MEASURING VALUE AT RISK ON EMERGING STOCK MARKETS: EMPIRICAL EVIDENCE FROM SERBIAN STOCK EXCHANGE

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Abstract. *This paper evaluates the performance of a variety of symmetric and asymmetric GARCH type models based on normal and Student t distribution in estimating and forecasting market risk in Serbian stock market. Using the daily returns of the Serbian stock index BELEX 15 we tested the relative performance of a variety of symmetric and asymmetric GARCH type models based on normal and Student t distribution for period of October 2005 to October 2012, a sufficiently long period which includes tranquil as well as crisis years. For investors, in the current global financial crisis, it is particularly important to accurately measure and allocate risk and efficiently manage their portfolio. The impact of extreme events on changes in the financial markets in emerging countries is even more pronounced, as such markets are characterized by lower levels of liquidity and significantly smaller market capitalization. The possibility of application of VaR methodology, which is basically designed and developed for liquid and developed markets, should be tested on the emerging markets, which are characterized by volatility, illiquidity and shallowness of the market. This motivates 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 assumption of normal distribution. Our empirical results indicate that the most adequate GARCH type model for estimating and forecasting volatility in the Serbian stock market is EGARCH model with assumption that the residuals follow the normal distribution and GARCH (1,1) model with assumption that the residuals follow the Student's t distribution. Our backtesting results for the last 200 observations based on the Kupiec POF test show that EGARCH model with normal distribution and GARCH(1,1) model with Student t distribution of residuals passed Kupiec test with 99% of confidence level, but not with 95% of confidence level, which imply that these models underestimate VaR at 95% confidence level.*

Key Words: *value at risk, BELEX 15 index, GARCH models, backtesting.*

INTRODUCTION

Banks, investment funds and other financial institutions often use the concept of value at risk (VaR) as a measure of market risk. Value at risk is the assessment of the maximum loss in value of portfolio over a given time horizon at a given confidence level. Based on the VaR financial institutions are able to determine the level of capital that provides cover losses and ensure the financial position of extreme market movement.

The importance of risk management, as well as estimation and prediction of market losses has significantly increased during and after global financial crisis. In the light of ongoing crisis in the Euro zone, appropriate measuring and forecasting of market losses seem to play an important role in developed and emerging financial markets. The growing interest of foreign financial investors to invest in emerging financial markets and increased fragility in these markets, highlight the importance of accurate market risk quantification and prediction (Bucevska, Bucevska, 2012).

Fundamental difference between emerging and developed markets is reflected in lower liquidity, frequent internal and external shocks as well as higher degree of insider trading which causes the market to be more volatile. Also, deviation from the normal distribution makes risk estimation more problematic and models that assume normal distribution are less reliable in emerging markets (Živković, Aktan, 2009). The application of VaR methodology, which is basically designed and developed for liquid and developed markets, is necessary to test on emerging markets that are characterized by extreme volatility, illiquidity and the shallowness of the market. Implementation of the VaR methodology in the investment process is directly related to the selection of appropriate method of estimation. In selecting the appropriate method of key importance is that it accurately determines the likelihood of losses.

Almost all researchers are unanimous that there is no single approach or a VaR model that is optimal in all markets and in all situations. In a number of papers VaR was evaluated for developed market economy, using similar methodology as we do [for instance Wong, Cheng and Wong (2002), Duffie et al., (1997), Guermat and Harris (2002), Persand and Brooks (2003), Alexander and Leigh (1997), Christoffersen, Hahn and Inoue (2001), Su and Knowles (2006), etc.]

Although there are a number of papers relating to the testing of different models of VaR and market risk management in developed and liquid markets, a number of papers relating to testing VaR models in less developed and less liquid markets are more limited [for instance Gençay et. al. (2004), Živković (2007), Anđelić, et. al. (2010), Nikolić-Đorić et. al (2011), Mladenović, Miletić and Miletić (2012)].

The purpose of this study is to test the relative performance of range of symmetric and asymmetric GARCH family models in estimating and forecasting Value-at-Risk in the Serbian stock exchange over long period which includes tranquil as well as stress years. A particular challenge is the possibility of using VaR in the financial markets of countries in transition. Given the recession business environment, the results of research will be, in particular, interesting to domestic and foreign investors. In addition, the results are relevant at the macro (social, economic, political, etc.) and at the microeconomic level (enterprise).

DEFINING THE CONCEPT OF VALUE AT RISK (VAR)

VaR is a measure that gives the maximum loss that can be realized 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:

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

where P_t is the price of a particular type of financial asset, and α represent 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:

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

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:

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

From this equation it follows that finding the VaR values is the same as finding a $100\alpha\%$ conditional quantiles. Formally, it is possible to develop models for the stock returns r_t as follows:

$$r_t = \mu_t + \varepsilon_t, \varepsilon_t = \alpha_t \eta_t, \mu_t = \mu(I_{t-1}|\theta), \sigma_t^2 = \sigma^2(I_{t-1}|\theta) \tag{5}$$

where I_{t-1} is a set of information available at time $t-1$, and where μ and σ are functions of a certain dimensional vector of parameter values θ. In this model ε_t is innovation, σ_t is the unobserved volatility, and η_t is martingale difference sequence satisfying:

$$E(\eta_t | I_{t-1}, \theta) = 0, V(\eta_t | I_{t-1}, \theta) = 1 \tag{6}$$

As a consequence, we have:

$$E(r_t | I_{t-1}, \theta) = \eta_t, V(r_t | I_{t-1}, \theta) = \sigma_t^2, \varepsilon_t | I_{t-1} \sim D(0, \sigma_t^2) \tag{7}$$

where $D(0, \sigma_t^2)$ represents the conditional distribution with zero mean value and variance σ_t^2.

If the return is modeled by a parametric distribution, VaR can be derived from the distributional parameters. Unconditioned parametric models were determined with $\mu_t = \mu$ and $\sigma_t = \sigma$. Therefore we assume that returns are independent and equally distributed with a given density function:

$$f_r(x) = \frac{1}{\sigma} f_{r^*}\left(\frac{x-\mu}{\sigma}\right) \tag{8}$$

where f_r is density function of distribution of r_t and f_{r^*} being density function of the standardized distribution of r_t.

GARCH TYPE MODELS

The GARCH type models successfully capture several characteristics of financial time series, such as thick tailed returns and volatility clustering. This type of models represents a 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:

$$y_t = a_0 + \sum_{i=1}^{m} a_i y_{t-i} + \varepsilon_t - \sum_{j=1}^{s} b_j \varepsilon_{t-j} \tag{9}$$

$$\varepsilon_t = z_t \sigma_t, \varepsilon_t | I_{t-1} \sim N(0, \sigma_i^2)$$

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

$$\alpha_0 > 0, \ \alpha_i \geq 0, \ \beta_j \geq 0, \ i = 1,...,q, \ j = 1,...,p$$

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

If $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$, for a sufficiently long horizon forecasts conditional variance of GARCH (p, q) process:

$$\sigma_t^2 = \alpha_0 (1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_j)^{-1} \tag{10}$$

is called unconditional variance of GARCH (p, q) process.

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 unity. 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 (1) has a unit root, and consequently a shock to the conditional variance is

persistent in the sense that it remains important for future forecasts of all horizons. A general IGARCH (p, q) process can be written in the following form:

$$\sigma_t^2 = \alpha_0 + A(L)\varepsilon_t^2 + B(L)\sigma_t^2, A(L) + B(L) = 1 \tag{11}$$

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

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

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{\infty} \pi_i g\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) \tag{12}$$

Asymmetric relation between returns and volatility change is given as function $g\left(\frac{\varepsilon_t}{\sigma_t}\right)$, which represent linear combination of $\dfrac{\varepsilon_t}{|\sigma_t|}$ and $\dfrac{\varepsilon_t}{\sigma_t}$:

$$g(\frac{\varepsilon_t}{\sigma_t}) = \theta\left(\left|\frac{\varepsilon_t}{\sigma_t}\right| - E\left|\frac{\varepsilon_t}{\sigma_t}\right|\right) + \gamma\left(\frac{\varepsilon_t}{\sigma_t}\right) \tag{13}$$

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 $0 < z_t < \infty$, $g(z_t)$, is linear function with slope coefficient $\theta + \gamma$, while for $-\infty < z_t \leq 0$ it is linear function with slope coefficient $\gamma - \theta$. First part of equation, $\theta(|z_t| - E | z_t|)$, captures the size effect, while second part, $\gamma(z_t)$, captures the leverage effect.

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

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i\varepsilon_{t-i}^2) + \sum_{i=1}^{q}(\gamma_i d(\varepsilon_{t-i} < 0)\varepsilon_{t-i}^2) + \sum_{j=1}^{p}(\beta_j\sigma_{t-j}^2) \tag{14}$$

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

$$d(\varepsilon_{t-i} < 0) = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0 & \varepsilon_{t-i} \geq 0 \end{cases} \tag{15}$$

TGARCH model allows 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 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.

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

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{q}\alpha_i(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^\delta + \sum_{j=1}^{p}(\beta_j\sigma_{t-j}^\delta) \tag{16}$$

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

Based on estimated parameters of GARCH type process it is possible to make forecast of $\hat{y}_t(k)$ and conditional volatility $\hat{\sigma}_t^2(k)$ for next k periods [for details see Mladenović et al. (2006)]. Forecasted value of return and the conditional volatility for the next period is obtained as follows:

$$\hat{y}_n(1) = a_0 + \sum_{i=1}^{m} a_i y_{n+1-i} + \varepsilon_t - \sum_{j=1}^{s} b_j \varepsilon_{n+1-j} \tag{17}$$

$$\hat{\sigma}_n^2(1) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{n+1-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{n+1-j}^2$$

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

$$\hat{y}_n(1) - 1.65\hat{\sigma}_n(1) \tag{18}$$

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

$$\hat{y}_n(1) - t_v \sqrt{\frac{v-2}{v}} \hat{\sigma}_n(1) \tag{19}$$

BACKTESTING

Backtesting represents a statistical procedure by which losses and gains are systematically compared to the appropriate valuation of VaR. In the backtesting process it can be statistically examined if the frequency exceptions, during the selected time interval, are in accordance with the chosen confidence level. These types of tests are known as tests of unconditional coverage. The most famous test in this group is the Kupiec test.

The Kupiec test

The Kupiec test, known as the proportions of failures test (POF), measures whether the number of exemptions is consistent with a given confidence level (Kupiec, 1995). If the null hypothesis is true, then the number of exemptions follows the binomial distribution. Therefore, to implement the POF test it is necessary to know the number of observations (n), the number of exceptions (x) and confidence level.

The null hypothesis of the POF test is:

$$H_0 : p = \hat{p} = \frac{x}{n}$$

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

$$LR_{POF} = -2\ln\left(\frac{(1-p)^{n-x}\,p^x}{\left[1-\left(\dfrac{x}{n}\right)\right]^{n-x}\left(\dfrac{x}{n}\right)^x}\right) \qquad (20)$$

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.

DATA AND DESCRIPTIVE STATISTICS

The sample of the research comprises daily returns of BELEX15 stock index. BELEX15, leading index of the Belgrade Stock Exchange, describes the movement of prices of the most liquid Serbian stocks (includes stocks of 15 companies) and is calculated in real time. The sample period covers 1790 trading days from 4. October 2005 to 30. October 2012. The data are obtained from national stock exchange website.
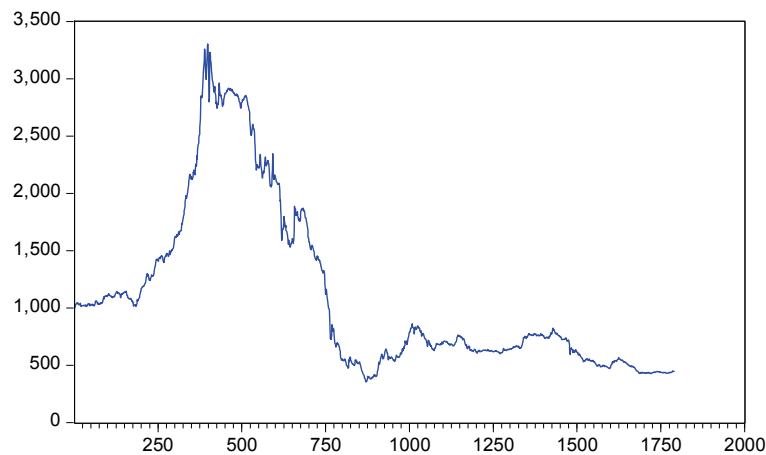

Chart 1. Daily closing values of the Serbian stock index BELEX15 in the period from 4th October 2005 to 30th October 2012

As it can be seen (see Chart 1) the period from 2005 to 2007 is characterized by significant increase in value of the index along with the entry of foreign investors in the domestic capital market. Simultaneously, local investors increasingly invested in domestic

capital market, which contributed to further growth of stocks prices on the Belgrade Stock Exchange.

In late 2007 the situation on the financial market in the world began to reflect on the capital market in Serbia, when BELEX15 index recorded a sharp decline. The trend of deterioration of the Belex 15 index continued in early 2008. The sudden decline of the index value was caused by the withdrawal of foreign portfolio investors from the market of Serbia due to expectations of further fall of stock prices and deepening of financial crisis. Belex 15 reached the highest value on 30th April 2007, when the value of the index was 3283 points. The first serious decline in the value of BELEX15 index was on 23 November 2007 when the value of the index fell to 2203 points. The downward trend of the index value continued during 2008 to the lowest value reached in March 2009, when Belex 15 worth 354 index points (Dragutinović et. al. 2009). The reason for the drastic decline in value of the index is the fact that approximately 50% of demand for stocks in the domestic market depends on foreign demand.

For BELEX15 index, 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 both cases we indicate the most prominent non-standard values and then regress 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 Chart 2). Volatility clustering is clearly visible in case of observed index.
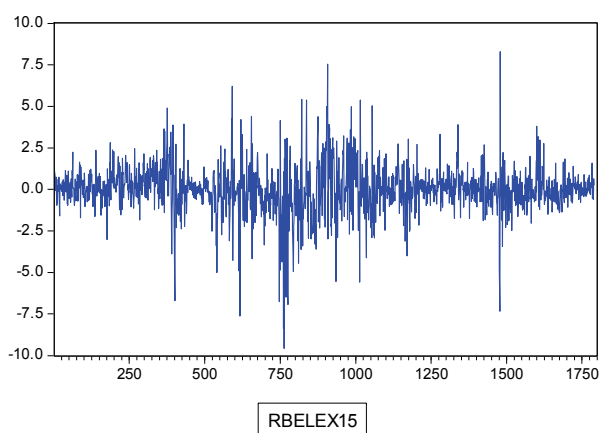

Chart 2. Stock exchange index BELEX15 daily log returns

Table 1 indicates that the daily returns of market stock index are not normally distributed. Negative skewness is evident; kurtosis is much greater than 3 and the *Jarque-Bera* statistics are highly significant. The results confirm the presence of fat tails, which suggest that the assumption of a normal distribution is not satisfied. These findings are consistent with the normal Q-Q and empirical Q-Q plot (Chart 2). Namely, the quantiles of an empirical distribution are plotted against the quantiles of a normal distribution. From the Chart 2 it is clear that QQ plot is not linear and that empirical distribution differs from the hypothesized normal distribution.

ARCH-LM test indicates presence of time varying volatility, and Box-Ljung statistics indicate evidence of autocorrelation in squared standardized residuals.

Table 1. Descriptive characteristics of BELEX15daily returns

	Skewness	Kurtosis	JB	$Q^2(10)$	$Q^2(30)$	ARCH-LM (10)	ARCH-LM (30)
BELEX15	-0.464	8.949	2704.49 (0.0)	568.00 (0.0)	895.15 (0.00)	308.87 (0.0)	348.90 (0.0)

Source: Author's calculations. Note: P values of corresponding test statistics are given in parentheses. JB represents Jarque-Bera statistics for normality testing, Q2 represents Box-Ljung statistics for testing autocorrelation in squared standardized residuals, while ARCH-LM test is test of autoregressive conditional heteroscedasticity.
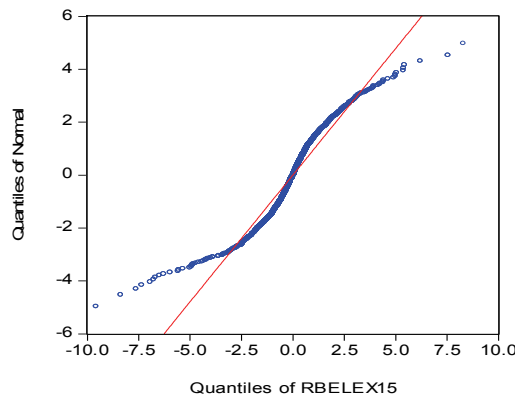

Chart 3. Q-Q plot of returns

The above obtained descriptive statistics allow to model the tails of the empirical distribution of the BELEX15 rates of return and to estimate the parameters of VaR using an econometric approach.

EMPIRICAL RESULTS

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

Estimates of parameters from different specifications of conditional heteroscedasticity models (GARCH, EGARCH, and TGARCH) together with associated tests of residual autocorrelation, normality and conditional heteroscedasticity are given in Table 2. Paremeters of APARCH model are not signiffican and results of this model are not presented in the table.

Table 2. Parameter estimates of the GARCH model for BELEX15 index daily returns

	Normal distribution			Student t distribution
	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)	GARCH (1,1)
Mean equation				
AR(1)	0.696 (0.00)	0.697 (0.00)	0.677 (0.00)	0.695 (0.00)
MA(1)	-0.479 (0.00)	-0.484 (0.00)	-0.457 (0.00)	-0.487 (0.00)
Volatility equation				
c	0.0572 (0.00)	-0.306 (0.00)	0.055 (0.00)	0.048 (0.00)
α	0.235(0.00)		0.199 (0.00)	0.216 (0.00)
β	0.755 (0.00)	0.943 (0.00)	0.760 (0.00)	0.781 (0.00)
θ		0.428 (0.00)		
γ		-0.041 (0.00)	0.063 (0.01)	
Number of degrees of freedom				
v			5	
Specification tests				
mod. AIC	0.10178248	0.096303	0.100836	0.11089776
Q2(30)	31.98 (0.275)	32.18 (0.267)	31.21 (0.030)	32.952 (0.238)
JB	375.25 (0.000)	257.67 (0.000)	313.11 (0.000)	370.434 (0.000)
ARCH (10)	14.19 (0.16)	15.04 (0.13)	15.09 (0.12)	16.426 (0.08)

Source: Author's calculations.

Based on estimated parameters by GARCH type models we make forecast of returns and volatility for one day ahead to get VaR estimates at 95% and 99% coverage of the market risk.

BELEX15 stock index returns best describes EGARCH (1,1) model with assumption that the residuals follow the normal distribution and GARCH (1,1) model with assumption that the residuals follow the Student's t distribution. In the mean equation autoregression component of the first order and component of moving average of the first order are significant. Signifficance of parameters of EGARCH model and negative value of γ point out that positive shocks generate less volatility, comparing to negative shocks.

Based on estimated results, it could be concluded that maximum daily loss for the BELEX15 index daily returns ranges from 138 to 153 euros on invested 10000 EUR at 95% confidence level. Predicted value at risk does not significantly change depending on assumed specification of conditional variance.

Table 3. Econometric estimation of the parameters of VaR for one-day-ahead for BELEX15 index daily returns

	Normal distribution	Student's t distribution
	EGARCH(1,1)	GARCH (1,1)
Forecasted return	-0.065	-0.063
Forecasted cond. volatility	0.788	0.708
VaR (1, 0.95)	1.529	1.376
VaR (1, 0.99)	2.133	2.256

Source: Author's calculations.

EGARCH model with normal distribution and GARCH(1,1) model with Student t distribution of residuals did not passed Kupiec test with 95% of confidence level (see Tabel 4). On the other hand EGARCH model with normal distribution and GARCH(1,1) model with t distribution of residuals passed Kupiec test with 99% of confidence level. It seems that EGARCH model with normal distribution and GARCH(1,1) model that suposed Student t distribution underestimate VaR at 95% confidence level.

Table 4. Backtesting results for BELEX15 index daily returns

	Normal distribution	Student's t distribution
	EGARCH(1,1)	GARCH (1,1)
Kupiec test 95%	20.517*	7.031*
Kupiec test 99%	4.020	4.020

Source: Author's calculation. Note: * denotes statistical significance of the test statistics.

CONLUDING REMARKS

This paper evaluates the performance of a variety of symetric and assimetric GARCH type models based on normal and Student t distribution in estimating and forecasting market risk in Serbian stock market. Using the daily returns of the Serbian stock index BELEX 15 we tested the relative performance of a variety of symetric and assymetric GARCH type models based on normal and Student t distribution for the period from October 2005 to October 2012, a sufficiently long period wich includes tranquil as well as crisis years. The growing interest of foreign investors to invest in CEE financial markets and the increased fragility in these markets in times of crisis highlighted the importance of adequate market risk quantification and prediction.

Descriptive statistics for BELEX 15 index showed the presence of skewness and kurtosis. Using ARCH-LM test at different lags, we detected high presence of ARCH effect in the residuals and evidence of clustering effect. The residuals obtained from diferent estimated GARCH models showed no presence of ARCH effect using ARCH-LM test. Standardized residuals and standardized residual squared were found to be white noise.

Results of estimation by GARCH (p,q) model, and by different type of asymmetric GARCH(p,q) model indicate that EGARCH (1,1) model with assumption that the residuals follow the normal distribution and GARCH (1,1) model with assumption that the residuals follow the Student's t distribution provides the most accurate volatility estimation of BELEX15 index. Models have appropriate statistical characteristics in terms of autocorrelation and eliminating ARCH effects. Finally, the *Jarque–Bera* statistic suggests that skewness and kurtosis in the standardized residuals are reduced but not completely eliminated.

Results of backtesting show that EGARCH model with normal distribution and GARCH (1,1) model with Student t distribution of residuals did not passed Kupiec test with 95% of confidence level. On the other hand EGARCH model with normal distribution and GARCH (1,1) model with Student t distribution of residuals passed Kupiec test with 99% of confidence level.

The research results may have important implications for investors and risk managers who operate in the turbulent markets of developing countries. However, the main limitation of this study is that empirical research referred to only Serbian capital market so that its results cannot be generalized to other emerging markets.

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MERENJE VREDNOSTI PRI RIZIKU KOD TRŽIŠTA U USPONU: EMPIRIJSKA ANALIZA TRŽIŠTA KAPITALA U SRBIJI

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Osnovni cilj ovoga rada jeste istraživanje performansi različitih specifikacija simetričnih i asimetričnih GARCH modela uz pretpostavku normalne i Studentove t distribucije u cilju procene i predviđanja tržišnog rizika na tržištu kapitala u Srbiji. Koristeći dnevne stope prinosa srpskog indeksa akcija BELEX15 testirali smo različite asimetrične i simetrične GARCH modele uz pretpostavku normalne i Studentove t distribucije za period oktobar 2005-octobar 2012 što predstavlja značajan vremenski period koji sadrži periode pre i tokom finansijske krize.

U uslovima globalne finansijske krize za investitore je naročito važno da što preciznije izmere i alociraju rizik i efikasnije upravljaju svojim portfolijom. Uticaj ekstremnih događaja na kretanja na finansijskim tržištima zemalja u razvoju je još izraženiji, budući da je reč o tržištima koje karakteriše niži stepen likvidnosti i znatno manja tržišna kapitalizacija. Mogućnost primene VaR metodologije, koja je u osnovi kreirana i razvijena za likvidna i razvijena tržišta, potrebno je testirati na tržištima u razvoju koja karakterišu volatilnost, nelikvidnost i plitkost tržišta. To nas je motivisalo da primenimo metode koje uključuju vremensku promenljivu volatilnost i teže repove empirijske distribucije prinosa. Testirali smo hipotezu da li je moguće tačnije predvideti tržišni rizik, posebno u vremenima krize, korišćenjem pretpostavke o težim repovima distribucije nego pod pretpostavkom normalne distribucije. Empirijski rezultati ukazuju da model EGARCH uz pretpostavku da reziduali prate normalnu distribuciju i model GARCH (1,1) uz pretpostaku Studentove t distribucije imaju najbolje statističke karakteristike. Naši backtesting rezultati za poslednjih 200 opservacija prinosa zasnovani na Kupiec-ovom POF testu pokazuju da EGARCH model uz pretpostavku da reziduali slede normalnu distribuciju i GARCH tipa uz pretpostavku Student-ove t distribucije daju dobre procene vrednosti VaR-a uz interval poverenja od 99%, dok za 95% navedeni modeli nisu prošli Kupiec-ov test, što ukazuje da potcenjuju stavrne gubitke.

Ključne reči: *vrednost pri riziku, BELEX 15 index, GARCH modeli, backtesting.*