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Comparison of Stock Market Volatilities in Central Eastern Europe and South Eastern Europe

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Declaration of Authorship

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

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Signature

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Abstract

The thesis offers a study on the stock market volatility in the countries of Central Eastern Europe and South Eastern Europe. We provide a univariate GARCH modeling of the stock market indices PX, BUX, and WIG from the CEE region and CROBEX, BELEX-15, and MBI from the SEE region.

Additionally, we present a bivariate GARCH models in order to examine the volatility transmissions and spillovers from the European equity market to the equity markets in CEE and SEE.

Our results suggest higher persistence of volatility in the CEE countries than in SEE countries, significant leverage effect more evident in the CEE region than in the SEE region, and high synchronization in the volatility between the CEE equity markets and the European equity market.

The multivariate GARCH results reveal certain statistically significant but small volatility spillovers from the European equity market to the equity market in Hungary, Poland, Serbia and Republic of Macedonia. The CEE equity markets record higher conditional correlation coefficient than the SEE countries towards the European equity market.

In general, the CEE equity markets are a relatively homogenous group in terms of volatility, while the SEE equity markets are a diversified group in terms of volatility with low synchronization and correlation with the European equity market.

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Acronyms

ACF	Auto correlation function
ADF	Augmented Dickey-Fuller test
AIC	Akaike Information Criteria
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BEKK-GARCH	Multivariate GARCH specification (Babba, Engle, Kraft, Kroner)
BELEX-15	Belgrade Stock Exchange index
BELEX-15_R	Belgrade Stock Exchange index returns
BUX	Budapest Stock Exchange index
BUX_R	Budapest Stock Exchange index returns
CEE	Central Eastern Europe
CROBEX	Zagreb Stock Exchange index
CROBEX_R	Zagreb Stock Exchange index returns
EGARCH	Exponential GARCH
Eq.	Equation
EU	European Union
EUR	Euro (currency)
G-7	Group of 7 countries: Canada, France, Germany, Italy, Japan, USA, UK
GARCH	General Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GJR-GARCH	Asymmetric GARCH specification
HQC	Hannan-Quinn Criterion
IMF	International Monetary Fund
LB	Ljung-Box
MA	Moving Average
MBI10	Macedonian Stock Exchange index

MBI10_R	Macedonian Stock Exchange index returns
MIL.	Millions
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PP	Phillips-Perron test
PX	Prague Stock Exchange index
PX_R	Prague Stock Exchange index returns
QGARCH	Quadratic GARCH
RSS	Residual Sum of Squares
SASX-10	Sarajevo Stock Exchange index
SASX-10_R	Sarajevo Stock Exchange index returns
SAX	Bratislava Stock Exchange index
SAX_R	Bratislava Stock Exchange index returns
SEE	South Eastern Europe
SIC	Schwarz Information Criterion
STD. DEV.	Standard Deviation
STOXX	Group of European stock markets indices
STOXX_R	Group of European stock markets indices returns
TARCH	Threshold GARCH
T-STAT.	T-statistics
UK	United Kingdom
US	United States
USD	United State dollar (currency)
VAR	Vector Autoregression
Var.	Variance
WIG	Warsaw Stock Exchange index
WIG_R	Warsaw Stock Exchange index returns

1. INTRODUCTION

The volatility of the equity markets is subject to continuous interest and research by the financial market players and the academic public. As Robert F. Engle, Nobel Prize winner in Economics for 2003, states – “the advantage of knowing about risks is that we can change our behavior to avoid them” – the financial market participants constantly assess the volatility of the financial assets and continuously search for the perfect forecast of the future equity markets developments and volatility movements.

The volatility – defined as the amount of uncertainty or risk about the size of changes in a security’s value – is usually analyzed when comparing: two assets with similar rates of returns, or two different portfolios, or separate stock exchanges in different countries.

The specific characteristics and nature of the equity markets returns time series implies that the normal linear regression techniques are not sufficient in successfully estimating the volatility of the equity returns. The emergence of the ARCH/GARCH type of models proved to be of immense importance for modeling stock markets’ volatility.

The implications for the investors from the level of integration of certain equity market are potentially significant and highly useful, since their actions are influenced by the level of volatility which is a measurement of the uncertainty in the future movements of the markets. The level of integration and the synchronization in the movement implies similar reactions in the integrated markets to unexpected future shock, information of major importance for investors and policy makers.

The aim of the thesis is initially to measure the volatility in a set of countries from two regions: Central Eastern Europe and South Eastern Europe. Subject of the study will be the stock market returns and volatility in 8 countries (4 from each region): Czech Republic, Poland, Hungary, and Slovakia as countries from the Central European region, and Republic of Macedonia, Croatia, Serbia, and Bosnia and Herzegovina as representative countries from the South Eastern European region. For this purpose the indices: PX (Prague Stock Exchange), WIG (Warsaw Stock Exchange), BUX (Budapest Stock Exchange), SAX (Bratislava Stock Exchange), MBI10 (Macedonian Stock Exchange), CROBEX (Zagreb Stock Exchange), BELEX15 (Belgrade Stock Exchange) and SASX-10 (Sarajevo Stock Exchange) are analyzed. An additional aim is to compare the volatilities between these regions and between the separate countries from the selected regions with intention to discover some significant differences between them.

The choice of the countries is motivated by their position in terms of the global financial markets. While the stock exchanges from the CEE countries are relatively integrated to the European financial markets as being part of the European Union, the SEE stock exchanges are on the way of EU accession, with Croatia closest to EU (expected to join in 2013) and the other countries with prospects of joining the EU in the future.

In this thesis we will also try to identify if there are significant synchronized movements between these markets by measuring and comparing them with a leading Euro area stock market index. The reference index, acting as a benchmark for the European equity markets movements and volatility, is the STOXX Europe 600 representing 18 countries from the European region. The rationale behind choosing this index is its broad range among components and countries. This part of the study should discover the extent of integration between this set of countries and the means of transmission of the volatility, with possible time lags in the volatility synchronization due to the fact that some of the countries are not as integrated in the international equity markets as others. The standard way of comparing the volatility coefficients of the modeled series is accompanied by comparison of the conditional standard deviation and conditional correlation between the STOXX Europe 600 index and the indices from the analyzed stock exchanges.

The degree of integration with the international equity markets would also, mean that the analyzed markets reacted differently to the last financial crisis. The expectations are that the indices in those countries whose markets are not significantly financially integrated would fall in a lesser extent than the highly integrated markets.

The motivation for undertaking such research is supported by several factors of our interest. The most important incentive is the lack of volatility studies for the stock exchanges in South Eastern Europe. Additionally, our interest is to discover similarities between the CEE and SEE equity markets volatility. The impact of the recent financial crisis on the different stock exchanges volatility is an additional field of interest. Finally, we also implement a multivariate

GARCH in order to discover volatility spillovers and transmissions from the European equity market to the markets of CEE and SEE.

Our results suggest similar conditional volatility processes for the CEE stock exchanges and more diversified volatility development for the SEE stock exchanges. The level of persistence of the volatility shock is to a certain extent higher in the CEE stock markets compared to the SEE stock markets. We also identify bigger similarity in the conditional volatility development between the CEE equity returns and the European equity returns than in the case between the SEE equity returns and the European equity returns. The results from the multivariate GARCH suggest some statistically significant but small volatility spillovers from the European equity markets towards the markets of selected CEE and SEE countries. In general, the conditional correlation between the SEE and European equity returns is on levels lower than the conditional correlation between CEE and European equity returns,

The thesis is structured as follows: Chapter 2 presents the previous studies related with the issue of integration of stock markets and the findings from the different authors about the matter of volatility measuring, the level of synchronization and similarity in the movements of the countries that are subject of this study. Chapter 3 introduces the methodology of measuring volatility, with ARCH (GARCH) as basic tool of estimating volatility, and formulates the specification of the univariate GARCH and TARCH models and the multivariate BEKK-GARCH specification. Chapter 4 discusses the empirical dimension of the work by analyzing the characteristics of each market and presents the results from the modeling of the volatility and measuring the level of volatility transmission and spillovers between the studied markets. Chapter 5 concludes all the findings.

2. LITERATURE REVIEW

The aim of this chapter is to present the previous findings in the area of volatility issues and specifically on the integration process between the analyzed regions and countries and the international (Euro area) equity markets. The level of integration has a huge influence on the way the Euro area shocks are transmitted through the regions analyzed in this thesis. High level of integration means that the euro area shocks dominate in the markets, while low level of integration implies that local shock characterize the markets.

However, measuring the level of integration is a difficult task. Undertaking such a task requires taking into account several dimensions, since the concept of financial integration has a broad meaning. Baele et al. (2004) define a "fully integrated market if all the potential market participants with the same relevant characteristics: (i) face a single set of rules when they decide to deal with those financial instruments and/or services; (ii) have equal access to the above-mentioned set of financial instruments and/or services; and (iii) are treated equally when they are active in the market." The essence of the financial integration definition is closely connected with the law of one price. As Baele et al. (2004) describe "the law of one price states that if assets have identical risks and returns, they should be priced identically regardless of where they are transacted." If this law does not hold, there are arbitrage opportunities for the financial markets players.

They also propose three dimensions for quantifying the level of integration: price-based, quantity-based and news-based measures. The price based measures cover the concept of the law of one price for assets with similar characteristics and are measured by quantifying beta and sigma convergence. The quantity based measures try to identify the existence of frictions and barriers and other market imperfections on the stock exchanges. The fact that the integrated markets have to be influenced more by the common factor of global effect than by local factors is underlined in the last class of measures – the news based. The benefits of the financial integration according to the authors are: risk sharing (the financial integration offers additional opportunities for risk sharing which enhances specialization in production), improved capital allocation ("the complete elimination of barriers to trading, clearing and settlement platforms will allow firms to choose the most efficient trading, clearing and/or settlement platforms"), and economic growth (the financial integration increases the financial development and the flows of funds for investment opportunities). On the other hand, financial integration can bring some destabilizing factors such as the usually mentioned herding behavior as a result of the openness of the financial markets. The financial integration also has a negative implication on the possibilities for the investors for portfolio diversification since the highly correlated markets imply lower potential for eliminating the systematic risk[1].

Babetskii et al. (2007) main research idea is the aspect of financial integration in Czech Republic, Hungary, Poland and Slovakia. Following that idea the authors test the existence and analyze the dynamics of integration in the stock markets. The used methodology for measuring the financial integration is based on two concepts: β-convergence (for measuring the speed of convergence) and σ-convergence (for measuring the degree of financial integration). The summarized conclusion from the study is that: "(i) the results unambiguously point to the existence of β-convergence of the stock markets under review at the national and sectoral levels; (ii) moreover, the speed at which shocks dissipate is quite high – less than half a week; (iii) we do not find a major impact of either EU enlargement or the announcement thereof on β-convergence." The same authors, Babeckii et al. (2010), also analyze the impacts of the financial crisis on the financial integration of Czech Republic, Hungary, and Poland by using price-based and news based methods. Their results show increasing financial integration since late 1990s and existence of a temporary price divergence as a result of the financial crisis on the financial markets in Czech Republic, Hungary and Poland.

The degree of integration between the stock markets in several new EU members and the euro area is subject of the research of Cappiello et al. (2006). Their analysis based on returns on equity markets suggests increasing degree of integration between the new EU members and the euro area in the process towards EU accession. The existence of close relations and linkage in stock markets movements between Czech Republic, Hungary and Poland is stressed in the paper.

There are several studies conducted about the level of integration of the stock markets in Central Eastern Europe (CEE) by employing cointegration tests methodology. Cerny (2004) conducted a study about the level of stock market integration and the speed of information

[1] Babecky et al. (2010) as costs from integration also mention: "(i) insufficient access to funding at times of financial instability, including capital concentration and procyclicality, (ii) inappropriate allocation of capital flows, (iii) loss of macroeconomic stability, and (iv) financial contagion and high volatility of cross-border capital flows."

transmission by studying the time structure in which the stock markets respond to new information and the speed by which the new information is reflected in the stock prices. The author findings reveal that the stock markets in Prague and Warsaw react to the information revealed in the stock market prices in Frankfurt with a time-lag of 40 minutes to 1 hour. However, it seems that the stock market in Prague has more integrated transmission mechanism than the one in Warsaw by the fact that the reaction in Prague occurs within 30 minutes, while in Warsaw it takes an hour.

Similar study like Cerny (2004) is undertaken by Egert & Kocenda (2007) who analyze the interconnections between the Western European stock markets and the stock markets in Budapest, Prague and Warsaw. The study implementing Granger causality tests and VAR framework and based on 5-minute tick intraday data from the mid 2003 to the early 2005 finds no robust cointegration relationship, but discovers some short-term spillover effects in terms of stock returns and stock price volatility with bidirectional causality. Their findings also suggest interaction of the Prague and Warsaw stock exchanges with the Budapest stock exchange.

Another cointergration tests research is provided by Gilmore et al. (2005) who discover increasing degree of integration of the Czech, Hungarian, and Polish equity markets with respect to the German and UK markets for the period from 1995 to 2005. The factor behind the increasing integration of the CEE stock markets is located in the process of alignment with the economic, financial and legal framework of the EU.

Since our intention is to measure the degree of co-movements and equities markets integration of selected CEE and SEE countries by measuring their volatilities and comparing the conditional volatility processes between the analyzed countries, we will present a review of several studies conducting conditional heteroskedasticity research.

The research performed by Égert & Koubaa (2004) investigating the conditional variance patterns between G-7 and selected countries from CEE studies the stock indices of Czech Republic, Hungary, Poland and Slovakia for the period from 1995 to 2002. After, employing various linear and asymmetric GARCH models (GARCH, GJR-GARCH, and QGARCH), their results show long persistence in volatility shocks for all countries. Their research show that the stock returns for the G-7 countries can be modeled by using linear specifications but, on the other hand, the stock indices from the CEE are better specified by employing asymmetric models. The conclusion from their findings is that CEE stock markets are influenced more intensely by negative news than by positive ones. Also, the conclusion suggests that the studied stock markets from CEE may collapse more suddenly and their recovery would be more slowly than the G-7 stock markets.

The aim of the study by Allen et al. (2010) is to examine the pre and post EU periods of twelve emerging countries' stock markets by adopting GARCH (1,1) model for assessing the dynamic volatility. Their paper stresses that the stock markets in Czech Republic, Hungary and Poland are recognized as advanced emerging markets. The undertaken correlation tests show that the stock markets in the mentioned countries exhibit stronger linkage with the developed stock markets around the world and are sensitive to the shock coming from those markets. According to their study the stock market in Slovakia appears to display more self-directed independent behavior compared to its peers.

The research of Patev & Kanaryan (2003) concentrates on the Central European stock market volatility by analyzing the Central European Stock Index for the period from May 1996 to June 2002 and similarly conclude that the asymmetric sufficiently characterizes the Central European stock market volatility. The authors, by segmenting the data in three periods (pre-crisis, crisis and post-crisis periods), find significant autocorrelations and asymmetry in conditional volatility and volatility persistence with increasing trend in crises periods. For their research purpose, the authors apply two symmetric and six asymmetric GARCH models and discover that after a financial crisis, the negative return shock exhibit higher volatility than positive return shocks. Patev and Karanyan (2003) conclude that: "asymmetric GARCH model with non-normal distributed residuals capture most of Central European stock market volatility characteristics: (1) asymmetric news impact, (2) volatility persistence and (3) fat-tailed distribution of stock market returns."

Scheicher (2001) focuses on the regional and global integration of stock market in Czech Republic, Poland and Hungary by estimating vector autoregression with multivariate GARCH as a method to evaluate the impact of price and volatility shocks. After employing such methodology on a data set starting from the beginning of 1995 till October 1997, the results show regional and global influences for returns, while the regional influences dominate for the volatility. Generally, the study discovers some degree of influence on the mentioned countries' stock markets by the Western financial markets, primarily as an influence on returns. The author also notes that there is a regional integration among the countries subject to the analysis, hence advises the investors that they may perceive the stock markets as one investment opportunity instead of two or three separate groups of assets.

Trying to estimate the co-movements in the equities returns and the potential transmissions and spillovers in volatility we follow the approach of Karolyi (1995) and Hassan & Malik (2007) who employ multivariate GARCH models in order to discover volatility shocks transmission between, in Karolyi (1995) case – New York and Toronto stock exchanges, and US equity sector indices in Hassan & Malik (2007) case[2]. In the line of these studies Kanas (1998) tests the volatility spillovers across the three largest European stock markets – London, Frankfurt, and Paris by employing univariate and bivariate EGARCH models. The findings imply high persistence of volatility, existing leverage effect, and bidirectional volatility spillovers between London and Paris, and Paris and Frankfurt, but one directional spillover from London to Frankfurt. The spillovers in all cases are asymmetric and exhibit higher intensity in the post-crisis periods.

Using the benefits of employing GARCH models for modeling financial time series and their capability of capturing the empirical observations in a return time series, (Kasch-Haroutounian & Price 2001) research the returns from stock in Czech Republic, Hungary, Poland and Slovakia. The results from the estimation of several univariate and multivariate GARCH models show that strong GARCH effects are characterizing the returns in all of the markets, but weak evidence is examined for the asymmetric impact of the news on volatility. However, the authors discover leverage effects (the tendency of negative shocks to have bigger impact on volatility than positive shocks) in the returns time series from Hungary and Czech Republic. Using bivariate BEKK model it is shown that the volatility in the Polish stock market is affected by the returns volatility and returns shocks that originate from the Hungarian stock market.

Compared to the number of research studies about the volatility and integration of the Central Eastern European countries, the number of paper analyzing the stock market in the South Eastern Europe is relatively smaller.

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[2] Similar studies offer (Worthington & Higgs 2004) who implement multivariate GARCH analysis to test the volatility spillovers in three developed and six emerging stock markets and (Bellotti & Williams 2004) who estimate the effects of volatility transmissions between 17 developed European stock markets plus US.

Samitas et al (2006) offer examination on the dynamics between the behavior of selected number of emerging Balkan stock markets and developed markets. For that purpose they use linear and non-linear estimation methods in order to discover some linkages between Balkan stock markets and developed stock markets (US, UK, Germany). Their advice for the investors can be summed up in the limited possibilities for portfolio diversification by investing in the analyzed Balkan's stock markets due to the existing interdependencies between these markets and the developed stock markets and the recommendation of following an active strategy rather than a passive one since the first offers more potential exceptional returns.

Vizek & Dadić (2006) offer another cointegration procedure study which analyses the integration between German equity markets, selected CEE equity markets and the Croatian equity market. The authors suggest that there is no evidence of integration between the Croatian and German equity. Similar conclusion is drawn for the other equity markets of the CEE with respect to the German equity markets.

Kovacic (2007) examines the behavior of the stock markets returns and their relationship with conditional volatility on the Macedonian Stock Exchange. The results from the testing in which one symmetric and four asymmetric GARCH types of models were used show that: "(i) the Macedonian stock returns time series display stylized facts such as volatility clustering, high kurtosis, and low starting and slow-decaying autocorrelation function of squared returns; (ii) the asymmetric models show a little evidence on the existence of leverage effect; (iii) the estimated mean equation provide only a weak evidence on the existence of risk premium; (iv) the results are quite robust across different error distributions; and (v) GARCH models with non-Gaussian error distributions are superior to their counterparts estimated under normality in terms of their in-sample and out-of-sample forecasting accuracy."

The evident lack of studies about the volatilities in SEE countries and the comparison of the volatility processes between CEE and SEE equity markets and additionally the potential volatility spillovers from the European equity markets to the SEE equity markets was the main motivation behind undertaking such research.

3. METHODOLOGY

3.1. Modeling Volatility

Analyzing the stock market movements and riskiness, the agents can perceive that in some periods the deviations of the returns from the mean are with higher amplitude. Moreover, it is usual these high volatile periods to be followed by periods with high variance of the returns, while low-variance periods tend to be followed by periods with low volatility. This fact implies that volatility can be used as a predictor of volatility in the next periods. The grouping of the volatility is known in the financial world as volatility clustering.

Mean reverting volatility is also a stylized fact about the returns time series of stock markets. This characteristic implies a normal level of volatility to which the volatility tends to converge.

Another feature characteristic for the financial time series is the fat tails in the distribution of the returns. It is rather common for the distribution of the returns to be peaked and with fat tails compared to a normal distribution. Such distributions, that record concentrated data around the mean, but higher volatility than normal distribution, are referred as leptokurtic.

Also, many empirical studies suggest that there is excess volatility in the assets returns that cannot be justified by the variations in the fundamental economic variables. Usually, the large variations in the returns are not explained by arrival of new information on the market.

Also, the stock markets are perceived to react differently to “good” and “bad” news, exhibiting asymmetric effect on the volatility. This tendency of negative news to produce higher volatility in future periods compared to the good news’ effect is referred to as “leverage effect”.

The volatility clustering, explained as the error term exhibiting time-varying heteroskedasticity (the unconditional standard deviations are not constant), the leptokurtic distribution of the stock exchanges returns, and the possibility of existence of leverage effects bear some restrictions on the usage of the models in estimating the stock markets’ volatility. In such circumstances, the linear models are unable to explain satisfactory the characteristics of the financial time series[3]. For modeling series that does not satisfy the assumption of homoskedasticity, ARCH and GARCH type of models are used. These kinds of models allow the variance to depend on its history. The ARCH model or Autoregressive Conditional Heteroskedasticity was developed by Engle in 1982 and it was extended by Bollerslev (1986) and Nelson (1991) to Generalized ARCH or GARCH. The ARCH model uses estimated weights for the historical volatility in order to estimate the variance. On the other hand, the most widely used GARCH specification states that the best estimation of the future variance is weighted average of the long-run average variance, the variance predicted for the current period and the new information in the current period, captured by the most recent squared residual Robert Engle (2001).

3.2. Univariate GARCH

The volatility can be defined as amount of uncertainty or risk about the size of changes in a security's value. Lower volatility of a given assets means that it has a low rate of change in price over a given period, while high volatility implies that the price of the assets can change dramatically over a short time period. It is necessary to note that the term volatility expresses both positive and negative changes in the asset's price.

Since the volatility can significantly influence the future cash flows, market agents are in a need of an estimate of the volatility. Initially the agents used the standard deviation as a measure, but its shortcoming was that it could not capture the changes over time. A simple approach is to use the historical volatility defined by Brooks (2008) as "historical volatility simply involves calculating the variance (or standard deviation) of returns in the usual way over some historical period, and this then becomes the volatility forecast for all future periods." The disadvantage of this approach is the inability to precisely decide the right period over which the estimates about the volatility will be made.

[3] For example, the OLS will provide wrong standard errors estimates if the assumption about the constant variance of the errors is violated

An alternative way of estimating the volatility is the exponentially weighted moving average (EWMA) which Brooks (2008) defines as "simple extension of the historical average volatility measure, which allows more recent observations to have a stronger impact on the forecast of volatility than older data points." Still, this approach is also characterized by limitation of not converging towards the unconditional variance with the increase of the forecasting horizon.

As an answer to all the mentioned shortcomings, Engle proposed the ARCH (Autoregressive Conditional Heteroskedasticity) model in 1982. About the invention of the ARCH model Engle says: "I was looking for a model that could assess the validity of a conjecture of Milton Friedman (1977) that the unpredictability of inflation was a primary cause of business cycles. He hypothesized that the level of inflation was not a problem; it was the uncertainty about future costs and prices that would prevent entrepreneurs from investing and lead to a recession. This could only be plausible if the uncertainty were changing over time so this was my goal. Econometricians call this heteroskedasticity" R. Engle (2004).

The ARCH model is specified as:

$$y_t = \mu + \rho y_{t-1+} + \varepsilon_t \qquad (3.1.)$$

where the term ε_t represents the innovations with mean zero and time varying conditional variance h_t^2

$$\varepsilon_t \sim N(0, h_t^2)$$

the ARCH model is fully specified by defining the conditional variance equation as:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 \qquad (3.2.)$$

Since the conditional variance (h_t^2) must always be non-negative the coefficients ω and α must be bigger or equal to zero ($\omega \geq 0$ and $\alpha \geq 0$).

Still, the ARCH models are not immune to limitations. The most common limitations as listed by Brooks (2008) are:

- the question about how the number of lags of the squared residual in the models should be decided;
- the fact that the number of lags of the squared errors required to catch all of the dependence in the conditional variance might be very large;
- the non negativity constraint might be violated.

An alternative model to ARCH was developed by Engle student Tim Bollerslev who introduced a generalized ARCH model in 1986. The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) allows a much more flexible lag structure and estimates the variance as a weighted average of three different variance forecasts. “One is a constant variance that corresponds to the long run average. The second is the forecast that was made in previous period. The third is the new information that was not available when the previous forecast was made. This could be viewed as a variance forecast based on one period of information. The weights on these three forecasts determine how fast the variance changes with new information and how fast it reverts to its long run mean” R. Engle (2004). As Bollerslev (1986) notes: “The extension of the ARCH process to the GARCH process bears much resemblance to the extension of the standard time series AR process to the general ARMA process”.

The term conditional heteroskedasticity refers to a variance that is changing in time based on its pattern in the past, or that the volatility is changing, conditional on the level of volatility in the previous period.

For specifying the GARCH model we first assume that a variable follows a process:

$$y_t = \mu + \rho y_{t-1+} + \varepsilon_t \qquad (3.3.)$$

we also assume that ρ < 1 so that the above process is stationary

In the previous equation ε_t denotes a stochastic process and if we assume that I_t is the information set of all information through time t, the GARCH (p,q) process is given by:

$$\varepsilon_t \,\big|\, I_{t-1} \sim \mathrm{N}(0,h_t)$$

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_i h_{t-1}^2 \qquad (3.4.)$$

where

$p \geq 0, \quad q > 0$

$\omega > 0, \quad \alpha_i \geq 0, i = 1,\ldots,q$

$\beta_i \geq 0, \quad i = 1,\ldots,p.$

Similarly like in the ARCH model, the assumptions $\omega > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$, are necessary in order for the non-negativity constraint not to be violated.

Since the most used specification of the model in practice is the GARCH (1,1) which basically estimates the conditional variance only by using the first lags of the past conditional variance and squared error term, the model takes the following form:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \qquad (3.5.)$$

In the GARCH equation estimated above, the best predictor for the next period variance is a weighted average (the weights are in brackets) of:

- Long term variance (ω)
- The current period actual variance, or the new information (α)
- The variance predicted for the current period (β)

It is easy to understand that if in the past there were high shocks, they will strongly influence the current conditional volatility, which in a way explains the presence of volatility clustering in the financial time series. Volatility clustering as mentioned before is the observation that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." Mandelbrot (1963)

The properties of the GARCH specification can turn out undesirable if the conditional variance coefficients estimates fail to satisfy the stationarity in variance. Since the unconditional variance of ε_t is constant and is defined by:

$$\text{var}(\varepsilon_t) = \frac{\omega}{1-(\alpha+\beta)} \qquad (3.6.)$$

violation of the assumption $\alpha + \beta < 1$ will lead to "non-stationarity in variance", while $\alpha + \beta = 1$ means "unit-root in variance". The stationarity in variance is tested by Wald test[4].

The advantage of GARCH over ARCH can be summarized in the facts that GARCH is more parsimonious and avoids over-fitting. Also, it is less likely that the model will breach the non-negativity constraints (the possibility that by including more parameters in the conditional variance equation it is more likely some of them to have negative estimated values) Brooks(2008).

Enders (2003) and Brooks (2008) suggest that the GARCH model and the equation of the conditional variance can be expressed as autoregressive moving average (ARMA) model. If we consider that $h_t^2 = \varepsilon_t^2 - e_t$ by substituting and arranging the conditional variance equation we will get:

$$\varepsilon_t^2 = \omega + (\alpha + \beta)\varepsilon_{t-1}^2 - \beta e_{t-1} + e_t \qquad (3.7.)$$

which represents a ARMA(1,1) process for the squared errors.

The GARCH model has number of different specifications for capturing several specific effects characteristic for financial time series. One of the fundamental restrictions to the basic GARCH model is the assumption that there is a symmetric response of volatility to positive and negative shocks. The GJR extension proposed by Glosten et al. (1993) estimates the presence of the already mentioned "leverage effect" in a certain time series by including an additional term for possible asymmetries. As explained this effect describes the asymmetric influence of the news on the volatility or the tendency of negative news to produce higher volatility in future periods compared to the good news' effect. The TARCH (1,1) specification is:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 \qquad (3.8.)$$

where $I_{t-1}=1$, if $\varepsilon_{t-1} < 0$ and 0 otherwise

in a case when $\gamma = 0$, there is no asymmetric effect, and GARCH=GJR.

[4] We present the results of the Wald test in Table 13

As already mentioned OLS, as a linear model, cannot be employed for GARCH estimation, since OLS minimizes the RSS which depends only on parameters in the mean equation and not on the parameters in the variance equation. For this reason the OLS technique must be substituted with maximum likelihood technique. Under normality assumption of the disturbances the log-likelihood function Brooks (2008) takes the form:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(h_t^2) - \frac{1}{2}\sum_{t=1}^{t}(y_t - \mu - \rho y_{t-1})^2/h_t^2 \qquad (3.9.)$$

where T denotes the number of observations.

Essentially, the method functions by finding the parameters in the parameter-space that maximize the log-likelihood function.

The basic use of the GARCH family of models is the notion that they can be employed for forecasting volatility of a series over time. Essentially, GARCH models are used to describe the movements in conditional variance of the error term, but since it can be proven that:

$$\text{var}\,(y_t \mid y_{t-1}, y_{t-1}, \ldots) = \text{var}\,(u_t \mid u_{t-1}, u_{t-2}, \ldots) \qquad (3.10.)$$

modeling the conditional variance of u, will produce forecasts for y_t.

3.3. Multivariate GARCH

The discussed univariate GARCH model estimates single variable volatility characteristics and volatility development through time. This one-dimensional feature of the univariate GARCH models can be improved by specifying a certain multivariate GARCH specification. While the univariate GARCH studies the variance of a single variable, the multivariate GARCH studies the interaction between several variables by estimating how the covariance between the variables develop through time. The multivariate GARCH model can be applied in several specific circumstances, but the most useful application is for studying the relation between the volatilities, variances and covariances between two different assets or markets. For the purpose of our study, we employ the multivariate GARCH to study the co-movements in the volatilities of the European stock market on one hand and the stock markets in the countries from CEE and SEE on the other hand. By implementing such GARCH specification we will try to detect volatility transmissions and spillovers between the stock exchanges. The multivariate GARCH models also estimates the effects of a volatility shock in one stock market to the volatility of another stock market. Additionally, the multivariate GARCH model produces a conditional correlation series, which approximates the co-movement of volatility of different markets through time. For the aim of the thesis, we will implement a bivariate specification.

Bauwens et al. (2006) established the multivariate GARCH for a vector stochastic process of dimension N x 1 defined as:

$$y_t = \mu_t + \varepsilon_t \tag{3.11.}$$

$$\varepsilon_t = H_t^{1/2} v_t \tag{3.12.}$$

where v_t is a N x 1 random vector satisfying $\mathrm{E}(v_t) = 0$ and $\mathrm{Var}(v_t) = I_N$, where I_N is an identity matrix.

The conditional variance matrix of y_t is specified as:

$$\begin{aligned} Var(y_t|\mathrm{I}_{t-1}) &= Var_{t-1}(y_t) = Var_{t-1}(\varepsilon_t) \\ &= H_t^{\frac{1}{2}} Var_{t-1}(v_t)(H_t^{\frac{1}{2}})^T \\ &= H_t \end{aligned} \tag{3.13.}$$

is any N x N positive definite matrix such that H_t is the conditional variance matrix of y_t

Engle & Kroner (1995) propose the following equation for expressing the conditional covariance matrix H_t:

$$H_t = \Omega^{\mathrm{T}}\Omega + \sum_{k=1}^{K} A_k^T \varepsilon_{t-1} \varepsilon_{t-1}^T A_k + \sum_{k=1}^{K} B_k^T H_{t-1} B_k \tag{3.14.}$$

This specification is known as BEKK-GARCH and will be used for the purpose of our study. “The summation limit K determines the generality of the process” - R. F. Engle & Kroner

(1995). We assume that K is equal to one, and also the lags (p and q) are both equal to one. Additionally, we assume system of two variables (N=2) labeling the model as bivariate.

The matrices A, B, and Ω are 2 x 2 matrices of parameters, with Ω representing an upper triangular matrix. The model specification in matrix notation takes the form:

$$\begin{bmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{bmatrix} = \begin{bmatrix} \omega_{11} & 0 \\ \omega_{12} & \omega_{22} \end{bmatrix} \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^T \begin{bmatrix} \varepsilon_{1t-1}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon_{2t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}^T \begin{bmatrix} h_{11t-1} & h_{12t-1} \\ h_{12t-1} & h_{22t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad (3.15.)$$

In our bivariate case, the expanded conditional variances and covariance are presented as:

$$h_{11t} = \omega_{11}^2 + a_{11}^2\varepsilon_{1t-1}^2 + 2a_{11}a_{21}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}^2\varepsilon_{2t-1}^2 + b_{11}^2 h_{11t-1} + 2b_{11}b_{21}h_{12t-1} + b_{21}^2 h_{22t-1} \quad (3.16.)$$

$$h_{22t} = (\omega_{12}^2 + \omega_{22}^2) + a_{12}^2\varepsilon_{1t-1}^2 + 2a_{12}a_{22}\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{22}^2\varepsilon_{2t-1}^2 + b_{12}^2 h_{11t-1} + + 2b_{12}b_{22}h_{21t-1} + b_{22}^2 h_{22t-1} \quad (3.17.)$$

$$h_{12t} = (\omega_{11}\omega_{12}) + a_{11}a_{12}\varepsilon_{1t-1}^2 + (a_{11}a_{22} + a_{12}a_{21})\varepsilon_{1t-1}\varepsilon_{2t-1} + a_{21}a_{22}\varepsilon_{2t-1}^2 + + b_{11}b_{12}h_{11t-1} + (b_{11}b_{22} + b_{12}b_{21})h_{12t-1} + b_{21}b_{22}h_{22t-1} \quad (3.18.)$$

The variables h_{11t} and h_{22t} represent the conditional variances, while h_{12t} denotes the conditional covariance. Bauwens et al. (2006) defines the condition for covariance-stationary as the eigenvalues of the A + B matrices are less than one in modulus.

The number of parameters to be estimated in the BEKK(1,1,1)-GARCH specification is is N(5N+1)/2, making them in our case 11, since N=2.

3.4. Empirical Methodology

The data necessary to run all the estimations is obtained by Reuters Wealth Manager. The sample period for analysis starts from the beginning of January 2006 and ends in the middle of May 2011.The daily closing levels of the indices PX (Prague Stock Exchange), WIG (Warsaw Stock Exchange), BUX (Budapest Stock Exchange), SAX (Bratislava Stock Exchange), MBI10 (Macedonian Stock Exchange), CROBEX (Zagreb Stock Exchange), BELEX15 (Belgrade Stock Exchange) and SASX-10 (Sarajevo Stock Exchange) are taken and subjected to analysis. All the mentioned indices are in national currencies. Additionally, we analyze the STOXX Europe 600 index as a certain benchmark of the equity markets movements in Europe. The STOXX Europe 600 (expressed in Euros) represents large, mid and small capitalization companies across 18 countries of the European region: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

In order to undergo a successful analysis of the volatility, first it's necessary to transform the indices level into returns. For that purpose, we subject the indices to the following way of calculating returns:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100 = (\ln(P_t) - \ln(P_{t-1})) * 100 \qquad (3.19.)$$

where P_t is the daily closing index value at time t and P_{t-1} is the closing value of the index in the previous day. The R_t represents the percentage returns time series, while the ln is the natural logarithm.

We begin the analysis of the returns time series by presenting the descriptive statistics. This type of analysis describes the basic features of the nine time series subject to our analysis. The descriptive statistics summarize the characteristics of the data by its mean, median, maximum, minimum, standard deviation, skewness, kurtosis, and Jarque-Bera test. The mean expresses the average value, the median is the numerical value separating the higher half of a distribution with the lower half, the maximum and the minimum express respectively the largest and the smallest observation of the population, the standard deviation shows the extent of variation from the average value, the skewness measures the asymmetry of the probability distribution of the returns time series, the kurtosis expresses the shape of the probability distribution, and the Jarque-Bera test measures how close (or far) the distribution is from normal distribution.

In addition to the descriptive statistics analysis, we provide results from stationarity testing with Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test. Both tests are unit root tests meaning that the rejection of the null hypothesis of unit root indicates that the tested time series are stationary. The non-rejection of the null hypothesis concludes certain time series as non-stationary. The need for stationarity testing is derived from the risk of spurious regression results from non-stationary time series. The complete results from the ADF and PP tests on the indices levels and returns time series are presented in the Appendix Table A.20.

For the analysis of the volatility and GARCH modeling including checking the results we use EViews 7 software. For the purpose of estimating multivariate GARCH we are using JMulTi.

In order to formulate the best ARMA specification of the return equation, we use the Box-Jenkins methodology as specified in Brooks (2008). The Box-Jenkins approach involves three steps: *Identification* (involves determining the order of the model using the graphical approach of plotting the time series and their autocorrelation (ACF) and partial autocorrelation (PACF) functions); *Estimation* (used for estimating the parameters of the proposed model by employing different techniques (least squares or maximum likelihood)); *Diagnostic checking* (step needed to confirm if the model is appropriately specified and estimated). The last step includes residuals diagnostics by using the ACF and PACF and the Ljung-Box tests.

We decided the most appropriate ARMA structure by comparing the information criteria (Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn criterion (HQC)) of the different ARMA specifications. The rule of deciding the most appropriate ARMA structure is choosing the model specification which minimizes the information criteria.

Although, the ARMA model may be sufficient to estimate the linear dependencies in the returns time series, we check whether it is required to use GARCH models by implementing the ARCH-LM test. If the ARCH effects are confirmed (the null hypothesis of no conditional heteroskedasticity is rejected) we use the GARCH estimation.

The GARCH model specifies the conditional variance equation as in (3.5.) and is sufficient to capture the ARCH effects. Usually the GARCH (1,1) is the best formalization for the variance equation. The exact specification of the return and variance equations of all the returns time series is presented in Table *5*.

We also check the estimates of GARCH models with different error distributions, in order to verify differences in the coefficients and diagnostics between the Normal and the Student's t-distribution.

Since our aim is to study the interactions between the European and the CEE and SEE stock exchanges we use the BEKK-GARCH model as specified in na stránce 17. Before estimating the unrestricted bivariate BEKK-GARCH model, we adjust the time series and use only the dates with recorded index values for both the STOXX Europe 600 and the index from some of the CEE and SEE countries. For multivariate GARCH estimation we use JMulTi which also provides several diagnostics tests. The estimates of the matrices Ω, A, and B are presented in the appendix Table A.25 and Table A.26, along with the Portmanteau, Multivariate ARCH-LM, and Jarque-Bera tests. The Ω, A, and B matrices are specified as:

$$\begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix} \qquad \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \qquad \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

3.5. Hypotheses

We would like to research the volatility in the different countries and answer several questions about the nature of their development and the typical features of the volatility in a specific country and as a region as well.

We can formulate our hypotheses as:

Our expectations are that the volatility of the indices returns time series of the analyzed stock exchanges can be satisfactory modeled by GARCH models. We also expect the different regions to exhibit diverse conditional volatility processes. Moreover, the multivariate estimation should show certain volatility spillovers from the European equity markets to the CEE and SEE equity markets. We expect the spillovers from the European markets to the CEE markets to be bigger than the spillover to the SEE markets.

4. EMPIRICAL PART

4.1. Initial Analysis

As a first step in the comparison of the stock markets from Central Eastern Europe and South Eastern Europe, tables with the basic indicators for 2009 about the biggest stock markets from the aforementioned regions are presented. As can be seen, all the stock markets subject to this analysis are relatively new. Actually, all of them were formed in the transitional period after the countries accepted the free market economy as an economic structure. The oldest stock exchange is the Belgrade Stock Exchange, (formed in 1894, but then closed in 1941, and being reestablished in 1989)[5], while the youngest is the Sarajevo Stock Exchange which was established in 2001.

The Warsaw Stock Exchange is the biggest according to the market capitalization in December 2010 with EUR 142272 million and the second biggest is Prague Stock Exchange with market capitalization of EUR 31922 million. The biggest stock market in South Eastern Europe is the Zagreb Stock Exchange recording market capitalization of USD 25295 million, while the Macedonian Stock Exchange has the lowest market capitalization in South Eastern Europe and in general from all the analyzed stock markets in this thesis.

The Warsaw Stock Exchange (EUR 38819 million) and the Zagreb Stock Exchange (USD 1415 million) also have the leading position in the respective regions according to the turnover. Similarly like in the previous classification, the Macedonian Stock Exchange is the smallest stock market if all the stock exchanges are compared according to the turnover.

An interesting remark about the general facts about all the stock market subject to the comparison is the relatively (on average) bigger number of listed companies in the stock exchanges in South Eastern Europe compared to the stock markets in CEE region. The leading stock exchange based on this criterion is the Belgrade Stock Exchange which has 1779 listed companies.

[5] FEAS BOOK: Annual Report June 2010

Except for the highest market capitalization and the biggest turnover, the Warsaw Stock Exchange is leading the stock markets in the Central European Region according to the number of employees. According to the FESE (Federation of European Securities Exchanges) 2009 Report, the Warsaw Stock Exchange has 198 employees, while the smallest stock exchange in the region, the Bratislava Stock Exchange has only 26. The Prague and Budapest Stock Exchanges are somewhere between these figures for the number of employees.

Table 1: Key Indicators of the CEE Stock Exchanges

Exchange	Prague SE	Budapest SE	Warsaw SE	Bratislava SE
Year established	1993	1990	1991	1991
Market Capitalization (Eur mil.)*	31922.18	20624.4	142272.23	3379.51
Number of Companies	25	46	486	172
Turnover (Eur mil.)**	17472	18957	38819	119
Number of employees	72	62	198	26
Index	PX	BUX	WIG	SAX

Notes: * - FESE Statistics December 2010; ** - FESE European Exchange Report 2009
http://www.fese.be/_lib/files/EUROPEAN_EXCHANGE_REPORT_2009_FV.pdf

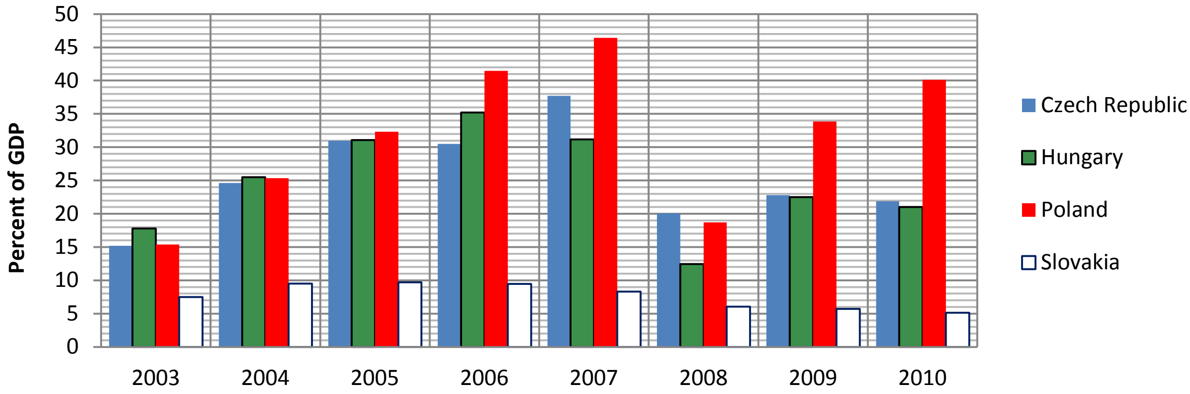
Table 2: Key Indicators of the SEE Stock Exchanges

Exchange	Belgrade SE	Macedonian SE	Sarajevo SE	Zagreb SE
Year established	1992	1995	2001	1991
Market Capitalization (US$ mil.)*	9690.33	2646.67	4941.87	25295.3
Number of Companies	1779	86	529	271
Total Vol.-Stocks (US$ mil.)*	562.12	65.14	153.69	1414.98
FEAS membership	2004	1996	2004	1995
Index	BELEX 15	MBI 10	SASX 10	CROBEX

Notes: * FEAS statistics for 2010; FEAS Statistics for 2009

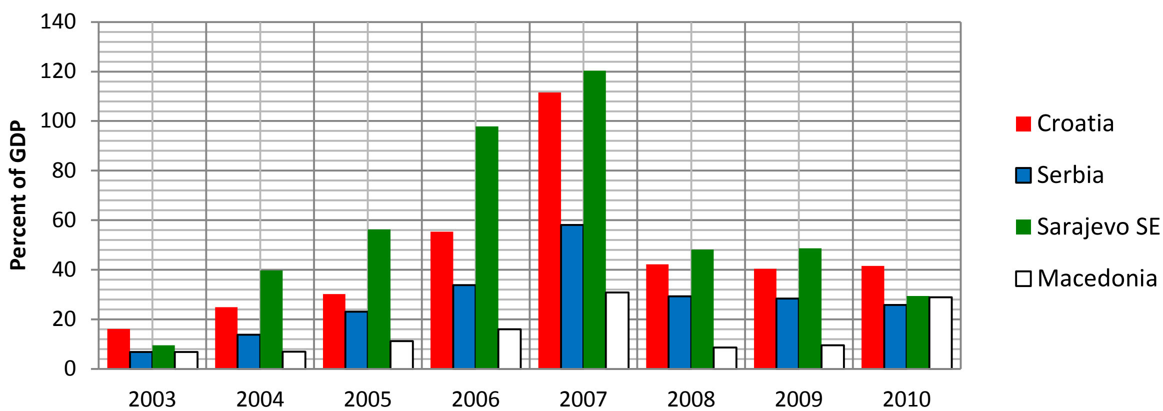
The graphs below depict the movement of the ratio of market capitalization as a percent of GDP of the analyzed countries for the period 2003-2010. This indicator steadily increases for all countries except Slovakia in the first four years, then exhibits more volatile movements – result of the financial crisis. To some extent this ratio develops similarly for Czech Republic, Hungary, and Poland in the first three years and reaches around 40% before the financial crisis. Uncharacteristically low and isolated from the neighboring stock exchange movements seems the path of the ratio for Slovakia (steadily under 10%) showing a sign of a segregated stock exchange market. The situation in the SEE countries is characterized by similar, but more volatile movements compared to the CEE countries – after the initial rise the ratio drops significantly after the recent financial crisis. The variation of this indicator in the SEE countries is significant – the developing SEE stock exchanges show higher volatility. The cases of Croatia and the Sarajevo stock exchange prove the mentioned fact (these ratios from less than 20% reached above 100% in a period of 5 years).

Figure 1: Market Capitalization in CEE countries, 2003-2010



Note: Author's calculation based on EUROSTAT data

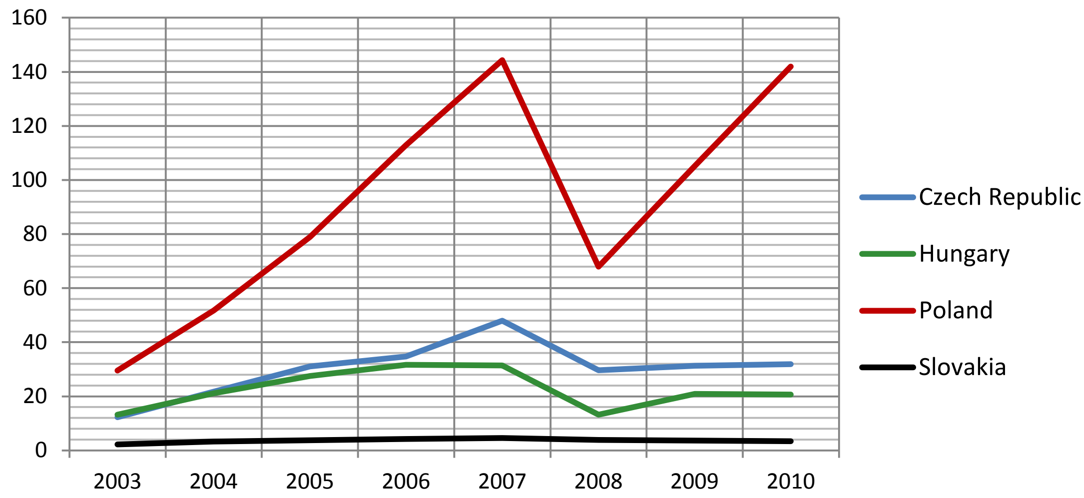
Figure 2: Market Capitalization in SEE countries, 2003-2010



Note: Author's calculation based on stock exchanges' data

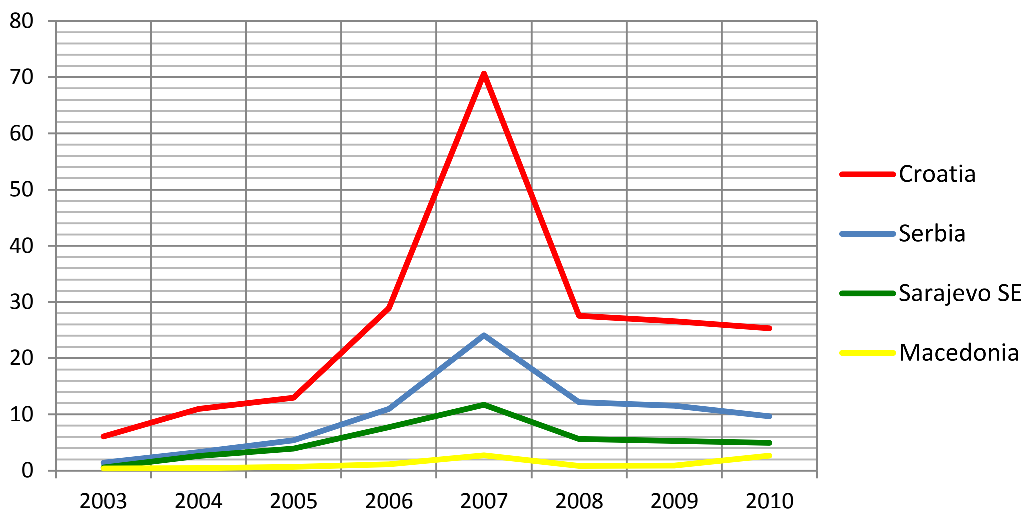
The levels for the market capitalization for the analyzed countries are shown in *Figure 1* and *Figure 2* . All the countries experienced inflated market capitalization prior to the recent financial crisis and considerable drop in 2008. Poland recorded the biggest market capitalization from all the countries in 2007 with EUR 144 billion and is continuously above the CEE countries according to this attribute. Croatia is Poland's counterpart among the SEE countries by possessing the biggest stock exchange market and reaching around USD 70 billion in 2007 before falling to levels around USD 26 billion. On the bottom according to the market capitalization are Slovakia and Macedonia, notion that establishes these markets as less important stock exchanges. In general the CEE region has considerably bigger market capitalization than the SEE region.

Figure 3: Market Capitalization in CEE countries (in EUR billion), 2003-2010



Note: Author's calculation based on EUROSTAT data

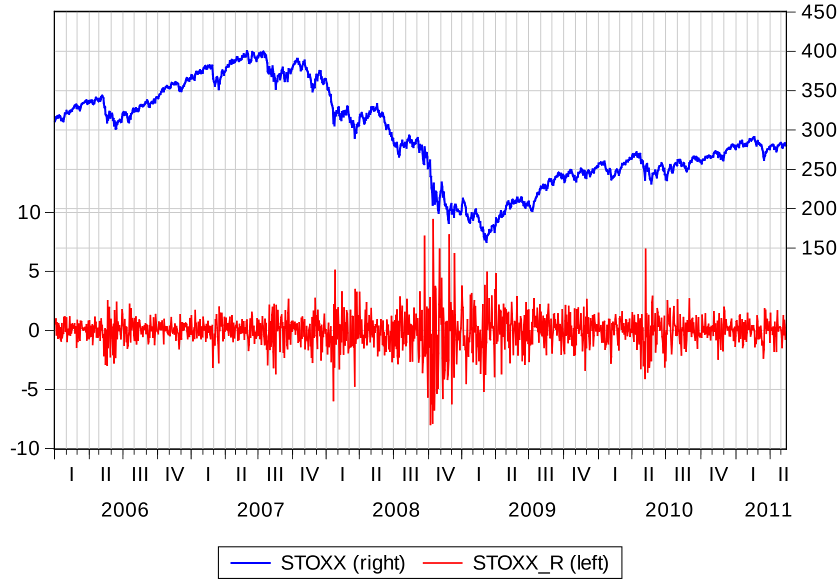
Figure 4: Market Capitalization in SEE countries (in EUR billion), 2003-2010



Note: Author's calculation based on stock exchanges' data

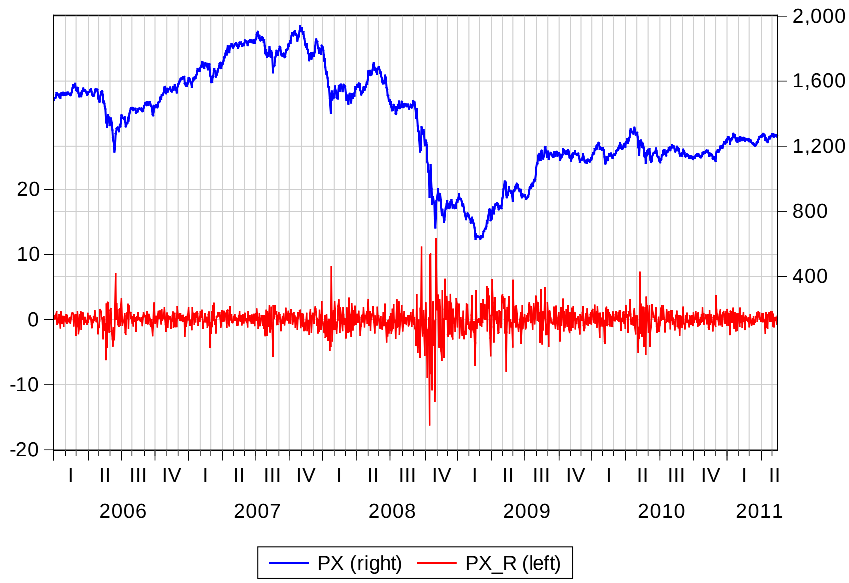
The figures below illustrate the development of the indices and the returns time series through the analyzed period. Firstly, the plot of STOXX is presented as a certain benchmark of the European equity movements. Noticeable characteristic of STOXX's development, a feature typical for all the indices, is the considerable slump caused by the global financial crisis. After the peak was reached in July 2007, a long period of decreasing trend was recorded. The lowest point was reached in first quarter of 2009 and established the index on a level half of the level of the last peak.

Figure 5: STOXX levels and returns, January 2006-May 2011



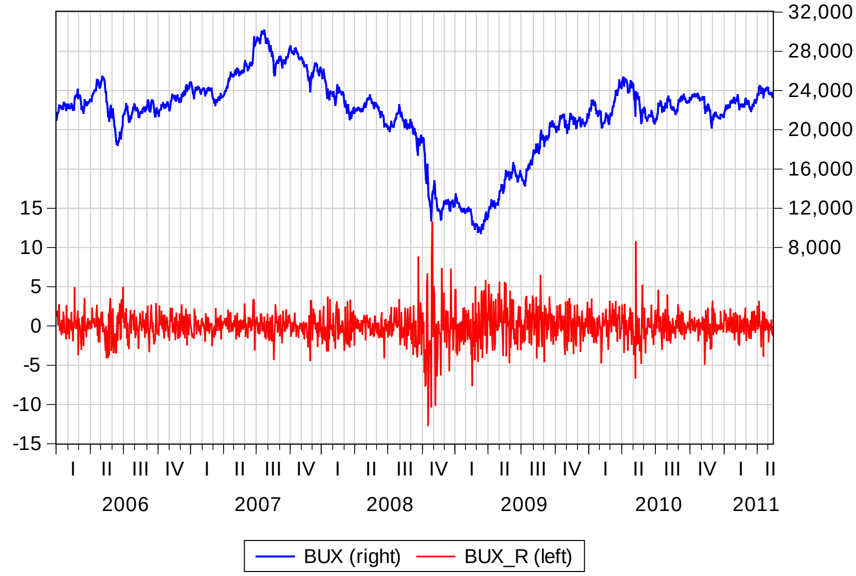
At the same time, the period of slump and the start of the recovery is the most volatile period in the return time series. The PX index has relatively similar movements like STOXX, but with higher volatility observed and slower recovery process. The most volatile period on the Prague Stock Exchange, and at the same time, for all the stock exchanges, is the last quarter of 2008, marked by the fall of Lehman Brothers and the worsening of the crisis.

Figure 6: PX levels and returns, January 2006-May 2011



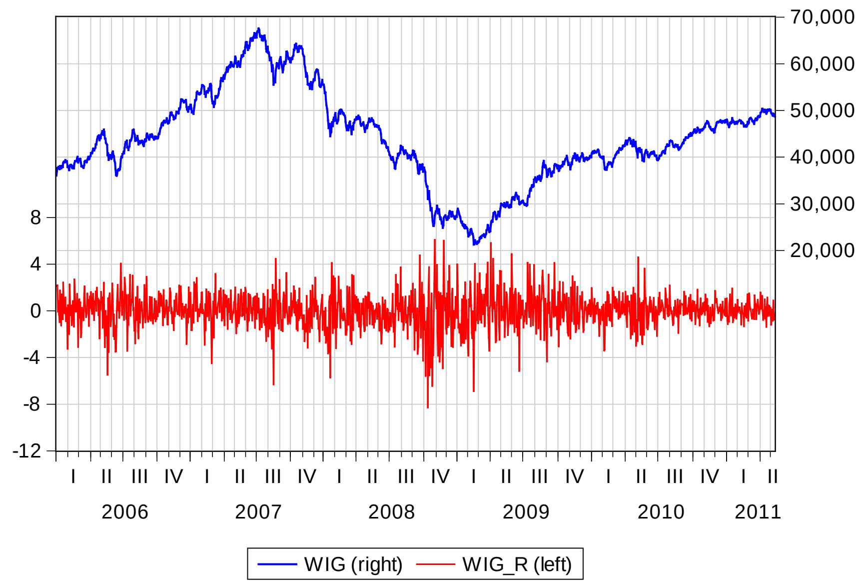
Relatively higher volatility, but faster recovery after the financial crisis compared to PX is noticed by the movements of the Budapest Stock Exchange index (BUX) and its returns time series. By visually inspecting the volatility it seems that the volatility on the Budapest Stock Exchange is more persistent and severs than two previously analyzed equity markets.

Figure 7: BUX levels and returns, January 2006-May 2011



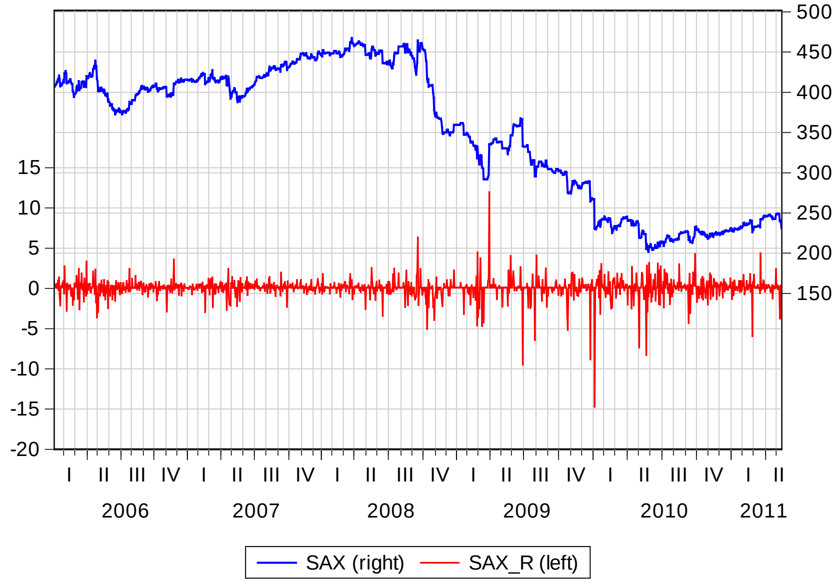
The visual inspection on the case of the Warsaw Stock Exchange index (WIG) concludes a relatively tranquil market with less severe volatility in the period 2007-2008 than the neighboring stock exchanges.

Figure 8: WIG levels and returns, January 2006-May 2011



Also, the process of recovery for the WIG index appears satisfactory as the level of the index is close to the pre-crisis peak.

Figure 9: SAX levels and returns, January 2006-May 2011

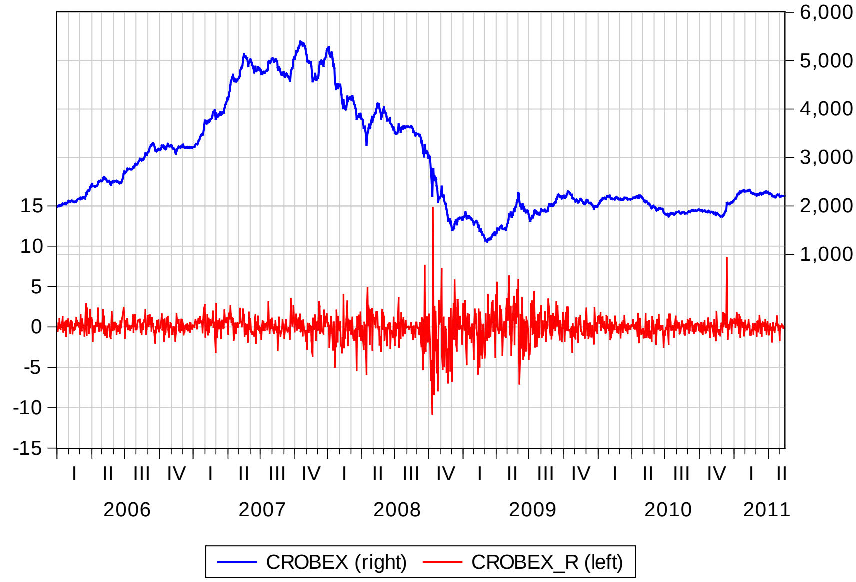


The Bratislava Stock Exchange is characterized by a specific development of its index-different compared to the other markets from the CEE region. The financial crisis and its impact on the Bratislava Stock Exchange proved to be a huge blow for the SAX index movements, since the level of the index is on a level much lower than prior to 2008. *Figure 9* also reflects the slow recovery process of the SAX index and the severe spikes in the returns time series. The SAX index is distinguished from the other indices subject of this thesis as it has a high number of zero return observations in the period from 2007 to 2009 due to the consecutive days with no change in the index level.

As the indices in the CEE region demonstrate similar movements between themselves, we also observe a degree of similarity in the development of the indices from the SEE region. The general characteristics for all the SEE stock exchanges are the huge growth before the crisis and even bigger fall as a consequence of the global turmoil. The most serious effect of the crisis for the SEE equity markets is the prolonged phase with no index growth. All the SEE indices are well below pre-crisis levels with no signs of significant recovery in the last year and a half.

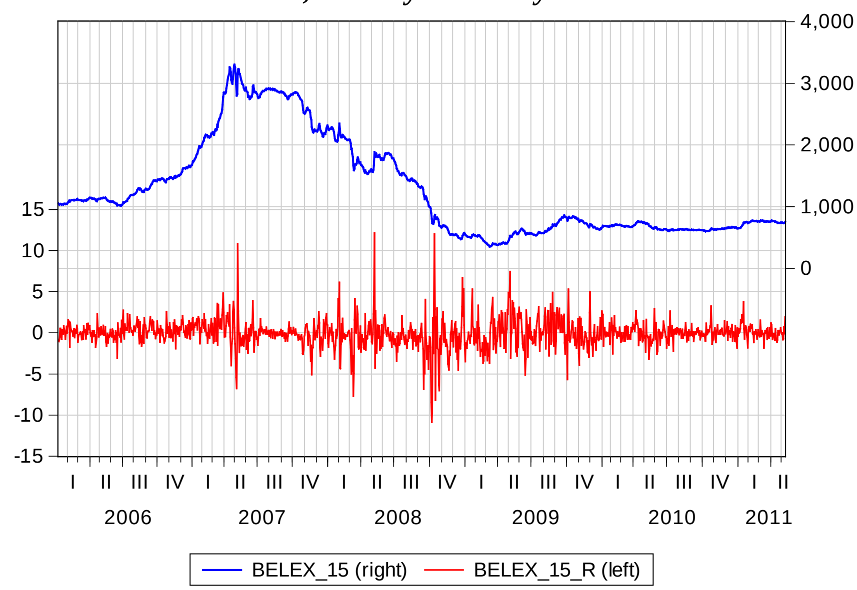
The CROBEX index depicted in *Figure 10* shows some slow recovery and a long memory in the volatility after the huge slowdown in 2008.

Figure 10: CROBEX levels and returns, January 2006-May 2011



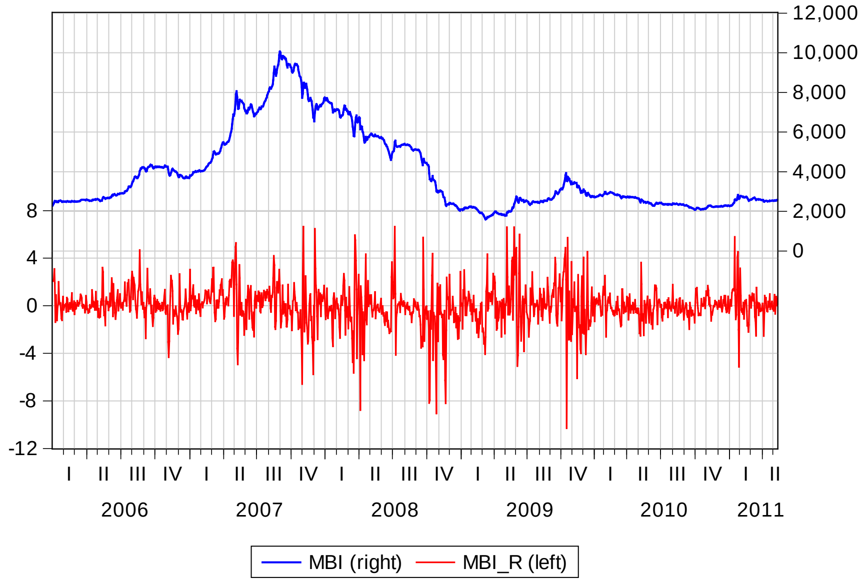
The Belgrade Stock Exchange index recorded even bigger fall than CROBEX and almost flat line in the last two years. The returns time series reveal several high volatility periods: May-June 2007; first half of 2008; and the most intense and lasting in the end of 2008 and beginning of 2009. By visual inspection, we can suppose a short memory in the volatility process with high spikes of negative and positive observations.

Figure 11: BELEX-15 levels and returns, January 2006-May 2011



The development of the Macedonian Stock Exchange index (MBI) is generally described by the established characteristics for the SEE region equity markets. Still, the returns time series of the MBI describe a somewhat different volatility process. The analyzed period is represented by several volatility clusters with moderate intensity and relatively short memory. Even the global crisis did not affected the MBI index with a single and severe shock, but a prolonged period of moderate volatility shocks that lasted more than two years. Some sign of recovery can be noticed in the second half of 2009, but it is followed by fall that established the MBI on equal levels with 2006.

Figure 12: MBI levels and returns, January 2006-May 2011



Similar conclusion can be drawn from the visual inspection of the SASX-10 index that has similar pattern like the other stock exchanges from the SEE. It is also characterized by several volatility clusters and a moderate volatility memory. After a period of less than two years when the index recorded continuous fall, at the beginning of 2009 the index reached one sixth from the record level in the beginning of 2007. As opposed to the others indices from the SEE region the SASX shows almost no recovery in the last two years. At the same time it is the most affected stock exchange from all the examined markets in this thesis, representing the devastating effect a global financial crisis can cause to a new and undeveloped stock exchange.

Figure 13: SASX-10 levels and returns, February 2006-May 2011

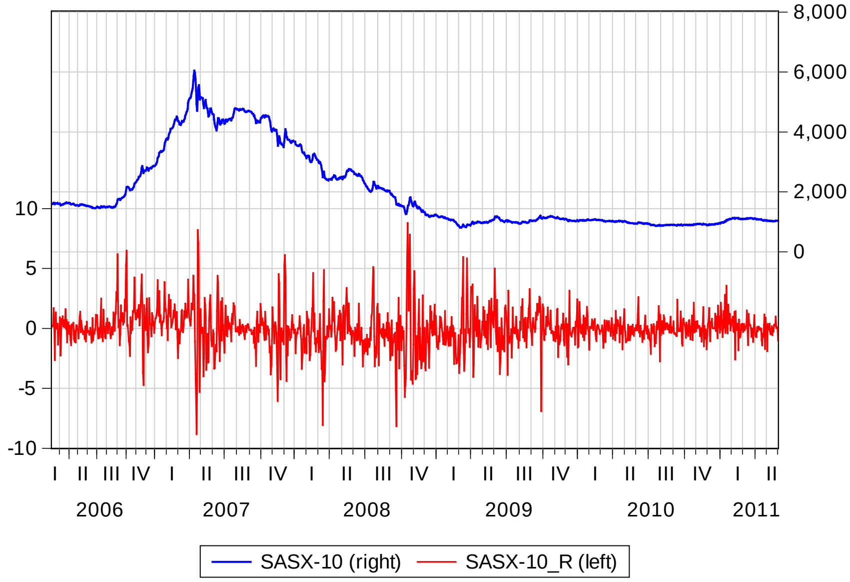


Table 3 presents the descriptive statistics for all the nine returns time series. The negative mean daily returns for five of the researched time series are relatively expected considering the chosen period for analysis-massive fall in the worldwide stock exchange indices as a result of the global financial crisis. The Warsaw Stock Exchange proved to be the best option for the investors between the markets analyzed here with 0.0223% daily return for the period January 2006-May 2011. On the other hand, the worst performance, with -0.0429% daily return, was recorded by the SAX index. The comparison of the maximum daily returns reveals the CROBEX index as the best achiever (14.779%), while the highest negative returns were realized on the Prague Stock Exchange (-16.1855%). The standard deviation reveals the BUX index as the most volatile measuring 1.9318%, while the least volatile is the SAX index-at the same time the index with the lowest return. As previously explained in the methodology part the skewness and the kurtosis measure how close a distribution is to a normal one. All returns time series have bigger value of kurtosis than 3, the value for normal distribution. The distribution with the highest peak is the returns time series of the SAX index (kurtosis=35.5807) mostly as a result of the high amount of zero returns. The results from the skewness and the kurtosis are confirmed by the Jarque-Bera test that measures the goodness of fit of departure from normal distribution. The high values of the test and the p-value mean that the null hypothesis of normality is rejected for all the returns time series. These statistics verify that the distribution of the returns is *leptokurtic*, a feature characteristic for the financial returns time series.

Table 3: Descriptive Statistics on the Returns Time Series

Variable	STOXX_R	CEE				SEE			
		PX_R	BUX_R	WIG_R	SAX_R	CROBEX_R	BELEX-15_R	MBI_R	SASX-10_R
Mean	-0.0076	-0.0119	0.0072	**0.0223**	-0.0429	0.0076	-0.0251	0.0089	-0.0351
Median	**0.0747**	0.0466	0.0369	0.0527	0	0.0667	-0.0285	0	-0.0651
Maximum	9.4100	12.3641	13.1778	6.0837	11.8803	**14.7790**	12.1576	6.6612	8.7566
Minimum	-7.9297	**-16.1855**	-12.6490	-8.2888	-14.8101	-10.7636	-10.8614	-10.2832	-8.8401
Std. Dev.	1.4280	1.8368	**1.9318**	1.4999	1.2216	1.6059	1.6775	1.6524	1.6616
Skewness	-0.0527	-0.4972	-0.0175	-0.3568	-2.0492	-0.0087	0.1689	-0.4042	0.1261
Ex. kurtosis	9.5864	15.3663	9.0764	5.6474	**35.5807**	14.1721	12.5470	8.6144	7.6717
Jarque-Bera	2476.97	8644.83	2069.29	421.62	59441.09	6953.32	5118.11	1776.33	1160.06
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	1370	1348	1345	1346	1323	1337	1346	1325	1272

Notes: author's calculations in EViews based on Reuters Wealth Manager data

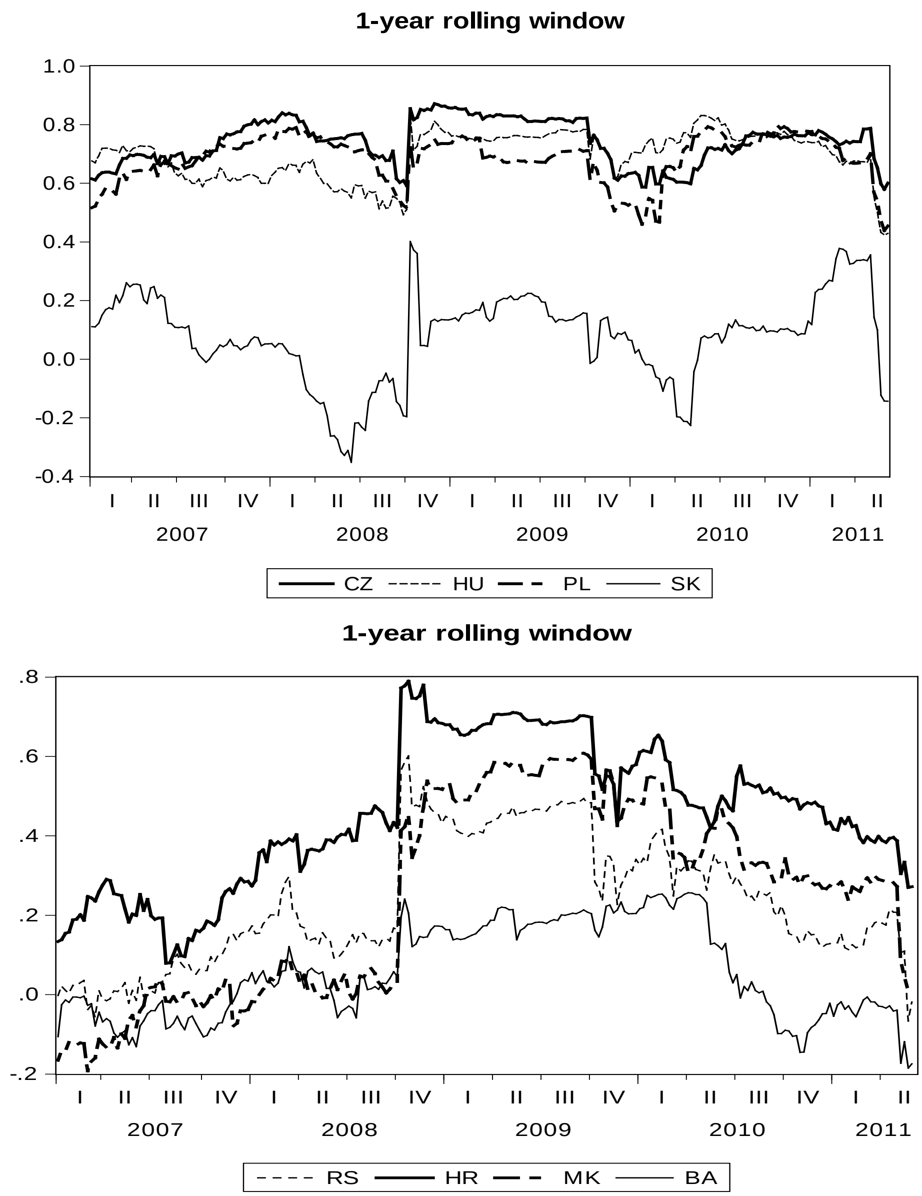
In addition, all the returns time series, confirmed by the ADF test presented in Table 4, are stationary. The ADF test has a null hypothesis of unit root and in all the cases (testing without constant, with constant, and with constant and trend) presented in the following table the unit root hypothesis is rejected at 1% significance level. In the appendix Table A.20 we also disclose the results for tested stationarity with the Phillips-Perron test. The results of the PP test are in accordance with the already established stationarity of the returns time series, while on the other hand, the index levels are confirmed as non-stationary.

Table 4: Stationarity test results

Variable	ADF test					
	no constant t-stat.	p value	constant t-stat.	p value	constant & trend t-stat.	p value
STOXX_R	-38.1248	0.000	-38.1121	0.000	-38.0998	0.000
PX_R	-27.7075	0.000	-27.6991	0.000	-27.6911	0.000
WIG_R	-25.8337	0.000	-25.8298	0.000	-25.8200	0.000
BUX_R	-27.4386	0.000	-27.4286	0.000	-27.4213	0.000
SAX_R	-24.8344	0.000	-24.8729	0.000	-24.8804	0.000
BELEX_15_R	-19.9159	0.000	-19.9122	0.000	-19.9223	0.000
CROBEX_R	-25.6557	0.000	-25.6468	0.000	-25.6881	0.000
MBI_R	-22.8525	0.000	-22.8440	0.000	-22.9034	0.000
SASX-10_R	-22.3823	0.000	-22.3836	0.000	-22.4192	0.000

We conclude the basic initial analysis by presenting the evolution of the CEE and SEE countries stock market returns in comparison to EU (approximated by STOXX 600 returns) by using rolling window correlations based on weekly data[6].

Figure 14: Rolling Correlation of National Stock Markets Returns compared to EU (weekly data, Jan. 2006-May 2011, one year rolling window)

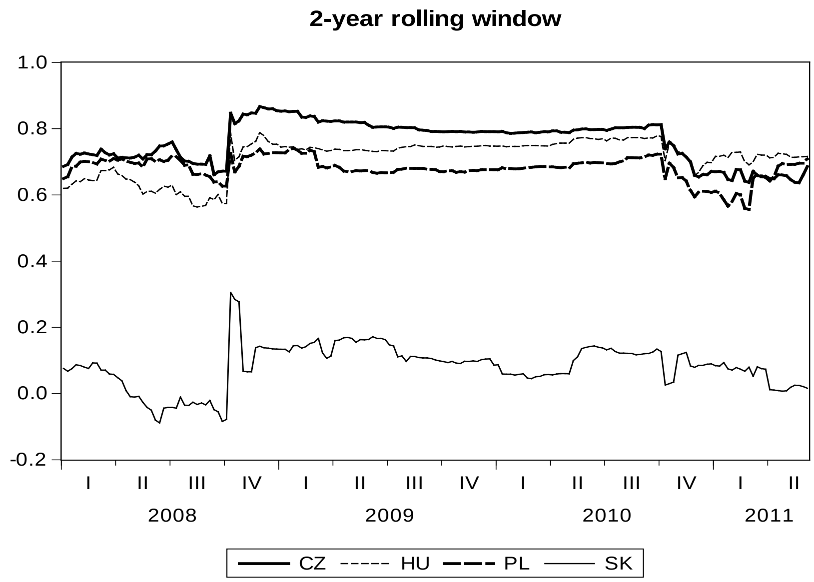


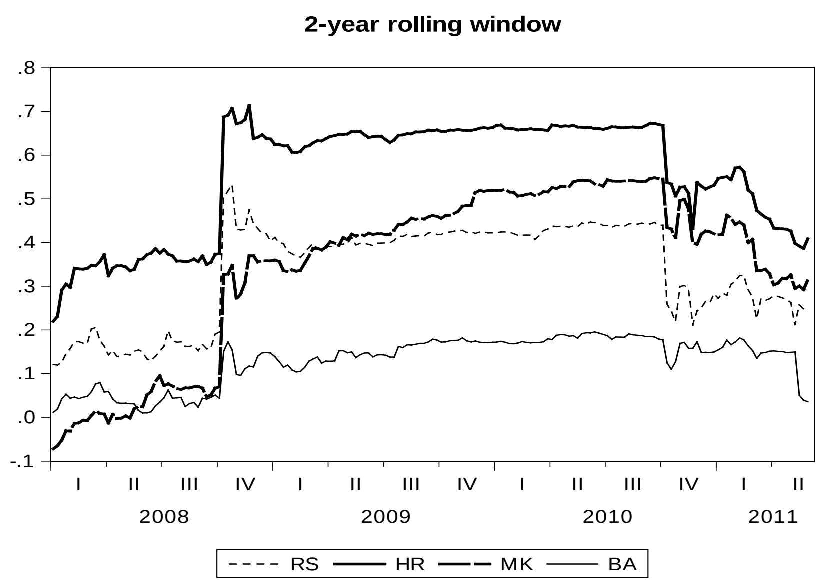
Notes: CZ=Czech Republic, HU=Hungary, PL=Poland, SK=Slovakia, RS=Serbia, HR=Croatia, MK= Republic of Macedonia, BA=Bosnia and Herzegovina. The length of the rolling window is one year. Source: Reuters Wealth Manager, author's calculations in EViews

[6] Babetskii et al.(2007) offer similar research by using 2 and 5 year rolling correlation windows between STOXX_R as proxy for the European stock markets returns and stock markets returns of the countries from CEE

While *Figure 14* shows the short-term correlation, represented by highly volatile correlation coefficient through the analyzed period, the *Figure 15* captures the medium term correlation between the stock markets returns and the EU. In the case of the CEE countries, the figures illustrate the close co-movement of the Czech, Hungarian and Polish returns time series.

Figure 15: Rolling Correlation of National Stock Markets Returns compared to EU (weekly data, Jan. 2006-May 2011, two years rolling window)





Notes: CZ=Czech Republic, HU=Hungary, PL=Poland, SK=Slovakia, RS=Serbia, HR=Croatia, MK= Republic of Macedonia, BA=Bosnia and Herzegovina. The length of the rolling window is two years. Source: Reuters Wealth Manager, author's calculations in EViews

These markets are moving in the 0.6-0.8 correlation coefficient band through the analyzed period, while the Slovak stock market returns exhibit less synchronization with the other three CEE markets returns and displays much lower correlation coefficient (continuously below 0.2) with the EU stock markets. The SEE stock markets correlation coefficient is much more volatile and less synchronized. The high volatility of this indicator is especially presented in the case of one year rolling window correlation. The figures establish the Croatian stock market as the most correlated with the EU, while the Bosnian is consistently the least correlated market. *Figure 15* reveals the most severe period of the global financial crisis as a stabilizer of the correlation between the CEE and SEE countries and EU.

In both rolling window correlation graphs we can notice a remarkable increase in the correlations during the most volatile period of the financial crisis. Baele et al. (2004) notes about this feature – "correlations are typically higher during periods of high volatility, which are often associated with business cycle troughs. Therefore, a rise in correlations may have been caused by the "cycle" rather than structural changes in the underlying economy and/or financial system." Thus, the rise in the correlations should be explained by experiencing the stock markets trough.

The initial analysis contributed establishing the general knowledge of the analyzed markets: their evolution, movements, synchronization and general statistical indicators. The following part investigates in detail the volatility by employing GARCH types of models. The SAX and SASX-10 returns will be excluded from the GARCH modeling as a result of the high number of missing observations and the low level of liquidity and correlation with the European markets (these two markets are the least correlated with the STOXX 600). An interesting remark is the high number of zero returns for the SAX index in the period of 2008-2010, when continuously the index remained at the same level for number of days.

4.2. Univariate GARCH Estimation

The main subject in this part of the thesis is presentation of the results and conclusions of the implemented GARCH type of models for the exchange markets returns time series. However, we first need to justify the need of employing GARCH-type models instead of undertaking an

ARMA analysis. By using the Box-Jenkins methodology, after identification of the lags by inspecting the correlograms and comparing the information criteria, we arrived at different specifications for the ARMA model imposed on the returns series. The residuals from these models were far from normality, but the most important reason for deciding on using GARCH models was the significant remaining ARCH effect in the residuals, confirmed by the ARCH test for all the returns series. Additionally the squared residuals correlograms showed significant correlations in the lags.

Most of the disadvantages of the ARMA modeling were addressed by establishing GARCH modeling with different specifications of the mean equation. While all the returns were modeled with GARCH (1,1) specification of the conditional variance, the indices returns differed in their mean equation specification. By using the goodness of fit criteria and referring to the parsimony principle majority of the returns are modeled as ARMA(1,1)-GARCH(1,1). The detailed specification of the ARMA and GARCH modeling of the returns time series is presented in Table *5*.

Table *5*: Specification of the ARMA-GARCH models

ARMA(1,1)-GARCH(1,1): **STOXX_R; WIG_R; BELEX_R; MBI_R**	$r_{st,wig,blx,mbi;t} = c_{st,wig,blx,mbi} + \rho r_{st,wig,blx,mbi;t-1} + \delta u_{st,wig,blx,mbi;t} + \varphi u_{st,wig,blx,mbi;t-1} + \varepsilon_{st,wig,blx,mbi;t}$ $\varepsilon_{st,wig,blx,mbi;t} \sim N(0,h_t^2)$ $h^2_{st,wig,blx,mbi;t} = \omega_{st,wig,blx,mbi} + \alpha_{st,wig,blx,mbi}\ \varepsilon^2_{st,wig,blx,mbi;t-1} + \beta_{st,wig,blx,mbi}\ h^2_{st,wig,blx,mbi;t-1}$ where $r_{st,wig,blx,mbi;t}$ is the daily return at time t $c_{st,wig,blx,mbi}$ is the constant term in the mean equation $\varepsilon_{st,wig,blx,mbi;t}$ is innovation with mean zero and time-varying conditional variance $h^2_{st,wig,blx,mbi;t}$ that follows a GARCH(1,1) process
ARMA(0,0)-GARCH(1,1): **PX_R; BUX_R**	$r_{px,bux;t} = c_{px,bux} + \varepsilon_{px,bux;t}$ $\varepsilon_{px,bux;t} \sim N(0,h_t^2)$ $h^2_{px,bux;t} = \omega_{px,bux} + \alpha_{px,bux}\,\varepsilon^2_{px,bux;t-1} + \beta_{px,bux}\,h^2_{px,bux;t-1}$ where $r_{px,bux;t}$ is the daily return at time t $c_{px,bux;t}$ is the constant term in the mean equation $\varepsilon_{px,bux;t}$ is innovation with mean zero and time-varying conditional variance $h^2_{px,bux;t}$ that follows a GARCH(1,1) process
ARMA(0,1)-GARCH(1,1): **CROBEX_R**	$r_{crb;t} = c_{st,wig,blx,mbi} + \delta u_{crb;t} + \varphi u_{crb;t-1} + \varepsilon_{crb;t}$ $\varepsilon_{crb;t} \sim N(0,h_t^2)$ $h^2_{crb;t} = \omega_{crb} + \alpha_{crb}\,\varepsilon^2_{crb;t-1} + \beta_{crb}\,h^2_{crb;t-1}$ where $r_{crb;t}$ is the daily return at time t $c_{crb;t}$ is the constant term in the mean equation $\varepsilon_{crb;t}$ is innovation with mean zero and time-varying GARCH(1,1) conditional variance $h^2_{crb;t}$

Notes: st=STOXX, wig=WIG, blx=BELEX_15, mbi=MBI, px=PX, bux=BUX, crb=CROBEX

The improvement from the GARCH modeling is evident in the residuals test, their distribution and correlograms of squared residuals. The GARCH residuals are much closer to normal distribution than the ARMA models residuals. They exhibit significantly lower peaks of the distribution, lower curtosis, and lower Jarque-Bera test statistics (Table A.21, Table A.22, Table A.23, and Table A.24). The ARCH effects in the residuals are eliminated for all the series except for the WIG_R for which the null hypothesis of no conditional heteroskedasticity is rejected at 5% significance. In all the other cases the null hypothesis cannot be rejected.

Table 6: Results from GARCH and TARCH models for STOXX_R

Variable	**STOXX_R**			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0615 ***	0.0742 ***	0.0123	0.0346
	(2.7759)	(3.5044)	(0.4784)	(1.4402)
AR(1)	0.7816 ***	0.7941 ***	0.5244	0.5584
	(5.8698)	(5.9554)	(1.4537)	(1.6086)
MA(1)	-0.8292 ***	-0.8342 ***	-0.5504	-0.5803 *
	(-7.1142)	(-6.9947)	(-1.5580)	(-1.7025)
Variance Equation				
C (variance constant)	0.0257 ***	0.0200 ***	0.0267 ***	0.0225 ***
	(4.4151)	(2.6128)	(6.2556)	(4.0796)
ARCH term	0.1209 ***	0.1140 ***	-0.0116	-0.0149
	(7.9408)	(5.9475)	(-0.9577)	(-0.9289)
Leverage effect	n/a	n/a	0.1887 ***	0.1885 ***
			(8.5485)	(6.8179)
GARCH term	0.8682 ***	0.8793 ***	0.8977 ***	0.9020 ***
	(53.7881)	(46.1566)	(67.3353)	(56.7140)

Notes: The signs ***, * denote significance at 1% and 10% respectively; the numbers in brackets are the z-statistics; the dataset includes 1369 daily observations from 03/01/2006 to 13/05/2011. The full results and all the residuals tests can be found in the Appendix; author's calculations in EViews based on Reuters Wealth Manager data

The results presented in the Table 6 are from the GARCH and TARCH modeling of the STOXX 600 index returns by assuming Normal and Student's t-distribution. The GARCH coefficients, all significant on 99% level, show little change by altering the distribution of the errors. The conditional variance (the GARCH term) is modeled as relatively high (approximately 0.87) which emphasizes the long memory and persistence in the volatility meaning it significantly depends on the past conditional variance. The TARCH model alters the estimation results in an unfavorable way by labeling all the variables, except one, in the return equation as insignificant. Additionally, the TARCH model confirms the existence of the leverage effect for the STOXX returns, and estimates the GARCH term as even higher. However the ARCH term becomes insignificant in the TARCH model.

Table 7: Results from GARCH and TARCH models for PX_R

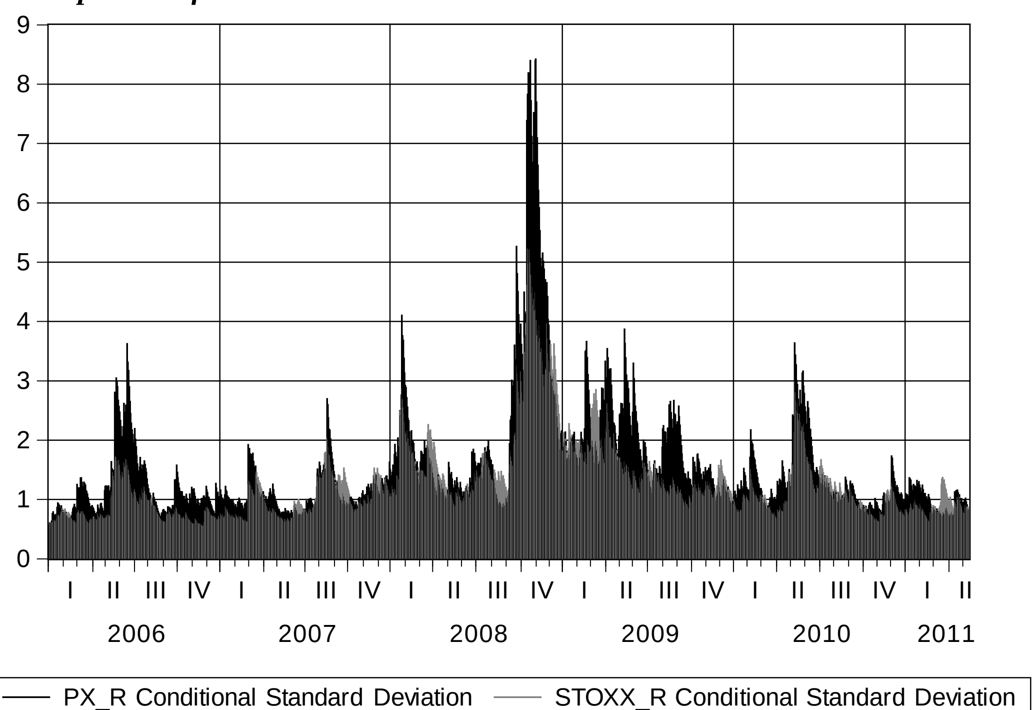
Variable	**PX_R**			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0566 *	0.0672 **	0.0232	0.0466
	(1.8275)	(2.2267)	(0.7161)	(1.5136)
Variance Equation				
C (variance constant)	0.0466 ***	0.0496 ***	0.0549 ***	0.0546 ***
	(4.1149)	(3.0379)	(4.6573)	(3.3456)
ARCH term	0.1620 ***	0.1441 ***	0.0960 ***	0.0903 ***
	(8.4427)	(5.9539)	(4.6694)	(3.3215)
Leverage effect	n/a	n/a	0.1177 ***	0.0975 ***
			(5.0517)	(2.9682)
GARCH term	0.8300 ***	0.8414 ***	0.8293 ***	0.8402 ***
	(43.8938)	(35.1523)	(42.0155)	(34.6709)

Notes: The signs ***, **, * denote significance at 1%, 5%, and 10% respectively; the numbers in brackets are the z-statistics; the dataset includes 1348 daily observations from 03/01/2006 to 13/05/2011. The full results and all the residuals tests can be found in the Appendix; author's calculations in EViews, Reuters Wealth Manager data

The effect of the GARCH term in the model of the PX returns is estimated as little lower than the one for STOXX returns. The effect of the persistence of the conditional volatility for the PX returns is approximately 0.84 and is significant at 1% level, like all the coefficients in the variance equation for the PX index. Similarly like STOXX, the PX index is characterized by a leverage effect (the "bad" news have bigger impact on the conditional volatility than the "good" news) and it is estimated to be around 0.1, which is lower than for STOXX. The only statistically insignificant coefficient in the conditional volatility modeling of the PX returns time series is the mean constant in the TARCH models. The existence of the leverage effect in the TARCH models decreases the ARCH term from approximately 0.15 in the GARCH to 0.9 in the TARCH estimation.

The GARCH type of models provides us with graph plotting the conditional variance and conditional standard deviation through time. These graphs are of significant descriptive importance and improve the estimation results by presenting the evolution of the volatility and decomposing the periods of high and low volatility. The comparison between the conditional standard deviations of the STOXX and PX returns reveals the PX returns as more volatile. The figure below demonstrates the higher volatility by the higher black peaks in the conditional standard deviation plot and also the more volatile response to the financial crisis in the last quarter of 2008. At the same time, this period, immediately after the fall of the Lehman brothers that caused the most severe phase of the latest global crisis, is characterized by the highest conditional standard deviation. It is notable to mention the existence of 'leftovers" of volatility in the PX returns after the most severe period, when an extended period of higher volatility was noticed. A notable increase in the volatility can be noticed in the second quarter of 2010 as a consequence of the worsening of the Greek debt crisis. The spike in the conditional standard deviation is caused by the Greek request for EU/IMF bailout package and the lowering of the Greek debt rating to "junk" status[7]. *Figure 16* also indicates the end of the 2010 and the first months of 2011 as one of the most tranquil period for the whole observational range. Although there is different impact on the level of the conditional standard deviation, the inspection of the figures leads to a conclusion that both returns follow relatively similar pattern of volatility.

Figure 16: Comparison of PX and STOXX returns Conditional Standard Deviations



Author's calculations in EViews based on Reuters Wealth Manager data

We continue the study on the volatility by showing the estimated results from the GARCH modeling on the Budapest Stock Exchange returns (BUX_R). The impact of the

[7] http://www.nytimes.com/2010/04/28/business/global/28drachma.html

GARCH term in the estimated GARCH(1,1) model (Table 8) is on a similar level as in the STOXX_R case. The same can be concluded for the ARCH term, which in both cases is around 0.11. Correspondingly to the Prague Stock Exchange returns, the BUX returns have variance equation estimates with significance at 1%, and significant leverage effect with similar impact on the volatility.

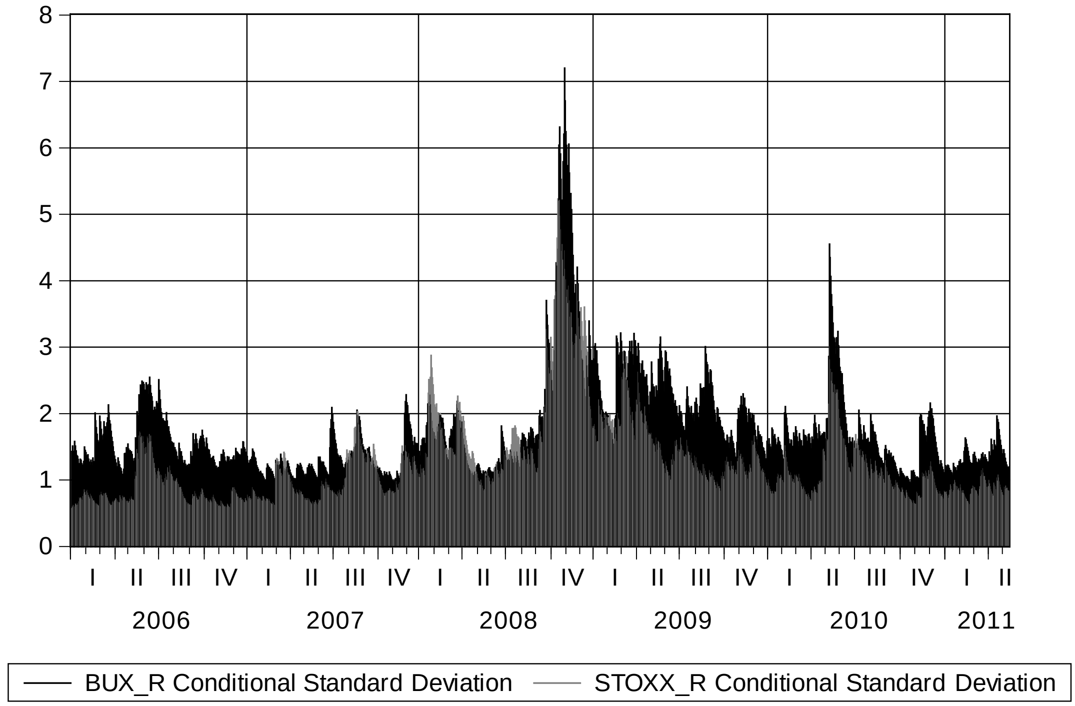
Table 8: Results from GARCH and TARCH models for BUX_R

Variable	**BUX_R**			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0602	0.0496	0.0158	0.0170
	(1.4656)	(1.2619)	(0.3815)	(0.4271)
Variance Equation				
C (variance constant)	0.0872 ***	0.0669 ***	0.0884 ***	0.0735 ***
	(4.8243)	(2.8492)	(4.7221)	(3.1256)
ARCH term	0.1147 ***	0.1116 ***	0.0533 ***	0.0572 ***
	(8.3306)	(5.8523)	(3.3354)	(2.8478)
Leverage effect	n/a	n/a	0.1024 ***	0.0997 ***
			(4.7939)	(3.4329)
GARCH term	0.8597 ***	0.8706 ***	0.8690 ***	0.8730 ***
	(52.2973)	(41.4266)	(49.9959)	(41.8937)

Notes: The signs ***, **, * denote significance at 1%, 5%, and 10% respectively; the numbers in brackets are the z-statistics; the dataset includes 1344 daily observations from 03/01/2006 to 13/05/2011. The full results and the residuals tests can be found in the Appendix; author's calculations in EViews, Reuters Wealth Manager data

Plotting the series of the conditional standard deviations for STOXX_R and BUX_R expose the similar evolution of the volatility for both indices. The similarity in the movement of the BUX_R and STOXX_R conditional standard deviation series is evident on *Figure 17*. However, the conditional standard deviation of BUX_R is consistently higher than STOXX_R as a consequence of the significantly higher variance constant coefficient – around 0.08 for BUX_R and around 0.02 for STOXX_R. After the relatively tranquil period from the beginning of 2006 till the middle of 2008, disrupted by small volatility increase in the middle of 2006 and beginning of 2008, the conditional standard deviation steeply increases as a result of the deterioration of the financial turmoil in the last months of 2008. The persistence of the BUX_R's conditional standard deviation is considerably bigger than STOXX_R's. Basically, through the whole 2009 Budapest Stock Exchange (BSE) returns have an elevated volatility which slowly decreases in the two year period before reaching level close to STOXX_R volatility in beginning of 2011. Another notable high but short-lived peak in the volatility of BUX_R is observed in the second quarter of 2010, a period of worsening of the Greek crisis. The graph below basically confirms the results from the descriptive statistics presented in Table 3, where the BUX_R standard deviation is the highest among all the analyzed returns time series.

Figure 17: Comparison of BUX and STOXX returns Conditional Standard Deviations



Author's calculations in EViews based on Reuters Wealth Manager data

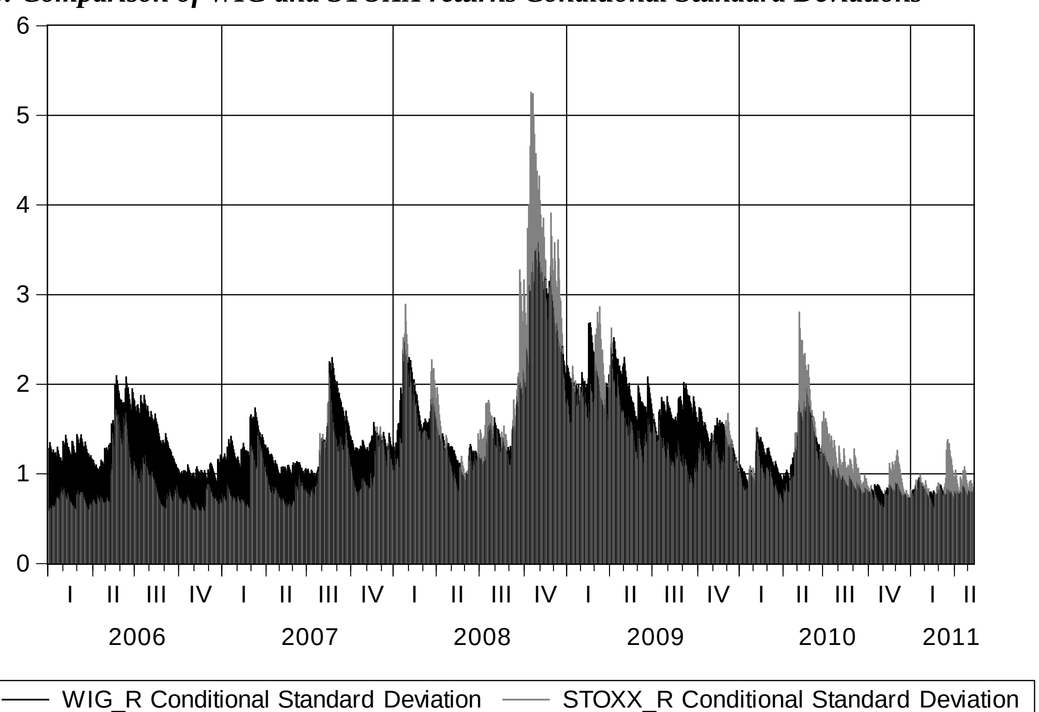
The last returns time series from the CEE region to be modeled by GARCH(1,1) are the returns of the WIG index from the Warsaw Stock Exchange - the biggest stock exchange from the analyzed according to the level of market capitalization. The ARMA(1,1)-GARCH(1,1) estimates establish the effect of the GARCH term on the volatility the highest among all the seven returns time series subjected to GARCH modeling. The high coefficient of the GARCH term (around 0.93) is accompanied by the smallest impact on the volatility by the ARCH term (approximately 0.06). Both of these estimates are significant at 1% in the GARCH model. The asymmetric response of volatility to negative and positive shocks is again confirmed at 1% significance by the TARCH model. In the WIG_R case the leverage effect, estimated around 0.07, is comparatively lower than for the previous stock market indices returns. The TARCH model estimates the effect of the past squared innovations as much smaller than GARCH and even insignificant with the Student's t-distribution. The AR(1) and MA(1) variables in the return equation are consistently estimated as significant at 1% in every model specifications.

Table 9: Results from GARCH and TARCH models for WIG_R

Variable	**WIG_R**			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0591 *	0.0710 **	0.0408	0.0517
	(1.7785)	(2.1887)	(1.2146)	(1.5797)
AR(1)	-0.9268 ***	-0.9480 ***	-0.9376 ***	-0.9469 ***
	(-109.122)	(-54.8123)	(-55.3715)	(-56.3248)
MA(1)	0.9766 ***	0.9768 ***	0.9745 ***	0.9770 ***
	(933.8486)	(86.1626)	(92.4564)	(90.6648)
Variance Equation				
C (variance constant)	0.0124 *	0.0143	0.0205 ***	0.0194 **
	(1.7396)	(1.6262)	(2.7167)	(2.2546)
ARCH term	0.0695 ***	0.0632 ***	0.0272 **	0.0232
	(7.5856)	(5.1885)	(2.0257)	(1.5053)
Leverage effect	n/a	n/a	0.0716 ***	0.0672 ***
			(4.8299)	(3.6378)
GARCH term	0.9261 ***	0.9312 ***	0.9270 ***	0.9329 ***
	(89.2442)	(69.5454)	(74.7006)	(66.5049)

Notes: The signs ***, **, * denote significance at 1%, 5%, and 10% respectively; the numbers in brackets are the z-statistics; the dataset includes 1345 daily observations from 03/01/2006 to 13/05/2011. The full results and all the residuals tests can be found in the Appendix; author's calculations in EViews, Reuters Wealth Manager data

Figure 18: Comparison of WIG and STOXX returns Conditional Standard Deviations



Author's calculations in EViews based on Reuters Wealth Manager data

The conditional standard deviation graph for WIG and STOXX returns series shows relatively different pattern of time varying volatility. The impact of the highest GARCH coefficient can be noticed in the persistence of the volatility shocks and the slow-decaying black peaks. The long memory in the volatility is the most visible in the first two years and in the period after the peak in conditional standard deviation in the crisis. *Figure 18* reveals the WIG_R as the least volatile time series, especially in the after-crisis period. The most striking remark from the graph above is the lower volatility than STOXX_R series in the worst period of the latest financial crisis. Starting from the Greek crisis in the second quarter of 2010 till the end of the analyzed period the STOXX_R conditional standard deviation is consistently higher than the conditional standard deviation of WIG_R. The WIG index seems like the safest alternative for investors in the most volatile stages of indices' returns evolution.

Table 10: Results from GARCH and TARCH models for CROBEX_R

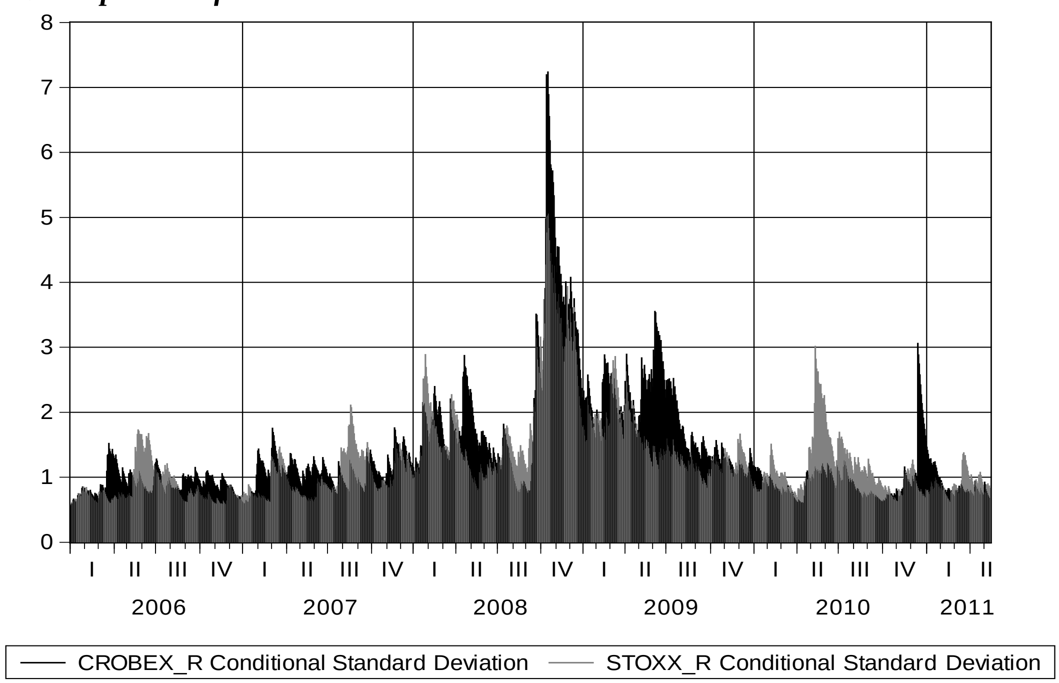
Variable	**CROBEX_R**			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0611**	0.0581**	0.0492	0.0486*
	(1.9485)	(2.0204)	(1.4271)	(1.6699)
MA(1)	0.1317***	0.1166***	0.1331***	0.1193***
	(4.9121)	(4.2881)	(4.8554)	(4.3907)
Variance Equation				
C (variance constant)	0.0292***	0.0243***	0.0312***	0.0267***
	(4.4230)	(2.6446)	(4.3482)	(2.8715)
ARCH term	0.1187***	0.1115***	0.0899***	0.0780***
	(10.2251)	(5.7603)	(7.3496)	(3.9554)
Leverage effect	n/a	n/a	0.0432***	0.0605**
			(2.9055)	(2.3040)
GARCH term	0.8736***	0.8816***	0.8778***	0.8822***
	(78.0258)	(49.5459)	(74.8971)	(49.5647)

Notes: The signs ***, **, * denote significance at 1%, 5%, and 10% respectively; the numbers in brackets are the z-statistics; the dataset includes 1336 daily observations from 03/01/2006 to 13/05/2011. The full results and all the residuals tests can be found in the Appendix; author's calculations in EViews, Reuters Wealth Manager data

As first returns time series from South Eastern Europe to be presented, the CROBEX_R exhibit similar impact of the past conditional variance on the volatility of the returns like STOXX 600 returns. The GARCH term for CROBEX_R is around 0.88 and stable in the different specifications of GARCH and TARCH. The effect of the ARCH term on the conditional volatility is similar to the one estimated for the BUX returns (around 0.11). The TARCH model in Table 10 reveals the existence of a statistically significant leverage effect in the returns series of the CROBEX index, but with coefficient of 0.04-0.06 makes the effect one with the least intensity. All the estimates, except the mean constant for the TARCH with normal distribution of errors, are statistically significant.

The CROBEX_R series are among the least volatile returns from the seven GARCH analyzed returns time series. The compared STOXX_R and CROBEX_R conditional standard deviation show low level of synchronization with different phases of high and low volatility. Except for the effect of the global financial crisis on the returns' conditional standard deviation, CROBEX_R and STOXX_R do not experience the main increases in volatility at the same time (the worsening of the Greek crisis seems not to cause any increase in the volatility of the Zagreb Stock Exchange). The CROBEX index returns, similarly like PX_R and BUX_R, recorded much higher conditional volatility through the most tumultuous phase of the financial turmoil and a notable increase in the conditional standard deviation in the middle of 2009.

Figure 19: Comparison of CROBEX and STOXX returns Conditional Standard Deviations



Author's calculations in EViews based on Reuters Wealth Manager data

The BELEX returns' conditional volatility is calculated to be the least influenced by the past conditional volatility (the GARCH term in both GARCH and TARCH specification is estimated around 0.64-0.65). The low GARCH term coefficient drives up the effect of the past squared inventions on the conditional volatility-estimated to be around 0.35-0.36. The ARCH term in the GARCH model for BELEX-15_R is considerably higher compared to the other stock exchange returns. The existence of a leverage effect is only confirmed in the TARCH model with normal distribution of errors; this variable in the TARCH with Student's t-distribution is labeled as statistically insignificant. Like for most of the returns series the ARCH and GARCH terms are statistically significant at 1%.

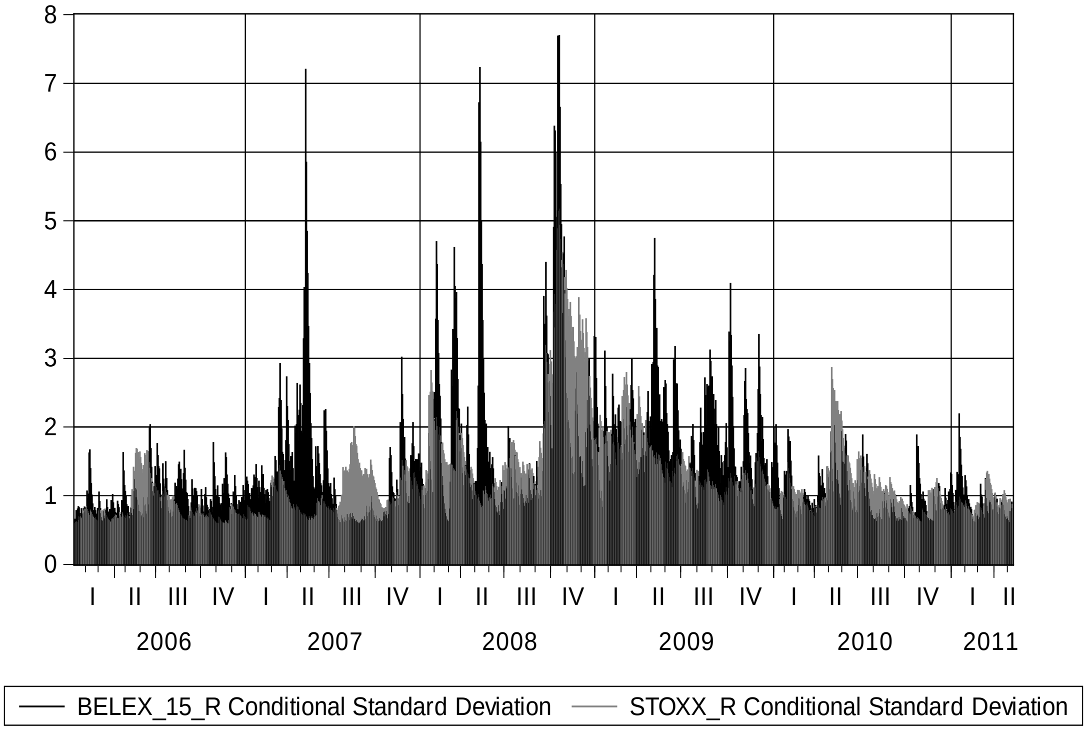
Table 11: Results from GARCH and TARCH models for BELEX-15_R

Variable	**BELEX-15_R**			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0546	-0.0035	0.0352	-0.0045
	(1.3321)	(-0.0835)	(0.8185)	(-0.1038)
AR(1)	0.4996***	0.5857***	0.4873***	0.5845***
	(6.7003)	(9.2900)	(6.3754)	(9.2500)
MA(1)	-0.2097**	-0.2979***	-0.2010**	-0.2967***
	(-2.2798)	(-3.8319)	(-2.1343)	(-3.809)
Variance Equation				
C (variance constant)	0.1160***	0.1141***	0.1118***	0.1136***
	(7.0299)	(4.0346)	(6.6784)	(4.0256)
ARCH term	0.3571***	0.3549***	0.3177***	0.3504***
	(12.8396)	(6.6528)	(10.4448)	(5.4314)
Leverage effect	n/a	n/a	0.0746**	0.0073
			(1.7572)	(0.0985)
GARCH term	0.6407***	0.6541***	0.6449***	0.6549***
	(30.0197)	(17.6775)	(29.3792)	(17.6627)

Notes: The signs ***, ** denote significance at 1%, and 5% respectively; the numbers in brackets are the z-statistics; the dataset includes 1344 daily observations from 10/01/2006 to 13/05/2011. The full results and all the residuals tests can be found in the Appendix; author's calculations in EViews, Reuters Wealth Manager data

The different and relatively unique estimation results for BELEX-15 returns can be clearly noticed on *Figure 20*. The high and spiky volatility shocks are a characteristic not visible in the plots of the other conditional standard deviations. These sharp increases and decreases can be attributed to the low GARCH term which implies short memory in the volatility. These notable surges in the conditional standard deviation of the BELEX-15 returns do not seem to be influenced by similar volatility movements in the European stock markets, since they are not actually synchronized. The inspection of the BELEX-15 returns volatility plot reveals a disproportional reaction to the STOXX_R conditional standard deviation shocks. Namely, the intensity of some small volatility rises is followed by similar impact to the BELEX_R like the impact caused to the volatility by the global financial crisis.

Figure 20: Comparison of BELEX-15 and STOXX returns Conditional Standard Deviations



Author’s calculations in EViews based on Reuters Wealth Manager data

The estimation results of the MBI returns are to some extent similar to the results for BELEX_R. The MBI_R’s GARCH term is not as high as in the CEE countries, but with 0.74 for the normal distribution and 0.65 in the case for assumed student’s t-distribution, comes close to the values modeled for the returns of the neighboring stock exchange index. The estimated relatively low impact of the past conditional volatility is reflected in one of the highest coefficients for the ARCH term (in the 0.25-0.36 band). The MBI returns react asymmetrically to the new information, but this effect is estimated as one of the smallest. Additionally, the TARCH model with Student’s t-distribution, similarly like in the BELEX_R model, does not confirm the leverage effect with statistical significance.

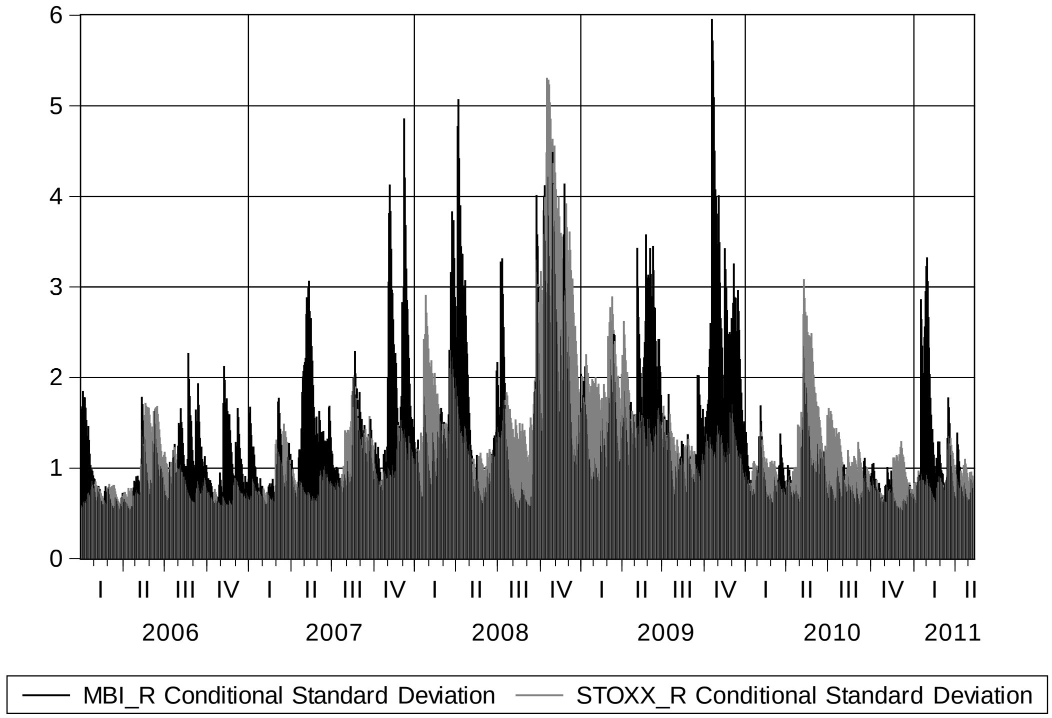
Table 12: Results from GARCH and TARCH models for MBI_R

Variable	MBI_R			
	GARCH with Normal distribution	GARCH with Student's t-distribution	TARCH with Normal distribution	TARCH with Student's t-distribution
Return Equation				
C (mean constant)	0.0255	0.0162	0.0014	0.0029
	(0.6342)	(0.3944)	(0.0296)	(0.0701)
AR(1)	0.2600***	0.3302***	0.2568***	0.3288***
	(4.4143)	(5.6879)	(4.3194)	(5.6847)
MA(1)	0.2087***	0.1392**	0.2106***	0.1413**
	(2.9408)	(2.1398)	(2.9474)	(2.1744)
Variance Equation				
C (variance constant)	0.0618***	0.1085***	0.0638***	0.1070***
	(7.9271)	(4.1373)	(8.0002)	(4.1583)
ARCH term	0.2578***	0.3642***	0.2309***	0.3113***
	(11.5764)	(5.9074)	(9.9642)	(4.8491)
Leverage effect	n/a	n/a	0.0577*	0.0911
			(1.8469)	(1.1652)
GARCH term	0.7482***	0.6525***	0.7458***	0.6571***
	(53.5966)	(18.4659)	(51.6733)	(18.7227)

Notes: The signs ***, **, * denote significance at 1%, 5%, and 10% respectively; the numbers in brackets are the z-statistics; the dataset includes 1323 daily observations from 05/01/2006 to 13/05/2011. The full results and all the residuals tests can be found in the Appendix; author's calculations in EViews, Reuters Wealth Manager data

The relative similarity of MBI_R's estimation results to the GARCH estimates for BELEX returns is reflected in similar plots of the conditional standard deviation. *Figure 21*, plotting STOXX_R and MBI_R conditional standard deviations, again reveals spiky volatility shocks with short persistence. A general conclusion is that the shocks in the conditional standard deviation of the MBI returns are not influenced by the volatility movements in the overall European equity market. The phases of low and high volatility usually happen at different periods of the returns series. The only exceptions are the effect to the volatility by the financial crisis, when both returns series reacted similarly although the Macedonian equity market returns' volatility experienced smaller intensity shock, and the Greek crisis in second quarter of 2010, when the Macedonian Stock Exchange experienced similar volatility shock like the STOXX_R but with shorter persistence. A considerable increase in the volatility of MBI's returns can be observed in the second quarter of 2008, as a result of the non-acceptance of Republic of Macedonia to NATO during the Bucharest Summit due to name dispute with Greece. Even more intense conditional standard deviation shock, at the same time bigger than the one caused by the financial turmoil, can be noticed in the second half of 2009.

Figure 21: Comparison of MBI and STOXX returns Conditional Standard Deviations



Author's calculations in EViews based on Reuters Wealth Manager data

We analyze how the separate stock exchange specification and estimation results satisfy the assumptions behind the GARCH models by comparing the coefficients of the ARCH and GARCH terms. Firstly, we examine the non-negativity constraints of the GARCH and TARCH models for each stock market's returns series. As we already establish in the methodology part, the non-negativity constraint requires all the coefficients in the conditional variance equation to be non-negative. This constraint is derived from the notion that the conditional variance must always be a positive number.

The non-negativity assumption is satisfied in all the models we specify for the seven stock exchanges returns series. The only exceptions are the coefficients of the ARCH term in the TARCH model with both residuals distribution for STOXX_R presented in Table 6.

As previously explained in na stránce 14 the sum of the coefficients of the ARCH and GARCH terms in the conditional variance equation should be lower than one. For $\alpha + \beta \geq 1$, non-stationarity in variance exists, while $\alpha + \beta = 1$ means "unit-root in variance". As (Brooks 2008) notes "the non-stationarity implies undesirable properties of the variance forecasts which would tend to infinity, as opposed to the stationarity case whose variance forecasts converge upon the long term average value of variance as the horizon increases."

Table 13: Wald tests results for GARCH abd TARCH models

Variable	STOXX_R	PX_R	WIG_R	BUX_R	BELEX_15_R	CROBEX_R	MBI_R
GARCH Normal	-0.011 (0.007)	-0.008 (0.008)	-0.004 (0.005)	-0.026 *** (0.009)	-0.002 (0.018)	-0.008 (0.007)	0.006 (0.012)
GARCH Student's t	-0.007 (0.009)	-0.014 (0.012)	-0.006 (0.006)	-0.018 (0.011)	0.009 (0.038)	-0.007 (0.010)	0.017 (0.041)
TARCH Normal	-0.020 *** (0.005)	-0.016 * (0.009)	-0.010 ** (0.005)	-0.027 * (0.009)	-0.0001 (0.018)	0.011 (0.007)	0.006 (0.013)
TARCH Student's t	-0.019 *** (0.007)	-0.021 * (0.012)	-0.010 * (0.006)	-0.020 * (0.011)	0.009 (0.038)	-0.010 (0.010)	0.014 (0.040)

Notes: Wald tests results for testing stationarity in variance ($\alpha+\beta<1$ for GARCH models and $\alpha+\beta+\gamma/2<1$ in TARCH models) with standard errors in parenthesis, H_0: $-1+\alpha+\beta=0$ for GARCH; H_0: $-1+\alpha+\beta+\gamma/2=0$ for TARCH; ***, **, * denote significance at 1%, 5% and 10%.

Table 13, reporting the Wald tests results, implies that most of the GARCH models have sums of the ARCH and GARCH terms lower than one, meaning that they are stationary in variance. Only in the case of MBI_R GARCH model the coefficients sum up above one. However, in all cases, except BUX_R with normal distribution, the null hypothesis of equality to one cannot be rejected.

Most of the TARCH models' coefficients also sum up below one suggesting stationarity in variance. Exceptions from this remark are the results for BELEX_15_R and CROBEX_R with Student's t-distribution and MBI_R. The results from the Wald test for the TARCH models differ in significance from the ones for GARCH models as more of the tests successfully reject the null hypothesis of equality to one at 1%, 5% and 10% of significance.

The univariate GARCH modeling helps us distinguish the nature of the volatility process of each index's returns, its persistency and intensity and offers a comparison of how close the studied stock exchange returns volatility are to the overall European equity markets' returns volatility. The results suggest that the three CEE stock exchanges are closer than the SEE stock exchanges to the European market in terms of volatility development. This suggestion, previously indicated to some degree by the rolling window correlation, is deduced from the similar GARCH coefficients and the synchronization of the volatility shocks evident on the plots of the conditional standard deviations. In order to check whether direct volatility transmissions and spillovers from the European stock exchanges to the CEE and SEE equity markets exist, we will perform a multivariate GARCH estimation.

4.3. Multivariate GARCH Estimation

The bivaritate BEKK-GARCH specification used for the multivariate GARCH estimation helps us discover the conditional volatility between each countries stock exchange returns and the European STOXX returns. The calculated multivariate GARCH functions for each model between index returns from one of the six GARCH analyzed countries and the STOXX index returns are shown in the following tables. In each table the index one represents one of the six returns series (PX_R, BUX_R, WIG_R, CROBEX_R, BELEX-15_R, and MBI_R), while the index two always represents the STOXX returns. This means that $\mathbf{h_{11,t}}$ stands for the conditional variance of one of the six previously listed returns, $\mathbf{h_{22,t}}$ always describes the conditional variance of the STOXX returns, while $\mathbf{h_{12,t}}$ represents the conditional covariance between one of the six CEE or SEE returns series and the STOXX returns series. The "ε" stands for the effect of the errors or "news" on the conditional volatility. The underlined coefficients are functions of statistically significant coefficients; on the other hand the non-underlined numbers are calculated by multiplying statistically insignificant coefficients. The complete results from the multivariate GARCH estimation and the residuals tests can be found in the Appendix Table A.25 and Table A.26.

The results from the multivariate GARCH estimation between PX_R and STOXX_R time series are of low quality since all of the coefficients in Table 14 are statistically insignificant. The reporting ability and usage of this specification therefore is poor and we will not interpret the results.

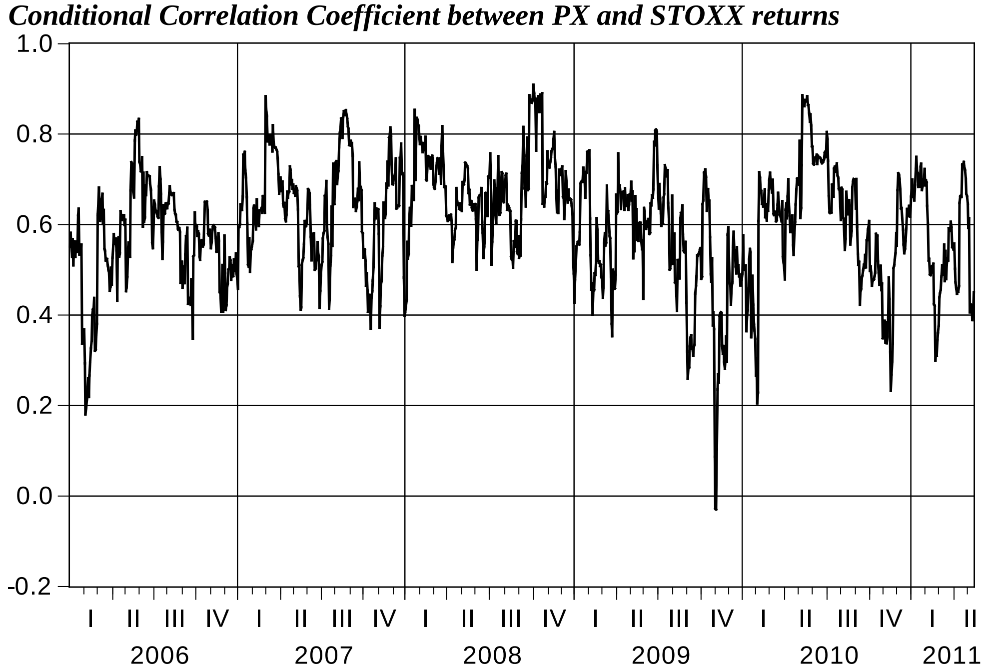
Table 14: Bivariate GARCH coefficients estimates for PX and STOXX returns

	constant term	$\varepsilon_{1\,,\,t-1}^{2}$	$\varepsilon_1\varepsilon_{2,\,t-1}$	$\varepsilon_{2\,,\,t-1}^{2}$	$h_{11,\,t-1}$	$h_{12,\,t-1}$	$h_{22,\,t-1}$
$h_{11,t}$	0.08886	0.09055	0.03789	0.00396	0.87147	-0.05482	0.00086
$h_{22,t}$	0.03389	0.000001	0.00059	0.08887	0.00004	0.01147	0.88656
$h_{12,t}$	0.01691	0.00030	0.08977	0.01877	0.00568	0.87881	-0.02765

Notes: the sample includes 1341 observations from 03/01/2006 to 13/05/2011; author's calculations in JMulTi based on Reuters Wealth Manager data

We can use the *Figure 22* as an illustrative tool for estimating the degree of correlation between PX_R and STOXX_R. This approximation of the volatility co-movements suggests volatile correlation ranging between 0.4 and 0.8 for the most of the observation period. The graph implies a small increase in the conditional correlation during the worst phase of the financial crisis (third quarter of 2008). The second half of 2009, on the other hand, is a period of decreasing co-movements between PX_R and STOXX_R. However, the conditional correlation graph should be taken with precaution since the model coefficients are insignificant.

Figure 22: Conditional Correlation Coefficient between PX and STOXX returns



The reporting ability of the multivariate GARCH model for BUX_R and STOXX_R is much higher taking into consideration the number of statistically significant coefficients in Table 15. The results show that the conditional variances of both BUX and STOXX returns are significantly affected by the past conditional variances; the influence of the own conditional volatility being bigger for BUX_R than for STOXX_R (0.938 against 0.876). On the other hand, STOXX_R is more influenced by its own past shocks, than BUX_R (0.096 to 0.046). The model reveals the conditional variance of BUX_R as being directly affected by the past shocks and past conditional variance in the European market represented by STOXX – however, these volatility spillovers are very small (0.013 and 0.002). Hungarian stock market returns are also estimated as indirectly affected by the past volatility shocks in the European stock market and negatively affected by the conditional covariance.

The conditional covariance is only influenced by the European stock markets volatility movements – positively by the past shock in volatility and negatively by the past conditional variance.

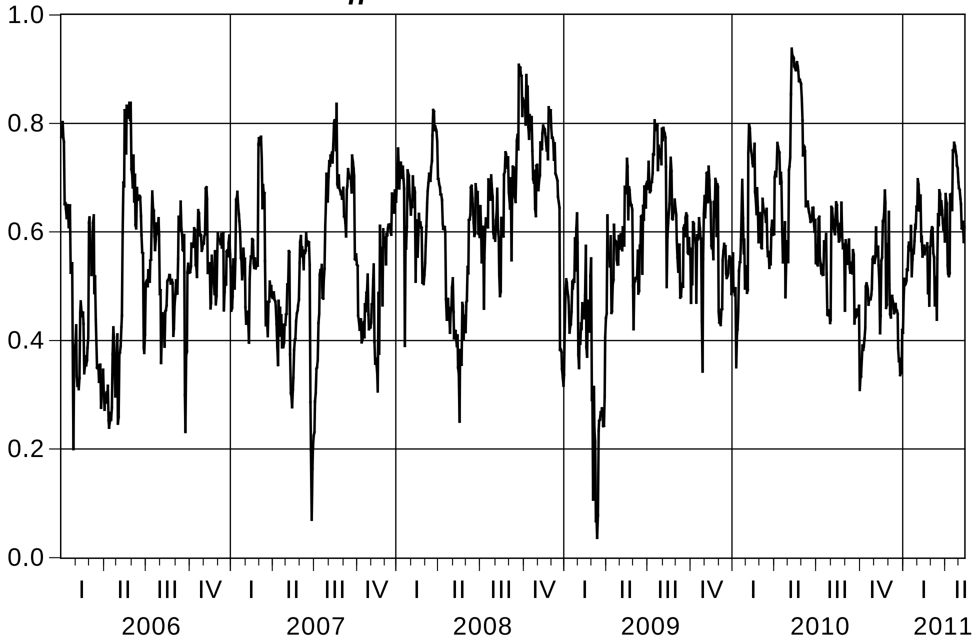
Table 15: Bivariate GARCH coefficients estimates for BUX and STOXX returns

	constant term	$\varepsilon_{1,t-1}^2$	$\varepsilon_1\varepsilon_{2,t-1}$	$\varepsilon_{2,t-1}^2$	$h_{11,t-1}$	$h_{12,t-1}$	$h_{22,t-1}$
$h_{11,t}$	<u>0.06725</u>	<u>0.04564</u>	<u>0.04815</u>	<u>0.01270</u>	<u>0.93777</u>	<u>-0.07933</u>	<u>0.00168</u>
$h_{22,t}$	<u>0.04001</u>	0.000041	-0.00399	<u>0.09612</u>	0.00000	0.00404	<u>0.87562</u>
$h_{12,t}$	<u>0.01988</u>	-0.00137	0.06551	<u>0.03494</u>	0.00209	0.90607	<u>-0.03833</u>

Notes: the sample includes 1339 observations from 03/01/2006 to 13/05/2011; author's calculations in JMulTi based on Reuters Wealth Manager data

The conditional correlation coefficient between the Hungarian and European stock markets returns is highly volatile – mostly moving in the range between 0.2 and 0.8 with periodical decreases (most notably in the beginning of 2009) and slight increases. Although it moves roughly in the same range, the conditional correlation coefficient between BUX_R and STOXX_R shows higher volatility compared to the one between PX_R and STOXX_R.

Figure 23: Conditional Correlation Coefficient between BUX and STOXX returns



Analyzing Table 16 we can deduce similar conclusions like BUX returns for the Warsaw Stock Exchange. The Polish equity market returns are highly affected by its past conditional variance (with the coefficient of 0.9697 even higher than BUX_R's 0.938); at the same time STOXX_R is influenced at 0.835. Again it is estimated that the CEE market is negatively influenced by the past conditional covariance, although in this case the influence is slightly smaller than for BUX_R. There is only negligible proof of volatility spillovers – statistically significant, but low influence to the WIG_R's conditional variance (0.00098) and the conditional covariance (-0.029) by the past conditional variance of STOXX_R. The impact of the past shocks is estimated as bigger for the STOXX_R conditional variance than for WIG_R conditional variance (0.133 against 0.034).

Table 16: Bivariate GARCH coefficients estimates for WIG and STOXX returns

	constant term	$\varepsilon_{1, t-1}^2$	$\varepsilon_1\varepsilon_{2, t-1}$	$\varepsilon_{2, t-1}^2$	$h_{11, t-1}$	$h_{12, t-1}$	$h_{22, t-1}$
$h_{11,t}$	0.01560	0.03513	0.03164	0.00712	0.96973	-0.06158	0.00098
$h_{22,t}$	0.05011	0.001747	-0.03046	0.13275	0.00024	0.02806	0.83488
$h_{12,t}$	0.02368	-0.00783	0.06476	0.03075	0.01512	0.89930	-0.02857

Notes: the sample includes 1334 observations from 03/01/2006 to 13/05/2011; author's calculations in JMulTi based on Reuters Wealth Manager data

The conditional correlation coefficient, after the moderate increase in 2006 and the first half of 2007, is rather stable in the range between 0.4 and 0.8 with only minor movements out of this range.

Figure 24: Conditional Correlation Coefficient between WIG and STOXX returns

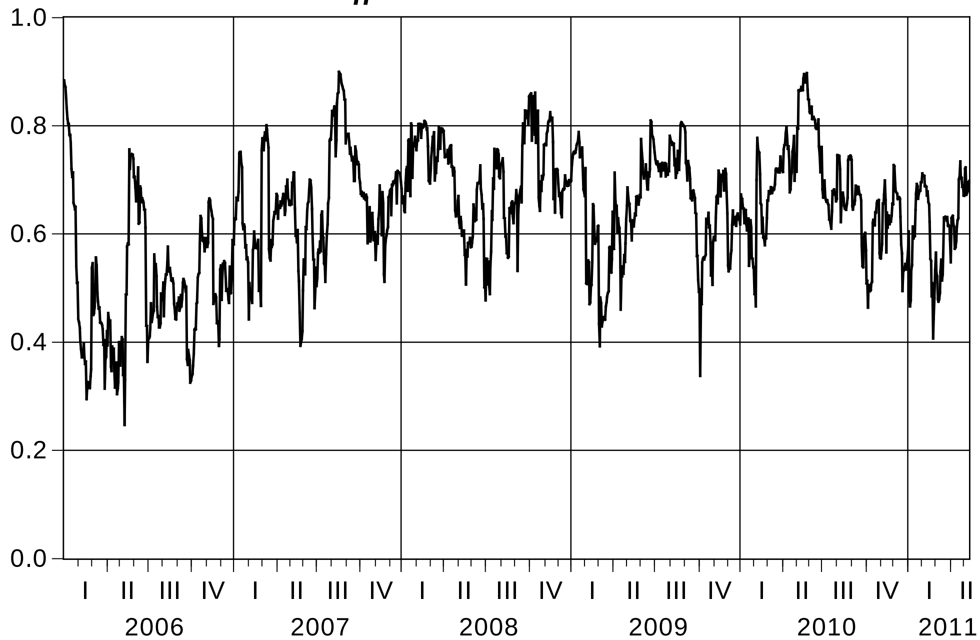


Figure 24 follows in line with the previous findings about the movement in the volatility of the returns in the Polish Stock Market. As previously suggested by the descriptive statistics, and by the plot of the conditional standard deviation the WIG returns are one of the CEE returns showing the lowest volatility, which qualifies them as the safest alternative for the investors.

The SEE stock exchanges returns are considerably more heterogeneous group in terms of their conditional volatility. Starting to analyze the multivariate GARCH models with the one between CROBEX_R and STOXX_R, we can notice no evidence of any volatility spillovers from the European markets to the Croatian market. There is only confirmation of statistically significant influence to the conditional volatilities by the own past shocks and conditional variances. Both stock markets returns series are affected with similar intensity by the past shocks (around 0.09) and by the past conditional variances (around 0.87-0.88). The persistence of the past volatility ranks the Croatian stock market returns close to the Czech equity returns – to some degree lower than the Polish and the Hungarian volatility persistence.

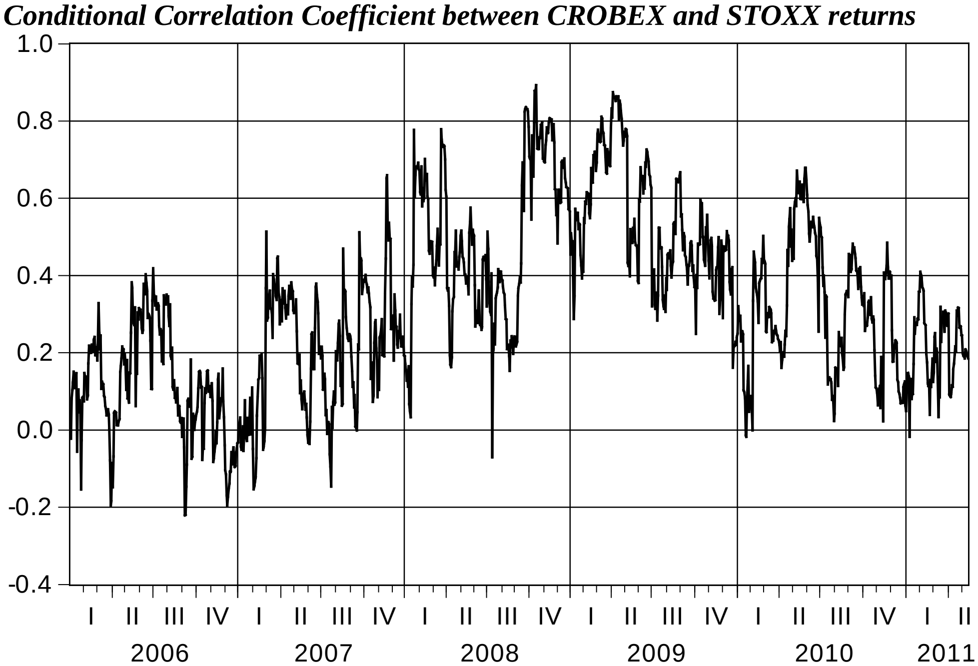
Table 17: Bivariate GARCH coefficients estimates for CROBEX and STOXX returns

	constant term	$\varepsilon_{1,t-1}^2$	$\varepsilon_1\varepsilon_{2,t-1}$	$\varepsilon_{2,t-1}^2$	$h_{11,t-1}$	$h_{12,t-1}$	$h_{22,t-1}$
$h_{11,t}$	<u>0.05699</u>	<u>0.09205</u>	0.02692	0.00197	<u>0.88244</u>	-0.02554	0.00018
$h_{22,t}$	0.04289	0.000212	-0.00905	<u>0.09661</u>	0.00025	0.02962	<u>0.87223</u>
$h_{12,t}$	0.00099	-0.00442	0.09366	0.01379	0.01490	0.87710	-0.01269

Notes: the sample includes 1333 observations from 03/01/2006 to 13/05/2011; author's calculations in JMulTi based on Reuters Wealth Manager data

The conditional correlation coefficient graph demonstrates a unique movement and significant volatility. In the observed period the conditional correlation varies massively – from above zero, the correlation decreases and enters into negative values by reaching -0.2; then significantly increases and achieves around 0.8 at the end of 2008, and then declines in the next two years. In the last four quarters it slightly deviates around 0.2. The conditional correlation coefficient plot can be expected to some extent considering the previous findings from the univariate GARCH model. The volatile conditional correlation coefficient depicted in *Figure 25* can be connected with the conditional standard deviation plot of CROBEX_R on *Figure 19* due to the low synchronization of the volatility movements in CROBEX and STOXX returns. Entering into negative values and the immense variation between 0.0 and 0.8 can be some explanation behind the low synchronization of the conditional standard deviation plots.

Figure 25: Conditional Correlation Coefficient between CROBEX and STOXX returns



The estimated results for the multivariate GARCH model for BELEX-15_R and STOXX_R demonstrate significant influence to the Serbian stock exchange returns volatility by the past shocks and past conditional volatility, but also by the past conditional covariance and by the European stock markets conditional volatility. As in the previous multivariate models, the European returns conditional volatility is significantly influenced only by the past shocks and past conditional volatility. With value of 0.10557, the effect of the past shock on the BELEX_R conditional volatility is slightly higher than in the CROBEX_R case. On the other hand, the impact of the past conditional variance on the Serbian conditional variance is slightly lower than the one estimated in the CROBEX_R model. The significant coefficient of -0.05745 implies negative impact of the past conditional covariance on the Serbian stock market volatility. Evidence for direct volatility spillover from the European to the Serbian stock market is presented through the significant but in fact small coefficient measuring 0.00094 (similar impact like in the WIG_R model).

In accordance with the previous models, there is no evidence of volatility spillovers in direction from the analyzed CEE or SEE stock markets towards the European stock markets. Table 18 shows that the European conditional variance is directly affected only by its own past shock in the volatility and its own past conditional variance.

Table 18: Bivariate GARCH coefficients estimates for BELEX-15 and STOXX returns

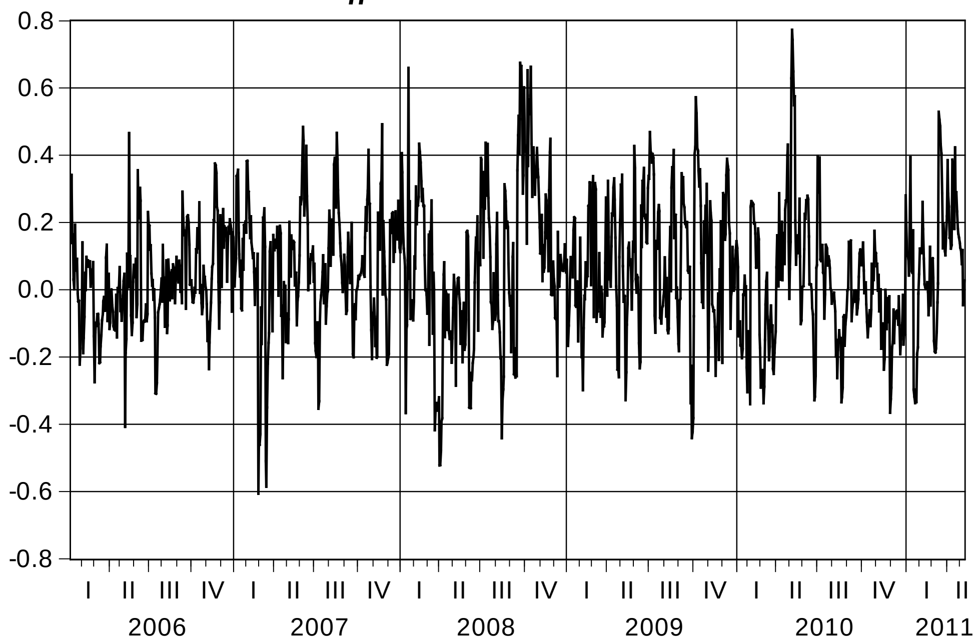
	constant term	$\varepsilon_{1}^{2}{}_{, t-1}$	$\varepsilon_1\varepsilon_{2, t-1}$	$\varepsilon_{2}^{2}{}_{, t-1}$	$h_{11, t-1}$	$h_{12, t-1}$	$h_{22, t-1}$
$h_{11,t}$	<u>0.04680</u>	<u>0.10557</u>	0.04859	0.00559	<u>0.87561</u>	<u>-0.05745</u>	<u>0.00094</u>
$h_{22,t}$	0.03589	0.000013	0.00214	<u>0.08970</u>	0.00002	0.00876	<u>0.89395</u>
$h_{12,t}$	0.00683	0.00116	0.09758	0.02240	0.00433	0.88459	<u>-0.02903</u>

Notes: the sample includes 1322 observations from 03/01/2006 to 10/05/2011; author's calculations in JMulTi based on Reuters Wealth Manager data

We can also confirm a significant influence of the past conditional variance on the conditional covariance. This effect is estimated to have a negative impact with calculated amount of -0.029.

The plot of the conditional correlation coefficient on *Figure 26* reveals remarkably low co-movements between the Serbian and European stock markets volatilities. The conditional correlation coefficient mostly oscillates around zero, with some increasing and decreasing tendencies. This conditional correlation coefficient graph drastically differs from the CEE conditional correlation graphs – it is much more volatile, it is quite low, and often is represented by negative values.

Figure 26: Conditional Correlation Coefficient between BELEX-15 and STOXX returns



Evidence for volatility spillovers from the European market to the Macedonian market is shown in Table 19 summarizing the results from the multivariate GARCH model of MBI_R and STOXX_R time series. The Macedonian stock market is directly affected by the past shocks in the European stock markets volatility (coefficient estimated as 0.021) and by the past STOXX_R conditional variance (estimated around 0.003). Both of these estimated coefficients are the highest among all CEE and SEE stock markets implying the highest degree of volatility spillovers to the Macedonian stock market. As expected, the conditional variance is affected by the past shocks (highest coefficients (0.184) among all countries) and by the own past conditional variance which is the lowest coefficient (0.787) among the analyzed CEE and SEE stock exchanges. The MBI_R conditional variance is in addition affected by the past conditional covariance (note the significant coefficient of 0.095 for $\mathbf{h_{12,\,t-1}}$).

The multivariate model for MBI_R and STOXX_R again confirms only the effect of the past shocks and past conditional variance on the STOXX_R conditional variance.

The conditional covariance from the model on Table 19 is affected only by the movements in the STOXX_R volatility – by the past shocks and past conditional variance of STOXX returns.

Table 19: Bivariate GARCH coefficients estimates for MBI and STOXX returns

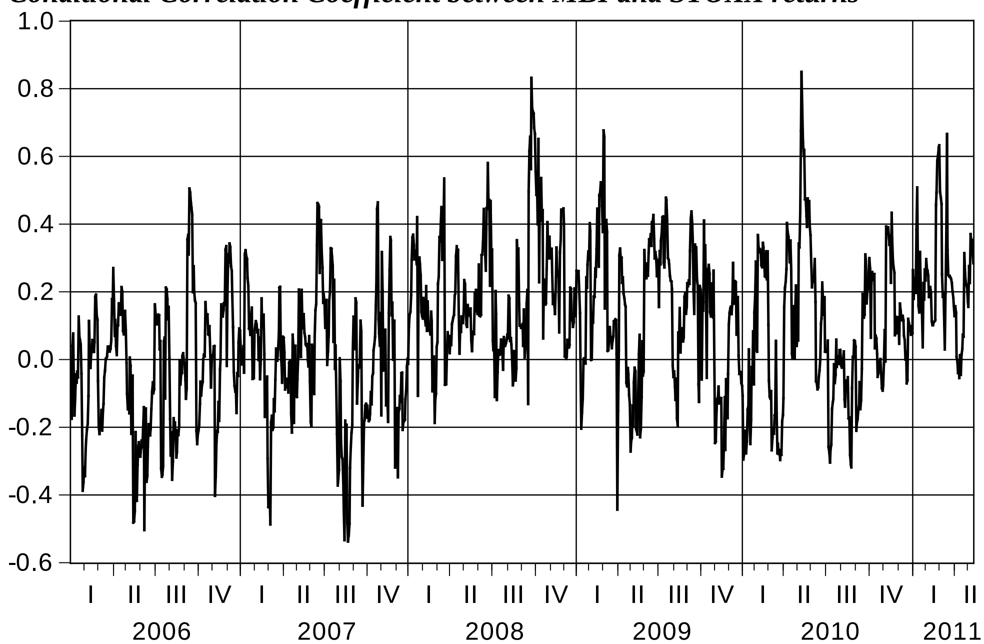
	constant term	$\varepsilon_{1,t-1}^{2}$	$\varepsilon_1\varepsilon_{2,t-1}$	$\varepsilon_{2,t-1}^{2}$	$h_{11,t-1}$	$h_{12,t-1}$	$h_{22,t-1}$
$h_{11,t}$	0.08727	0.18372	-0.12306	0.02061	0.78720	0.09491	0.00286
$h_{22,t}$	0.03634	0.001224	0.02039	0.08489	0.00019	-0.02591	0.89403
$h_{12,t}$	-0.01039	0.01500	0.11986	-0.04183	-0.01216	0.83818	0.05057

Notes: the sample includes 1304 observations from 05/01/2006 to 13/05/2011; author's calculations in JMulTi based on Reuters Wealth Manager data

This model and all the other multivariate models show no evidence of volatility spillovers from the small CEE or SEE stock exchanges to the big European stock market. Only some stock exchanges experience significant, but quite small, almost negligible, volatility spillovers from the European stock market.

By illustrating the degree of conditional correlation between MBI_R and STOXX_R we

Figure 27: Conditional Correlation Coefficient between MBI and STOXX returns



can notice somewhat similar plot as *Figure 26*. Again, we conclude the movement of the conditional correlation coefficient as quite volatile, registering low levels and even recording negative correlation. After the initial period when the coefficient varies around zero, an increasing tendency in 2008 can be noticed. Still, a period of decreasing conditional correlation follows in 2009. Mainly, the coefficient records values ranging from -0.2 to 0.4, which is similar with the other SEE stock markets, but rather low considering the CEE level of conditional correlation with the European stock markets.

Although the previous multivariate GARCH models provided some general and rather interesting findings, we should be careful with deriving definite conclusions. The reporting ability of the models is quite poor as a result of the outcomes of the residuals diagnostics test. Significant ARCH effect still remain in the residuals of all models as confirmed by the multivariate ARCH-LM tests; the Jarque-Bera test confirms the non-normality of the residuals; and except for BUX, there is autocorrelation remaining in all the other models. These unfavorable results from the residuals checks and the estimation results can be found in the Appendix Table A.25 and Table A.26.

5. CONCLUSION

The thesis motivation is analyzing and comparing stock market volatilities between eight countries from Central Eastern Europe and South Eastern Europe. The relatively uninvestigated stock market volatility of the SEE countries is the motive for undertaking such type of research.

We pursue our research idea by employing two types of univariate GARCH models for determining the conditional volatility processes of the separate equity returns series and the development of the conditional volatility through time. Additionally, we implement multivariate BEKK-GARCH specification to test the transmissions of volatility between the global European equity market and the equity markets in the selected CEE and SEE countries.

The results suggest that the variance equation for all returns time series follows a GARCH process. The estimation results indicate statistically significant leverage effect for the volatilities of all analyzed stock exchanges. The leverage effect is more emphasized for the CEE equity markets volatilities. Analyzing the GARCH terms in the conditional volatility models for the CEE stock exchanges, we notice higher persistence in the volatility shocks than in the SEE stock exchanges GARCH models. This finding imply bigger unpredictability of the volatility in the SEE equity markets, as the lower persistence implies the volatility shock die out sooner.

The conditional volatility estimation results for Czech Republic, Hungary and Poland are in line with the estimates for STOXX Europe 600 GARCH models. Those results are reflected in the high synchronization between the plots of the conditional standard deviation between the CEE equity markets and the European equity market.

The results from the multivariate GARCH models indicate certain statistically significant but small volatility spillovers from the European equity market to the equity markets in Hungary, Poland, Serbia, and Republic of Macedonia. The BEKK-GARCH model implies that the conditional variance is mostly influenced by the past conditional variance. The plots of the conditional correlation coefficient between the equity markets in the separate countries of the CEE and SEE region and the European equity market show variation of the coefficient in the band 0.4-0.8 for the CEE countries, and more volatile development of the coefficient for the SEE countries. In general the conditional correlation coefficient between the SEE countries equity markets and the European equity market is quite low, and even negative in some periods. Still, we should be careful about the implications of the multivariate GARCH results due to the unfavorable diagnostics tests.

Summarized the applied models identify the CEE countries as a homogenous and interconnected group in terms of the development of its equity markets and their volatility. This conclusion is motivated by the similar conditional volatility process, the relative synchronization in the conditional standard deviation plots, and the comparable conditional correlations between the CEE countries equity markets on one side and the European equity markets on the other.

The SEE countries equity markets exhibit more diversified volatility processes with low correlation with the European equity markets. The Croatian stock market is the most closely integrated SEE equity market to the European market. The Belgrade and the Macedonian stock exchange show the lowest correlation and synchronization with the European equity market labeling these markets as the least integrated to the European equity markets.

In this thesis we evaluated the equity markets volatility of the CEE and SEE countries and their co-movements and interconnection with the European equity market. The implications for the thesis for the investors are potentially significant and useful, as the less integrated SEE equity markets offer diversification possibilities.

In the future the thesis can be extended by analyzing longer period of data for the developing stock exchanges of the SEE region and implementing alternative GARCH specifications. We expect the process of implementing EU legislation on the road to EU accession for the SEE countries will provoke acceleration in the integration process of the SEE countries stock markets with respect to the European stock market.

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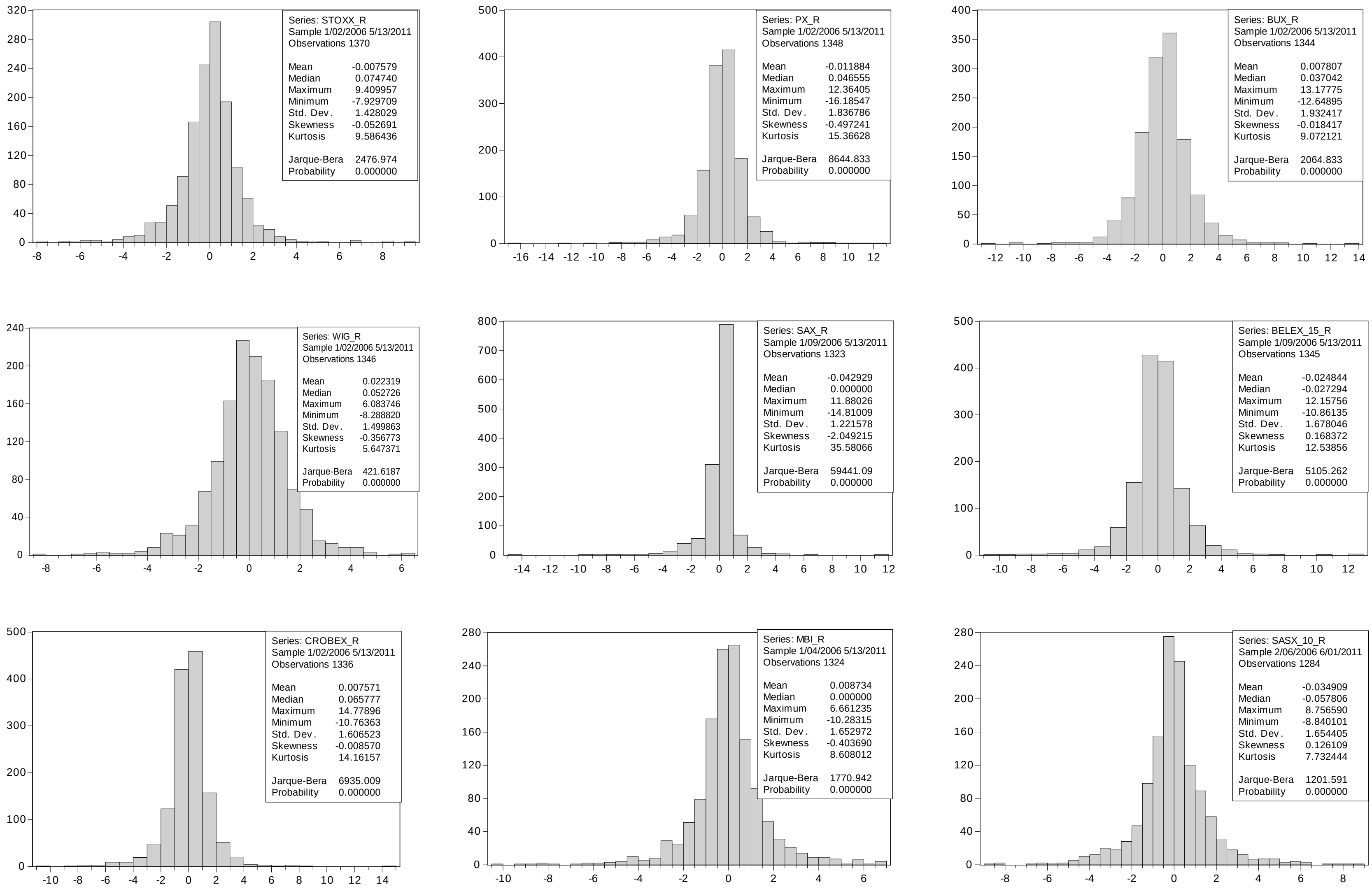
APPENDIX

Table A.20: Results of the ADF and PP stationarity test on indices' levels and returns

Variable	Test		STOXX_R	PX_R	WIG_R	BUX_R	SAX_R	BELEX _15_R	CROBEX_ R	MBI_R	SASX-10_R
		sample	1369	1346	1344	1343	1321	1344	1335	1323	1270
RETURNS	**ADF**	no const. t-stat	-38.1248	-27.7075	-25.8337	-27.4386	-24.8344	-19.9159	-25.6557	-22.8525	-22.3823
		p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		const. t-stat	-38.1121	-27.6991	-25.8298	-27.4286	-24.8729	-19.9122	-25.6468	-22.8440	-22.3836
		p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		const. & trend t-stat	-38.0998	-27.6911	-25.8200	-27.4213	-24.8804	-19.9223	-25.6881	-22.9034	-22.4192
		p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	PP	no const. t-stat	-38.3977	-34.8039	-33.6636	-33.8622	-37.5216	-25.1794	-32.7622	-22.7078	-22.2921
		p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		const. t-stat	-38.3849	-34.7917	-33.6566	-33.8491	-37.5647	-25.1741	-32.7513	-22.6987	-22.2862
		p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		const. & trend t-stat	-38.3731	-34.7800	-33.6440	-33.8369	-37.5711	-25.1393	-32.7584	-22.7312	-22.2958
		p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		sample	1370	1347	1345	1344	1322	1345	1336	1324	1271
LEVELS	**ADF**	no const. t-stat	-0.4517	-0.5759	0.2097	-0.1876	-1.3279	-0.5857	-0.2237	-0.4961	-0.7073
		p value	0.519	0.468	0.747	0.619	0.171	0.464	0.606	0.502	0.411
		const. t-stat	-1.1541	-1.3188	-1.2424	-1.6468	-0.3530	-0.7828	-0.9313	-1.1652	-0.9878
		p value	0.696	0.623	0.658	0.459	0.915	0.823	0.779	0.692	0.760
		const. & trend t-stat	-1.4328	-1.5218	-1.3275	-1.6491	-1.7979	-1.6532	-1.9227	-1.7806	-1.9868
		p value	0.851	0.823	0.881	0.774	0.706	0.772	0.643	0.714	0.608
	PP	no const. t-stat	-0.4534	-0.5644	0.2298	-0.1359	-1.3242	-0.5307	-0.2815	-0.4072	-0.5805
		p value	0.519	0.473	0.753	0.637	0.172	0.487	0.585	0.537	0.466
		const. t-stat	-1.0422	-1.2584	-1.2933	-1.5622	-0.3307	-0.5606	-1.0392	-1.0258	-0.6388
		p value	0.740	0.651	0.635	0.502	0.918	0.877	0.741	0.746	0.859
		const. & trend t-stat	-1.2807	-1.4612	-1.3940	-1.5699	-1.8085	-1.5381	-1.9248	-1.7205	-1.8080
		p value	0.892	0.842	0.863	0.805	0.700	0.816	0.641	0.742	0.701

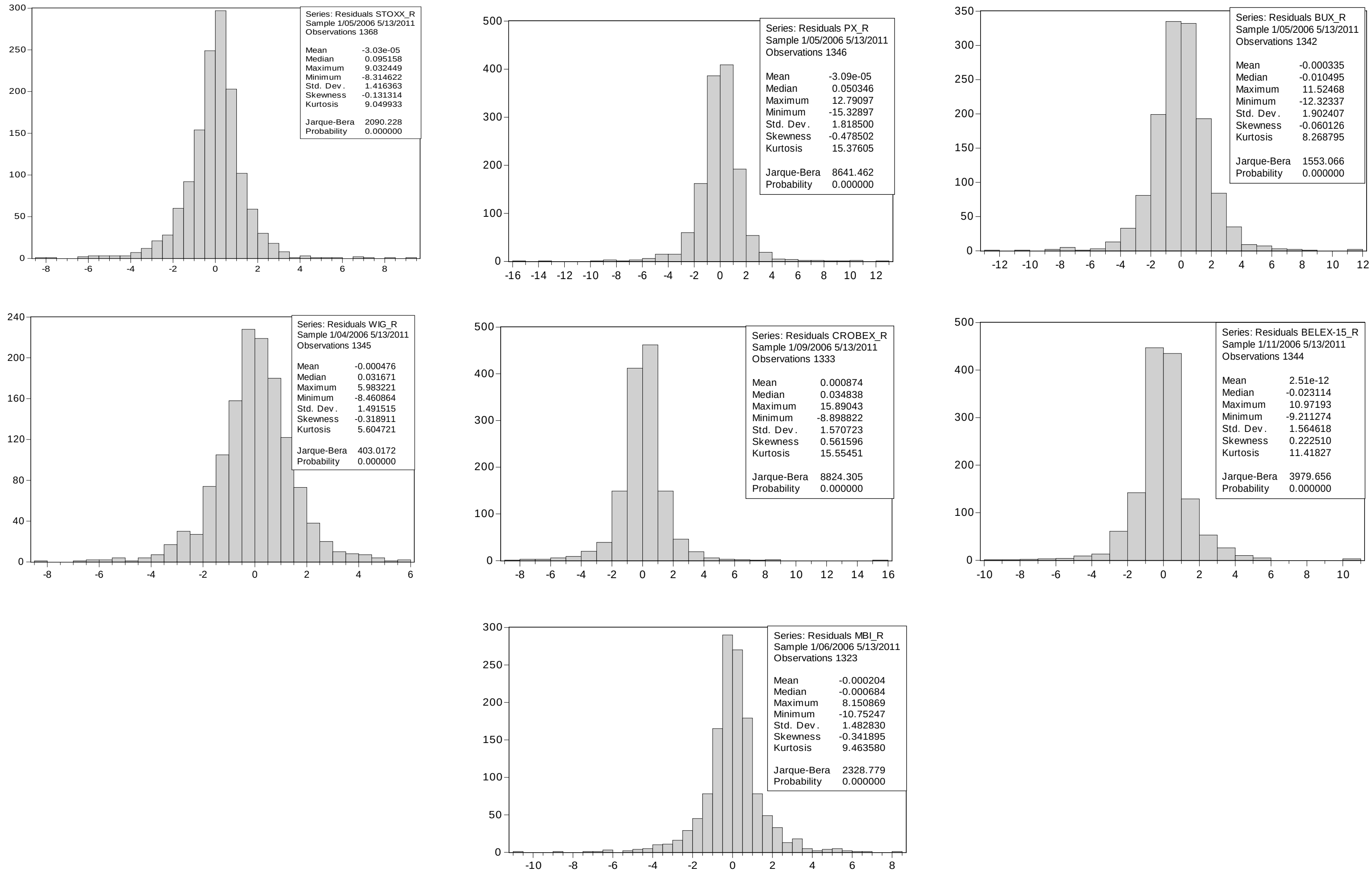
Note: Author's calculations in EViews based on Reuters Wealth Manager data

Figure A.28: Distribution Histograms of the Indices' Returns Series



Note: Author's calculations in EViews based on Reuters Wealth Manager data

Figure A.29: Distribution Histograms of Residuals from the ARMA modeling



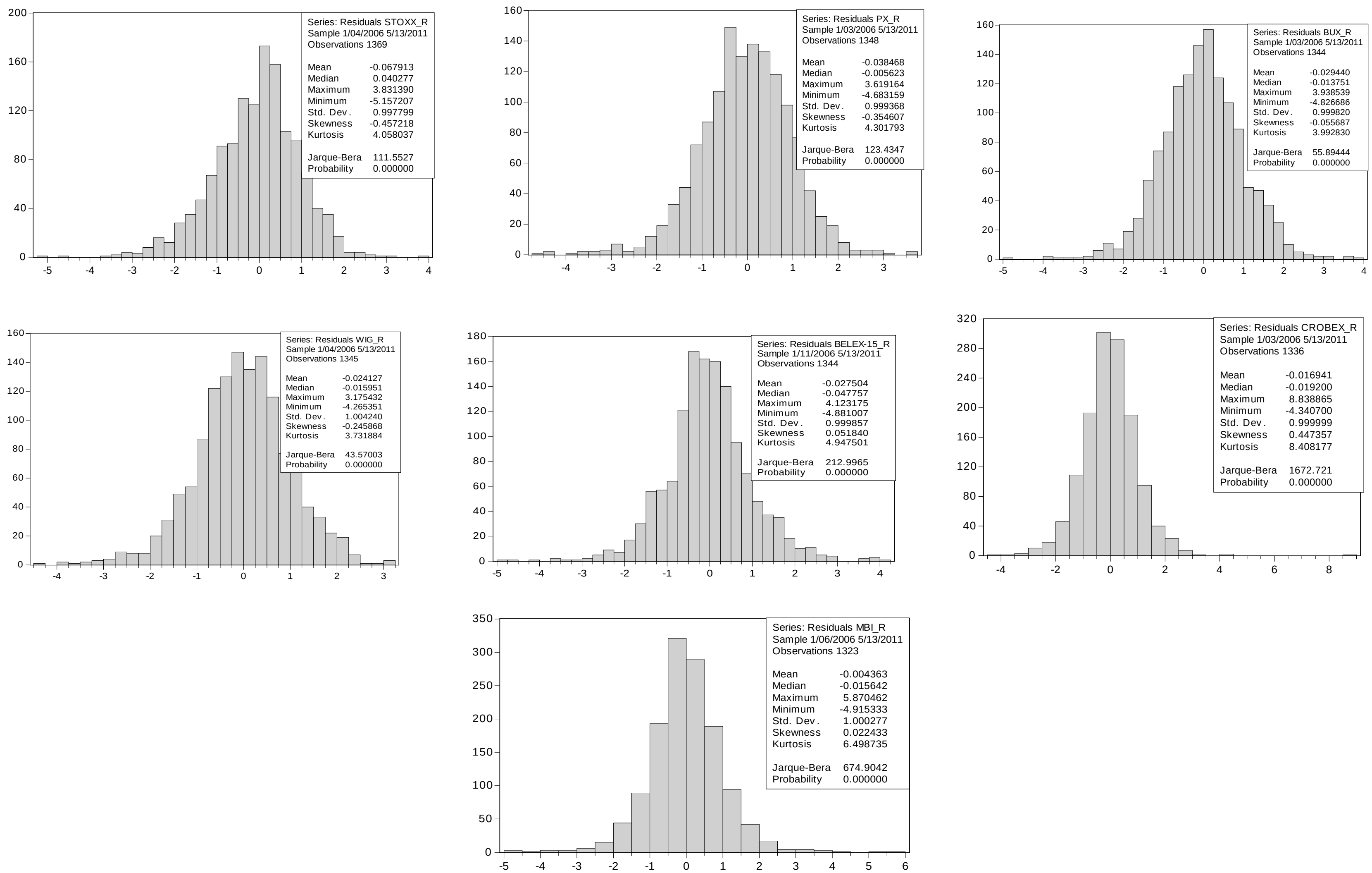
Note: Author’s calculations in EViews based on Reuters Wealth Manager data

Table A.21: GARCH Model (Normal Distribution) Estimates of Stock Indices Returns

Variable	STOXX_R		PX_R		WIG_R		BUX_R		BELEX_R		CROBEX_R		MBI_R	
Obs.	1369		1348		1345		1344		1344		1336		1323	
Return Eq.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
C	0.0615	***	0.0566	*	0.0591	*	0.0602		0.0546		0.0611	**	0.0255	
	(2.7759)		(1.8275)		(1.7785)		(1.4656)		(1.3321)		(1.9485)		(0.6342)	
AR(1)	0.7816	***	n/a		-0.9268	***	n/a		0.4996	***	n/a		0.2600	***
	(5.8698)				(-109.122)				(6.7003)				(4.4143)	
MA(1)	-0.8292	***	n/a		0.9766	***	n/a		-0.2097	**	0.1317	***	0.2087	***
	(-7.1142)				(933.8486)				(-2.2798)		(4.9121)		(2.9408)	
Var. Equation														
ω = constant	0.0257	***	0.0466	***	0.0124	*	0.0872	***	0.1160	***	0.0292	***	0.0618	***
	(4.4151)		(4.1149)		(1.7396)		(4.8243)		(7.0299)		(4.4230)		(7.9271)	
α=ARCH term	0.1209	***	0.1620	***	0.0695	***	0.1147	***	0.3571	***	0.1187	***	0.2578	***
	(7.9408)		(8.4427)		(7.5856)		(8.3306)		(12.8396)		(10.2251)		(11.5764)	
β=GARCH term	0.8682	***	0.8300	***	0.9261	***	0.8597	***	0.6407	***	0.8736	***	0.7482	***
	(53.7881)		(43.8938)		(89.2442)		(52.2973)		(30.0197)		(78.0258)		(53.5966)	
AIC	3.1066		3.4650		3.4335		3.8337		3.2523		3.2321		3.2016	
SIC	3.1295		3.4804		3.4567		3.8491		3.2755		3.2515		3.2252	
HQC	3.1152		3.4708		3.4422		3.8395		3.2610		3.2394		3.2105	
Residuals	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
LB RES (15)	9.5023	[0.734]	27.8700	[0.022]	19.5870	[0.106]	18.8450	[0.221]	40.7170	[0.000]	32.7160	[0.003]	58.1650	[0.000]
LB SQRES (15)	16.2970	[0.233]	18.6210	[0.231]	30.3340	[0.004]	10.6320	[0.778]	22.5110	[0.048]	5.2404	[0.982]	4.5790	[0.983]
Skewness	-0.4572		-0.3546		-0.2459		-0.0557		0.0518		0.4473		0.0224	
Kurtosis	4.0580		4.3018		3.7319		3.9928		4.9475		8.4082		6.4987	
ARCH-LM (15)	16.6711	[0.339]	18.4609	[0.239]	28.2127	[0.020]	10.2102	[0.806]	22.2479	[0.102]	5.2053	[0.990]	4.4888	[0.996]
Jarque Bera	111.5527	[0.000]	123.4347	[0.000]	43.5700	[0.000]	55.8944	[0.000]	212.9965	[0.000]	1672.7210	[0.000]	674.9042	[0.000]

Notes: The signs ***, **, * denote significance at 1%, 5% and 10% respectively; the numbers in parenthesis are the z-statistics; the p-values of the Ljung-Box Q statistics (lag k=15), ARCH-LM tests and Jarque-Bera tests are in brackets; the dataset includes daily observations from 03/01/2006 to 13/05/2011; Author's calculations in EViews based on Reuters Wealth Manager data.

Figure A.30: Distribution Histograms of GARCH model (Normal Distribution) Standardized Residuals



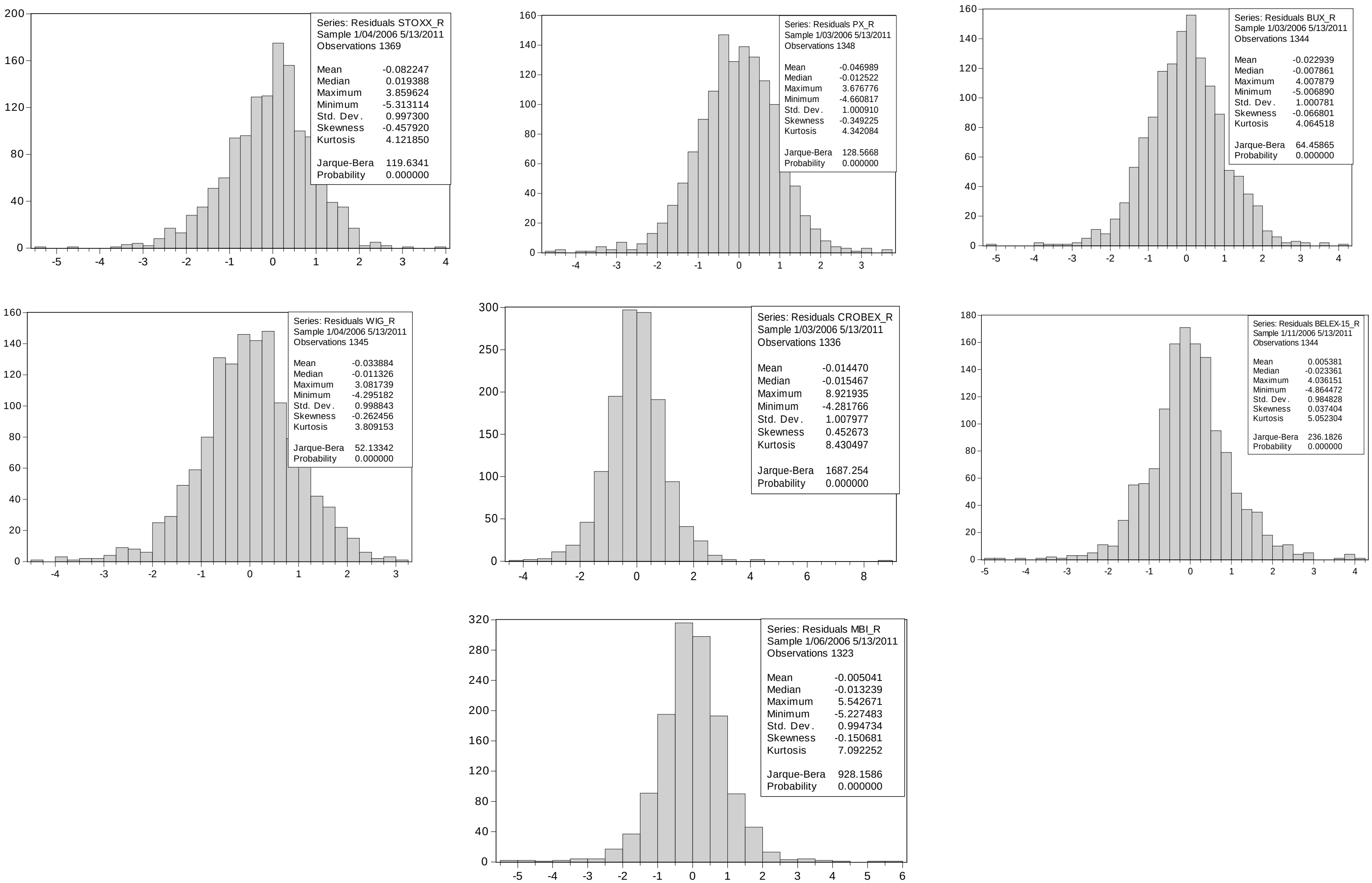
Note: Author’s calculations in EViews based on Reuters Wealth Manager data

Table A.22: GARCH Model (Student's t-Distribution) Estimates of Stock Indices Returns

Variable	STOXX_R		PX_R		WIG_R		BUX_R		BELEX_R		CROBEX_R		MBI_R	
Obs.	1369		1348		1345		1344		1344		1336		1323	
Return Eq.														
C	0.0742	***	0.0672	**	0.0710	**	0.0496		-0.0035		0.0581	**	0.0162	
	(3.5044)		(2.2267)		(2.1887)		(1.2619)		(-0.0835)		(2.0204)		(0.3944)	
AR(1)	0.7941	***	n/a		-0.9480	***	n/a		0.5857	***	n/a		0.3302	***
	(5.9554)				(-54.8123)				(9.2900)				(5.6879)	
MA(1)	-0.8342	***	n/a		0.9768	***	n/a		-0.2979	***	0.1166	***	0.1392	**
	(-6.9947)				(86.1626)				(-3.8319)		(4.2881)		(2.1398)	
Var. Equation														
ω = constant	0.0200	***	0.0496	***	0.0143		0.0669	***	0.1141	***	0.0243	***	0.1085	***
	(2.6128)		(3.0379)		(1.6262)		(2.8492)		(4.0346)		(2.6446)		(4.1373)	
α=ARCH term	0.1140	***	0.1441	***	0.0632	***	0.1116	***	0.3549	***	0.1115	***	0.3642	***
	(5.9475)		(5.9539)		(5.1885)		(5.8523)		(6.6528)		(5.7603)		(5.9074)	
β=GARCH term	0.8793	***	0.8414	***	0.9312	***	0.8706	***	0.6541	***	0.8816	***	0.6525	***
	(46.1566)		(35.1523)		(69.5454)		(41.4266)		(17.6775)		(49.5459)		(18.4659)	
T-DIST. DOF	8.7175	***	8.3871	***	9.4696	***	9.8144	***	4.8888	***	5.7301	***	4.2921	***
	(4.6652)		(4.9210)		(3.7961)		(4.1832)		(6.5222)		(7.1459)		(8.1190)	
AIC	3.0837		3.4361		3.4155		3.8153		3.1884		3.1526		3.0897	
SIC	3.1104		3.4554		3.4426		3.8347		3.2155		3.1759		3.1172	
HQC	3.0936		3.4434		3.4257		3.8226		3.1986		3.1613		3.1000	
Residuals														
LB RES (15)	8.0955	[0.837]	27.8570	[0.022]	15.4730	[0.279]	18.5000	[0.237]	36.2520	[0.001]	35.2740	[0.001]	47.5530	[0.000]
LB SQRES (15)	16.0320	[0.247]	19.4300	[0.195]	31.4910	[0.003]	9.8708	[0.828]	22.4800	[0.048]	5.4644	[0.978]	8.3082	[0.823]
Skewness	-0.4579		-0.3492		-0.2624		-0.0668		0.0374		0.4527		-0.1507	
Kurtosis	4.1218		4.3421		3.8091		4.0645		5.0523		8.4305		7.0922	
ARCH-LM (15)	16.5705	[0.345]	19.0971	[0.209]	29.2395	[0.015]	9.4691	[0.852]	22.0136	[0.107]	5.3631	[0.989]	8.5587	[0.899]
Jarque Bera	119.6341	[0.000]	128.5668	[0.000]	52.1334	[0.000]	64.4586	[0.000]	236.1826	[0.000]	1687.2540	[0.000]	928.1586	[0.000]

Notes: The signs ***, ** denote significance at 1% and 5% respectively; the numbers in parenthesis are the z-statistics; the p-values of the Ljung-Box Q statistics (lag k=15), ARCH-LM tests and Jarque-Bera tests are in brackets; the dataset includes daily observations from 03/01/2006 to 13/05/2011; Author's calculations in EViews based on Reuters Wealth Manager data.

Figure A.31: Distribution Histograms of GARCH model (Student's t-Distribution) Standardized Residuals



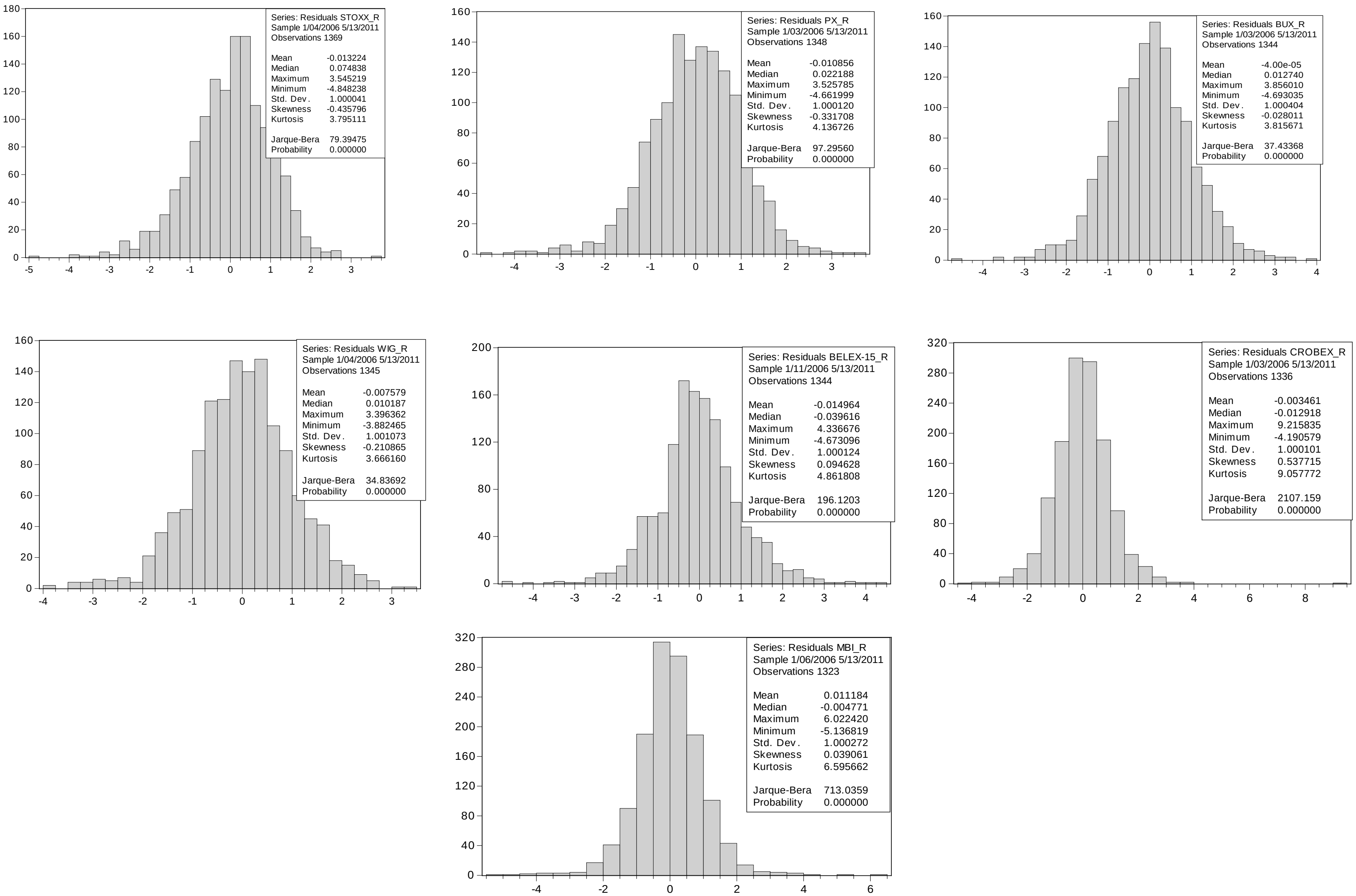
Note: Author's calculations in EViews based on Reuters Wealth Manager data

Table A.23: TARCH Model (Normal Distribution) Estimates of Stock Indices Returns

Variable	STOXX_R		PX_R		WIG_R		BUX_R		BELEX_R		CROBEX_R		MBI_R	
Obs.	1369		1348		1345		1344		1344		1336		1323	
Return Eq.														
C	0.0123		0.0232		0.0408		0.0158		0.0352		0.0492		0.0014	
	(0.4784)		(0.7161)		(1.2146)		(0.3815)		(0.8185)		(1.4271)		(0.0296)	
AR(1)	0.5244		n/a		-0.9376	***	n/a		0.4873	***	n/a		0.2568	***
	(1.4537)				(-55.3715)				(6.3754)				(4.3194)	
MA(1)	-0.5504		n/a		0.9745	***	n/a		-0.2010	**	0.1331	***	0.2106	***
	(-1.5580)				(92.4564)				(-2.1343)		(4.8554)		(2.9474)	
Var. Equation														
ω = constant	0.0267	***	0.0549	***	0.0205	***	0.0884	***	0.1118	***	0.0312	***	0.0638	***
	(6.2556)		(4.6573)		(2.7167)		(4.7221)		(6.6784)		(4.3482)		(8.0002)	
α=ARCH term	-0.0116		0.0960	***	0.0272	**	0.0533	***	0.3177	***	0.0899	***	0.2309	***
	(-0.9577)		(4.6694)		(2.0257)		(3.3354)		(10.4448)		(7.3496)		(9.9642)	
γ=Leverage effect	0.1887	***	0.1177	***	0.0716	***	0.1024	***	0.0746	**	0.0432	***	0.0577	*
	(8.5485)		(5.0517)		(4.8299)		(4.7939)		(1.7572)		(2.9055)		(1.8469)	
β=GARCH term	0.8977	***	0.8293	***	0.9270	***	0.8690	***	0.6449	***	0.8778	***	0.7458	***
	(67.3353)		(42.0155)		(74.7006)		(49.9959)		(29.3792)		(74.8971)		(51.6733)	
AIC	3.0598		3.4547		3.4188		3.8214		3.2524		3.2303		3.2014	
SIC	3.0865		3.4740		3.4459		3.8407		3.2795		3.2537		3.2289	
HQC	3.0698		3.4619		3.4289		3.8286		3.2626		3.2391		3.2117	
Residuals														
LB RES (15)	7.7300	[0.861]	27.3310	[0.026]	13.8340	[0.386]	19.1180	[0.208]	41.0300	[0.000]	34.0260	[0.002]	61.2580	[0.000]
LB SQRES (15)	16.2430	[0.236]	14.4670	[0.490]	30.4180	[0.004]	10.2200	[0.806]	21.3330	[0.067]	4.5090	[0.992]	4.0559	[0.991]
Skewness	-0.4358		-0.3317		-0.2109		-0.0280		0.0946		0.5377		0.0391	
Kurtosis	3.7951		4.1367		3.6662		3.8157		4.8618		9.0578		6.5957	
ARCH-LM (15)	16.4731	[0.351]	14.5370	[0.485]	29.7290	[0.013]	10.2165	[0.806]	21.0602	[0.135]	4.5102	[0.995]	4.0039	[0.998]
Jarque Bera	79.3947	[0.000]	97.2956	[0.000]	34.8369	[0.000]	37.4337	[0.000]	196.1203	[0.000]	2107.1590	[0.000]	713.0359	[0.000]

Notes: The signs ***, **, * denote significance at 1%, 5% and 10% respectively; the numbers in parenthesis are the z-statistics; the p-values of the Ljung-Box Q statistics (lag k=15), ARCH-LM tests and Jarque-Bera tests are in brackets; the dataset includes daily observations from 03/01/2006 to 13/05/2011; Author's calculations in EViews based on Reuters Wealth Manager data.

Figure A.32: Distribution Histograms of TARCH model (Normal Distribution) Standardized Residuals



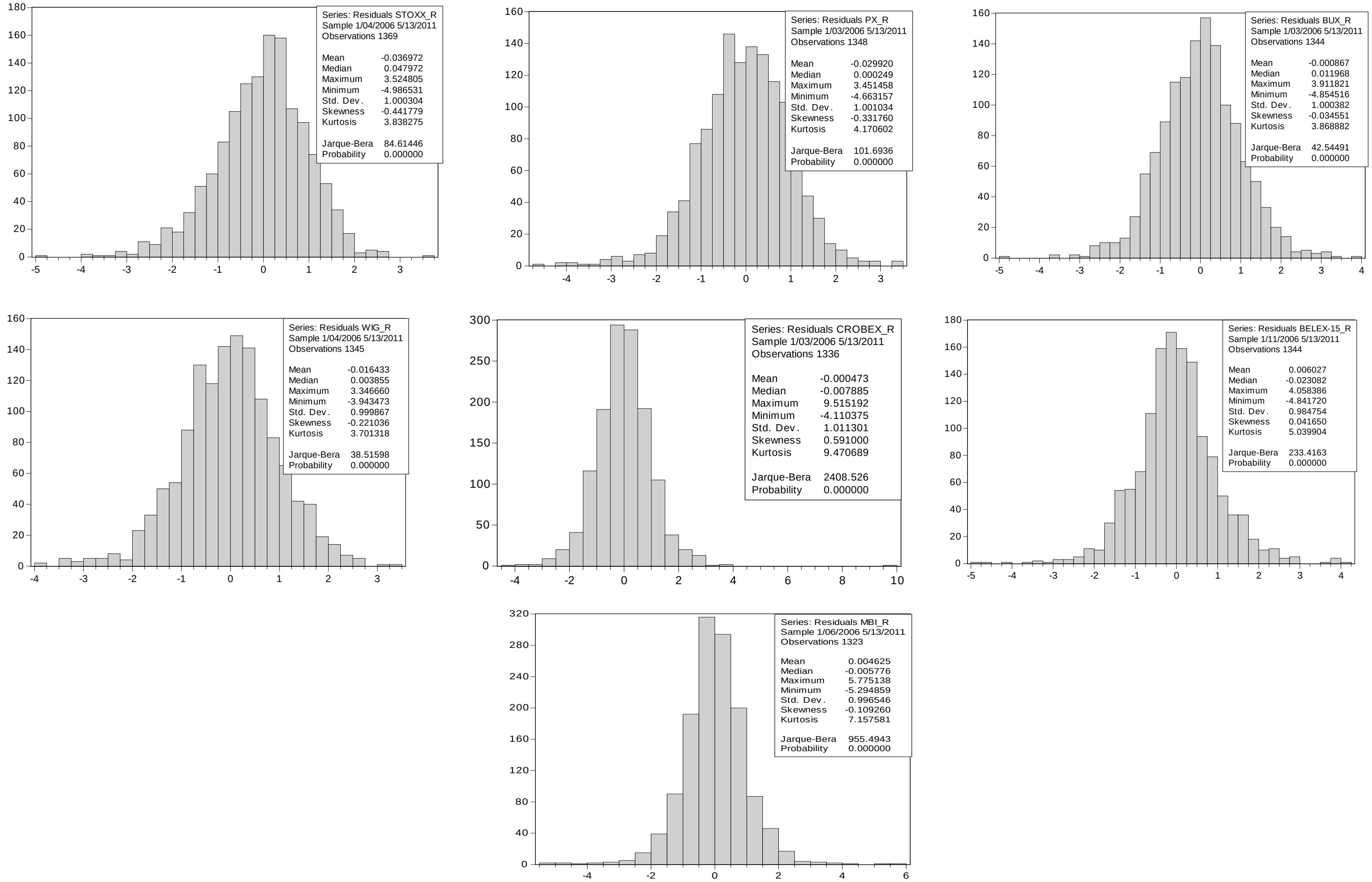
Note: Author’s calculations in EViews based on Reuters Wealth Manager data

Table A.24: GARCH Model (Student's t-Distribution) Estimates of Stock Indices Returns

Variable	STOXX_R		PX_R		WIG_R		BUX_R		BELEX_R		CROBEX_R		MBI_R	
Obs.	1369		1348		1345		1344		1344		1336		1323	
Return Eq.														
C	0.0346		0.0466		0.0517		0.0170		-0.0045		0.0486	*	0.0029	
	(1.4402)		(1.5136)		(1.5797)		(0.4271)		(-0.1038)		(1.6699)		(0.0701)	
AR(1)	0.5584		n/a		-0.9469	***	n/a		0.5845	***	n/a		0.3288	***
	(1.6086)				(-56.3248)				(9.2500)				(5.6847)	
MA(1)	-0.5803	*	n/a		0.9770	***	n/a		-0.2967	***	0.1193	***	0.1413	**
	(-1.7025)				(90.6648)				(-3.809)		(4.3907)		(2.1744)	
Var. Equation														
ω = constant	0.0225	***	0.0546	***	0.0194	**	0.0735	***	0.1136	***	0.0267	***	0.1070	***
	(4.0796)		(3.3456)		(2.2546)		(3.1256)		(4.0256)		(2.8715)		(4.1583)	
α=ARCH term	-0.0149		0.0903	***	0.0232		0.0572	***	0.3504	***	0.0780	***	0.3113	***
	(-0.9289)		(3.3215)		(1.5053)		(2.8478)		(5.4314)		(3.9554)		(4.8491)	
γ=Leverage effect	0.1885	***	0.0975	***	0.0672	***	0.0997	***	0.0073		0.0605	**	0.0911	
	(6.8179)		(2.9682)		(3.6378)		(3.4329)		(0.0985)		(2.3040)		(1.1652)	
β=GARCH term	0.9020	***	0.8402	***	0.9329	***	0.8730	***	0.6549	***	0.8822	***	0.6571	***
	(56.7140)		(34.6709)		(66.5049)		(41.8937)		(17.6627)		(49.5647)		(18.7227)	
T-DIST. DOF	10.8589	***	8.9790	***	10.4047	***	10.4022	***	4.8915	***	5.8917	***	4.3529	***
	(3.8056)		(4.5295)		(3.3975)		(3.6685)		(6.4340)		(7.2151)		(8.1214)	
AIC	3.0462		3.4311		3.4064		3.8069		3.1899		3.1496		3.0899	
SIC	3.0767		3.4543		3.4374		3.8301		3.2209		3.1768		3.1213	
HQC	3.0576		3.4398		3.4180		3.8156		3.2015		3.1598		3.1017	
Residuals														
LB RES (15)	8.1512	[0.834]	27.1960	[0.027]	13.3560	[0.421]	18.5330	[0.236]	36.1510	[0.001]	36.9980	[0.001]	49.4100	[0.000]
LB SQRES (15)	15.0020	[0.307]	14.8450	[0.463]	31.0870	[0.003]	9.1764	[0.868]	22.3630	[0.050]	4.3333	[0.993]	7.3009	[0.886]
Skewness	-0.4418		-0.3318		-0.2210		-0.0345		0.0416		0.5910		-0.1093	
Kurtosis	3.8383		4.1706		3.7013		3.8689		5.0399		9.4707		7.1576	
ARCH-LM (15)	15.0620	[0.447]	14.7771	[0.468]	30.3517	[0.011]	9.1412	[0.870]	21.8926	[0.111]	4.3442	[0.996]	7.4997	[0.942]
Jarque Bera	84.6145	[0.000]	101.6936	[0.000]	38.5159	[0.000]	42.5445	[0.000]	233.4163	[0.000]	2408.5260	[0.000]	955.4943	[0.000]

Notes: The signs ***, **, * denote significance at 1%, 5% and 10% respectively; the numbers in parenthesis are the z-statistics; the p-values of the Ljung-Box Q statistics (lag k=15), ARCH-LM tests and Jarque-Bera tests are in brackets; the dataset includes daily observations from 03/01/2006 to 13/05/2011; Author's calculations in EViews based on Reuters Wealth Manager data

Figure A.33: Distribution Histograms of TARCH model (Student's t-distribution) Standardized Residuals



Note: Author's calculations in EViews based on Reuters Wealth Manager data

Table A.25: BEKK-GARCH models estimates for PX, BUX and WIG Returns and STOXX Returns

	Ω		A		B						
PX-STOXX							Log Likelihood	-4120.83	JARQUE-BERA		
							PORTMANTEAU TEST		variable	xi_1	xi_2
	0.2981	0.1343	0.3009	0.0010	0.9335	0.0061	(H0:Rh=(r1,...,rh)=0)				
	(10.1934)	(4.8421)	(9.8911)	(0.0443)	(65.0311)	(0.5206)	tested order:	16	teststat	298.7406	75.753
	(0.0793)	*(0.1126)*	*(0.0316)*	*(0.0001)*	*(0.9546)*	*(0.0016)*	adjusted test statistic:	119.0218			
							p-value:	0.000	p-Value(χ^2)	0.000	0.000
	0.0000	0.1259	0.0630	0.2981	-0.0294	0.9416	Multivariate ARCH-LM TEST	k=16			
	(0.0000)	(6.6047)	(1.8380)	(11.4701)	(-2.0492)	(99.9717)	test statistic:	94.2326	skewness	-0.4558	-0.2785
	(0.0000)	*(0.4880)*	*(0.0024)*	*(0.0770)*	*(-0.0036)*	*(0.3793)*	p-value(χ^2):	0.000	kurtosis	5.125	4.0225
BUX-STOXX	**Ω**		**A**		**B**		Log Likelihood	-4355.55	JARQUE-BERA		
							PORTMANTEAU TEST		variable	xi_1	xi_2
	0.2593* **	**0.1334*** **	**0.2136*** **	-0.0064	**0.9684*** **	0.0022	(H0:Rh=(r1,...,rh)=0)				
	(6.8375)	(4.3687)	(9.0940)	(-0.3435)	(125.5318)	(0.3065)	tested order:	16	teststat	75.4022	137.4589
	(6.2713)	*(4.3700)*	*(5.5263)*	*(-0.1861)*	*(102.3234)*	*(0.2893)*	adjusted test statistic:	72.2848			
							p-value:	0.1329	p-Value(χ^2)	0.000	0.000
	0.0000	**0.1490*** **	**0.1127*** **	**0.3100*** **	**-0.0410*** **	**0.9357*** **	Multivariate ARCH-LM TEST	k=16			
	(0.0000)	(8.5129)	(3.1877)	(13.6367)	(-3.0999)	(112.1520)	test statistic:	233.1617	skewness	-0.0439	-0.4657
	(0.0000)	*(5.3729)*	*(2.5880)*	*(7.1552)*	*(-2.6374)*	*(73.3451)*	p-value(χ^2):	0.000	kurtosis	4.1592	4.2634
WIG-STOXX	**Ω**		**A**		**B**		Log Likelihood	-4008.68	JARQUE-BERA		
							PORTMANTEAU TEST		variable	xi_1	xi_2
	0.1249* **	**0.1823*** **	**0.1874*** **	-0.0418	**0.9847*** **	0.0154	(H0:Rh=(r1,...,rh)=0)				
	(4.0346)	(5.0341)	(7.7478)	(-1.4021)	(149.1652)	(1.8074)	tested order:	16	teststat	84.0367	125.769
	(4.6903)	*(3.2190)*	*(4.2105)*	*(-0.5961)*	*(131.8500)*	*(1.2231)*	adjusted test statistic:	79.3581			
							p-value:	0.0479	p-Value(χ^2)	0.000	0.000
	0.0000	**0.1299*** **	0.0844	**0.3644*** **	**-0.0313** **	**0.9137*** **	Multivariate ARCH-LM TEST	k=16			
	(0.0000)	(4.0198)	(2.9826)	(11.5216)	(-2.5627)	(76.5022)	test statistic:	242.9768	skewness	-0.3301	-0.2699
	(0.0000)	*(3.3324)*	*(1.6408)*	*(4.0987)*	*(-2.4191)*	*(26.0859)*	p-value(χ^2):	0.000	kurtosis	4.0373	4.4041

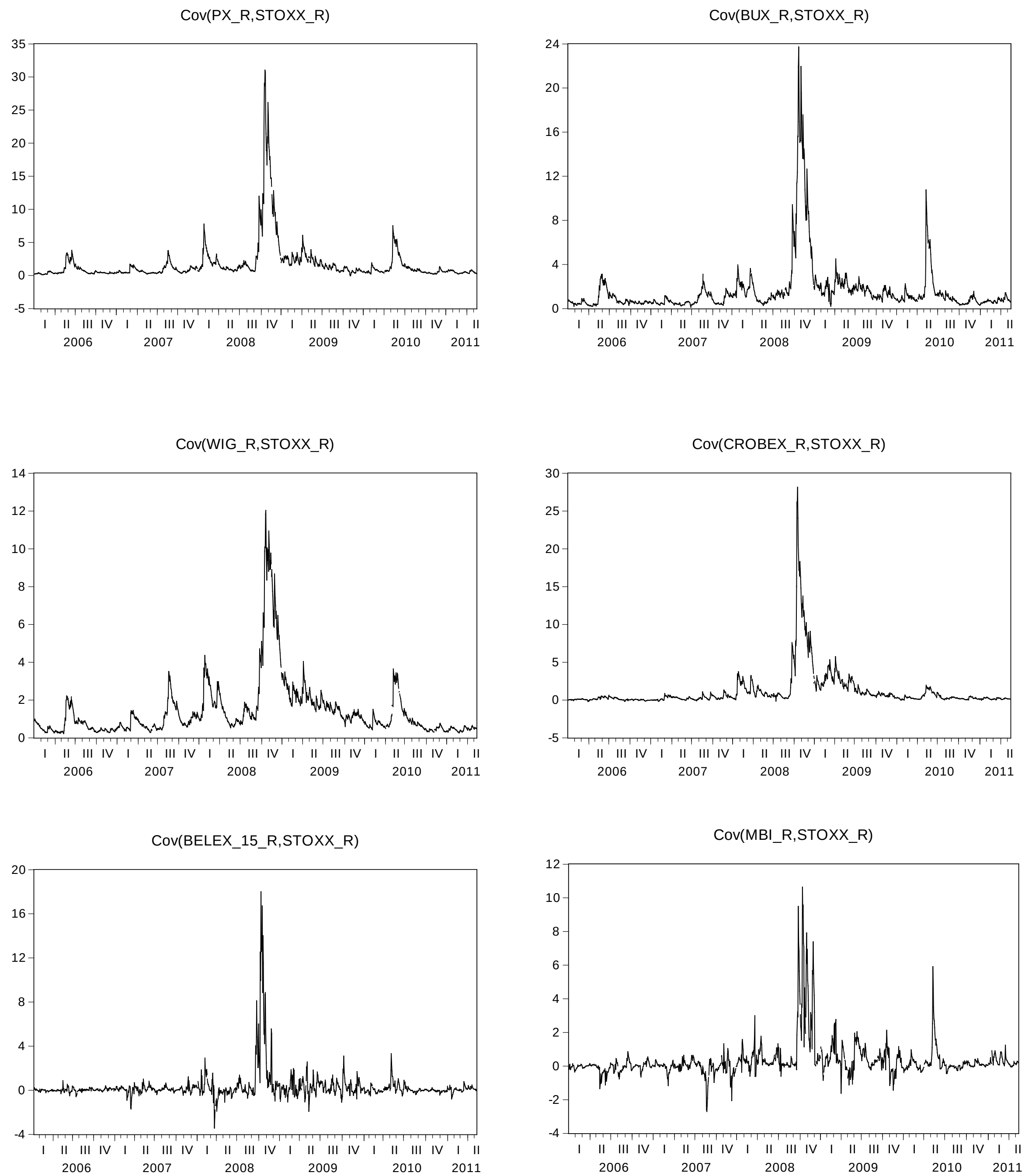
Notes: The signs ***, ** denote significance at 1% and 5% respectively; the coefficients are estimated using QML (Quasi Maximum Likelihood); the italic numbers in parenthesis are the t-values exact; the numbers in parenthesis are the t-values normal; the dataset includes daily observations from 03/01/2006 to 13/05/2011; Author’s calculations in JMulTi based on Reuters Wealth Manager data.

Table A.26: BEKK-GARCH models estimates for CROBEX, BELEX and MBI Returns and STOXX Returns

	Ω		A		B						
CROBEX-STOXX							Log Likelihood	-4143.69	JARQUE-BERA		
							PORTMANTEAU TEST		variable	xi_1	xi_2
	0.2387 ***	0.0048	0.3034 ***	-0.0146	0.9394 ***	0.0159	(H0:Rh=(r1,...,rh)=0)				
	(9.3629)	(0.1232)	(15.2801)	(-0.6823)	(101.4276)	(1.6896)	tested order:	16	teststat	1205.20985.063	
	(4.8399)	(0.15253)	(7.3697)	(-0.5606)	(73.4725)	(1.1958)	adjusted test statistic:	170.7593			
							p-value:	0.000	p-Value(χ^2)	0.000	0.000
	0.0000	0.2071 ***	0.0444	0.3108 ***	-0.0136	0.9339 ***	Multivariate ARCH-LM TEST	k=16			
	(0.0000)	(9.3191)	(1.8571)	(12.8281)	(-1.1910)	(91.5895)	test statistic:	180.639	skewness	0.3202	-0.279
	(0.0000)	(6.5465)	(1.2524)	(11.1698)	(-0.7363)	(85.2808)	p-value(χ^2):	0.0208	kurtosis	7.614	4.104
BELEX-STOXX	Ω		A		B		Log Likelihood	-4333.15	JARQUE-BERA		
							PORTMANTEAU TEST		variable	xi_1	xi_2
	0.2163 ***	0.0368	0.3249 ***	0.0036	0.9357 ***	0.0046	(H0:Rh=(r1,...,rh)=0)				
	(9.7859)	(1.0057)	(24.5269)	(0.2533)	(162.1318)	(0.6724)	tested order:	16	teststat	587.4865112.212	
	(2.2025)	(1.4121)	(3.1881)	(0.1059)	(22.6955)	(0.3782)	adjusted test statistic:	381.8442			
							p-value:	0.000	p-Value(χ^2)	0.000	0.000
	0.0000	0.1859 ***	0.0748	0.2995 ***	-0.0307 *	0.9455 ***	Multivariate ARCH-LM TEST	k=16			
	(0.0000)	(10.5994)	(4.6860)	(17.7981)	(-4.2208)	(157.1936)	test statistic:	241.805	skewness	0.1563	-0.285
	(0.0000)	(6.2962)	(1.2627)	(8.5713)	(-1.7532)	(90.1697)	p-value(χ^2):	0.000	kurtosis	6.2508	4.308
MBI-STOXX	Ω		A		B		Log Likelihood	-4260.37	JARQUE-BERA		
							PORTMANTEAU TEST		variable	xi_1	xi_2
	0.2954 ***	-0.0571	0.4286 ***	0.0350	0.8872 ***	-0.0137	(H0:Rh=(r1,...,rh)=0)				
	(14.3519)	(-1.6622)	(23.9069)	(2.2727)	(128.1526)	(-1.6703)	tested order:	16	teststat	321.346994.911	
	(7.7032)	(-1.5885)	(12.7560)	(1.6332)	(67.2776)	(-1.2815)	adjusted test statistic:	489.2028			
							p-value:	0.000	p-Value(χ^2)	0.000	0.000
	0.0000	0.1819 ***	-0.1436 ***	0.2914 ***	0.0535 **	0.9455 ***	Multivariate ARCH-LM TEST	k=16			
	(0.0000)	(7.0717)	(-7.7390)	(15.6988)	(7.3200)	(135.2046)	test statistic:	230.0247	skewness	-0.0667	-0.350
	(0.0000)	(6.4444)	(-3.0582)	(10.3664)	(2.2026)	(92.3384)	p-value(χ^2):	0.000	kurtosis	5.4283	4.120

Notes: The signs ***, **, and * denote significance at 1%, 5%, and 10% respectively; the coefficients are estimated using QML (Quasi Maximum Likelihood); the italic numbers in parenthesis are the t-values exact; the numbers in parenthesis are the t-values normal; the dataset includes daily observations from 03/01/2006 to 13/05/2011; Author’s calculations in JMulTi based on Reuters Wealth Manager data.

Figure A.34: Conditional Covariance Processes from Multivariate GARCH models



Note: Author's calculations in EViews based on Reuters Wealth Manager data