

An Empirical Evaluation of GARCH Models in Value-at-Risk Estimation: Evidence from the Macedonian Stock Exchange



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Abstract

Background: In light of the latest global financial crisis and the ongoing sovereign debt crisis, accurate measuring of market losses has become a very current issue. One of the most popular risk measures is Value-at-Risk (VaR). **Objectives:** Our paper has two main purposes. The first is to test the relative performance of selected GARCH-type models in terms of their ability of delivering volatility estimates. The second one is to contribute to extend the very scarce empirical research on VaR estimation in emerging financial markets. **Methods/Approach:** Using the daily returns of the Macedonian stock exchange index-MBI 10, we have tested the performance of the symmetric GARCH (1,1) and the GARCH-M model as well as of the asymmetric EGARCH (1,1) model, the GARCH-GJR model and the APARCH (1,1) model with different residual distributions. **Results:** The most adequate GARCH family models for estimating volatility in the Macedonian stock market are the asymmetric EGARCH model with Student's t-distribution, the EGARCH model with normal distribution and the GARCH-GJR model. **Conclusion:** The econometric estimation of VaR is related to the chosen GARCH model. The obtained findings bear important implications regarding VaR estimation in turbulent times that have to be addressed by investors in emerging capital markets.

Keywords: Value-at-Risk, GARCH models, forecasting volatility, financial crisis, Macedonia

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Introduction

The impetus for Value-at-Risk (VaR), the most well-known financial risk measurement, came from failures of financial institutions and the responses of regulators to these failures. Following the increase in financial instability in the beginning of the 70's years as a result of the advent of derivative markets and floating exchange rates, several methods of risk measurement have been developed. However, VaR is the most popular one.

Value-at-Risk (VaR) is defined as the worst loss over a target horizon with a given level of confidence (Jorion, 2007). The first regulatory measures that evoke Value-at-Risk, were initiated in the 80s, when the Securities Exchange Commission (SEC) tied the capital requirements of financial service firms to the losses that would be incurred, with 95% confidence over a thirty-day interval, in different security classes. In parallel with that, the trading portfolios of financial institutions were becoming larger and more volatile, creating a need for more sophisticated and timely risk measurement. By the early 90s, many banks have developed different rudimentary measures of Value-at-Risk. As a consequence of the big financial disasters that occurred between 1993 and 1995, there was a growing need for a response to those market losses by banks and other financial institutions, central bankers and academics in terms of building accurate models for measuring market risk. The popularity of VaR and the debate over the validity of the underlying statistical assumptions increased since

1994, when JP Morgan made available to its Risk Metrics methodology through the Internet. The free accessibility of the Risk Metrics triggered academics and practitioners to find the best-performing market risk quantification method.

The importance of risk measurement and estimation and prediction of market losses has significantly increased during the 2007-08 global financial crisis. It is not a long time since the world financial system is recovering from its latest and severest financial crisis that we are again dealing with a new one - the Europe's sovereign-debt crisis. In the light of the ongoing crisis in the Euro zone, accurate measuring and forecasting of market losses seems to play a crucial role both in developed and emerging financial markets.

Unlike the financial markets of developed countries, the emerging financial markets are characterized with insufficient liquidity, the small scale of trading and asymmetrical and low number of trading days with certain securities (Andjelić, Djaković and Radišić, 2010). The emerging stock markets as relatively young markets are not sufficiently developed to identify all information which affects the stock prices and therefore, does not respond quickly to the publicly disclosed information (Benaković and Posedel, 2010). In their study of 16 emerging markets in Europe, Latin America and Asia Dimitrakopoulos, Kavussanos and Spyrou (2010) point out that average daily returns are not significantly different from zero for the emerging markets. Their return volatilities are twice the volatilities of developed markets (Dimitrakopoulos et al., 2010). Furthermore, return series exhibit significant positive or negative skewness coefficients (Dimitrakopoulos et al., 2010). Emerging market's kurtosis values are on average higher than those of developed markets suggesting fatter tailed distributions (Dimitrakopoulos et al., 2010). Batten and Szilagyi (2011) point out that emerging stock market volatility is characterized by a complex dynamics, mainly during crises and turbulent periods. The above-described differences between the developed and emerging financial markets, the growing interest of foreign financial investors to invest in emerging financial markets and the increased financial fragility in these markets, highlight the importance of accurate market risk quantification and prediction.

The purpose of this paper is to test the relative performance of a range of symmetric and asymmetric GARCH family models in estimating and forecasting Value-at-Risk in the Macedonian stock exchange over a long sample period which includes tranquil as well as stress years.

As an EU candidate country with a high potential for stock market growth, Macedonia is an interesting destination for foreign financial investors, who, due to the distinctions between developed and emerging financial markets and the turbulent market environment, need to test the possibility to apply GARCH models in VaR estimation and forecasting in the Macedonian stock market.

Our empirical results indicate that the most adequate GARCH family models for estimating and forecasting volatility in the Macedonian stock market are the asymmetric EGARCH model with Student's *t*-distribution, the EGARCH model with normal distribution and the GARCH-GJR model which are robust with regard to the estimation.

The rest upon the paper is organized as follows. In Section 2 we give a brief literature review. In Section 3 we describe the symmetric and asymmetric GARCH family models used throughout our study. Section 4 presents the data used and the results of the preliminary analysis. In Section 5 we present our empirical results and in Section 6 we discuss the obtained results and draw conclusions.

Literature review

VaR models were created and tested in the developed financial markets for measuring market risks.

Despite the extensive literature and empirical research of estimation of VaR models in the major developed financial markets, literature dealing with VaR calculation in emerging financial market is very scarce (Hagerud, 1997; Gokcan, 2000; Brooks and Persaud, 2000; Magnusson and Andonov, 2002; Da Silva, Beatriz and de Melo Mendes, 2003; Parrondo, 1997; Valentinyi-Enrdesz, 2004; Bao, Lee and Saltoglu, 2006; Zikovic and Bezic, 2006; McMillan and Speght, 2007; Kovacic, 2007; Zikovic and Aktan, 2009; Zikovic and Filler, 2009; Andjelic et al., 2010). The main reason for that was the short historical time-series data (most of the stock markets in these countries were established in the early nineties) which did not allow performing a reliable econometric analysis.

The situation is even worse as far as the Macedonian stock exchange is concerned. Namely, there is only one empirical study (Kovacic, 2007), to the best of our knowledge, which applies the same methodology as in our paper to estimate and forecast the volatility in the Macedonian stock exchange. However, one of the shortcomings of this study is the short time series return data, which does not allow precise estimation of VaR.

Another limitation of the existing empirical studies on VaR estimation and forecasting in emerging stock market is that only a few of them have tried to consider the effect of a financial crisis on Value-at Risk (VaR) estimation. Namely, Zikovic and Aktan (2009) investigate the relative performance of a wide array of VaR models with the daily returns of Turkish (XU100) and Croatian (Crobex) stock index prior to and during the global 2008 financial crisis. Zikovic and Filler (2009) test the relative performance of VAR and ES models using daily returns for sixteen stock market indices (eight from developed and eight from emerging markets) prior to and during the 2008 financial crisis. However, the main limitation of their studies is the fact that they have tested the relative performances of VaR models at the very beginning of the global financial crisis. Due to the short sample period, their results should be taken with caution and future research with the inclusion of a longer period is needed in order to obtain estimates with greater precision.

Our paper tries to extend the limited empirical research on VaR estimation and forecasting in emerging financial markets and to overcome the above stated limitations of the previous empirical studies by testing the relative performance of a number of symmetric and asymmetric GARCH family models in the estimation of the Macedonian stock exchange volatility.

The theoretical contribution of our study is that it is the first study, to the best of our knowledge, on VaR estimation and forecasting in the Macedonian stock market over a long sample period (from the 4th January 2005 to the 31st October 2011), which includes stable as well as turbulent years (the years of the latest global financial crisis and the ongoing Europe's sovereign-debt crisis).

Methodology

Symmetric GARCH models

Accurate volatility estimates are essential for producing robust VaR estimates. In this context, different methods were developed to estimate volatility. The traditional methods of measuring volatility (variance or standard deviation) are unconditional and cannot capture the characteristics of financial time-series data, such as, changing volatility, clustering, asymmetry, leverage effect and long memory properties (Angelidis and Degiannakis, 2005). One of the most accepted models that captures the above patterns of volatility has proven to be the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. In this paper, we are focusing upon the use of selected GARCH models to estimate and forecast daily VaR of the Macedonian stock exchange in turbulent times.

With model volatility of financial time series, Engle (1982) introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model. The general form of the ARCH (q) model is as follows:

$$\sigma_t^2 = \alpha + \sum_{i=1}^q \beta_i \varepsilon_{t-i}^2 \quad (1)$$

where σ_t^2 is the conditional variance, and ε_t is the error term. For the conditional variance to be positive, the parameters α and β should be greater than zero since standard deviation and variance must be nonnegative and β should be less than one in order for the process to be stationary (Angabini and Wasiuzzaman, 2011). In the ARCH (q) model today's expected volatility depends on the squared forecast errors of the previous days (Balaban, 2002).

In many applications of the ARCH model the required length of the lag, q might be very large (Bollerslev, Chou and Kroner, 1992). In order to overcome this limitation to the ARCH model, Bollerslev, et al. (1992) extended the ARCH model to have a more flexible lag

structure and a longer memory by adding a lagged conditional variance for the model as well. The model that they proposed was called Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev et al., 1992).

The GARCH (p, q) model permits a more persistent volatility which is typical for most stock data (Angabini and Wasiuzzaman, 2011). This model allows the conditional variance to be dependent on its previous lagged values. The general form of the GARCH (p, q) model is given by:

$$R_t = \mu + \varepsilon_t$$

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

where p is the order of GARCH and q is the order of ARCH process, R_t are returns of the financial time series (stock exchange index) at time t in natural log (logs), μ are mean value of the returns; ε_t is the error term at time t which is assumed to be normally distributed with zero mean and conditional variance σ_t^2 , and $\mu, \omega, \alpha_i, \beta_j$ are parameters. All parameters in variance equation must be positive. We expect the value of ω to be small. Parameter α_i is the measure of volatility response to movements in the market and parameter β_j expresses how persistent shocks are that were caused by extreme values of conditional variance. We expect the sum of $\alpha + \beta < 1$.

Thanks to the high degree of persistence typically found when estimating GARCH model, this model can account for the characteristics of financial time-series data (fat tails, volatility clusters of returns, etc.). It expresses the conditional variance as a linear function of past information allowing the conditional heteroskedasticity of returns (Curto, Pinto and Tavares, 2009).

According to Brooks (2008), the lag order (1,1) model is sufficient to capture all the volatility clustering in the data. In most empirical applications (French, Schwert and Stambaugh, 1987; Pagan and Schwert, 1990; Franses and Van Dijk, 1996 and Gokcan, 2000), the basic GARCH (1,1) model fits the changing conditional variance of the majority of financial time series reasonably well. The first notation of (1,1) shows ARCH effect and the second one moving average.

The GARCH (1,1) model is given by the following equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

To guarantee a positive variance at all instances, it is imposed that $\omega > 0$ and that $\alpha, \beta \geq 0$.

Engle, Lilien and Robins (1987) extended the GARCH model to GARCH-in-Mean (GARCH-M) model which allows the conditional mean to be a function of conditional variance. The GARCH-M model is given by:

$$R_t = \mu + \beta_2 \sigma_t^2 + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \sigma_t^2) \quad (4)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-i}^2 + \beta_1 \sigma_{t-1}^2$$

In order to ensure that the conditional variance, σ_t^2 is positive, we must impose the non-negativity constraint on the coefficients in the above equation. In GARCH-M (1,1) as the sum of the coefficients approaches unity, the persistence of shocks to volatility is greater. However, volatility could have a significant impact on the stock returns only if these shocks

are permanent over a longer period of time. The GARCH-M model also implies that there are serial correlations between return series (Hien, 2008).

Asymmetric GARCH models

The above-described GARCH-type models consider negative and positive error terms to have symmetric effects on volatility, i.e. that negative and positive shocks have the same effect on volatility. However, there is a large literature documenting that the sign of the shock does matter (Black, 1976; Christie, 1982; French et al., 1987; Schwert, 1990; Nelson, 1991; Campbell and Hentschel, 1992; Cheung and Ng, 1993; Glosten, Jagannathan and Runkle, 1993; Bae and Karolyi, 1994; Braun, Nelson and Sunier, 1995; Duffee, 1995; Bekaert and Harvey, 1997; Ng, 2000; Bekaert and Guojun, 2000, etc.). A general finding across these studies is that negative returns tend to be followed by periods of greater volatility than positive returns of equal size. In other words, bad news tends to increase volatility more than good news (Angabini and Wasiuzzaman, 2011). An explanation for the asymmetric response of return volatility to the sign of the shock is that positive and negative shocks lead to different values of a firm's financial leverage (its debt-to-equity ratio), which in turn will result in different volatilities (Black, 1976). The term leverage stems from the empirical observation that the conditional variance of stock returns often increases when returns are negative, i.e. when the financial leverage of the firm increases. In order to capture the asymmetry in return volatility ("leverage effect"), a new class of models was developed, termed the asymmetric ARCH models. Among the most widely spread asymmetric ARCH, models are the Exponential GARCH (EGARCH), GJR and the Asymmetric Power ARCH (APARCH) model.

One of the earliest and most popular asymmetric ARCH models is the EGARCH model that was proposed by Nelson (1991). The EGARCH (p,q) model is given by

$$\log \sigma_t^2 = \omega + \sum_{i=1}^q \beta_i \log \sigma_{t-i}^2 + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \quad (5)$$

The conditional variance in the above Nelson's EGARCH model is in the logarithmic form which ensures its non-negativity without the need to impose additional non-negativity constraints. The term $\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$ in the above equation represents the asymmetric effect of shocks.

A negative shock leads to higher conditional variance in the following period which is not the case with a positive shock (Poon and Granger, 2003).

A special variation of the EGARCH (p,q) model is the EGARCH (1,1) model, which is given by:

$$\log \sigma_t^2 = \omega + \beta_1 \log \sigma_{t-1}^2 + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (6)$$

For a positive shock $\frac{\varepsilon_{t-1}}{\sigma_{t-1}} > 0$, the above equation becomes

$$\log \sigma_t^2 = \omega + \beta_1 \log \sigma_{t-1}^2 + (\alpha + \gamma) \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (7)$$

whereas for a negative shock $\frac{\varepsilon_{t-1}}{\sigma_{t-1}} < 0$, the above equation becomes

$$\log \sigma_t^2 = \omega + \beta_1 \log \sigma_{t-1}^2 + (\alpha - \gamma) \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (8)$$

The exponential nature of the EGARCH model guarantees that the conditional variance is always positive even if the coefficients are negative (Angabini and Wasiuzzaman, 2011). By

testing the hypothesis that $\gamma = 0$, we can determine if there is a leverage effect. If $\gamma \neq 0$, the impact is asymmetric. By inclusion of the parameter β in the EGARCH (1,1) model, the persistence of volatility shocks is captured.

The EGARCH model has a number of advantages over the GARCH (p,q) model. The most important one is its logarithmic specification, which allows for relaxation of the positive constraints among the parameters. Another advantage of the EGARCH model is that it incorporates the asymmetries in stock return volatilities. The parameters α and γ capture two important asymmetries in conditional variances. If $\gamma < 0$ negative shocks increase the volatility more than positive shocks of the same magnitude. Due to the parameter α expected to be positive, large shocks of any sign will comparable larger impact compared to small shocks. Another advantage of the EGARCH model is that it successfully captures the persistence of volatility shocks. Based on these advantages, we apply the EGARCH model for estimating the volatility of the Macedonian stock market.

GARCH-GJR model is another type of asymmetric GARCH models, which was proposed by Glosten, Jagannathan and Runkle (1993). Its generalized version is given by:

$$\sigma_t^\delta = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2 \quad (9)$$

where α, β and γ are constant parameters, and I is a dummy variable (indicator function) that takes the value zero (respectively one) when ε_{t-i} is positive (negative). If γ is positive, negative errors are leveraged (negative innovations or bad news has a greater impact than the positive ones). We assume that the parameters of the model are positive and that $\alpha + \beta + \gamma/2 < 1$.

Ding, Engle and Granger (1993) introduced the asymmetric power ARCH model called APARCH (p,q). The variance equation of APARCH (p,q) can be written as

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

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

This model changes the second order of the error term into a more flexible varying exponent with an asymmetric coefficient which allows for the leverage effect.

In our paper we estimate conditional volatility using the probability distributions that are available in the GARCH package: the normal and the Student t -distribution. Engle (1982), who introduced the ARCH model, assumed that asset returns follow a normal distribution. However, it is usually referred in the literature that asset returns distribution are not normally distributed, so that the normality assumption could cause significant bias in VaR estimation and could underestimate the volatility (Mandelbrot, 1963). A number of authors (Vilasuso, 2002; Brooks and Persaud, 2000) evidenced that standard GARCH models with normal empirical distributions have inferior forecasting performance compared to models that reflect skewness and kurtosis in innovations. To capture the excess kurtosis of financial asset returns, Bollerslev (1987) introduced the GARCH model with a standardized Student's t distribution with $\nu > 2$ degrees of freedom.

After describing the properties of selected GARCH family models, we turn now to the question how we can estimate GARCH models when the only variable on which there are available data is the data on asset returns. The common methodology used for GARCH estimation is maximum likelihood assuming i.i.d. innovations.

The parameters of the GARCH model can be found by maximizing the objective log-likelihood function:

$$\ln L(\theta) = -\frac{1}{2} \sum_{t=1}^n [\ln(2\pi) + \ln(\sigma_t^2(\theta)) + z_t^2(\theta)] \quad (11)$$

where θ is the vector of parameters $(\mu, \omega, \alpha_i, \beta_j)$ estimated that maximize the objective function $\ln L(\theta)$; z_t represents the standardized residual calculated as $\frac{\Delta y_t - \mu}{\sqrt{\sigma_t^2}}$. The other

symbols have the same meaning as above described.

Maximum likelihood estimates of the parameters can be obtained via nonlinear least squares using Marquardt's algorithm. Engle (2001) suggests an even simpler answer to use software such as EViews, SAS, GAUSS, TSP, Matlab, RATS and others. In our paper we estimate the GARCH family models using the econometric computer package EViews 6.

Data and descriptive statistics

In this paper we examine the relative performance of selected symmetric GARCH models, such as, the GARCH (1,1) model with normal and Student's t -distribution and the GARCH-M model and the asymmetric GARCH models, such as, the EGARCH (1,1) with normal and Student's t -distribution and the APARCH (1,1), model with regard to evaluation and forecasting VaR in the Macedonian stock exchange under crisis times. For emerging economies, such as Macedonia, a significant problem for a serious and statistically significant analysis is the short histories of their market economies and active trading in financial markets (Andjelic et al., 2010). Because of the short time series of individual stock returns, Andjelic et al. (2010) suggest analyzing the stock indices of these countries. The stock indices represent a portfolio of selected stocks from an individual stock market. Thus data used in this paper are the daily return series of the Macedonian stock index -MBI 10. MBI 10 is a price index weighted by market capitalization and consists of up to 10 listed ordinary shares, chosen by the Macedonian Stock Exchange Index Commission. The index was introduced with a base level of 1.000 on the 30th December 2004.

The data for our study are collected from the official website of the Macedonian stock exchange <http://www.mse.org.mk>. VaR figures are calculated for a one-day ahead horizon with 95% and 99% confidence levels (coverage of the market risk). The data span the period from the 4th of January 2005 to the 31st October 2011 and comprise 1638 observations. The

daily stock return is calculated as $r_t = \log\left(\frac{x_t}{x_{t-1}}\right) \times 100$

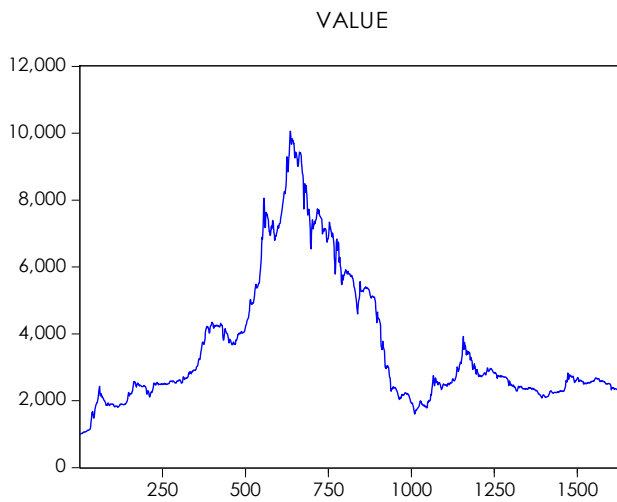
where x_t is the daily closing value of the stock market on day t . In this paper we use the daily closing values of the Macedonian stock market.

The daily closing values of the Macedonian stock index MBI-10 and its returns are displayed in Figure 1 and Figure 2, respectively.

As it can be seen from Figure 1 the closing values of MBI-10 show a random walk. From Figure 2 it is evident that the daily returns are stationary.

Figure 1

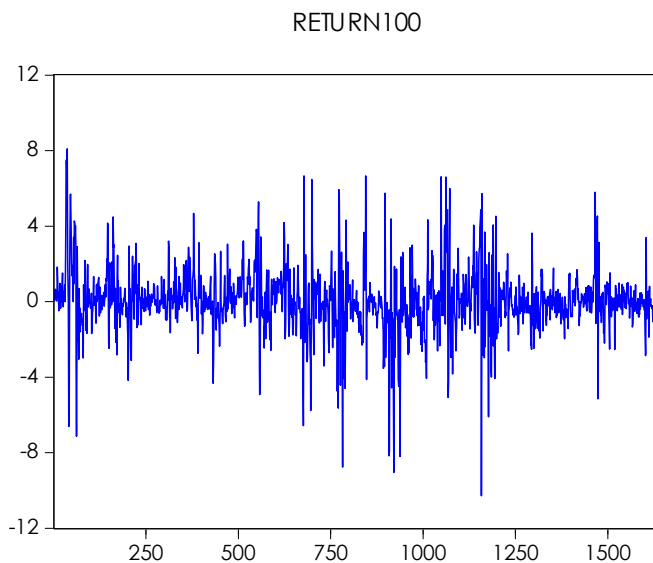
Daily Closing Values of the Macedonian Stock Index MBI-10 in the Period from the 4th January 2005 to the 31st October 2011



Source: The Official Web Site of the Macedonian Stock Exchange <http://www.mse.org.mk>

Figure 2

Daily Stock Returns of the Macedonian Stock Index MBI-10 in the Period from the 4th January 2005 to the 31st October 2011



Source: The Official Web Site of the Macedonian Stock Exchange <http://www.mse.org.mk>

The return data is tested for autocorrelation both in log returns as well as in squared log returns (see Table 1 and Table 2). We test the presence of autocorrelation in log returns using the ACF, PACF and the mean adjusted Ljung-Box Q-statistics, and autocorrelation in squared log returns is tested by ACF, PACF, Ljung-Box Q-statistic and Engle's ARCH test (Zikovic, 2007). If we detect the presence of autocorrelation in log returns, we can remove it by fitting the simplest plausible ARMA (p, q) model to the data. On the other hand, if autocorrelation is detected in the squared log returns, heteroskedasticity from the series could be removed by fitting the simplest plausible GARCH model to the ARMA filtered data (Zikovic, 2007).

Table 1

Correlogram of Daily Stock Returns of the Macedonian Stock Index MBI-10 in the Period from the 4th January 2005 to the 31st October 2011

Lag	AC	PAC	Q-Stat	Prob
1	0.463	0.463	351.060	0.000
2	0.097	-0.148	366.630	0.000
3	0.021	0.050	367.370	0.000
4	0.005	-0.016	367.410	0.000
5	-0.006	-0.004	367.470	0.000
6	0.043	0.064	370.500	0.000
7	0.029	-0.028	371.910	0.000
8	0.038	0.047	374.270	0.000
9	0.080	0.058	384.730	0.000
10	0.091	0.033	398.430	0.000
11	0.104	0.066	416.300	0.000
12	0.127	0.066	442.960	0.000
13	0.088	0.003	455.830	0.000
14	0.035	-0.001	457.890	0.000
15	0.037	0.031	460.170	0.000
16	0.070	0.051	468.310	0.000
17	0.059	0.002	474.120	0.000
18	0.027	-0.013	475.300	0.000
19	0.045	0.044	478.710	0.000
20	0.020	-0.037	479.400	0.000
21	0.032	0.035	481.100	0.000
22	0.085	0.055	493.220	0.000
23	0.052	-0.039	497.720	0.000
24	-0.009	-0.031	497.850	0.000
25	0.025	0.042	498.850	0.000
26	0.042	0.004	501.860	0.000
27	0.030	-0.001	503.350	0.000
28	0.018	-0.019	503.880	0.000
29	0.025	0.018	504.920	0.000
30	0.029	0.012	506.280	0.000

Source: Author's Calculations

The Ljung and Box Q statistics on the 1st, 10th and 20th lags of the sample autocorrelations functions of the return series indicate significant serial correlation. ARCH effect is present in all time series in accordance with the Ljung-Box Q statistics of the stock indices' squared returns on the 30th lags and Engle's ARCH test on the 10th lags.

The empirical distribution of the daily return rates deviates from the normal distribution. Namely, the Macedonian stock market returns display significant negative skewness as well as large kurtosis, suggesting that the return distribution is a fat-tailed one. Skewness and kurtosis values satisfy the Jarque-Bera tests for normality which is rejected. The Q-Q plot, which displays the quantiles of return data series against the quantiles of the normal distribution (see Figure 3), shows that there is a low degree of fit of the empirical distribution to the normal one.

Table 2

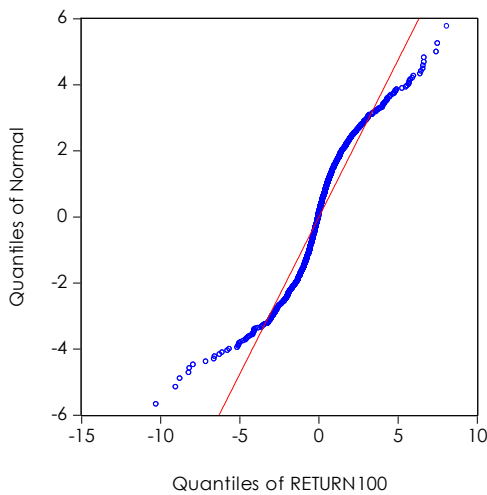
Correlogram of Squared Daily Stock Returns of the Macedonian Stock index MBI-10 in the Period from the 4th January 2005 to the 31st October 2011

Lag	AC	PAC	Q-Stat	Prob
1	0.330	0.330	178.970	0.000
2	0.254	0.162	284.550	0.000
3	0.201	0.089	350.740	0.000
4	0.207	0.105	421.220	0.000
5	0.123	-0.005	446.230	0.000
6	0.172	0.091	495.050	0.000
7	0.125	0.016	520.680	0.000
8	0.092	-0.008	534.560	0.000
9	0.097	0.030	550.120	0.000
10	0.141	0.072	583.050	0.000
11	0.083	-0.010	594.320	0.000
12	0.173	0.117	643.600	0.000
13	0.149	0.041	680.110	0.000
14	0.059	-0.070	685.780	0.000
15	0.033	-0.035	687.570	0.000
16	0.065	0.006	694.620	0.000
17	0.115	0.084	716.640	0.000
18	0.043	-0.040	719.760	0.000
19	0.072	0.017	728.300	0.000
20	0.055	0.005	733.410	0.000
21	0.071	0.030	741.800	0.000
22	0.037	-0.029	744.090	0.000
23	0.074	0.025	753.230	0.000
24	0.064	0.018	760.150	0.000
25	0.058	-0.005	765.670	0.000
26	0.032	-0.012	767.380	0.000
27	0.039	0.005	769.870	0.000
28	0.023	0.003	770.730	0.000
29	0.049	-0.000	774.710	0.000
30	0.020	-0.023	775.350	0.000

Source: Author's Calculations

Figure 3

Q-Q Plot of Daily Stock Returns of the Macedonian Stock index MBI-10 in the Period from the 4th January 2005 to the 31st October 2011



Source: Author's Calculations

The summary of the descriptive statistics for the daily logarithmic stock index returns of the MBI-10 is presented in Table 3.

Table 3

Summary Descriptive Statistics for the Daily Returns of the Macedonian Stock Index MBI-10 for the Period 04.01.2005-31.10.2011

Descriptive statistics	
Mean	0.0477
Median	0.0000
Maximum	8.0897
Minimum	-10.2831
Std. Dev.	1.6698
Skewness	-0.1425
Kurtosis	8.6211
Normality tests	
Jarque-Berra statistic	2160.6960
p-value	0.0000
Lilliefors	0.1058
p-value	0.0000
ARCH tests	
Q ² (10)	398.4300
Q ² (30)	506.2800
Unit root tests	
ADF	-24.3180
P-P	-23.8274

Source: Author's Calculations

Empirical results

Since there are ARCH effects in the stock return data, we can proceed with estimation of GARCH models.

We estimate the following symmetric GARCH models: the GARCH (1,1) model with normal and Student's *t*-distribution and the GARCH-M model as well as the following asymmetric GARCH models: the EGARCH (1,1) model with normal and Student's *t*-distribution, the GARCH-GJR model and the APARCH model.

The parameters of the estimated models and the residual tests of autocorrelation, normality and conditional heteroskedasticity are given in Table 4.

Once we estimated the symmetric and asymmetric GARCH models, we conduct the ARCH-LM test proposed by Engle (1982) in order to detect if there are any ARCH effects in the residuals left and to prove that the above estimated GARCH-type models successfully capture the persistence of volatility shocks. Table 4 exhibits the p-values of LM test and the standardized squared residuals. To test whether our GARCH family models were correctly specified, we perform diagnostic checks. The results of these checks for all tested models show that the Q-statistics for the standardized squared residuals are insignificant with high p-values, which supports the conclusion that the above specified GARCH models adequately capture the serial correlation in conditional means and variances.

We have to note that there are no ARMA components in the estimated models. The parameters are estimated using BHHH algorithm (Berndt, et al., 1974).

According to the results of the sign and size bias test proposed by Engle and Ng "(Engle and Ng, 1993)", there is a strong evidence of asymmetric effects, which makes the use of asymmetric GARCH models justified (see Table 5 and Table 6).

Table 4

Estimated GARCH Models for the Daily Returns of the Macedonian Stock Index MBI-10

	GARCH normal distribution	GARCH t-distribution	EGARCH normal distribution	EGARCH t-distribution	GARCH-GJR	APARCH	GARCH-M
α_0	0.0877	0.1490	-0.3494	-0.4546	0.0879	0.0864	0.0882
α_1	0.3416	0.6160	0.5313	0.7069	0.3165	0.3497	0.3436
β_1	0.6781	0.4964	0.9264	0.8947	0.6762	0.6595	0.6764
γ			-0.0263	-0.0253	0.0579		
ω						0.0388	
δ						2.2846	
Skewness	-0.0888	-0.3798	-0.0984	-0.3259	-0.0568	-0.0569	-0.0831
Kurtosis	6.3992	9.0423	6.6122	7.9355	6.3753	6.3002	6.4114
Jarque-Bera	789.7841	2528.1160	892.0988	1689.4490	777.4950	743.3075	795.2002
ARCH (10)	13.5711	9.1340	11.5987	8.4399	12.7535	12.3460	12.9104
prob	0.1935	0.5194	0.3128	0.5859	0.2378	0.2626	0.2287
Q ² (30)	26.3290	17.7080	26.2320	25.2430	25.9550	25.3650	25.4930
prob	0.6580	0.9630	0.6630	0.7130	0.6770	0.7070	0.7010

Source: Author's Calculations

Table 5

Engle and Ng Joint Test for Sign and Size Bias

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.0285	0.2772	7.3168	0.0000
S	-0.0278	0.3825	-0.0726	0.9421
S*RESIDUALS(-1)	-1.2926	0.1624	-7.9576	0.0000
S ² *RESIDUALS(-1)	1.6506	0.1611	10.2447	0.0000
R ²	0.0940	Mean dependent var		2.7908
Adjusted R ²	0.0923	S.D. dependent var		7.6962
S.E. of regression	7.3324	Akaike info criterion		6.8249
Sum squared resid	87688.1600	Schwarz criterion		6.8381
Log likelihood	-5575.3670	Hannan-Quinn criter.		6.8298
F-statistic	56.3969	Durbin-Watson stat		1.6922
Prob(F-statistic)	0.0000			

Source: Author's Calculations

To capture the dynamic process of data generating and the presence of the "leverage effect" in the MBI-10 index, we use the nonlinear asymmetric models EGARCH and GJR-GARCH model. The coefficient γ in the case of GJR-GARCH is statistically significant at level of significance of 7% implying that there is an asymmetry. On the other hand, its positive value indicates presence of the "leverage effect". The coefficient γ in the EGARCH model is significantly different from zero, which indicates presence of asymmetry. The value of γ which is less than zero, implies presence of the "leverage effect".

We have forecasted future return rate and volatility for one-day-ahead based on the estimated parameters of the models. These forecasted values are necessary for the estimation of VaR. The estimated values of the VaR parameters at risk for one-day-ahead as well as the probabilities of 95% and 99% are exhibited in Table 7.

Table 6
Engle and Ng Joint Test Statistic

Wald Test:			
Equation: EQENGLENGJOINT			
Test Statistic	Value	df	Probability
F-statistic	56.3969	(3, 1631)	0.0000
Chi-square	169.1908	3	0.0000
Null Hypothesis Summary:			
Normalized Restriction (= 0)	Value	Std. Err.	
C(2)	-0.0278	0.3825	
C(3)	-1.2926	0.1624	
C(4)	1.6506	0.1611	
Restrictions are linear in coefficients.			

Source: Author's Calculations

Table 7
Econometric Estimation of the Parameters of VaR for One-Day-Ahead Period

Model	GARCH normal distribution	GARCH <i>t</i> -distribution	EGARCH normal distribution	EGARCH <i>t</i> -distribution	GARCH-GJR	APARCH	GARCH-M
Forecasted return	0.0215	0.0013	0.0166	-0.0115	0.0107	0.0098	0.0721
Forecasted conditional variance	1.4342	1.2740	0.9720	0.8959	1.4166	1.1982	1.4027
VaR 0.95	-1.9545%	-1.8611%	-1.6102%	-1.5733%	-1.9532%	-1.7963%	-1.8821%
Var 0.99	-3.0683%	-2.9109%	-2.5271%	-2.4535%	-3.0601%	-2.8143%	-2.9835%

Source: Author's Calculations

Please note that the estimated VaR values obtained with the GARCH approach are negative. The negative sign is usually ignored since we assume that we are talking about indicator of loss.

With probability of 95% we can expect that the maximum loss due to having stocks in amount of MKD 10,000 in the Macedonian stock exchange is around MKD 195 in a one day period.

Discussion and conclusion

This paper tests the relative performance of a range of symmetric and asymmetric GARCH family models based on two residual distributions (normal and Student's *t*-distribution) in terms of their ability of estimating VaR in the Macedonian stock market.

Using the daily returns of the Macedonian stock index-MBI 10 we have tested the relative performance of the GARCH (1,1) model with normal and Student's *t*-distribution, the GARCH-M model, the EGARCH (1,1) with normal and Student's *t*-distribution and the APARCH (1,1) model in the period from the 4th January 2005 to the 31st October 2011, a sufficiently long period which includes tranquil as well as crisis years.

Descriptive statistics for the MBI-10 show presence of skewness and kurtosis. The results of the conducted ARCH-LM test point out significant presence of ARCH effect in the residuals as well as volatility clustering effect. Standardized residuals and standardized residuals squared were white noise.

We have shown that the econometric estimation of VaR can be related to the chosen GARCH model. Therefore a first step in estimation of the parameters of VaR is a detailed specification analysis of the potential models.

The empirical results have indicated that the most adequate GARCH models for estimating and forecasting VaR in the Macedonian stock market are the EGARCH model with Student's

t -distribution, the EGARCH model with normal distribution and the GARCH-GJR model which are robust with regard to estimation.

The findings reported in this paper bear very important implications regarding VaR estimation in turbulent times, market timing, portfolio selection etc. that have to be addressed by investors and other risk managers operating in emerging capital markets.

However, the main limitation of our study is that in our empirical research we have focused solely on the Macedonian stock exchange and therefore the obtained findings can not be generalized to other emerging financial markets. In the future research we will attempt to overcome this limitation by using a wider sample of emerging markets - the EU candidate and potential candidate countries which are attractive destinations for foreign investors.

Another issue for future research agenda is the inclusion of other asymmetric GARCH-type models and testing and comparing their predictive performance.

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