Charles University in Prague

Faculty of Social Sciences

Institute of Economic Studies

MASTER THESIS

Comovements of Central European Stock Markets: What Does the High Frequency Data Tell Us?

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Academic Year: **2010/2011**

Declaration of Authorship

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

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Prague, July 29, 2011

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Acknowledgments

I would like to thank to PhDr. Jozef Baruník for his encouragement, many useful comments and the willingness to discuss all of my questions. Moreover, I would like to thank to him for providing me with the data.

Abstract

In this thesis, we inquire interdependencies and comovements between CEE capital markets within each other. German market is also included in the analysis as a benchmark to CEE capital markets. We have chosen German capital market as it represents more developed market from the same geographical region. We study a unique high-frequency dataset of 5 minutes, 30 minutes and 1 hour data frequencies covering the the crisis period and post-crisis "tranquil" period. Daily data frequency is also involved in the analysis.

Using different econometric techniques, we found no steady long-term relationships among stock market indices. The only strong relationship was detected between the DAX and WIG20 indices during both crisis and "tranquil" periods. The frequency of interactions changed across periods. The strongest interdependencies were recognized in 5 minute data frequency which indicates fast reactions between markets. Information inefficiency was revealed between markets according to cointegration tests in most cases.

JEL Classification	C22, F30, F36, G15
Keywords	high frequency data, European emerging markets, comovements

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Bibliographic Record

Roháčková, H. (2011): "*Comovements of Central European Stock Markets: What Does The High Frequency Data Tell Us?*". Master thesis, Charles University in Prague, Faculty of Social Sciences, Institute of Economic Studies, pages 86. Supervisor: PhDr. Jozef Baruník.

The thesis was typesetted in MiKTEX 2.9 using *IES Thesis Template* created by Tomáš Havránek.

Abstrakt

V této práci zkoumáme vzájemné závislosti a pohyby mezi kapitálovými trhy středoevropského regionu. Dále sledujeme vztahy těchto trhů s německým kapitálovým trhem, který jsme vybrali jako zástupce vyspělého trhu ze stejné geografické oblasti. Pro naši analýzu disponujeme jedinečnými vysokofrekvenčními daty s pětiminutovou, třicetiminutovou a hodinovou frekvencí, která pokrývají období krize a pokrizové "klidné" období. Denní data jsou též zahrnuta v analýze.

Použitím několika ekonometrických metod jsme neobjevili žádné dlouhodobě trvající vztahy mezi jednotlivými indexy kapitálových trhů. Jediný silný vztah byl nalezen mezi indexy DAX a WIG20 na datech z období krize i klidného období. Rychlost interakcí se měnila pro jednotlivá období. Nejsilnější vzájemné vztahy byly rozeznány na datech s pětiminutovou frekvencí, což napovídá, že trhy reagují na sebe navzájem velmi rychle. Odhalili jsme, že trhy nejsou ve většině případů mezi sebou informačně efektivní.

Klasifikace JEL	C22, F30, F36, G15
Klíčová slova	vysokofrekvenční data, evropské rozvojové trhy, vzájemné chování

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Acronyms

ADF test Augmented Dickey-Fuller test

BUX Stock index of Budapest Stock Exchange

CAPM Capital Asset Pricing Model

CEE region Central and Eastern European region

CEESEG CEE Stock Exchange Group

DAX Stock index of Deutsche Boerse

EGARCH Exponential Generalized Autoregressive Conditional Heteroskedasticity

GARCH Generalized Autoregressive Conditional Heteroskedasticity

KPSS test Kwiatkowski, Phillips, Schmidt, and Shin test

PP test Phillips-Perron test

PX Stock index of Prague Stock Exchange

SWARCH A switching AutoRegressive Conditional Heteroskedasticity

VECM Vector Error-Correction Model

WIG20 Stock index of Warsaw Stock Exchange

Master Thesis Proposal

Author	Bc. Hana Roháčková
Supervisor	PhDr. Jozef Baruník
Proposed topic	Comovements of Central European Stock Markets: What Does the High Frequency Data Tell Us?

Topic characteristics The European Capital Market Integration is a frequently discussed topic nowadays. There is a public intention to unify capital markets in Europe to be sufficiently competitive and able to deal with powerful capital markets such as in the U.S. National stock markets also tend to behave in this manner.

In this thesis, there will be demonstrated what patterns could be present in capital markets' behavior with respect to each other and how these behaviors change in time. All analyses will be aimed on the region of CEE countries (the Czech Republic, Hungary and Poland) and markets in France, Great Britain and Germany as the most developed capital markets within the EU. Stock market index returns will be used in the analyses.

Thesis will consist of two parts. The first part will test daily data and show whether there are any information transmission and co-movements as written in Podpiera (2001), Horobet, Lupu (2009) and Voronkova (2004). Inspired by Jokipii, Lucey (2007), there will be also investigated whether there is any interdependence or contagion by comparing the correlation coefficients among investigated markets.

The second part will deal with high-frequency (HF) data (the frequency higher than daily - 5, 10, 20, 30, 40, 50 and 60 minutes). Inspired by Cerny (2004), Egert, Kocenda (2007), there is intention to discover capital market co-movements and the presence of the information transmission testing HF data. Using intraday data can give the exact pattern in relationships between markets. Changes in behavior among capital markets over time will be the core

analysis of the thesis. This study will update the results of previous studies concerning the same topic. The main contribution will be in examination of patterns in changes of behavior among markets regarding recent mortgage crisis.

Hypotheses The hypothesis 1 will be tested only on the daily data. The hypotheses 2 - 7 will be tested on both daily and HF data.

1. Hypothesis: Test whether there is no contagion (only interdependence) under null hypothesis or its alternative of contagion.
2. Hypothesis: Test whether time series are stationary or not I(1).
3. Hypothesis: Test whether pairs of time series are cointegrated.
4. Hypothesis: The logarithm of price development on one market does or not Granger cause logarithm of price development on another market.
5. Hypothesis: Inquiry of stock market volatility.
6. Hypothesis: Investigation of the present spillover effects between stock markets.
7. Hypothesis: Test how the co-movements and interdependence between markets change over time especially with respect to mortgage crisis.

Methodology

- Ad Hypothesis 1: There will be counted the cross-country correlations and consequently applied a two-sample t-test (as described in Jokipii, Lucey (2007)).

- Ad Hypothesis 2: The stationarity of time series will be tested by using Augmented Dickey-Fuller (null hypothesis states that there is the presence of a unit root, thus non-stationarity) and Philips-Perron unit root tests.

- Ad Hypothesis 3: If both series are I(1), I use the cointegration test for this hypothesis. On estimated residuals, I apply ADF test and in case of rejection of null hypothesis, I will claim that stock market indices are cointegrated.

- Ad Hypothesis 4: For testing the null hypothesis about whether logarithm of price development on one market does or not Granger cause logarithm

of price development on another market, there will be applied Granger Causality test (Granger (1969)).

- Ad Hypothesis 5: The hypothesis about stock market volatility will be tested with the use of GARCH (Egert, Kocenda (2007)).
- Ad Hypothesis 6: To validate this hypothesis about the presence of spillover effects, we use VAR model that includes stock market returns and stock market volatility obtain using the GARCH or another extension of ARCH.
- Ad Hypothesis 7: Data will be divided into different time periods and there will be monitored the differences in behavior of relationships using the above mentioned methods - cointegration test (with error-correction estimations), Granger causality test, GARCH, VAR.

Outline

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Chapter 1

Introduction

Capital markets serve as an efficient tool to raise capital for companies all over the world. Many capital markets began to emerge in past decades. The amount of them increased so rapidly that their integration appeared to be the next inevitable step. Along this process, the study of interdependencies, comovements and degree of integration among capital markets has become an attractive and urgent topic to discover interrelations among different capital markets.

The focus on such topic is important for several reasons. Firstly, the investors who are willing to diversify their portfolios internationally need to make effective investment decisions based on good information. And such information are not available in the area of capital markets that are cointegrated. Secondly, findings about whether there are any interlinkages among countries help to coordinate policy-making decisions. If any price linkages between particular markets are evident, the higher degree of policy-making coordination is required in order to acquire all benefits of greater interdependence. Thirdly, to study such topic may provide the insight about the level of integration which may help to decide whether to create integrated common financial market and if there exists suitable environment for the adoption of a common currency (Azmi *et al.* (2005)).

The range of literature to study this topic is really extensive and researchers usually involved in their studies the data from the greatest world capital markets. We would like to devote this study to the area of CEE region. The key question is how much are these markets interrelated and whether we find any features of comovements among these capital markets. Jin (2005) mentions that the economies in close geographical proximity and cultural similarity ex-

hibit significant stock price comovements. For such reason, we will include German capital market in this study as the representative of a developed capital market which is in fact from the same geographical region and is considered to be one of the leader economy in Europe.

We use several tests to reveal the interdependencies among capital markets. The test based on correlation coefficients will help us to distinguish between contagion and interdependence among capital markets. This test has further important implications for monetary policy, optimal asset allocation and risk measurement (Jokipii & Lucey (2007)).

Granger causality test will be also included in the study. This test became very popular and is frequently used in any literature discovering the information transmission among capital markets. It was pioneered by Granger (1969) and provides the information about whether causality appears between two related variables (two capital markets in our case). Moreover, it tells the direction of causality. Podpiera (2001) deepens the hypothesis and states that if causality appears in either or both directions, it suggests that the markets are fragmented. On the other side, if there is no causality in either of directions, the capital markets may be integrated but it can also mean that the markets are not related at all.

Last but not least tests included in our analysis will be the cointegration tests. We will use the most common methods of cointegration tests - the Engle-Granger cointegration test (Engle & Granger (1987)) and Johansen cointegration test (Johansen (1988)). Testing for cointegration relationships became very popular in applied econometrics after these papers were published. Moreover, Robert F. Engle together with Clive W. J. Granger received the Nobel prize in 2003 which made this field of study even more attractive. For cointegration test, the tested time series must be stationary processes because if they are not, it leads the whole analysis to spurious regression. Therefore we discover at first the stationarity of time series using a battery of unit root tests.

The test of correlation coefficients together with Johansen method of cointegration test will be used in the vector autoregression (VAR) framework. The VAR model is nowadays one of the most successful, flexible and easy to use models for the analysis of multivariate time series[1]. This regressions were ini-

[1]This is taken from the lecture notes of Eric Zivot, the professor of economics at the University of Washington. Available at http://faculty.washington.edu/ezivot/econ584/notes/varModels.pdf

tially introduced by Sims (1980) and have lately been incorporated in many more advanced econometric models.

To see how sensitive are markets within each other, we involve the high frequency data to precisely find out in what intervals the information revealed on one market hits another one. We initially became attracted to this field of study by the papers Cerny (2004) and Cerny & Koblas (2008) that investigate the speed of information transmission between CEE capital markets on high frenquency data. Daily data will be also included in this study.

The analysis of data from this geographical area is quite unique. Moreover, analysis of high frequency data from this area can provide meaningful insight of the reactions of these capital markets within each other. We have also now the exquisite opportunity to investigate the data of the period between 2008 and 2010 covering the recent global financial turmoil which occured after the stock market crash in the U.S. in 2007 and hit all international capital markets for the second time after the fall of Lehman&Brothers in 2008.

The thesis will keep the following structure. We dedicated section two to the literature overview of either testing daily or high frequency datasets. We will introduce the capital markets involved in this analysis in section three. The detailed description of models used in this thesis takes place in section four. Section five provides the information about datasets, the methods of adjustment and important data features. The sensitive results of all tests are finally provided and commented in section six.

Chapter 2

Existing Literature on Comovements and Contagion

The study of interrelationships between the world capital markets are nowadays highly important to help to control the global financial system, to understand the information flows between markets and how markets become more or less integrated. That should enhance the market efficiency and overall ability of credit risk control. We have a unique opportunity now to be one of the first researchers that could apply this field of study on the period of recent global financial crisis. We begin with the review of previous literature written and dealing with the similar topic.

2.1 Interdependence vs. Contagion

A great discussion about the presence of contagion between markets all around the world has arisen with every arrival of turmoil on world financial markets. The literature focuses on the events as is Asian crisis in 1997, Mexican so-called "Tequila" effect in 1994 or recent U.S. mortgage crisis in 2007. A vast amount of literature investigating whether these periods express symptoms of contagion landed. All authors agree on the statement that the transmission mechanism during crisis substantially differs from the one in tranquil periods. Correlations are also accompanied by higher volatility in crisis periods but that does no necessarily show the evidence of contagion (see Kleimeier *et al.* (2003), Jokipii & Lucey (2007), Bodart & Candelon (2008)).

2.1.1 Definitions of Contagion and Interdepence

In order to acquaint reader with this topic, it is necessary to introduce the notion "*contagion*". Many researchers complain that the notion contagion does not have proper, single definition (see Forbes & Rigobon (2002), Baele & Inghelbrecht (2006), Bekaert *et al.* (2005)). Contagion was expressed in many definitions. Neverthless, World Bank summarizes all of them as follows:

1. Contagion is the cross-country transmission of shocks or the general cross-country spillover effects.
2. Contagion is the transmission of shocks to other countries; it is also a stronger evidence of co-movement usually explained by herding behavior.
3. There is a presence of contagion if correlations across countries rise during crisis periods compared to the calm periods.

Interdependence is on the other hand observable in such situation that the stability between two or more countries remains constant and stable over time and no change of the relationship is evident. Policy makers emphasize to search for the circumstances under which contagion occurs. Their aim is to create and adjust such policies that ensure financial stability for all countries involved in greater unions; a country involved in a union with another countries may have its own policies that differ substantially from the policies of another countries in a union. These new policies or restrictions require deeper supervision and only such well-supervised system can provide then relevant information about monetary policy, optimal asset allocation and risk measurements. Examining the interdependence and contagion can give us useful hints when we forecast the reaction of one country to crisis in another country. However, to be able to forecast, it is required that the relation remains stable over time (Jokipii & Lucey (2007)).

2.1.2 Recent Literature on Testing Contagion by Using Correlation Coefficients

Edwards & Susmel (2001) in their study test Latin American countries and their relation to Hong Kong. They are provided by weekly data of stock exchange indices in the period between 1989 and 1999. Using SWARCH model, they find more interdependence than contagion. They reveal high-volatility period

that are short-lived and usually show up in time of international crisis. They find that volatility in Asian market evolves with the same features as in Latin American markets, on the other hand the volatility in Asian market does not influence the one in Latin America.

Rigobon (2002) describes more extensively different methods of measuring contagion with their shortcomings. He claims that such shortcomings are present in form of simultaneous equations, omitted variables, conditional and unconditional heteroskedasticity, serial correlation, nonlinearity, and nonnormality. Author presents the most commonly used methodologies based on OLS estimates, principal components and correlation coefficients. He wants to uncover whether there is a change in coefficients of two different samples - first covering crisis and second "*tranquil*" periods. He also presents here these periods with respect to high or low volatility.

Forbes & Rigobon (2002) make survey of data during Asian crisis in 1997, Mexican devaluation in 1994, and U.S. market crash in 1987 across the whole world - East Asia, Latin America, OECD countries and others. They show that tests used for inquiring contagion based on cross-market correlation coefficients are heteroskedastic (thus biased and imprecise) because they are conditional on market volatility. If no adjustment to market volatility is made, the evidence of contagion is found. They present the method of adjusting for the heteroscedasticity which is based on the assumption of no omitted variables and endogeneity. When using unconditional correlation coefficients, no evidence contagion across markets is found, instead a high degree of market comovements appears during stable period as well as crises which is considered as interdependence.

Kleimeier *et al.* (2003) contravenes the result of "*no contagion, only interdependence*" (Forbes & Rigobon (2002)) when testing the Asian crisis. They reveal some contagion and some interdependence. Pointing out the problem of overestimation and thus biases of conditional correlation coefficients in crisis periods (already mentioned in Forbes & Rigobon (2002)), they address to another problem of biased estimation - synchronized data. They claim that to be able to interpret the crisis correctly, the synchronous data must be used.

Bodart & Candelon (2008) test also contagion during the Asian and "*Tequila*" crisis with brand-new techniques that enable to differentiate between temporary and permanent movements of cross-market linkages. They specifically focus on so-called shift-contagion which is characteristic for temporary and significant increase in linkages across countries (not only across markets). They use causality test in the frequency domain which has following advantages: it

is developed to deal with several statistical problems considering the method of correlation coefficients and it can recognize temporary and permanent shifts across-market linkages. Temporary shifts mean contagion while permanent shifts appear when interdependence among markets occurs. Causality test is executed in VAR framework which helps to explain the propagation of shocks over time and moreover it omits the problems connected with correlation coefficients methodology - omitted variables. Results show that the spillover effects of crises were concentrated geographically nearby the shock occurred. Thus the conclusion is that contagion is regionally limited. The possibility that the shock was transferred from one country to another through some third involved country is not discussed. But author emphasizes the necessity of this discussion in further research.

Bekaert *et al.* (2005) test the contagion and integration of capital markets in three regions - Europe, South-East Asia, and Latin America. They study national equity markets in 22 countries in the period between 1980 and 1998. They apply three models based on two factors; these are "*a world capital asset pricing model (CAPM), a CAPM with the U.S. equity return as the benchmark asset, and a regional CAPM with a regional portfolio as the benchmark*" for which they use standard GARCH framework. They conclude with "*no evidence of additional contagion caused by the Mexican crisis*"; however they find growth of residual correlation in Asia especially during the Asian crisis. Their contribution is in investigating time variation of behavioral patterns between regional and world market correlations and also ability to measure proportions of variance which is caused by global, regional and local factors. Moreover, they discuss how these proportions change over time.

Baele & Inghelbrecht (2006) react on the paper of Bekaert *et al.* (2005). They develop another methodology of testing contagion. Contagion is strictly defined in both papers as "*correlation over and above what one would expect from economic fundamentals*". Weekly total returns in U.S. dollars are used here for 14 European equity markets in the period between 1973 and 2004. They want to inquire to what extent must be the model complex to give the proper results about contagion. Based on GARCH framework, they distinguish between contagion tests and misspecification tests. They found out that higher degree of complexity decrease the misspecification of model. They conclude that it is necessary to consider time-varying equity market interdependencies when testing contagion (in their opinion, contagion related to Asian crisis and terrorist attacks on the 11th September 2001 was not properly identified by

Bekaert *et al.* (2005)).

Gilmore *et al.* (2008) investigate the static and dynamic, short-run and long-run comovements of CEE capital markets with developed markets in London and Frankfurt for the period between 1995 and 2005. Static analyses reveal short-term correlations as well as only few cases of statistically significant cointegration. Dynamic one-year rolling-window approach shows unstable short-term correlations with the highest correlations in the years 1996 and 1997 and discontinuous long-run cointegration. The method of dynamic principal components however finds stable factor that can explain major features of behavior of a five-market sample as a group.

Jokipii & Lucey (2007) examine the persistence of contagion between three largest Central and Eastern European Countries based on tests of the unadjusted and adjusted correlation coefficients where adjusting means the involvement of good or bad macroeconomic announcement in form of dummy variables. They make use of daily data from the period between 1994 and 2004 and find the evidence of contagion only between the Czech Republic and Hungary. They confirm this result by further adjusting the data to the problems of simultaneous equations, omitted variables and heteroskedasticity and detect contagion for most of the year 1996. They further show the same direction of contagion (from the Czech Republic to Hungary) by the Granger-Causality test.

2.2 Information Transmission and Spillover Effects

Another papers pay more attention to reveal information transmission and spillover effects and thus degree of integration and comovements across capital markets. Azizan *et al.* (2007) studies transmissions of return and volatility information between the Malaysian futures and cash market on daily data in the period between 1990 and 2003. They put emphasis on discovery of information transmissions contained in volatility information[1]. This can serve as a risk information and therefore it should be the substantial component of many financial decisions. Because the volatility is time-varying[2], they adopt GARCH and EGARCH to inquire the volatility spillover effects between markets; whether they occur at first moment, second moment or both. There are

[1]Volatility is defined here as the dispersion around the mean returns.

[2]This is caused by continual flow of information into the market, thus the level of risk tends to change in time.

three reasons for choosing ARCH[3] model: firstly, it is a simple model and it does not have any problems of computing function opposite to stochastic models (the volatility is an unobserved part in the model); secondly it can handle heteroskedasticity, volatility accumulating and problems of nonnormality of time series data well; thirdly, it is widely used in previous studies, hence the findings can be compared. They conclude that the markets are interconnected in terms of both mean and volatility but volatilities of both markets are not asymmetric in Malaysia.

Cheung *et al.* (2010) investigate the interrelationships between the U.S. capital market and other global financial markets (UK, Hong Kong, Japan, Australia and China) with respect to the recent U.S. mortgage crisis and consequent global financial crisis. They especially focus on the changes in relationships between markets. They are considered to be the first who study trivariate relationship among the change in the TED[4] spread, returns in U.S. index and returns in other global market indices. They use standard econometric methods (Dickey-Fuller test for stationarity at the beginning, VAR estimations, Granger causality test, cointegration test, and impulse-response functions). The results say that causal relationships and cointegration were intensified during the crisis and "*the TED spread adjusts to new information rapidly and serves as a leading "fear" indicator, not only for the U.S. market but also for other global markets*". Moreover, during crisis time, the TED spread shows five times higher impact on global market indices while the impact of shock from U.S. (the origin market of the crisis) on the global indices increases only twice. The spillover effects show that there is a severe presence of contagion and policy makers must pay attention when forming measures to mitigate the crisis.

Fu & Liu (2010) investigate cointegration among contruction prices from different geographical and industrial areas in Australia using Engle-Granger cointegration test and error-correction model. They find these indices to be highly integrated.

Podpiera (2001) shows information flows on the data of companies from CEE region that are cross-listed[5] on London Stock Exchange (LSE) in the period between 1993 and 2000. He firstly examines whether the prices of

[3]This is an abbreviation for Autoregressive Conditional Heteroscedastic (ARCH) family.

[4]TED means the difference between the 3-month T-bill interest rate and the 3-month London Interbank Offered Rate (LIBOR).

[5]Cross-listing is a situation when shares of a company are listed on one or more foreign stock exchanges in addition to its domestic stock exchange at the same time (Rohackova (2009)).

cross-listed stocks are cointegrated and also the impact of cross-listing on the volatility (variance) of local returns[6]. He uses the Granger causality test and cointegration/error correction estimations for both analyses. He finds the cointegration between markets and information flows in both directions but stronger flows are detected from London Stock Exchange to CEE capital markets. That implies the markets are still fragmented. The increased variance of local returns is caused according to his results by tighter interactions with foreign markets due to cross-listing and investor's behavior.

Beirne *et al.* (2009) seek for volatility spillovers using conditional variances. They confirm the spillovers from mature to emerging markets (emerging markets are denoted as EME and it represents 41 emerging markets included in the analysis) and they do find the evidence of change in dynamics of conditional variances of returns in majority EME countries. Spillover parameters also tend to change during turbulent episodes in developed markets.

Horobet & Lupu (2009) investigate the international market integration focused on CEE region. They use data of stock market returns (in logarithms) of different frequencies (daily, weekly, monthly) to discover the causality and cointegration between CEE capital markets (the Czech Republic, Hungary, Poland, Romania, and the Russian Federation) and developed European equity markets as are Austria, France, Germany, the United Kingdom and within each other in both groups. Data are from the period between 2003 and 2007. Their results indicate the flows of information going in both directions (from developed markets to emerging ones, and vice versa). Based on the cointegration it is confirmed that markets have sustainable long-term interrelations within each other. They also involve correlation coefficients which show the higher correlation among developed markets than among emerging markets. They finally conclude that markets become more integrated.

Cointegration analysis is also used by Baxa (2007). He uses Johansen cointegration test, vector autoregression (VAR) and vector error-correction models (VECM) to discover the cointegration relationships between particular stocks listed on the Prague Stock Exchange. Stocks are expressed as natural logarithms of prices; data are in daily and weekly frequencies from the period between 2001 and 2006. The results indicate more cointegration when VECM method is used in weekly data frequency (this may be caused by higher noise in daily data).

[6]This study was unique at presenting the results focused on the volatility. Other researchers aimed their study only on returns of cross-listed securities.

2.3 Existing Literature Using High-Frequency Data

The first enthusiasm to test high-frequency data came with Cerny (2004) and Cerny & Koblas (2008). They use data with five, ten, twenty, thirty, fourty and fifty minute, hourly and daily data frequencies from the period between June 2003 and February 2004. The research is aimed on data from the CEE capital markets, then on stock markets in Frankfurt, London and Paris, furthermore the U.S. indices (S&P 500 and DJIA[7]) are also included in the analysis. They use the standard methodologies of Granger causality test (Granger (1969)) and Engle-Granger cointegration test (Engle & Granger (1987)) and they propose that "*if the reaction of prices on one market to the information revealed in prices on the second market occurs faster than within one day, then we should not detect coinegration or Granger causality with daily data*" because in such frequency, the markets should already be efficiently informed. His findings are that markets react to each other's information very fast. Prague reacts to information from Frankfurt within thirty minutes which is faster than reaction of Warsaw; Warsaw reacts to Frankfurt within one hour.

The core literature for the study of using high frequency data in the Central and Eastern European (CEE) region became Egert & Kocenda (2007). They use a variety of statistical methods testing 5 minute intraday data to explore the interdependencies between stock market indices of the CEE markets and Western European markets (DAX30, CAC40, UKX[8]). They found short-term spillovers from Western markets to CEE markets but also in the opposite direction (from BUX and WIG20 to DAX and UKX, respectively). However, no long-term, robust cointegration relationship was detected.

Hanousek & Kocenda (2009) also use the 5 minute intraday stock market index returns. They test how capital markets in the Czech Republic, Hungary and Poland react to a wide range of macroeconomic announcements made in the eurozone and in the U.S.. Macroeconomic announcements are sorted according to specific groups: prices, economy, monetary and business climate and consumer confidence. Findings confirm that CEE markets are strongly determined by developed stock markets as well as macroeconomic announcements originating there. Their paper gives closer look into the process of stock market integration within the EU and portfolio allocation on the CEE markets.

[7]Dow Jones Industrial Average

[8]DAX30 is the index of the stock market in Frankfurt, CAC40 is the French stock market index and UKX index is of the stock market in London.

2.3.1 Wavelet Analysis

Currently the newest method of analysing time series has become wavelets analysis. Percival & Walden (2006) in their book introduced wavelet transform as "*a synthesis of older ideas with new elegant mathematical results and efficient computational algorithms*". Wavelet analysis seems to be more efficient than the prior frequently used Fourier transfom. Fourier transform analyses time series by superposing sines and cosines to find the representation by other functions. The imperfections of this method has been found. As Graps (1995) mentions, by Fourier transform we can look at the signal via large range; then we are able to detect only gross features. But if we test the signals via small range, only local features can be observed. These obstacles of Fourier transform were removed by introducing wavelets and as Dr. Vacha mentions, wavelet transform offers localized frequency decomposition as well as information about what frequency components are present and where they are occuring[9].

Time series are currently analysed using wavelets in many scientific areas, for instance quantum mechanics, meteorology, seismology, analyses of DNA, etc. For instance, Gabbanini *et al.* (2004) describes in their paper the use of wavelet packets with adapting of iterated sum of squares algorithm for local variance change points. Their initial interest was in applying this method to time series of crack widths, particularly on Brunelleschi dome of the Santa Maria del Fiore cathedral in Florence. Their results revealed new information about dynamics of crack evolution. Nevertheless, the aim of our interest is using wavelets for the analysis of economic time series. Several papers covering this topic follow.

Horobet & Lupu (2006) applied a multifractal spectral (MFS) analysis[10] on the data preceding the stock market crash in October 1987. They took 2000 observations of each DJIA, NASDAQ and S&P500[11] and discovered interesting patterns in behavior. Their results say that there was higher regularity and low diversity of financial multifractionality and lack of multifractial randomness. That indicates an increased dependence between market participants and their behaviours. When the crash hit, more irregularities or suddennesses were revealed, the degree of persistence on a stock market was reduced which all

[9]Cited from the lecture notes for the course Quantitative Finance II taught at the Institute of Economic Studies, Faculty of Social Sciences, Charles University in Prague.

[10]wavelet-based analysis

[11]DJIA stands for Dow Jones Industrial Average, NASDAQ stands for the index of American stock exchange and S&P500 is the index of stocks of large publicly held companies that are traded either on the New York Stock Exchange or the NASDAQ or both.

could assure a good functioning of a stock market. They conclude with the hypothesis that despite more rules, regulations with more institutional restrictions in a stock market can make a market more persistent, it may have the tendency of crashing.

Rua & Nunes (2009) use wavelet analysis to discover comovements between the stock markets in Germany, Japan, United Kingdom and United States using their stock market indices and particular economic sector indices. Their period spans from January 1973 until December 2007 and the data are of monthly frequency. The highest comovements from the pairs of indices were detected in case of the U.S. and UK stock markets. Japanese stock market does show on the other side a weak correlation with other developed markets in this time-frequency space. Germany comoves closely with the US and UK at a lower frequency during the whole period and since the 90s, the comevement are stonger also for other frequencies. They also applied the analysis on the data converted to common currency and it did not significantly changed the results of the analysis.

Another method of wavelet analysis is used in Madaleno & Pinho (2011). They particularly use continuous wavelet and cross-wavelet analysis. They tested stock market indices FTSE100, the Bovespa, the Nikkei225[12] and DJIA30 in daily frequency of the period from October 1st, 1997 to March 6th, 2009. The analysis incorporated the comparison to important financial events that may influence the stock market index development. Generally tigher linkages between the countries appear in case of those stock markets that are economically and geographically close. The stronger relationship between Bovespa and FTSE100 and Nikkei225 was only during Russian financial crisis and Brasilian collapse, other periods are weak in comovements. Historical transmissions show the decreasing importance but again appear to be significant during the period between 2007 and 2009.

The only so far known paper using wavelet analysis on high frequency financial data is Barunik *et al.* (2010). They contribute to the wavelet analysis by using dataset of intraday 5 minute frequency data. The results of daily data are also presented. They inquire the comovements between the CEE stock markets (Czech Republic, Hungary, Poland) and German stock market using their corresponding indices in the period between 2008 and 2009. The most distinctive comovements were discovered between PX and WIG indices in the period

[12]FTSE100 is the index of the stock market in London and Bovespa stands for Brazilian stock market index. Nikkei225 is the Japanese stock market index.

from half of the year 2008. The correlations in this moment were significant in the monthly period (low frequency). The strong comevements continued to the half of the year 2009 when the correlations were the most significant within one week period (higher frequency). The main conlusion from these results is that interconections between stock markets change over time.

Chapter 3

Market Characteristics

We introduced a wide range of literature testing the interrelationships between two or more countries in the previous chapter. Now we would like to present the markets under study. This analysis is focused on the capital markets from the Central and Eastern European (CEE) region. The interdependencies of CEE stock markets will be furthemore tested in relation with Deutsche Boerse which is the representative of developed capital market from the same geographical area. The description of recent development on these capital markets will follow.

3.1 Emerging European Stock Markets - CEE Region

CEE countries represent the potential benefits for international investors to diversify their portfolios (Gilmore *et al.* (2008)). Countries such as the Czech Republic, Hungary, and Poland are well known for its moderate correlations and relatively high returns and within the access to European Union their predictions develop in the view of political and economical stability. The accession to the EU, tighter trade and economic linkages of the CEE markets with more developed markets in Western Europe may on the other hand decrease the potential benefits for international portfolio diversification. Table 3.1 shows the development of market capitalisation, its share on the gross domestic product (GDP) as well as proportions of foreign issues.

The stock markets in CEE region stand on long-term steady fundamentals and are well established. Despite the recent financial crisis in the years 2007 and 2008 which slowed the economic growth down and thrilled the situation

Table 3.1: Market Capitalisation with Share of Foreign issues on CEE Stock Markets

Year	Budapest			Prague			Warsaw		
	Total Equity MC (bn. HUF)	Foreign Issues (%)	MC to GDP Ratio (%)	Total Equity MC (bn. CZK)	Foreign Issues (%)	MC to GDP Ratio (%)	Total Equity MC (mil. PLN)	Foreign Issues (%)	MC to GDP Ratio (%)
1990	16	0.0	0.5	-	-	-	-	-	-
1991	38	0.0	1.5	-	-	-	161	0	0.2
1992	47	0.0	1.6	-	-	-	351	0	0.3
1993	82	0.0	2.3	-	-	-	5 845	0	0.4
1994	182	0.0	4.2	353	0.0	29.5	7 450	0	0.3
1995	328	0.0	6.0	479	0.0	32.6	11 271	0	3.3
1996	853	1.8	12.9	539	0.0	32.0	24 000	0	5.7
1997	3 058	0.3	36.6	496	0.0	27.4	43 766	0	8.5
1998	3 020	0.3	29.9	416	0.0	20.8	72 442	0	12.1
1999	4 145	0.3	36.1	480	0.0	23.0	123 411	0	18.5
2000	3 394	0.9	28.3	443	0.0	20.2	130 085	0	17.5
2001	2 849	0.5	19.4	340	0.0	14.5	103 370	0	13.3
2002	2 947	0.2	19.5	478	25.1	19.4	110 565	0	13.7
2003	3 470	0.4	18.8	645	29.6	25.0	140 001	16.5	16.6
2004	5 130	0.3	26.1	976	32.3	34.7	214 313	26.5	23.2
2005	6 972	0.2	31.7	1 331	32.3	44.6	308 418	27.4	31.4
2006	7 995	0.2	33.6	1 592	40.1	49.4	437 719	31.2	41.3
2007	8 239	3.1	32.4	1 842	30.7	52.1	509 887	52.8	43.3
2008	3 554	0.7	13.0	1 092	27.8	29.6	267 359	42.5	21.0
2009	5 713	1.0	21.0	1 294	36.2	35.7	421 178	41.2	31.4
2010	5 816	1.2	21.8	1 388	42.0	37.8	542 646	31.9	38.3

Source: BSE, PSE, WSE, www.czso.cz, www.stat.gov.pl, Egert & Kocenda (2007). HUF=Hungarian forint, CZK=Czech koruna, PLN=Polish zloty, MC=market capitalisation

on the stock markets in CEE region and elsewhere, the overall atmosphere on these stock markets enhanced considerably in 2010. These development of CEE stock markets is supported by the Table 3.1. We can see here the share of stock market capitalisation to GDP in three CEE countries over last twenty years and the markable slump in the "crisis" year 2008. However, the overall development of the CEE stock markets was different for each country.

Warsaw stock exchange has become the strongest of the CEE stock exchanges. Due to successful privatisation via IPO in 1990s, Polish stock market gained confidence of many investors. Also the large population of Poland predetermines the IPO activity on Polish market to be significantly higher compared to other CEE stock markets. Polish stock markets is attractive for IPOs even nowadays. In the year 2009 when Warsaw stock exchange already demonstrated recovery and WSE indices turned to grow slowly again, the launch of IPOs stagnated in Poland. On the other hand Polish market with 13 IPOs on the regulated markets has turned to be the most successful from all European markets in number of IPO launch and the third most successful in terms of value of the offerings.

The share of market capitalisaton in Poland in time of reopening in 1991 was 0,2 % of GDP. Such a small share continued untill 1998 when it first beated the 10 % share level. The increase of a share in 1999 to 18,5 % was followed by the decrease by percentage points in the years 2000 - 2002. In 2003, the share began to grow again and the trend continued until the year 2007 when it reached the highest percentage on GDP of 43,3 %. The crisis years 2008 and 2009 registered the fall of the share on GDP to 21 % and 31,4 %, respectively. The market capitalisation share is slighly lower than before crisis period but still keeps a considerable level. Currently almost one third of the issues are foreign.

Both Prague stock exchange and Budapest stock exchange together with Ljubljana and Vienna stock exchange are the members of the CEE Stock Exchange Group (CEESEG), which entered the market in September 2009. So far, there has not been created the unified trading platform among all members of this group, however the plans for implementing common trading platform exist as a medium-term target[1]. The following Figure 3.1 shows the structure of international investor of the CEE Stock Exchange Group. The investor are mainly institutional; 30 % is from USA, 16 % from UK followed by 11 % from

[1]The common trading platform is called XETRA and was implemented so far only on Vienna and Ljubljana stock exchange.

Austria, 8 % Germany, 5 % France and also 3 % are from Poland and 2 % from the Czech Republic[2].

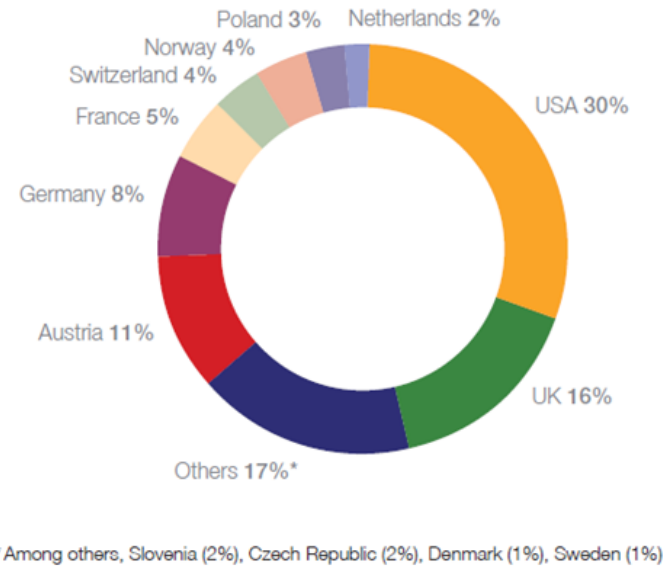

Figure 3.1: Investor's Structure of CEE Stock Exchange Group (2010)
Source: CEESEG Annul Report 2010, available at www.ceeseg.com

Since December 2010, the trading hours of Budapest stock exchange were prolonged until 5:10 pm to be able to trade in line with the U.S. market. With the extension of trading hours, it was indended to attract more investors and hence increase liquidity caused by higher trading opportunities. However, Hungarian stock market has nowadays suffered from the elections at the beginning of 2010, uncertain and doubtful tax system approved by government. The market capitalisation increased at the beginning of 2010 mainly because of IPO increase, listing of 6 new companies and higher prices on the stock market but fell to the level of the previous year due to domestic currency depreciation.

Budapest stock exchange was re-opened one year before Warsaw stock exchange with the share of 0,5 % on the total GDP. The level of 10 % share was overcome in 1996 when it was 12,9 %. In 1997, the share grew substantially - almost three times as much - when it reached the level of 36,6 %, decreased. This increase may have been caused by launching a new trading system[3] on the stock exchange in 1996 and by coming of recently privatized companies to market. The year 1998 registered the fall below 30 % level of share but in 1999

[2]Information is provided by financial information provider lpreo and taken from the Annual Report 2010 of Prague Stock Exchange.
[3]Multi-Market Trading System (MMTS)

increased again to a share of 36,1 %. The following period 2000 - 2003 there was a decreasing trend and again in 2004, the share of market capitalisation again rose to 26,1 %. In years 2005 - 2007 the share beated the level of 30 % up to 33,6 % in 2006 but it does not reach the level as in 1997 and 1999. There was a significant fall of a share to 13 % in the "crisis" year 2008 which was one third compared to the previous year's share. The years 2009 and 2010 show a slight increase of a share to 21 % which is the lowest share in this years compared to the Polish and Czech stock markets. The foreign issues create along to all mentioned period tiny part that does not reach the level of 3,1 % in 2007.

Prague Stock Exchange exhibitted poorly in 2009 due to economic imbalances and overall still-lasting uncertainty on the world capital markets. This was the right situation for entering the alliance with other European stock exchange, CEESEG. The important step took place already on December 8th, 2008 when Wiener Boerse AG has become the majority shareholder with overtaking a 92,739 % share in the Exchange's capital. The primary goal was to be able to compete the more developed world capital markets and become more attractive for new potential investors. The year 2010 already showed typical signs of the recovery period.

The ratio of market capitalisation to GDP in the Czech Republic after the reopening[4] in 1994 was 29,5 %. Such high percentage was caused mainly by large wave of privatization that took place in the Czech Republic. This event followed by the delisting of companies in 1997 and was the main reason for the fall of a share to GDP to 20,8 % in 1998. The period of unstability during 1999 - 2003 followed by perceptible share increase to 34,7 % in 2004. Due to IPOs of large companies in the following year 2005 - 2007[5] which peaked at the level of 52,1 % in 2007. Due to the unfavourable economic situation on the world stock markets, some of the IPOs were postponed, which would cause even higher growth of a market capitalisation share on GDP. These favourable conditions were replaced by "crisis" period 2008 - 2009 when there was a 29,6 % and 35,7 % share on GDP, respectively. In 2010, the situation is expected to be stabilizing and the share is 37,8 %. The foreign issues have increasing

[4]The market was closed after the II World War, hence there was no capital markets in the Czech Republic for nearly 50 years.

[5]For instance, the shares of Orco and Central EuropeanMedia Enterprises Ltd. in 2005, Pegas Nonwovens SA and Erste Bank in 2006 and AAA Auto Group N.V. with VGP NV have been listed in 2007.

trend on the Czech stock market and they currently represent two fifths of the overall issues.

3.2 German Stock Market

Deutsche Boerse on the opposite side from the above mentioned stock markets belongs to one of the most developed stock markets in Europe. Deutsche Boerse exploits mainly from its position to be the worldwide industry's technology leader in the degree of eleboration of trading, clearing and settlement systems. Despite the year 2010 presented some good results compared to the previous "crisis" years, both the share price and market capitalisation fell, the share price by 11 % and market capitalisation from 10,8 billion EUR to 9,6 billion EUR. However, Germany has just overtaken the UK as the most attractive investment destination according to European Investor Intentions Survey, 2011[6]. The situation was best described by Reto Francioni, Chief Executive Officer, as "*optimism and recovery on one side but still lasting uncertainty on the other side*".

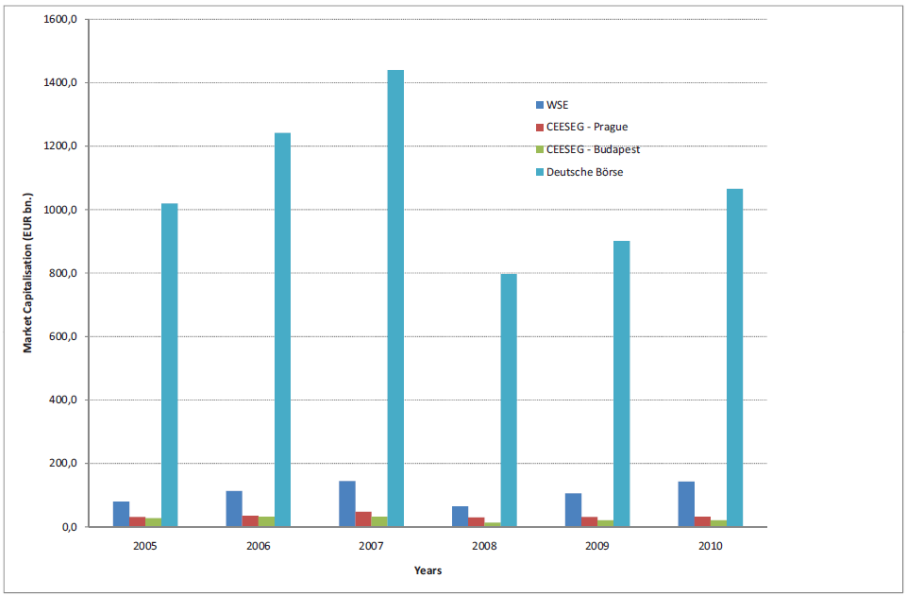

Figure 3.2: Market Capitalisation 2005 - 2010 (EUR bn.)
Source: FESE Statistics 2011, available at www.fese.be

Germany presents concededly the leader economy in terms of Europe and European Union. For our analysis, Deutsche Boerse deserves to be included

[6]available online at http://www.ecpm.cz/cz/clanky/3203-european-investor-intentions-in-2011

because we might find apparently some interdependencies and comovements of CEE markets along with Deutsche Boerse because of their close geographical location and because of no time change. For better visual comparison, the Figures 3.2 and 3.3 show the market capitalisation and the market capitalisation to GDP ratio of all markets under consideration, respectively.

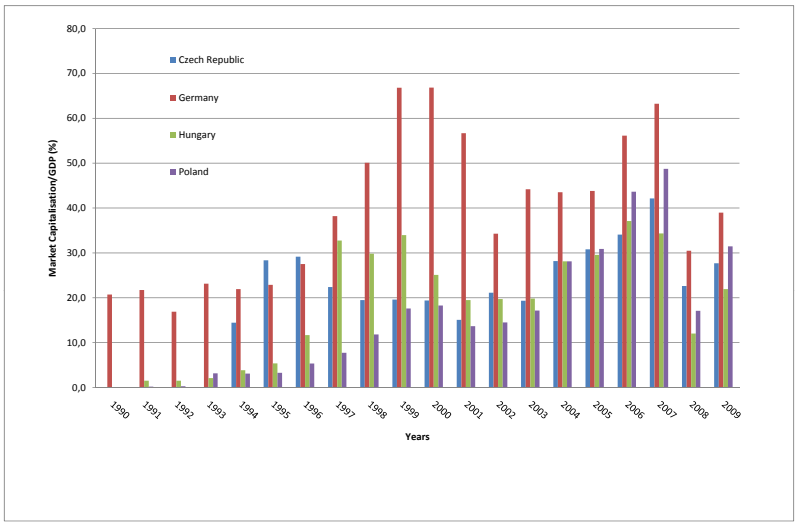

Figure 3.3: Market Capitalisation to GDP Ratio (1990 - 2009)
Source: World Bank 2011, available at data.worldbank.org

As we introduced the situation on the capital markets included the study, we will continue to present the tests used in the analysis in the following chapter 4.

Chapter 4

Methodology

There are different ways how to measure interrelationships between capital markets. Numerous papers investigated interdependence and comovements between particular capital markets by different models using correlation coefficients, Granger causality test, coitegration test, VECM[1], VAR estimations. We also adopt standard methodology of these models for several reasons: the up-to-date data (including the year 2010) have been tested using these models only rarely yet (what we know so far), thus we will try to fill this gap. Moreover, it will be comparable to the results of already existing literature.

4.1 Unit Root and Stationarity Tests

We will apply at first the unit root tests to all time series of capital market indices under this study. Augmented Dickey-Fuller (ADF) test (Dickey & Fuller (1979)), Phillips-Perron (PP) test (Phillips & Perron (1986)) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski *et al.* (1991)) will be used. The standard errors in the ADF test are based on the OLS method[2]. In the PP test, errors are based on the correction to OLS standard errors, so the problem of autocorrelation as well as heteroskedasticity is corrected. However, according to Al-Fayoumi *et al.* (2009) ADF and PP tests are generally known for their low power, thus conducting KPSS test is recommended to support the results.

The difference between tests is also discussed by Aggarwal & Kyaw (2005). He mentions that KPSS is very useful to supplement the ADF and PP tests.

[1] Vector Error Correction Model
[2] ordinary least squares method

ADF and PP have potential problem when the null hypothesis states that there exist a unit root. If we test the null hypothesis of non-stationary time series, the strong evidence against the null must be found to be able to reject it. But these alternatives are also close to being I(1), hence unit root tests are not able to discern between highly persistent stationary processes and nonstationary processes properly. Furthermore, if we include deterministic term as trend into test regression, the power of unit root test weakens[3]. On the opposite side, there is KPSS test with null hypothesis of stationary series. The formal explanation of KPSS test stands on that it is the Lagrange multiplier test of hypothesis that the random walk has a zero variance (Kwiatkowski *et al.* (1991)).

In case of ADF and PP tests we test the hypotheses

H_0 : unit root is present

H_A : no unit root in the data series

But in case of KPSS the null hypothesis is that the time series are stationary. Based on these tests, we will conclude whether market indices are stationary or whether they are stationary in their first differences. In addition, we show the time series in their second differences to see their behaviour.

4.2 Testing Correlation Coefficients

Based on the test of correlation coefficients, we would like to discover whether the comovements are driven by eiher interdependence or cotagion between markets. Inspired by the theory of Jokipii & Lucey (2007) we will test the null hypothesis of H_0 of no presence of contagion, only interdependence against the alternative hypothesis H_A about the presence of contagion influencing comovements between markets.

All test will be run on the VAR residuals. According to Jokipii & Lucey (2007), the great advantage of using VAR residuals is the avoidance of simultaneity bias problems. Moreover, VAR can reveal a serial correlation in stock market returns and any form of exogenous global shocks. We define the tranquil and crisis period. The standard VAR model keeps the form

$$A(L)x_t + By_t = u_t \tag{4.1}$$

with

[3]This thought is taken from the lecture notes of Barry Falk, Iowa State University, available at http://www2.econ.iastate.edu/classes/econ674/falk/

$A(L) = 1 - A_1L - A_2L^2 - ... - A_pL^p$
$Eu_t = 0$
$E(u_t, u_t^{'}) = \Sigma$
$E(u_t, u_s^{'}) = 0 fort \gneqq s$
$E(x_t, u_t) = 0$
and
$y_t = Const$

where A is a $(N \times N)$ matrix of coefficients, L stands for the lag operator, x_t is a $(1 \times N)$ vector of daily changes of the capital market indices in the Czech Republic (CZ_t), Hungary (HU_t), Poland (PL_t), France (FR_t), Germany (GE_t), Great Britain (GB_t) and u_t represents a $(N \times 1)$ vector of white noise disturbance terms. Following both the Schwarz and Hannan/Quinn information criteria, we estimate the VARs with AR(2)[4].

After getting the results of correlations, we employ a two-sample t-test to inspect whether there are significantly higher correlations appeared in the crisis period. Let $\rho_{i,j}^t$ be the correlation coefficient between country i and country j over the period t. Then we test the hypotheses
$H_0 : \rho_{i,j}^{tranquil} \geq \rho_{i,j}^{crisis}$
$H_A : \rho_{i,j}^{tranquil} < \rho_{i,j}^{crisis}$

We will use a Fisher transformation in order to make the correlation coefficients approximately normally distributed with mean μ_t and variance σ_t^2 equaled to

$$\mu_t = \frac{1}{2} ln \left[\frac{1 + \rho_{i,j}^t}{1 - \rho_{i,j}^t} \right] \tag{4.2}$$

and

$$\sigma_t^2 = \frac{1}{n_t - 3} \tag{4.3}$$

The test statistics take the following form

$$U = \frac{\bar{X}_{tranquil} - \bar{X}_{crisis}}{(\frac{S_{tranquil}^2}{n_{tranquil}} + \frac{S_{crisis}^2}{n_{crisis}})^{\frac{1}{2}}} \tag{4.4}$$

where X_t and S_t^2 are the estimated sample mean and variance following the Fisher transformation. The test statistics will follow t-distribution. The degrees of freedom are computed as

[4] AR(2) stands for autoregressive order of two.

$$\frac{(S^2_{tranquil}/n_{tranquil} + S^2_{crisis}/n_{crisis})^2}{\frac{(S^2_{tranquil}/n_{tranquil})^2}{n_{tranquil}-1} + \frac{(S^2_{crisis}/n_{crisis})^2}{n_{crisis}-1}} \tag{4.5}$$

The critical values of the t-test at one per cent level is 2.336 for degrees of freedom equaled to 437 and 2.331 for degrees of freedom equaled to 42794.79[5]. Any statistic greater than the critical values 2.221 and 2.336 for daily data and 5 minute frequency data with overnight returns, respectively, will indicate contagion (C) and any statistic less than critical values will signalize no contagion (N)[6].

4.3 Granger Causality Test

According to Granger (1969), the cross-spectral methods enable a skillful analysis of the relationship between two (or more) variables when one causes the other(s). Compared to basic correlation tool, Granger causality test can discover the causality between correlated variables Horobet & Lupu (2009). The model is defined as follows (Granger (1969)).

Definition 4.1 (Definition). Let x_t and y_t be two stationary time series with zero means. The simple causal model is

$$x_t = \sum_{j=1}^{m} \alpha_j x_{t-j} + \sum_{j=1}^{m} \beta_j y_{t-j} + \varepsilon_t \tag{4.6}$$

$$y_t = \sum_{j=1}^{m} \gamma_j x_{t-j} + \sum_{j=1}^{m} \delta_j y_{t-j} + \eta_t \tag{4.7}$$

where ε_t, η_t are taken to be two uncorrelated white-noise series, i. e. $E[\eta_t \eta_s] = E[\varepsilon_t \varepsilon_s] = 0$, $s \neq t$, and $E[\varepsilon_t \varepsilon_s] = 0$ for all s, t

There may be m equal to infinity in the system of equations but in practice (and due to the finite length of the available data), m appears to be a finite

[5]The number 437 is the lowest number of degrees of freedom computed for daily data and 42794.79 is the highest number counted for 5 minute frequency data including overnight returns.

[6]We mention here the critical values only for daily and 5 minute frequency data with overnight returns. Time series of other data frequencies used in the analysis were of the critical values in the interval between 2.331 and 2.336, so we do not present them here. As will be shown later, the values of statistics were either markedly higher or lower than the computed critical values, so we could easily decide whether to reject null hypothesis about no contagion.

number and shorter than the given time series. Based on this model, we want to find out whether to reject the null hypothesis of no causality. Rejection would lead to the idea that the capital market indices are not integrated. By other words, we can say that y_t causes x_t with some β_j significantly different from zero (Equation 4.6) or x_t causes y_t if some γ_j is significantly different from zero (Equation 4.7). Thus if we reject the null hypothesis, there are information flows from y_t to x_t at some level of significance and vice versa.

4.4 Cointegration Test

Cointegration test will help us to discover whether stock market indices are cointegrated, i.e. if any evidence of any long-run relationship appears between indices (Al-Fayoumi *et al.* (2009)). Cointegration in another words can mean that there is a common trend between stock market indices and moreover, that either a unidirectional or bidirectional causalities between indices are found (in Granger sense). Let us define cointegration.

Definition 4.2 (Definition). An $(n \times 1)$ vector time series x_t is said to be cointegrated if each of the series taken individually is $I(1)$, that is, nonstationary with a unit root or integrated of order one, while some linear combination $\beta' x_t$ is stationary, or $I(0)$, for some non-zero $(n \times 1)$ vector β. Such vector is said to be the cointegration vector. (Hamilton (1994))

Gregory *et al.* (2004) classify cointegration tests into categories of either single-equation residual-based tests or system-based tests. The augmented Dickey-Fuller test proposed by Engle & Granger (1987) belongs to the first category and Johansen test suggested in Johansen (1988), Johansen (1991) and Johansen (1995) represents the system-based category. The utility of using particular cointegration tests depends on the purpose of the research and data character. If we want to discover the particular relation, the single-equation approach is more likely to be used but for multivariate population, system-based approach seems to be more satisfactory. However, many papers do present the results for both approaches to allow reader to see the result (dis)similarities.

We will apply the cointegration techniques proposed by Engle & Granger (1987) that is residual-based cointegration method and by Johansen (1988) which is considered as an efficient instrument for testing the number of cointegrating vectors in a VAR framework (Egert & Kocenda (2007)).

4.4.1 Engle-Granger Cointegration Test

The Engle-Granger cointegration test is able to identify the pairwise cointegration relationships between variables. Variables must not satisfy the conditions of stationarity; if their differencing at the same differencing level is found to be stationary (so they have the same integration order), there can be detected the cointegration relationships. Once the pairwise coitegration relationships are identified, there can be constructed cointegration equations and based on them, there can be furthermore found the causal linkages between variables via cointegration models. Engle-Granger model is held in two steps. We will interpret the model according to Fu & Liu (2010). At first, regression equations are formulated as

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{4.8}$$

$$y_t = \beta_0 + \chi t + \beta_1 x_t + \varepsilon_t \tag{4.9}$$

for $t = 1, 2, 3, ..., n$ where n is the dimension of vector variable; x_t and y_t are two time series, the coefficient β_0 is a non-zero deflection, β_1 is the coefficient of time series x_t, ε_t denotes the series of disturbances and χt express a deterministic time trend.

These equations state two sorts of Engle-Granger cointegration test: one is without deterministic time trend represented by Equation 4.8) and second one involves the deterministic time trend (Equation 4.9).

The corresponding residual time series is computed as follows

$$e_t = y_t - (\hat{\beta}_0 + \hat{\beta}_1 x_t) \tag{4.10}$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ stand for the estimations of coefficients β_0 and β_1, respectively.

In the second step, there will be tested whether series of residuals are stationary. For $t = 1, 2, 3, ..., n$ where n is the dimension of vector variable, the equations are denoted as follows:

$$\Delta e_t = \gamma e_{t-1} + \sum_{i=1}^{m} \lambda_i \Delta e_{t-i} + \varepsilon_t \tag{4.11}$$

$$\Delta e_t = \alpha + \gamma e_{t-1} + \sum_{i=1}^{m} \lambda_i \Delta e_{t-i} + \varepsilon_t \tag{4.12}$$

$$\Delta e_t = \alpha + \delta t + \gamma e_{t-1} + \sum_{i=1}^{m} \lambda_i \Delta e_{t-i} + \varepsilon_t \tag{4.13}$$

where Δe_t stands for the first difference of series of residuals from the equation (7), e_{t-i} is the i-th lagged term of residual e_t, ε_t denotes the generated series of residuals of the equation for stationarity test, α stands here for a non-zero deviation, δt denotes a deterministic time trend.

If series of residuals are tested for its stationarity applying the unit root test on e_t and regression equation is also the cointegration regression equation, then the pairwise cointegration relationhips are indicated. On the other side, no pairwise cointegration relationships are between the pairs of variables if the series of residuals are detected to be non-stationary. In such cases the regression equations are apocryphal.

To summarize this method, the variables x_t and y_t are supposed to be cointegrated if the series of residuals e_t are stationary (if not, there is no cointegration relationship between the variables x_t and y_t).

Error correction estimations This model does not have to detect the equilibrium relationships. The pairwise cointegration relationships can occur among pairs of variables, but these relationships do not neccesarily last forever because they might be found in the short-term disequilibrium. This was a motive to develop methodology that keeps the relationships among variables in the long-term sustainable equilibrium. Engle & Granger (1987) show that if two nonstationary variables are cointegrated, an error correction term should be then included in the model testing the time series in their first differences. Hence error correction model have arisen to be implemented and to show the causality among pairs of variables.

The model consists of following equations. For $t = 1, 2, 3, ..., n$ where n is the dimension of vector variable is stated

$$\Delta y_t = \alpha_0 \Delta x_t + \phi ECM_{t-1} + \mu_t \tag{4.14}$$

$$ECM_{t-1} = y_{t-1} - \beta_0 - \beta_1 x_{t-1} \tag{4.15}$$

where Δy_t denotes the time series of the first differences derived from the time series y_t and Δx_t stands for the time series of the first differences derived from x_t. Both y_t and x_t are meant to be integrated of order one $I(1)$ which

implies that they are both integrated $I(1)$ at the first differences as well. α_0 stands for short-term elasticity, ϕ shows the speed of adjusting back to equilibrium status, μ_t is the residual of ECM with ECM_{t-1} being the error correction term. In the Equation 4.15, β_0 is the constant and β_1 denotes the long-term elasticity. Hence computing ECM_{t-1} and residual value of the cointegration regression equation will be derived from this system of equations.

The known limitation of Engle-Granger cointegration test stands on the fact that the variables must be integrated of the same order[7]. If the order of integration is different, the variables cannot be cointegrated right away from the definition. However, if one time series is integrated of the first order and second time series is integrated of the second order and there is found the linear combination of these time series integrated of order one, such linear combination can be cointegrated with another time series integrated of order one. Another potential disadvantage of Engle-Granger test refers to the fact that the test assumes only one unique cointegrating vector (Committee (2003)). Thus if there are more variables, there may occur more than one cointegrating vector. And in such case, the results lose their power. Johansen cointegration test brings the enhancement from this point of view when it formally stand on the multivariate extension of ADF test.

4.4.2 Johansen Cointegration Test

Model of Johansen (1988) will take place here. According to Wassell & Saunders (2008), Johansen test has the advantageous property compared to Engle-Granger test that all test variables are treated as endogenous variables. The description of the methodology is taken from Baxa (2007). The set of variables $\beta' x_t$ which are integrated of order one $I(1)$ will be presented here in VAR(p) framework[8]. Assume

$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + ... + A_p x_{t-p} + \varepsilon_t \tag{4.16}$$

This VAR(p) model (Equation 4.16) in the VECM term is expressed by following equation

$$\Delta x_t = \Pi x_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-1} + \varepsilon_t \tag{4.17}$$

[7]In other words, cointegration is a linear combination of non-stationary time series.
[8]There is described the derivation of VAR(p) process in more details in the Appendix A.

where
$\Pi = \sum_{i=1}^{p} A_i - I$
and
$\Gamma_i = -\sum_{j=i+1}^{p} A_j$

If the rank of cofficients matrix Π is lower than n ($r < n$), then there exist matrices α and β that are $n \times r$ with ranks r such that it holds $\Pi = \alpha\beta'$ and $\beta' x_t$ is integrated of order zero ($I(0)$). r denotes the number of cointegration relations in the model and the matrix β stands for a matrix of cointegrating vectors[9].

Hence Johansen (1988) proposed the method that diagnoses the existence and structure of cointegrating relations. In other words, this method recognizes how many eigenvalues has the matrix Π[10].

There are two tests calculated simultaneously: the trace test and the λ_{max} test. These tests should optimally provide consistent results.

The trace test is based on the following hypotheses
H_0 : no cointegrated equations
H_A : there is at least one cointegrating relation
The test statistics for these hypotheses is

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{4.18}$$

where $\hat{\lambda}$ denotes the estimated eigenvalues derived from estimated Π matrix, T is the number of observations. Thus in the situation when $rank(\Pi) = 0$, no cointegration is detected, all eigenvalues are equal to zero and the test statistic λ_{trace} has zero value as well.

The λ_{max} test is based on the hypotheses
H_0 : there is r cointegrating equations
H_A : there is r+1 cointegrating equations
with the test statistics

$$\lambda_{max}(r, r+1) = -Tln(1 - \hat{\lambda_{r+1}}) \tag{4.19}$$

As Baxa (2007) mentions, critical values are not compared to χ^2 distribu-

[9]It also holds: if $rank(\Pi) = 0$, then VECM relation and VAR(p) are identical and the matrix is null; if $rank(\Pi) = n$ holds vice versa, then VAR(p) is stationary and the number of cointegrating relations is r in all other cases.

[10]The number of eigenvalues is equal to the rank of matrix.

tion; they were gained using Monte Carlo simulations. Econometric softwares usually have these values already incorporated.

We introduced here Engle-Granger and Johansen cointegration tests. However, it is necessary to mention that the wave of new forms of cointegration tests has revealed lately. For instance, Bayer & Hanck (2008) developed new meta test compiled from Engle & Granger (1987) and Johansen (1988) cointegration tests which already avoids the decision which test to use due to conflicting results. We will keep these two traditional forms of cointegration test to be able to compare results with previous papers.

Chapter 5

Data Description

The previous chapter introduced all tests and their hypotheses that will be used on the data of capital markets from CEE region and Germany. The main aim is to include the intraday data to find out how fast these capital markets react to each other. However, intraday data are highly sensitive to any distortions. We will attempt to describe here how we treated the intraday datasets.

All tests will be conducted on the intraday data of frequencies 5 minutes, 30 minutes, 1 hour; daily data will be also used for the analysis. We involve the following stock market indices from the stock exchanges mentioned in the parentheses: DAX (Frankfurt), BUX (Budapest), PX (Prague) and WIG20 (Warsaw). The datasets cover the period from the beginning of January 2008 to the end of November 2010. Due to high correlations between these stock indices, it is not necessary to convert stock indices into the same currency. Therefore data are held for the analysis in their national currencies. These stock markets are from the same geographical location, hence no time difference between markets is present (all markets under consideration are from the area of GMT+1:00) and the analysis should not suffer from the overlapping problems due to different trading hours. We perceive that as a potential benefit.

We show at first how the data were synchronized. Each pair of time series from a group of the same data frequency was aligned within each other in order to obtain both observations of time series in the corresponding date and time. The intraday time spans for high frequency time series are in the following Table 5.1.

Table 5.1: Intraday Data Periods

	Start	End
5min Data Frequency		
DAX	9:05	17:36
BUX	9:05	16:30
PX	9:32	16:00
WIG20	9:35	16:10
30min Data Frequency		
DAX	9:30	17:30
BUX	9:30	16:30
PX	9:57	16:00
WIG20	10:00	16:10
1hour Data Frequency		
DAX	10:00	17:30/17:36
BUX	10:00	16:30
PX	10:27	16:00
WIG20	10:30	16:10

In case of 5 minute data frequency, DAX index goes every 5 minutes since 9:05 to 17:35 and it ends by the observation at 17:36. To correct this, we erased the last clock state to have a real 5 minute frequency. In case of PX in 5 minute frequency, the data are clock stated 9:32 - 15:57 reqularly and the last observation is at 16:00. To enable comparison to other indices, we aligned 9:32 - 15:57 to 9:30 - 15:55 and remained the last observation at 16:00 in the time series.

In 30 minute data frequency, DAX kept regular frequency since 9:30 to 17:30 for the years 2008 and 2009 and added last observation at 17:36 since the beginning of 2010. We made the alignment in form of erasing the last clock state at 17:36. In case of PX, it is recorded regularly since 9:57 to 15:57 and the last observation is at 16:00. We aligned 9:57 - 15:57 to 10:00 - 16:00 and erased the last observation at 16:00. WIG20 has a regular 30 minute frequency time series since 10:00 to 16:00 and the last observation is at 16:10. This last observation was erased to align it with the other series.

1 hour data frequency time series also needed some adjustments. DAX kept regular frequency since 10:00 to 17:00 and the last two observations were at 17:30 and 17:36. In this case, these last two observations were erased. In case of PX, it goes regularly since 10:27 to 15:27 and the last observation is at 16:00. We aligned 10:27 - 15:27 to 10:00 - 15:00 and left the last observation in the analysis. BUX index went regularly 10:00 - 16:00 and last observation was at 16:30. To be able to compare to other time series, we erased observation at 16:30. In case of WIG20, the regular frequency went in the intraday period 10:30 - 15:30 and the last observation was at 16:10. We aligned 10:30 - 15:30 to 10:00 - 15:00 and changed the clock state in case of last observation from 16:10 to 16:00. Then the comparison was enabled.

After above mentioned adjustments, the dates which may distort the result

were inspected. Such dates are especially holidays when the trading on the stock markets has shorter intraday period and thus the illiquidity of such dates could cause deviation of statistics. After such inspection, we erased the date December 30th, 2008 and 2009 in case of DAX and December 31th, 2008 and 2009 in case of BUX and WIG20.

We had to overcome another potential problems. As we test the data covering the crisis periods (the year 2008 in our case), we do not include data frequency higher than 5 minutes. We decided to omit such data from the analysis because this data are very problematic especially in the year 2008; some observations are missing for days when the data record malfunctioned due to capital market crashes. Frequencies higher than 5 minutes exhibit microstructure noise in such situations and computing any statistics leads to misleading results. 5 minute data frequency seemed to serve as a sufficient frequency inquiring the intraday comovements.

The next already observed obstacle mentioned for instance in Egert & Kocenda (2007) and Barunik *et al.* (2010) is addressed to the absolute returns and volatility. If we compute squared returns of stock price developments, it expresses the U-shape during one observed day in both developed and emerging markets due to different news announcement during the day. It causes that values start on higher level at the beginning of the day when the news are frequent on all markets, then it gradually decreases afterwards and it increases again at the end of the day.

To present this behaviour on our data, we computed average squared returns and show them in the Figure 5.1. We have got clear U-shape for all indices; the strongest U-shape expressed the BUX and WIG20 indices and PX with DAX show these patterns more weakly. There is apparent that Deutsche Boerse as stroger, more developed capital market does not fluctuate during the day as much as emerging CEE capital markets. All indices perform a huge amplitude around 14:40. That is slighly after 14:30 when USA publish their macroeconomic announcement which definitely has a great impact on these markets and on markets all around the world. As mentioned before, CEE stock markets usually open on a higher price compared to the closing price of the day before. The explanation of the overnight price increase is that the other world capital markets including the U.S. market trade a long time after the markets in Europe are already closed. Hence many overnight information are gathered during a night and it is reflected in this price increase.

In order to prevent the results from possible data distortions by above men-

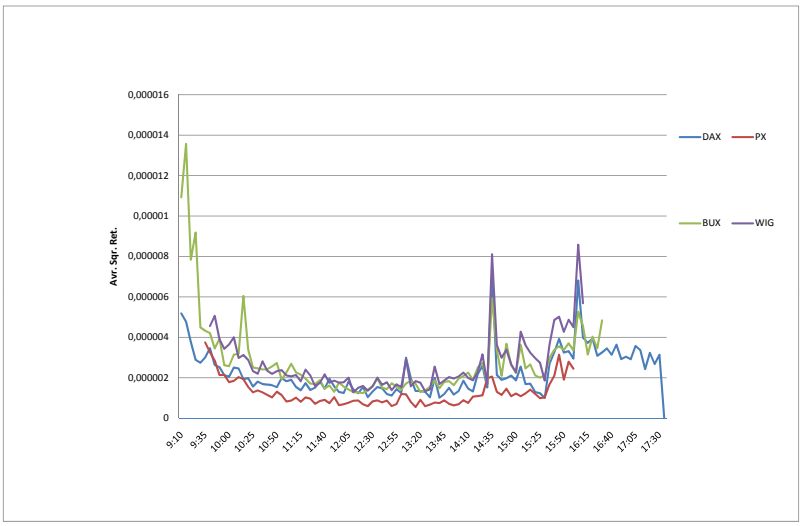

Figure 5.1: Average Squared Returns
Source: Author's Computations

tioned problems, we will use the daily returns and daily logarhitmic differences (its formulas follow in the next paragraph) which are computed for each trading day separately, by other words where each trading day forms separate subset. In case of 5 minute frequency data, we will use three different dataset to be able to inspect whether there are any distortions in results: at first, we use returns and differences of all data included the overnight records for returns and differences (such dataset holds the label "*5 min all*"), secondly we use only daily returns and differences (such data are labeled by "*5 min daily*") and the third dataset will cover only daily returns and differences which are taken from the beginning of the day until 14:40 when all markets under consideration are affected by US macroeconomic announcement (results for this dataset labeled by "*5 min 14:40*").

For the purpose of the tests inspected in this thesis, we use two types of data adjustment: for analysis of interdependence vs. Contagion, we will use stock market returns (RET_t). The returns will be computed as the ratio of the closing price in time t (P_t) substracted by closing price in time $t-1$ (P_{t-1}) to closing price in time $t-1$ (P_{t-1}):

$$RET_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{5.1}$$

In case of the other tests used in analysis (Granger causality test, Engle-Granger cointegration test, Johansen cointegration test) we will include the first differences of logarithms (ΔR_t). They will be computed as relative difference in logarithms where P_t is the closing price in time t and P_{t-1} is the closing price in time $t-1$.

$$\Delta R_t = ln(\frac{P_t}{P_{t-1}}) \tag{5.2}$$

The thesis primarily focus on how comovements and interactions between markets change over time, especially with respect to the recent mortgage crisis in 2008. Using intraday data helps furthermore to disclose properly reactions to structural turmoil. The examined period covers both crisis and tranquil periods and the comparison of results from both periods should provide interesting features about how interrelationships change considering the character of period.

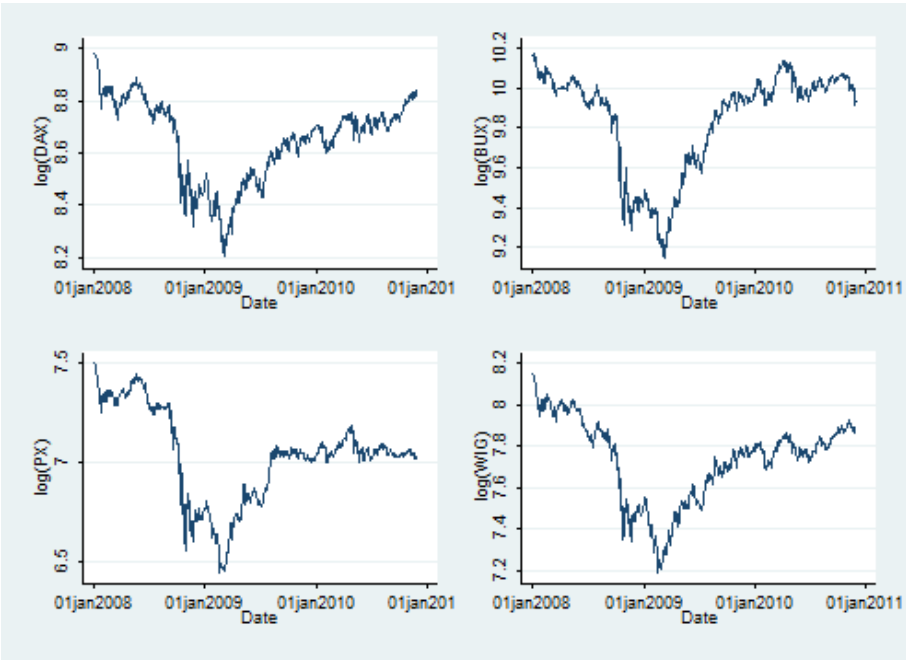

Figure 5.2: Development of Stock Indices in Logs (January 2008 - November 2010)

Source: Author's Computations

As we want to discover whether some changes in results appear across different periods, we need to divide the total period into two "subperiods" presenting

the "crisis" and "tranquil" times in order to acquire two periods of a different character. We demonstrate the price index developments in the Figure 5.2. The development of stock indices in their logarhitmic levels shows the point where the stock indices hitted their bottom levels. DAX reached its lowest index price on March 6th, 2009, PX on Febuary 18th, 2009, BUX on March 12th, 2009 and WIG20 on Febuary 18th, 2009. BUX index was the latest in order that fell to the lowest level on March 12th, 2009. According to these developments, we decided to divide the periods into crisis period from the beginning of January 2008 to March 12th, 2009 and tranquil period covering the period of March 13th, 2009 - November 30th, 2010.

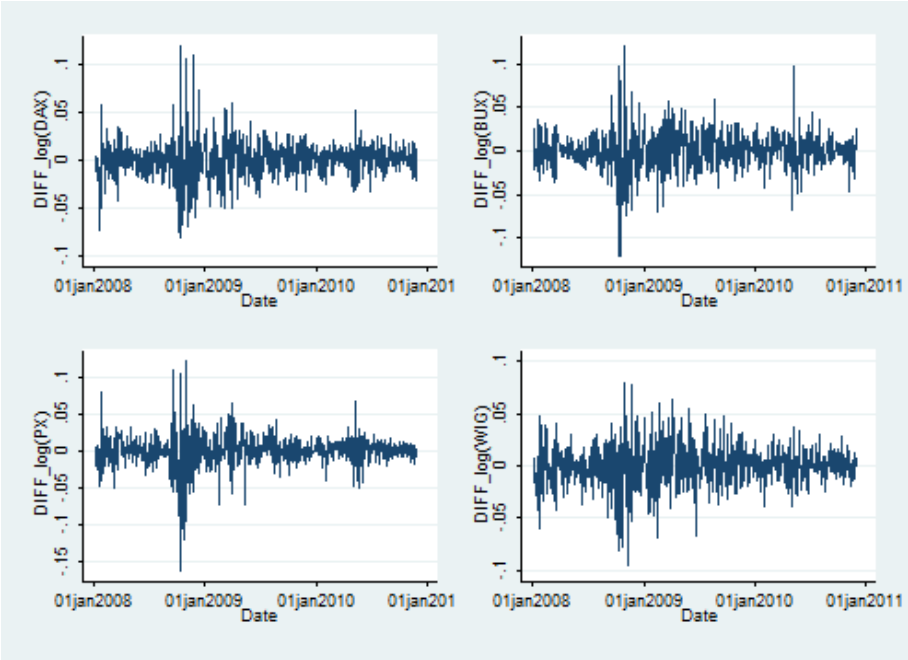

Figure 5.3: Development of Stock Indices in First Differences (January 2008 - November 2010)
Source: Author's Computations

Logarhitmic differences are visible on the Figure 5.3. They are more volatile in crisis period than in tranquil period. The greatest amplitudes are around October 2008. The differences are visibly lowest for logarhitmic level of PX which may indicate that PX index development was relatively stable despite crisis period.

Summary statistics for all prices and all frequencies are depicted in the Tables 5.2, 5.3 and 5.4. In case of all data frequencies, we can see huge differences in standard deviations and thus in variances for all indices. As we compare the variances from the total, crisis and tranquil period, the highest

values are for the indices in crisis period, lowest on the other hand for the tranquil period as expected. We can also see that German capital market is much less volatile than emerging markets in CEE region. The markets here are of similar volatility, however the Polish stock market is less volatile followed by Czech market and the most volatile seems to be Hungarian stock market. The values of expected skewness and excess kurtosis does indicate that the data are not normally distributed. This is supported by Jarque-Bera statistics and acccording to its p-value, we reject the null hypothesis about that the data are normally distributed. As mentioned in Madaleno & Pinho (2011), the negative values for skewness indicate that the distributions of series are left-sloped and positive values right-sloped. The daily average prices are the highest for Hungarian market and in this case, it is along with the common knowledge about "*high risk - high return*".

Table 5.2: Descriptive Statistics - Total Period

Caption: *Log Levels* stands for price development of stock indices. *Log Diff.* stands for logarhitmic differences of stock price indices computed according to the Equation 5.2. *5 min all* express 5 minute data frequency including the overnight differences, *5 min daily* express 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* express daily data frequency.

	DAX		BUX		PX		WIG20	
	Log Levels	Log Diff.	Log Levels	Log Diff.	Log Levels	Log Diff.	Log Levels	Log Diff.
5 min all								
Mean	8.650289	-0.000002	9.84	-0.0000035	7.03	-0.000009	7.73	-0.000005
Median	8.688395	0.000002	9.95	0.0000000	7.05	0.000000	7.78	0.000004
Maximum	8.998624	0.07	10.17	0.10	7.51	0.09	8.16	0.0521
Minimum	8.186991	-0.08	9.14	-0.11	6.41	-0.14	7.13	-0.0550
Std. Dev.	0.156426	0.00	0.25	0.00	0.23	0.00	0.20	0.0022
Skewness	-0.628826	-0.07	-1.08	-1.49	-0.34	-3.94	-0.61	-0.3974
Kurtosis	2.727197	179.72	2.84	294.80	2.68	646.59	2.71	82.6875
Jarque-Bera	5271.26	99396842	12843.34	232000000	1378.08	986000000	3855.47	15470622
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	660795.60	-0.18	642416.40	-0.23	401931.40	-0.49	452098.00	-0.27
Sum Sq. Dev.	1869.18	0.26	4227.88	0.36	3062.36	0.26	2335.64	0.27
Observations	76390	76389	65257	65256	57151	57150	58466	58465
5 min daily								
Mean	8.65	-0.000007	9.84	-0.00001	7.03	-0.000019	7.73	-0.000012
Median	8.69	0.000000	9.95	0.00000	7.05	0.000000	7.78	0.000004
Maximum	9.00	0.03	10.17	0.06	7.51	0.02	8.16	0.0276
Minimum	8.19	-0.03	9.14	-0.05	6.41	-0.01	7.13	-0.0177
Std. Dev.	0.16	0.00	0.25	0.00	0.23	0.00	0.20	0.0016
Skewness	-0.63	0.08	-1.09	0.21	-0.34	-0.19	-0.61	0.1958
Kurtosis	2.73	22.21	2.84	51.77	2.68	20.18	2.72	16.6906
Jarque-Bera	5232.67	1161518	12726.24	6386295	1360.59	694319	3817.67	450477
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	653295.40	-0.53	634338.70	-0.80	396846.00	-1.04	445681.10	-0.67
Sum Sq. Dev.	1848.88	0.17	4170.99	0.19	3023.55	0.07	2303.55	0.16
Observations	75522	75522	64435	64435	56428	56428	57635	57635
5 min 14:40								
Mean	8.65	-0.000004	9.84	-0.0000196	7.03	-0.0000194	7.73	-0.000015
Median	8.69	0.000003	9.95	0.0000000	7.05	0.0000000	7.78	0.000003
Maximum	9.00	0.03	10.17	0.06	7.51	0.02	8.16	0.03
Minimum	8.19	-0.02	9.14	-0.05	6.41	-0.01	7.13	-0.02
Std. Dev.	0.16	0.00	0.25	0.00	0.23	0.00	0.20	0.00
Skewness	-0.63	0.34	-1.09	0.29	-0.35	-0.21	-0.62	0.20
Kurtosis	2.73	31.13	2.85	68.61	2.68	21.68	2.72	17.67
Jarque-Bera	3433.95	1637749	9594.51	8701438	1081.23	652361	2950.67	399427
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	429440.10	-0.19	477556.10	-0.95	315483.70	-0.87	344078.30	-0.65
Sum Sq. Dev.	1219.486	0.10	3138.72	0.13	2404.14	0.05	1780.82	0.10
Observations	49645	49645	48508	48508	44858	44858	44495	44495
30 min								
Mean	8.650324	-0.00001	9.84	-0.00002	7.03	-0.00005	7.73	-0.00003
Median	8.688480	0.00003	9.95	-0.00002	7.05	0.00	7.78	0.00
Maximum	8.997927	0.07	10.17	0.10	7.51	0.09	8.15	0.05
Minimum	8.189442	-0.08	9.14	-0.12	6.42	-0.11	7.15	-0.06
Std. Dev.	0.156349	0.00	0.25	0.01	0.23	0.01	0.20	0.01
Skewness	-0.629387	-0.24	-1.08	-1.12	-0.34	-0.90	-0.61	-0.29
Kurtosis	2.728325	39.01	2.83	65.76	2.68	73.79	2.71	20.97
Jarque-Bera	922.23	721321.10	2140.14	1787483.00	244.30	2116650.00	674.29	137812.40
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	115455.90	-0.19	107086.80	-0.22	71248.24	-0.49	79135.47	-0.28
Sum Sq. Dev.	326.24	0.26	704.83	0.35	542.71	0.28	408.65	0.26
Observations	13347	13346	10878	10877	10131	10130	10234	10233
1 hour								
Mean	8.65	-0.00003	9.84	-0.00004	7.03	-0.0001	7.73	-0.0001
Median	8.69	0.00004	9.95	0.00008	7.05	0.0001	7.78	0.0000
Maximum	9.00	0.10	10.17	0.12	7.50	0.09	8.15	0.05
Minimum	8.19	-0.09	9.15	-0.17	6.42	-0.12	7.16	-0.05
Std. Dev.	0.16	0.01	0.25	0.01	0.23	0.01	0.20	0.01
Skewness	-0.63	-0.02	-1.08	-1.46	-0.34	-0.46	-0.61	-0.18
Kurtosis	2.73	31.80	2.83	67.48	2.68	40.96	2.71	12.15
Jarque-Bera	461.63	230703.80	1140.85	1007097.00	122.16	304277.00	336.60	17889.07
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	57748.83	-0.19	57116.26	-0.23	35627.49	-0.49	39582.81	-0.28
Sum Sq. Dev.	163.28	0.27	375.99	0.37	271.35	0.30	204.35	0.28
Observations	6676	6675	5802	5801	5066	5065	5119	5118
1 day								
Mean	8.65	-0.0002	9.84	-0.0003	7.03	-0.0007	7.73	-0.0004
Median	8.69	0.0006	9.95	-0.0003	7.05	0.0001	7.78	-0.0003
Maximum	8.98	0.1187	10.17	0.1204	7.50	0.1209	8.15	0.0789
Minimum	8.21	-0.0809	9.15	-0.1197	6.44	-0.1630	7.19	-0.0948
Std. Dev.	0.16	0.0189	0.25	0.0222	0.23	0.0222	0.20	0.0200
Skewness	-0.63	0.3644	-1.08	-0.1238	-0.34	-0.4654	-0.60	-0.2509
Kurtosis	2.70	9.4841	2.82	7.5794	2.67	12.6095	2.68	5.3749
Jarque-Bera	51.32	1316.28	142.12	635.34	17.56	2807.92	47.49	179.46
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	6426.68	-0.17	7146.49	-0.22	5091.20	-0.49	5659.92	-0.27
Sum Sq. Dev.	18.13	0.26	47.01	0.36	38.77	0.35	29.12	0.29
Observations	743	742	726	725	724	723	732	731

Table 5.3: Descriptive Statistics - Crisis Period

Caption: *Log Levels* stands for price development of stock indices. *Log Diff.* stands for logarhitmic differences of stock price indices computed according to the Equation 5.2. *5 min all* express 5 minute data frequency including the overnight differences, *5 min daily* express 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* express daily data frequency.

	DAX		BUX		PX		WIG20	
	Log Levels	Log Diff.	Log Levels	Log Diff.	Log Levels	Log Diff.	Log Levels	Log Diff.
5 min all								
Mean	8.664438	-0.000023	9.78	-0.0000384	7.09	-0.000042	7.75	-0.000035
Median	8.755950	-0.000012	9.93	-0.0000069	7.27	0.000000	7.86	-0.000017
Maximum	8.998624	0.07	10.17	0.10	7.51	0.09	8.16	0.0521
Minimum	8.186991	-0.08	9.14	-0.11	6.41	-0.14	7.13	-0.0550
Std. Dev.	0.200160	0.00	0.30	0.00	0.32	0.00	0.26	0.0027
Skewness	-0.607042	-0.15	-0.62	-2.43	-0.63	-4.52	-0.58	-1.0518
Kurtosis	1.998247	145.74	1.76	287.92	1.79	480.42	1.87	73.5696
Jarque-Bera	3228.30	26548669	3421.45	89690029	2943.38	221000000	2586.27	4961647
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	270963.00	-0.71	259279.40	-1.02	164646.90	-0.98	185184.50	-0.84
Sum Sq. Dev.	1252.883	0.18	2342.80	0.22	2394.65	0.19	1669.66	0.17
Observations	31273	31272	26509	26508	23226	23225	23891	23890
5 min daily								
Mean	8.66	-0.000019	9.78	-0.00003	7.09	-0.000035	7.75	-0.000024
Median	8.76	-0.000012	9.93	-0.00001	7.27	0.000000	7.86	-0.000017
Maximum	9.00	0.03	10.17	0.06	7.51	0.02	8.16	0.0276
Minimum	8.19	-0.03	9.14	-0.05	6.41	-0.01	7.13	-0.0177
Std. Dev.	0.20	0.00	0.30	0.00	0.32	0.00	0.26	0.0020
Skewness	-0.61	0.18	-0.63	0.12	-0.63	-0.19	-0.58	0.3341
Kurtosis	2.00	18.51	1.77	52.95	1.79	14.71	1.88	14.3571
Jarque-Bera	3206.55	310091	3385.07	2720258	2906.12	131054	2559.44	126959
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	267794.90	-0.58	255941.90	-0.86	162562.30	-0.80	182491.60	-0.56
Sum Sq. Dev.	1238.46	0.11	2310.29	0.10	2364.37	0.05	1645.62	0.10
Observations	30906	30906	26166	26166	22932	22932	23542	23542
5 min 14:40								
Mean	8.66	-0.000018	9.78	-0.0000471	7.09	-0.0000387	7.75	-0.000038
Median	8.76	-0.000012	9.93	-0.0000104	7.27	0.0000000	7.86	-0.000016
Maximum	9.00	0.03	10.17	0.06	7.51	0.02	8.16	0.03
Minimum	8.19	-0.02	9.14	-0.05	6.41	-0.01	7.13	-0.02
Std. Dev.	0.20	0.00	0.30	0.00	0.32	0.00	0.26	0.00
Skewness	-0.61	0.49	-0.63	0.14	-0.63	-0.27	-0.58	0.24
Kurtosis	2.01	25.61	1.77	66.56	1.79	15.64	1.89	14.53
Jarque-Bera	2096.23	433085	2544.96	3316288	2308.33	121495	1973.13	100830
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	175907.30	-0.37	192683.30	-0.93	129220.60	-0.71	140915.10	-0.68
Sum Sq. Dev.	814.2818	0.07	1737.80	0.08	1879.86	0.04	1273.03	0.07
Observations	20301	20301	19698	19698	18228	18228	18178	18178
30 min								
Mean	8.664373	-0.00013	9.78	-0.00023	7.09	-0.00024	7.75	-0.00020
Median	8.756128	-0.00006	9.93	-0.00015	7.27	0.00	7.86	0.00
Maximum	8.997927	0.07	10.17	0.10	7.51	0.09	8.15	0.05
Minimum	8.189442	-0.08	9.14	-0.12	6.42	-0.11	7.15	-0.06
Std. Dev.	0.200169	0.01	0.30	0.01	0.32	0.01	0.26	0.01
Skewness	-0.607310	-0.25	-0.62	-1.77	-0.62	-1.13	-0.58	-0.54
Kurtosis	1.997204	31.36	1.76	63.68	1.78	55.39	1.87	18.56
Jarque-Bera	564.92	183166.40	570.39	680148.80	521.75	471467.80	452.94	42380.57
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	47350.80	-0.71	43220.67	-1.01	29177.23	-0.98	32407.45	-0.84
Sum Sq. Dev.	218.93	0.18	390.71	0.22	424.42	0.20	292.12	0.16
Observations	5465	5464	4419	4418	4116	4115	4181	4180
1 hour								
Mean	8.66	-0.00026	9.78	-0.00043	7.09	-0.0005	7.75	-0.0004
Median	8.76	-0.00009	9.93	-0.00015	7.27	-0.0001	7.86	-0.0003
Maximum	9.00	0.10	10.17	0.12	7.50	0.09	8.15	0.05
Minimum	8.19	-0.09	9.15	-0.17	6.42	-0.12	7.16	-0.05
Std. Dev.	0.20	0.01	0.30	0.01	0.32	0.01	0.26	0.01
Skewness	-0.61	0.01	-0.62	-2.02	-0.62	-0.60	-0.58	-0.29
Kurtosis	2.00	24.82	1.75	65.90	1.78	30.42	1.87	10.60
Jarque-Bera	282.59	54202.25	304.26	390008.80	260.92	64564.72	226.60	5060.73
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	23679.49	-0.71	23052.47	-1.01	14588.45	-0.98	16207.39	-0.84
Sum Sq. Dev.	109.48	0.19	208.49	0.23	212.25	0.21	146.09	0.17
Observations	2733	2732	2357	2356	2058	2057	2091	2090
Daily								
Mean	8.66	-0.0023	9.78	-0.0034	7.09	-0.0034	7.75	-0.0028
Median	8.76	-0.0016	9.92	-0.0040	7.27	-0.0038	7.86	-0.0022
Maximum	8.98	0.1187	10.17	0.1204	7.50	0.1209	8.15	0.0789
Minimum	8.21	-0.0809	9.15	-0.1197	6.44	-0.1630	7.19	-0.0948
Std. Dev.	0.20	0.0244	0.30	0.0260	0.32	0.0294	0.26	0.0243
Skewness	-0.60	0.6068	-0.61	-0.1774	-0.62	-0.2736	-0.57	-0.2733
Kurtosis	1.98	7.9202	1.74	7.7711	1.77	9.3065	1.85	4.5901
Jarque-Bera	31.75	324.23	38.09	280.40	37.40	489.21	32.46	35.10
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	2633.74	-0.70	2884.85	-1.01	2083.80	-0.98	2317.39	-0.84
Sum Sq. Dev.	12.14	0.18	26.13	0.20	30.33	0.25	20.75	0.17
Observations	304	303	295	294	294	293	299	298

Table 5.4: Descriptive Statistics - Tranquil Period

Caption: *Log Levels* stands for price development of stock indices. *Log Diff.* stands for logarhitmic differences of stock price indices computed according to the Equation 5.2. *5 min all* express 5 minute data frequency including the overnight differences, *5 min daily* express 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* express daily data frequency.

	DAX		BUX		PX		WIG20	
	Log Levels	Log Diff.	Log Levels	Log Diff.	Log Levels	Log Diff.	Log Levels	Log Diff.
5 min								
Mean	8.640481	0.000012	9.89	0.0000204	6.99	0.000015	7.72	0.000016
Median	8.666529	0.000009	9.96	0.0000038	7.04	0.000000	7.76	0.000015
Maximum	8.839632	0.03	10.15	0.06	7.18	0.05	7.92	0.0357
Minimum	8.279847	-0.03	9.18	-0.05	6.53	-0.05	7.28	-0.0287
Std. Dev.	0.115868	0.00	0.21	0.00	0.13	0.00	0.14	0.0017
Skewness	-0.955231	0.35	-1.41	1.22	-1.53	2.38	-1.11	1.3237
Kurtosis	3.512643	38.50	4.17	98.55	4.58	216.37	3.59	57.9911
Jarque-Bera	7355.32	2370055	15006.59	14750873	16807.40	64383132	7589.72	4366571
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	389832.60	0.53	383137.00	0.79	237284.50	0.50	266913.50	0.57
Sum Sq. Dev.	605.6963	0.08	1704.50	0.14	544.53	0.07	652.06	0.11
Observations	45117	45117	38748	38748	33925	33925	34575	34575
5 min daily								
Mean	8.64	0.000001	9.89	0.000002	6.99	-0.000007	7.72	-0.000003
Median	8.67	0.000008	9.96	0.000002	7.04	0.000000	7.76	0.000013
Maximum	8.84	0.01	10.15	0.04	7.18	0.02	7.92	0.0228
Minimum	8.28	-0.02	9.18	-0.02	6.53	-0.01	7.28	-0.0131
Std. Dev.	0.12	0.00	0.21	0.00	0.13	0.00	0.14	0.0013
Skewness	-0.95	-0.25	-1.41	0.36	-1.53	0.02	-1.11	-0.1532
Kurtosis	3.51	10.66	4.16	32.53	4.58	18.62	3.59	13.7402
Jarque-Bera	7235.12	109554	14761.09	1391225	16585.83	340371	7444.86	163995
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	385500.50	0.05	378396.80	0.06	234283.70	-0.24	263189.50	-0.11
Sum Sq. Dev.	599.54	0.06	1684.94	0.08	537.59	0.02	643.67	0.06
Observations	44616	44616	38269	38269	33496	33496	34093	34093
5 min 14:40								
Mean	8.64	0.000006	9.89	-0.0000008	6.99	-0.0000063	7.72	0.000001
Median	8.67	0.000010	9.96	0.0000000	7.04	0.0000000	7.76	0.000012
Maximum	8.84	0.01	10.15	0.04	7.18	0.02	7.92	0.02
Minimum	8.28	-0.02	9.18	-0.02	6.53	-0.01	7.28	-0.01
Std. Dev.	0.12	0.00	0.21	0.00	0.13	0.00	0.14	0.00
Skewness	-0.95	-0.30	-1.41	0.58	-1.53	0.26	-1.11	0.08
Kurtosis	3.49	13.90	4.17	46.72	4.58	21.51	3.59	15.71
Jarque-Bera	4755.66	145750	11121.97	2295697	13182.93	380599	5755.64	177090
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	253532.80	0.18	284872.80	-0.02	186263.10	-0.17	203163.20	0.03
Sum Sq. Dev.	397.7436	0.03	1269.20	0.06	427.35	0.02	496.70	0.04
Observations	29344	29344	28810	28810	26630	26630	26317	26317
30 min								
Mean	8.64	0.00006	9.89	0.00012	6.99	0.00008	7.72	0.00009
Median	8.67	0.00007	9.96	0.00005	7.04	0.00	7.76	0.00
Maximum	8.84	0.03	10.15	0.07	7.18	0.05	7.92	0.04
Minimum	8.28	-0.03	9.18	-0.03	6.53	-0.04	7.28	-0.04
Std. Dev.	0.12	0.00	0.21	0.00	0.13	0.00	0.14	0.00
Skewness	-0.95	0.11	-1.41	0.77	-1.53	1.09	-1.11	0.49
Kurtosis	3.52	14.45	4.17	19.14	4.59	32.68	3.60	14.64
Jarque-Bera	1283.01	43063.54	2502.58	70774.77	2986.58	221894.90	1327.63	34392.03
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	68105.08	0.51	63866.16	0.74	42071.01	0.47	46728.02	0.55
Sum Sq. Dev.	105.49	0.08	283.92	0.13	96.51	0.08	114.11	0.10
Observations	7882	7881	6459	6458	6015	6014	6053	6052
1 hour								
Mean	8.64	0.00013	9.89	0.00022	6.99	0.0002	7.72	0.0002
Median	8.67	0.00010	9.96	0.00023	7.04	0.0001	7.76	0.0002
Maximum	8.84	0.04	10.15	0.07	7.18	0.06	7.92	0.04
Minimum	8.28	-0.04	9.19	-0.04	6.53	-0.04	7.28	-0.03
Std. Dev.	0.12	0.00	0.21	0.01	0.13	0.01	0.14	0.01
Skewness	-0.96	0.11	-1.41	0.52	-1.53	0.92	-1.11	0.30
Kurtosis	3.52	10.14	4.17	12.61	4.59	18.33	3.59	8.89
Jarque-Bera	644.43	8385.36	1334.74	13405.72	1494.90	29871.84	661.90	4417.80
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	34069.34	0.51	34063.79	0.75	21039.04	0.47	23375.42	0.55
Sum Sq. Dev.	52.88	0.08	151.34	0.13	48.23	0.08	57.05	0.11
Observations	3943	3942	3445	3444	3008	3007	3028	3027
Daily								
Mean	8.64	0.0012	9.89	0.0017	6.99	0.0011	7.72	0.0013
Median	8.67	0.0016	9.96	0.0009	7.04	0.0012	7.77	0.0007
Maximum	8.84	0.0590	10.14	0.0967	7.18	0.0677	7.92	0.0634
Minimum	8.28	-0.0502	9.20	-0.0682	6.54	-0.0723	7.28	-0.0675
Std. Dev.	0.12	0.0138	0.21	0.0188	0.13	0.0152	0.14	0.0163
Skewness	-0.95	-0.0625	-1.41	0.2699	-1.54	-0.0986	-1.10	0.2175
Kurtosis	3.50	4.3262	4.18	4.7464	4.62	6.4311	3.60	4.4143
Jarque-Bera	70.23	32.38	167.61	59.86	216.94	211.13	94.27	39.41
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	3792.95	0.52	4261.64	0.74	3007.40	0.47	3342.53	0.57
Sum Sq. Dev.	5.89	0.08	18.82	0.15	6.90	0.10	8.20	0.11
Observations	439	438	431	430	430	429	433	432

Chapter 6

Sensitive Results

After we introduced all markets included in this study, methodology and the datasets with their adjustments, the most interesting findings will be presented in this chapter.

6.1 Unit Root Tests

We initialy inquire whether the time series of stock market indices are stationary. We applied a battery of most frequently used unit root tests: ADF test, PP test and KPSS test. ADF and PP test the null hypothesis whether the time series have a unit root. On the opposite side, the tested null hypothesis of KPSS test is whether the time series are stationary. The tested models are either with included constant or with included constant and trend. All results are presented in the tables 6.1, 6.2 and 6.3. We show the results for logarhitmic levels of stock market indices and for the first differences. Moreover, we present here the results for the second differences in order to find any features of integration of order two.

Taking the total period of dataset, we clearly see that the data are not stationary in their logarhitmic levels for any frequency according to each unit root test. ADF and PP do not reject the null hypothesis about the presence of a unit root and KPSS rejects the null that the time series are stationary at one per cent level of significance.

The time series become stationary in their first differences in case of ADF and PP tests when we reject the null about presence of a unit root even at one per cent level of significance in both models including constant and including both constant and trend. The KPSS test does confirm such results; we cannot

reject the null hypothesis about stationary data in both models for all time series[1].

As for the second differences, the ADF test does reject the hypothesis about presence of unit root in all cases but the PP does not reject the null hypothesis for all indices in case of frequencies 5 minutes (including the overnight returns), 30 minutes and 1 hour for both models including constant and including constant and trend. KPSS approves the results of ADF test for the second differences; we do not reject the null hypothesis about stationary time series for all indices in both models including constant and including both constant and trend.

When testing the time series covering only crisis period, the null hypothesis about presence of a unit root is not rejected for all indices in their logarhitmic levels in both models including constant and including both contant and trend in case of both ADF and PP tests. The null about stationary time series is rejected for all time series even at one per cent level of significance when using KPSS test.

Testing the first diffrences of time series, the null is rejected in case of ADF and PP tests in all cases and the null about stationary data is not rejected in case of KPSS test for all indices in all data frequencies.

If we test the time series in their second differences, we reject the null hypothesis in all cases using ADF test with one exception - in the model including both constant and trend, we do not reject the null about presence of a unit root in case of PX index in its 5 minute frequency with only daily differences. PP test does reject the null hypothesis about presence of a unit root for all stock market indices in their frequencies of 5 minutes including only daily differences, 5 minutes including the daily differences only until 14:40, 1 hour and daily frequency for both models including constant and both constant and trend. We also reject the null hypothesis for BUX index in case of 30 minute frequency time series for both models including constant and including both constant and trend. The null is not rejected for all indices in case of 5 minute frequency data including the overnight differences and 30 minute data frequency with exception of BUX index. KPSS test does not reject the null about stationary data in all cases with the exception of PX index in its 30 minute data frequency and

[1]There are some exceptions, for instance we reject the null hypothesis at ten per cent level of significance. We do not take such rejections of null hypothesis into consideration because with widening of critical range, the tests lose their confidence and become improper.

in case of WIG20 in its daily frequency; the null is rejected in both cases at five per cent level of significance in the model including both constant and trend.

The results of unit root tests in tranquil period are not as clear as for total and crisis periods. When testing the logarhitmic levels of stock market indices, ADF test rejects the null hypohesis about presence of a unit root in case of DAX index for all three 5 minute frequency datasets, 30 minute data frequency and 1 hour data frequency at five per cent level of significance in the model with both constant and trend. We reject the null at one per cent level of significance for all frequencies in the model including only constant in case of BUX and PX and in case of WIG20, we reject the null about a presence of a unit root at five per cent level of significance only in case of daily data for both models including constant and including both constant and trend. PP test does reject the null about presence of a unit root for DAX in its 5 minute data frequency including only daily differences, 5 minutes frequency including daily differences only until 14:40, 30 minute and 1 hour data frequency in the model including both constant and trend. We reject the null hypothesis about presence of a unit root in all frequencies in the model including only constant in case of BUX and PX indices and as for WIG20, we reject the the null at five per cent level of significance in its daily frequency in the model including only constant. In all other cases, ADF and PP tests does not reject the null hypothesis. If we use KPSS test, we reject the null hypothesis about stationary data for all indices in all frequencies even at one per cent level of significance which is in most cases in confrontance with the results of ADF and PP tests used on the stock market indices in their logarhitmic levels.

When testing the first differences, ADF and PP tests do reject the null hypothesis about a presence of a unit root in all cases even at one per cent level of significance. If we use KPSS test, we do not reject the null about stationary data series in case of DAX and WIG20 in all frequencies in both models including constant and including both constant and trend. We do not reject the null about stationary data for all frequencies in the model including both constant and trend in case of BUX and PX indices and also in case of only PX in the model including only constant in its 5 minute data frequency including only daily differences and 5 minute data frequency including the daily differences only until 14:40.

If we test the second differences, the null hypothesis about presence of a unit root is rejected for all stock market indices in all frequencies in both models using ADF test. If we use PP test, the null hypothesis is rejected at one per cent

level of significance for all indices in their frequencies of 5 minutes including only daily differences and including differences taken until 14:40, in 1 hour and daily data frequency. KPSS does not reject null hypothesis in most cases with exceptions of PX index in its 5 minute data frequency including the overnight differences in the model with constant and trend (the null is rejected at one per cent level of significance) and in its 5 minute data frequency including only daily differences and including only daily differences until 14:40 in the model including constant (the null is rejected at five per cent and one per cent level of significance, respectively). Another exception is in case of WIG20 index in its 5 minute data frequency including only daily differences and including only daily differences until 14:40 in the model including constant.

Discovering the time series in their first and second differences helped us to decide about the integration of order one and two, respectively. As the results confirmed the integration of order one and two in most cases, we claim that the time series under study are difference-stationary processes.

Table 6.1: Unit Root Tests - Total Period

Caption: Log Levels stands for price development of stock indices. *Log Diff.* stands for logarhitmic differences of stock price indices computed according to the Equation 5.2. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency. *Const.* represents the model including only constant and *Trend + Const.* stands for the model including both constant and trend. *,**,*** denotes the rejection of null hypothesis at 10, 5, 1 % level of significance.

		ADF		**PP**		**KPSS**	
		Const.	Trend + Const.	Const.	Trend + Const.	Const.	Trend + Const.
Log Levels							
DAX	5 min	-2.22	-2.17	-2.21	-2.16	6.90 ***	6.94 ***
	5 min daily	-2.22	-2.17	-2.21	-2.17	6.86 ***	6.90 ***
	5 min 14:40	-2.25	-2.20	-2.23	-2.18	5.64 ***	5.67 ***
	30 min	-2.22	-2.17	-2.23	-2.18	2.90 ***	2.91 ***
	Hourly	-2.15	-2.11	-2.23	-2.18	1.96 ***	1.97 ***
	Daily	-2.18	-2.13	-2.11	-2.13	0.65 **	0.65 ***
BUX	5 min	-1.51	-1.83	-1.54	-1.87	8.29 ***	5.89 ***
	5 min daily	-1.50	-1.83	-1.53	-1.85	8.22 ***	5.85 ***
	5 min 14:40	-1.56	-1.87	-1.55	-1.86	7.10 ***	5.05 ***
	30 min	-1.54	-1.86	-1.54	-1.86	3.21 ***	2.28 ***
	Hourly	-1.50	-1.83	-1.54	-1.86	2.43 ***	1.72 ***
	Daily	-1.40	-1.74	-1.51	-1.83	0.79 ***	0.56 ***
PX	5 min	-2.04	-1.75	-2.04	-1.76	6.26 ***	5.33 ***
	5 min daily	-2.03	-1.74	-2.05	-1.77	6.19 ***	5.27 ***
	5 min 14:40	-2.04	-1.74	-2.06	-1.78	5.54 ***	4.71 ***
	30 min	-2.05	-1.76	-2.09	-1.83	2.52 ***	2.14 ***
	Hourly	-2.04	-1.75	-2.09	-1.83	1.81 ***	1.54 ***
	Daily	-2.08	-1.82	-2.08	-1.84	0.65 **	0.55 ***
WIG20	5 min	-2.04	-1.93	-2.04	-1.92	5.97 ***	6.02 ***
	5 min daily	-2.04	-1.92	-2.04	-1.92	5.92 ***	5.96 ***
	5 min 14:40	-2.04	-1.93	-2.04	-1.92	5.20 ***	5.24 ***
	30 min	-2.04	-1.93	-2.09	-1.98	2.40 ***	2.42 ***
	Hourly	-2.06	-1.95	-2.09	-1.98	1.73 ***	1.74 ***
	Daily	-2.07	-1.96	-2.07	-1.95	0.62 **	0.63 ***
Log Levels - First Differences							
DAX	5 min	-159.23 ***	-159.25 ***	-277.20 ***	-277.21 ***	0.35 *	0.05
	5 min daily	-120.02 ***	-120.02 ***	-278.01 ***	-278.01 ***	0.17	0.05
	5 min 14:40	-98.10 ***	-98.11 ***	-228.45 ***	-228.47 ***	0.23	0.04
	30 min	-112.68 ***	-112.70 ***	-112.65 ***	-112.67 ***	0.35 *	0.05
	Hourly	-24.16 ***	-24.21 ***	-84.38 ***	-84.41 ***	0.35 *	0.05
	Daily	-28.22 ***	-28.31 ***	-28.23 ***	-28.35 ***	0.33	0.05
BUX	5 min	-110.31 ***	-110.31 ***	-255.74 ***	-255.74 ***	0.30	0.14 *
	5 min daily	-122.26 ***	-122.27 ***	-246.73 ***	-246.73 ***	0.21	0.15 *
	5 min 14:40	-107.17 ***	-107.18 ***	-214.71 ***	-214.71 ***	0.27	0.15 *
	30 min	-97.18 ***	-97.19 ***	-97.30 ***	-97.29 ***	0.30	0.14
	Hourly	-51.26 ***	-51.27 ***	-74.76 ***	-74.76 ***	0.30	0.14 *
	Daily	-20.43 ***	-20.48 ***	-24.82 ***	-24.86 ***	0.33	0.16 **
PX	5 min	-161.52 ***	-161.53 ***	-225.79 ***	-225.78 ***	0.34	0.12 *
	5 min daily	-104.24 ***	-104.25 ***	-194.04 ***	-194.04 ***	0.29	0.07
	5 min 14:40	-92.05 ***	-92.06 ***	-173.05 ***	-173.04 ***	0.28	0.07
	30 min	-96.59 ***	-96.60 ***	-97.42 ***	-97.40 ***	0.29	0.10
	Hourly	-68.39 ***	-68.41 ***	-68.74 ***	-68.74 ***	0.29	0.11
	Daily	-20.32 ***	-20.37 ***	-24.87 ***	-24.88 ***	0.30	0.11
WIG20	5 min	-172.79 ***	-172.80 ***	-240.06 ***	-240.08 ***	0.45 *	0.08
	5 min daily	-103.94 ***	-103.95 ***	-236.92 ***	-236.92 ***	0.24	0.03
	5 min 14:40	-151.00 ***	-151.02 ***	-207.93 ***	-207.94 ***	0.43 *	0.07
	30 min	-98.83 ***	-98.85 ***	-99.05 ***	-99.05 ***	0.41 *	0.07
	Hourly	-71.03 ***	-71.07 ***	-71.11 ***	-71.13 ***	0.41 *	0.07
	Daily	-26.53 ***	-26.62 ***	-26.52 ***	-26.64 ***	0.43 *	0.08
Log Levels - Second Differences							
DAX	5 min	-60.03 ***	-60.03 ***	-12054.40	-12054.00	0.01	0.01
	5 min daily	-151.34 ***	-151.34 ***	-507.90 ***	-508.20 ***	0.25	0.03
	5 min 14:40	-132.28 ***	-132.28 ***	-350.10 ***	-350.25 ***	0.27	0.04
	30 min	-30.96 ***	-30.96 ***	-2123.63	-2123.62	0.01	0.01
	Hourly	-25.22 ***	-25.22 ***	-1177.16	-1177.11	0.02	0.02
	Daily	-15.18 ***	-15.17 ***	-462.56 ***	-480.37 ***	0.03	0.03
BUX	5 min	-57.47 ***	-57.47 ***	-10821.87	-10822.20	0.02	0.01
	5 min daily	-188.51 ***	-188.51 ***	-383.43 ***	-383.50 ***	0.15	0.03
	5 min 14:40	-156.98 ***	-156.98 ***	-306.32 ***	-306.36 ***	0.14	0.03
	30 min	-30.02 ***	-30.02 ***	-8838.38	-9519.56	0.04	0.04
	Hourly	-27.03 ***	-27.02 ***	-1076.57	-1076.36	0.02	0.02
	Daily	-15.70 ***	-15.69 ***	-470.14 ***	-471.96 ***	0.27	0.25
PX	5 min	-55.17 ***	-55.17 ***	-9492.59	-9492.98	0.01	0.01
	5 min daily	-187.63 ***	-187.63 ***	-281.19 ***	-281.20 ***	0.12	0.06
	5 min 14:40	-161.07 ***	-161.07 ***	-239.90 ***	-239.90 ***	0.10	0.06
	30 min	-28.16 ***	-28.16 ***	-3940.24	-3943.42	0.02	0.02
	Hourly	-25.23 ***	-25.22 ***	-4795.30	-4800.33	0.23	0.22
	Daily	-12.79 ***	-12.78 ***	-311.34 ***	-315.32 ***	0.12	0.11
WIG20	5 min	-54.46 ***	-54.46 ***	-8205.00	-8204.72	0.01	0.01
	5 min daily	-146.35 ***	-146.35 ***	-384.76 ***	-384.87 ***	0.29	0.12 *
	5 min 14:40	-146.43 ***	-146.43 ***	-307.31 ***	-307.36 ***	0.26	0.12 *
	30 min	-28.92 ***	-28.92 ***	-2285.27	-2285.49	0.02	0.02
	Hourly	-25.13 ***	-25.13 ***	-1264.28	-1263.87	0.04	0.03
	Daily	-14.99 ***	-14.98 ***	-320.58 ***	-320.63 ***	0.19	0.19

Source: Author's Computations

Table 6.2: Unit Root Tests - Crisis Period

Caption: Log Levels stands for price development of stock indices. *Log Diff.* stands for logarhitmic differences of stock price indices computed according to the Equation 5.2. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency. *Const.* represents the model including only constant and *Trend + Const.* stands for the model including both constant and trend. *,**,*** denotes the rejection of null hypothesis at 10, 5, 1 % level of significance.

		ADF		**PP**		**KPSS**	
		Const.	Trend + Const.	Const.	Trend + Const.	Const.	Trend + Const.
Log Levels							
DAX	5 min	-0.84	-2.52	-0.84	-2.52	20.05 ***	3.26 ***
	5 min daily	-0.85	-2.53	-0.84	-2.52	19.80 ***	3.25 ***
	5 min 14:40	-0.79	-2.59	-0.76	-2.53	15.71 ***	2.58 ***
	30 min	-0.84	-2.50	-0.86	-2.55	8.39 ***	1.39 ***
	Hourly	-0.89	-2.59	-0.85	-2.54	5.75 ***	0.96 ***
	Daily	-0.80	-2.53	-0.66	-2.42	1.91 ***	0.35 ***
BUX	5 min	0.03	-1.97	-0.03	-2.04	19.29 ***	3.43 ***
	5 min daily	0.06	-1.93	-0.01	-2.04	19.02 ***	3.41 ***
	5 min 14:40	-0.06	-2.08	-0.06	-2.10	16.66 ***	2.99 ***
	30 min	-0.04	-2.06	-0.02	-2.04	7.48 ***	1.35 ***
	Hourly	0.06	-1.93	-0.01	-2.05	5.32 ***	0.97 ***
	Daily	0.33	-1.70	0.15	-1.84	1.86 ***	0.35 ***
PX	5 min	-0.18	-1.69	-0.18	-1.71	17.33 ***	3.52 ***
	5 min daily	-0.17	-1.69	-0.19	-1.71	17.12 ***	3.48 ***
	5 min 14:40	-0.12	-1.65	-0.18	-1.72	15.46 ***	3.15 ***
	30 min	-0.14	-1.65	-0.31	-1.88	6.98 ***	1.43 ***
	Hourly	-0.18	-1.70	-0.32	-1.90	5.21 ***	1.07 ***
	Daily	-0.29	-1.84	-0.20	-1.76	1.81 ***	0.38 ***
WIG20	5 min	-0.61	-2.19	-0.62	-2.22	18.38 ***	2.82 ***
	5 min daily	-0.60	-2.18	-0.61	-2.20	18.10 ***	2.83 ***
	5 min 14:40	-0.59	-2.23	-0.58	-2.20	16.17 ***	2.51 ***
	30 min	-0.61	-2.15	-0.63	-2.22	7.37 ***	1.15 ***
	Hourly	-0.64	-2.21	-0.63	-2.20	5.36 ***	0.85 ***
	Daily	-0.64	-2.27	-0.61	-2.31	1.93 ***	0.33 ***
Log Levels - First Differences							
DAX	5 min	-178.42 ***	-178.42 ***	-178.41 ***	-178.41 ***	0.04	0.03
	5 min daily	-179.55 ***	-179.54 ***	-179.54 ***	-179.53 ***	0.05	0.05
	5 min 14:40	-148.11 ***	-148.11 ***	-148.71 ***	-148.72 ***	0.09	0.03
	30 min	-71.72 ***	-71.71 ***	-71.69 ***	-71.68 ***	0.04	0.03
	Hourly	-54.80 ***	-54.79 ***	-54.78 ***	-54.77 ***	0.04	0.04
	Daily	-18.26 ***	-18.23 ***	-18.38 ***	-18.36 ***	0.06	0.04
BUX	5 min	-69.15 ***	-69.16 ***	-163.03 ***	-163.02 ***	0.11	0.03
	5 min daily	-78.15 ***	-78.15 ***	-154.85 ***	-154.85 ***	0.08	0.04
	5 min 14:40	-101.97 ***	-101.98 ***	-134.56 ***	-134.56 ***	0.21	0.06
	30 min	-60.66 ***	-60.66 ***	-60.64 ***	-60.64 ***	0.11	0.03
	Hourly	-32.02 ***	-32.03 ***	-47.64 ***	-47.63 ***	0.11	0.03
	Daily	-13.58 ***	-13.62 ***	-14.79 ***	-14.81 ***	0.14	0.04
PX	5 min	-143.55 ***	-143.55 ***	-143.60 ***	-143.60 ***	0.12	0.06
	5 min daily	-75.74 ***	-75.74 ***	-122.07 ***	-122.07 ***	0.09	0.08
	5 min 14:40	-58.34 ***	-58.34 ***	-109.05 ***	-109.05 ***	0.07	0.06
	30 min	-61.76 ***	-61.76 ***	-62.25 ***	-62.24 ***	0.10	0.05
	Hourly	-43.77 ***	-43.76 ***	-44.00 ***	-44.00 ***	0.10	0.05
	Daily	-13.76 ***	-13.77 ***	-16.09 ***	-16.06 ***	0.12	0.06
WIG20	5 min	-152.36 ***	-152.36 ***	-152.36 ***	-152.35 ***	0.05	0.05
	5 min daily	-149.01 ***	-149.01 ***	-148.99 ***	-148.98 ***	0.07	0.06
	5 min 14:40	-130.95 ***	-130.94 ***	-131.00 ***	-130.99 ***	0.08	0.07
	30 min	-63.52 ***	-63.51 ***	-63.53 ***	-63.53 ***	0.05	0.05
	Hourly	-46.32 ***	-46.31 ***	-46.31 ***	-46.30 ***	0.05	0.05
	Daily	-17.38 ***	-17.36 ***	-17.39 ***	-17.37 ***	0.06	0.04
Log Levels - Second Differences							
DAX	5 min	-47.58 ***	-47.58 ***	-10790.08	-10789.70	0.01	0.01
	5 min daily	-112.09 ***	-112.08 ***	-314.50 ***	-314.50 ***	0.02	0.01
	5 min 14:40	-83.68 ***	-83.68 ***	-221.29 ***	-221.30 ***	0.04	0.01
	30 min	-28.72 ***	-28.72 ***	-1124.44	-1124.31	0.01	0.01
	Hourly	-20.06 ***	-20.06 ***	-183.60 ***	-183.56 ***	0.01	0.01
	Daily	-13.84 ***	-13.82 ***	-165.79 ***	-165.27 ***	0.07	0.06
BUX	5 min	-41.19 ***	-41.18 ***	-3488.83	-3488.80	0.06	0.03
	5 min daily	-119.17 ***	-119.17 ***	-230.17 ***	-230.19 ***	0.08	0.01
	5 min 14:40	-99.66 ***	-99.66 ***	-185.29 ***	-185.29 ***	0.06	0.01
	30 min	-25.31 ***	-25.31 ***	-943.86 ***	-943.83 ***	0.03	0.03
	Hourly	-15.95 ***	-15.95 ***	-970.79 ***	-970.71 ***	0.05	0.04
	Daily	-10.90 ***	-10.88 ***	-33.38 ***	-33.31 ***	0.01	0.01
PX	5 min	-39.97 ***	-39.97 ***	-8495.93	-8499.40	0.03	0.03
	5 min daily	-118.15 ***	-118.15	-176.92 ***	-176.92 ***	0.06	0.02
	5 min 14:40	-150.44 ***	-150.43 ***	-151.15 ***	-151.15 ***	0.07	0.02
	30 min	-24.39 ***	-24.39 ***	-1528.14	-1528.12	0.19	0.19 **
	Hourly	-18.73 ***	-18.72 ***	-646.91 ***	-646.56 ***	0.07	0.07
	Daily	-12.44 ***	-12.41 ***	-56.11 ***	-55.97 ***	0.01	0.01
WIG20	5 min	-40.94 ***	-40.94 ***	-4085.46	-4085.34	0.01	0.01
	5 min daily	-113.48 ***	-113.48 ***	-243.20 ***	-243.26 ***	0.12	0.05
	5 min 14:40	-93.73 ***	-93.74 ***	-196.94 ***	-197.03 ***	0.15	0.03
	30 min	-22.43 ***	-22.43 ***	-1040.38	-1040.21	0.05	0.05
	Hourly	-19.57 ***	-19.56 ***	-509.15 ***	-509.03 ***	0.03	0.03
	Daily	-10.74 ***	-10.72 ***	-146.97 ***	-146.67 ***	0.19	0.19 **

Source: Author's Computations

Table 6.3: Unit Root Tests - Tranquil Period

Caption: Log Levels stands for price development of stock indices. *Log Diff.* stands for logarhitmic differences of stock price indices computed according to the Equation 5.2. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency. *Const.* represents the model including only constant and *Trend + Const.* stands for the model including both constant and trend. *,**,*** denotes the rejection of null hypothesis at 10, 5, 1 % level of significance.

		ADF		**PP**		**KPSS**	
		Const.	Trend + Const.	Const.	Trend + Const.	Const.	Trend + Const.
Log Levels							
DAX	5 min	-2.60 *	-3.66 **	-2.54	-3.64	22.38 ***	3.28 ***
	5 min daily	-2.57 *	-3.67 **	-2.58 *	-3.67 **	22.29 ***	3.26 ***
	5 min until 14:40	-2.58 *	-3.61 **	-2.58 *	-3.60 **	17.58 ***	2.61 ***
	30 min	-2.58 *	-3.67 **	-2.58 *	-3.65 **	9.20 ***	1.38 ***
	Hourly	-2.57 *	-3.66 **	-2.57 *	-3.65 **	6.31 ***	0.96 ***
	Daily	-2.74	-3.96	-2.82 *	-3.87 **	2.27 ***	0.38 ***
BUX	5 min	-4.00 ***	-2.65	-3.97 ***	-2.65	18.02 ***	4.89 ***
	5 min daily	-4.01 ***	-2.63	-3.96 ***	-2.64	18.66 ***	5.07 ***
	5 min until 14:40	-3.93 ***	-2.60	-3.93 ***	-2.60	15.47 ***	4.20 ***
	30 min	-3.95 ***	-2.64	-3.88 ***	-2.60	7.13 ***	1.96 ***
	Hourly	-4.00 ***	-2.63	-3.93 ***	-2.64	5.41 ***	1.49 ***
	Daily	-3.89 ***	-2.67	-4.19 ***	-2.62	1.93 ***	0.55 ***
PX	5 min	-3.97 ***	-2.94	-3.88 ***	-2.97	13.63 ***	4.30 ***
	5 min daily	-3.96 ***	-2.95	-3.86 ***	-2.96	13.47 ***	4.24 ***
	5 min until 14:40	-3.93 ***	-2.96	-3.85 ***	-2.97	12.22 ***	3.85 ***
	30 min	-3.92 ***	-2.98	-3.85 ***	-3.00	5.80 ***	1.84 ***
	Hourly	-3.96 ***	-2.98	-3.81 ***	-3.02	3.95 ***	1.26 ***
	Daily	-3.88 ***	-3.04	-3.97 ***	-3.02	1.56 ***	0.51 ***
WIG20	5 min	-2.59 *	-3.10	-2.59 *	-3.11	18.75 ***	3.72 ***
	5 min daily	-2.60 *	-3.10	-2.60 *	-3.13	18.63 ***	3.69 ***
	5 min until 14:40	-2.60 *	-3.11	-2.60 *	-3.12	16.40 ***	3.26 ***
	30 min	-2.61 *	-3.08	-2.60 *	-3.17 *	7.91 ***	1.60 ***
	Hourly	-2.61 *	-3.13 *	-2.60 *	-3.24 *	5.38 ***	1.10 ***
	Daily	-2.81 **	-3.43 **	-2.97 **	-3.25 *	2.13 ***	0.46 ***
Log Levels - First Differences							
DAX	5 min	-152.88 ***	-152.88 ***	-210.66 ***	-210.66 ***	0.18	0.05
	5 min daily	-151.50 ***	-151.50 ***	-209.64 ***	-209.64 ***	0.19	0.09
	5 min until 14:40	-123.66 ***	-123.66 ***	-169.51 ***	-169.51 ***	0.09	0.06
	30 min	-87.75 ***	-87.76 ***	-87.75 ***	-87.76 ***	0.16	0.05
	Hourly	-62.69 ***	-62.71 ***	-62.70 ***	-62.71 ***	0.15	0.05
	Daily	-21.58 ***	-21.61 ***	-21.81 ***	-21.94 ***	0.22	0.07
BUX	5 min	-198.06 ***	-198.10 ***	-198.05 ***	-198.09 ***	0.95 ***	0.06
	5 min daily	-93.88 ***	-93.94 ***	-193.97 ***	-193.97 ***	0.87 ***	0.05
	5 min until 14:40	-80.73 ***	-80.79 ***	-169.31 ***	-169.34 ***	0.85 ***	0.05
	30 min	-77.26 ***	-77.36 ***	-77.36 ***	-77.39 ***	0.80 ***	0.05
	Hourly	-57.56 ***	-57.70 ***	-57.57 ***	-57.74 ***	0.87 ***	0.05
	Daily	-21.13 ***	-21.49 ***	-21.14 ***	-21.76 ***	0.79 ***	0.06
PX	5 min	-174.60 ***	-174.64 ***	-175.57 ***	-175.54 ***	0.70 **	0.07
	5 min daily	-80.15 ***	-80.16 ***	-154.09 ***	-154.06 ***	0.14	0.03
	5 min until 14:40	-71.89 ***	-71.91 ***	-137.00 ***	-136.93 ***	0.22	0.06
	30 min	-73.96 ***	-74.04 ***	-74.27 ***	-74.28 ***	0.59 **	0.05
	Hourly	-52.29 ***	-52.40 ***	-52.61 ***	-52.63 ***	0.55 **	0.05
	Daily	-18.95 ***	-19.17 ***	-18.90 ***	-19.16 ***	0.55 **	0.06
WIG20	5 min	-187.17 ***	-187.17 ***	-187.16 ***	-187.17 ***	0.21	0.04
	5 min daily	-135.67 ***	-135.67 ***	-186.89 ***	-186.89 ***	0.07	0.06
	5 min until 14:40	-163.94 ***	-163.94 ***	-163.94 ***	-163.94 ***	0.15	0.10
	30 min	-75.38 ***	-75.40 ***	-75.43 ***	-75.44 ***	0.18	0.03
	Hourly	-53.08 ***	-53.10 ***	-53.14 ***	-53.15 ***	0.17	0.03
	Daily	-19.98 ***	-20.03 ***	-20.31 ***	-20.61 ***	0.29	0.06
Log Levels - Second Differences							
DAX	5 min	-49.14 ***	-49.14 ***	-4780.99	-5052.20	0.10	0.10
	5 min daily	-107.83 ***	-107.83 ***	-431.40 ***	-431.40 ***	0.06	0.04
	5 min until 14:40	-104.85 ***	-104.85 ***	-279.24 ***	-279.28 ***	0.09	0.03
	30 min	-31.91 ***	-31.91 ***	-2801.53	-2800.09	0.09	0.09
	Hourly	-27.90 ***	-27.90 ***	-784.95 ***	-784.84 ***	0.04	0.02
	Daily	-11.73 ***	-11.71 ***	-224.27 ***	-222.30 ***	0.11	0.09
BUX	5 min	-47.54 ***	-47.53 ***	-2680.12	-2680.80	0.02	0.01
	5 min daily	-104.38 ***	-104.38 ***	-326.36 ***	-326.42 ***	0.09	0.02
	5 min until 14:40	-122.32 ***	-122.32 ***	-258.86 ***	-258.93 ***	0.15	0.03
	30 min	-26.06 ***	-26.06 ***	-1735.12	-1734.92	0.03	0.03
	Hourly	-21.72 ***	-21.71 ***	-738.86 ***	-738.79 ***	0.02	0.02
	Daily	-12.45 ***	-12.44 ***	-155.94 ***	-155.70 ***	0.15	0.07
PX	5 min	-45.81 ***	-45.81 ***	-2590.77	-2591.64	0.33	0.28 ***
	5 min daily	-118.61 ***	-118.64 ***	-224.98 ***	-225.18 ***	0.62 **	0.05
	5 min until 14:40	-129.10 ***	-129.13 ***	-191.06 ***	-191.26 ***	0.75 ***	0.07
	30 min	-25.63 ***	-25.63 ***	-2461.74	-2460.62	0.02	0.02
	Hourly	-21.20 ***	-21.19 ***	-971.30 ***	-970.91 ***	0.13	0.09
	Daily	-11.86 ***	-11.84 ***	-184.52 ***	-185.69 ***	0.27	0.26
WIG20	5 min	-44.13 ***	-44.12 ***	-3327.02	-3327.22	0.01	0.01
	5 min daily	-115.24 ***	-115.27 ***	-302.91 ***	-303.56 ***	0.67 **	0.02
	5 min until 14:40	-112.66 ***	-112.69 ***	-237.59 ***	-237.98 ***	0.66 **	0.02
	30 min	-27.25 ***	-27.25 ***	-1329.31	-1329.18	0.02	0.02
	Hourly	-21.46 ***	-21.45 ***	-605.89 ***	-605.78 ***	0.02	0.02
	Daily	-11.88 ***	-11.87 ***	-169.84 ***	-169.06 ***	0.10	0.08

Source: Author's Computations

6.2 Interdependence vs. Contagion

We will begin the analysis of comovements by testing whether there is interdependence or contagion between capital markets pioneered by King & Wadhwani (1990) and used for instance by Jokipii & Lucey (2007). We will test the returns of stock market indices included in our analysis. This test is based on correlation coefficients which are computed according to the set of Equations 4.1. We show correlation coefficients for each pair of countries in the next Tables 6.4, 6.5 and 6.6. The correlation coefficients are calculated for all frequencies, so we are able to see how correlations differ across frequencies.

The correlations are positive for all pairs of indices in all frequencies. At the first glance, 5 minute data frequency correlations have evidently higher values especially if we test the data that includes the overnight returns (the lower triangle in the Table 6.4). It may be again because of the significant dependence on the development of other world markets which continue trading a long time after the European markets are closed. Opening prices also usually increase as we can see on the Figure 5.1 and thus overnight returns cause biased results. The effect seems to be similar on all markets under consideration when the increase in correlations is proportionally the same for each pair. The correlations of 5 minute data frequency with overnight returns are quite similar in all data samples - in crisis, tranquil and total periods. However, when we exclude the overnight returns, differences between crisis and tranquil periods are already visible (upper triangle in the Table 6.4). The correlations from tranquil period are higher for all pairs than in crisis period. The results of correlations for 5 minute data frequency with daily returns taken until 14:40 are a little lower than for all daily returns (lower triangle in the Table 6.5). These results seem to be the most accurate when we excluded all potential discrepancies in dataset. The correlations are in most cases higher in tranquil period than in crisis period. The highest correlation is between German and Polish capital markets in both crisis (39 per cent) and tranquil (45 per cent) periods, the correlation of German with Czech capital market follows (37 per cent in both periods).

Table 6.4: Correlations of 5minute Data Frequency Including Overnight Returns (lower triangle) and Including Only Daily Returns (upper triangle)

	Germany	**Hungary**	**Czech Republic**	**Poland**
Total Sample				
Germany	1	0.28	0.38	0.43
Hungary	0.55	1	0.17	0.27
Czech Republic	0.67	0.63	1	0.25
Poland	0.61	0.53	0.57	1
Crisis Period (January 2008 - March 12th, 2009)				
Germany	1	0.22	0.38	0.41
Hungary	0.57	1	0.14	0.24
Czech Republic	0.70	0.67	1	0.25
Poland	0.61	0.53	0.59	1
Tranquil Period (March 13th, 2009 - November 2010)				
Germany	1	0.38	0.38	0.48
Hungary	0.53	1	0.22	0.31
Czech Republic	0.61	0.55	1	0.27
Poland	0.62	0.53	0.53	1

Source: Author's Computations

Table 6.5: Correlations of 5minute Data Frequency Including Returns Taken until 14:40 (lower triangle) and 30minute Data Frequency (upper triangle)

	Germany	**Hungary**	**Czech Republic**	**Poland**
Total Sample				
Germany	1	0.49	0.52	0.62
Hungary	0.26	1	0.43	0.47
Czech Republic	0.37	0.16	1	0.49
Poland	0.41	0.23	0.25	1
Crisis Period (January 2008 - March 12th, 2009)				
Germany	1	0.44	0.52	0.61
Hungary	0.20	1	0.43	0.45
Czech Republic	0.37	0.13	1	0.49
Poland	0.39	0.21	0.24	1
Tranquil Period (March 13th, 2009 - November 2010)				
Germany	1	0.56	0.52	0.64
Hungary	0.36	1	0.45	0.50
Czech Republic	0.37	0.20	1	0.48
Poland	0.45	0.27	0.28	1

Source: Author's Computations

When we take 30 minute data frequency including only its daily returns (Table 6.5), the residual correlation coefficients do show higher values than for 5 minute data frequency and the results for tranquil and crisis period are not markedly different. However, correlations in crisis period show slightly lower values than in tranquil period. On the other side, correlation between the Czech and Polish capital market is slightly higher in crisis period than in tranquil period. The highest correlation coefficient is again between German and Polish market in both crisis (61 per cent) and tranquil (64 per cent) periods and it is followed by correlation of German with Czech capital market in crisis period (52 per cent) and German with Hungarian capital market in tranquil period (56 per cent).

The correlations computed for 1 hour frequency data with only daily returns show higher values for tranquil period than for crisis period (lower triangle in the Table 6.6). The relations change from period to period. In crisis period, the highest values have correlations between Czech and Polish market (56 per cent) followed by German and Czech market (49 per cent). The highest correlation coefficients in tranquil period are recorded for German with Hungarian market (60 per cent) followed by Czech with Polish market (54 per cent).

The highest values of residual correlation coefficients do show returns of daily data for each pair of indices (upper triangle in the Table 6.6). The results show apparently higher values in crisis period than in tranquil period (in contrast with other frequencies of data) for all pairs but with the exception of German with Polish capital market; the correlation is higher in tranquil period in this case. The highest correlations in crisis period are between the Czech and Hungarian capital markets (75 per cent) followed by German and Czech capital markets (73 per cent). In tranquil period, the correlations are highest for German with Polish capital market (70 per cent) followed by German with Hungarian capital market and Polish with Hungarian capital market (both 69 per cent).

As we can see from these results, the correlations are higher for lower frequencies. Daily data frequency particularly shows the highest values and 5 minute data frequency shows the lowest values of residual correlation coefficients. This feature is well supported by previous literature; Lundin *et al.* (1998) confirm that correlations of higher frequencies have lower values because of the higher microstructural noise and thus such correlations may be biased.

Table 6.6: Correlations of 1hour Data Frequency Including Only Daily Returns (lower triangle) and Daily Data Frequency (upper triangle)

	Germany	**Hungary**	**Czech Republic**	**Poland**
Total Sample				
Germany	1	0.69	0.68	0.67
Hungary	0.52	1	0.71	0.70
Czech Republic	0.50	0.35	1	0.70
Poland	0.41	0.34	0.55	1
Crisis Period (January 2008 - March 12th, 2009)				
Germany	1	0.70	0.73	0.65
Hungary	0.47	1	0.75	0.70
Czech Republic	0.49	0.29	1	0.72
Poland	0.39	0.33	0.56	1
Tranquil Period (March 13th, 2009 - November 2010)				
Germany	1	0.69	0.59	0.70
Hungary	0.60	1	0.67	0.69
Czech Republic	0.53	0.46	1	0.67
Poland	0.47	0.37	0.54	1

Source: Author's Computations

Table 6.7: Summary of Correlation Coefficients (5min Data Frequency with Overnight Returns)

	Total Sample		Crisis		Tranquil		Test Stat.	Contagion?
	ρ	σ	ρ	σ	ρ	σ		
Germany								
Hungary	0.55	0.0039	0.57	0.0062	0.53	0.0051	-345789.19	NO
Czech Rep.	0.67	0.0042	0.70	0.0066	0.61	0.0054	-1313190.26	NO
Poland	0.61	0.0041	0.61	0.0065	0.62	0.0054	104235.13	YES
Hungary								
Germany	0.55	0.0039	0.57	0.0062	0.53	0.0051	-345789.19	NO
Czech Rep.	0.63	0.0042	0.67	0.0066	0.55	0.0055	-1166015.92	YES
Poland	0.53	0.0042	0.53	0.0066	0.53	0.0054	17102.76	NO
Czech Republic								
Germany	0.67	0.0042	0.70	0.0066	0.61	0.0054	-1313190.26	NO
Hungary	0.63	0.0042	0.67	0.0066	0.55	0.0055	-1166015.92	YES
Poland	0.57	0.0043	0.59	0.0067	0.53	0.0055	-416247.31	NO
Poland								
Germany	0.61	0.0041	0.61	0.0065	0.62	0.0054	104235.13	YES
Hungary	0.53	0.0042	0.53	0.0066	0.53	0.0054	17102.76	NO
Czech Rep.	0.57	0.0043	0.59	0.0067	0.53	0.0055	-416247.31	NO

Source: Author's Computations

The residual correlation coefficients are consequently rewritten in the Tables 6.7, 6.8, 6.9, 6.10, 6.11 and 6.12 to be able to overview easily whether there is either interdependence or contagion between capital markets. 5 minute data frequency with overnight returns does show that there is contagion in two cases - when testing German with Polish capital market and Hungarian with Czech capital market. In all other cases, there is detected only interdependence between markets. When we clean up the data from overnight returns, we can see that contagion is detected for all pairs of stock market indices. We obtain the same results when we test the 5 minute data frequency including daily returns taken until 14:40.

When testing the returns of 30 minute data frequency, there is only interde-

Table 6.8: Summary of Correlation Coefficients (5min Data Frequency - Daily Returns)

	Total Sample		Crisis		Tranquil		Test Stat.	Contagion?
	ρ	σ	ρ	σ	ρ	σ		
Germany								
Hungary	0.28	0.0040	0.22	0.0062	0.38	0.0051	683844.57	YES
Czech Rep.	0.38	0.0042	0.38	0.0066	0.38	0.0055	8998.08	YES
Poland	0.43	0.0042	0.41	0.0065	0.48	0.0054	346247.67	YES
Hungary								
Germany	0.28	0.0040	0.22	0.0062	0.38	0.0051	683844.57	YES
Czech Rep.	0.17	0.0043	0.14	0.0067	0.22	0.0055	242164.59	YES
Poland	0.27	0.0042	0.24	0.0066	0.31	0.0055	245284.51	YES
Czech Republic								
Germany	0.38	0.0042	0.38	0.0066	0.38	0.0055	8998.08	YES
Hungary	0.17	0.0043	0.14	0.0067	0.22	0.0055	242164.59	YES
Poland	0.25	0.0043	0.25	0.0067	0.27	0.0056	78144.62	YES
Poland								
Germany	0.43	0.0042	0.41	0.0065	0.48	0.0054	346247.67	YES
Hungary	0.27	0.0042	0.24	0.0066	0.31	0.0055	245284.51	YES
Czech Rep.	0.25	0.0043	0.25	0.0067	0.27	0.0056	78144.62	YES

Source: Author's Computations

Table 6.9: Summary of Correlation Coefficients (5min Data Frequency until 14:40)

	Total Sample		Crisis		Tranquil		Test Stat.	Contagion?
	ρ	σ	ρ	σ	ρ	σ		
Germany								
Hungary	0.26	0.0046	0.20	0.0072	0.36	0.0059	459247.90	YES
Czech Rep.	0.37	0.0047	0.37	0.0074	0.37	0.0061	10876.21	YES
Poland	0.41	0.0047	0.39	0.0074	0.45	0.0062	210969.25	YES
Hungary								
Germany	0.26	0.0046	0.20	0.0072	0.36	0.0059	459247.90	YES
Czech Rep.	0.16	0.0048	0.13	0.0075	0.20	0.0062	163321.40	YES
Poland	0.23	0.0048	0.21	0.0075	0.27	0.0062	149387.82	YES
Czech Republic								
Germany	0.37	0.0047	0.37	0.0074	0.37	0.0061	10876.21	YES
Hungary	0.16	0.0048	0.13	0.0075	0.20	0.0062	163321.40	YES
Poland	0.25	0.0048	0.24	0.0075	0.28	0.0062	80817.67	YES
Poland								
Germany	0.41	0.0047	0.39	0.0074	0.45	0.0062	210969.25	YES
Hungary	0.23	0.0048	0.21	0.0075	0.27	0.0062	149387.82	YES
Czech Rep.	0.25	0.0048	0.24	0.0075	0.28	0.0062	80817.67	YES

Source: Author's Computations

Table 6.10: Summary of Correlation Coefficients (30min Data Frequency)

	Total Sample		Crisis		Tranquil		Test Stat.	Contagion?
	ρ	σ	ρ	σ	ρ	σ		
Germany								
Hungary	0.49	0.0100	0.44	0.0157	0.56	0.0129	51374.29	YES
Czech Rep.	0.52	0.0108	0.52	0.0169	0.52	0.0140	-2463.25	NO
Poland	0.62	0.0107	0.61	0.0168	0.64	0.0139	22596.58	YES
Hungary								
Germany	0.49	0.0100	0.44	0.0157	0.56	0.0129	51374.29	YES
Czech Rep.	0.43	0.0109	0.43	0.0171	0.45	0.0141	7109.41	YES
Poland	0.47	0.0108	0.45	0.0170	0.50	0.0140	16202.03	YES
Czech Republic								
Germany	0.52	0.0108	0.52	0.0169	0.52	0.0140	-2463.25	NO
Hungary	0.43	0.0109	0.43	0.0171	0.45	0.0141	7109.41	YES
Poland	0.49	0.0108	0.49	0.0170	0.48	0.0141	-2969.43	NO
Poland								
Germany	0.62	0.0107	0.61	0.0168	0.64	0.0139	22596.58	YES
Hungary	0.47	0.0108	0.45	0.0170	0.50	0.0140	16202.03	YES
Czech Rep.	0.49	0.0108	0.49	0.0170	0.48	0.0141	-2969.43	NO

Source: Author's Computations

pendence between German and Czech capital markets and between Czech and Polish capital markets. The contagion is detected in all other cases (German with Hungarian capital market, German with Polish capital market, Czech with Hungarian capital market and Polish with Hungarian capital market).

Looking at the summary of residual correlation coefficients of one hour data frequency, we see the contagion in all cases with one exception of Czech with Polish capital market. On the other side, if we test the returns of daily data, we obtain only one comovement in form of contagion between German and Polish capital markets. All other pairs of markets show only interdependence between markets on daily basis. What is interesting from these results are the changes in comovements across frequencies. Jokipii & Lucey (2007) found the contagion between each pair of CEE capital markets (excluding German capital market). They received the same results of testing both the stock market indices and banking indices. The difference between their and our results may be in the character of crisis when the development of markets in 90s was not monitored as carefully as nowadays and that markets nowadays watch each other closely and their comovements in even such periods as is crisis may consequently show the same patterns of interdependence (contagion). We will continue investigating the interdependencies and comovements in the next section where we present the results of Granger Causality test.

Table 6.11: Summary of Correlation Coefficients (1 Hour Data Frequency)

	Total Sample		Crisis		Tranquil		Test Stat.	Contagion?
	ρ	σ	ρ	σ	ρ	σ		
Germany								
Hungary	0.52	0.0152	0.47	0.0239	0.60	0.0198	18942.55	YES
Czech Rep.	0.50	0.0152	0.49	0.0239	0.53	0.0197	4916.58	YES
Poland	0.41	0.0151	0.39	0.0237	0.47	0.0197	7954.02	YES
Hungary								
Germany	0.52	0.0152	0.47	0.0239	0.60	0.0198	18942.55	YES
Czech Rep.	0.35	0.0154	0.29	0.0242	0.46	0.0200	14404.33	YES
Poland	0.34	0.0153	0.33	0.0241	0.37	0.0199	3219.38	YES
Czech Republic								
Germany	0.50	0.0152	0.49	0.0239	0.53	0.0197	4916.58	YES
Hungary	0.35	0.0154	0.29	0.0242	0.46	0.0200	14404.33	YES
Poland	0.55	0.0153	0.56	0.0241	0.54	0.0199	-3884.87	NO
Poland								
Germany	0.41	0.0151	0.39	0.0237	0.47	0.0197	7954.02	YES
Hungary	0.34	0.0153	0.33	0.0241	0.37	0.0199	3219.38	YES
Czech Rep.	0.55	0.0153	0.56	0.0241	0.54	0.0199	-3884.87	NO

Source: Author's Computations

Table 6.12: Summary of Correlation Coefficients (Daily Data)

	Total Sample		Crisis		Tranquil		Test Stat.	Contagion?
	ρ	σ	ρ	σ	ρ	σ		
Germany								
Hungary	0.69	0.0375	0.70	0.0595	0.69	0.0485	-315.31	NO
Czech Rep.	0.68	0.0374	0.73	0.0593	0.59	0.048	-3467.15	NO
Poland	0.67	0.0372	0.65	0.0584	0.70	0.0486	1070.78	YES
Hungary								
Germany	0.69	0.0375	0.70	0.0595	0.69	0.0485	-315.31	NO
Czech Rep.	0.71	0.0380	0.75	0.0605	0.67	0.0494	-3630.83	NO
Poland	0.70	0.0377	0.70	0.0601	0.69	0.0491	-536.36	NO
Czech Republic								
Germany	0.68	0.0374	0.73	0.0593	0.59	0.0486	-3467.15	NO
Hungary	0.71	0.0380	0.75	0.0605	0.67	0.0494	-3630.83	NO
Poland	0.70	0.0379	0.72	0.0603	0.67	0.0492	-1748.11	NO
Poland								
Germany	0.67	0.0372	0.65	0.0584	0.70	0.0486	1070.78	YES
Hungary	0.70	0.0377	0.70	0.0601	0.69	0.0491	-536.36	NO
Czech Rep.	0.70	0.0379	0.72	0.0603	0.67	0.0492	-1748.11	NO

Source: Author's Computations

6.3 Granger Causality Test

The results of Granger Causality test are presented in this section. The test is applied on all frequencies and all pairs of indices. The results were computed using the software STATA and we have decided for maximum of ten lags to run the analysis. The optimal number of lags was chosen according to Akaike (AIC) and Schwarz Bayes information Criteria (SIC)[2]. We wanted to choose such maximum number of lags to omit the situation when the model becomes too complicated because of too many variables included in the model. As we applied the unit root tests as the first tests of this chapter, we could see that time series are difference-stationary processes. Therefore we used the first differences to compute the results for Granger Causality test. The optimal number of lags varied frequency to frequency. However, the available maximum lags were lower for datasets with lower frequency (Table 6.13). In case of 1 hour and daily data frequency, the maximum number of available lags that could be used in Grager Causality test was five and four lags, respectively. The number of lags varied from 5 to 10 in case of 5 minute and 30 minute data frequency, the number of lags in models ranged from 1 to 5 lags in case of 1 hour and daily data frequencies for each total, crisis and tranquil dataset.

[2]If different number of lags was suggested by AIC and SIC, we followed the number of lags suggested by AIC.

Table 6.13: Possible Maximum Number of Lags in Granger Causality and Engle-Granger Cointegration Tests

Indices	Dataset	Frequency					
Pair		5 min (all)	5 min (daily)	5 min (14:40)	30 min	1 hour	1 day
DAX and BUX	Total	10	10	10	10	5	4
	Crisis	10	10	10	10	5	4
	Tranquil	10	10	10	10	5	4
DAX and PX	Total	10	10	10	10	5	4
	Crisis	10	10	10	10	5	4
	Tranquil	10	10	10	10	5	4
DAX and WIG20	Total	10	10	10	10	5	4
	Crisis	10	10	10	10	5	4
	Tranquil	10	10	10	10	5	4
BUX and PX	Total	10	10	10	10	5	4
	Crisis	10	10	10	10	5	4
	Tranquil	10	10	10	10	5	4
BUX and WIG20	Total	10	10	10	10	5	4
	Crisis	10	10	10	10	5	4
	Tranquil	10	10	10	10	5	4
PX and WIG20	Total	10	10	10	10	5	4
	Crisis	10	10	10	10	5	4
	Tranquil	10	10	10	10	5	4

If we look at the results of the dataset covering total period, we can see that strong information flows are between German capital market and CEE capital markets in the highest 5 minute data frequency. By other words, as we test the null hypothesis about no Grager causality between stock indices we can say that German and CEE stock markets are Granger-caused by each other at 5 minute frequency level[3]. If we look at other frequencies, we see that German and Hungarian markets are Granger-caused by each other at 30 minute and 1 hour frequency level. When we use daily data frequency, there is detected only unidirectional causality going from Hungarian stock market to German stock market. When looking at the causality of German with Czech stock market, we can see bidirectional causality between markets in 1 hour data frequency at one per cent level of significance, German stock market Granger-causes the Czech stock market and the causality is only unidirectional in 30 minute and daily data frequency. German stock market Granger-causes Polish stock market in all frequencies and Polish stock market Granger-causes German market only in 30 minute and 1 hour data frequency. The causality in daily data frequency is only unidirectional. The causality between CEE markets is bidirectional in case of 5 minute data frequency for all 5 minute datasets. Hungarian with Czech stock market and Hungarian with Polish stock market show bidirectional causality in 30 minute data frequency. No causality is detected between Czech and Polish stock markets in 30 minute data frequency. If we look at 1 hour data frequency results, we cannot reject the null hypothesis about no causality between Hungarian and Czech stock markets in both directions, however unidi-

[3]The statement, that we reject the null hypothesis about no causality between indices, is more accurate.

rectional causality going from Polish to Hungarian stock market appeared and Czech with Polish stock market shows bidirectional causality. In daily data frequency, only unidirectional information flows between CEE stock markets are detected - from Hungarian to Czech stock market, from Polish to Hungarian stock market and from Czech to Polish stock market.

If we inspect the crisis period, bidirectional information flows between all combinations of markets under consideration are found in all datasets of 5 minute frequency. German capital market Granger-causes Hungarian and Czech stock markets in 30 minute and 1 hour data frequency, then German stock market Granger-causes Polish stock market in all frequencies. Hungarian and Czech stock markets Granger-cause German stock market in 1 hour data frequency and Polish stock market Granger-causes German stock market in 30 minute and 1 hour data frequencies. No causality is detected between German and Hungarian stock markets and German and Czech stock markets on daily basis. Hungarian stock market Granger-causes Czech stock market in 1 hour and daily data frequencies and Czech stock market Granger-causes Hungarian stock market in 30 minute data frequency. Hungarian stock market Granger-causes Polish stock market in 30 minute data frequency and Polish stock market Granger-causes Hungarian in 1 hour data frequency. No causality was found in daily frequency. Finally, Czech stock market Granger-causes Polish stock market in crisis period in all frequencies and the causality is bidirectional for all frequencies with the exception of daily data when the causality is only unidirectional.

The tranquil period does show the same results as total and crisis periods for all 5 minute frequency datasets; bidirectional causalities appeared in all cases. German stock market does Granger-cause the Hungarian stock market in 30 minute data frequency, it Granger-causes the Czech stock market in 30 minute and daily data frequency and Polish stock market in 30 minute data frequency. German stock index is vice versa Granger-caused by Czech and Polish stock indices in 1 hour data frequency. Bidirectional information flows between CEE stock markets are detected in 30 minute data frequency and only unidirectional information flows from Czech and Polish capital markets to Hungarian capital market is found in 1 hour data frequency.

The results of Granger Causality test are subsequently supported by more accurate results - results of Engle-Granger cointegration test and Johansen cointegration test - in next section.

Table 6.14: Granger Causality Test - Total Period

Data	N	lnY_tGClnX_t				lnX_tGClnY_t			
Frequency		Lags	H0: No causality (F-statistics)	R2	G. Causality	Lags	H0: No causality (F-statistics)	R2	G. Causality
Yt=DAX; Xt=BUX									
5 min (all)	58416	9	287.98***	0.0451	YES	9	3.23***	0.0011	YES
5 min (daily)	56867	10	250.99***	0.0446	YES	10	3.69***	0.0015	YES
5 min (14:40)	41758	9	194.89***	0.043	YES	9	2.60***	0.002	YES
30 min	2880	10	5.28***	0.0312	YES	10	2.26**	0.018	YES
1 hour	2164	3	6.13***	0.0125	YES	3	3.32**	0.0205	YES
1 day	566	1	1.64	0.0124	NO	1	4.58**	0.0082	YES
Yt=DAX; Xt=PX									
5 min (all)	49781	10	54.40***	0.0613	YES	10	78.40***	0.0168	YES
5 min (daily)	48964	10	54.60***	0.0612	YES	10	77.61***	0.0171	YES
5 min (14:40)	37452	10	55.88***	0.0652	YES	10	74.10***	0.0211	YES
30 min	2159	9	7.74***	0.0544	YES	9	1.41	0.0293	NO
1 hour	3610	1	20.69***	0.0069	YES	1	185.82***	0.0605	YES
1 day	407	2	8.26***	0.0437	YES	2	1.26	0.0087	NO
Yt=DAX; Xt=WIG20									
5 min (all)	54653	5	506.97***	0.0456	YES	5	12.60***	0.0019	YES
5 min (daily)	50166	10	230.70***	0.0461	YES	10	5.47***	0.0023	YES
5 min (14:40)	37070	10	170.23***	0.0463	YES	10	4.33***	0.003	YES
30 min	3634	7	10.39***	0.0222	YES	7	3.75***	0.0262	YES
1 hour	2188	3	6.20***	0.0132	YES	3	54.33***	0.0867	YES
1 day	128	4	5.24***	0.1842	YES	4	1.07	0.0567	NO
Yt=BUX; Xt=PX									
5 min (all)	48720	10	14.64***	0.0519	YES	10	179.97***	0.0372	YES
5 min (daily)	48724	9	16.23***	0.0518	YES	9	198.54***	0.0369	YES
5 min (14:40)	37432	9	16.14***	0.0518	YES	9	158.37***	0.0389	YES
30 min	2118	9	3.25***	0.0378	YES	9	3.60***	0.0406	YES
1 hour	706	5	1.86*	0.0425	NO	5	0.75	0.0335	NO
1 day	545	1	18.30***	0.0674	YES	1	1.11	0.0177	NO
Yt=BUX; Xt=WIG20									
5 min (all)	49827	10	25.67***	0.0072	YES	10	80.93***	0.0182	YES
5 min (daily)	49051	10	26.24***	0.0075	YES	10	80.44***	0.0185	YES
5 min (14:40)	36968	9	16.06***	0.006	YES	9	71.79***	0.0203	YES
30 min	1420	10	4.31***	0.0469	YES	10	2.77***	0.0567	YES
1 hour	2138	3	2.48*	0.0111	NO	3	39.20***	0.0561	YES
1 day	552	1	2.92*	0.0053	NO	1	4.27**	0.0209	YES
Yt=PX; Xt=WIG20									
5 min (all)	48148	10	190.36***	0.0401	YES	10	28.55***	0.0565	YES
5 min (daily)	47441	10	188.99***	0.0404	YES	10	28.15***	0.0563	YES
5 min (14:40)	36113	10	137.32***	0.0391	YES	10	30.29***	0.0593	YES
30 min	1413	10	3.24	0.0428	NO	10	0.96	0.0371	NO
1 hour	708	5	6.62***	0.0657	YES	5	2.83**	0.0443	YES
1 day	114	4	2.83**	0.1468	YES	4	2.20*	0.1923	NO

Notes: N is a sample size. *,**,*** denotes the rejection of null hypothesis of no Granger causality at 10, 5, 1 % level of significance, respectively. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

Table 6.15: Granger Causality Test - Crisis Period

Data	N	lnY_tGClnX_t				lnX_tGClnY_t			
Frequency		Lags	H0: No causality (F-statistics)	R2	G. Causality	Lags	H0: No causality (F-statistics)	R2	G. Causality
Yt=DAX; Xt=BUX									
5 min (all)	23706	9	121.08***	0.0482	YES	9	2.75***	0.0022	YES
5 min (daily)	23068	10	105.91***	0.0483	YES	10	3.63***	0.0032	YES
5 min (14:40)	16936	9	80.98***	0.0469	YES	9	2.29**	0.0036	YES
30 min	1168	10	4.29***	0.0655	YES	10	1.74*	0.0357	NO
1 hour	878	3	5.54***	0.0298	YES	3	2.82**	0.0437	YES
1 day	107	3	0.66	0.0917	NO	3	1.18	0.0356	NO
Yt=DAX; Xt=PX									
5 min (all)	20559	9	21.46***	0.0664	YES	9	37.05***	0.0175	YES
5 min (daily)	19924	10	20.51***	0.0657	YES	10	33.04***	0.0185	YES
5 min (14:40)	15236	10	22.49***	0.0693	YES	10	32.91***	0.024	YES
30 min	879	9	4.54***	0.0857	YES	9	1.19	0.059	NO
1 hour	1469	1	15.60***	0.0106	YES	1	80.59***	0.0753	YES
1 day	105	3	1.62	0.1777	NO	3	1.2	0.0389	NO
Yt=DAX; Xt=WIG20									
5 min (daily)	20493	10	96.68***	0.0483	YES	10	3.85***	0.0042	YES
5 min (all)	21135	9	105.73***	0.0462	YES	9	4.00***	0.0041	YES
5 min (14:40)	15147	10	68.75***	0.0474	YES	10	2.84***	0.0052	YES
30 min	1782	6	11.97***	0.0437	YES	6	3.82***	0.0446	YES
1 hour	893	3	4.59***	0.0251	YES	3	24.56***	0.1135	YES
1 day	52	4	3.15**	0.3267	YES	4	2.03	0.2324	NO
Yt=BUX; Xt=PX									
5 min (all)	19802	10	4.58***	0.0551	YES	10	78.84***	0.0412	YES
5 min (daily)	19803	9	5.08***	0.0551	YES	9	86.67***	0.0406	YES
5 min (14:40)	15211	9	4.77***	0.0529	YES	9	73.76***	0.0453	YES
30 min	861	9	1.85*	0.062	NO	9	3.43***	0.0994	YES
1 hour	287	5	2.55**	0.1043	YES	5	0.68	0.0857	NO
1 day	221	1	11.84***	0.0911	YES	1	2.04	0.0517	NO
Yt=BUX; Xt=WIG20									
5 min (all)	20262	10	9.98***	0.008	YES	10	43.05***	0.0236	YES
5 min (daily)	19941	10	10.52***	0.0085	YES	10	42.67***	0.0239	YES
5 min (14:40)	15028	9	4.54***	0.0064	YES	9	37.09***	0.0258	YES
30 min	867	9	2.92***	0.0553	YES	9	1.80*	0.0841	NO
1 hour	578	4	1.64	0.0367	NO	4	8.90***	0.0937	YES
1 day	223	1	1.64	0.0074	NO	1	3.67*	0.0594	NO
Yt=PX; Xt=20									
5 min (all)	21311	4	198.18***	0.0372	YES	4	45.42***	0.1186	YES
5 min (daily)	19584	9	87.24***	0.0415	YES	9	15.85***	0.0631	YES
5 min (14:40)	14976	9	62.44***	0.0401	YES	9	17.59***	0.0659	YES
30 min	1440	7	3.31***	0.0222	YES	7	2.71***	0.0363	YES
1 hour	288	5	4.35***	0.1247	YES	5	3.34***	0.1131	YES
1 day	47	4	2.88**	0.321	YES	4	0.2	0.3014	NO

Notes: N is a sample size. *,**,*** denotes the rejection of null hypothesis of no Granger causality at 10, 5, 1 % level of significance, respectively. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

Table 6.16: Granger Causality Test - Tranquil Period

Data	N	lnY_tGClnX_t				lnX_tGClnY_t			
Frequency		Lags	H0: No causality (F-statistics)	R2	G. Causality	Lags	H0: No causality (F-statistics)	R2	G. Causality
Yt=DAX; Xt=BUX									
5 min (all)	36860	4	408.91***	0.0436	YES	4	4.11***	0.0008	YES
5 min (daily)	36373	4	408.81***	0.0456	YES	4	4.38***	0.001	YES
5 min (14:40)	26962	4	295.47***	0.0453	YES	4	7.02***	0.0023	YES
30 min	5564	1	23.27***	0.0108	YES	1	3.11*	0.0008	NO
1 hour	2144	1	0.65	0.0063	NO	1	0.02	0.0003	NO
1 day	337	1	0	0.0003	NO	1	0.21	0.0024	NO
Yt=DAX; Xt=PX									
5 min (all)	29516	10	43.72***	0.0563	YES	10	44.53***	0.0164	YES
5 min (daily)	29040	10	43.11***	0.0554	YES	10	44.87***	0.0165	YES
5 min (14:40)	22216	10	37.91***	0.0608	YES	10	39.96***	0.0191	YES
30 min	4274	2	61.82***	0.0402	YES	2	0.06	0.0003	NO
1 hour	2141	1	0.44	0.0094	NO	1	95.12***	0.0427	YES
1 day	333	1	17.35***	0.0627	YES	1	0.02	0.0001	NO
Yt=DAX; Xt=WIG20									
5 min (all)	32326	5	306.56***	0.047	YES	5	2.57**	0.001	YES
5 min (daily)	31843	5	301.19***	0.0471	YES	5	2.39**	0.001	YES
5 min (14:40)	24521	4	315.17***	0.05	YES	4	5.50***	0.0019	YES
30 min	4737	1	16.49***	0.0035	YES	1	0.1	0.0002	NO
1 hour	1295	3	0.51	0.0043	NO	3	22.02***	0.0499	YES
1 day	337	1	0.87	0.0044	NO	1	0.13	0.0006	NO
Yt=BUX; Xt=PX									
5 min (all)	30185	7	26.89***	0.0489	YES	7	144.56***	0.0344	YES
5 min (daily)	29766	7	24.54***	0.0491	YES	7	144.29***	0.0349	YES
5 min (14:40)	23063	7	25.91***	0.0548	YES	7	102.19***	0.0328	YES
30 min	4616	1	97.43***	0.035	YES	1	14.10***	0.0111	YES
1 hour	419	5	1.43	0.0574	NO	5	3.05**	0.071	YES
1 day	231	2	2.46*	0.0615	NO	2	0.48	0.0208	NO
Yt=BUX; Xt=WIG20									
5 min (all)	30849	7	3.47***	0.0008	YES	7	61.24***	0.0157	YES
5 min (daily)	30391	7	2.61**	0.0006	YES	7	59.80***	0.0156	YES
5 min (14:40)	24065	4	44.50***	0.0085	YES	4	97.66***	0.0187	YES
30 min	4649	1	9.03***	0.002	YES	1	16.61***	0.0106	YES
1 hour	846	4	1.23	0.0083	NO	4	9.11***	0.0516	YES
1 day	237	2	1.47	0.0321	NO	2	1.47	0.0181	NO
Yt=PX; Xt=WIG20									
5 min (all)	29846	7	167.65***	0.0405	YES	7	20.08***	0.0479	YES
5 min (daily)	29426	7	166.49***	0.0412	YES	7	21.00***	0.0476	YES
5 min (14:40)	22700	7	126.16***	0.0395	YES	7	22.93***	0.0537	YES
30 min	4633	1	7.06***	0.0016	YES	1	73.38***	0.0288	YES
1 hour	420	5	1.6	0.0362	NO	5	0.87	0.0457	NO
1 day	322	1	0.65	0.0042	NO	1	1.86	0.0224	NO

Notes: N is a sample size. *,**,*** denotes the rejection of null hypothesis of no Granger causality at 10, 5, 1 % level of significance, respectively. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

6.4 Cointegration Tests

After we presented estimated results of Granger Causality test, we will present the estimated results of Cointegration tests, particularly Engle-Granger and Johansen Cointegration tests in this section. These tests were developed to detect the firm interrelationships between capital markets.

6.4.1 Engle-Granger Method

We will use the Engle-Granger cointegration test here to discover whether any long-term relationships appear between CEE capital markets within each other and between CEE capital markets and German capital market. Moreover, we want to inquire how these relationships do change across different periods. The results are given in the Tables 6.17, 6.18 and 6.19. As the time series of stock market index developments must be integrated of the same order to able to test for cointegrating relationships, we previously applied the battery of unit root tests. The time series were detected to be integrated of order one in all cases for all total, crisis and tranquil periods, therefore we can excercise both Engle-Granger and consequently Johansen cointegration tests on all pairs of indices. In previous papers, Engle-Grager test was based only on ADF test. We will supplement here the testing of residuals by Phillips-Perron (PP) test. The null hypothesis whether no cointegration relationship between stock indices appears is therefore rejected according to either ADF or PP tests. Both values of ADF and PP tests were computed in the software STATA. To be able to decide whether to reject the null hypohtesis based on ADF and PP tests, we needed to compute the critical values for these tests. The critical values were computed according to MacKinnon (2010) and his estimated critical statistic for cointegration

$$EstimatedCriticalValue = \beta_\infty + \frac{\beta_1}{T} + \frac{\beta_2}{T^2} \tag{6.1}$$

where T stands for sample size, β_∞ is estimated asymptotic critical value, β_1 demonstrates the "*coefficient on* $T-1$ *in response surface regression*" and β_2 stands for "*coefficient on* $T-2$ *in response surface regression*". The values β_∞, β_1 and β_2 were computed for the number of $I(1)$ series for which the null hypothesis of no cointegration is being tested (in principle for two). The values are also computed for different levels of significance (i. e. 1 %, 5 %, 10 % level of significance), see MacKinnon (2010) for more details. The computed

values are not presented here but are available on request. As ADF and PP test statistics gave us different values, we took the value which was more likely to reject the null hypothesis.

The results of Engle-Grager cointegration test for total period of dataset demonstrate only few cointegrating relationships. There is evident strong pairwise cointegration between DAX index and WIG20 index; we reject the null hypothesis of no cointegration even at one per cent level of significance for all frequncies. Thus it is evident that the markets react to each other promptly even if we cover the total period including the crisis and tranquil times. The error-correction terms in case of pair DAX and WIG20 are significant in all cases at least at five per cent level of significance. There is also detected a significant cointegration between BUX and WIG20 indices. In this case, BUX index responses to the deviations from long-run equilibrium in 5 minute data frequency at five per cent level of significance. Such result is for the data cleansed from the overnight differences and U. S. macroeconomic announcement at 14:30. If we allowed to accept the rejection of null hypothesis at ten per cent level of significance, cointegration relationship between BUX and WIG20 would be found for all 5 minute and also for 30 minute data frequencies. The same reaction exhibits DAX and PX indices where DAX index reacts to deviations from long-run equilibrium in 5 minute data frequency with overnight differences and 30 minute data frequency and also between PX and WIG20 where PX does react to deviations in daily data frequency. The error-correction term is however significant in only few cases where at least weak cointegration relationship was detected (particularly, in case of DAX and PX in 5 minute data frequency including overnight differences, BUX and WIG20 in both 5 minute data frequency with and without overnight differences). The error-correction term shows the significance of negative value of coefficients in most cases at different levels of significance but the cointegration test did not verify such results unless it is mentioned above.

Unexpectedly, the results change markedly when we test the data of crisis period. Strong pairwise cointegration relationships are within the pairs DAX and BUX in all data frequencies, DAX and PX in 5 minute data frequencies both with and without overnight differences, 30 minute and daily data frequencies. DAX and WIG20 indices show the pairwise cointegration relationships in all 5 minute data frequencies, and 30 minute data frequency. All cointegration relationships are detected at least at 5 per cent level of significance. The cointegration between CEE stock indices and German stock index are supported

by significantly negative error correction terms in most cases, in the pair of DAX and BUX in all 5 minute and 1 hour data frequencies, in the pair of DAX and PX in 5 minute data frequencies both with and without overnight differences and daily data frequency and finally in the pair of DAX and WIG20 in all 5 minute data frequencies. The strongest pairwise cointegration relationship was detected in the pair of BUX and PX index in 5 minute data frequency with only daily differences, in 30 minute and daily data frequencies. The error-correction term shows the significance at least at five per cent level of significance in daily data frequency when both BUX and PX indices react to deviations from long-run equilibrium relationship. Cointegration in the pair of BUX and WIG20 indices is detected in 5 minute data frequencies both with and without overnight differences and daily data frequency. In such cases, the error correction term is significant for both models in daily data frequency. The last pair of PX and WIG20 indices shows pairwise cointegration relationship at five per cent level of significance in case of all 5 minute data frequencies and daily data frequency. Both error-correction terms are significant at least at five per cent level of significance in 5 minute data frequencies both with and without overnight differences.

The results from tranquil period show only few cointegration relationships betweeen stock indices. The pair DAX and WIG20 demonstrates pairwise cointegration at least at five per cent level of significance in all 5 minute data frequencies, 30 minute and daily data frequencies. In pair of DAX and WIG20 error-correction term occurs to be negatively significant at least at five per cent level of significance in all frequencies; cointegration test validates the significant cointegration relationships. The cointegration relationship is detected also for the pair of BUX and PX indices at five per cent significance level in 30 minute data frequency. The negative error correction term is in such case also significant at least at five per cent level of significance.

Table 6.17: Engle-Granger Cointegration Test - Total Period

Data Frequency	ADF Test on Residuals from											
	$lnY_t = c + \alpha lnX_t + \varepsilon_t$						$lnX_t = c + \alpha lnY_t + \varepsilon_t$					
	N	Lags	ADF	P-P	Coint.	ECT	N	Lags	ADF	P-P	Coint.	ECT
Yt=DAX; Xt=BUX												
5 min (all)	58417	8	-2.32	-2.81	NO	-0.0002612***	58417	8	-1.71	-2.64	NO	-0.0000359
5 min (daily)	57588	8	-2.27	-2.74	NO	-0.0002575***	57588	8	-1.70	-2.07	NO	-0.0000252
5 min (14:40)	41758	8	-1.70	-2.25	NO	-0.000215**	40318	10	-1.35	-1.61	NO	-0.0000125
30 min	2160	10	-1.631	-2.45	NO	-0.0015268***	2160	10	-1.565	-1.94	NO	-0.0005043
1 hour	720	4	-1.877	-2.02	NO	-0.0035126**	720	4	-1.548	-1.20	NO	-0.0008799
1 day	414	1	-2.035	-2.96	NO	-162.4244***	414	1	-2.194	-2.71	NO	-164.0012
Yt=DAX; Xt=PX												
5 min (all)	49057	10	-3.063	-2.57	NO *	-0.0002602**	49057	10	-2.762	-2.34	NO	-0.0001775***
5 min (daily)	48241	10	-3.036	-2.79	NO	-0.00026**	48241	10	-2.764	-2.58	NO	-0.000171***
5 min (14:40)	36730	10	-2.597	-2.37	NO	-0.0002428**	36730	10	-2.861	-2.65	NO	-0.0001922***
30 min	719	10	-1.132	-3.27	NO *	-0.0018587	719	10	-0.427	-2.98	NO	-0.0010665
1 hour	719	4	-1.144	-2.51	NO	-0.0030975**	719	4	-0.496	-2.12	NO	-0.0021101**
1 day	125	3	-1.546	-2.35	NO	-72.30297	125	3	-1.596	-2.48	NO	-17.92632
Yt=DAX; Xt=WIG20												
5 min (all)	53188	6	-7.16	-6.53	YES ***	-.0011741***	53188	6	-7.229	-6.45	YES ***	-0.0007896***
5 min (daily)	52359	6	-7.087	-6.42	YES ***	-0.0011426***	52359	6	-7.182	-6.39	YES ***	-0.0008827***
5 min (14:40)	37800	8	-5.21	-5.12	YES ***	-.0008774***	37800	8	-5.491	-5.28	YES ***	-0.0009158***
30 min	3634	6	-4.268	-6.42	YES ***	-0.0069973***	3634	6	-4.575	-6.64	YES ***	-0.0043374***
1 hour	728	4	-1.148	-4.68	YES ***	-0.0135145***	728	4	-0.901	-4.76	YES ***	-0.0073103**
1 day	417	1	-2.847	-4.28	YES ***	-506.0001**	417	1	-3.158	-4.35	YES ***	-0.1161491***
Yt=BUX; Xt=PX												
5 min (all)	48012	10	-1.382	-1.54	NO	-0.0000328	48012	10	-2.235	-2.33	NO	-0.000092**
5 min (daily)	47306	10	-1.332	-1.33	NO	-0.000033	47306	10	-2.14	-2.16	NO	-0.0000923**
5 min (14:40)	36016	10	-0.43	-0.56	NO	5.70e-06	36016	10	-1.875	-1.89	NO	-0.0000952**
30 min	706	10	-1.126	-1.20	NO	-0.0005873	706	10	-0.654	-2.04	NO	-0.0009356
1 hour	706	4	-1.464	-1.26	NO	-0.0020303	706	4	-1.002	-1.84	NO	-0.0008667
1 day	113	3	-2.464	-1.68	NO	-.0072749	391	1	-1.72	-2.68	NO	-0.0132439**
Yt=BUX; Xt=WIG20												
5 min (all)	49111	10	-2.221	-2.02	NO	-0.0000408	49111	10	-3.195	-2.77	NO *	-0.000318***
5 min (daily)	48336	10	-2.098	-1.75	NO	-0.0000356	48336	10	-3.152	-2.51	NO *	-0.000319***
5 min (14:40)	35540	10	-2.191	-1.63	NO	-5.32e-06	35540	10	-3.359	-2.45	YES **	-.0003824***
30 min	5690	3	-2.079	-1.96	NO	-0.0005866	5690	3	-3.123	-3.18	NO *	-0.0000638
1 hour	712	4	-0.272	-1.55	NO	-0.0012612	1424	3	-1.099	-2.31	NO	-0.0028974*
1 day	399	1	-1.801	-2.24	NO	-0.0118531*	399	1	-2.357	-2.79	NO	-0.0257047***
Yt=PX; Xt=WIG20												
5 min (all)	51009	5	-1.905	-2.01	NO	-0.0001941***	51009	5	-2.347	-2.34	NO	-0.00013
5 min (daily)	50301	5	-1.838	-2.08	NO	-0.000203***	50301	5	-2.335	-2.42	NO	-0.0001264
5 min (14:40)	35400	10	-1.453	-2.22	NO	-0.0001877***	35400	10	-1.741	-2.24	NO	-0.000118
30 min	3538	6	-0.519	-1.43	NO	-0.001625	3538	6	-1.072	-1.99	NO	-0.0005385
1 hour	708	4	0.72	-1.09	NO	-0.0023055	708	4	0.68	-1.53	NO	0.00282
1 day	390	1	-2.185	-3.03	NO	-0.0193238	390	1	-2.276	-3.15	NO *	-0.0263588

Notes: N is a sample size. ADF stands for Augmented Dickey-Fuller statistic, P-P for Phillips-Perron test. *,**,*** in the column cointegration (denoted *coint.*) stands for the rejection of null hypothesis of no cointegration at 10, 5, 1 % level of significance, respectively. ECT is the error-correction term. *,**,*** in the column of ECT indicates the statistical significance of the ECT at 10, 5, 1 % level of significance, respectively. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

Table 6.18: Engle-Granger Cointegration Test - Crisis Period

Data Frequency	ADF Test on Residuals from											
	$lnY_t = c + \alpha lnX_t + \varepsilon_t$						$lnX_t = c + \alpha lnY_t + \varepsilon_t$					
	N	Lags	ADF	P-P	Coint.	ECT	N	Lags	ADF	P-P	Coint.	ECT
Yt=DAX; Xt=BUX												
5 min (all)	23707	8	-5.271	-5.51	YES ***	-.0016825***	23707	8	-5.041	-5.36	YES ***	-.0007125***
5 min (daily)	23360	8	-5.325	-5.90	YES ***	-.0017153***	23360	8	-5.099	-5.61	YES ***	-.000644***
5 min (14:40)	16352	10	-3.895	-4.89	YES ***	-.0013531***	16352	10	-3.62	-4.57	YES ***	-.0006238**
30 min	876	10	-3.143	-5.178	YES ***	-.0144454***	876	10	-3.088	-4.939	YES ***	-.0050482*
1 hour	292	4	-2.268	-4.025	YES ***	-.0206413***	292	4	-2.072	-3.727	YES **	-.0080922**
1 day	166	1	-3.843	-4.612	YES ***	-.1065395*	166	1	-3.857	-4.46	YES ***	-.1354314***
Yt=DAX; Xt=PX												
5 min (all)	19972	10	-3.861	-3.674	YES **	-.0011473***	19972	10	-3.694	-3.555	YES **	-.000661***
5 min (daily)	19631	10	-3.977	-3.877	YES ***	-.0010773***	19631	10	-3.82	-3.777	YES **	-.0006459***
5 min (14:40)	14943	10	-3.217	-3.17	NO *	-.0008847**	14943	10	-3.28	-3.259	NO *	-.0006988***
30 min	293	10	-0.718	-4.358	YES ***	-.0089716**	293	10	-0.616	-4.219	YES ***	-.0023355
1 hour	293	4	-1.271	-3.535	YES **	-.0144548***	293	4	-1.104	-3.354	NO *	-.0073502***
1 day	165	1	-2.527	-3.83	YES **	-.109241**	165	1	-2.586	-3.895	YES **	-.144621***
Yt=DAX; Xt=WIG20												
5 min (all)	20540	10	-4.55	-4.293	YES ***	-.0012147***	20540	10	-4.643	-4.305	YES ***	-.0008868***
5 min (daily)	20790	8	-4.311	-4.331	YES ***	-.0013017***	20790	8	-4.403	-4.35	YES ***	-.0009067***
5 min (14:40)	14850	10	-4.075	-3.631	YES ***	-.0009358***	14850	10	-4.259	-3.714	YES ***	-.0011169***
30 min	1188	7	-2.405	-4.226	YES ***	-.0053764**	1485	6	-2.989	-4.441	YES ***	-.0027522
1 hour	297	4	-0.234	-2.951	NO	-.0144618***	297	4	-0.152	-3.111	NO *	-.0063652
1 day	170	1	-1.492	-2.392	NO	-.0990719	170	1	-1.823	-2.476	NO	-.1478577***
Yt=BUX; Xt=PX												
5 min (all)	19516	10	-3.198	-3.239	NO *	-.0004522*	19516	10	-3.456	-3.443	YES **	-.0007755***
5 min (daily)	19229	10	-3.386	-3.079	YES **	-.0004579*	19229	10	-3.614	-3.296	YES **	-.0007751***
5 min (14:40)	14637	10	-1.727	-1.574	NO	-.0001377	14637	10	-2.14	-1.928	NO	-.0006406***
30 min	287	10	-0.161	-3.672	YES **	-.0058033*	287	10	-0.212	-3.905	YES **	-.0075962**
1 hour	287	4	-1.921	-3.296	NO *	-.0119697	287	4	-1.894	-3.46	YES **	-.01101
1 day	47	3	-0.338	-3.832	YES **	-.0908171***	47	3	-0.288	-4.109	YES **	-.097306***
Yt=BUX; Xt=WIG20												
5 min (all)	19973	10	-3.194	-3.665	YES **	-.0004104	19973	10	-3.633	-4.002	YES ***	-.0011915***
5 min (daily)	19652	10	-3.24	-3.565	YES **	-.0003987	19652	10	-3.692	-3.879	YES **	-.0011661***
5 min (14:40)	14450	10	-2.602	-2.905	NO	.0000155	14450	10	-3.056	-3.204	NO *	-.0013642***
30 min	2312	3	-2.82	-2.627	NO	-.0043538	2312	3	-3.283	-3.14	NO *	-.0041636
1 hour	289	4	-0.437	-3.002	NO	-.009001	289	4	-0.572	-3.388	YES **	-.0074161
1 day	161	1	-4.803	-3.752	YES ***	-.0995045***	161	1	-5.119	-4.001	YES ***	-.1099021***
Yt=PX; Xt=WIG20												
5 min (all)	20448	6	-2.951	-3.354	YES **	-.0006083***	20448	6	-3.239	-3.577	YES **	-.000703**
5 min (daily)	20736	4	-2.885	-3.362	YES **	-.0005462***	20736	4	-3.139	-3.565	YES **	-.0006157**
5 min (14:40)	15840	5	-2.922	-3.369	YES **	-.0005***	15840	5	-3.005	-3.377	YES **	-.0006061*
30 min	1440	6	-1.327	-2.637	NO	-.0033962	1440	6	-1.682	-2.958	NO	-.0036575
1 hour	864	2	-0.986	-2.072	NO	-.0079545	864	2	-1.322	-2.399	NO	.0014007
1 day	160	1	-2.778	-3.292	YES **	-.0831035	160	1	-2.942	-3.452	YES **	-.0418004

Notes: N is a sample size. ADF stands for Augmented Dickey-Fuller statistic, P-P for Phillips-Perron test. *,**,*** in the column cointegration (denoted *coint.*) stands for the rejection of null hypothesis of no cointegration at 10, 5, 1 % level of significance, respectively. ECT is the error-correction term. *,**,*** in the column of ECT indicates the statistical significance of the ECT at 10, 5, 1 % level of significance, respectively. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

Table 6.19: Engle-Granger Cointegration Test - Tranquil Period

Data Frequency	ADF Test on Residuals from											
	$lnY_t = c + \alpha lnX_t + \varepsilon_t$						$lnX_t = c + \alpha lnY_t + \varepsilon_t$					
	N	Lags	ADF	P-P	Coint.	ECT	N	Lags	ADF	P-P	Coint.	ECT
Yt=DAX; Xt=BUX												
5 min (all)	36430	4	-0.362	-0.727	NO	-.000105	36430	4	-0.433	-1.291	NO	-.0000454
5 min (daily)	35944	4	-0.521	-0.64	NO	-.0000925	35944	4	-0.57	-0.97	NO	-.0000366
5 min (14:40)	26534	4	-0.408	-0.521	NO	-.0000849	26534	4	-0.637	-1.09	NO	-.0000334
30 min	5136	1	-0.634	-0.727	NO	-.0006455	5136	1	-0.643	-0.974	NO	-.0004192
1 hour	1715	1	-0.108	-0.079	NO	-.0005934	1715	1	-0.325	-0.086	NO	.0005421
1 day	247	1	1.146	-0.635	NO	-.0098582	247	1	0.966	-0.681	NO	-.0155875
Yt=DAX; Xt=PX												
5 min (all)	30809	6	-1.477	-1.07	NO	-.0001443	32102	3	-1.839	-1.342	NO	-.0001734**
5 min (daily)	30330	6	-1.674	-1.355	NO	-.0001402***	29470	8	-2.15	-1.614	NO	-.0001664**
5 min (14:40)	22645	8	-1.912	-1.287	NO	-.0001742	22645	8	-2.604	-1.95	NO	-.0001934**
30 min	2134	6	-0.342	-2.212	NO	-.0006199	2134	6	0.326	-2.382	NO	-.0012419**
1 hour	1283	2	-1.004	-1.213	NO	-.0011897	1712	1	-0.92	-1.096	NO	-.0014301
1 day	73	3	-0.664	-1.393	NO	-.0078599	73	3	-0.86	-2.238	NO	-.0261145**
Yt=DAX; Xt=WIG20												
5 min (all)	32326	4	-4.59	-4.768	YES ***	-.000974***	32326	4	-4.549	-4.523	YES ***	-.0008253***
5 min (daily)	31843	4	-4.552	-4.594	YES ***	-.00097***	31843	4	-4.512	-4.458	YES ***	-.0008355***
5 min (14:40)	23655	5	-3.637	-3.549	YES **	-.0008361***	23655	5	-3.879	-3.732	YES **	-.0007091***
30 min	4305	1	-4.136	-4.548	YES ***	-.0052151***	4305	1	-4.029	-4.474	YES ***	-.0043558***
1 hour	1727	1	-2.421	-3.343	YES **	-.0130531***	1727	1	-2.287	-3.089	NO *	-.0058029
1 day	246	1	-2.352	-4.165	YES ***	-.0742676***	246	1	-2.351	-4.207	YES ***	-.0880119***
Yt=BUX; Xt=PX												
5 min (all)	30608	5	-2.747	-3.022	NO	-.0002342*	30608	5	-2.797	-3.102	NO *	-.0003046**
5 min (daily)	30189	5	-2.834	-2.852	NO	-.000247**	30189	5	-2.757	-2.978	NO	-.0002801**
5 min (14:40)	22642	7	-3.192	-2.926	NO *	-.0002846**	22642	7	-3.156	-3.192	NO *	-.0003383***
30 min	4195	1	-2.855	-3.472	YES **	-.001706**	2515	5	-1.343	-3.458	YES **	-.0028684***
1 hour	1678	1	-1.411	-2.632	NO	-.0041973	1678	1	-1.103	-2.428	NO	-.0037795
1 day	65	3	-0.395	-2.391	NO	-.0294455*	65	3	-0.264	-3.087	NO	-.0585178***
Yt=BUX; Xt=WIG20												
5 min (all)	31705	4	-1.488	-1.673	NO	-.0001273	31705	4	-1.283	-1.416	NO	-.0002615
5 min (daily)	31245	4	-1.51	-1.692	NO	-.0001371	31245	4	-1.279	-1.549	NO	-.0002803
5 min (14:40)	23640	4	-1.617	-1.807	NO	-.0001782	23640	4	-1.588	-1.878	NO	-.0003219
30 min	4225	1	-1.468	-1.632	NO	-.0006913	4225	1	-1.233	-1.47	NO	-.0015498
1 hour	423	4	-0.327	-1.852	NO	-.0010834	423	4	-0.042	-1.429	NO	-.0030669
1 day	149	2	-1.555	-2.398	NO	-.0209831	149	2	-1.399	-2.396	NO	-.0147939
Yt=PX; Xt=WIG20												
5 min (all)	31127	3	-1.636	-1.485	NO	-.0001752**	30273	5	-1.223	-0.968	NO	-.0000653
5 min (daily)	30707	3	-1.644	-1.431	NO	-.0002151***	29853	5	-1.238	-1.008	NO	-.0000818
5 min (14:40)	23975	3	-1.891	-1.615	NO	-.0002299***	23550	4	-1.539	-1.239	NO	-.000166
30 min	4209	1	-2.022	-2.012	NO	-.0016333***	4209	1	-1.439	-1.65	NO	-.000502
1 hour	1263	2	0.343	-0.964	NO	-.0002158	1263	2	0.571	-0.505	NO	.0072843
1 day	229	1	-2.36	-2.945	NO	-.0371408***	229	1	-1.406	-2.155	NO	-.0235399*

Notes: N is a sample size. ADF stands for Augmented Dickey-Fuller statistic, P-P for Phillips-Perron test. *,**,*** in the column cointegration (denoted *coint.*) stands for the rejection of null hypothesis of no cointegration at 10, 5, 1 % level of significance, respectively. ECT is the error-correction term. *,**,*** in the column of ECT indicates the statistical significance of the ECT at 10, 5, 1 % level of significance, respectively. *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

6.4.2 Johansen Method

We will consequently present here the results of Johansen cointegration test. To perform this test, we used the software Eviews where is incorporated its VAR-based version with methodology developed in Johansen (1991) and Johansen (1995). We decided again for the maximum number of ten lags. The optimal number of lags was consequently chosen based on the value of Likelihood ratio (LR); the best model is with the lowest value of LR test. After we discovered the optimal number of lags, we chose the optimal model fitting to our data. There is five versions of Johansen cointegration test incorporated in Eviews: 1) no deterministic trend in original series and no intercept in cointegrating equations, 2) no deterministic trend in original series and with intercepts in cointegrating equations, 3) linear trend in original series and intercepts in cointegrating equations, 4) linear deterministic trends both in original series and cointegrating equations and 5) quadratic deterministic trend in original series and linear trend in cointegrating equations. We followed Akaike (AIC) and Schwarz-Bayes (SIC) Information Criteria to select the best fitting model. If the results were not unanimous, we chose the model according to SIC. The model with no deterministic trend in original series and with intercepts in cointegrating equations was chosen for all cases.

Johansen test assesses the possible cointegrating relationships based on the trace test or maximum eigenvalue test. The papers discussing which test is more efficient has already appeared. For instance, the trace test is preferred in Lüutkepohl *et al.* (2001). They justify such verdict by stating that the power performance of trace test is superior to the performance of maximum eigenvalue. "*The trace tests are advantageous if there are at least two more cointegrating relations in the process than are specified under the null hypothesis.*" Egert & Kocenda (2007) also used only trace test to present their results of Johansen cointegration test. We present here results of both trace and maximum eigenvalue tests.

Fistly, we discuss the results of Johansen cointegration test gained for the total period of dataset. We can see only few cointegrating equations. One cointegrating equation for the pair of DAX and BUX is found based on maximum eigenvalue test[4] in all 5 minute data frequencies. The pair of DAX and WIG20 indices does have one cointegrating equation in all tested frequencies based on

[4]The results of trace statistics are introduced in the Tables 6.20, 6.21 and 6.22 but we do not present here the maximum eigenvalue statistics due to lack of space. However, the number of cointegrating equations is quoted from both trace and maximum eigenvalue tests.

both trace and maximum eigenvalue tests. No other cointegrating equation was indicated for the total period of datasets.

The situation changes notably when we test the data from crisis period. One cointegrating equation according to both trace and maximum eigenvalue test appeared for all tested frequencies when we inspect the relationship of DAX and BUX indices and DAX and PX indices. One cointegrating equation was also found in the pair of DAX and WIG20 indices in all 5 minute and 30 minute data frequencies. The same relations were detected for the pair of PX and WIG20 indices. The pair of BUX and WIG20 indices does show one cointegrating equation in all 5 minute data frequencies and daily frequency according to both trace and maximum eigenvalue tests. No cointegrating relationship between BUX and PX indices was found.

Stock market indices produce different profile of relationships in tranquil period compared to total and crisis periods. One cointegrating equation was detected between the pair of DAX and BUX indices in all data frequencies. The relationship of DAX and PX indices shows one cointegrating equation in daily data frequency based on trace statistic. However, cointegrating relationship was found for all data frequencies when we consider the maximum eigenvalue statistic. The pair of DAX and WIG20 indices shows even two cointegrating equations in tranquil period for all data frequencies based on trace statistic, maximum eigenvalue test does not detect any cointegration relationship in 5 minute data frequency with daily differences taken until 14:40 and 30 minute data frequency. Two cointegrating equations are also found in the pair of BUX and PX indices in all 5 minute data frequencies, 30 minute and 1 hour data frequencies. Only one cointegrating relationship appeared in daily data frequency using both trace and maximum eigenvalue tests. One cointegrating equation was also found in the pair of BUX and WIG20 indices in all frequencies except 30 minute data frequency; even two cointegrating equations using both trace and maximum eigenvalue tests were found in 30 minute data frequency. The pair of PX and WIG20 indices shows one cointegrating equation for all 5 minute data frequencies, 30 minute and 1 hour data frequencies. No cointegrating relation was detected in daily data frequency. In the pair of PX and WIG20 indices, the results of trace statistic conform with the results of maximum eigenvalue statistic.

Table 6.20: Johansen Cointegration Test - Total Period

Data Frequency	Lags	R	Trace Statistic	SIC	ROOTS	Coint. Vectors (Lambda max/Max eigenvalue)
Yt=DAX; Xt=BUX						
5 min (all)		0	18.25352*	-19.19567*		
	8	1	2.15	-19.195	OK	0/1
		2		-19.194		
5 min (daily)		0	18.58345*	-19.18704*		
	10	1	2.22	-19.186	OK	0/1
		2		-19.186		
5 min (14:40)		0	18.69343*	-18.54190*		
	10	1	2.35	-18.54	OK	0/1
		2		-18.54		
30 min		0	17.16	-15.60174*		
	10	1	2.24	-15.599	OK	0/0
		2		-15.594		
1 hour		0	14.42	-13.98888*		
	8	1	2.10	-13.982	OK	0/0
		2		-13.973		
1 day		0	12.64	-10.28147*		
	8	1	1.77	-10.251	OK	0/0
		2		-10.207		
Yt=DAX; Xt=PX						
5 min (all)		0	12.34	-19.53830*		
	5	1	5.09	-19.54	OK	0/0
		2		-19.54		
5 min (daily)		0	12.62	-19.52083*		
	5	1	5.08	-19.52	OK	0/0
		2		-19.52		
5 min (14:40)		0	11.59	-18.98808*		
	9	1	5.06	-18.99	OK	0/0
		2		-18.99		
30 min		0	11.65	-15.73626*		
	2	1	5.01	-15.73	OK	0/0
		2		-15.73		
1 hour		0	10.42	-14.31016*		
	10	1	4.17	-14.30	OK	0/0
		2		-14.29		
1 day		0	8.44	-10.35955*		
	6	1	3.69	-10.32	OK	0/0
		2		-10.28		
Yt=DAX; Xt=WIG20						
5 min (all)		0	38.63593***	-19.38971*		
	8	1	4.61	-19.39	OK	1/1
		2		-19.39		
5 min (daily)		0	38.78949***	-19.34099*		
	8	1	4.59	-19.34	OK	1/1
		2		-19.34		
5 min (14:40)		0	39.39006***	-18.82188*		
	9	1	4.56	-18.82	OK	1/1
		2		-18.82		
30 min		0	36.93919***	-15.80634*		
	9	1	4.61	-15.80	OK	1/1
		2		-15.80		
1 hour		0	33.81895***	-14.22193*		
	8	1	4.58	-14.22	OK	1/1
		2		-14.21		
1 day		0	40.77561***	-10.47		
	7	1	3.47	-10.47666*	OK	1/1
		2		-10.44		
Yt=BUX; Xt=PX						
5 min (all)		0	10.10	-18.90705*		
	10	1	2.22	-18.91	OK	0/0
		2		-18.91		
5 min (daily)		0	9.96	-18.89689*		
	10	1	2.17	-18.90	OK	0/0
		2		-18.90		
5 min (14:40)		0	9.85	-18.29515*		
	10	1	2.21	-18.29	OK	0/0
		2		-18.29		
30 min		0	9.41	-15.13860*		
	8	1	2.07	-15.13	OK	0/0

Note: Table to be continued on the next page

Table 6.20: (continued)

Data Frequency	Lags	R	Trace Statistic	SIC	ROOTS	Coint. Vectors (Lambda max/Max eigenvalue)
		2		-15.13		
1 hour		0	8.12	-13.68802*		
	9	1	1.71	-13.68	OK	0/0
		2		-13.67		
1 day		0	5.39	-9.910683*		
	10	1	1.30	-9.87	OK	0/0
		2		-9.82		
Yt=BUX; Xt=WIG20						
5 min (all)		0	16.23	-18.86585*		
	10	1	2.36	-18.87	OK	0/0
		2		-18.86		
5 min (daily)		0	16.24	-18.83259*		
	10	1	2.37	-18.83	OK	0/0
		2		-18.83		
5 min (14:40)		0	16.01	-18.19505*		
	10	1	2.40	-18.19	OK	0/0
		2		-18.19		
30 min		0	15.05	-15.19283*		
	4	1	2.33	-15.19	OK	0/0
		2		-15.18		
1 hour		0	14.55	-13.70502*		
	7	1	2.15	-13.70	OK	0/0
		2		-13.69		
1 day		0	10.31	-10.20771*		
	6	1	2.05	-10.17	OK	0/0
		2		-10.13		
Yt=PX; Xt=WIG20						
5 min (all)		0	17.69	-19.21303*		
	8	1	4.57	-19.212	OK	0/0
		2		-19.211		
5 min (daily)		0	17.60	-19.20924*		
	8	1	4.54	-19.21	OK	0/0
		2		-19.21		
5 min (14:40)		0	16.77	-18.69778*		
	9	1	4.50	-18.70	OK	0/0
		2		-18.70		
30 min		0	16.46	-15.56886*		
	2	1	4.41	-15.56	OK	0/0
		2		-15.56		
1 hour		0	13.35	-14.08074*		
	8	1	4.48	-14.07	OK	0/0
		2		-14.06		
1 day		0	5.64	-10.13749*		
	10	1	1.47	-10.10	OK	0/0
		2		-10.05		

Notes: R is the rank and the number in this column is the actual tested rank under consideration. *,**,*** indicates the rejection of the "R" number of cointegration vectors at 10, 5, 1 % level of significance, respectively. SIC stands for the Schwarz information criterion in the model with a contant and no trend. "ROOTS" denotes whether the VAR system is stable, hence no roots lie outside of unit circle (in such case OK). *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

Table 6.21: Johansen Cointegration Test - Crisis Period

Data Frequency	Lags	R	Trace Statistic	SIC	ROOTS	Coint. Vectors (Lambda max/Max eigenvalue)
Yt=DAX; Xt=BUX						
5 min (all)		0	28.82641***	-18.24135*		
	9	1	3.99	-18.240	OK	1/1
		2		-18.239		
5 min (daily)		0	29.29454***	-18.24017*		
	10	1	3.75	-18.239	OK	1/1
		2		-18.237		
5 min (14:40)		0	30.12643***	-17.52666*		
	9	1	3.75	-17.53	OK	1/1
		2		-17.52		
30 min		0	27.85735***	-14.55289*		
	10	1	3.99	-14.549	OK	1/1
		2		-14.539		
1 hour		0	24.41672**	-12.89913*		
	8	1	4.01	-12.889	OK	1/1
		2		-12.870		
1 day		0	27.95262***	-9.517168*		
	3	1	5.35	-9.497	NO	1/1
		2		-9.418		
Yt=DAX; Xt=PX						
5 min (all)		0	27.37028***	-18.47153*		
	6	1	4.40	-18.47	OK	1/1
		2		-18.47		
5 min (daily)		0	27.53107***	-18.45319*		
	5	1	4.42	-18.45	OK	1/1
		2		-18.45		
5 min (14:40)		0	25.40168***	-17.92837*		
	3	1	4.58	-17.93	OK	1/1
		2		-17.92		
30 min		0	26.11215***	-14.65224*		
	2	1	4.33	-14.65	OK	1/1
		2		-14.64		
1 hour		0	22.26001**	-13.16215*		
	9	1	3.10	-13.15	OK	1/1
		2		-13.13		
1 day		0	21.85897**	-9.314038*		
	4	1	3.71	-9.28	NO	1/1
		2		-9.19		
Yt=DAX; Xt=WIG20						
5 min (all)		0	21.54661**	-18.42171*		
	8	1	3.90	-18.42	OK	1/1
		2		-18.42		
5 min (daily)		0	21.68873**	-18.36320*		
	8	1	3.86	-18.36	OK	1/1
		2		-18.36		
5 min (14:40)		0	21.91768**	-17.81173*		
	9	1	3.96	-17.81	OK	1/1
		2		-17.81		
30 min		0	21.08499**	-14.82058*		
	9	1	3.45	-14.81	OK	1/1
		2		-14.80		
1 hour		0	18.11838*	-13.18078*		
	8	1	3.29	-13.17	OK	0/0
		2		-13.15		
1 day		0	16.15	-9.390161*		
	5	1	3.73	-9.34	OK	0/0
		2		-9.25		
Yt=BUX; Xt=PX						
5 min (all)		0	19.31	-17.89772*		
	10	1	4.17	-17.90	OK	0/0
		2		-17.89		
5 min (daily)		0	18.80983*	-17.88429*		
	10	1	4.23	-17.88	OK	0/0
		2		-17.88		
5 min (14:40)		0	18.73525*	-17.25080*		
	10	1	4.26	-17.25	OK	0/0
		2		-17.25		
30 min		0	19.10655*	-14.09076*		
	6	1	4.24	-14.08	OK	0/0

Note: Table to be continued on the next page

Table 6.21: (continued)

Data Frequency	Lags	R	Trace Statistic	SIC	ROOTS	Coint. Vectors (Lambda max/Max eigenvalue)
		2		-14.07		
1 hour		0	18.97698*	-12.59183*		
	9	1	3.62	-12.58	OK	0/0
		2		-12.56		
1 day		0	14.45	-9.185045*		
	3	1	4.29	-9.12	NO	0/0
		2		-9.04		
Yt=BUX; Xt=WIG20						
5 min (all)		0	21.0422**	-18.02696*		
	10	1	4.52	-18.03	OK	1/1
		2		-18.02		
5 min (daily)		0	21.20361**	-17.99088*		
	10	1	4.52	-17.99	OK	1/1
		2		-17.99		
5 min (14:40)		0	21.73135**	-17.29608*		
	10	1	4.58	-17.29	OK	1/1
		2		-17.29		
30 min		0	18.48696*	-14.29960*		
	4	1	4.50	-14.29	OK	0/0
		2		-14.28		
1 hour		0	19.70788*	-12.78755*		
	7	1	4.39	-12.77	OK	0/0
		2		-12.76		
1 day		0	14.50488**	-9.116949*		
	10	1	2.18	-9.08	OK	1/1
		2		-9.01		
Yt=PX; Xt=WIG20						
5 min (all)		0	23.71401**	-18.25726*		
	8	1	4.27	-18.256	OK	1/1
		2		-18.254		
5 min (daily)		0	23.79061**	-18.25271*		
	7	1	4.27	-18.25	OK	1/1
		2		-18.25		
5 min (14:40)		0	22.24512**	-17.72393*		
	9	1	4.24	-17.72	OK	1/1
		2		-17.72		
30 min		0	22.09014**	-14.65761*		
	2	1	4.21	-14.65	OK	1/1
		2		-14.64		
1 hour		0	17.69	-13.07449*		
	8	1	4.00	-13.06	OK	0/0
		2		-13.04		
1 day		0	10.69	-8.922782*		
	10	1	2.65	-8.85	OK	0/0
		2		-8.76		

Notes: R is the rank and the number in this column is the actual tested rank under consideration. *,**,*** indicates the rejection of the "R" number of cointegration vectors at 10, 5, 1 % level of significance, respectively. SIC stands for the Schwarz information criterion in the model with a contant and no trend. "ROOTS" denotes whether the VAR system is stable, hence no roots lie outside of unit circle (in such case OK). *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

Table 6.22: Johansen Cointegration Test - Tranquil Period

Data Frequency	Lags	R	Trace Statistic	SIC	ROOTS	Coint. Vectors (Lambda max/Max eigenvalue)
Yt=DAX; Xt=BUX						
5 min (all)	8	0	23.40395**	-20.31660*	OK	1/1
		1	2.861442	-20.31576		
		2		-20.31447		
5 min (daily)	5	0	23.30526**	-20.30983*	OK	1/1
		1	2.899329	-20.30898		
		2		-20.30767		
5 min (14:40)	6	0	22.35843**	-19.79102*	OK	1/1
		1	2.674782	-19.78991		
		2		-19.78822		
30 min	2	0	23.06969**	-16.86042*	OK	1/1
		1	2.546823	-16.85659		
		2		-16.84975		
1 hour	8	0	21.36252**	-15.22315*	OK	1/1
		1	2.551545	-15.21518		
		2		-15.20087		
1 day	1	0	20.31471**	-11.38714*	OK	1/1
		1	2.25444	-11.35852		
		2		-11.29287		
Yt=DAX; Xt=PX						
5 min (all)	10	0	19.68297	-20.87006*	OK	0/1
		1	1.495683	-20.86906		
		2		-20.86756		
5 min (daily)	7	0	19.67618*	-20.86174*	OK	0/1
		1	1.406937	-20.86073		
		2		-20.85921		
5 min (14:40)	7	0	19.70879*	-20.33253*	OK	0/1
		1	1.487436	-20.3313		
		2		-20.32943		
30 min	2	0	19.96095*	-17.08626*	OK	0/1
		1	1.4191	-17.08155		
		2		-17.0735		
1 hour	8	0	17.92041	-15.64538*	OK	0/1
		1	1.76511	-15.63637		
		2		-15.62174		
1 day	2	0	20.51417**	-11.61482*	OK	1/1
		1	2.028773	-11.58715		
		2		-11.52085		
Yt=DAX; Xt=WIG20						
5 min (all)	7	0	26.50724***	-20.55557*	OK	2/2
		1	10.36697**	-20.55452		
		2		-20.55331		
5 min (daily)	5	0	26.40507***	-20.53046*	OK	2/2
		1	10.48312**	-20.52939		
		2		-20.52816		
5 min (14:40)	3	0	26.35315***	-20.08600*	OK	2/0
		1	10.53979**	-20.08466		
		2		-20.08312		
30 min	2	0	25.82587***	-17.00956*	OK	2/0
		1	10.30922**	-17.00428		
		2		-16.99801		
1 hour	10	0	29.0273***	-15.37821*	OK	2/2
		1	9.978519**	-15.37037		
		2		-15.35902		
1 day	1	0	27.92903***	-11.74156*	OK	2/2
		1	9.578657**	-11.71372		
		2		-11.66549		
Yt=BUX; Xt=PX						
5 min (all)	10	0	30.70783***	-20.18868*	OK	2/2
		1	9.749895**	-20.18774		
		2		-20.18647		
5 min (daily)	9	0	30.60015***	-20.19327*	OK	2/2
		1	9.669061**	-20.19232		
		2		-20.19103		
5 min (14:40)	9	0	30.59461***	-19.62436*	OK	2/2
		1	9.974312**	-19.6232		
		2		-19.62163		
30 min	2	0	31.36891***	-16.45438*	OK	2/2
		1	10.12545**	-16.45013		

Note: Table to be continued on the next page

Table 6.22: (continued)

Data Frequency	Lags	R	Trace Statistic	SIC	ROOTS	Coint. Vectors (Lambda max/Max eigenvalue)
		2		-16.44368		
1 hour	6	0	31.32033***	-14.98736*	OK	2/2
		1	11.8149**	-14.97954		
		2		-14.96866		
1 day	8	0	29.12524***	-10.94136*	OK	1/1
		1	7.94667*	-10.91967		
		2		-10.86578		
Yt=BUX; Xt=WIG20						
5 min (all)	8	0	29.59114***	-19.74894*	OK	1/1
		1	8.719317*	-19.74802		
		2		-19.74673		
5 min (daily)	5	0	30.73448***	-19.72255*	OK	1/1
		1	9.133858*	-19.72163		
		2		-19.72035		
5 min (14:40)	5	0	29.90261***	-19.18088*	OK	1/1
		1	8.685415*	-19.17973		
		2		-19.1781		
30 min	2	0	30.8018***	-16.16245*	OK	2/2
		1	9.263863**	-16.15829		
		2		-16.1517		
1 hour	10	0	30.36872***	-14.59218*	OK	1/1
		1	8.636457*	-14.58529		
		2		-14.57322		
1 day	6	0	23.76627**	-10.77333*	OK	1/1
		1	3.020721	-10.75074		
		2		-10.68564		
Yt=PX; Xt=WIG20						
5 min (all)	6	0	21.61285**	-20.36402*	OK	1/1
		1	3.223647	-20.363		
		2		-20.36151		
5 min (daily)	6	0	21.72433**	-20.36723*	OK	1/1
		1	3.215312	-20.3662		
		2		-20.36469		
5 min (14:40)	3	0	21.87626**	-19.86532*	OK	1/1
		1	3.212283	-19.86407		
		2		-19.86222		
30 min	2	0	21.96537**	-16.64073*	OK	1/1
		1	3.139726	-16.63602		
		2		-16.62821		
1 hour	7	0	20.28112**	-15.18851*	OK	1/1
		1	3.934961	-15.17946		
		2		-15.16549		
1 day	6	0	16.87247	-11.29419*	OK	0/0
		1	2.647732	-11.25584		
		2		-11.18959		

Notes: R is the rank and the number in this column is the actual tested rank under consideration. *,**,*** indicates the rejection of the "R" number of cointegration vectors at 10, 5, 1 % level of significance, respectively. SIC stands for the Schwarz information criterion in the model with a contant and no trend. "ROOTS" denotes whether the VAR system is stable, hence no roots lie outside of unit circle (in such case OK). *5 min all* expresses 5 minute data frequency including the overnight differences, *5 min daily* expresses 5 minute data frequency including only daily differences, *5 min 14:40* stands for 5 minute data frequency with daily differences taken until 14:40. *30 min* is 30 minute data frequency, *1 hour* stands for 1 hour data frequency and *1 day* expresses daily data frequency.

Source: Author's Computations

6.5 Discussion over Results of 5 Minute Frequency Datasets

We are going to discuss now the findings about the 5 minute data frequency datasets. We created three 5 minute data frequency datasets: the one consists of all differences or returns covering even the overnight computations, second covers only daily returns or differences and the last dataset consists of daily returns or differences that are taken until 14:40 of a given day. The purpose was to find out whether any differences in test results computed on such datasets will appear.

It is necessary to mention that even though we consider the datasets with the daily returns or differences taken only until 14:40 the most accurate, these datasets involve less information due to removed observations. However, it is empirically proved that such observations can be affected by information sent from another markets (e.g. U.S. or Asian markets) than from markets included in this analysis Egert & Kocenda (2007). High-frequency data are characterictic for its high sensitivity to such information. Thus to gain a firm results of interdependencies or co-movements by testing high-frequency data, it is necessary to vanish all unuseful influencing elements.

Both datasets of daily returns and daily returns taken until 14:40 show the contagion explicitly for each pair of time series. The dataset including the overnight returns left the cotagion only between the pair of Germany and Poland and the pair of the Czech Republic and Hungary. The test based on correlation coefficients was the only one that allowed the straight comparison of crisis and tranquil period when the comparison of correlation coefficients from crisis and tranquil periods is already incorporated in the null hypothesis. The rest of the tests executed on datasets of crisis and tranquil periods gain results separately for each period.

Granger Causality test indicates that in all datasets of 5 minute data frenquencies was discovered Granger causality between all pairs of stock market indices. Such causalities were disclosed in both directions. Podpiera (2001) states that such situation of causality in either or both directions means that markets still are fragmented.

Cointegration test using the Engle-Granger cointegration approach in all datasets of 5 minute data frequency did provide various results. In total period, we found just few cointegrating relationships, for instance between German and

Polish stock indices. Another cointegrating relationship is detected between the pair of Hungarian and Polish stock indices indicating that Polish stock index reacted more to the deviations from long-run equilibrium in the years from 2008 until 2010. If we test cointegration by Engle-Granger approach in crisis period, we see the differences between results of each type of 5 minute data frequency. The cointegrating relationships are more frequent over the list of results in crisis period. The cointegration occured between all pair of stock indices with the exception of the pair of BUX and PX indices in 5 minute data frequency including only daily differences. We obtained the same results in 5 minute data frequency involving the overnight returns. Possible explanation could be that in crisis times, the markets are more sensitive to the price changes on another markets and the overnight influences from the other world capital markets also do have a stronger influence. If we take the dataset with daily differences taken until 14:40, the cointegrating pairs are DAX-BUX, DAX-WIG20 and BUX-WIG20. Such relationships are not suprising; the thoughts about CEE stock markets comoving in line with DAX index price changes were already before executing tests. The overview of results given from the data of tranquil period, the only cointegrating relationship is again in the pair DAX and WIG20 indices. Such situation may indicate that Polish and German markets are closely interconnected in 5 minute data frequency.

Johansen Cointegration approach furthermore confirms the close relationship of German and Polish capital markets in 5 minute data frequency. In total period, at least one cointegrating vector is detected in each dataset of 5 minute data frequency in the pair of DAX and BUX indices and DAX and WIG20 indices. The results of crisis period do confirm the stronger overall tightness of all capital markets included in this study. At least one cointegrating vector was found in all datasets of 5 minute data frequency with only one exception of the pair of BUX and PX indices; no cointegrating relation was found in this relationship according to Johansen approach. Data of tranquil period display more cointegrating vectors over the whole table of results indicating that markets are more interrelated in tranquil period which is in contradiction of the results of Engle-Granger test for tranquil period.

The overall presentation of all three datasets of 5 minute data frequency indicates the high degree of sensitivity of the tests on the adjustment of high frequency data. Moreover, the cointegration tests in tranquil period provided contradictory results using Engle-Granger and Johansen approach. It may indicate that some other more advanced cointegration test should be used for

these intraday datasets to gain synchronous results.

Chapter 7

Conclusion

The aim of this thesis was to discover the interrelationships and comovements between the emerging markets from the CEE region. As these markets are geographically very close to German capital market which is considered to be one of the leaders among capital markets in Europe, we also inquired how important role it plays for CEE capital market region, whether it dominates and influence these emerging markets. The strength of such comparison is that there is no time lag between markets and that the markets are interlinked via trading of the same stocks for instance in form of dual listing.

We applied several econometric tests such as test based on correlation coefficients computed in VAR framework, Granger causality test and cointegration tests using both Engle-Granger and Johansen approach. Using intraday data with frequencies of 5 minutes, 30 minutes and 1 hour, we wanted to discover the speed in which the markets react to each other. Daily data frequency were included into analysis as well.

Above mentioned tests are frequently used instruments to discover the interdependencies between markets and were also involved in many papers, e.g. Egert & Kocenda (2007), Cerny (2004) and Cerny & Koblas (2008) among others. The novelty of this study lies in using the unique dataset of the period from the beginning of 2008 to November 2010 covering recent financial crisis. We wanted to discover how the interrelationships are changing over time. For this purpose, we tested three different periods to see the differences in stock market comovements - total, crisis and tranquil periods.

Our estimated results indicate that differences between periods were perceptible especially when applying cointegration tests. Markets were more cointegrated within each other in crisis period when using the Engle-Granger ap-

proach. However, the higher cointegration relationships were discovered in tranquil period when using Johansen procedure.

Both tests confirmed the strong cointegration relationship of German and Polish stock price developments in intraday frequencies for both crisis and tranquil periods. Cointegrating relationship was detected between the pairs of DAX and BUX indices, DAX and PX indices, then BUX and WIG20 indices and PX and WIG20 indices in crisis period according to both tests, cointegration in tranquil period for all these pairs is confirmed only by the Johansen approach. The pair of BUX and PX indices shows the cointegrating relationship in tranquil period using both tests, however cointegration in crisis period was found only using the Engle-Granger approach.

As Cerny (2004) and Cerny & Koblas (2008) pointed out addressing to Granger Causality test and Engle-Granger cointegration test, if prices in market A do react to price information revealed on the market B in higher speed that within one day, then there should not be detected any cointegration or causality between those markets in daily data frequency. If cointegration appears, markets are not informationally efficient. Following this statement, the information efficiency was revealed only rarely, e.g. between German and Polish markets in crisis period and between Hungarian and Czech markets in crisis period. It was also uncovered between Czech and Polish market in both crisis and tranquil periods but that is confirmed only by using Johansen approach of cointegration test. Such results may indicate that no long-term cointegration relationship is between markets which is in line with the study Egert & Kocenda (2007).

Granger causality was detected in most cases in all three periods. According to Podpiera (2001), the markets are still not integrated. Test of correlation coefficients performed in VAR framework indicated contagion between markets in most cases but it discovered only one case of contagion between German and Polish markets in daily data frequency which moreover confirms the strong interconnections between these markets.

The implications of the results presented in this study is that the markets comove tightly when the reactions of one to another market come faster than within a day but the steady driving power remains in that the local markets have better access to information about local companies and thus should not be easily influenced by information coming from somewhere else. However all CEE markets are very sensitive to acting of mighty German capital market whose shocks would definitely affect CEE markets promptly.

We are aware that our analysis was rather focused on static models. We are encouraged to go further and examine the time-varying dependence on realized variances as well as correlation which might be the inspiration for the next analysis.

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Appendix A

Vector Autoregression Model (VAR) and Vector Error-Correction Model (VECM)

Cointegrated system with more than one variable is depicted below. Suppose that there is n time series $x_{i,t}$ that are integrated of order one $I(1)$ with long-term relationships denoted in system of Equations A.1. If all time series are cointegrated, then all residuals ε_i would be stationary.

$$\begin{aligned} x_{1,t} &= c_1 + \xi_{1,2}x_{2,t} + \xi_{1,3}x_{3,t} + ... + \xi_{1,n}x_{n,t} + \varepsilon_{1,t} \\ x_{2,t} &= c_2 + \xi_{2,1}x_{1,t} + \xi_{2,3}x_{3,t} + ... + \xi_{2,n}x_{n,t} + \varepsilon_{2,t} \\ &... \\ x_{n,t} &= c_n + \xi_{n,1}x_{1,t} + \xi_{n,2}x_{2,t} + ... + \xi_{n,n-1}x_{n-1,t} + \varepsilon_{n,t} \end{aligned} \tag{A.1}$$

Due to the superconsistent estimated coefficients which would be caused by $I(1)$ variables, vector error-correction model (VECM) denoted in the system of Equations A.2 is considered to be more suitable for such analysis of $I(1)$ variables (Baxa (2007)).

$$
\begin{aligned}
\Delta x_{1,t} &= \alpha_1 + \textstyle\sum_{k=1}^{K} \delta_{1,k} e_{k,t-1} + \sum_{i=1}^{p} \gamma_{1,i}^{1} \Delta x_{1,t-i} + \sum_{i=1}^{p} \gamma_{2,i}^{1} \Delta x_{2,t-i} + ... \\
&\quad + \textstyle\sum_{i=1}^{p} \gamma_{n,i}^{1} \Delta x_{n,t-i} + \varepsilon_{1,t} \\
\Delta x_{2,t} &= \alpha_2 + \textstyle\sum_{k=1}^{K} \delta_{2,k} e_{k,t-1} + \sum_{i=1}^{p} \gamma_{1,i}^{2} \Delta x_{1,t-i} + \sum_{i=1}^{p} \gamma_{2,i}^{2} \Delta x_{2,t-i} + ... \\
&\quad + \textstyle\sum_{i=1}^{p} \gamma_{n,i}^{2} \Delta x_{n,t-i} + \varepsilon_{2,t} \\
&... \\
\Delta x_{n,t} &= \alpha_n + \textstyle\sum_{k=1}^{K} \delta_{n,k} e_{k,t-1} + \sum_{i=1}^{p} \gamma_{1,i}^{n} \Delta x_{1,t-i} + \sum_{i=1}^{p} \gamma_{2,i}^{n} \Delta x_{2,t-i} + ... \\
&\quad + \textstyle\sum_{i=1}^{p} \gamma_{n,i}^{n} \Delta x_{n,t-i} + \varepsilon_{n,t}
\end{aligned}
\tag{A.2}
$$

If no cointegration relationships are found between any pair of time series, residuals are not stationary and results using VECM would not be accurate. Thus VAR framework applied to the first differences would give more appropriate results (expressed by system of Equations A.3). The only difference between the systems of Equations A.2 and A.3 is in omitting the term $\sum_{k=1}^{K} \delta_{n,k} e_{n,t-i}$ in every equation from the system of Equations A.2. However, if cointegration was found, omitting this term would lead to misspecification of the model.

$$
\begin{aligned}
\Delta x_{1,t} &= \alpha_1 + \textstyle\sum_{i=1}^{p} \gamma_{1,i}^{1} \Delta x_{1,t-i} + \sum_{i=1}^{p} \gamma_{2,i}^{1} \Delta x_{2,t-i} + ... + \sum_{i=1}^{p} \gamma_{n,i}^{1} \Delta x_{n,t-i} + \varepsilon_{1,t} \\
\Delta x_{2,t} &= \alpha_2 + \textstyle\sum_{i=1}^{p} \gamma_{1,i}^{2} \Delta x_{1,t-i} + \sum_{i=1}^{p} \gamma_{2,i}^{2} \Delta x_{2,t-i} + ... + \sum_{i=1}^{p} \gamma_{n,i}^{2} \Delta x_{n,t-i} + \varepsilon_{2,t} \\
&... \\
\Delta x_{n,t} &= \alpha_n + \textstyle\sum_{i=1}^{p} \gamma_{1,i}^{n} \Delta x_{1,t-i} + \sum_{i=1}^{p} \gamma_{2,i}^{n} \Delta x_{2,t-i} + ... + \sum_{i=1}^{p} \gamma_{n,i}^{n} \Delta x_{n,t-i} + \varepsilon_{n,t}
\end{aligned}
\tag{A.3}
$$