5. Performance of VaR in Developed and CEE Countries during the Global Financial Crisis

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Abstract

The aim of this paper is to compare performance of Value at Risk (VaR) models in selected developed and emerging countries in Central and Eastern Europe before and during the financial crisis. Daily returns of stock indices are analysed during the period October 4, 2005- May 31, 2007, and during the post crisis period, June 1, 2007 – October 7, 2015. We employ symmetric and asymmetric GARCH models as VaR forecast models. The performance of the VaR is assessed by the Kupiec test of unconditional coverage. The results of backtesting show that such a GARCH-type VaR assuming Student's t distribution of standardized returns is in most cases a superior measure of downside risk at 99% of confidence level for both sample periods. Results also indicate that VaR is a beter measure of market risk for the developed than the CEE countries during the pre-crisis period, while during the crisis period the results are opposite.

Keywords: Value-at-risk (VaR), global financial crisis, GARCH Models, backtesting, Kupiec test

JEL Classification: G24, G32 C14, C22, C52

I. Introduction

The recent global financial crisis was a major turmoil event, which permeated all over the world regardless of whether it was a developed or an emerging country. Probably, it is the largest crisis after the Great Recession of the 1930s that affected both the real and financial sectors (Lianto and Badiola, 2010). This crisis, which was triggered by the subprime mortgage crisis in the United States, got the worst momentum in 2008 with the failure, merger or conservation of several large financial institutions exposed to packaged subprime loans and credit default swaps issued to insure these loans and their issuers. This crisis rapidly evolved into a global credit crisis, resulting in a number of bank failures in Europe and sharp reductions in the value of stocks worldwide. In the

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EU, many countries had supported their financial institutions. As a result, the cost of dealing with the consequences of the crisis created huge budget deficits and contributed to the low economic growth in the small EU countries, as well in the more advanced economies (Koksal and Orhan, 2012). In response to the financial crisis, the Basel Committee on Banking Supervision established revised global standards (Basel III).

Value-at-risk (VaR) is a useful risk measure broadly used by the financial institutions all over the world. VaR is popular among researchers, practitioners and regulators of financial institutions (Iqbal, Azher, Ijza, 2010). Financial innovation and deregulation significantly change the structure of financial institutions, so that the financial intermediaries must do more complicated trading and increase the frequency of trading activities than before. Accompanying the financial crisis, which began with the subprime market meltdown in the summer of 2007 and culminated with the bankruptcy of Lehman Brothers Holdings Inc., the importance of market risk management is getting more and more important (Su, Tsui, Chen, 2012)

Value-at-risk is the assessment of the maximum loss in the value of portfolio over a given time horizon at a given confidence level. Based on VaR, the financial institutions are able to determine the level of capital that provides cover losses and ensure the financial position of extreme market movements. VaR provides mechanism for investors to value their market exposure in terms of risk, thereby providing them with a basis to allocate risk more efficiently (Engle and Manganelli, 2004). Implementation of the VaR methodology in the investment process is directly related to the selection of the appropriate method of estimation. In selecting the appropriate method, of key importance is that it accurately determines the likelihood of losses.

One such approach is represented by the time-varying volatility models, which were expressed by Engle (1982) as autoregressive conditional heteroskedasticity (ARCH) model and extended by Bollerslev (1986) into the generalised ARCH (GARCH) model. These models recognise the difference between the conditional and the unconditional volatility of stochastic process, where the former varies over time while the latter remains constant. In addition, these models have triggered a range of extensions covering a wide spectrum of observed behaviours in the stock markets, including the asymmetric impact of returns on volatility and long memory dynamics in stock return volatility (McMillan and Thupayagale, 2010).

This paper tests the applicability of the concept of VaR to the markets of selected developed and emerging countries in Central and Eastern Europe before and during the financial crisis. The analysis was conducted for the folowing stock market indices: S&P500 (New York Stock Exchange), NIKEI225 (Tokio Stock Exchange), DAX (Frankfurt Stock Exchange), PX50 (Prague Stock Exchange), BUX (Budapest Stock Exchange), BELEX15 (Belgrade Stock Exchange), CROBEX (Zagreb stock exchange). We employ a symmetric GARCH and three asymmetric GARCH models, namely EGARCH, TGARCH and APARCH, with variations in their mean equations: AR(1), MA(1), and ARMA(1,1), ARCH in mean, as VaR forecast models. One-day-ahead VaR performance at 90%, 95%, 99% and 99.5% confidence levels is evaluated with realized profit and loss for the last 200 observations of the selected stock market indices.

In the recent years, a lot of research was conducted on VaR in the developed markets, while papers dealing with VaR calculation in the CEE are rare. Furthermore, the VaR models created and suited for liquid and well-developed markets that assume normal distribution are less reliable for the capital markets in the emerging economies, such as the CEE European Union member and candidate states. Since the capital markets in the European emerging economies are highly volatile, less liquid and strongly dependent on the unexpected external shocks, the market risk estimation based on normality assumption in the CEE countries is more problematic.

This motives us to implement methods that involve time-varying volatility and heavy tails of the empirical distribution of returns. We test the hypothesis that using the assumption of heavy tailed distribution it is possible to forecast market risk more precisely, especially in times of crisis, than under the assumption of normal distribution. Therefore, we employ symmetric and asymmetric GARCH models with assumptions that the residuals follow the Student's t distribution, too.

In addition, this is one of few empirical studies that compare the performance of VaR across a sample of developed and emerging CEE market economies (see also, Koksal and Orhan, 2012).

The paper is structured as follows. Literature review is presented in the second chapter. The third chapter presents the GARCH approach to obtain the VaR estimate. The fourth chapter presents the results of empirical analysis and backtesting. Finally, the concluding remarks are given in the fifth chapter.

II. Literature Review

There is now a huge and increasing literature on value-at-risk. Some selected papers are reviewed here. In the empirical literature, the most used models are the EWMA, the GARCH (particularly the long memory model) and the extreme value theory (EVT). We primarily emphasize the literature related to the VaR assessment for the crisis period. Wong, Cheng and Wong (2002) concluded that although the GARCH models in many cases show superior prediction of volatility, they consistently fail to pass the backtesting analysis of the Basel agreement. In several studies, the authors conducted a comparison of different models of VaR. Guermat and Harris (2002) indicate that the EWMA model made estimates of volatility unnecessarily high when the returns are conditionally normally distributed, but tend to have tails. The main reason is that the EWMA models provide significantly higher weights of extreme values return. Persand and Brooks (2003) conclude that the performance of different models for volatility depends on the use of loss functions. Some authors emphasize that the results of selected models of VaR vary depending on the chosen confidence interval. For instance, Su and Knowles (2006) point out that the standard error of VaR values increases as the confidence interval increases. According to the results of this analysis, with the confidence interval of 99%, the parametric model (delta normal VaR) produces more abnormal values of VaR than with the confidence interval of 95%. Živković and Aktan (2009) investigated the performance of a wide array of VaR with the daily returns of Turkish (XU100) and Croatian (CROBEX) stock index prior to and during the financial crisis. Authors also studied the behaviour of conditional and unconditional extreme value theory (EVT) and hybrid historical simulation (HHS) models to generate 95%, 99% and 99.5% confidence level estimates. They conclude that during the crisis period all the tested VaR models, except for the EVT and the HHS models, underestimate the true level of risk, with the EVT models doing so at higher cost of capital as compared to the HHS model. Mladenović, Miletić and Miletić (2012) consider the adequacy of VaR models in selected emerging economies with the daily returns of Bulgarian (SOFIX), Croatian (CROBEX), Czech (PX50), Hungarian (BUX), Romanian (BET) and Serbian (BELEX15) stock exchange indices before and during the financial turmoil. They conclude that the GARCH models with Student's t error distribution give better 5% and 1% VaR estimation as compared to the normal error GARCH models. The authors emphasize that the GARCH models for most confidence levels are not outperformed by the EVT approach and the estimations derived from the POT.

In several papers, VaR was evaluated by using a methodology similar to ours. McMilllan and Speight (2007) investigated the value-at-risk in the emerging equity markets. Comparative evidence for symmetric, asymmetric, and long-memory GARCH models is also provided. In the analysis of daily index data for eight emerging stock markets in the Asia-Pacific region, in addition to the US and the UK benchmarks, they found both asymmetric and long memory features to be important considerations in providing improved VaR estimates

Iqbal, Azher, Ijza (2010) analyze the accuracy of the VaR measure for Pakistan's emerging stock market using daily data from the Karachi Stock Exchange-100 index (KSE) for the period January 1992 to June 2008. The authors computed VaR by employing data on annual basis, as well as for the whole 17 year period. Overall, they found that the VaR measures are more accurate when the KSE index return volatility is estimated by the GARCH (1,1) model, especially at 95% confidence level. At 99% confidence level, the authors find that no method generally gives accurate VaR estimates. They found that portfolios with higher VaR have higher average returns and conclude that VaR as a measure of downside risk is associated with higher returns. Mokni, Mighri, Mansouri (2009) investigated GARCH family models, such as GARCH, IGARCH, and GJR-GARCH, adjusted on the basis of three residuals distributions; normal, Student's t and skewed Student's t. Using American stock market data, the authors found that dynamic volatility is different during the stable and the crisis period. They suggest that this finding could be explained by the volatility clustering effect. The empirical results of research showed that the GJR-GARCH model performs better in both sub-sample periods, as compared to the GARCH and IGARCH models. In addition, the authors conclude that the Student-t and skewed Student-t distributions are preferred in the stable period, while the normal distribution is recommended during the turbulent period.

Koksal and Orhan (2012) compare the performance of widely used measure VaR across a large sample of developed and developing countries. Results indicate that the performance of VaR is much worse for the developed countries than the developing countries. The authors conclude that one possible reason might be the deeper initial impact of global financial crisis on the developed countries than on the developing markets. They also emphasize that the results provide evidence of decoupling, finding that the emerging market economies were isolated from the developments in the U.S. financial markets at the beginning of financial crisis, but followed the rest of the developed countries afterwards from the perspective of VaR.

III. Methodology

III.1. Defining the Concept of Value-at-risk (VaR)

VaR is a measure that gives the maximum loss from certain investments over a given time horizon (usually 1 day or 10 days), with a certain probability (Jorion, 2001). Mathematically, VaR for the period of the k day in day t can be represented as follows:

$$P\left(P_t - P_{t-k} \leq VaR(t,k,\alpha)\right) = \alpha \tag{1}$$

where: P_t is the price of a particular type of financial asset, and α represents a given level of probability.

VaR can be expressed in terms of a percentile of the return distributions. Specifically, if q_α is the α-th percentile of the continuously compound return, VaR is calculated as follows:

$$VaR(t,k,\alpha) = \left(e^{q_\alpha} - 1\right)P_{t-k} \tag{2}$$

The previous equation implies that a good estimate of VaR can only be produced with accurate forecast of the percentiles, q_α, which is obtained on the corresponding volatility modeling. Therefore, below we discuss the value of VaR for a series of returns.

Define a one-day return on day t as:

$$r_t = \log(P_t) - \log(P_{t-1}) \tag{3}$$

For the time series of return r_t, VaR can be expressed as:

$$P(r_t < VaR_t | I_{t-1}) = \alpha \tag{4}$$

where: I_{t-1} is a set of information available at time t-1. From this equation, it follows that finding the VaR values is the same as finding a 100α% conditional quantiles.

III.2. The GARCH Models

The GARCH models successfully capture several characteristics of the financial time series, such as thick tailed returns and volatility clustering. This type of models represents the standard and very often used approach for getting VaR estimate. A general GARCH(p,q) model proposed by Bollerslev (1986) can be written in the following form:

$$y_t = a_0 + \sum_{i=1}^{m} a_i y_{t-i} + \varepsilon_t - \sum_{j=1}^{s} b_j \varepsilon_{t-j}$$

$$\varepsilon_t = z_t \sigma_t, \quad \varepsilon_t | I_{t-1} \sim N\left(0, \sigma_t^2\right) \tag{5}$$

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

$$\alpha_0 > 0, \quad \alpha_i \geq 0, \quad \beta_j \geq 0, \quad i = 1,\dots,q, \; j = 1,\dots,p$$

The first equation actually describes the percentage level of return,y_t=100*r_t, which is presented in the form of autoregressive and moving average terms, i.e. ARMA(m,s) process. Error term ε_t in the first equation is a function of z_t, which is a random component with the properties of white noise. The third equation describes the conditional variance of return, y_t, which is function of squared errors of q previous periods and conditional variance of p previous periods. The stationarity condition for GARCH(p, q) is $\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j < 1$.

The size of α and β parameters in the equation determines the observed short-term volatility dynamics obtained from the series of returns. The high value of β coefficient indicates that the shocks to conditional variance need a long time to disappear, so that volatility is constant. The high value of α coefficient means that volatility reacts intensively to the changes in the market.

By standard arguments, the model is covariance stationary if and only if all the roots of $\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j = 1$ lie outside the unit circle. In many applications with high frequency financial data, the estimate for $\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j$ turns out to be very close to unit. This provides an empirical motivation for the so-called integrated GARCH(p,q), or IGARCH(p,q), model (see Bollerslev *et al*., 1994). In the IGARCH class of models, the autoregressive polynomial in equation (5) has a unit root, and, consequently, a shock to the conditional variance

where A(L) and B(L) are lag operators.

In order to capture the asymmetry, Nelson (1991) proposed the exponential GARCH process or EGARCH for the conditional variance:

$$\log\left(\sigma_t^2\right) = \alpha_0 + \sum_{i=1}^{\infty}\pi_i\, g\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) \tag{6}$$

The asymmetric relation between returns and volatility change is given as a function $g\left(\frac{\varepsilon_t}{\sigma_t}\right)$, which represents the linear combination of $\left|\frac{\varepsilon_t}{\alpha_t}\right|$ and $\frac{\varepsilon_t}{\alpha_t}$:

$$g(\frac{\varepsilon_t}{\sigma_t}) = \theta\left(\left|\frac{\varepsilon_t}{\sigma_t}\right| - E\left|\frac{\varepsilon_t}{\sigma_t}\right|\right) + \gamma\left(\frac{\varepsilon_t}{\sigma_t}\right) \tag{7}$$

where: θ and γ are constants.

By construction, equation is a zero mean process (bearing in mind that $z_t = \varepsilon_t / \sigma_t$). For $0 < z_t < \infty$, $g(z_t)$, it is a linear function with slope coefficient θ + γ, while for $-\infty < z_t \leq 0$ it is a linear function with slope coefficient γ - θ. The first part of the equation, $\theta\left(|z_t| - E|z_t|\right)$, captures the size effect, while second part, $\gamma(z_t)$, captures the leverage effect.

Zakoian (1994) proposed the TGARCH (p,q) model as an alternative to the EGARCH process, where the asymmetry of positive and negative inovations is incorporated into the model by using an indicator function:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\left(\alpha_i \varepsilon_{t-i}^2\right) + \sum_{i=1}^{q}\left(\gamma_i d\left(\varepsilon_{t-i} < 0\right)\varepsilon_{t-i}^2\right) + \sum_{j=1}^{p}\left(\beta_j \sigma_{t-j}^2\right) \tag{8}$$

where: γ_i are parameters that have to be estimated, $d(\cdot)$ denotes the indicator function defined as:

$$d\left(\varepsilon_{t-i} < 0\right) = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0 & \varepsilon_{t-i} \geq 0 \end{cases} \tag{9}$$

The TGARCH model allows for good news, ($\varepsilon_{t-1} > 0$), and bad news, ($\varepsilon_{t-1} < 0$) to have differential effects on the conditional variance. For instance, in the case of a TGARCH (1,1) process, good news has an impact of α_1, while bad news has an impact of $\alpha_1+\gamma_1$. For $\gamma_1>0$, the leverage effect exsists.

The APARCH (p,q) process, proposed by Ding, Granger and Engle (1993), includes seven different GARCH models (ARCH, GARCH, AGARCH, TGARCH, TARCH NGARCH i Log-GARCH):

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{q}\alpha_i\left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{j=1}^{p}\left(\beta_j \sigma_{t-j}^{\delta}\right) \tag{10}$$

where: $\alpha_0 > 0$, $\delta \geq 0$, $\beta_j \geq 0$, j=1, ..., p, $\alpha_i \geq 0$, $-1 < \gamma_i < 1$ and i=1,..., q.

Parameter δ in the equation denotes the exponent of conditional standard deviation, while parameter γ describes the asymmetry effect of good and bad news on conditional volatility. Positive value of γ means that negative shocks from the previous period have higher impact on the current level of volatility, and otherwise.

If residuals z_t follow a standardized normal distribution, VaR at 95% confidence level could be calculated as:

$$\hat{y}_n(1) - 1.65\,\hat{\sigma}_n(1) \tag{11}$$

while if residuals z_t follow a standardized t^s distribution with v degrees of freedom, then VaR could be calculated as:

$$\hat{y}_n(1) - t_{v}\sqrt{\frac{v-2}{v}}\,\hat{\sigma}_n(1) \tag{12}$$

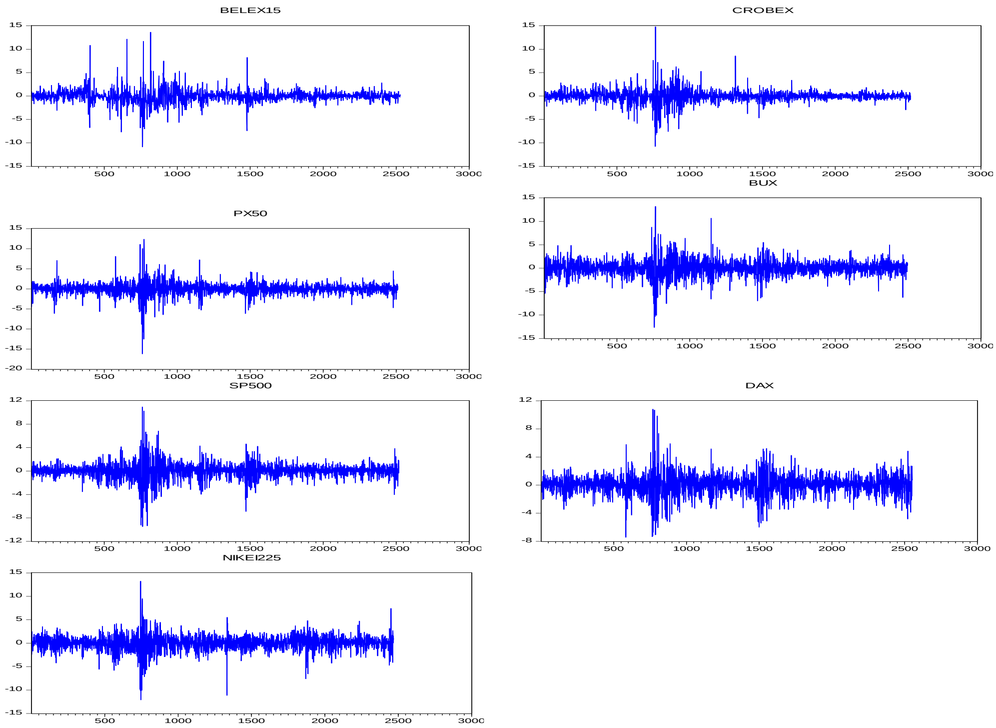
IV. Results of Empirical Analysis and Backtesting

We use the country indices for three selected developed (USA, Japan and Germany) and four emerging countries in Central and Eastern Europe (the Czech Republic, Hungary, Croatia and Serbia) obtained from the national stock exchanges and Yahoo Finance websites. The sample analysis of research comprises the daily returns of stock indices of the selected developed and emerging countries in Central and Eastern Europe. The tested stock indices are S&P500, NIKEI225, DAX, PX50, BUX, CROBEX, during the period January 4, 2000 - October 7, 2015, and BELEX15 during the period October 4, 2005 – October 7, 2015, respectively. In addition, we estimated the conditional standard deviation for VaR calculation for both pre-crisis (up to June 1, 2007) and during the crisis and post-crisis period (since June 1, 2007, up to October 7, 2015). For all indices, we compute daily logarithmic returns, i.e. $r_t = (\log P_t - \log P_{t-1})*100$.

Bearing in mind that the one-time structural breaks may lead to erroneous statistical conclusions, in all seven cases we indicate the most prominent non-standard values and then regress the series of returns on constant and dummy variables that take non-zero values for the observations with the most prominent nonstandard values. New adjusted *series* of daily returns are used in empirical analysis (see Figure 1). Volatility clustering is clearly visible in all cases.

Figure 1

Stock Exchange Indices Daily Returns



IV.1. Results of Analysis for the Pre-Crisis Period

Results of analysis for the pre-crisis period comprises the daily returns of stock indices of selected developed (USA, Japan and Germany) and emerging countries in Central and Eastern Europe (the Czech Republic, Hungary, Croatia, and Serbia) during the period January 1, 2000 - May 31, 2007 and BELEX15 during the period October 4, 2005 - May 31, 2007, respectively.

Table 1 indicates that the daily returns of all seven market stock indices are not normally distributed. In most cases, skewness is evident; kurtosis is in all cases much higher than

3, and the Jarque-Bera statistics are highly significant. Negatively skewed distributions are reported for the PX50 stock index, in the case of emerging countries, while in the case of developed countries for the NIKEI225 and the DAX stock indices. Positive skewnes was observed for the BELEX15, the CROBEX and the BET stock indices, in the case of emerging countries, while in the case of developed countries for the S&P500 stock index, which indicates the possibility of large positive returns. The coefficient of excess kurtosis is in all cases much higher than 3, indicating that the distribution of returns is leptokurtic, which means that the distribution has fatter tails. The largest coefficient of excess kurtosis is reported for the CROBEX and the BELEX15 indices, in the case of emerging economies, and for the S&P500 and the DAX indices, in the case of developed economies. The results confirm the presence of fat tails, which suggests that the assumption of a normal distribution is not satisfied. The ARCH-LM test indicates the presence of time-varying volatility, and the Box-Ljung statistics indicate the evidence of autocorrelation in squared standardized residuals.

Table 1

Descriptive Characteristics of Stock Exchange Indices Daily Returns

	Skewness	Kurtosis	JB statistics	$Q^2(10)$	Q^2 (30)	ARCH-LM (10) test	ARCH-LM (30) test
BELEX15	1.060	19.336	4703.71 (0.0)	107.04 (0.0)	138.05 (0.0)	77.87 (0.0)	178.66 (0.0)
BUX	0.115	4.484	174.56 (0.0)	191.56 (0.0)	273.67 (0.0)	106.55 (0.0)	127.79 (0.0)
CROBEX	0.416	7.620	1702.68 (0.0)	187.98 (0.0)	342.84 (0.0)	117.20 (0.0)	1185.42 (0.0)
PX50	-0.262	5.035	342.43 (0.0)	306.01 (0.0)	526.26 (0.0)	153.28 (0.0)	203.51 (0.0)
NIKEI225	-0.147	4.691	223.65 (0.0)	208.23 (0.0)	356.60 (0.0)	1140.12 (0.0)	165.05 (0.0)
S&P500	0.075	5.776	599.63 (0.0)	731.98 (0.0)	1434.7 (0.0)	284.17 (0.0)	332.87 (0.0)
DAX	-0.042	5.661	556.34 (0.0)	1664.9 (0.0)	3484.5 (0.0)	495.50 (0.0)	538.88 (0.0)

Source: Authors' calculations.

Note: P values of coresponding test statistics are given in parentheses. JB represents the Jarque-Bera statistics for normality testing; Q2 represents the Box-Ljung statistics for testing autocorelation in sqared standardized residuals, while the ARCH-LM test is the test of autoregressive conditional heteroscedasticity.

Bearing in mind that the Box-Ljung autocorrelation test for squared standardized residuals and the ARCH-LM tests indicate the presence of ARCH effects, we estimate models of conditional autoregressive heteroscedasticity (GARCH models). The model selection was done according to the modified Akaike criteria. Model parameters are calculated using the maximum likelihood estimation method. Maximum likelihood estimates of the parameters are obtained by numerical maximization of the log-likelihood function using the BHHH algorithm.

Table 2

Parameter Estimates of the GARCH Model of the Standardized Residuals for CEE Countries Indices Daily Returns

	Normal distribution				*Student's t* distribution			
	BUX	BELEX15	CROBEX	PX50	BUX	BELEX15	CROBEX	PX50
Mean equation								
Constant	-0.029 (0.02)	0.192 (0.00)			-0.029 (0.02)	0.169 (0.02)		
AR(1)		0.633 (0.00)		0.079 (0.00)		0.746 (0.00)		0.068 (0.00)
MA(1)		-0.436 (0.00)				-0.547 (0.00)		
Volatility equation								
c	0.010 (0.00)	0.105 (0.00)	0.098 (0.00)	0.088 (0.00)	0.011 (0.00)	0.178 (0.01)	-0.164 (0.00)	0.069 (0.00)
α	0.047 (0.00)	0.218 (0.00)	0.146 (0.00)	0.102 (0.00)	0.047 (0.00)	0.239 (0.00)		0.100 (0.00)
β	0.884 (0.00)	0.691 (0.00)	0.802 (0.00)	0.848 (0.00)	0.887 (0.00)	0.601 (0.00)	0.942 (0.00)	0.866 (0.00)
θ							0.246 (0.00)	
γ	-0.216 (0.00)		-0.032 (0.02)	0.642 (0.00)	-0.218 (0.00)		0.044 (0.02)	0.586 (0.00)
δ	2.669 (0.00)			0.806 (0.00)	2.537 (0.00)			0.857 (0.00)
Number of degrees of freedom								
v					12	6	4	10
Specification tests								
Q2(30)	27.48 (0.59)	23.31 (0.71)	25.85 (0.68)	33.01 (0.27)	27.73 (0.58)	30.05 (0.36)	24.97 (0.72)	31.30 (0.35)
JB	58.28 (0.00)	19.60 (0.00)	1275.26 (0.00)	106.92 (0.00)	59.49 (0.00)	29.30 (0.00)	1506.64 (0.00)	124.22 (0.00)
ARCH (10)	7.63 (0.66)	2.99 (0.16)	6.10 (0.80)	13.88 (0.17)	7.99 (0.62)	2.60 (0.98)	8.23 (0.60)	13.62 (0.19)

Source: Authors' calculations.

Results of estimating ARMA (m,s)-GARCH (p,q) model, and different types of asymmetric ARMA (m,s)-GARCH (p,q) model with assumption that the residuals follow normal or Student's t distribution for the CEE and developed countries suggest the following conclusions (Tables 2 and 3). On the assumption that the residuals follow the normal distribution, the GARCH model provides the most accurate volatility estimation in the case of DAX and BELEX15 stock indices, the TGARCH in the case of CROBEX and NIKEI225 stock indices and the APARCH model in the case of PX50, BUX and S&P500 stock indices. On the assumption that the residuals follow the Student's t distribution, the GARCH model provides the most accurate volatility estimation in the case of BELEX15 and DAX stock indices, the TGARCH in the case of NIKEI225 stock index, the EGARCH in the case of CROBEX stock index and the APARCH model in the case of BUX, PX50 and S&P500 stock indices. The models have appropriate statistical characteristics, i.e. the autocorrelation and ARCH effects do not exist in standardized residual. Furthermore, the Jarque-Bera statistics show that skewness and kurtosis in standardized residuals are reduced, but not completely eliminated.

Table 3

Parameter Estimates of the GARCH Model of the Standardized Residuals for Developed Countries Indices Daily Returns

Normal distribution				*Student's t* distribution		
	DAX	NIKEI225	S&P500	DAX	NIKEI225	S&P500
Mean equation						
Constant	0.069 (0.00)			0.078 (0.00)		
Volatility equation						
c	0.018 (0.00)	0.038 (0.00)	0.017 (0.00)	0.014 (0.00)	0.030 (0.00)	0.013 (0.00)
α	0.085 (0.00)	0.041 (0.00)	0.054 (0.00)	0.086 (0.00)	0.031 (0.01)	0.054 (0.00)
β	0.904 (0.00)	0.896 (0.00)	0.947 (0.00)	0.906 (0.00)	0.911 (0.00)	0.948 (0.00)
θ						
γ		0.086 (0.00)	0.996 (0.00)		0.084 (0.00)	0.996 (0.00)
δ			0.669 (0.00)			0.807 (0.00)
Number of degrees of freedom						
v				24	12	15
Specification tests						
Q2(30)	23.21 (0.80)	28.52 (0.54)	27.08 (0.61)	22.43 (0.83)	27.07 (0.61)	25.91 (0.68)
JB	25.40 (0.00)	133.69 (0.00)	108.55 (0.00)	28.35 (0.00)	150.73 (0.00)	155.50 (0.00)
ARCH (10)	9.71 (0.46)	14.60 (0.14)	10.51 (0.39)	8.40 (0.58)	14.27 (0.16)	10.38 (0.40)

Source: Authors' calculations.

Based on parameters estimated by the GARCH models, we forecast the returns and volatility for one day ahead to get the VaR estimates at 90%, 95%, 99% and 99.5% coverage of the market risk. Results are given in Tables 4 and 5 and they represent percentage values. The obtained VaR values can be significantly different, depending on the assumptions that residuals have normal or Student's t distribution. Value-at-risk measure at 99% and 99.5% confidence level in most cases is higher on the assumption that residuals follow Student's t distribution, while at 90% and 95% confidence level it is oposite.

For instance, based on estimated results for the CEE countries, it may be concluded that the maximum daily loss for the BUX stock index daily returns is 79 EUR on invested 10000 EUR at 95% confidence level, and ranges from 111 to 117 EUR at 99% confidence level. The maximum daily loss for the CROBEX stock index daily returns ranges from 204 to 206 EUR on invested 10000 EUR at 95% confidence level, and from 289 to 363 EUR at 99% confidence level. Based on the estimated results for the developed countries, the maximum daily loss for the S&P500 index daily returns ranges from 88 to 90 EUR at 95% confidence level, and from 128 to 131 EUR at 99% confidence level, while the maximum daily loss for the NIKEI225 index daily returns ranges from 128 to 151 EUR at 95% confidence level, and from 213 to 223 EUR at 99% confidence level.

Table 4

Econometric Estimation of the Parameters of VaR for One-day-ahead Period for the CEE Indices Daily Returns

BELEX15			CROBEX		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	GARCH(1,1)	GARCH(1,1)		TGARCH(1,1)	EGARCH(1,1)
Forecasted return	-0.062	-0.198	Forecasted return	0.000	0.000
Forcasted cond.volatility	1.430	1.018	Forcasted cond.volatility	1.534	1.873
VaR (1,0.90)	1.592	1.384	VaR (1,0.90)	1.585	1.483
VaR (1, 0.95)	2.035	1.798	VaR (1, 0.95)	2.044	2.063
VaR (1, 0.99)	2.848	2.787	VaR (1, 0.99)	2.886	3.626
VaR(1,0.995)	3.135	3.251	VaR (1,0.995)	3.183	4.455
BUX			PX50		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	APARCH(1,1)	APARCH(1,1)		APARCH(1,1)	APARCH(1,1)
Forecasted return	-0.029	-0.029	Forecasted return	0.004	0.002
Forcasted cond.volatility	0.216	0.218	Forcasted cond.volatility	0.957	0.682
VaR (1,0.90)	0.624	0.608	VaR (1,0.90)	1.247	1.010
VaR (1, 0.95)	0.796	0.790	VaR (1, 0.95)	1.609	1.335
VaR (1, 0.99)	1.113	1.174	VaR (1, 0.99)	2.274	2.039
VaR (1,0.995)	1.224	1.333	VaR (1,0.995)	2.509	2.338

Source: Authors' calculations.

Table 5

Econometric Estimation of the Parameters of VaR for One-day-ahead Period for Developed Countries Indices Daily Returns

DAX			NIKEI225		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	GARCH(1,1)	GARCH(1,1)		TGARCH(1,1)	TGARCH(1,1)
Forecasted return	0.069	0.078	Forecasted return	0.000	0.000
Forcasted cond. volatility	0.606	0.584	Forcasted cond. volatility	0.834	0.829
VaR(1,0.90)	0.927	0.886	VaR(1,0.90)	1.169	1.127
VaR(1, 0.95)	1.215	1.174	VaR(1, 0.95)	1.507	1.281
VaR(1, 0.99)	1.745	1.745	VaR(1, 0.99)	2.128	2.228
VaR(1,0.995)	1.932	1.969	VaR(1,0.995)	2.347	2.539

S&P500		
	Normal distribution	*Student's t* distribution
	APARCH(1,1)	APARCH(1,1)
Forecasted return	0.000	0.000
Forcasted cond. volatility	0.302	0.292
VaR(1,0.90)	0.704	0.675
VaR(1, 0.95)	0.907	0.883
VaR(1, 0.99)	1.281	1.310
VaR(1,0.995)	1.413	1.484

Source: Authors' calculations.

The applied methods were evaluated by backtesting procedure for the last 200 observations. The accuracy of VaR estimated by GARCH models is tested by the Kupiec POF test[3] for 90%, 95%, 99% and 99.5% confidence level (Table 6). In the case of the BELEX15 stock index, the GARCH models pass the test at 95% and 99% confidence level, on the assumption that residuals follow normal as well as Studen's t distribution, while in the case of the CROBEX stock index the GARCH models pass the

[3] The basic idea is to determine if the observed excess rate $\hat{p}$ is significantly different from p, the excess rate being determined by the given confidence level. According to Kupiec (1995), the POF test is best implemented as a likelihood-ratio test (LR). The statistical test has the following form:

$$LR_{POF} = -2\ln\left((1-p)^{n-x} p^x / \left[1-\left(\frac{x}{n}\right)\right]^{n-x}\left(\frac{x}{n}\right)^x\right)$$

If the null hypothesis is correct, LR_{POF} statistics in asymptotic conditions has χ^2 distribution with a single degree of freedom. If the value of LR_{POF} statistics exceeds the critical value of χ^2 distribution, the null hypothesis is rejected and the model is considered to be imprecise.

Kupiec test at 99% and 99.5% confidence level, with the assumption that residuals follow normal as well as Studen's t distribution. VaR was good measure of market risk in the case of BUX and PX50 stock indices, where GARCH type models performs well and passes test at all confidence level.

Table 6

The Kupiec Test Results for the CEE Countries

BELEX15			BUX		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	GARCH(1,1)	GARCH(1,1)		APARCH(1,1)	APARCH(1,1)
Kupiec test 90%	8.285*	4.090*	Kupiec test 90%	0.840	0.840
Kupiec test 95%	1.953	1.053	Kupiec test 95%	0.396	0.869
Kupiec test 99%	1.565	1.565	Kupiec test 99%	1.565	0
Kupiec test 99.5%	27.810*	27.810*	Kupiec test 99.5%	2.005	2.005
CROBEX			PX50		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	TGARCH(1,1)	EGARCH(1,1)		APARCH(1,1)	APARCH(1,1)
Kupiec test 90%	12.219*	10.126*	Kupiec test 90%	8.285*	0.056
Kupiec test 95%	13.814*	13.814*	Kupiec test 95%	1.953	0.108
Kupiec test 99%	0.618	4.020	Kupiec test 99%	0.437	1.565
Kupiec test 99.5%	2.00	2.005	Kupiec test 99.5%	0.777	2.611

Source: Authors' calculations.

*Note to tables: *denotes statistical significance of the test statistics. Critical value of x2 test with one degree of freedom at 90%, 95%, 99% and 99.5% confidence level is respectively: 2.706, 3.849, 6.635 and 7.789.*

Table 7 reports the performance of VaR for the developed countries. Overall, the conclusion from Table 7 is that the assesed VaR for the GARCH models is adequate for 90%, 95%, 99% and 99.5% confidenece level, with the assumption that residuals follow normal and Student's t distribution for all stock idices in the developed countries.

Althrough it is informative to look at VaR model properties at different confidence levels, the Basel Committee prescribes testing VaR model adequacy at 99% confidence level (Mladenović, Miletić, Miletić, 2012). At these confidence levels, our results show that VaR calculation based on the GARCH models is accepted for three stock exchange market indices in the case of the CEE countries and for all three stock exchange market indices in the case of the developed countries.

Table 7

The Kupiec Test Results for the Developed Countries

DAX			NIKEI225		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	GARCH (1,1)	GARCH (1,1)		TGARCH (1,1)	TGARCH (1,1)
Kupiec test 90%	0.524	0.054	Kupiec test 90%	0.524	0.056
Kupiec test 95%	1.053	0.450	Kupiec test 95%	0.396	0.869
Kupiec test 99%	0.437	0.437	Kupiec test 99%	3.208	3.208
Kupiec test 99.5%	0.777	0.777	Kupiec test 99.5%	2.611	2.611
S&P500					
	Normal distribution	*Student's t* distribution			
	APARCH (1,1)	APARCH (1,1)			
Kupiec test 90%	2.210	2.210			
Kupiec test 95%	0.108	0.108			
Kupiec test 99%	1.565	1.565			
Kupiec test 99.5%	0.777	0.777			

Source: Authors' calculations.

4.2. Results of Analysis for the Crisis Period

The second subsample comprises daily returns of selected stock indices during the period June 1, 2007 – December 21, 2012, which overlaps the global financial crisis.

Results of descriptive statistics presented in Table 8 show a similar pattern as compared to the pre-crisis period; daily returns of all seven market stock indices are not normaly distributed, in most cases skewness is evident and kurtosis is much higher than 3. Only the DAX and the BUX stock market indices have positive skewnes. The ARCH-LM test also indicates the presence of time-varying volatility, and the Box-Ljung statistics indicate evidence of autocorelation in squared standardized residuals.

Table 8

Descriptive Characteristics of Stock Exchange Indices Daily Returns

	Skewness	Kurtosis	JB statistics	$Q^2(10)$	Q^2 (30)	ARCH-LM (10) test	ARCH-LM (30) test
BELEX15	--0.508	10.973	5708.23(0.0)	783.86(0.0)	1326.8(0.0)	409(0.00)	470.68(0.0)
BUX	0.009	6.379	991.09(0.0)	675(0.0)	1671.9(0.0)	296.22(0.0)	421.44(0.0)
CROBEX	-0.475	13.008	8840.6(0.0)	1131(0.0)	2798(0.0)	388.68(0.0)	505.58(0.0)
PX50	-0.491	17.420	18252.6(0.0)	1172.4(0.0)	2346.9(0.0)	447.23(0.0)	526.53(0.0)
NIKEI225	-0.286	5.602	810.34(0.00)	1092(0.0)	1897(0.0)	389.61(0.0)	466.86(0.0)
S&P500	-0356	7.873	2125.78(0.00)	1761.5(0.0)	3713.4(0.0)	523.62(0.0)	581.55(0.0)
DAX	-0.415	6.171	954.81(0.00)	705.25(0.0)	1528.8(0.0)	293.65(0.0)	380.87(0.0)

Source: Authors' calculations.

On the assumption that the residuals follow the normal distribution, the GARCH-M model provides the most accurate volatility estimation in the case of the DAX stock index, the EGARCH in the case of the BELEX15 stock index, the TGARCH in the case of the BUX, CROBEX and PX50 stock indices, while the APARCH model in the case of the NIKEI22 stock index.

On the assumption that the residuals follow the Student’s t distribution, the GARCH-M model provides the most accurate volatility estimation in the case of the DAX stock index, the TGARCH in the case of the CROBEX, BUX and PX50 stock indices and the APARCH model in the case of the NIKEI225 stock index. In the case of the BELEX15 stock index, neither of the models provides accurate volatility estimation. In the case of the S&P500 stock index, neither of the models (with the assumption that the residuals follow the normal and Student's t distribution) provides accurate volatility estimation, because the autocorrelation and ARCH effect still exist in the standardized residuals.

Table 9

Parameter Estimates of the GARCH Model with Normal Distribution of the Standardized Residuals for the CEE Countries

	Normal distribution				*Student’s t* distribution			
	BUX	BELEX15	CROBEX	PX50	BUX	BELEX15	CROBEX	PX50
Mean equation								
AR(1)		0.621 (0.00)	0.05 (0.03)			0.611 (0.00)	0.062 (0.00)	
MA(1)		-0.425 (0.00)				-0.425 (0.00)		
Volatility equation								
c	0.048 (0.00)	-0.304 (0.00)	0.08 (0.00)	0.049 (0.00)	0.031 (0.00)	0.03 (0.00)	0.009 (0.00)	0.043 (0.00)
α	0.042 (0.00)		0.053 (0.00)	0.073 (0.00)	0.o38 (0.00)	0.225 (0.00)	0.044 (0.00)	0.073 (0.00)
β	0.80 (0.00)	0.954 (0.00)	0.913 (0.00)	0.854 (0.00)	0.914 (0.00)	0.778 (0.00)	0.912 (0.00)	0.865 (0.00)
θ		0.403 (0.00)						
γ	0.080 (0.00)	-0.045 (0.00)	0.066 (0.00)	0.092 (0.00)	0.071 (0.00)		0.079 (0.00)	0.075 (0.00)
δ								
Number of degrees of freedom								
ν					9	5	5	9
Specification tests								
Q2(30)	16.97 (0.97)	34.90 (0.17)	8.68 (1.00)	26.10 (0.67)	16.92 (0.97)	34.81 (0.17)	8.13 (1.00)	26.45 (0.65)
JB	177.09 (0.00)	389.57 (0.00)	5990.08 (0.00)	117.43 (0.00)	216.31 (0.00)	527.37 (0.00)	6776.88 (0.00)	127.43 (0.00)
ARCH (10)	2.41 (0.99)	15.89 (0.10)	2.33 (0.99)	6.61 (0.76)	2.46 (0.99)	15.08 (0.12)	2.07 (0.99)	7.45 (0.68)

Source: Authors’ calculations.

Table 10

Parameter Estimates of the GARCH Model of the Standardized Residuals for the Developed Countries Indices Daily Returns

Normal distribution				*Student's t* distribution		
	DAX	NIKEI225	S&P500	DAX	NIKEI225	S&P500
Mean equation						
σ	0.033 (0.00)			0.036 (0.00)		
Volatility equation						
c	0.030 (0.00)	0.046 (0.00)	0.023 (0.00)	0.024 (0.00)	0.042 (0.00)	0.020 (0.00)
α	0.087 (0.00)	0.096 (0.00)	0.115 (0.00)	0.086 (0.00)	0.086 (0.00)	0.117 (0.00)
β	0.898 (0.00)	0.893 (0.00)	0.869 (0.00)	0.905 (0.00)	0.903 (0.00)	0.874 (0.00)
θ						
γ		0.416 (0.00)			0.623 (0.00)	
δ		1.199 (0.00)			1.105 (0.00)	
Number of degrees of freedom						
ν				7	11	7
Specification tests						
Q2(30)	28.58 (0.53)	38.19 (0.14)	42.22 (0.04)	28.61 (0.53)	37.46 (0.16)	43.38 (0.052)
JB	182.11 (0.00)	187.88 (0.00)	121.89 (0.00)	190.01 (0.00)	340.08 (0.00)	125.18 (0.00)
ARCH(10)	10.83 (0.00)	10.35 (0.40)	20.328 (0.02)	10.84 (0.37)	12.78 (0.23)	19.88 (0.03)

Source: Authors' calculations.

Based on the estimated results for the CEE countries, it may be concluded that the maximum daily loss for the CROBEX index daily returns ranges from 107 to 112 EUR on invested 10000 EUR at 95% confidence level, and from 159 to 178 EUR at 99% confidence level. Maximum daily loss for the BUX index daily returns ranges from 192 to 193 EUR on invested 10000 EUR at 95% confidence level, and from 271 to 296 EUR at 99% confidence level. Based on the estimated results for the developed countries, maximum daily loss for the DAX index daily returns ranges from 282 to 286 EUR at 95% confidence level, and from 409 to 454 EUR at 99% confidence level, while maximum daily loss for the NIKEI225 index daily returns ranges from 326 to 328 EUR at 95% confidence level, and from 463 to 489 EUR at 99% confidence level.

Table 11

Econometric Estimation of the Parameters of VaR for One-day-ahead Period for the CEE Indices Daily Returns

BELEX15			CROBEX		
	Normal distribution			Normal distribution	*Student's t* distribution
	EGARCH (1,1)			TGARCH(1,1)	TGARCH(1,1)
Forecasted return	0.013497		Forecasted return	-0.00197	-0.002852
Forcasted cond. volatility	0.160264		Forcasted cond. volatility	0.467095	0.469019
VaR(1,0.90)	0.498925		VaR(1,0.90)	0.876	0.785
VaR(1, 0.95)	0.647047		VaR(1, 0.95)	1.129	1.071
VaR 1, 0.99)	0.919271		VaR(1, 0.99)	1.594	1.787
VaR(1, 0.995)	1.01535		VaR(1,0.995)	1.758	2.141
BUX			PX50		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	TGARCH (1,1)	TGARCH(1,1)		TGARCH(1,1)	TGARCH(1,1)
Forecasted return	0.000	0.000	Forecasted return	0.000	0.000
Forcasted cond. volatility	1.361	1.424786	Forcasted cond. volatility	1.05321	1.081486
VaR(1,0.90)	1.493	1.455877	VaR(1,0.90)	1.313	1.268
VaR(1, 0.95)	1.925	1.92959	VaR(1, 0.95)	1.693	1.681
VaR(1, 0.99)	2.710	2.969653	VaR(1, 0.99)	2.391	2.587
VaR(1,0.995)	2.998	3.421259	VaR(1,0.995)	2.637	2.980

Source: Authors' calculations.

Table 12

Econometric Estimation of the Parameters of VaR for One-day-ahead Period for the Developed Countries Indices Daily Returns

DAX			NIKEI225		
	Normal distribution	Student's t distribution		Normal distribution	Student's t distribution
	GARCH-M(1,1)	GARCH-M(1,1)		APARCH(1,1)	APARCH(1,1)
Forecasted return	0.109385	0.124885	Forecasted return	0.000	0.000
Forcasted cond. volatility	3.258073	3.402915	Forcasted cond. volatility	3.96337	3.959853
VaR(1,0.90)	2.201	2.081	VaR(1,0.90)	2.548	2.469554
VaR(1, 0.95)	2.868	2.829	VaR(1, 0.95)	3.284	3.261539
VaR(1, 0.99)	4.096	4.549	VaR(1, 0.99)	4.638	4.892309
VaR(1,0.995)	4.529	5.330	VaR(1,0.995)	5.116	5.590696

Source: Authors' calculations.

The overall conclusion of Table 13 is that the assesed VaR for the GARCH models passed the Kupiec test for 90%, 95%, 99% and 99.5% confidenece level for the BUX and the PX50 stock indices. In the case of the BELEX15 (on the assumption that the residuals follow the normal distribution) and the CROBEX stock indices (on the assumption that the residuals follow the Student's t distribution), the GARCH models perform well and pass the test at 99% and 99.5% confidence level, but not at 90% and 95% confidence level. Results presented in Table 13 show that the GARCH model is too conservative; i.e overestimates VaR at 99.5% confidence level in the case of the BUX, CROBEX and PX50 stock indices.

Table 13

The Kupiec Test Results for the CEE Countries

BELEX15			BUX		
	Normal distribution			Normal distribution	Student's t distribution
	EGARCH (1,1)			TGARCH (1,1)	TGARCH(1,1)
Kupiec test 90%	10.122*		Kupiectest 90%	0.947	0.524
Kupiec test 95%	28.315*		Kupiec test 95%	0.450	0.450
Kupiec test 99%	4.020		Kupiec test 99%	0	0
Kupiec test 99.5%	2.005		Kupiec test 99.5%	0.777	0.777
CROBEX			PX50		
	Normal distribution	Student's t distribution		Normal distribution	Student's t distribution
	TGARCH(1,1)	TGARCH(1,1)		TGARCH(1,1(	TGARCH(1,1)
Kupiec test 90%	14.614*	0.524	Kupiec test 90%	0.524	0.229
Kupiec test 95%	9.894*	0.108	Kupiec test 95%	0.450	0.450
Kupiec test 99%	0.618	0.618	Kupiec test 99%	0.437	0.437
Kupiec test 99.5%	0	0	Kupiec test 99.5%	2.611	0

Source: Authors' calculations.

Table 14 reports the performance of VaR for the developed countries. The VaR methodology performed poorly in the case of the DAX stock index, where the null hypotesis of the Kupiec test was rejected for all confidence levels. In the case of the NIKEI225 stock index, the GARCH models passed test at 90% and 95% confidence levels, but not at 99% and 99.5% confidence levels. The results presented in Table 14 show that the GARCH models underestimate VaR at 99% and 99.5% confidence levels for the NIKEI225 stock index.

Table 14

The Kupiec Test Results for the Developed Countries

DAX			NIKEI225		
	Normal distribution	*Student's t* distribution		Normal distribution	*Student's t* distribution
	GARCH-M (1,1)	GARCH-M(1,1)		APARCH(1,1)	APARCH(1,1)
Kupiec test 90%	6.898*	6.898*	Kupiec test 90%	0.215	0.479
Kupiec test 95%	17.031*	17.031*	Kupiec test 95%	2.296	2.296
Kupiec test 99%	27.289*	16.516*	Kupiec test 99%	16.516*	16.516*
Kupiec test 99.5%	28.465*	8.175*	Kupiec test 99.5%	19.520*	15.4258*

Source: Authors' calculations.

V. Concluding Remarks

Financial innovation and deregulation significantly change the structure of financial institutions. Accompanying the financial crisis, the importance of market risk management is getting more and more important. Market risk in selected developed and emerging economies from Central and Eastern Europe is estimated by the econometric framework. We tested the S&P500, NIKEI225, DAX, PX50, BUX, CROBEX stock indices during the pre-crisis and during the crisis period. Econometric methodology is based on a different version of GARCH specification. One-day-ahead VaR performance at 90%, 95%, 99% and 99.5% confidence levels is evaluated with realized profit and loss for the last 200 observations of the selected stock market indices.

Estimates obtained by our calculation imply that the countries considered were characterized by different levels of market risk when high confidence levels were chosen. Thus, adequate VaR estimation needs carefull modeling for each stock index return series individually. In addition, comparison of results for the pre-crisis and crisis periods show that the maximum daily losses are higher for the CEE than for the developed countries during the pre-crisis period, while during the crisis period the results are opposite.

Results of backtesting show that a GARCH-type VaR assuming a Student's t distribution of standardized returns is in most cases a superior measure of downside risk at 99% confidence level, for both sample periods. The results also indicate that VaR is a beter measure of market risk for the developed countries than the CEE countries during the pre-crisis period, while during the crisis period the results are opposite, i.e. VaR is a better measure of market risk for the emerging CEE countries than the developed economies. One of the posible reasons could be the fact that the financial crisis had deeper initial impact in the developed countries than in the emerging CEE markets.

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