diagonal matrix, with the covariance of the *kth* GARCH model in its *kth* diagonal bllok. Every covariance matrix is in fact the robust (or "sandwich") covariance matrix presented in equation 5.19. While, the asymptotic covariance of the DCC parameters $\widehat{\boldsymbol{\psi}}$ is quite complicated and is explicitely expressed in Engle (2002).

Practical issues

In order to get meaningful results we have to deal with two practical issues. First, how to handle the missing values. As we know, there exist particular days for which some stock exchanges operate, while the others do not. As the number of missing values in each series is small[11], we will put them equal to the previous day's value.

Second, how to deal with estimation difficulties. When maximizing the log–likelihood function (both for univariate and multivariate GARCH models), we are interested in finding the global maxima. The log–likelihood function is quite flat at the optimum and we can reach a local maxima instead of a global one. In this case, starting values play an important role in finding the optimum. To be sure we have found the global maximum, we will follow these steps:

1. In the beginning, we will evaluate the GARCH (DCC) log–likelihood function using a grid search of 45 (36) points, finding in this way the appropriate starting values.

2. Then, we will employ a quasi–Newton method (BFGS algorithm) to find the optimum, using the aforesaid starting values as inputs.

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[11]2.3%, 2.2%, 2.2% and 0.6% for BUX, PX, WIG and STOXX50, respectively.

Chapter 6

Data and empirical results

6.1 Data description

The data set comprises daily closing price indices of three CEE countries and eurozone, for the period from December 20, 2001 to October 31, 2011, a total of 2,533 observations. It consists of stock indices of the Czech Republic (PX), Hungary (BUX), Poland (WIG) and the eurozone (STOXX50).

PX is a blue–chip price index composed of 14 shares listed on Prague Stock Exchange (PSE). BUX and WIG are total return indices[1], with the former composed of 11 blue–chip shares quoted on Budapest Stock Exchange (BSE) and the latter composed of 354 shares listed on the Main List market of Warsaw Stock Exchange (WSE). STOXX50 is chosen as a representative index for the eurozone and includes 50 blu–chip shares from 18 European countries[2]: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. BUX, PX and WIG are denominated in their local currency, while STOXX50 is denominated in Euro. Figure 6.1 presents plots of the indices.

All the above mentioned price series P_t are transformed by taking the log first–difference, producing the return series $r_t = \log(P_t/P_{t-1})$ (see figure 6.2). Table 6.1 summarizes the descriptive statistics and a few tests performed on index returns. Initially, we have tested for stationarity of returns using augmented Dickey–Fuller (ADF) test. In all series, the null hypothesis of unit root is rejected at 5% significance level. Furthermore, returns are found to be

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[1]A total return index takes into account dividend payouts.
[2]A representation of supersector leaders in Europe.

	BUX	PX	WIG	STOXX50
Mean	3.5275e-04	3.4042e-04	4.3087e-04	-1.6693e-04
Std. Dev.	0.0169	0.0156	0.0134	0.0143
Skewness	-0.1243	-0.5846	-0.3704	0.0999
Kurtosis	9.4	16.61	6.12	9.58
Minimum	-0.1265	-0.1619	-0.0829	-0.09
Maximum	0.1318	0.1236	0.0608	0.1022
Jarque–Bera stat.	4,323	19,687	1,083	4,573
$Q(8)$ stat.[a]	48	44.87	25.65	66.42
ARCH–LM stat.[b]	328.2	511.55	245.86	449.67
ADF stat.[c]	-20.21	-20.71	-27.62	-23.6

Table 6.1: **Summary statistics.** [a] Q stands for Ljung–Box Q test. [b] 4 lags are used in ARCH–LM test. [c] We have employed ADF test with automated lag selection, where the optimal lag length is determined using AIC. AIC selected a 5 lag model for BUX, PX and STOXX50 and a 2 lag model for WIG. For all the tests a 5% significance level is used.

negatively skewed (except STOXX50 which is slightly positively skewed) and leptokurtotic, indicating that they are not normally distributed. Also, using Jarque–Bera test we strongly reject the null hypothesis of normality at 5% significance level. In addition, we have tested the presence of autocorrelation and ARCH effects in returns using Ljung–Box Q and ARCH–LM tests. The null hypotheses of no autocorrelation and no ARCH effects are rejected for all the series at 5% significance level. Significant autocorrelation in returns and mainly in squared returns (indicating the presence of ARCH effects) are also observed in the sample autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of (squared) returns given in the appendix B. In conclusion, all the above–mentioned return series exhibit the standard features of a financial time series.
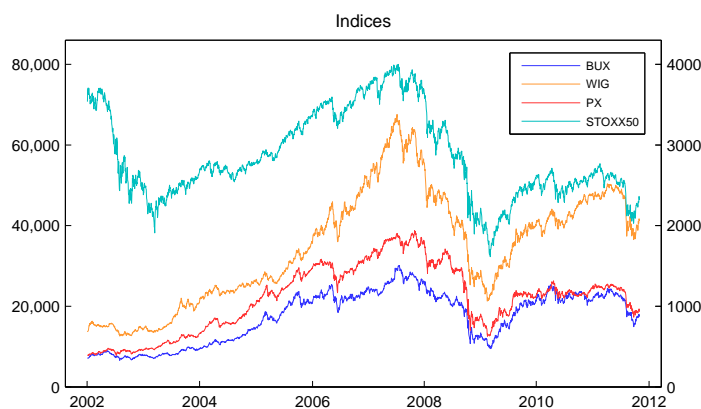

Figure 6.1: **Indices.** The values of BUX and WIG are given on the left y–axis and the values of PX and STOXX50 are given on the right y–axis.
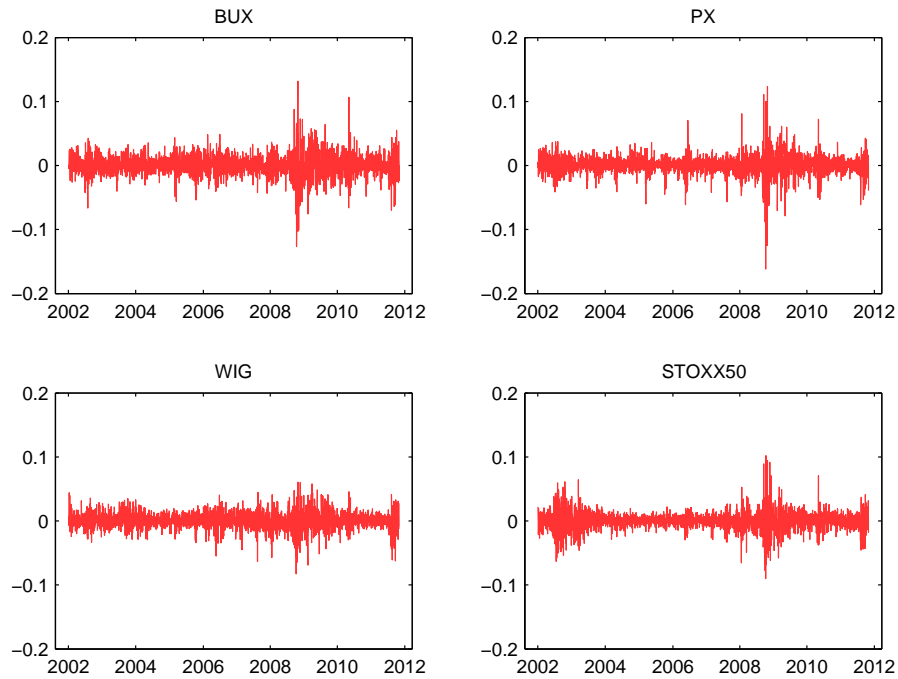
Figure 6.2: **Returns**

Table 6.2 gives the Pearson correlations[3] (or the unconditional correlations) between index return series. Unconditional correlations among CEE markets tend to be higher than the unconditional correlations vis–à–vis eurozone. The most interconnected markets among the CEE region are Czech and Polish markets, whereas the least interconnected are Czech and Hungarian markets. Moreover, the Hungarian market appears to be the least correlated market with the eurozone, while Polish and Czech markets share almost the same correlation coefficient. This is a simplified analysis and the results should be interpreted with caution. In order to elaborate more on this topic we will switch to dynamic correlation models.

	BUX	PX	WIG	STOXX50
BUX	1.0000	0.5797	0.6045	0.5281
PX		1.0000	0.6366	0.5505
WIG			1.0000	0.5542
STOXX50				1.0000

Table 6.2: **Unconditional correlations**

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[3]Pearson correlation is given as $\widehat{\rho} = \dfrac{\sum_{t=1}^{T}(x_t-\overline{x})(y_t-\overline{y})}{\sqrt{\sum_{t=1}^{T}(x_t-\overline{x})^2(y_t-\overline{y})^2}}$ where $\overline{x}$ and $\overline{y}$ are the sample means of x_t and y_t.

6.2   Empirical results

6.2.1   ARMA results

In the beginning, we will filter the return series using an AR(1) model. In this way, we can remove the dependence in returns and produce the zero–mean *i.i.d.* innovation ϵ_t.

$$r_t = \phi_0 + \phi_1 r_{t-1} + \epsilon_t$$

Table 6.3 presents the AR(1) results. In all cases, the intercept parameter ϕ_0 is statistically insignificant even at 10% significance level, while the slope parameter ϕ_1 is statistically significant at 5% significance level.

	BUX	PX	WIG	STOXX50
ϕ_0	3.3757e-04	3.1314e-04	3.9621e-04	-1.8211e-04
	(1.0087)	(1.0126)	(1.4932)	(-0.64)
ϕ_1	0.0497**	0.0815**	0.0868**	-0.0397**
	(2.5048)	(4.1093)	(4.3834)	(-1.9972)

Table 6.3: **AR results.** **Denotes statistical significance at 5% level. Numbers in parentheses are *t*-statistics.

6.2.2   GARCH results

In the second step we will fit a GARCH–type model for each residual series ϵ_t obtained from the AR(1) specification. For this purpose four GARCH models (GARCH, GJR–GARCH, AVGARCH and TGARCH) will be considered and the best model will be chosen using BIC. We will use specifications up to two lags. All the aforementioned models can be expressed in nested form using 1 lag for each term as:

$$\sigma_t^\delta = \omega + \alpha_1 |\epsilon_{t-1}|^\delta + \gamma_1 |\epsilon_{t-1}|^\delta I_{[\epsilon_{t-1} < 0]} + \beta_1 \sigma_{t-1}^\delta$$

where $\delta = 1, 2$ depending on whether we parameterize the conditional standard deviation or the conditional variance.

Table 6.4 presents the GARCH results. According to BIC we select a GJR–GARCH(1,1,1) model for BUX, PX and WIG and a GARCH(1,1) model for STOXX50. All parameters are significant at 1% significance level. Results confirm the presence of asymmetric effects in the conditional variances of BUX, PX and WIG. The asymmetric innovation parameter γ_1 lies between 0.046–0.13 and is larger than its symmetric counterpart α_1, which lies between 0.04–0.064.

The lagged variance parameter β_1 is relatively large ranging from 0.84 to 0.92, indicating high volatility persistence. In all the cases, models that evolved in squares outperformed models that evolved in absolute values.

	BUX	PX	WIG	STOXX50
ω	6.7325e-06***	6.1022e-06***	2.0045e-06***	1.6482e-06***
	(3.605)	(3.703)	(2.901)	(3.104)
α_1	0.055***	0.0643***	0.0402***	0.1046***
	(4.257)	(4.659)	(4.778)	(6.404)
γ_1	0.0712***	0.1295***	0.0461***	$-$
	(3.179)	(3.516)	(2.877)	($-$)
β_1	0.8837***	0.8421***	0.9253***	0.8884***
	(50.4295)	(40.6234)	(83.7986)	(57.096)
Model	GJR–GARCH	GJR–GARCH	GJR–GARCH	GARCH
BIC	-2.7942	-2.9743	-2.9978	-3.068

Table 6.4: **GARCH results.** ***Denotes statistical significance at 1% level. Numbers in parentheses are robust t-statistics.

Table 6.5 shows some diagnostic tests performed on standardized residuals $u_t = \epsilon_t / \sigma_t$. Using Ljung–Box Q test and ARCH–LM test we do not reject the nulls of no autocorrelation and no ARCH effects (except WIG) in standardized residuals, which is also confirmed by sample ACFs and PACFs of (squared) standardized residuals given in the appendix B. As mentioned above, in case of WIG we rejected the null hypothesis of no ARCH effects and tried to estimate models with higher orders. Again, we could not explain such ARCH effects and in most cases the added terms turned the estimated parameters statistically insignificant. Nevertheless, we can neglect it because it only appears to be a marginal effect as indicated by sample ACF and PACF of squared standardized residuals of WIG (see figure 6.3) . Moreover, Jarque–Bera tests show that standardized residuals are highly non–normal and the use of robust standard errors is justified.

	BUX	PX	WIG	STOXX50
$Q(8)$ stat.	10.908	10.937	6.000	7.005
ARCH–LM stat.	1.323	3.826	19.476	7.544
Jarque–Bera stat.	79.996	288.448	86.495	124.782

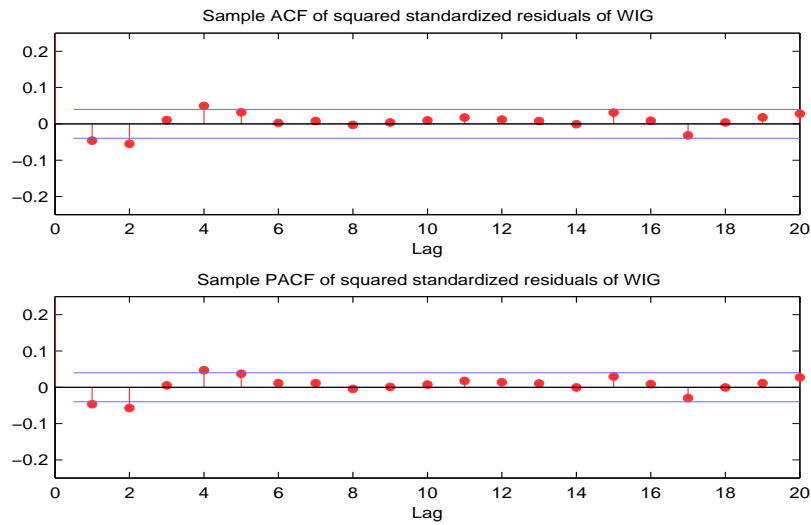Table 6.5: **Diagnostic tests on standardized residuals.** For all tests a 5% significance level is used.

Figure 6.3: **Sample P/ACF of squared standardized residuals of WIG**

Figure 6.4 below shows the plots of conditional standard deviations. We can easily observe a sharp increase in volatility during the recent financial crises. Prague and Budapest stock markets have experienced higher volatility during the crises compared to Warsaw stock market and the aggregate european market. As we are primarily interested in quantifying market comovements, we will not further extend the volatility analysis and will proceed with the correlation analysis.
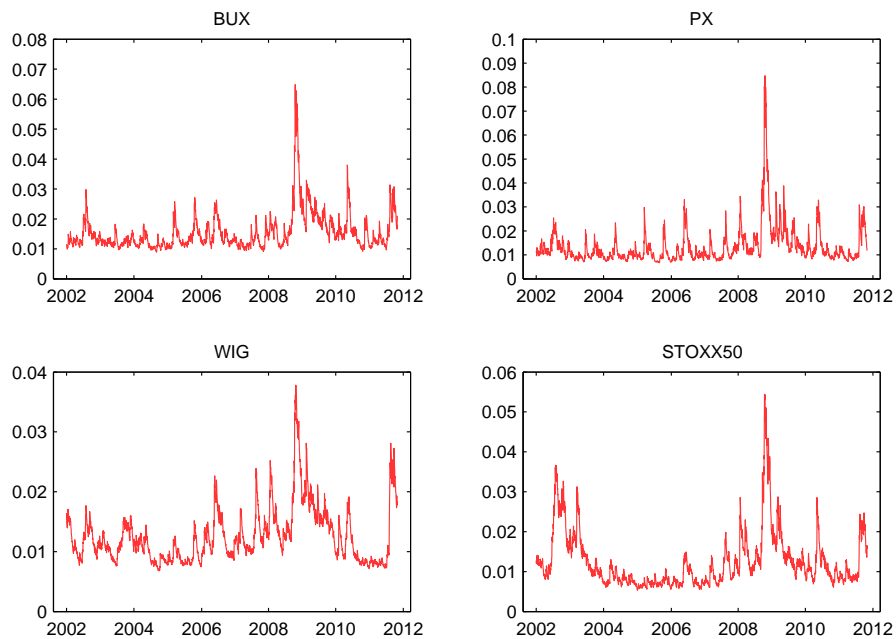
Figure 6.4: **Conditional standard deviations**

6.2.3   DCC results

After having estimated the conditional variances, we will fit pairwise DCC models on standardized residuals $\boldsymbol{u}_t = \boldsymbol{\epsilon}_t \oslash \boldsymbol{\sigma}_t$. This choice is made because correlations in DCC follow a scalar BEKK–like process and it is too restrictive to apply the model on all series at once. In addition to DCC, the asymmetric DCC model will be employed. The ADCC(1,1,1)[4] model is expressed as:

$$\boldsymbol{Q}_t = (1 - \theta_1 - \varphi_1)\,\overline{\boldsymbol{Q}} - \tau_1\overline{\boldsymbol{N}} + \theta_1\left(\boldsymbol{u}_{t-1}\boldsymbol{u}'_{t-1}\right) + \tau_1\left(\boldsymbol{n}_{t-1}\boldsymbol{n}'_{t-1}\right) + \varphi_1\boldsymbol{Q}_{t-1}$$

We will divide the analysis in two parts. The first part will be devoted to comovements among CEE stock markets and the second part to comovements between CEEs and eurozone. Table 6.6 below presents the A/DCC results.

Among CEEs			
	BUX–PX	BUX–WIG	PX–WIG
θ_1	0.0093**	0.0172**	0.0234***
	(2.3048)	(2.1186)	(2.5582)
τ_1	–	0.0233**	–
	(–)	(2.2579)	(–)
φ_1	0.9869***	0.9552***	0.9676***
	(143.86)	(57.237)	(65.431)

CEEs–Eurozone			
	BUX–STOXX50	PX–STOXX50	WIG–STOXX50
θ_1	0.0371**	0.0222***	0.0136**
	(2.1863)	(4.7938)	(2.5385)
τ_1	–	–	–
	(–)	(–)	(–)
φ_1	0.9354***	0.9665***	0.984***
	(25.672)	(119.869)	(138.922)

Table 6.6: **DCC results.** **Denotes statistical significance at 5% level and *** at 1% level. Numbers in parentheses are robust t-statistics.

In general, asymmetries in correlations are not as widespread as in conditional variances[5]. We have found asymmetric effects only in BUX–WIG pair,

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[4]DCC is a special case of ADCC when $\tau_1 = 0$.

[5]3 out of 4 series (BUX, PX and WIG) exhibited asymmetries in conditional variances while only 1 pair out of 6 (BUX–WIG) exhibited assymetries in correlations.

while for all the other pairs the asymmetric term was statistically insignificant even at 10% significance level. θ_1 parameter is found to be relatively small (0.0093–0.0371), whereas φ_1 parameter is even larger than in the univariate case (0.9354–0.9869). All parameters are significant at 1% and 5% significance levels.

Correlations among CEEs

Figure 6.5 shows time–varying correlations among CEE stock markets. For BUX–PX pair, we observe low to medium correlations in a range of 0.3–0.5 until 2005, followed by two consecutive sharp increases in 2005–2006. After 2006, correlations remain comparatively high, lying between 0.5–0.7. These findings are in line with Savva & Aslanidis (2010) that detect a double shift in correlations between BUX and PX, although the time span between the shifts is quite short.

For BUX–WIG pair, correlations appear to be much volatile until mid 2005, varying between 0.2–0.7. This is followed by a moderate increase and a reduced variation until the end of the sample, leading to higher correlations in average (0.4–0.8).

In case of PX–WIG, an increasing trend in correlations is noticed for the period from mid 2003 to 2009, followed by a decrease afterwards. From the visual inspection we can deduce that correlations among CEE markets tend to increase in time, even though the time shifts differ for different pairs.

Correlations between CEEs and eurozone

It is important to understand how CEE stock markets are linked to the rest of eurozone. For the sake of simplicity we have not used different indices for different EU countries, but a single aggregate index representing EU stock market. Figure 6.6 shows correlations of CEE markets vis–à–vis eurozone. At the beginning of 2006, we notice a shift in correlations for BUX–STOXX50 pair and the average correlation after 2006 is higher than before.

For WIG–STOXX50 pair, correlations range between 0.2–0.5 prior to 2006, followed by a steady increase until 2008 when they reach a high value of 0.7. After 2008 they move between 0.5–0.8.

Until the end of 2005, correlations between PX–STOXX50 varied mainly between 0.2–0.5, then similar to WIG–STOXX50 case are steadily increased until 2008. This is followed by some large downward and upward movements

until the end of the sample.

Even though Czech Republic, Poland and Hungary joined the EU in May 2004, their financial markets and the eurozone market seem to become more interconnected only after 2006.
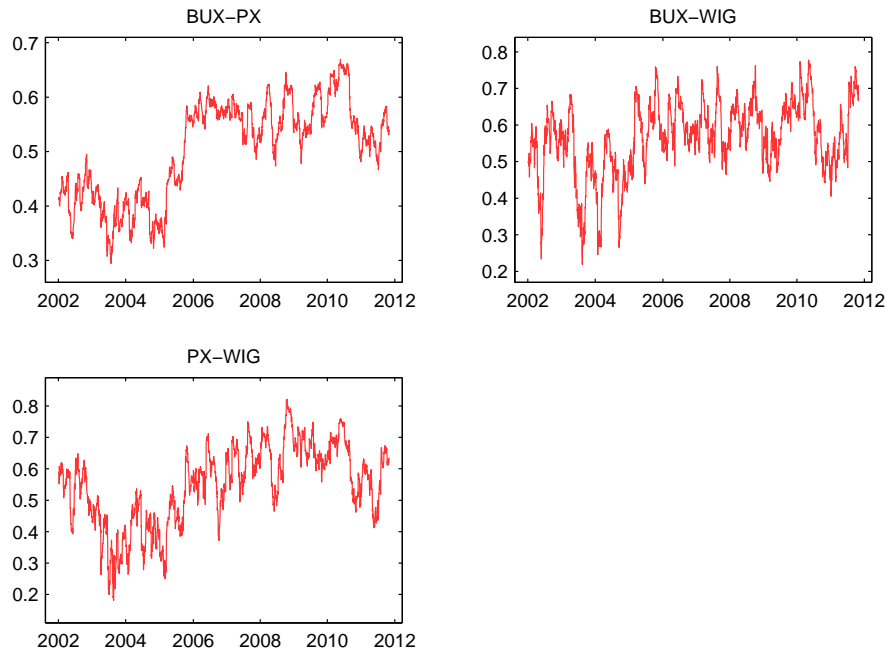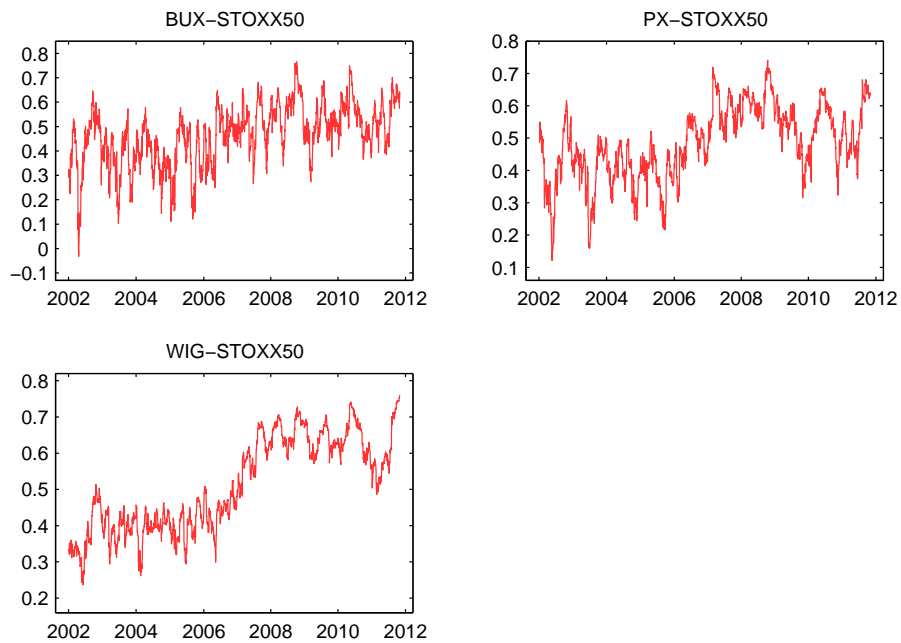

Figure 6.5: **Dynamic correlations among CEEs**

Figure 6.6: **Dynamic correlations between CEEs and eurozone**

Evolution of correlations in time

Visually, we notice a strengthen in comovements among CEE stock markets and between CEEs and eurozone. We will regress the conditional correlations on a constant and a time trend to better understand whether correlations are increased over time. Furthermore, the difference between the first and the last fitted values of the regression will be calculated. In this way, we can also figure out for which pairs, correlations are increased the most. Table 6.7 gives the estimated parameters and the percantage change between the first and the last fitted values ($\Delta\rho$).

$$\rho_{ij,t} = a + b\,t + \epsilon_{ij,t}$$

Among CEEs

	a	$(1000^*)\,b$	R^2	$\Delta\rho$
BUX–PX	0.392*** (46.257)	0.09*** (14.96)	0.54	57.8%
BUX–WIG	0.496*** (33.652)	0.055*** (5.809)	0.16	28.1%
PX–WIG	0.426*** (25.003)	0.097*** (8.599)	0.32	57.4%

CEEs–Eurozone

	a	$(1000^*)\,b$	R^2	$\Delta\rho$
BUX–STOXX50	0.35*** (21.921)	0.089*** (9.114)	0.29	64.6%
PX–STOXX50	0.37*** (25.646)	0.087*** (8.897)	0.29	59.5%
WIG–STOXX50	0.327*** (36.128)	0.144*** (20.632)	0.69	111.5%

Table 6.7: **Correlation analysis.** ***Denotes statistical significance at 1% level. Numbers in parentheses are t-statistics and are calculated using Newey-West covariance estimator. $\Delta\rho$ is the difference between the last and the first fitted values of the regression $\rho_{ij,t} = a+b\,t+\epsilon_{ij,t}$.

In all the pairs, slope parameter b is greater than zero and statistically significant at 1% level, which indicates that correlations are increased over time. Among the CEE markets, correlations between BUX–PX and PX–WIG are increased by 57.8% and 57.4%, respectively. On the contrary, correlations for

BUX–WIG pair are increased by only 28.1%, which is quite small compared to the other pairs. Between CEE markets and euro area, the highest increase is observed for WIG–STOXX50 pair by 111.5%. While, for BUX–STOXX50 and PX–STOXX50 there is a 64.6% and 59.5% increase. In summary, correlations are increased in time both among CEEs and between CEEs and eurozone, with the highest increase observed in CEEs–eurozone pairs.

Correlations during the recent financial crises

Besides the evolution of correlations in tranquil periods, it is also important to measure the impact of the crises on correlation dynamics. As our sample includes the recent financial crises, we will try to understand whether correlations are strengthened during it. For this purpose, we will regress conditional correlations on a constant and a dummy variable for the crises.

$$\rho_{ij,t} = c + dI_{crises} + \epsilon_{ij,t}$$

Among CEEs

	c	d	R^2
BUX–PX	0.474*** (60.857)	0.097*** (9.6)	0.25
BUX–WIG	0.549*** (62.35)	0.05*** (3.695)	0.06
PX–WIG	0.507*** (48.24)	0.129*** (8.511)	0.23

CEEs–Eurozone

	c	d	R^2
BUX–STOXX50	0.427*** (42.739)	0.113*** (7.863)	0.19
PX–STOXX50	0.452*** (44.009)	0.087*** (5.692)	0.12
WIG–STOXX50	0.452*** (47.336)	0.18*** (14.777)	0.44

Table 6.8: **Correlations during the recent financial crisis.** ***Denotes statistical significance at 1% level. Numbers in parentheses are *t*-statistics and are calculated using Newey-West covariance estimator.

We have conducted these regressions both among CEE markets and between CEEs and eurozone. Table 6.8 above presents the regression results. For all the pairs, slope coefficient d is positive and statistically significant at 1% level, indicating that the crises has shifted the correlations upward. The magnitude by which correlations are increased varies from 0.05 to 0.18. Among the CEE markets the lowest increase is observed for BUX–WIG (0.05) pair and the highest for PX–WIG (0.13), while between CEEs and euro area the lowest increase is observed for PX–STOXX50 (0.09) pair and the highest for WIG–STOXX50 (0.18). For CEEs–eurozone pair, correlations are increased more then among CEEs itself.

It is very important to emphasize that diversification benefits are reduced if comovements among stock markets are strengthened. We have concluded that correlations of CEEs vis–à–vis eurozone are increased over time and also during the recent financial crises, leading to less diversification benefits in CEE stock markets.

The relationship between conditional correlations and conditional volatilities

This last part will be devoted to the relationship between conditional correlations and conditional volatilities. It is crucial to understand whether correlations and volatilities are positively or negatively related. If volatilities and correlations move in the same direction (i.e. correlations are strengthened when the level of risk is increased), then long run risks are higher than they appear in the short run (Capiello et al. 2006b). To uncover this important relationship the following regression will be estimated:

$$\rho_{ij,t} = \pi + \kappa_1 \sigma_{i,t} + \kappa_2 \sigma_{j,t} + \epsilon_{ij,t}$$

where i corresponds to a specific CEE market (Czech, Polish or Hungarian market) and j to the aggregate eurozone market. If κ_2 is positive (negative), correlations between a CEE market and the eurozone market should be increased (decreased) whenever volatility in eurozone market is increased. Table 6.9 below presents the regression results. Both for BUX–STOXX50 and PX–STOXX50 pairs we observe a positive κ_2, which is statistically significant at 5% level. This indicates that correlations for these pairs are strengthened during high volatility periods. Whereas, for WIG–STOXX50 pair, κ_2 is negative but statistically insignificant. This means that during high volatility periods, diver-

sification benefits by investing in Polish stock market are higher. Nevertheless, we cannot say this with certainty since the effect is statistically insignificant. In addition, the relationship may not be constant in time, but time–varying as claimed by Syllignakis & Kouretas (2011). Therefore, we will use the rolling "stepwise[6]" regression methodology. A time window of 120 days is chosen, leading to 2,413 rolling windows. We have ploted the time–varying κs and the R-squared of the regressions in figures 6.7, 6.8 and 6.9. Most of the time κ_2 is greater than zero, even though exist time periods when it becomes negative. So, this relationship is niether constant in time nor strictly positive or negative during all the sample period, but rather time–varying with periods of being higher or lower than zero. The R–squared varies from 0 to 90%.

	π	κ_1	κ_2	R^2
BUX–STOXX50	0.333***	6.064***	2.861**	0.2
	(16.947)	(4.083)	(2.271)	
PX–STOXX50	0.383***	4.844***	2.538**	0.2
	(23.873)	(4.036)	(2.074)	
WIG–STOXX50	0.343***	14.088***	-0.849	0.23
	(17.816)	(6.351)	(-0.562)	

Table 6.9: **Conditional correlations and conditional volatilities.** ** and *** denotes statistical significance at 5% and 1% significance level. Numbers in parentheses are t-statistics and are calculated using Newey-West covariance estimator.
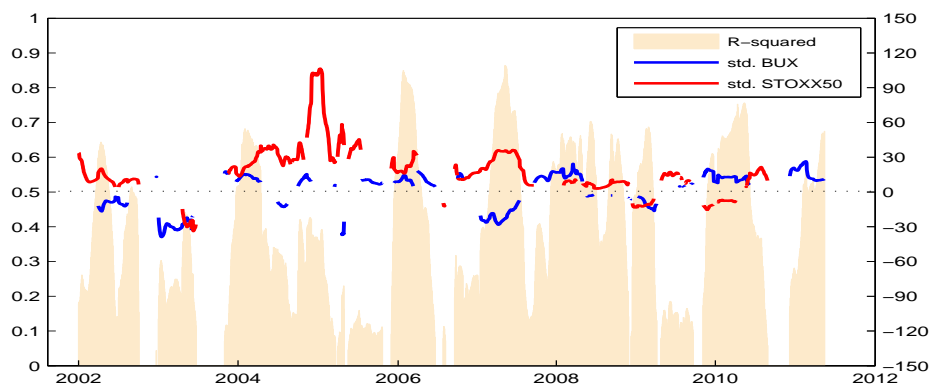
Figure 6.7: **Time-varying κ coefficients for BUX–STOXX50 pair.** On the left y–axis are given the R–squared values, while on the right y–axis are given the values of time–varying parameters.
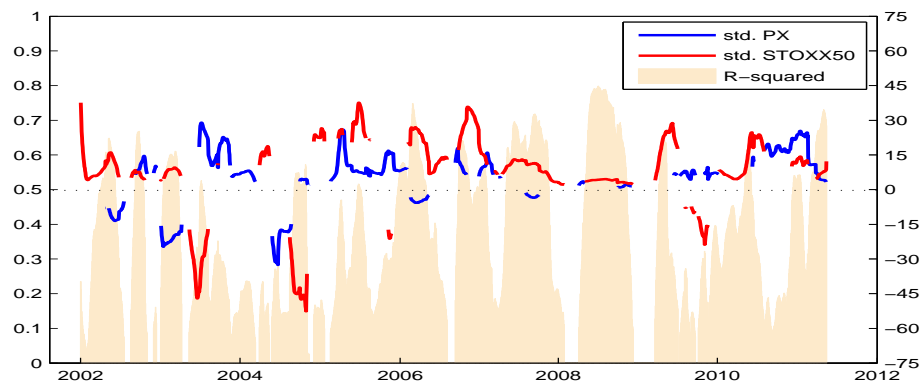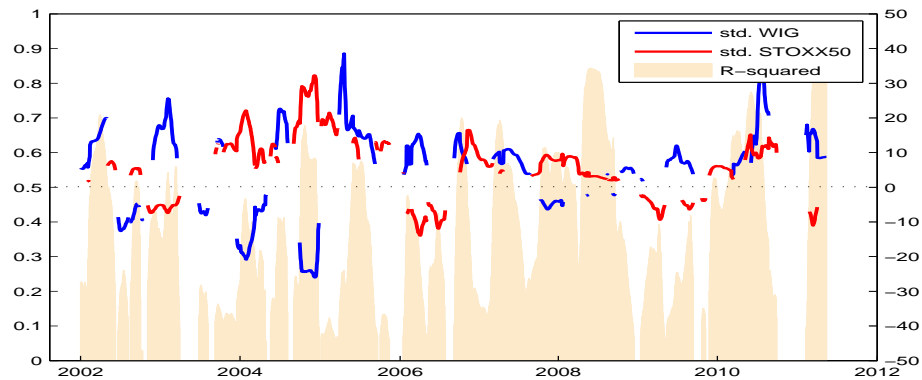
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[6]See appendix A for the algorithm used.

Figure 6.8: **Time-varying κ coefficients for PX–STOXX50 pair.** On the left y–axis are given the R–squared values, while on the right y–axis are given the values of time–varying parameters.

Figure 6.9: **Time-varying κ coefficients for WIG–STOXX50 pair.** On the left y–axis are given the R–squared values, while on the right y–axis are given the values of time–varying parameters.

Chapter 7

Conclusions

In this research, we have studied stock market comovements among three major CEE markets (the Czech Republic, Poland and Hungary) and between CEEs vis–à–vis the aggregate eurozone market. For this purpose, we have employed a complex econometric methodology consisting in the application of DCC model and its asymmetric version (ADCC). Additionally, OLS regressions were conducted to study the evolution of correlations in time, during the recent financial crises and the relationship between conditional correlations and conditional volatilities.

Firstly, we have found asymmetric effects in conditional variances of BUX, PX and WIG. Secondly, models that evolved in squares (models of conditional variances) outperformed models that evolved in absolute values (models of conditional standard deviations).

Regarding the conditional correlations, we found asymmetric effects only in BUX–WIG pair. For the other pairs, the asymmetric term was statistically insignificant even at 10% level. So, asymmetries in correlations are not as widespread as in conditional variances.

Another important finding is that correlations are increased over time for both pairs (CEEs–CEEs and CEEs–eurozone). This is not only supported by the visual inspection of conditional correlations, but also by the OLS regressions of conditional correlations on a time trend. Furthermore, correlations between CEEs vis–à–vis eurozone are increased by more than correlations among CEEs itself. Even though Czech Republic, Poland and Hungary joined the EU in May 2004, their financial markets and the eurozone market seem to become more interconnected only after 2006.

Also, we observe higher correlation coefficients (on average) during the re-

cent financial crises. The magnitude by which correlations are increased varies from 0.05–0.18. Again, the increase is higher for CEEs–eurozone pairs. The aforementioned facts imply that diversification benefits in CEE region, from the point of view of a European investor, are reduced over time.

Finally, following Syllignakis & Kouretas (2011) we investigated the relationship between correlations and volatilities, using the simple OLS method on the whole sample data and the rolling "stepwise" regression methodology. Using the OLS method, we found a positive and statistically significant relationship between conditional correlations of BUX–STOXX50 and PX–STOXX50 and the conditional variances of STOXX50. On the contrary, conditional correlations of WIG–STOXX50 and conditional variances of STOXX50 were negatively related. Nevertheless, the latter relationship is statistically insignificant and we cannot say much about the diversification benefits in Polish stock market during high volatility periods. Applying the rolling "stepwise" regression methodology we have mainly found a positive relationship between correlations and volatilities, even though there exist time periods when it becomes negative. So, this relationship is niether constant in time nor strictly positive or negative during all the sample period, but rather time–varying with periods of being higher or lower than zero.

Bibliography

Babetskii, I., Komárek, L. & Komárková, Z. (2007), 'Financial integration of stock markets among new eu member states and the euro area', *Czech Journal of Economics and Finance* **57**(7-8), 341–362.

Bollerslev, T. (1986), 'Generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics* **31**(3), 307 –327.

Bollerslev, T. (1990), 'Modelling the coherence in short-run nominal exchange rates: A multivariate generalized arch model', *The Review of Economics and Statistics* **72**(3), 498 –505.

Capiello, L., Engle, R. F. & Sheppard, K. (2006b), 'Asymmetric dynamics in the correlations of global equity and bond returns', *Journal of Financial Econometrics* **4**(4), 537–572.

Cappiello, L., Gérard, B., Kadareja, A. & Manganelli, S. (2006a), Financial integration of new eu member states, Working Paper Series no. 683, European Central Bank.

Egert, B. & Kocenda, E. (2005), Contagion across and integration of central and eastern european stock markets: Evidence from intraday data, Working Paper Series no. 798, William Davidson Institute.

Egert, B. & Kocenda, E. (2011), 'Time-varying synchronization of european stock markets', *Empirical Economics* **40**(2), 393–407.

Engle, R. F. (1982), 'Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation', *Econometrica* **50**(4), 987–1007.

Engle, R. F. (2002), 'Dynamic conditional correlation', *Journal of Business and Economic statistics* **20**(3), 339–350.

Engle, R. F. & Sheppard, K. (2001), Theoretical and empirical properties of dynamic conditional correlation multivariate garch, Working paper no. 8554, National Bureau of Economic Research.

Gilmore, C. G. & McManus, G. M. (2002), 'International portfolio diversification: Us and central european equity markets', *Emerging Markets Review* **3**(1), 69–83.

Glosten, L. R., Jagannathan, R. & Runkle, D. E. (1993), 'On the relation between the expected value and the volatility of the nominal excess return on stocks', *The Journal of Finance* **48**(5), 1779–1801.

Horvath, R. & Petrovski, D. (2012), International stock market integration: Central and south eastern europe compared, Technical Report Working Paper Series no. 1028, William Davidson Institute.

Kasch-Haroutounian, M. & Price, S. (2001), 'Volatility in the transition markets of central europe', *Applied Financial Economics* **11**(1), 93–105.

Patev, P., Kanaryan, N. & Lyroudi, K. (2006), 'Stock market crises and portfolio diversification in central and eastern europe', *Managerial Finance* **32**(5), 415–432.

Savva, C. S. & Aslanidis, C. (2010), 'Stock market integration between new eu member states and the euro-zone', *Empirical Economics* **39**(2), 337–351.

Scheicher, M. (2001), 'The comovements of stock markets in hungary, poland and the czech republic', *International Journal of Finance & Economics* **6**(1), 27–39.

Syllignakis, M. & Kouretas, G. (2006), Long and short-run linkages in cee stock markets: Implications for portfolio diversification and stock market integration, Working Papers Series no. 832, William Davidson Institute.

Syllignakis, M. N. & Kouretas, G. P. (2011), 'Dynamic correlation analysis of financial contagion: Evidence from the central and eastern european markets', *International Review of Economics & Finance* **20**(4), 717–732.

Syriopoulos, T. (2007), 'Dynamic linkages between emerging european and developed stock markets: Has the emu any impact?', *International Review of Financial Analysis* **16**(1), 41–60.

Taylor, S. J. (1986), *Modeling financial time series*, JohnWiley and Sons Ltd.

Tudor, C. (2011), 'Changes in stock markets interdependencies as a result of the global financial crisis: Empirical investigation on the cee region.', *Panoeconomicus* **58**(4), 525–543.

Voronkova, S. (2004), 'Equity market integration in central european emerging markets: A cointegration analysis with shifting regimes', *International Review of Financial Analysis* **13**(5), 633–647.

Wang, P. & Moore, T. (2008), 'Stock market integration for the transition economies: Time-varying conditional correlation approach', *The Manchester School* **76**, 116–133.

Zakoian, J.-M. (1994), 'Threshold heteroskedastic models', *Journal of Economic Dynamics and Control* **18**(5), 931–955.

Appendix A

Rolling "stepwise" regresssion algorithm

```matlab
for i = 1:(length(corr¹)-120+1)

    c = corr(i:i+120-1);
    v = std²(i:i+120-1, :);
    [B, TSTAT, S2, VCVNW, R2, RBAR, YHAT]=olsnw³(c, v);
    PVAL = 2-2*normcdf(abs(TSTAT));
    if any(PVAL(2:3) > 0.05)
        [B1, TSTAT1, S21, VCVNW1, R21, RBAR1, YHAT1] = olsnw(c, v(:, 1));
        [B2, TSTAT2, S22, VCVNW2, R22, RBAR2, YHAT2] = olsnw(c, v(:, 2));
        PVAL1 = 2-2*normcdf(abs(TSTAT1));
        PVAL2 = 2-2*normcdf(abs(TSTAT2));
        if PVAL1(2) < 0.05 && PVAL2(2) > 0.05
            B = [B1; NaN];
            TSTAT = [TSTAT1; NaN];
            R2 = R21;
        elseif PVAL1(2) > 0.05 && PVAL2(2) < 0.05
            B = [B2(1); NaN; B2(2)];
            TSTAT = [TSTAT2(1); NaN; TSTAT2(2)];
            R2 = R22;
        elseif PVAL1(2) < 0.05 && PVAL2(2) < 0.05
            if R21 > R22
                B = [B1; NaN];
                TSTAT = [TSTAT1; NaN];
                R2 = R21;
            else
                B = [B2(1); NaN; B2(2)];
                TSTAT = [TSTAT2(1); NaN; TSTAT2(2)];
                R2 = R22;
            end
        else
            B = [NaN; NaN; NaN];
            TSTAT = [NaN; NaN; NaN];
            R2 = NaN;
        end
    end
    param = [param B];
    tstat = [tstat TSTAT];
    r2 = [r2 R2];

end
```

---

[1]Corr is the (nr. of observations x 1) vector of conditional correlations, e.g. correlations between BUX–STOXX50.

[2]Std is the (nr. of observations x 2) matrix of conditional standard deviations, e.g. [BUX_std STOXX50_std].

[3]Linear regression estimation with Newey-West HAC standard errors (see MFE matlab toolbox).

Appendix B

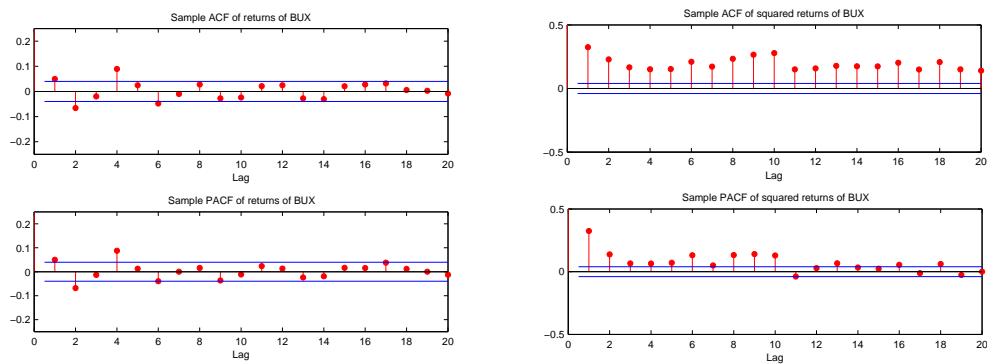## Sample P/ACF of returns and squared returns of the indices
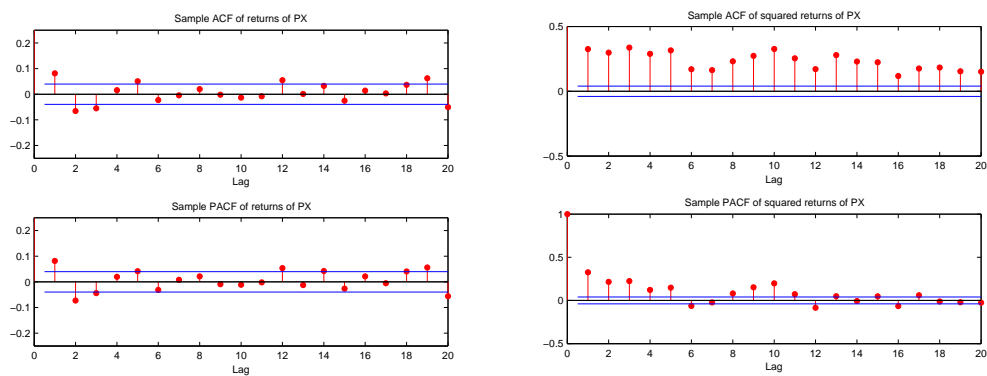

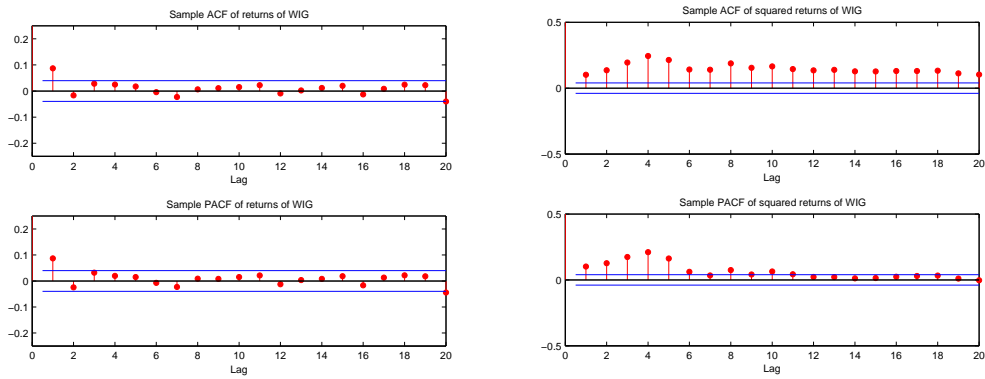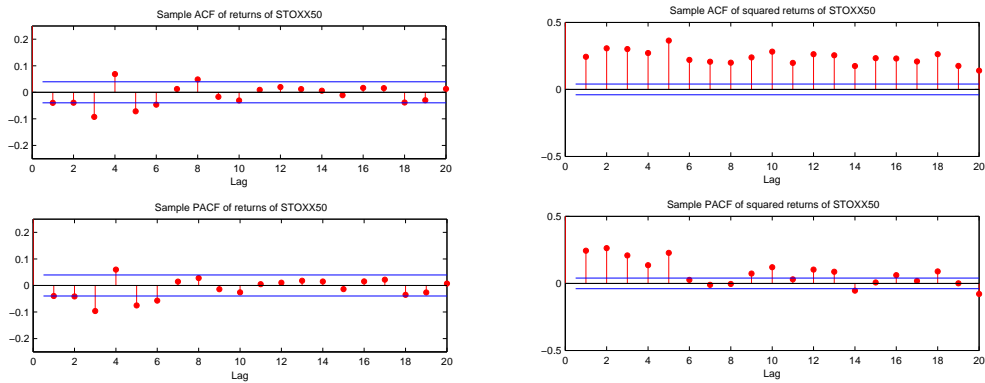Figure 1: BUX

Figure 2: PX

Figure 3: WIG

Figure 4: STOXX50

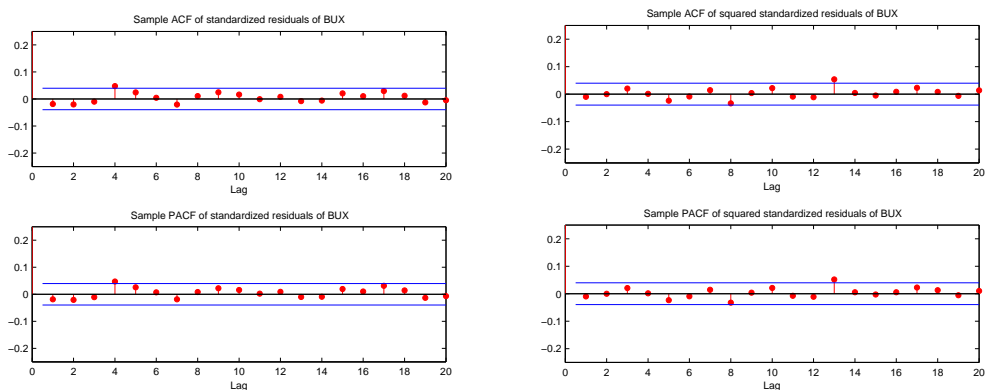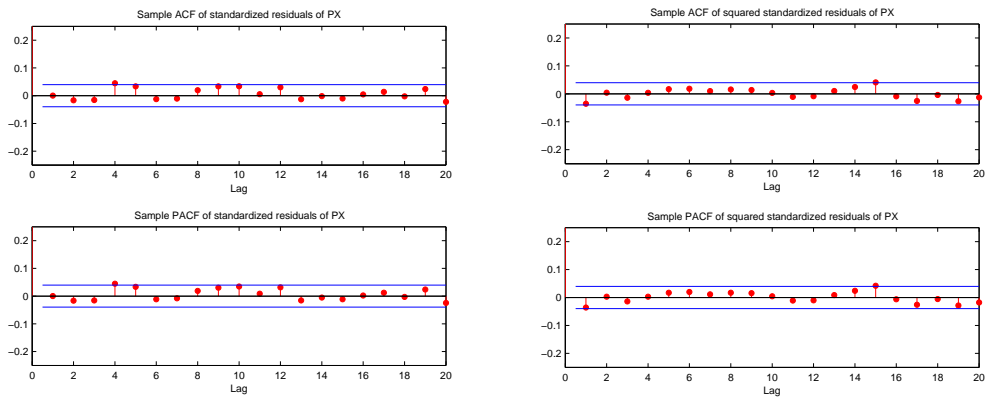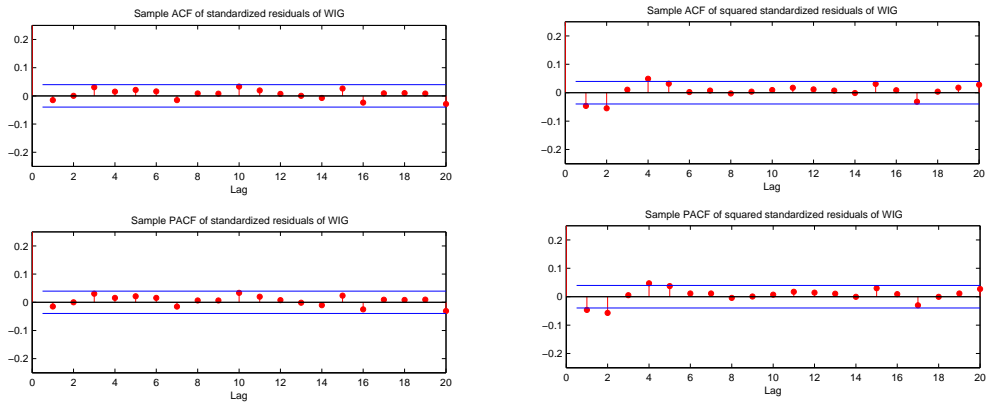# Sample P/ACFs of standardized residuals and squared standardized residuals of the indices.
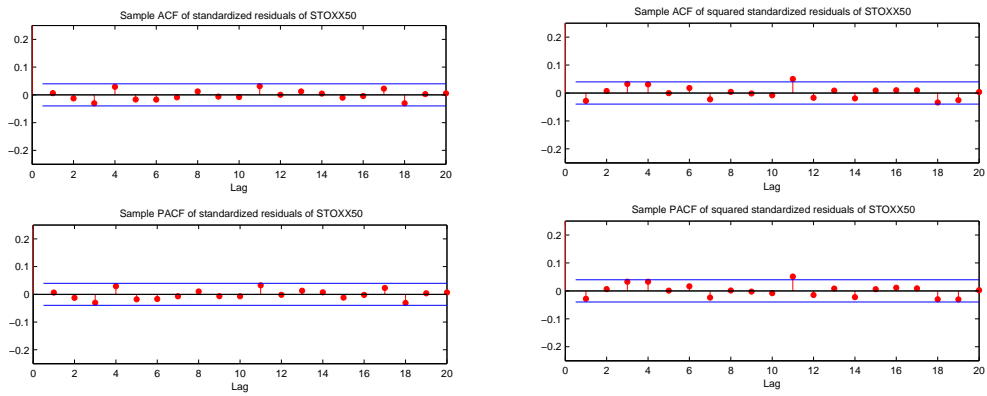

Figure 5: BUX

Figure 6: PX

Figure 7: WIG

Figure 8: STOXX50