# Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER THESIS

# Volatility Spillovers and Response Asymmetry: Empirical Evidence from the CEE Stock Markets

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Academic Year: **2013/2014**

## Declaration of Authorship

The author hereby declares that she compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, May 12, 2014

Signature

## Acknowledgments

I would like to thank my supervisor, PhDr. Jozef Baruník, Ph.D., for his encouragement, many valuable comments and suggestions and for his willingness to answer all my questions. I am also very grateful to him for providing me with the data.

# Abstract

In this thesis, we examine the volatility spillovers and its response asymmetry due to negative or positive shocks with the use of volatility spillover indices proposed by Baruník *et al.* (2013). This novel methodology extends the original spillover index framework introduced by Diebold & Yilmaz (2009) by utilizing the non-parametric measures of volatility based on the high frequency data, the realized variance and realized semivariances. Our analysis is performed on two datasets, the first one covering the selected Central and Eastern European stock market indices of the Czech Republic, Hungary and Poland, and the second one extending the original sample by the inclusion of the German DAX index that represents the mature European stock markets. The data employed in our study spans from January 2, 2008 to November 30, 2010, thus covers the period of the recent global financial crisis, from its outbreak to the early recovery phases. In the static analysis, we find the Czech stock market to transmit the highest amount of volatility shocks to the other markets what might be attributed to the potential role of the Czech market as a channel of volatility shocks transmission among the included and non-included stock markets. Furthermore, the results of dynamic analysis reveal the presence of asymmetry in the volatility spillovers due to negative and positive shocks to returns. We find that, on average, the contribution of negative shocks to volatility spillovers is higher compared with the positive ones. In addition, the development pattern of the volatility spillover indices is found to coincide with the main crisis events and to reflect the economic and financial situation on the markets.



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| **JEL Classification** | C58, G01, G02, G15 |
| **Keywords** | Volatility, Spillovers, Realized semivariances, Asymmetry, CEE stock markets |



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## Abstrakt

Táto práca sa zameriava na skúmanie prelievania volatility a jeho asymetrie v reakcii na pozitívne alebo negatívne šoky s použitím indexov prelievania volatility navrhnutými Baruníkom ai. (2013). Daná metodológia rozširuje pôvodnú techniku konštrukcie indexu prelievania volatility zavedenú Dieboldom a Yilmazom (2009) o použitie neparametrických odhadov volatility v podobe realizovaných variancií a semivariancií, ktoré sú vypočítané z vysokofrekvenčných dát. Analýzu aplikujeme na dva datasety, pričom prvý zahŕňa akciové indexy vybraných krajín strednej a východnej Európy, Českú republiku, Maďarsko a Poľsko. Druhý dataset obohacujeme o nemecký DAX index, ktorý zastupuje rozvinuté európske akciové trhy. V našej štúdii používame dáta od 2.januára 2008 do 30.novembra 2010, teda zachytávame obdobie globálnej finančnej krízy, od jej vzniku až po prvé náznaky oživenia. Statická analýza preukazuje, že český akciový trh je najväčším prenášačom šokov vo volatilite do ostatných akciových trhov, čo by mohlo byť spôsobené možnou funkciou českého trhu ako kanálu prelievania šokov vo volatilite medzi zahrnutými a nezahrnutými akciovými trhmi. Výsledky dynamickej analýzy ďalej odhaľujú existenciu asymetrie v prelievaní volatility z negatívnych a pozitívnych šokov vo výnosoch akciových indexov, pričom negatívne šoky prispievajú v priemere k väčšiemu prelievaniu volatility ako pozitívne šoky. Vývoj indexov prelievania volatility naviac naznačuje jeho prepojenosť na hlavné udalosti počas krízy, reflektujúc aktuálnu ekonomickú a finančnú situáciu na trhoch.



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| **Klasifikácia JEL** | C58, G01, G02, G15 |
| **Kľúčové slová** | Volatilita, Prelievanie, Realizované semivariancie, Asymetria, Akciové trhy strednej a východnej Európy |



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# Acronyms

**ADCC** Asymmetric Dynamic Conditional Correlation

**ADF** Augmented Dickey-Fuller

**AIC** Akaike Information Criterion

**ARMA** Autoregressive Moving Average

**B-G** Breusch-Godfrey

**BSE** Budapest Stock Exchange

**BUX** Budapest Stock Index

**CCC** Constant Conditional Correlation

**CEE** Central and Eastern Europe

**CEESEG** CEE Stock Exchange Group

**DAX** German Stock Index

**DCC** Dynamic Conditional Correlation

**EGARCH** Exponential GARCH

**E-G** Engle-Granger

**EU** European Union

**FESE** Federation of European Securities Exchanges

**GARCH** Generalized Autoregressive Conditional Heteroscedasticity

**HQ** Hannan-Quinn Criterion

**IMF** International Monetary Fund

**IPO** Initial Public Offering

**KPSS** Kwiatkowski-Phillips-Schmidt-Schin

**MA** Moving Average

**ML** Maximum Likelihood

**MSE** Mean Squared Error

**OLS** Ordinary Least Squares

**PSE** Prague Stock Exchange

**PP** Phillips-Perron

**PX** Prague Stock Index

**QV** Quadratic Variation

**RS** Realized Semivariances

**RV** Realized Variance

**SAM** Spillover Asymmetry Measure

**SC** Schwarz Criterion

**STCC** Smooth Transition Conditional Correlation

**TSRV** Two-Scales RV

**UK** United Kingdom

**US** United States

**VAR** Vector Autoregression

**VECM** Vector Error Correction Model

**WIG** Warsaw Stock Index

**WSE** Warsaw Stock Exchange

# Master Thesis Proposal

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| **Author** | Bc. Veronika Dovhunová |
| **Supervisor** | PhDr. Jozef Baruník, Ph.D. |
| **Proposed topic** | Volatility Spillovers and Response Asymmetry: Empirical Evidence from the CEE Stock Markets |

**Topic characteristics** The aim of this thesis is to examine volatility spillovers among selected stock markets in the Central and Eastern European (CEE) region (Budapest, Prague and Warsaw) and further in our original sample extended by adding the German stock market as the representative of one of the most developed stock markets in Europe by constructing the Spillover Indexes. The methodology applied for its construction is based on the paper of Diebold and Yilmaz (2009). In order to obtain the more accurate values of the Spillover Indexes we will modify the original spillover index framework proposed by Diebold and Yilmaz (2009) by using the Realized Volatility (square root of the sum of squared intraday returns) in our analysis. Employing the high frequency data of the Budapest (BUX), Prague (PX), Warsaw (WIG), and Frankfurt (DAX) stock market indices spaning the period from 2008 to 2013 will enable us to study the evolution of volatility spillovers with respect to the character of the observed period - both during crisis and recovery phases. Moreover, applying the concept of Realized Semivariances introduced by Barndorff-Nielsen, Kinnebrock and Shephard (2010) will allow us to study the asymmetry in the behaviour of volatility spillovers in response to negative or positive shocks (Barunik et al., 2013). We will examine if the magnitude of volatility spillover effects varies with respect to the sign of returns which caused the volatility and if the negative shocks result in the stronger volatility spillover effects.

The main contribution of this thesis lies not only in the implementation of the approach of Diebold and Yilmaz (2009) on the high frequency data for the purposes of analyzing volatility spillovers among the selected CEE stock markets, but moreover the understanding of the mechanism of volatility transmission across markets provide us the useful insight into how the different kinds of shocks, important economic events and decisions, or information disseminate across markets. In addition, to the best of my knowledge, this should be the first study investigating the asymmetry in the behaviour of spillovers using the concept of Realized Semivariances in the CEE region.

**Hypotheses**

1. The intensity of volatility spillovers varies over time.
2. The volatility spillovers tend to increase during periods of crisis events.
3. Shocks in German stock market affect volatility in the selected CEE stock markets.
4. Volatility spillover effects due to negative shocks tend to be greater than due to positive shocks.

We are also going to examine whether the behaviour and intensity of volatility spillovers differ for each of our samples and if the response asymmetry in volatility spillover effects can be observed in both of them.

**Methodology** The methodology applied in this thesis is based on Diebold and Yilmaz (2009) who proposed the construction of the Spillover Index on the basis of decomposition of the forecast error variance of a Vector Autogressive (VAR) model. This approach enables us to determine the portion of the forecast error variance of one market which could be attributed to the shocks of other market, hence to capture the level of cross market spillovers, and subsequently to aggregate spillover effects across markets into a single index (Diebold and Yilmaz, 2009). In order to obtain more accurate results we will employ the concept of Realized Volatility constructed from high frequency intraday returns. To capture the potential response asymmetry in volatility spillover effects due to positive or negative shocks we will use the recently proposed estimator introduced by Barndorff-Nielsen, Kinnebrock and Shephard (2010) - the Realized Semivariances. This concept will enable us to decompose the Realized Variance into two parts: the first one which relates to positive high frequency returns and the second one relating to negative high frequency returns (Barndorff-Nielsen et al., 2010). The methodology of studying the asymmetric volatility transmission with the use of Realized Semivariances is proposed by Barunik et al. (2013).

## Outline

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5. Empirical Analysis and Discussion of Results
6. Conclusion

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# Chapter 1

# Introduction

Over the recent decades the interconnectedness among countries has increased substantially due to growing integration and globalization process. However, apart from its positive impact on the economic development, the strengthening of these linkages has made countries more prone to the shocks emanating from abroad. The issue of the cross-country shock transmission has become even more pronounced after the outbreak of the recent global financial crisis when financial markets worldwide were hit extensively. This financial turmoil induced sharp increase in volatilities of stock returns that spread quickly across the markets (Yilmaz 2010). Therefore, to determine the degree of market interconnectedness and its susceptibility to the distress originating in the other markets it is useful to study the mechanism of volatility transmission. Moreover, it is interesting to examine the evolution of volatility spillovers over the period rich on many economic shocks and financial instability, different kinds of interventions conducted by both national governments and central banks, and the substantial fluctuations of market confidence and uncertainty.

Furthermore, studying the evolution of volatility spillovers, thus development of linkages among stock markets, is also of interest for investors due to potential international portfolio diversification benefits. Hence, to be able to compose a portfolio of stocks that would be exposed to negative shocks originating abroad to the lowest possible extent, it might be useful to understand how volatilities from different shocks to returns, based on its signs, propagate across the stock markets. There is a substantial part of empirical literature confirming that market volatility exhibits asymmetric behaviour with respect to the sign of shocks to returns. Hence, we can expect the resulting volatility spillovers due to negative or positive shocks to transmit differently as well.

In this thesis, we examine the volatility spillovers and its response asymmetry among the selected stock markets in the Central and Eastern European region (Budapest, Prague and Warsaw) and further in our original sample extended by the inclusion of the German stock market as the representative of one of the most developed stock markets in Europe by constructing the spillover indices. The methodology for its construction is based on Baruník *et al.* (2013) who extend the original spillover index framework proposed by Diebold & Yilmaz (2009) by employing the concept of positive and negative realized semivariances introduced by Barndorff-Nielsen *et al.* (2010). This concept enables us to compute the asymmetric spillover indices and thus to capture the potential asymmetry in the behaviour of volatility spillovers that are due to negative or positive shocks. Moreover, using the dynamic approach we are able to observe the evolution of these indices over time.

The remainder of this thesis is organized as follows. Chapter 2 provides the review of the empirical literature on the stock market interdependencies focusing on the Central and Eastern European region. Chapter 3 briefly introduces the stock markets included in our analysis. The methodology regarding the construction of the volatility spillover indices as well as the realized measures employed for its construction are presented in Chapter 4. The data and the results of the empirical analysis are provided in Chapter 5 and Chapter 6, respectively. Finally, Chapter 7 concludes and discusses the possible extensions of our analysis.

# Chapter 2

# Literature Review

This chapter provides a brief review of the empirical literature on stock market interdependencies focusing on the Central and Eastern European (CEE) region. The literature analysing the linkages among the CEE and mature stock markets employs various econometric techniques, with Granger causality tests, cointegration techniques or a generalized autoregressive conditional heteroscedasticity (GARCH) model and its different specifications being the most commonly applied. In what follows, we firstly present the main research papers on this topic. Thereafter, we summarize the main findings and at the end of the chaper we provide a rationale for the relevance of our analysis in the context of existing literature.

A substantial part of the empirical literature focused on the CEE region explores the long-term and short-term linkages not only among the CEE stock markets and the mature capital markets from Europe or the United States (US) but also among the markets within the CEE group by employing the cointegration techniques. However, the results of these studies vary with regard to the time period, frequency of data, or the methodology applied.

The early study of Linne (1998) provides some evidence of cointegration within a group of the major CEE markets over the 1991-1997 period. However, no cointegration relations between the CEE and developed stock markets were found.

Similar results are provided by Gilmore & McManus (2002) who examine the long-run and short-run interrelationships between the CEE stock markets of the Czech Republic, Hungary, and Poland, and the developed US capital market over the period from 1995 to 2001. Applying the Johansen cointegration procedure the authors find no cointegrating relation between the US capital market and both the individual CEE markets and the CEE markets as a group. Furthermore, the authors report low values of the correlation coefficients between the emerging markets and the US stock market that are increasing over time. All these findings imply not only short-term but also long-term diversification benefits for the US investors that can yet be reduced with growing integration of these countries with the developed markets.

By contrast to the previous studies, MacDonald (2001) finds the significant long-run comovements of a group of the CEE stock markets with each of the three developed equity markets, Germany, the United Kingdom (UK) and the US, over the period from 1994 to 1999.

Furthermore, Vizek & Dadić (2006) investigate the integration of the selected CEE equity markets (namely the Czech, Hungarian, Polish, and Slovenian capital markets) including the equity market of Croatia and the German equity market over the 1997-2005 period with the use of Johansen cointegration procedure. Although no evidence of bilateral integration is found between the equity markets of Germany and both Croatia and the other CEE countries in the sample, the existence of multilateral integration not only among all the considered CEE stock markets but also between them and the German stock market is confirmed. The authors then conclude that there could be *" . . . common global underlying factors that are only captured in multilateral cases that drive these markets towards integration"* (Vizek & Dadić 2006, p. 641-642).

However, the static cointegration analysis as employed in the former studies does not allow for the possibility of time-varying long-run relations, thus rely on the assumption of stability of these long-run relationships. Eventhough the time series under consideration are allowed to deviate from its long-run equilibrium in the short term, in the long term they return to its long-run value which is cosidered to be stable, unchanging. Therefore, if these long-run relations are changing over time they will not be revealed by the application of static cointegration tests. (Gilmore *et al.* 2008)

Voronkova (2004) uses the approach of Gregory & Hansen (1996) enabling to test for cointegration in the presence of one-time regime shift at unknown time. Applying this methodology on the major CEE stock markets of the Czech Republic, Hungary, and Poland, and their mature counterparts in Europe (Germany, France, and the UK) and the one of the US over the 1993-2002 period the author finds significant long-run links both between the equity markets within the CEE region and between the CEE and developed stock markets.

Employing the Johansen cointegration procedure and the vector error correction model (VECM) Syriopoulos (2006) investigates dynamic linkages among the major CEE markets and the developed stock markets of Germany and the US over the period from 1997 to 2003 and finds one cointegrating vector among the studied markets. Moreover, the tendency of the individual CEE markets to have stronger links with their mature counterparts than with the other CEE neighbours is revealed. Using the asymmetric exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model the persistent feature of volatility is found to be significant for the emerging CEE stock markets, while the asymmetric effects are found to be significant for the developed markets.

Gilmore *et al.* (2008) investigate the short- and long-term comovements between the CEE stock markets and those of Germany and the UK by employing both static and dynamic methodologies. The static tests do not detect any long-run relationship among these markets during the whole examined 1995-2005 period. However, by applying dynamic cointegration and principal component analyses using the rolling-window approach the authors reveal that the periods of cointegration alternate with the periods during which the short-run dynamics is more important.

Another extensive strand of the empirical literature analysing the interdependence among the CEE and mature stock markets employs the multivariate GARCH models or its alternative specifications. Using daily data spanning the period from 1994 through 1998 Kasch-Haroutounian & Price (2001) study the volatility transmission between four emerging stock markets of CEE (the Czech Republic, Hungary, Poland, and Slovakia) with the use of two different representations of the multivariate GARCH model: the constant conditional correlation (CCC) and the BEKK specifications. Applying the CCC model the authors find the positive and significant conditional correlations between the Hungarian equity market and the Polish market as well as between the Hungarian and Czech equity markets. Furthermore, the results from the BEKK model provide the evidence about the existence of return volatility spillovers from Hungary to Poland but not the other way around.

Scheicher (2001) investigates the comovements between the emerging stock markets of the Czech Republic, Hungary, and Poland, over the 1995-1997 period using the vector autoregression (VAR) with multivariate GARCH. The results indicate that return series are influenced by both regional and global shocks, while for volatility series the regional spillovers dominate. The finding that the Polish stock market is influenced by shocks from Hungary both in returns and volatility is in line with Kasch-Haroutounian & Price (2001).

Tse *et al.* (2003) explore the information transmission between the transition stock market of Poland and the developed US market for the period from 1994 to 2003 by employing the exponential GARCH-t (EGARCH-t) model. The authors find that return volatilities of both markets are persistent and exhibit the asymmetric behaviour with respect to the character of news arrived in the market (the positive or negative ones). However, this asymmetric volatility effect is strongly significant for the US stock market, but rather marginal for Poland. Furthermore, no volatility spillovers are detected between these markets, while, on the other hand, the spillovers in the conditional mean returns from the US to Poland are found to be significant. The authors conclude that the latter finding could be caused by the nonsynchronous trading problem. Applying cointegration tests no long-run relationship between these stock markets is confirmed.

Li & Majerowska (2008) investigate the linkages between the emerging equity markets of the CEE and the mature markets of Germany and the US during the 1998-2005 period using daily returns of the stock market indices. Applying multivariate asymmetric BEKK-GARCH model the evidence of both return and volatility spillovers from the mature markets to the emerging ones is found. While there are linkages among the Hungarian and Polish stock markets and the mature markets in Frankfurt and the US in terms of both returns and volatility, regarding the Czech market only returns and volatility spillovers stemming from the US market are found. No such connections are detected in relation to the German stock market. Moreover, the selected emerging CEE markets are linked in terms of volatility. Unlike Tse *et al.* (2003) who find solely the return spillovers coming from the US market to the Polish one, Li & Majerowska (2008) also confirm the presence of volatility linkages between these markets. In addition, the authors further focus on the cross-market asymmetric responses among the studied markets. They reveal that the stock markets in Warsaw and Budapest exhibit asymmetry in responses to the shocks emanating from the German market. In addition, the German stock market reacts stronger to the negative shocks of the Hungarian and the US market, whereas the US market respond asymmetrically to the shocks of both Polish and German stock markets. Estimating the time-varying conditional covariances and variance decompositions in order to determine the extent of integration among the examined stock exchanges the authors find the evidence of weak linkages between the emerging markets and the developed ones.

Using the CCC and smooth transition conditional correlation (STCC) models Aslanidis & Savva (2010) investigate the stock market integration among the selected CEE stock markets (the Czech Republic, Hungary, Poland, Slovakia, and Slovenia) and the Euro-zone market in the 2001-2007 period. Regarding the correlations between the individual CEE markets and the Euro-zone, the stock markets in Prague and Warsaw exhibit an increased correlation over the observed period. For the Hungarian market the correlation to the Euro-zone market remains unchanged, but relatively high. However, only low degree of correlation is found for the Slovakian and Slovenian stock markets. Furthermore, the evidence about strong linkages among the three CEE markets of the Czech Republic, Hungary, and Poland, and among them and the Euro-zone is provided.

Caporale & Spagnolo (2011) study the integration among the CEE stock markets of the Czech Republic, Hungary, and Poland, and the ones of the UK and Russia over the period from 1996 to 2008 using the VAR-GARCH-in-mean model. The analysis confirms the presence of volatility spillovers from both the UK and Russia to all CEE stock markets, however, not in the opposite direction. The introduction of euro as well as the accession of the considered CEE countries to the European Union (EU) are found to induce the shift in the spillover coefficients. Furthermore, the authors find the evidence of increasing correlations of the emerging CEE stock markets with both the UK and Russia after 2004, thus after the accession of selected CEE countries to the EU, with the degree of stock market integration to be higher for the UK than for Russia.

Syllignakis & Kouretas (2011) examine the time-varying conditional correlations among the stock markets of the US, Germany, Russia and of the seven emerging countries from the CEE region (the Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia, and Slovenia) during the period 1997-2009 by employing the multivariate dynamic conditional correlation (DCC)-GARCH model. The authors find the evidence of increase in the stock market correlations implying the reduced diversification potential of the CEE stock markets. This finding is in line with the previous results of Aslanidis & Savva (2010), Li & Majerowska (2008), and Caporale & Spagnolo (2011). Moreover, the estimated coefficients of conditional correlation exhibit a significant variation, especially during the period of recent financial crisis (2007-2009).

In order to explore the volatility transmission mechanism from the mature to 41 emerging stock markets from Asia, Europe, Middle East and North Africa, and Latin America during the period from 1996 (for Asian emerging countries from 1993) to 2008 Beirne *et al.* (2013) employ the multivariate BEKK-GARCH model. The results suggest the presence of both mean and volatility spillovers running from the mature markets to majority of emerging markets. Furthermore, the authors find the evidence of the shift in volatility transmission from the mature stock markets to the emerging ones during the turbulent periods, thus the evidence of volatility contagion. For some emerging economies volatility spillovers from the mature markets occur only during the episodes of financial distress in these markets.

Using the BEKK-GARCH model Horváth & Petrovski (2013) investigate the comovements between the Central (the Czech Republic, Hungary, and Poland) and South Eastern (Croatia, Macedonia, and Serbia) European stock markets vis-*à*-vis the mature Western European market over the period from 2006 through 2011. The stock markets from the Central European region are found to be more integrated (with conditional correlation values being around 0.6) with the Western part than the South Eastern European region. The conditional correlations of Macedonia and Serbia with the Western Europe are zero on average, whereas the stock market of Croatia exhibits low, but positive degree of integration with the developed Western European stock market. Finally, the authors conclude that the recent financial crisis did not alter the degree of stock market correlations substantially.

Gjika & Horváth (2013) investigate the comovements among the three CEE stock markets (the Czech Republic, Hungary, and Poland) and between these selected markets and the aggregate euro area market over the 2001-2011 period with the use of the multivariate asymmetric dynamic conditional correlation (ADCC)-GARCH model. The authors find increasing correlations both among the stock markets within the CEE region and between the CEE markets and the euro area, with the largest increase being observable after the accession of the CEE countries to the EU. The conditional correlations remain at these high levels also during the recent financial crisis. Finally, the results indicate positive relationship between the conditional variance and correlation implying diminished diversification benefits during more volatile episodes.

With an increasing availability of high-frequency data on the CEE region there has emerged another part of the literature focused on this region that employs this type of data as opposed to the previous studies that use the data of daily or weekly frequency. Employing the 5-minute high-frequency data of the selected stock indices Égert & Kočenda (2007) study the interdependence both among the CEE stock markets in Budapest, Prague, and Warsaw, and among these emerging markets and the Western European ones in Frankfurt, London, and Paris, over the period from June 2003 through February 2005. Performing different cointegration tests no robust long-term relationship between the examined markets is detected. Regarding the short-term spillover effects the return spillovers among the stock markets both within the CEE region and within the Western Europe, and from the markets in Western Europe to the CEE are found. The volatility spillovers also occur among the stock markets within the CEE region as well as within the Western Europe. However, there can also be observed volatility spillovers running from the Hungarian and Polish markets to the ones of Germany and the UK, respectively.

Černý & Koblas (2008) examine the stock market integration and the speed of information transmission among the three CEE equity markets (the Czech Republic, Hungary, and Poland) and the advanced markets in Frankfurt, London, Paris, and the US using the high-frequency data for the period from June 2003 to June 2005. The authors conduct the standard cointegration and Granger causality tests with data of different frequencies, from 5 minutes to one day. The results indicate the fast reaction of stock markets to the information comming from the other markets. Moreover, it is shown that the considered CEE stock markets react to the information from Frankfurt within 40 minutes to one hour.

Hanousek *et al.* (2009) employ the high-frequency five-minute intraday data over the period spanning from mid-2003 through the end of 2006 in order to study the responses of composite stock returns in the selected emerging EU markets (the Czech Republic, Hungary, and Poland) to the macroeconomic news. The results provide an evidence of significant spillover effects through the stock returns from the EU, the US and the neighbouring countries that affect directly the examined EU markets, with the Hungarian stock market displaying the strongest spillover effects. Furthermore, the stock markets in Budapest and Warsaw are indirectly influenced by the EU announcements with the latter one being impacted only marginally, while the Czech market is more sensitive to the news comming from the US.

Applying a dynamic conditional correlation (DCC)-GARCH model on the high-frequency five-minute data over the 2003-2006 period Égert & Kočenda (2011) investigate the time-varying intraday comovements among the CEE stock markets of the Czech Republic, Hungary, and Poland, and among them and three Western European markets (France, Germany, and the UK). The authors find strong correlations among the developed equity markets of Western Europe, whereas the correlations among the emerging CEE markets and between them and the stock markets of the advanced Western European economies are found to be rather weak during the trading day. The results also reveal an increase in the correlations in the emerging markets in the second half of the sample, thus after the accession of these countries to the EU.

Hanousek & Kočenda (2011a) examine the spillovers and the effect of macroeconomic announcements on the selected emerging stock markets of CEE (the Czech Republic, Hungary, and Poland) in the time-varying GARCH framework using five-minute high-frequency data for the 2004-2007 period. The results indicate that the spillover effects running from the other regional as well as from the mature markets of Germany and the US affect the returns of the considered CEE markets. Regarding the effects of the mature markets, spillovers from Frankfurt dominate the ones from the US. Regional spillovers are of a smaller or comparable magnitude to the ones originating from the US. Finally, the authors conclude that both the spillovers and news from mature stock markets have an influence on the emerging markets from the CEE region.

Employing the five-minute high-frequency data over the period from 2007 to 2009 Baruník & Vácha (2013) study the comovements and contagion among three CEE stock markets (the Czech Republic, Hungary, and Poland) and the mature German market with the use of wavelet techniques. Firstly, the findings reveal that the correlations, thus interconnectedness, between the studied markets change not only in time but also across frequency. Furthermore, the authors find an evidence of low correlations between the stock markets in the CEE region and Germany on higher frequencies implying that these markets are connected to the mature Western European market only in terms of longer investment horizons. These correlations are found to decrease with the outbreak of the recent financial crisis.

In summary, the previous literature reveals the presence of low but increasing correlations both among the CEE stock markets and among them and the developed ones. In many studies the comovements are found to strengthen after the entry of the CEE countries into the EU. Furthermore, majority of research papers detect both return and volatility spillovers running predominantly from the mature to emerging markets. In addition, Li & Majerowska (2008) find some evidence of cross-market asymmetric volatility responses. Regarding the long-term relationship among studied stock markets there is discrepancy in the results obtained by different studies. While some research papers find these stock markets to be related in the long-run, the other ones do not detect any cointegration relationship.

In this thesis, we would like to contribute to the existing literature on volatility transmission focusing on the CEE region by applying the novel approach of Baruník *et al.* (2013) which allows us to capture the potential asymmetry in the behaviour of volatility spillovers that are due to negative or positive shocks. In their seminal paper, the authors extend the original volatility spillover index methodology proposed by Diebold & Yilmaz (2009) by employing the concept of positive and negative realized semivariances introduced by Barndorff-Nielsen *et al.* (2010). This concept enables them to compute the asymmetric spillover indices using these nonparametric high-frequency measures. Since the original volatility spillover index is based on the orthogonal decomposition of forecast error variance from the vector autoregression, its results depend on the ordering of variables in the system. Therefore, to eliminate this problem, Baruník *et al.* (2013) apply the algorithm of Klößner & Wagner (2012) that calculates the spillovers over all possible permutations, thus volatility spillovers robust to the ordering.[1]

Baruník *et al.* (2013) perform their improved methodology on the data of the 30 US stocks during the period from 2004 through 2011 to investigate the intra-market volatility spillovers. The results confirm the existence of asymmetries in volatility spillovers due to negative and positive returns and conclude that the economic situation, its ups and downs, has an impact on the volatility transmission mechanism and its sensitivity to negative and positive shocks. The authors find that during period of economic growth positive returns spill more across the US market than the negative ones, while with the onset of recent financial crisis negative returns transmit more.

Regarding the contribution of this thesis, to the best of our knowledge, it is the first study applying this methodology on the CEE region while examining the behaviour of asymmetric volatility spillovers using the concept of realized semivariances among the CEE stock markets.

[1]The volatility spillover index methodology as applied in our thesis is described more properly in Chapter 4.

# Chapter 3

# Central and Eastern European Stock Markets

This chapter provides an overview of the three CEE emerging stock markets of the Czech Republic, Hungary and Poland. First, we focus on the main characteristics and the evolution of these markets. Since in our analysis we also include the German equity market as a representative of the mature European stock markets, we further compare the stock market in Germany with the emerging ones in terms of market characteristics, such as market capitalization, equity trading turnover, or the number of listed companies, among others.

## 3.1 Market Characteristics

The Czech Republic, Hungary and Poland represent countries from the same geographical area that are connected not only culturally and historically, but also economically. The history of the national stock exchanges in the CEE region traces back to the 19th century, with the first stock exchange in this region being established in 1817 in Warsaw, followed by the Budapest and Prague stock exchanges founded in 1864 and 1872, respectively. However, its activities were interrupted during the both World Wars and finally terminated with the onset of the communist regime in these countries. The fall of communism in the early 1990s was marked by the efforts to change these centrally planned economies to the market oriented systems. The transition process of the CEE countries characterized by the liberalisation of markets and prices and privatisation of state-owned enterprises, among others, was accompanied by the re-emergence of the stock exchanges. The first reestablished stock exchange was the one in Budapest in 1990, followed by the stock exchanges in Warsaw and Prague that reopened in 1991 and 1992, respectively.

The development of these stock markets was influenced to a large extent by privatization strategies adopted by the individual countries (EBRD 1995). The Czech Republic implemented the method of mass privatization with the mandatory listing of the privatized companies on the Prague Stock Exchange (PSE). This led to a substantial increase of the number of listed companies during the early stages of privatization. However, in 1997 the PSE exhibited massive delisting mainly due to insufficient liquidity of the majority of companies, which harmed the confidence in the market. Hungary and Poland decided for another, rather gradual, approach to privatization via the initial public offerings (IPOs) or direct sales to strategic investors (Rozlucki 2011).

Prior to the accession to the EU, the considered CEE countries were obliged to comply with the EU legislation. This EU integration process enhanced the interest and confidence of foreign investors to participate in these markets. In 2004, after the entry of the Czech Republic, Hungary and Poland to the EU they also became the members of the Federation of European Securities Exchanges (FESE). The favourable development, which these CEE stock markets experienced during the post-accession period, not only in terms of its increased size as measured by the market capitalization, but also higher level of liquidity, was interrupted by the onset of the recent global financial crisis in 2008. The Czech Republic and Hungary together with the Ljubljana and Vienna stock exchanges are members of the largest exchange group in the region of Central and Eastern Europe, the CEE Stock Exchange Group (CEESEG), which launched its activities in 2009.

Table 3.1 provides an overview of the main market characteristics of the Budapest, Prague and Warsaw stock exchanges, including market capitalization, equity trading volume, number of listed companies and the number of IPOs, during the period spanning from 2002 to 2012, which captures not only the pre- and post-accession period of the CEE countries to the EU, but also the pre-crisis and crisis years as well as the early recovery phase.[1] Regarding the values of market capitalization, which proxies size of the market, an upward

trend can be observed for all the examined CEE stock exchanges during 2002-

[1]Since we consider equity trading value and market capitalization in EUR, the interpretation of these figures might be subject to bias stemming from the fluctuations of the particular domestic currency values.

Table 3.1: Market Characteristics

| | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Budapest** | | | | | | | | | | | |
| Equity trading value | 6245 | 7231 | 10763 | 19417 | 24626 | 34610 | 20967 | 18726 | 20007 | 13799 | 8440 |
| Market capitalization | 12493 | 13228 | 21040 | 27586 | 31687 | 31528 | 13326 | 20888 | 20624 | 14630 | 15742 |
| Nr. of listed companies | 48 | 51 | 46 | 44 | 41 | 41 | 43 | 46 | 52 | 54 | 52 |
| Domestic | 47 | 50 | 45 | 44 | 41 | 39 | 40 | 42 | 48 | 52 | 51 |
| Foreign | 1 | 1 | 1 | 0 | 0 | 2 | 3 | 4 | 4 | 2 | 1 |
| Nr. of IPOs | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| **Prague** | | | | | | | | | | | |
| Equity trading value | 5880 | 7471 | 15073 | 34909 | 30015 | 36581 | 34179 | 17565 | 15391 | 15131 | 9984 |
| Market capitalization | 9796 | 12288 | 21720 | 31059 | 34693 | 47987 | 29615 | 31265 | 31922 | 29203 | 28193 |
| Nr. of listed companies | 45 | 38 | 55 | 39 | 32 | 32 | 29 | 25 | 27 | 26 | 28 |
| Domestic | 44 | 37 | 53 | 35 | 26 | 24 | 19 | 16 | 16 | 15 | 17 |
| Foreign | 1 | 1 | 2 | 4 | 6 | 8 | 10 | 9 | 11 | 11 | 11 |
| Nr. of IPOs | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 0 | 1 | 1 | 0 |
| **Warsaw** | | | | | | | | | | | |
| Equity trading value | 8308 | 8777 | 13147 | 24111 | 43235 | 63876 | 47854 | 41405 | 59693 | 70161 | 50169 |
| Market capitalization | 27055 | 29350 | 51888 | 79353 | 112826 | 144323 | 65178 | 105157 | 142272 | 107483 | 134755 |
| Nr. of listed companies | 202 | 189 | 216 | 241 | 265 | 375 | 458 | 486 | 585 | 777 | 867 |
| Domestic | 202 | 188 | 211 | 234 | 253 | 352 | 432 | 470 | 570 | 757 | 844 |
| Foreign | 0 | 1 | 5 | 7 | 12 | 23 | 26 | 16 | 15 | 20 | 23 |
| Nr. of IPOs | 0 | 0 | 1 | 0 | 27 | 105 | 93 | 38 | 110 | 204 | 106 |

*Note:* Data retrieved from the Federation of European Securities Exchange. Equity trading value and market capitalization in EUR million. All market characteristics in year-end values.

2007 period, which was interrupted by the global financial crisis. In 2008, all CEE markets experienced a decrease in the values of market capitalization. Neither of the examined stock exchanges was able to recover its values of market capitalization to the pre-crisis levels, although the Warsaw Stock Exchange (WSE) appears to be the most successful. From the figures presented in Table 3.1 we can see that the WSE maintained its leading position in terms of market capitalization during the whole examined period.

In terms of equity trading value the WSE has the highest figures over the observed period, except for years 2004 and 2005, when WSE was outperformed by the PSE. However, relating the equity trading turnover to market capitalization indicates that the WSE was the least liquid stock exchange till 2010, whereas from 2011 the PSE ranked the last. Since 2007 the Budapest Stock Exchange (BSE) has achieved the highest relative values among the three CEE exchanges.

Regarding the number of listed companies the WSE dominates the other markets, with the value of 844 in 2012. During the whole examined period its number of listed enterprises increased more than four times. Such a substantial increase was supported by the high number of IPOs that is almost negligible for the two other stock exchanges. It could be concluded that both the BSE and the PSE are nearly inactive in IPOs in comparison with the WSE. The share of listed foreign companies is most pronounced in case of the PSE, with an increasing trend prior to the outbreak of recent financial crisis. In contrast, foreign companies represent only a minor part of all the equity issues on the BSE and the WSE.

Table 3.2: German Stock Market Characteristics

| | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|
| Equity trading value | 3207213 | 1658498 | 1744108 | 1525849 | 1078121 |
| Market capitalization | 797063 | 900772 | 1065713 | 912420 | 1127370 |
| Nr. of listed companies | 832 | 783 | 765 | 746 | 747 |
| Domestic | 742 | 704 | 690 | 670 | 665 |
| Foreign | 90 | 79 | 75 | 76 | 82 |
| Nr. of IPOs | 5 | 5 | 30 | 29 | 11 |

*Note:* Data retrieved from the Federation of European Securities Exchange. Equity trading value and market capitalization in EUR million. All market characteristics in year-end values.

Table 3.2 summarizes the main characteristics of the stock exchange in Germany, Deutsche Boerse. Comparing the CEE stock exchanges with the developed Deutsche Boerse in terms of market capitalization we can observe that Deutsche Boerse is of approximately 8.4 times larger magnitude than the WSE. However, there is a higher number of companies listed on the WSE compared to the German one indicating rather small companies traded on the WSE. Regarding the number of IPOs the WSE conducted considerably higher amount compared to Deutsche Boerse.

# Chapter 4

# Methodology

This chapter provides theoretical background regarding the construction of volatility spillover indices using high frequency data. By utilizing the recently proposed concept of realized semivariances of Barndorff-Nielsen *et al.* (2010), Baruník *et al.* (2013) extend the application of the standard spillover approach of Diebold & Yilmaz (2009) by allowing to account for asymmetries that may be present in the transmission process of volatility as a result of different sign of returns. Moreover, employing the high frequency data for the construction of realized volatility estimators enables us to obtain the more accurate results. This approach thus constitutes an important extension of the original framework.

In what follows, we describe the realized measures (realized variance and realized semivariances) employed in our analysis. After that we present the methodology for computing the volatility spillover index. In the next section, a measure for quantifying the extent of asymmetries in volatility spillovers due to both negative and positive returns proposed by Baruník *et al.* (2013) is introduced. Finally, we provide a description of a VAR model estimation procedure.

## 4.1 Realized Measures

### 4.1.1 Realized Variance

Consider a continuous-time stochastic logarithmic price process, $p_t$, defined on a probability space ($\Omega$, $\mathcal{F}$, P), evolving over the time interval [0,T], where T is positive finite integer. Moreover, consider the natural filtration, $(\mathcal{F}_t)_{t\in[0,T]} \subseteq \mathcal{F}$, associated to the $p_t$ process, where $\mathcal{F}_t$ represents the information set consisting of all the asset prices and other relevant state variables observable up to time t. The price process, which consists of a continuous component and a pure jump component, takes the following form,

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t, \tag{4.1}$$

where $\mu$ denotes the locally bounded predictable drift process, $\sigma$ is strictly positive càdlàg (right-continuous with left limits) volatility process, $W$ is a standard Brownian motion, and J represents a pure jump process. The quadratic variation (QV) of the logarithmic prices, $p_t$, is defined as

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0<s\leq t} (\Delta p_s)^2, \tag{4.2}$$

where $\Delta p_s = p_s - p_{s-}$ represents jumps, if present.[1] The first component on the right-hand side of the equation denotes the integrated variance of the price process, while the second term captures the jump variation. Further, it can be observed that the QV of the predictable drift process $\mu$ equals zero, hence it has no impact on the QV of the logarithmic prices (Andersen *et al.* 2003).[2]

Andersen *et al.* (2001a) and Barndorff-Nielsen & Shephard (2002) proposed a natural estimator for the QV constructed as a sum of squared returns, termed realized variance (RV). Before introducing the formal notation for the RV estimator, let us firstly define returns corresponding to the logarithmic price process.

For simplicity, the time interval [0,t] is normalized to one trading day and divided into $n$ equidistant subintervals, each of length $t/n$. Hence, by sampling prices $n$ times per day we obtain $n+1$ equally spaced observations $p_0, ..., p_n$. Afterwards, we are able to construct the i-th intraday return $r_i$ as follows

$$r_i = p_i - p_{i-1},\ i = 1, \ldots, n. \tag{4.3}$$

The intraday RV of the logarithmic price process can then be expressed as

$$RV = \sum_{i=1}^{n} r_i^2 \tag{4.4}$$

[1]The notation $p_{t-}$ denotes a càdlàd (left-continuous with right limits) process, whose value at $s$ can be defined as $p_{s-} = lim_{u\to s, u\leq s}\ p_s$.

[2]The irrelevance of the mean component for the QV follows from the properties of the QV process as discussed by Andersen *et al.* (2003).

According to the theory of QV (see for example Andersen *et al.* (2010)) as the sampling frequency increases, thus $n \to \infty$, and the length of each time interval between observations shrinks to zero, the RV converges in probability to the QV of the underlying price process

$$RV = \sum_{i=1}^{n} r_i^2 \xrightarrow{p} [p_t, p_t] \tag{4.5}$$

However, the requirement of the QV theory to sample at the highest possible frequencies in an attempt to approach the continuously observed prices is accompanied by the problem stemming from the market microstructure noise. In the presence of microstructure frictions, such as bid-ask bounce, late reporting, or discreteness of prices, among others, the underlying price process tends to deviate from its true values (Bandi & Russell 2008). As a result, summing an increasing number of contaminated squared returns entails a substantial noise accumulation leading to the noise-induced bias of the RV estimator. To mitigate the impact of the microstructure effects several approaches have been proposed striving to achieve a balance between an increased accuracy from using all the available high frequency data in order not to loose any information and the adverse effects introduced by the market microstructure noise.

The common practice to avoid the undesirable bias is to select such a sampling frequency that is both high enough to produce the volatility estimate free of measurement errors and at the same time low enough to circumvent the biases induced by the microstructure noise. The standard length of sampling interval usually employed in many empirical studies ranges from 1 to 30 minutes (Liu *et al.* 2012). Bandi & Russell (2008) and Zhang *et al.* (2005) proposed a way of determining an optimal sampling frequency by minimizing the mean squared error (MSE) of the RV estimator. As an alternative to the previous approach Zhang *et al.* (2005) introduced an estimator utilizing all the available high frequency data that is based on subsampling, averaging and bias-correction, termed the two-scales RV (TSRV). Moreover, TSRV is consistent estimator of the QV, even in the presence of the microstructure noise (Ait-Sahalia & Mancini 2008). Other related estimators correcting for the bias generated by the microstructure noise include those using the pre-whitening techniques such as the moving-average filter employed in Andersen *et al.* (2001b) and Hansen *et al.* (2008), or the autoregressive filter of Bollen & Inder (2002). Another class of realized measures, the kernel type estimators, was studied by Barndorff-Nielsen *et al.* (2008), Hansen & Lunde (2004;

2006), or Zhou (1996). The more comprehensive survey on the modified RV estimators designed to avoid the impact of microstructure noise is provided by Andersen *et al.* (2010). In addition, a review of the growing literature on the existing RV estimators is presented in McAleer & Medeiros (2008) or Pigorsch *et al.* (2012).

Since the main purpose of our analysis is not to find the most appropriate price variation measure in the presence of microstructure frictions, we use the five-minute sampling interval for each of the analyzed stock market indices what is in line with most of the existing empirical literature (see for instance Andersen *et al.* (2001b), Andersen *et al.* (2007), Baruník *et al.* (2013), Hanousek & Kočenda (2011b), or Hanousek & Novotný (2012)).

However, employing the RV disregards the information contained in the sign of returns. Hence, to be able to distinguish between the variation due to negative or positive returns we also apply the concept of realized semivariances described in the following part.

### 4.1.2 Realized Semivariances

An important contribution to the recent advances in the area of volatility modeling using the realized measures has been provided by Barndorff-Nielsen *et al.* (2010) who introduced new estimators of asset price variation based on signed returns named realized semivariances (RS). These estimators can be formalized as follows

$$RS^{-} = \sum_{i=1}^{n} r_i^2 I_{[r_i<0]} \tag{4.6}$$

$$RS^{+} = \sum_{i=1}^{n} r_i^2 I_{[r_i>0]} \tag{4.7}$$

where $RS^{-}$ stands for the downside realized semivariance which captures the variation determined entirely by the asset price falls and $RS^{+}$ denotes the corresponding upside realized semivariance. The term $I$ is the indicator function which takes the value of one if the argument in the square brackets holds.

Moreover, the concept of RS enables us to decompose the RV into two parts, the first one which can be attributed to the negative high frequency returns and the second one relating to the positive high frequency returns, hence $RV = RS^- + RS^+$. This decomposition holds not only for any $n$ but also in the limit.

Regarding the limiting behaviour of the realized semivariances each of the RS converges to one-half of the integrated variance and the sum of squared jumps either with negative or positive sign

$$RS^- \xrightarrow{p} \frac{1}{2}\int_0^t \sigma_s^2 ds + \sum_{0\leq s\leq t} \Delta p_s^2 I_{[\Delta p_s<0]} \tag{4.8}$$

$$RS^+ \xrightarrow{p} \frac{1}{2}\int_0^t \sigma_s^2 ds + \sum_{0\leq s\leq t} \Delta p_s^2 I_{[\Delta p_s>0]} \tag{4.9}$$

thus, analogously to the RV, it involves variation due to both the continuous and the jump part of the asset price process, as shown by Barndorff-Nielsen *et al.* (2010).

## 4.2 Spillover Index

To measure volatility spillovers we follow the methodology recently proposed by Baruník *et al.* (2013) which allows us to capture the asymmetries in volatility transmission due to negative or positive shocks to returns by combining the original spillover index framework introduced by Diebold & Yilmaz (2009) with the concept of RS formalized in Barndorff-Nielsen *et al.* (2010).

The Diebold & Yilmaz (2009) volatility spillover index is derived from the variance decomposition of the forecast errors in a VAR model fitted to the volatility time series. Such a decomposition enables us to determine the shares of the forecast error variance of some variable that can be attributed to its own shocks and the shares that can be assigned to the shocks emanating from the other variables in the system. Thereafter, we are able to quantify the total volatility spillover measure as a single number by aggregating the information regarding the contributions of shocks to the forecast error variances over all variables.

To obtain a variance decomposition Diebold & Yilmaz (2009) employ the Cholesky factorization of the covariance matrix of VAR residuals. However, using this technique constitutes the main drawback of the proposed methodology which relates to the potential dependence of the variance decomposition results on the ordering of variables within the underlying VAR process. To eliminate the sensitivity of the spillover measure to the variables' arrangement, Diebold & Yilmaz (2012) improve their original approach by adopting the generalized vector autoregressive framework which produces the order-invariant forecast error variance decomposition. However, using the generalized variance decomposition framework tends to overestimate the spillover index as it considers each variable in the VAR system to be the leading one (Klößner & Wagner 2012). Another solution has been offered by Klößner & Wagner (2012) who developed an algorithm for the calculation of minimum, maximum, and average values of the spillover index over all N! possible permutations of the model's variables. To avoid the potential problem stemming from the order-dependency of results they suggest the use of the average spillovers. Regarding both alternatives we have decided to apply the algorithm of Klößner & Wagner (2012) and thus proceed with the construction of the average volatility spillover indices.

In the original framework of Diebold & Yilmaz (2009) the range based volatility estimator of Garman & Klass (1980) incorporating the information on low, high, open, and closing prices, is employed to calculate the volatility spillover index. However, since this volatility measure disregards the sign of returns causing the volatility, it would restrict our analysis to measure only the total volatility spillovers. On the other hand, using the realized volatility estimators based on high frequency data as proposed by Baruník *et al.* (2013) extends the standard spillover approach of Diebold & Yilmaz (2009) by accounting for asymmetric effects related to both positive and negative returns. Furthermore, employing the high frequency data enables us to obtain more accurate estimate of volatility. Therefore, to measure the total volatility spillover index we utilize the vector of RV, $RV_t = (RV_{1t}, \ldots, RV_{nt})'$. In order to capture the volatility spillovers related to negative and positive returns we use $RS_t^- = (RS_{1t}^-, \ldots, RS_{nt}^-)'$ and $RS_t^+ = (RS_{1t}^+, \ldots, RS_{nt}^+)'$, thus negative and positive RS, respectively.

In what follows, we describe the methodology regarding the construction of the volatility spillover index as proposed by Diebold & Yilmaz (2009).

Consider a covariance stationary p-th order N-variable vector autoregressive VAR(p) model defined as

$$Y_t = \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + \epsilon_t = \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t \tag{4.10}$$

where $Y_t = (Y_{1t}, \ldots, Y_{nt})'$ denotes a vector of volatilities, $\epsilon_t \sim N(0, \Sigma_\epsilon)$

stands for a vector of independently and identically distributed error terms and $\Phi_i$ for $i = 1, \ldots, p$ represents the matrices of coefficients.

Under the assumption of weak stationarity, the moving average (MA) representation of the VAR process exists and is given by

$$Y_t = \epsilon_t + \Psi_1 \epsilon_{t-1} + \Psi_2 \epsilon_{t-2} + \ldots = \sum_{i=0}^{\infty} \Psi_i \epsilon_{t-i} \tag{4.11}$$

where the $N \times N$ coefficient matrices $\Psi_i$ can be computed recursively using $\Psi_i = \sum_{j=1}^{p} \Phi_j \Psi_{i-j}$ with $\Psi_0 = I_N$ being the $N \times N$ identity matrix and $\Psi_i = 0$ for $i < 0$. Furthermore, consider the H-step ahead forecast at time t, $\widehat{Y}_{t+H} = E_t(Y_{t+H} | Y_t, Y_{t-1}, \ldots)$, and the corresponding forecast error vector

$$\begin{aligned}
e_{t+H} &= Y_{t+H} - \widehat{Y}_{t+H} = \\
&= Y_{t+H} - E_t(\epsilon_{t+H} + \Psi_1 \epsilon_{t+H-1} + \Psi_2 \epsilon_{t+H-2} + \ldots | Y_t, Y_{t-1}, \ldots) = \\
&= Y_{t+H} - (\Psi_H \epsilon_t + \Psi_{H+1} \epsilon_{t-1} + \Psi_{H+2} \epsilon_{t-2} + \ldots) = \\
&= \epsilon_{t+H} + \Psi_1 \epsilon_{t+H-1} + \Psi_2 \epsilon_{t+H-2} + \ldots + \Psi_{H-1} \epsilon_{t+1} = \\
&= \epsilon_{t+H} + \sum_{i=1}^{H-1} \Psi_i \epsilon_{t+H-i}
\end{aligned}$$

Thereafter, the covariance matrix of the forecast error can be expressed as follows

$$\Sigma_{e,H} = \Sigma_\epsilon + \Psi_1 \Sigma_\epsilon \Psi_1^{'} + \ldots + \Psi_{H-1} \Sigma_\epsilon \Psi_{H-1}^{'} = \sum_{h=0}^{H-1} \Psi_h \Sigma_\epsilon \Psi_h^{'} \tag{4.12}$$

with $\Sigma_\epsilon$ denoting the covariance matrix of VAR disturbances $\epsilon_t$. In order to derive the spillover index, we need to decompose the forecast error variance of each variable (the elements on the diagonal of $\Sigma_{e,H}$) to the portions attributable both to its own shocks and shocks to the other variables in the system. Following the approach of Diebold & Yilmaz (2009), we employ the unique lower-triangular Cholesky factor $L$ of the covariance matrix of $\epsilon_t$, such that $LL^{'} = \Sigma_\epsilon$, to obtain the variance decomposition. Thereafter, for every $h$ the expression $\Psi_h \Sigma_\epsilon \Psi_h^{'}$ can be rewritten as $(\Psi_h L)(\Psi_h L)^{'}$, thus the forecast error variance of the $i$-th variable can be expressed as $\left(\Psi_h \Sigma_\epsilon \Psi_h^{'}\right)_{ii} = \sum_{j=1}^{N} (\Psi_h L)^2$. Defining the cross variance shares, or spillovers, to be the contributions of shocks to variable $j$ to the forecast error variance of variable $i$ as $\sum_{h=0}^{H-1} (\Psi_h L)_{ij}^2$ for $i \neq j$, the volatility spillover index can then be defined as follows

$$S_H = 100 \times \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{j \neq i} \sum_{h=0}^{H-1} (\Psi_h L)_{ij}^2}{\sum_{h=0}^{H-1} (\Psi_h \Sigma_\epsilon \Psi_h')_{ii}} \tag{4.13}$$

with its values falling into the [0, 100] interval. By substituting the vector of volatilities considered in this general case with the vector of negative or positive RS, $RS^-$ and $RS^+$ respectively, the asymmetric volatility spillovers can be simply computed following the described procedure.

## 4.3 Spillover Asymmetry Measure

For the purposes of quantifying the extent of response asymmetry in volatility trasmission Baruník *et al.* (2013) introduced a spillover asymmetry measure (SAM), which takes the following form

$$SAM_H = 100 \times \left[ \frac{S_H^+ - S_H^-}{0.5(S_H^+ + S_H^-)} \right] \tag{4.14}$$

where $S_H^-$ and $S_H^+$ denote the volatility spillover indices related to negative ($RS^-$) and positive ($RS^+$) realized semivariances with the H-step ahead forecast at time t. If the spillovers emerging from $RS^-$ and $RS^+$ equal, the resulting value of $SAM_H$ is zero. Moreover, while the positive value of $SAM_H$ implies the larger impact of variation arising from the positive returns on the volume of volatility spillovers compared with the negative ones, the opposite holds true regarding the minus sign of this asymmetry measure, $SAM_H$.

## 4.4 Estimation Procedure of VAR Model

As it has been mentioned in the previous section the construction of the spillover index is based on a VAR model. Hence, in the initial phase of the index computation process, it is important to specify the VAR model properly. Therefore, the last part of this chapter is dedicated to the description of the estimation procedure of a VAR model as well as to the problems, which can arise, while trying to find its most accurate specification.[3] The whole procedure is performed in three main steps: lag length determination, model estimation, and model diagnostics. However, before we proceed to the vector autoregres-

[3]The methodology covered in this section follows the econometric textbooks of Brooks (2008), Cipra (2008), Hill *et al.* (2007), Kočenda & Černý (2007), Lütkepohl (2005), Tsay (2005), Wooldridge (2002), as well as the R documentation of Pfaff (2008).

sion analysis the individual time series are examined for stationarity to ensure that we avoid a problem of spurious regression which can stem from the use of non-stationary variables for the construction of a VAR model.[4]

### 4.4.1 Unit Root Analysis

In order to test for the presence of a unit root in the time series the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are applied. However, these tests suffer from low power to distinguish between the series that are integrated of order one, I(1), or near-unit root processes, thus it is recommended to use these tests in conjuction with the Kwiatkowski-Phillips-Schmidt-Schin (KPSS) test which, on the contrary, examines the null hypothesis of stationarity.

Let us assume a time series $y_t$, $t = 1, \ldots, T$. The ADF test considers the following regression equation

$$\Delta y_t = \mu + \lambda t + \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \tag{4.15}$$

where $\Delta y_t = y_t - y_{t-1}$, $\mu$ denotes an intercept term, $t$ stands for a linear time trend, while $u_t$ is a white noise. The inclusion of an intercept, a linear time trend, or both is optional. The null hypothesis of $\psi = 0$, thus claiming that the series $y_t$ contains a unit root, is tested against the stationary alternative. The ADF test statistics do not follow the usual t-distribution, but the non-standard one, for which special critical values were calculated using simulation methods. However, regarding the implementation of the test there arises a practical issue related to the determination of the optimal number of lagged first difference terms of the dependent variable so that the potential autocorrelation in residuals is removed. Firstly, we can base our decision on the frequency of data. Nevertheless, for higher frequency data this choice is not so straigthforward as in case of monthly or quarterly data where 12 or 4 lags are used, respectively. Furthermore, the lag length selection can also be based on the information criteria or the sequential testing procedure, which eliminates the insignificant lag coefficients one by one starting from the highest lag after

[4]The spurious regression can occur if trending or unit root time series are employed in the regression analysis. It means that we can obtain results indicating a significant relationship between these variables while in fact they are entirely unrelated. (Brooks 2008) However, according to Hill *et al.* (2007) we do not have to worry about spurious regression results if we use series which are stationary or non-stationary and cointegrated.

the maximum number of lags employed in this procedure is firstly predetermined.[5] As an alternative to the ADF test Phillips & Perron (1988) proposed a nonparametric approach (modification of the original Dickey-Fuller test) to testing for a unit root, which allows the error terms to be weakly dependent and heterogeneously distributed. The conclusion obtained by applying the PP test is usually identical to the one obtained when the ADF test is performed. Both the PP and ADF procedures examine the null hypothesis of a unit root against the alternative of stationarity.

The last test introduced in this section, the KPSS test, assumes the following time series decomposition

$$y_t = \beta t + r_t + u_t \tag{4.16}$$

where $\beta t$ stands for a deterministic trend, $r_t$ is a random walk, thus $r_t = r_{t-1} + \epsilon_t$, with $\epsilon_t$ being i.i.d. with zero mean and variance $\sigma_\epsilon^2$, and $u_t$ is a stationary error term. We are able to control for the autocorrelation structure of $u_t$ by allowing it to follow an autoregressive moving average (ARMA) process. The null hypothesis of $\sigma_\epsilon^2 = 0$ implying the trend stationarity of the time series is tested against the unit root or non-stationary alternative. Under $H_0$, $r_t = r_0$ for all $t$, where $r_0$ is an initial fixed value of $r_t$ treated as an intercept. Removing $\beta t$ from Equation 4.16 enables us to examine the null hypothesis of level stationarity.

By performing both the unit root and stationarity tests we are able to obtain more reliable results regarding the stationarity of the examined time series. Hence, a time series is considered to be stationary (nonstationary) if the ADF/PP test rejects (confirms) the null hypothesis of a unit root and at the same time the KPSS test confirms (rejects) the null of stationarity. However, it may happen that the tests provide us with contradictory findings, so we cannot draw an unambiguous conclusion.

As some financial time series, such as financial asset return volatity, have been found to experience a long-run persistence pattern, we can use the long-memory parameter, d, to determine whether series is stationary, unit root, or exhibiting a long memory (Andersen *et al.* (2001b), Cipra (2008), among others). The long-memory parameter of a time series can be estimated using the semiparametric log-periodogram estimator proposed by Geweke & Porter-Hudak (1983) (GPH). A time series is stationary with short memory if $d = 0$,

[5]The information criteria will be discussed in detail in Subsection 4.4.3.

while for $d = 1$ the series follows a random walk, thus contains a unit root. Moreover, the series is weakly stationary either with long memory in case of $0 < d < 0.5$ or with negative memory if $-0.5 < d < 0$. Last but not least, the process is non-stationary and possesses long memory if $d \geq 0.5$.

After deciding if the time series are stationary or not we are able to choose the most appropriate VAR model specification. If all series to be employed in a model are confirmed to be stationary a VAR model in levels should be used. In case of unit root or non-stationary variables a VAR model in differences is recommended. However, this kind of transformation could imply a loss of information about the potential long-run relationship between the original variables. Such a relationship is called cointegration and can be expressed as a stationary linear combination of non-stationary variables. In this case, the VAR in differences would be an incorrect modeling strategy. Hence, if the time series are both non-stationary and cointegrated, a VECM should be employed. If the time series are found to be non-stationary, but not cointegrated, then there is no long-run relationship between them, and the VAR in differences should be used. Testing for unit roots and cointegration can thus serve as a guide for choosing the most appropriate model specification.

### 4.4.2 Cointegration Analysis

Consider the N-dimesional vector $y_t = (y_{1t}, \ldots, y_{Nt})^{'}$ for which $y_{it} \sim I(d)$, thus each component of $y_t$ is integrated of order $d$. Moreover, let assume the vector $\beta = (\beta_1, \ldots, \beta_N)^{'} \neq 0$. Then the process $y_t$ is said to be cointegrated of order (d, b), CI(d, b), if there exists a linear combination

$$z_t = \beta^{'} y_t = \beta_1 y_{1t} + \ldots + \beta_N y_{Nt} \tag{4.17}$$

that is integrated of order $(d - b)$. This linear combination is called cointegrating relation and the vector $\beta$ is termed the cointegrating vector. This vector is not uniquely identified, as we can get another cointegrating vector by multiplying it by a nonzero constant. Also, there may be more than one linearly independent cointegrating relations, $r$, if $N > 2$, such that $0 \leq r \leq N - 1$.

In practice, the analysis is often restricted to the case of having the vector $y_t$ comprising only the unit root I(1) variables, as many economic time series are integrated of order 1 rather than of higher order (Kočenda & Černý 2007). Then the process is said to be cointegrated of order (1,1) if there exists a non-trivial linear combination $z_t = \beta^{'} y_t$ that is stationary. The stationarity implies that the time series $z_t$ fluctuates around a constant long-term mean with a finite variance that does not change in time. Therefore this long-term mean determines the long-run equilibrium relation among the non-stationary variables. The term $z_t$ then represents the time series of deviations from this long-run equilibrium relationship. Thus, it can be concluded that the variables can depart from its equilibrium level in the short run. However, in the long term they will always be pushed back towards it due to the presence of some economic forces.

The Engle-Granger (E-G) and Johansen methodologies are the two most commonly applied procedures of testing for cointegration. However, both are restricted to the assumption of all series being I(1) processes. The E-G methodology suffers from the serious limitations, especially if we have more than two variables in the system, as it is only able to detect cointegration but unable to determine the number of cointegrating relationships among variables. On the other hand, by performing Johansen test we are capable of finding the number of cointegrationg vectors. Therefore, in the multivariate setting, what is our case, the Johansen procedure is the preferred alternative.

Consider the following representation of a VECM model [6]

$$\Delta y_t = \Psi D_t + \Pi y_{t-1} + \sum_{i=1}^{p} \Pi_i \Delta y_{t-i} + u_t \tag{4.18}$$

with $y_t = (y_{1t}, \ldots, y_{Nt})'$ denoting the vector of $N$ variables which may be cointegrated. $\Psi$ is a $N \times d$ matrix of coefficients, while $D$ represents a $d \times 1$ vector of deterministic terms. In case of presence of some deterministic component it takes a value of 1, or 0 otherwise. Both $\Pi$ and $\Pi_i$ are $N \times N$ coefficient matrices and $u_t = (u_{1t}, \ldots, u_{Nt})'$ is a vector of error terms that are normally distributed. The matrix $\Pi$ can be rewritten as $\Pi = \alpha\beta'$, where $\alpha$ and $\beta$ are $N \times r$ matrices of dimension $r$. Then the $\Pi$ is also of the same dimension. While $\alpha$ denotes a matrix of adjustment coefficients, $\beta$ is a matrix of cointegrating vectors. Recalling the definition of cointegration the term $\beta y_{t-1}$ represents the cointegrating relations among variables in the system. In order to determine the number of cointegrating vectors, thus to find out the extent to which the system of variables is cointegrated, we are interested in the rank of the matrix $\Pi$. The matrix $\Pi$ is hence of the main concern of the Johansen test. Regarding the rank of $\Pi$ the following three cases can arise. First, if the rank of $\Pi$ is zero,

[6] The theory of the Johansen procedure covered in this part is taken from the econometric textbook of Kočenda & Černý (2007).

denoted $rk(\Pi) = 0$, there are no cointegrating relationships among variables in the system and a VAR model in first differences should be used. If $rk(\Pi) = r$ for $0 < r \leq N - 1$ there are $r$ cointegrating vectors among variables under consideration and a VECM should be estimated. Finally, $rk(\Pi) = N$ implies stationarity of all components of $y_t$ and therefore a VAR in levels is considered. To test for the number of cointegrating vectors the Johansen procedure employs the trace and maximum eigenvalue test statistics which take the following forms

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{N} ln(1 - \hat{\lambda}_i) \tag{4.19}$$

$$\lambda_{max}(r + 1) = -Tln(1 - \hat{\lambda}_{r+1}) \tag{4.20}$$

with $T$ standing for the total number of observations and $\hat{\lambda}_i$ being the $i$th estimated eigenvalue of $\Pi$, for $i = 1, \ldots, N$, such that the expression $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_N$ holds. The number of nonzero eigenvalues of $\Pi$ is equivalent to its rank. Using the trace statistic we test for the null hypothesis of $rk(\Pi) \leq r$, thus that the number of cointegrating vectors is less than or equal to $r$, against the alternative of $rk(\Pi) > r$. The maximum eigenvalue statistic test the null hypothesis of $rk(\Pi) \leq r$ against the alternative of having the $r+1$ cointegrating relations.

### 4.4.3 Lag Length Identification

In the initial stage of a VAR model specification procedure the appropriate lag length of a model is selected. One of the most commonly applied methods for choosing this order is the application of the information criteria, such as the Akaike (AIC), Hannan-Quinn (HQ), or Schwarz (SC) criterion, which determine the lag order by minimizing the value of the respective criterion over all possible orders $m = 0, \ldots, p_{max}$. Its multivariate versions are formulated as follows

$$AIC(m) = ln \left| \hat{\Sigma}_u(m) \right| + \frac{2mN^2}{T} \tag{4.21}$$

$$HQ(m) = ln \left| \hat{\Sigma}_u(m) \right| + \frac{2lnlnT}{T} mN^2 \tag{4.22}$$

$$SC(m) = ln\left|\hat{\Sigma}_u(m)\right| + \frac{lnT}{T}mN^2 \tag{4.23}$$

where $\left|\hat{\Sigma}_u\right|$ is the determinant of the estimated variance-covariance matrix of residuals, $m$ represents the lag order, and $T$ denotes the number of observations. However, the order estimated using these information criteria may differ.[7] Moreover, as stated by Lütkepohl (2011, p.11) *"The HQ and SC criteria are both consistent, that is, under general conditions the order estimated with these criteria converges in probability or almost surely to the true VAR order p if $p_{max}$ is at least as large as the true lag order. AIC tends to overestimate the order asymptotically with a small probability"*.

### 4.4.4 Estimation of the VAR Model

According to Cipra (2008) we can estimate a VAR model using the maximum likelihood (ML) method, or in case of reduced-form VAR also the ordinary least squares (OLS) can be applied. Under general conditions both methods are asymptotically equivalent with estimates being asymptotically normally distributed. Since in our analysis we consider a reduced form of a VAR model, that is, the model where only lagged variables can be found on the right-hand side of each equation, it can be estimated equation by equation using the OLS.

### 4.4.5 Diagnostics of the VAR Model

The last step of the model selection procedure consists in checking the adequacy of a fitted model. First, the stability of the estimated VAR model is examined. The VAR(p) process as defined by Equation 4.10 is stable and the time series it generates are stationary if and only if all roots of its reverse characteristic polynomial do not lie on or inside the complex unit circle, thus if the following condition holds

$$det(I_{Np} - \Phi z) = det(I_N - \phi_1 z - \ldots - \phi_p z^p) \neq 0 for\, |z| \leq 1 \tag{4.25}$$

[7] According to Lütkepohl (2005) for the order chosen by these information criteria the following inequality holds

$$\hat{p}(SC) \leq \hat{p}(HQ) \leq \hat{p}(AIC) \tag{4.24}$$

with $\hat{p}$ denoting the order estimated by the particular criterion.

In the next stage of the diagnostic procedure, the validity of the white noise assumptions imposed on the residuals of a VAR model is investigated. The autocorrelation of residuals of the estimated model is examined using the Portmanteau and Breusch-Godfrey tests that test the null hypothesis of no serial correlation. The Jarque-Bera test for multivariate series is applied on the residuals to test if they are normally distributed. Finally, the ARCH-LM test of heteroscedasticity is performed.

# Chapter 5

# Description of Data

In our analysis, we use five-minute high-frequency data of the three emerging CEE stock market indices - Budapest (BUX), Prague (PX), and Warsaw (WIG), and of the Frankfurt (DAX) stock market index, obtained from Tick Data. Each index represents the particular stock market. The data spans from January 2, 2008 to November 30, 2010, thus covers the period of recent global financial crisis, from its outbreak to the early recovery phases. The dataset employed in our analysis is the extended version of the one used in Baruník & Vácha (2013). Specifically, the data available for the purposes of our analysis are in the form of logarithmic high-frequency returns. Before we move on to the construction of the realized measures, we turn our attention to the description and the adjusting procedure of the original dataset applied in Baruník & Vácha (2013).

## 5.1 Original Dataset

After being adjusted for missing observations, the original data were sampled at five-minute frequencies in order to eliminate the microstructure noise which contaminates the price process.[1] Moreover, due to different trading hours of the selected stock exchanges the number of observations for each trading day varies among the analyzed indices. Therefore, only the time period from 9:30 to 16:00 CET, for which data for all stock indices were available, was considered.

[1] In many empirical studies (Andersen *et al.* (2001b), Hassler *et al.* (2012)) it is a common practice to sample data over five-minute intervals as this sampling is considered to balance both the advantage of increased estimation accuracy when using the data with the highest possible frequency and the unfavourable effects of microstructure noise included in such a frequency.

Other observations were excluded from the dataset. Overview of the business hours at the analyzed stock exchanges is presented in Table 5.1.

Table 5.1: Overview of Trading Hours

| Stock Exchange | Open | Close |
|---|---|---|
| Budapest Stock Exchange | 9:00 | 16:30 |
| Prague Stock Exchange | 9:30 | 16:00 |
| Warsaw Stock Exchange | 9:30 | 16:00 |
| Frankfurt Stock Exchange | 9:00 | 17:30 |

*Source:* Baruník & Vácha (2013).

In the next step, the five-minute high-frequency returns were computed as the logarithmic first differences of price series. To avoid distortion of our results by overnight returns the log returns were calculated for each trading day separately. All in all, by discarding major public holidays all these adjustments lead to a final sample of 691 trading days with approximately 77 observations for each index per day.

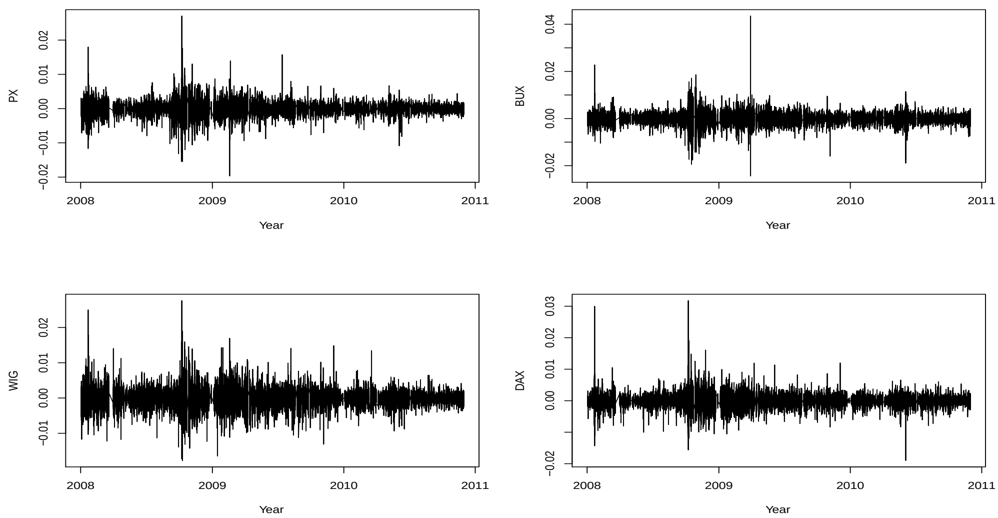
Table 5.2: Descriptive Statistics of 5-minute High-Frequency Returns

| | PX | BUX | WIG | DAX |
|---|---|---|---|---|
| Mean | $-1.4821 \times 10^{-5}$ | $-2.4517 \times 10^{-5}$ | $-1.2790 \times 10^{-5}$ | $-2.6011 \times 10^{-6}$ |
| Std. Dev. | 0.001127996 | 0.001529287 | 0.001604042 | 0.001343707 |
| Skewness | -0.03797113 | 0.01486093 | 0.20223725 | 0.33150286 |
| Kurtosis | 27.76359 | 28.57131 | 15.34340 | 23.45418 |
| Min | -0.01966756 | -0.02435837 | -0.01771509 | -0.01897948 |
| Max | 0.02701572 | 0.04346682 | 0.02761982 | 0.03176930 |
| Observations | 53 201 | 53 201 | 53 201 | 53 201 |

*Source:* Author's computations.

Table 5.2 provides descriptive statistics of 5-minute high-frequency logarithmic returns for all of our selected stock market indices. The statistics point out more or less similar features of our return series. The mean value of each series during the study period is close to zero, though slightly negative. While the PX index experiences the lowest volatility of its returns according to the value of the standard deviation, the largest one can be assigned to the Polish WIG index. In addition, all return series except the Czech Republic exhibit a positive skewness. This right-skewed return distribution with asymmetric right tail indicates the occurence of not only frequent small losses, but also of few extreme gains. Moreover, high positive values of kurtosis imply the leptokurtic shape of the distribution of our four series what is a common feature of many financial data (Bai *et al.* 2004). Leptokurtic distribution could be characterized by higher peak and fatter tails. Hence, there are more returns concentrated around the mean and also in the tails compared with the normal distribution. Finally, the Hungarian stock index obtains both the lowest and the highest values among all indices. However, although it has the biggest difference between its maximum and minimum values, it is not the most volatile index in our sample.

Figure 5.1: Plots of High-Frequency Returns




*Source:* Author's computations.

Figure 5.1 shows the plots of high-frequency return series of the selected stock market indices during the whole analyzed period. The visual inspection points to the pronounced volatility clustering. Turbulent periods characterized by increased volatility of returns correspond to the onset of the global financial crisis in mid-2008 and continue till early 2009. Moreover, another though less influential increase in volatility level (substantial decrease of returns) in mid-2010 could be assigned to the European debt crisis which fully developed in May 2010. Looking at Figure 5.1 it can be concluded that among all analyzed indices the performance of DAX index was most affected by the event occured in 2010. The second half of year 2010 seems to be less volatile and relatively tranquil period.

## 5.2 Construction of Realized Measures

In this section, we proceed with construction of the realized measures - realized variance and realized semivariances, with the use of logarithmic 5-minute high-frequency returns described in the previous part. The calculation of these measures is based on the formulas introduced in the preceding chapter which provides theoretical background required for the purposes of our analysis. In what follows, the plots and descriptive statistics of RV and of both negative and positive RS for all selected stock markets are presented.

Table 5.3: Descriptive Statistics for Daily Realized Variance

| | PX | BUX | WIG | DAX |
|---|---|---|---|---|
| Mean | $9.797683 \times 10^{-5}$ | $1.801040 \times 10^{-4}$ | $1.981037 \times 10^{-4}$ | $1.390095 \times 10^{-4}$ |
| Std. Dev. | $1.588677 \times 10^{-4}$ | $2.816159 \times 10^{-4}$ | $2.420431 \times 10^{-4}$ | $2.187251 \times 10^{-4}$ |
| Skewness | 5.547722 | 6.4744483 | 5.064303 | 6.709061 |
| Kurtosis | 44.05488 | 58.10955 | 39.56663 | 65.96184 |
| Min | $3.043034 \times 10^{-6}$ | $1.437942 \times 10^{-5}$ | $1.496765 \times 10^{-5}$ | $4.838043 \times 10^{-6}$ |
| Max | 0.001701687 | 0.003448622 | ´0.002688327 | 0.002779688 |
| Observations | 691 | 691 | 691 | 691 |

*Source:* Author's computations.

Table 5.4: Descriptive Statistics for Daily Negative Realized Semivariances

| | PX | BUX | WIG | DAX |
|---|---|---|---|---|
| Mean | $5.150519 \times 10^{-5}$ | $9.535568 \times 10^{-5}$ | $1.006175 \times 10^{-4}$ | $6.989133 \times 10^{-5}$ |
| Std. Dev. | $9.159723 \times 10^{-5}$ | $1.583719 \times 10^{-4}$ | $1.183833 \times 10^{-4}$ | $1.006619 \times 10^{-4}$ |
| Skewness | 5.928770 | 7.152815 | 4.765351 | 4.804834 |
| Kurtosis | 51.43614 | 76.48606 | 43.70398 | 36.36295 |
| Min | $1.356476 \times 10^{-6}$ | $6.463849 \times 10^{-6}$ | $6.806297 \times 10^{-6}$ | $2.370526 \times 10^{-6}$ |
| Max | 0.001136046 | 0.002310894 | 0.001573875 | 0.001112031 |
| Observations | 691 | 691 | 691 | 691 |

*Source:* Author's computations.

The basic summary statistics for the resulting time series of our realized measures are reported in Table 5.3 - 5.5. For all selected indices, the mean value of the downside RS is found to be slightly higher than that of $RS^{+}$.

Table 5.5: Descriptive Statistics for Daily Positive Realized Semivariances

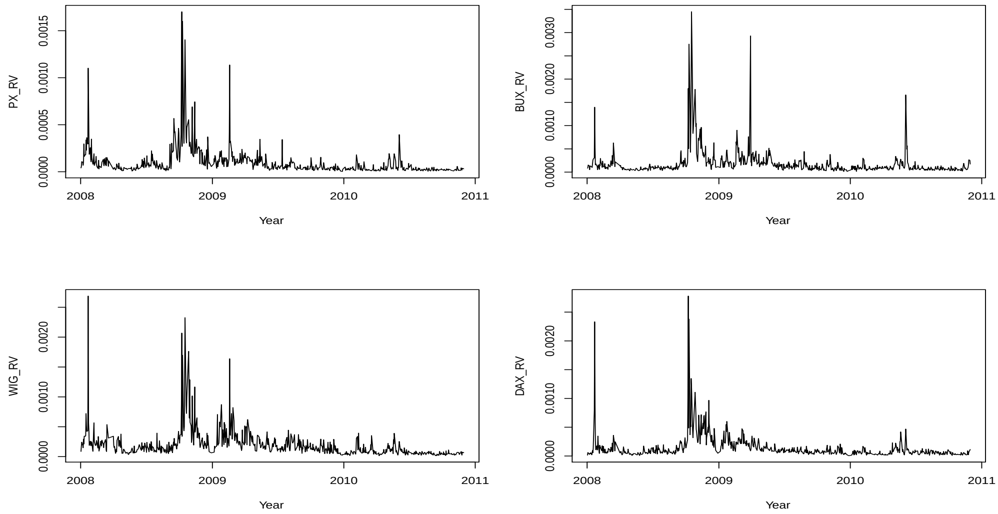
| | PX | BUX | WIG | DAX |
|---|---|---|---|---|
| Mean | $4.647165 \times 10^{-5}$ | $8.474830 \times 10^{-5}$ | $9.748626 \times 10^{-5}$ | $6.911813 \times 10^{-5}$ |
| Std. Dev. | $8.306587 \times 10^{-5}$ | $1.404924 \times 10^{-4}$ | $1.432697 \times 10^{-4}$ | $1.259051 \times 10^{-4}$ |
| Skewness | 7.073087 | 7.437754 | 6.699326 | 8.018744 |
| Kurtosis | 75.66219 | 80.11610 | 69.95989 | 87.57583 |
| Min | $9.883143 \times 10^{-7}$ | $5.145855 \times 10^{-6}$ | $5.845570 \times 10^{-6}$ | $2.277394 \times 10^{-6}$ |
| Max | 0.001174086 | 0.002071183 | 0.002046221 | 0.001667657 |
| Observations | 691 | 691 | 691 | 691 |

*Source:* Author's computations.

In addition, as it generates more than half of RV, it can be concluded that, on average, the higher part of the RV can be assigned to the negative returns, thus to negative shocks. Regarding the values of the standard deviation of the PX and BUX indices the negative RS seems to be more volatile than the positive RS, while for the WIG and DAX indices the opposite could be observed. It implies that the upward RS fluctuates more compared with the $RS^-$. Furthermore, it can be seen that the distributions of $RV$, $RS^-$, and $RS^+$ are extremely right skewed and leptokurtic for all analyzed indices. Hence, it can be deduced that they are not normally distributed. Moreover, the series of daily positive RS exhibit a higher degree of positive skewness and kurtosis compared with the ones of the daily negative RS. The most substantial difference can be observed regarding the German DAX index. While the value of skewness for $RS^+$ is almost twice as high as that for $RS^-$, the value of kurtosis more than doubled.

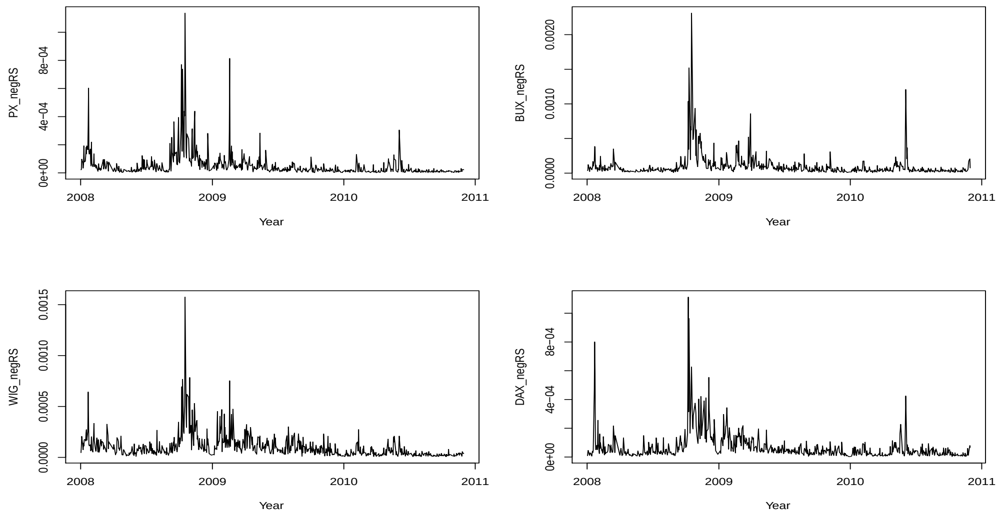
Figure 5.2 - 5.4 display the plots of $RV$, $RS^-$, and $RS^+$ for all selected stock market indices during the whole analyzed period, from January 2, 2008 to November 30, 2010. The visual inspection of the examined time series enables us to observe the dynamics of the realized measures as well as its responses to the crisis events. Until early 2009, at each analyzed market, the volatility triggered by the positive shocks tends to be higher compared with the one caused by the negative shocks. It could be assigned to the fact that the optimistic sentiment of market participants from the pre-crisis period was still persisting. However, after the first months of 2009 it can be seen that the fluctuations are more substantial for the series of the negative realized semivariances what could be attributed to the increasing market uncertainty and scepticism.

Figure 5.2: Plots of Daily Realized Variances



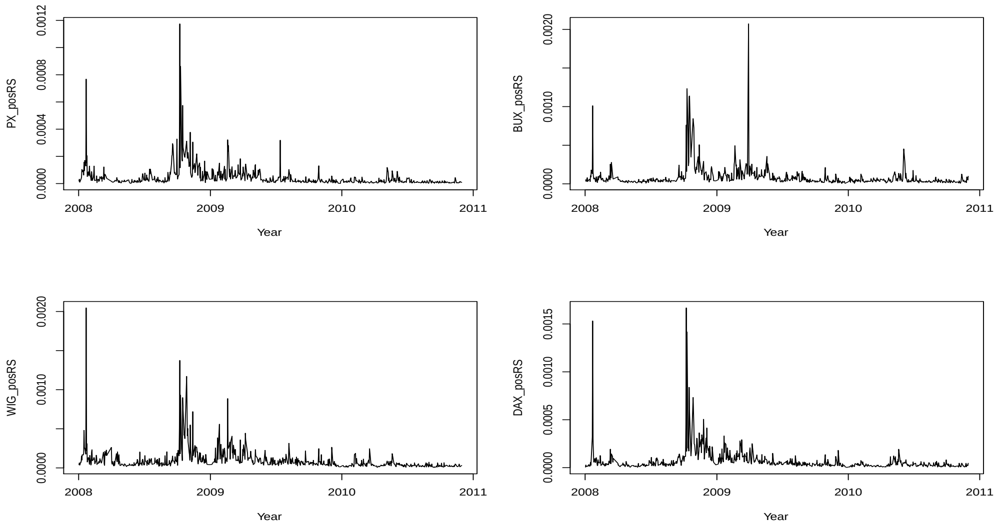

*Source:* Author's computations.

Figure 5.3: Plots of Daily Negative Realized Semivariances ($RS^-$)




*Source:* Author's computations.

Figure 5.4: Plots of Daily Positive Ralized Semivariances ($RS^{+}$)




*Source:* Author's computations.

# Chapter 6

# Empirical Analysis and Discussion of Results

In the previous chapters, we have introduced the stock markets included in our study as well as the theoretical framework for the construction of total and asymmetric volatility spillover indices. This chapter is therefore dedicated to the application of this methodology on our two datasets, the first one covering the selected CEE stock market indices of the Czech Republic, Hungary and Poland, and the second one extending the original sample by the inclusion of the German DAX index. All computations and estimations have been performed using the statistical software R.

This chapter is organized as follows. In Section 6.1, we describe a VAR model selection procedure since choosing an appropriate VAR model specification is important for the subsequent volatility spillover analysis. The next section, 6.2, provides a static full-sample spillover analysis. In Section 6.3 and 6.4 we perform a dynamic total and asymmetric volatility spillover analysis, respectively.

## 6.1 Model Selection

Before proceeding to the model selection we subject all our time series of realized measures to the unit root and stationarity tests. Based on the visual inspection of the plots of our data (Figure 5.2, 5.3 and 5.4) there arises a suspicion about the potential nonstationarity of all examined time series. In order to verify our suggestion and hence determine the integration status of our series we further apply a battery of unit root tests. To conserve space we present results of these tests in Appendix (Table A.1 and A.2). Performing both the augmented Dickey-Fuller and Phillips-Perron tests the null hypothesis of the presence of a unit root is strongly rejected for each of our time series, even at the 1% level of significance. On the other hand, the KPSS stationarity test provides us with contradictory result as it reveals an overwhelming evidence against stationarity of each of our time series. As discussed in Subsection 4.4.1, many financial data, including volatility of stock returns, possess a long-memory behavior. Therefore, to ascertain the order of integration of the studied series we estimate a memory parameter, $d$, using the GPH semiparametric log-periodogram estimator. Regarding the results reported in Appendix (Table A.3) we can conclude that all our series are fractionally integrated with values of $d$ ranging from 0.53 to 0.75, thus in the nonstationary region. This implies that our data series are nonstationary, but mean-reverting.

Taking into account the nonstationary character of the series involved, in the next step, we should proceed with testing for the presence of cointegrating relationships among series within each group, since assessing cointegration status will help us to choose the appropriate model specification.[1,2] However, prior to conducting cointegration analysis we have to determine a lag length of a VAR model. To select the order of a model we employ the information criteria that are calculated for different maximum number of lags. For the purposes of comparability of the results obtained from the subsequent volatility spillover analysis performed on the series of RV as well as on the series of negative and positive RS we will consider the same VAR order as the one selected for a system of RV for both negative and positive RS. Table 6.1 and 6.2 report the lag lengths suggested by each criterion. To avoid fitting a model with too large orders we base our decision on the HQ and SC, since they provide consistent estimates of the VAR order. Regarding both CEE and CEE+DAX Samples, the HQ criterion suggests the inclusion of 5 lags, whereas the SC criterion rec-

[1] In our analysis, we have six datasets, thus groups, in hand, three per each sample of stock markets. Each sample consists of the dataset of realized variances as well as of the datasets of both negative and positive realized semivariances. In what follows, we will refer to the sample of the selected CEE stock markets as to CEE Sample and to the extended sample, which includes Germany, as to CEE+DAX Sample.

[2] If we are interested in studying the long-run relationships among variables in the system, it is important to employ a VECM. Otherwise, we can transform a VECM into an equivalent VAR in levels, thus MA($\infty$), representation. Then, the estimated VAR coefficients would capture this long-run term, however, we would not be able to detect and hence to interpret it. In addition, since the main concern of our analysis is not to examine the long-run relationships, for the purposes of our study it is therefore not crucial to find the most appropriate specification of the model.

ommends 4 lags. The final model specifications will then be chosen based on the results of the diagnostic checking of the fitted models.

Table 6.1: Estimation of the VAR Order Using Information Criteria: CEE Sample

| | Lags Selected by | | |
|---|---|---|---|
| Max. lags | AIC | HQ | SC |
| 5-6 | 5 | 5 | 4 |
| 7-9 | 7 | 5 | 4 |
| 10 | 10 | 5 | 4 |

*Source:* Author's computations.

Table 6.2: Estimation of the VAR Order Using Information Criteria: CEE+DAX Sample

| | Lags Selected by | | |
|---|---|---|---|
| Max. lags | AIC | HQ | SC |
| 5 | 5 | 5 | 4 |
| 6 | 6 | 5 | 4 |
| 7 | 7 | 5 | 4 |
| 8 | 8 | 5 | 4 |
| 9 | 9 | 5 | 4 |
| 10 | 10 | 5 | 4 |

*Source:* Author's computations.

Since we have already determined the lag lengths of VAR model for each set of variables we can carry on with cointegration analysis. To determine the cointegration status we apply Johansen's maximum eigenvalue and trace tests on all groups and for both 4 and 5 lags. However, we have to be aware of the shortcomings in form of high spurious rejection rates stemming from the application of the standard cointegration procedures on the fractionally integrated variables, since these techniques assume the examined series to be I(1) processes. Tables A.4 - A.7 in Appendix show the estimated results obtained by performing these cointegration tests on all groups. Regarding the datasets of realized measures covered in CEE Sample both maximum eigenvalue and trace tests reject the null hypothesis of zero cointegrating relationships at the 1% level of significance. Also the subsequent hypotheses of at most 1 and 2 cointegrating relationships, respectively, are rejected at the 1% level. We can then conclude that the considered VAR model in levels is stationary and hence should be adopted for further analysis. Applying both Johansen's tests on the datasets of CEE+DAX Sample all null hypotheses of $r = 0, 1, 2,$ and 3 are also strongly rejected at the 1% level of significance. These findings imply that we should proceed with an adoption of a VAR model in levels in both considered cases.

To choose the most appropriate VAR model specification we subject all estimated models with lag lengths of 4 and 5, as suggested by SC and HQ criteria, respectively, to the diagnostic checking. First, we examine stability of the selected models. According to results reported in Appendix (Figure A.1) we can see that for each sample all eigenvalues of the coefficient matrix lie within the unit circle, thus are less than one in absolute values. This indicates not only stability of each VAR model specifications, but also stationarity of series generated by these VAR models. Therefore, as confirmed by stability test, we can conclude that even though we have applied the standard cointegration tests on the fracionally integrated series we have not obtained the spurious results.

In the next stage of the diagnostic procedure we examine the validity of the assumptions imposed on the residuals of a VAR model. The results of these diagnostic tests are summarized in Table 6.3. By applying the Portmanteau and Breusch-Godfrey (B-G) tests we investigate the autocorrelation properties of the residual series. Both tests reveal a substantial evidence of the presence of serial autocorrelation in the estimation residuals. Even the inclusion of the additional lags of the dependent variables into the model does not lead to the rejection of the null hypothesis of no serial autocorrelation.[3] This problem may be linked to the model misspecification, that is, there are some other variables that should have been included in our model. However, since the major concern of our analysis is to investigate the volatility transmission only among the selected stock markets, we will proceed with our analysis using the original datasets. Furthermore, the results of the multivariate Jarque-Bera test indicate that the residual series are not normally distributed. Conducting the ARCH-LM test the estimated residuals are found to exhibit conditional heteroscedasticity. Regarding the fact that the time-varying volatility is a common feature of many financial time series, this finding is not that surprising. The heteroscedasticity in the residuals could be further modeled using the multivariate GARCH. Nevertheless, such an advanced modeling is beyond the scope of our analysis.

[3]We have performed the Portmanteau and B-G tests on the residual series of the estimated VAR model with the lag length up to 30.

Table 6.3: Diagnostic Tests of the Residuals

| | VAR(4) model | | VAR(5) model | |
|---|---|---|---|---|
| | Sample | | Sample | |
| | CEE | CEE+DAX | CEE | CEE+DAX |
| Portmanteau test | $2.8 \times 10^{-14}$ | $< 2.2 \times 10^{-16}$ | $1.6 \times 10^{-10}$ | $< 2.2 \times 10^{-16}$ |
| Breusch-Godfrey test | $1.3 \times 10^{-8}$ | $< 2.2 \times 10^{-16}$ | $1.1 \times 10^{-6}$ | $< 2.2 \times 10^{-16}$ |
| Jarque-Bera test | $< 2.2 \times 10^{-16}$ | $< 2.2 \times 10^{-16}$ | $< 2.2 \times 10^{-16}$ | $< 2.2 \times 10^{-16}$ |
| ARCH-LM test | $< 2.2 \times 10^{-16}$ | $< 2.2 \times 10^{-16}$ | $< 2.2 \times 10^{-16}$ | $< 2.2 \times 10^{-16}$ |

*Source:* Author's computations.

To conclude, even though none of our model specifications satisfies the assumption of the white noise residuals, we have decided to adopt the VAR(4) and VAR(5) models for CEE Sample and CEE+DAX Sample, respectively, since they possess slightly better properties in comparison with the other alternatives considered. However, we will keep these insufficiencies in mind through the rest of our analysis. Furthermore, our decision to adopt a VAR model is in line with the rest of the existing literature employing the spillover index proposed by Diebold & Yilmaz (2009) (see for instance, Baruník *et al.* (2013), Fujiwara & Takahashi (2012), McMillan & Speight (2010), Yilmaz (2010)). In addition, the robustness of this methodology of measuring spillovers with respect to the number of lags employed in a VAR model has been shown by all these studies. However, since not all of them report their results, we have decided to perform a robustness analysis and show that the lag length of a VAR model does not affect our findings substantially.

## 6.2 Static Analysis

In this section, we provide a full-sample analysis of volatility spillovers among the selected stock markets for both samples. The calculations of the total volatility spillover indices are based on variance decompositions of 10-days-ahead forecast errors from the VAR models selected in the previous part.[4] A full set of the variance decompositions generates the main part of a spillover table with its diagonal elements standing for the own variance shares and off-diagonal entries representing the cross-variance shares, thus the spillovers. The

[4]The length of the forecasting horizon employed in our analysis is in line with many empirical studies such as Baruník *et al.* (2013), Diebold & Yilmaz (2009), among others. The issue concerning its determination will be discussed in detail in the robustness check.

value of the total volatility spillover index is then reported in the lower right corner of the table.

The volatility spillover table for the sample of three emerging CEE stock markets is provided in Table 6.4. Regarding the total volatility spillover index its value of 45.62% indicates that almost half of the total variance of forecast errors can be attributed to the volatility shocks to other stock markets, whereas the remaining, just slightly higher part of the variance, can be assigned to the idiosyncratic volatility shocks. Therefore, as suggested by the total spillover index, the diagonal components are higher than the off-diagonal ones, hence the domestic shocks dominate. While the share of own shocks ranges from 47% to 64%, the share of volatility shocks from other markets is substantially lower, with values ranging from 11-35%. In terms of off-diagonal entries, we can conclude that the volatility shocks to the PX affect the most the other equity markets, hence the Czech market is the main transmitter of volatility shocks among our CEE countries. However, the volatility shocks originating in the Hungarian stock market are found to be the least influential ones. Furthermore, the Hungarian market receives nearly two times more shocks than it transfers. The opposite is true for the Prague market which transmits approximately double amount of the shocks it receives. In case of Poland, these effects are almost balanced.

Table 6.4: Spillover Table for CEE Sample, Jan 2, 2008 to Nov 30, 2010

| | From | | | |
|---|---|---|---|---|
| To | WIG | PX | BUX | Contribution From Others |
| WIG | 52.39 | 34.15 | 13.46 | 47.61 |
| PX | 25.02 | 63.71 | 11.27 | 36.29 |
| BUX | 17.86 | 35.09 | 47.05 | 52.95 |
| Contribution to Others | 42.88 | 69.24 | 24.73 | 136.85 |
| Contribution including own | 95.27 | 132.95 | 71.78 | Spillover Index = 45.62% |

*Source:* Author's computations.

Table 6.5 reports the total volatility spillover index along with the corresponding spillover table for our second sample that includes the mature German stock market besides the previous CEE markets. The total volatility spillover index of 52.73% implies that more than half of the total forecast error variance can be explained by the shocks propagating from the other stock markets. The total spillover index yields a higher value compared to the previous one obtained for the sample of the CEE countries. Furthermore, the inclusion of the German stock market has induced declines in both the own variance shares and cross-variance shares. The own variance shares capture not only the own, but also the hidden effects stemming from the other, non-included stock markets. Therefore, adding some country that has impact on our sample can decrease its values. Regarding the cross-variance shares, it could be a case that the non-included market influences our sample markets indirectly through some markets already included in the sample. Hence, the shock of non-included market could transmit or amplify the shocks of some countries included in our analysis what could subsequently strengthen the impact of shocks of included country on the other countries in the sample. Therefore, it would be an interesting extension to include the other developed as well as emerging stock markets to our sample and observe the impact of its inclusion on the volatility spillover index. In terms of the values of the diagonal components, own shocks tend to explain the highest part of the forecast error variance. Focusing on the off-diagonal components we can observe that the Czech stock market transmits the highest amount of volatility shocks to the other stock markets, followed by Germany and Poland, with Hungary having the smallest impact. The DAX and WIG are shown to receive more shocks than to transmit. However, these differences are not substantial. Regarding the Czech Republic and Hungary, the same situation as in the previous case occurs. The contribution of the volatility shocks from the BUX to other markets is only half of these it obtains, whereas for the PX the opposite holds true. Regarding the PX, its role of the main transmitter in both of our samples could be assigned to the indirect influence of some other non-included country (the US as found by Li & Majerowska (2008), or the UK and Russia as suggested by Caporale & Spagnolo (2011)).

Summarizing the results obtained from the static analysis we can confirm the presence of volatility spillovers among the selected stock markets in both samples. Regarding the group of the CEE stock markets, our findings complement the ones of Li & Majerowska (2008) who detect the connectedness of these markets in terms of volatility over the pre-crisis period, from 1998 to 2005. Taking into account the results of our analysis conducted on the sample covering the mature German and the emerging CEE markets as well as the results of Li & Majerowska (2008) and Égert & Kočenda (2007) it seems that the linkages among these markets have increased since 2008, thus in the period after the accession of the selected CEE countries to the EU. While the earlier

Table 6.5: Spillover Table for CEE+DAX Sample, Jan 2, 2008 to Nov 30, 2010

| | From | | | | |
|---|---|---|---|---|---|
| To | DAX | WIG | PX | BUX | Contribution From Others |
| DAX | 45.36 | 19.31 | 27.62 | 7.70 | 54.63 |
| WIG | 17.60 | 42.72 | 29.83 | 9.86 | 57.29 |
| PX | 17.80 | 17.36 | 56.52 | 8.31 | 43.47 |
| BUX | 14.25 | 11.40 | 29.86 | 44.49 | 55.51 |
| Contribution to Others | 49.65 | 48.07 | 87.31 | 25.87 | 210.9 |
| Contribution including own | 95.01 | 90.79 | 143.83 | 70.36 | Spillover Index = 52.73% |

*Source:* Author's computations.

study of Li & Majerowska (2008) provides an evidence of volatility spillovers running from the developed stock market of Germany to the Hungarian and Polish markets, but not the other way around, no such a connection is detected in case of the Czech market. Furthermore, performing their analysis on the high-frequency data over the period from mid-2003 to the early months of 2005 Égert & Kočenda (2007) reveal that volatilities of the CEE markets are influenced by changes in volatilities in the other two stock markets. However, only a weaker impact of changes in volatilities of the BUX and the PX on one another and of the WIG on the PX can be observed, whereas no such an effect of the PX on the WIG and the WIG on the BUX is present. Moreover, similarly to our findings, they find volatility spillovers running from the CEE markets to the DAX, even though in case of the PX its volatility has rather smaller impact on volatility of the DAX. In addition, they reveal the volatility spillover effects from the DAX to the CEE markets, except for the WSE. However, this result contradicts our finding of the presence of volatility spillovers going also from the DAX to the WIG.

## 6.3 Dynamic Analysis

In the preceding part, we have focused on the investigation of the average behaviour of volatility spillovers during the whole sample period. Therefore, in this section, we proceed with the dynamic analysis of volatility spillovers which enables us to examine the evolution of the volatility spillover index over time. In the subsequent analysis, a rolling estimation window approach with window length set to 125 days is employed.[5] After that, we provide the robustness check of our results with respect to the choice of the different model specifications and parameter values (window width and the forecasting horizon).

### 6.3.1 Total Volatility Spillovers

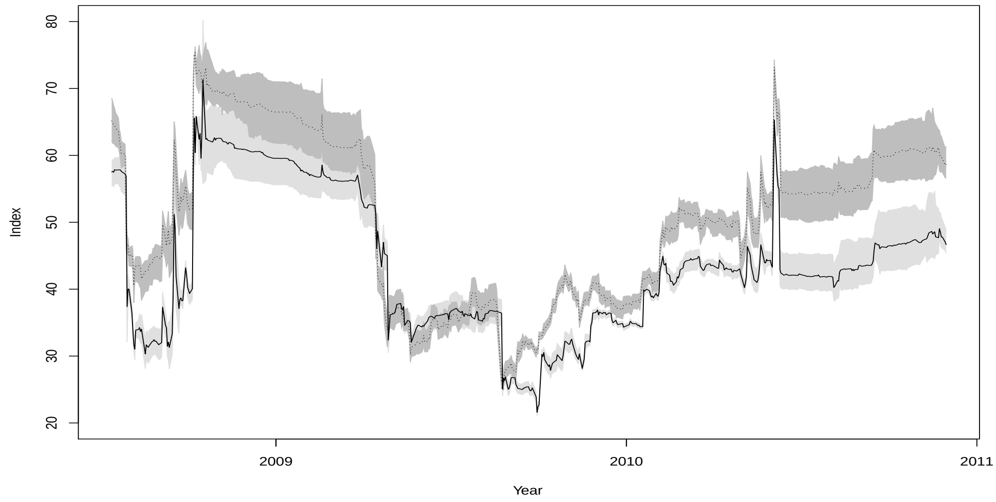
The dynamic volatility spillover indices for both CEE Sample and CEE+DAX Sample are plotted in Figure 6.1. Both indices evolve in very similar manner with the difference ranging from 5 to 10 percentage points and with the higher values being achieved by the second index during the whole observed period. Hence, the volatility spillover index of the second sample appears to be an upward-shifted version of the first one. Therefore, in what follows, we provide a description of both indices jointly. The development pattern of the indices corresponds to the main crisis events and reflects the economic and financial situation on the markets what is in line with Baruník *et al.* (2013) and Diebold & Yilmaz (2009).[6] No long-run trend is observable, however, several short-run trends can be noticed.

The period of favourable financial development was interrupted by the outbreak of the US sub-prime mortgage crisis in the late summer of 2007. This early stage of the financial turmoil was characterized by an increased uncertainty and market tensions, the loss of confidence in the solvency of financial institutions as many of them suffered from liquidity shortages, as well as by the failures of banking institutions such as Bear Stearns in the US or Northern Rock in the UK, among others. The national governments and central banks adopted measures aimed primarily at providing sufficient amount of liquidity to the financial system. The actions taken by these authorities were also suggested to reduce the market tensions and enhance the deteriorated confidence. All these efforts together with the decreased uncertainty on the stock markets of the euro area and the US during July and August 2008 as reported in ECB

[5]Since our dataset captures only three years of daily observations, we have decided to employ the length of the rolling window corresponding to the half of year (we consider one year to have, on average, 250 days, that is, 52 weeks a year times 5 working days, less approximately 10 days of public holidays) in order not to lose too much information. Moreover, we have calculated the spillover indices for the longer rolling windows (200 and 250 days) and they have shown the similar development pattern as our original indices. Therefore, we have decided to apply the shorter window length which enables us to cover also the period before the collapse of Lehman Brothers in September 2008.

[6]Note that even though both studies examine the different stock markets during different time period, we just want to point to the detected sensitivity of the volatility spillover index to the main economic events.

Figure 6.1: Total Volatility Spillovers




*Note:* A solid line represents the total volatility spillover index for CEE Sample, whereas a dotted line depicts the total volatility spillover index for CEE+DAX Sample. The grey band represents the minimum-maximum interval.
*Source:* Author's computations.

(2008) could contribute to the substantial decrease of the initial value of both spillover indices over the early months of the second half of 2008.

After the short period of decreased intensity of volatility spillovers the indices jumped sharply by approximately 40 percentage points from mid-August to September 2008 while reaching its highest level over the whole observed period. This peak coincides with the collapse of Lehman Brothers in September 2008 in the United States after which the US sub-prime mortgage crisis turned into the global recession.

The volatility spillovers remained at its high levels even during the first months of 2009 when the high degree of market uncertainty and re-emerged concerns about the health and stability of the financial system prevailed on the markets. However, over the period after the fall of Lehman Brothers till late 2009 the volatility spillovers are shown to decline gradually. This downward trend is most likely due to the governments' interventions aimed at providing the support and stabilization of the financial system. Moreover, the central banks reduced its key policy rates and continued to provide the liquidity as well.

This downward trend was interrupted at the end of 2009 when the volatility spillover indices began to rise again from its lowest values. In May 2010, both indices experienced the second biggest jump as they increased by approximately

20 percentage points. After that, the intensity of volatility spillovers stabilized and continued to maintain its slightly increasing trend. The evolution of the spillover indices over the second half of our sample period corresponds to the development of the European sovereign debt crisis that originated in Greece in late 2009 after the newly elected Greece government had announced the true level of its budget deficit. Subsequently, there arose the concerns about the fiscal solvency of the other PIGS countries, what is in line with the further moderate increase in the spillover intensity.[7] In April 2010, Greece requested the EU and the International Monetary Fund (IMF) for the financial assistance. However, the doubts concerning the offering and implementation of this bailout package provided in May 2010 could cause this substantial temporary increase of the spillover indices.

### 6.3.2 Robustness Check

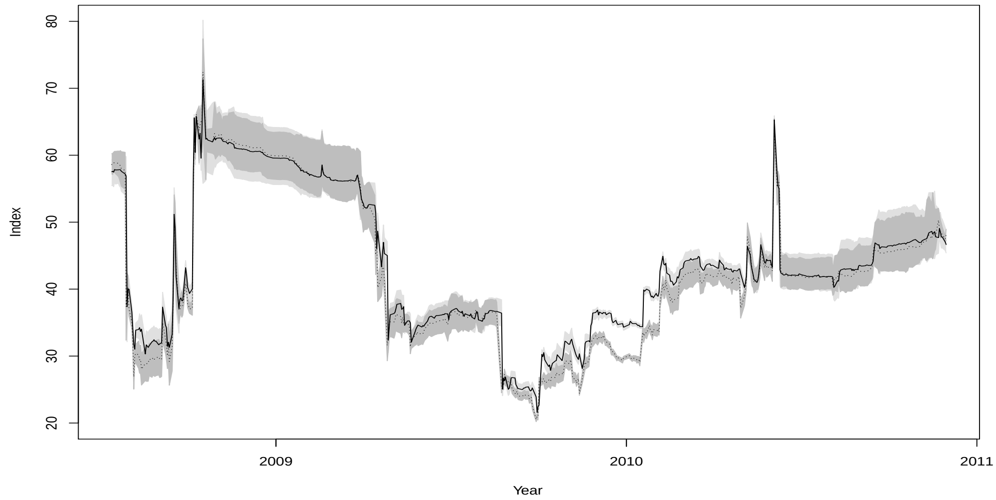
Before we proceed to the asymmetric volatility spillover analysis we check the robustness of our results with respect to the choice of the model specification, the window width and the forecasting horizon. Since we employ the algorithm of Klößner & Wagner (2012) to calculate the volatility spillover indices we do not have to be concerned about the issue of ordering of the stock markets in the VAR system.[8]

In the first step, we perform the robustness analysis focused on the choice of the underlying model specification. In Section 6.1, we have examined the properties of the VAR models with 4 and 5 lags for each of our samples of the stock markets. Therefore, in this part, we have decided to estimate the dynamic volatility spillover indices for the model alternatives not chosen initially, thus a VAR(5) model for CEE Sample and VAR(4) for CEE+DAX Sample. In Figures 6.2 and 6.3 we present the spillover plots produced using the original and the alternative model specifications for CEE Sample and CEE+DAX Sample, respectively. Comparing the dynamic behaviour of the volatility spillover indices obtained from the VAR(4) and VAR(5) models as depicted in Figures 6.2 and 6.3 it can be seen that there are almost any differences observable for both of our samples. Therefore, we can conclude that the volatility spillover indices are robust to the choice of the VAR model specification employed for the further construction of the indices.

[7]The PIGS is an acronym for Portugal, Ireland, Greece and Spain.

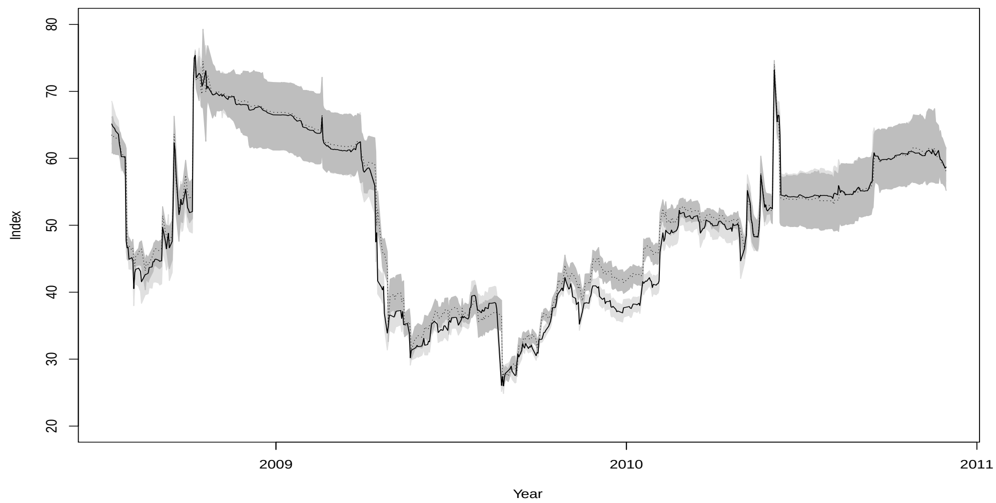
[8]The algorithm of Klößner & Wagner (2012) enables us to calculate the average volatility spillover indices over all possible permutations, as well as its minimum and maximum values.

Figure 6.2: Robustness of the Total Volatility Spillovers to VAR Model Specification for CEE Sample




*Note:* A solid line represents the VAR(4)-based spillover index, whereas a dotted line depicts the VAR(5)-based index. The grey band represents the minimum-maximum interval.
*Source:* Author's computations.

Figure 6.3: Robustness of the Total Volatility Spillovers to VAR Model Specification for CEE+DAX Sample



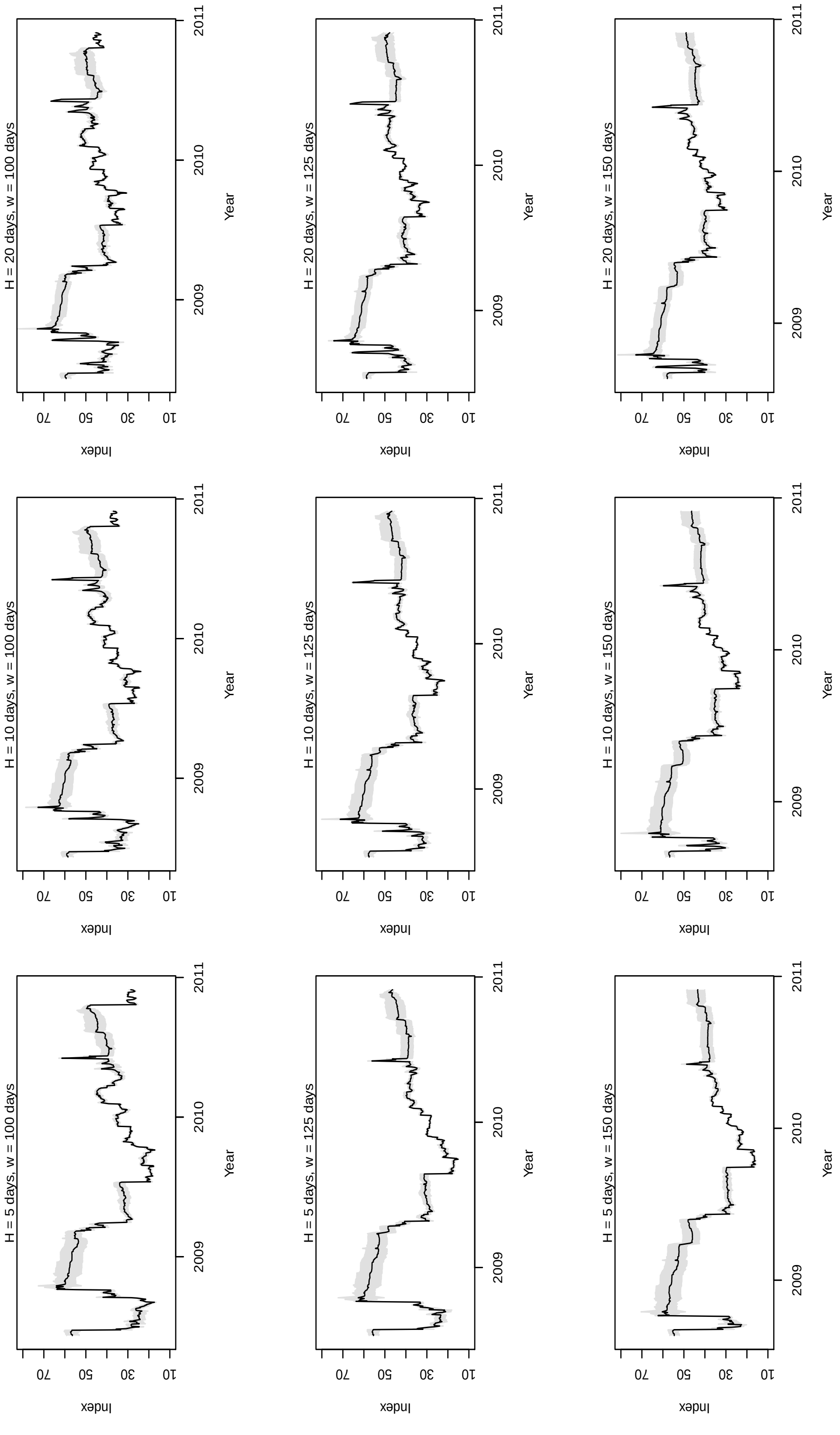

*Note:* A solid line represents the VAR(5)-based spillover index, whereas a dotted line depicts the VAR(4)-based index. The grey band represents the minimum-maximum interval.
*Source:* Author's computations.

In the second part of this section, we provide a robustness check with respect to the length of the rolling window and the forecasting horizon. Regarding the window width we use the alternative values of 100 and 150 days along with our benchmark of 125 days. In terms of the forecasting horizon, H, 5 and 20 days corresponding to one week and one month, respectively, are considered as the alternatives to our benchmark set to 10 days. The dynamic volatility spillover indices estimated for each window width and forecasting horizon are depicted in Figures 6.4 and 6.5 for CEE Sample and CEE+DAX Sample, respectively. Based on the visual inspection of both figures we can observe that all indices share the similar development pattern that becomes smoother with rising length of the rolling window.

Since it can take the longer time for some volatility shocks to transmit to other stock markets, it does not have to be reflected in the volatility spillover index for too small value of H. However, the probability of shocks to be found to spill over to other markets increases with lengthening of the forecasting horizon, H. (Diebold & Yilmaz 2011; 2013) Therefore, looking at Figures 6.4 and 6.5 it can be seen that for the higher values of H the increases in the intensity of the volatility spillover indices become more apparent.

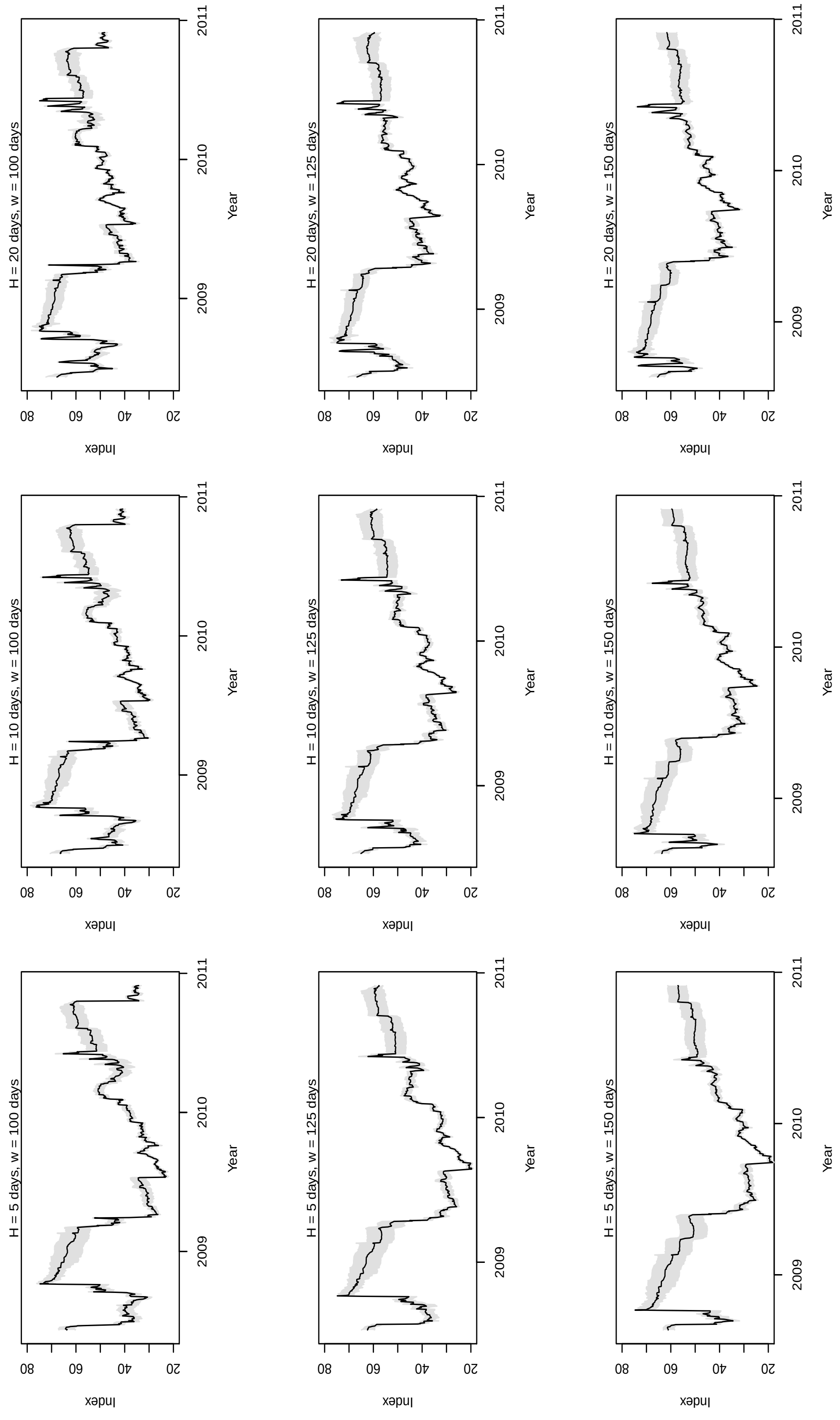
To sum up, we have found that our results appear to be robust not only to the choice of model specification, but also to the length of both the rolling window and the forecasting horizon.

Figure 6.4: Robustness of the Total Volatility Spillovers with Respect to the Window Width, w, and Forecasting Horizon, H, for CEE Sample




*Source:* Author's computations.

Figure 6.5: Robustness of the Total Volatility Spillovers with Respect to the Window Width, w, and Forecasting Horizon, H, for CEE+DAX Sample




*Source:* Author's computations.

## 6.4 Dynamic Asymmetric Analysis

The existence of volatility spillovers among the stock markets under study has already been confirmed in the previous sections by performing both static and dynamic analyses. Therefore, in the last part of this chapter, we focus on the investigation of potential asymmetries in the transmission process of volatilities that are due to negative or positive shocks.

The theoretical reasoning for this asymmetric analysis can be inferred from the prospect theory proposed by Kahneman & Tversky (1979). This theory, sometimes termed as the theory of average behaviour as it provides a description of the average behaviour of an individual or a group of individuals under the uncertainty, assumes that the individuals possess asymmetric attitudes toward gains and losses (Altman 2010). That is, on average, they are more sensitive to losses than to gains of the same magnitude (Barberis 2013). Therefore, we can summarize the underlying intuition as follows.

Growing integration and globalisation of the markets increase its interconnectedness and countries are becoming more prone to be affected by the shocks originating in the other countries. The shocks to prices, irrespective of its signs, induce an increase in the volatility, thus the uncertainty, in the stock market that is further transmitted to the other markets. However, based on the prospect theory we know that, on average, the investors react more strongly to negative shocks. Therefore, we can expect the volatility from negative shocks to have, on average, a stronger impact on the volatilities in other markets, hence to be transmitted more than the one from the positive shocks.

Therefore, in the following part, we explore the hypothesis that, on average, volatility spillovers from negative RS are larger than the ones from the positive RS, thus, on average, a higher part of volatility spillovers can be attributed to the negative shocks since they produce a higher degree of uncertainty.

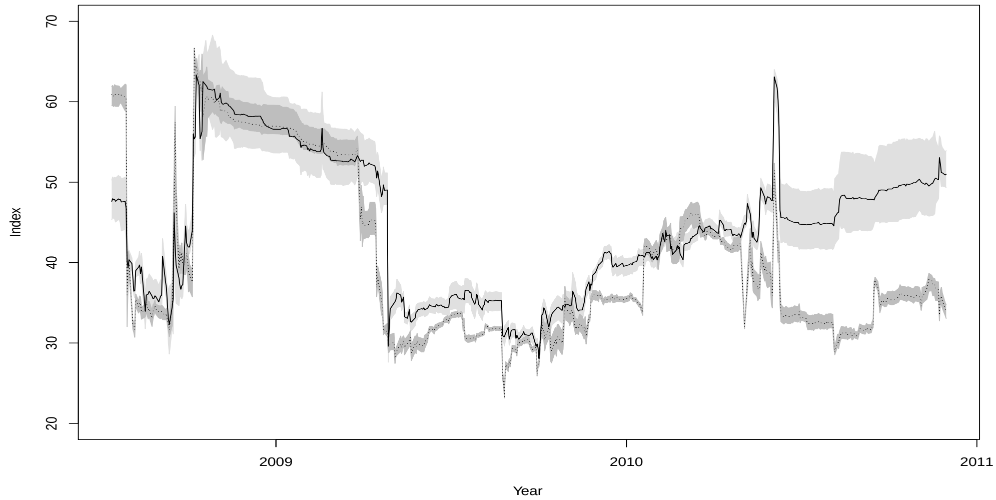
In what follows, we first describe the evolution of the asymmetric spillover indices for both samples of our stock markets. After that, to quantify the extent of this asymmetry a spillover asymmetry measure is provided.

### 6.4.1 Asymmetric Volatility Spillovers

Figures 6.6 and 6.7 present the dynamic asymmetric volatility spillover indices for CEE Sample and CEE+DAX Sample, respectively. A solid line represents spillovers from negative realized semivariances, whereas a dotted line denotes spillovers from the positive realized semivariances. The shaded area indicates the minimum-maximum interval. Based on the visual inspection it can be seen that the periods, during which the spillovers from either positive or negative RS dominate, alternate over the whole observed period. However, on average, the contribution of negative shocks to volatility spillovers is higher compared with the positive ones. This is in line with our hypothesis presented in the introduction of this final section.

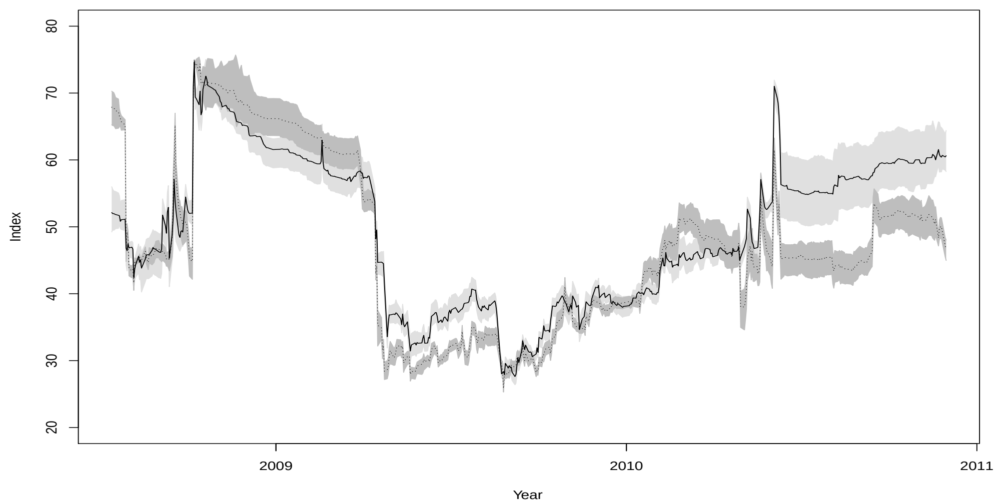
Looking at both figures it can be observed that, at the beginning of our sample period, in mid-2008, the asymmetric volatility spillover indices from positive RS achieved higher values than from negative RS. This might be attributed to the optimistic sentiment persisting from the prosperous pre-crisis period or to the governments' interventions aimed at support of harmed financial institutions that could exert positive influence on the market confidence. In case of CEE+DAX Sample, the dominance of spillovers from positive RS re-emerged even during the period from late 2008, after the fall of Lehman Brothers, till early 2009. However, for our CEE Sample, we observe rather interchangeable impact of positive and negative shocks on the volatility spillovers during the mentioned period. The subsequent periods, till mid-2010, are characterized by only small and varying differences between the asymmetric volatility spillover indices. This finding corresponds with the highly unstable situation when the investors were not able to interpret the signals arriving to the markets. From mid-2010, as the European sovereign debt crisis exacerbated and Greece was forced to ask for financial assistance, volatility spillovers from negative RS began again to dominate substantially. Finally, regarding the development of the asymmetric volatility spillovers, we can conclude that our findings contradict the common knowlegde that the negative shocks affect the volatility more than the positive shocks of the same magnitude.

Figure 6.6: Asymmetric Volatility Spillovers for CEE Sample




*Note:* A solid line represents the spillover index from negative RS, whereas a dotted line depicts the spillover index from positive RS. The shaded area represents the minimum-maximum interval.
*Source:* Author's computations.

Figure 6.7: Asymmetric Volatility Spillovers for CEE+DAX Sample

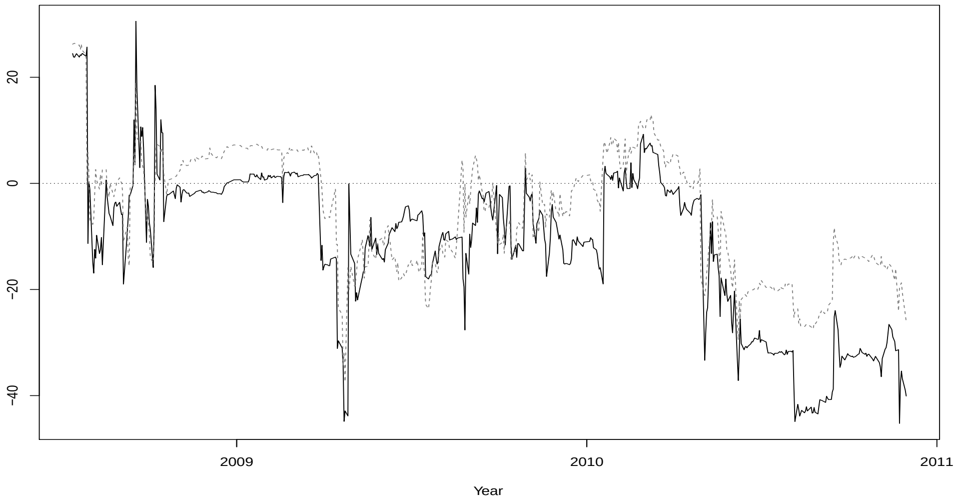



*Note:* A solid line represents the spillover index from negative RS, whereas a dotted line depicts the spillover index from positive RS. The shaded area represents the minimum-maximum interval.
*Source:* Author's computations.

### 6.4.2 Spillover Asymmetry Measure

Finally, to quantify the difference between the spillovers due to negative and positive volatility we use the SAM measures defined in Equation 4.14. Looking at Figure 6.8 that depicts the SAM for both CEE and CEE+DAX Samples we can observe that these measures of asymmetry fluctuate substantially over the whole sample period. The asymmetries in spillovers from negative and positive RS range from approximately -50% to +30% for CEE Sample, while from around -40% to +30% for CEE+DAX Sample. This finding indicates that the impact of negative shocks on volatility spillovers is stronger. Moreover, we can conclude that the spillovers from negative RS are higher for CEE Sample. This might be assigned to the potential higher loss aversion of the investors in the CEE region who then react more sensitively to the negative shocks to returns that are consequently transmitted more heavily across the selected CEE stock markets. Regarding the extended sample the reduced asymmetry in spillovers from negative and positive realized semivariances in the negative interval could be attributed to the potential diversification benefits stemming from the inclusion of the DAX as the stock market index of the stable and economically strong country to the portfolio covering only the CEE indices. Hence, including the DAX into the CEE portfolio could partially eliminate the extent of volatility spillovers from negative shocks, thus mitigate a potential risk of losses stemming from the negative shocks originating in the other countries in the sample. To sum up, since, on average, the contribution of negative shocks to volatility spillovers is higher than from the positive ones, we can infer that these results are in line with the hypothesis presented above.

Figure 6.8: Spillover Asymmetry Measure




*Note:* A solid line represents the SAM for CEE Sample, whereas a gray dashed line depicts the SAM for CEE+DAX Sample.
*Source:* Author's computations.

# Chapter 7

# Conclusion

In this thesis, we aim at analysing of volatility spillovers with the use of volatility spillover indices proposed by Baruník *et al.* (2013). This novel methodology extends the original spillover index framework introduced by Diebold & Yilmaz (2009) by utilizing the non-parametric measures of volatility based on the high frequency data, the realized variance and realized semivariances. These realized measures enable us not only to obtain a better estimate of volatility, but also to examine volatility spillovers from negative and positive RS, thus to explore spillovers due to negative and positive shocks, separately. The main concern of our analysis then lies in the investigation of the asymmetry in the transmission process of volatility with respect to the sign of the shocks that triggered this volatility.

The spillover index methodology is applied on two datasets, the first one covering the selected CEE stock market indices of the Czech Republic, Hungary and Poland, and the second one extending the original sample by the inclusion of the German DAX index that represents the mature European stock markets. The data used for subsequent construction of realized measures are of a high frequency (five-minute data). The sample period employed in our analysis spans from 2008 to 2010, thus captures the turbulent episodes characterized by the outbreak of the recent global financial crisis that hit substantially the financial markets all over the world as well as by the worsening economic situation in Europe that subsequently led to the European sovereign debt crisis in late 2009.

Our empirical analysis consists of three main parts. The first one is dedicated to the construction of the total volatility spillover index over the whole period, therefore it is termed the static analysis. The other two parts provide us with both dynamic total and asymmetric volatility spillover analyses, hence they enable us to observe the evolution of the spillover indices over time.

The results of the static analysis confirm the presence of volatility spillovers among the stock markets under study. The total volatility spillover index is found to be higher for the second sample including the German market. Furthermore, in both samples, the Czech stock market is found to transmit the highest amount of the volatility shocks to the other markets. Its role of the main transmitter could be assigned to the indirect influence of some other non-included country (the US as found by Li & Majerowska (2008), or the UK and Russia as suggested by Caporale & Spagnolo (2011)). Regarding the Hungarian stock market its shocks are shown to be the least influential ones.

The total dynamic spillover analysis reveals that the development pattern of the volatility spillover indices corresponds to the main crisis events and reflects the economic and financial situation on the markets. The sharpest jump in the intensity of volatility spillovers coincides with the fall of Lehman Brothers in September 2008. Moreover, the evolution of volatility spillovers is also in line with the course of events related to the sovereign debt crisis observed in Europe from late 2009.

The potential asymmetries in the transmission process of volatilities that are due to negative or positive shocks are investigated in the last part by conducting the dynamic asymmetric analysis. The main findings confirm our hypothesis that, on average, the volatility from negative shocks to returns is transmitted more than the one from the positive shocks. Furthermore, we find that the periods, during which volatility spillovers from either negative or positive realized semivariances dominate, alternate over the whole observed period. Hence, our results contradict the common knowledge that suggests the negative shocks to affect the volatility more than the positive shocks of the same magnitude. In addition, we reveal that volatility spillovers due to negative shocks are higher for CEE Sample. This might be assigned to the potential higher loss aversion of the investors in the CEE region who then react more sensitively to the negative shocks to returns that are consequently transmitted more heavily across the selected CEE stock markets. Regarding the extended sample the reduced asymmetry in spillovers from negative and positive realized semivariances in the negative interval could be attributed to the potential diversification benefits stemming from the inclusion of the DAX as the stock market index of the stable and economically strong country to the portfolio covering only the CEE indices. Hence, including the DAX into the CEE portfolio could partially eliminate the extent of volatility spillovers from negative shocks, thus mitigate a potential risk of losses stemming from the negative shocks originating in the other countries in the sample.

Finally, we propose three directions of the possible extensions of this analysis. First, the implementation of a longer data sample covering both the EU pre-accession period and the recent years might enable us to observe the evolution of the interconnectedness among the selected stock markets not only during turbulent, but also during tranquil episodes, as well as the evolution of the strength of the reaction of volatility spillovers with respect to the different shocks. Thus, to investigate if there is any evidence of an increasing tendency of shocks to spill more to other markets over time. Furthermore, the inclusion of the other countries, such as the US, the UK, or the other European emerging countries, could provide us with the useful insight about the impact of the shocks originating in another mature and developing markets on the volatilities in our CEE sample. Last but not least, the calculation of the directional volatility spillovers would enable us to see which country is the main transmitter or receiver of the shocks to volatility and how it evolves over time.

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# Appendix A

# Outputs from R

This appendix reports complementary results to Chapter 6 obtained using the statistical software R. The R codes employed in this thesis can be provided on request.

Table A.1: ADF Unit Root Tests

| no drift | lags | p-value for RV | lags | p-value for $RS^-$ | lags | p-value for $RS^+$ |
|---|---|---|---|---|---|---|
| WIG | 10 | $< 2.2 \times 10^{-16}$ | 6 | $< 2.2 \times 10^{-16}$ | 10 | $< 2.2 \times 10^{-16}$ |
| PX | 6 | $< 2.2 \times 10^{-16}$ | 6 | $< 2.2 \times 10^{-16}$ | 5 | $< 2.2 \times 10^{-16}$ |
| BUX | 4 | $< 2.2 \times 10^{-16}$ | 4 | $< 2.2 \times 10^{-16}$ | 4 | $< 2.2 \times 10^{-16}$ |
| DAX | 5 | $< 2.2 \times 10^{-16}$ | 5 | $< 2.2 \times 10^{-16}$ | 5 | $< 2.2 \times 10^{-16}$ |
| with drift | | | | | | |
| WIG | 10 | $< 2.2 \times 10^{-16}$ | 6 | $< 2.2 \times 10^{-16}$ | 10 | $< 2.2 \times 10^{-16}$ |
| PX | 6 | $< 2.2 \times 10^{-16}$ | 4 | $< 2.2 \times 10^{-16}$ | 5 | $< 2.2 \times 10^{-16}$ |
| BUX | 4 | $< 2.2 \times 10^{-16}$ | 4 | $< 2.2 \times 10^{-16}$ | 4 | $< 2.2 \times 10^{-16}$ |
| DAX | 5 | $< 2.2 \times 10^{-16}$ | 4 | $< 2.2 \times 10^{-16}$ | 5 | $< 2.2 \times 10^{-16}$ |

*Note:* Both versions of ADF unit root test, with and without drift, have been performed. Maximum number of lags have been set equal to 20.
*Source:* Author's computations.

Table A.2: PP Unit Root and KPSS Stationarity Tests

| | PP p-value | | | KPSS p-value | | |
|---|---|---|---|---|---|---|
| | RV | $RS^-$ | $RS^+$ | RV | $RS^-$ | $RS^+$ |
| WIG | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ |
| PX | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ |
| BUX | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ |
| DAX | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ | $< 0.01$ |

*Note:* The truncation lag parameter has been set to 6 for both tests. Moreover, the PP unit root test including an intercept has been employed in our analysis.
*Source:* Author's computations.

Table A.3: Long Memory Parameter

| | RV | RS- | RS+ |
|---|---|---|---|
| WIG | 0.64 | 0.66 | 0.54 |
| PX | 0.75 | 0.69 | 0.71 |
| BUX | 0.57 | 0.55 | 0.53 |
| DAX | 0.59 | 0.63 | 0.56 |

*Note:* Long memory parameters, thus the integration orders of the studied series of realized measures, have been estimated using the semiparametric log-periodogram GPH estimator.
*Source:* Author's computations.

Table A.4: Johansen Tests for the Number of Cointegrating Relationships for CEE Sample: Var(4)

| Hypothesis | $\lambda_{max}$ | 1% crit.value | $\lambda_{trace}$ | 1% crit.value |
|---|---|---|---|---|
| $r \leq 2$ | 31.47 | 11.65 | 31.47 | 11.65 |
| $r \leq 1$ | 81.35 | 19.19 | 112.82 | 23.52 |
| $r = 0$ | 87.67 | 25.75 | 200.49 | 37.22 |

*Source:* Author's computations.

Table A.5: Johansen Tests for the Number of Cointegrating Relationships for CEE Sample: Var(5)

| Hypothesis | $\lambda_{max}$ | 1% crit.value | $\lambda_{trace}$ | 1% crit.value |
|---|---|---|---|---|
| $r \leq 2$ | 24.65 | 11.65 | 24.65 | 11.65 |
| $r \leq 1$ | 74.29 | 19.19 | 98.94 | 23.52 |
| $r = 0$ | 87.21 | 25.75 | 186.14 | 37.22 |

*Source:* Author's computations.

Figure A.1: Stability Results

```
A. CEE Sample - VAR(4) model

 [1] 0.9528180 0.8192004 0.8192004 0.6792355 0.6792355 0.6486486 0.6486486
 [8] 0.6388862 0.6388862 0.4386880 0.4386880 0.3027538


B. CEE Sample - VAR(5) model

  [1] 0.9623551 0.8480440 0.8480440 0.7483388 0.7483388 0.6398849 0.6398849
  [8] 0.6215107 0.6215107 0.6108617 0.6108617 0.5554277 0.5338269 0.5338269
 [15] 0.1166267


C. CEE+DAX Sample - VAR(4) model

 [1] 0.94851355 0.81540899 0.81540899 0.72567603 0.68209504 0.68209504 0.67358610
 [8] 0.67358610 0.63498251 0.63498251 0.55050801 0.55050801 0.50520725 0.43170022
[15] 0.43170022 0.07702206


D. CEE+DAX Sample - VAR(5) model

 [1] 0.961775788 0.831952161 0.831952161 0.813661656 0.777544596 0.777544596 0.740240383
 [8] 0.740240383 0.630013463 0.630013463 0.629217559 0.629217559 0.625491607 0.613335397
[15] 0.613335397 0.518080085 0.518080085 0.502169470 0.502169470 0.005814299
```

*Note:* This R output reports the modulus of eigenvalues of the coefficient matrix for each considered model specification and data sample. For model to be stable all eigenvalues have to be less than one in the absolute values. Stability checking results are provided only for the RV series. However, the stability of models of both RS series has also been confirmed and its results can be provided on request.
*Source:* Author's computations.

Table A.6: Johansen Tests for the Number of Cointegrating Relationships for CEE+DAX Sample: Var(4)

| Hypothesis | $\lambda_{max}$ | 1% crit.value | $\lambda_{trace}$ | 1% crit.value |
|---|---|---|---|---|
| $r \leq 3$ | 32.93 | 11.65 | 32.93 | 11.65 |
| $r \leq 2$ | 70.81 | 19.19 | 103.75 | 23.52 |
| $r \leq 1$ | 86.63 | 25.75 | 190.38 | 37.22 |
| $r = 0$ | 110.75 | 32.14 | 301.13 | 55.43 |

*Source:* Author's computations.

Table A.7: Johansen Tests for the Number of Cointegrating Relationships for CEE+DAX Sample: Var(5)

| Hypothesis | $\lambda_{max}$ | 1% crit.value | $\lambda_{trace}$ | 1% crit.value |
|---|---|---|---|---|
| $r \leq 3$ | 24.51 | 11.65 | 24.51 | 11.65 |
| $r \leq 2$ | 64.86 | 19.19 | 89.37 | 23.52 |
| $r \leq 1$ | 88.25 | 25.75 | 177.62 | 37.22 |
| $r = 0$ | 97.91 | 32.14 | 275.53 | 55.43 |

*Source:* Author's computations.