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Testing popular VaR models in EU new member and candidate states[*1]

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Abstract

The impact of allowing banks to calculate their capital requirement based on their internal VaR models, and the impact of regulation changes on banks in transitional countries has not been well studied. This paper examines whether VaR models that are created and suited for developed markets apply to the volatile stock markets of EU new member and candidate states (Bulgaria, Romania, Croatia and Turkey). Nine popular VaR models are tested on five stock indexes from EU new member and candidate states. Backtesting results show that VaR models commonly used in developed stock markets are not well suited for measuring market risk in these markets. Presented findings bear very important implications that have to be addressed by regulators and risk practitioners operating in EU new member and candidate states. Risk managers have to start thinking outside the frames set by their parent companies or else investors present in these markets may find themselves in serious trouble, dealing with losses that they have not been expecting. National regulators have to take into consideration that simplistic VaR models that are widely used in some developed countries are not well suited for these illiquid and developing stock markets.

Key words*: EU new member and candidate states, stock indexes, risk management, market risk, GARCH*

JEL classification*: C22, C53, G15, G18, G20*

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1. Introduction

Banks in EU new member and candidate states, as well as in the rest of Europe, are increasingly investing in marketable securities. This is done either indirectly through founding and management of pension and investment funds, or directly through banks' balance sheets. At the same time companies operating in transitional countries, are starting to discover a tempting alternative to standard banking loans - issuing debt securities (commercial papers and bonds) and shares (ordinary and preferential). Especially attractive are initial public offerings (IPOs) of large state owned companies, where there is no direct, visible cost, such as with debt securities (except for the cost of IPO) but as a result dilute control of the company, making them easier acquisition targets. The newly discovered possibilities of trading securities in these countries and potential high profits are tempting for all investors, from households to banks and pension funds. Most of the investors investing in these high-growth markets bear significant risks of which they are unaware. Not understanding and underestimating the risks associated with investing in capital markets is easy to understand when it comes to smaller investors, but such behaviour from institutional investors is deeply troubling. Allowing banks, and pension funds to invest in transitional equity markets is in itself risky, but allowing them to do so while using faulty measuring instruments is equal to driving blindfolded. Gambling with the soundness of a country's financial system is not an option any responsible state can accept, especially in countries that have only begun to catch up with the rest of Europe and are thus more vulnerable to any sort of financial crises. Since it would be very unpractical and almost impossible to forbid banks and pension funds from investing in equities, it is necessary to set up adequate risk measurement and management mechanisms. The dangers and challenges have always been here, but with the adoption of Basel Committee's standards, they have become clearly visible. The impact of allowing banks to calculate their capital requirement for market risk based on their internal Value at Risk (VaR) models, as well as the impact of regulation changes on banks in less developed countries, has not been well studied. In the EU not even all the members of the EU-15 countries have systematically conducted research on the consequences and impact of these changes on their banking sector. EU new member and candidate states are even further behind these issues. The group of EU new member and candidate states is comprised of the following countries: Bulgaria, Romania, Croatia and Turkey. Bulgaria and Romania became full EU members in January 2007. Croatia is expected to become a full EU member in 2009, which is not the case with Turkey, which still has a long journey ahead of it. Although, very different and unique in their own way, when looking through a financial prism, these countries are similar in certain aspects. EU new member and candidate states are all significantly lagging behind the most developed EU countries in many fields but especially in matters of: financial legislation, market discipline, insider trading, disclosure of information (financial and other), embezzlement, knowledge of financial instruments, markets and associated risks. Banks and investment funds when investing in these equity markets employ the same risk measurement models for measuring market risk and forming of provision as they do in the developed markets. This means that risk managers presume equal or similar characteristics and behaviour in these markets, as they would expect in developed markets. Using VaR models that are created and suited for developed and liquid markets, in developing markets raises serious concerns whether VaR models developed and tested in these equity markets apply equally to the volatile and shallow markets of EU new member and candidate states. This paper therefore attempts to provide an answer to the question whether commonly used VaR models adequately capture market risk in EU new member and candidate states' equity markets. Employing VaR models in the format of bank's provisions that are not suited to developing markets can have serious consequences, resulting in big losses in banks' portfolio that could be undetected by the employed risk measurement models, leaving the banks unprepared for such events. Banks could also be penalized by regulators, via higher scaling factor when forming their market risk provisions, due to the use of a faulty risk measurement model.

To test the applicability of popular VaR models in these transitional markets, simple parametric methods, historical simulation, time weighted historical simulation, RiskMetrics and parametric approach using GARCH forecasts are used to estimate VaR for official stock indexes from each of the EU new member and candidate states over a period of 500 trading days. In a next step, the performance of the various models is compared over the simulation period with the help of a range of backtesting procedures to determine how accurately the models match the specified confidence intervals. The paper is structured as follows: Section 2 gives an overview of the most significant, recent empirical research in the area of VaR models and their use in transitional economies. Section 3 briefly outlines the VaR approaches on which the calculations in this paper are based. Section 4 provides a brief description of the analysed data. Section 5 presents and explains the results. Finally, section 6 contains a number of concluding remarks.

2. Literature review

After gaining the deserved place in developed economies, risk measurement and management is also gaining importance in transitional economies. The capital market is witness to turbulent changes effecting simultaneously commodity prices, interest rates and stock prices. Although disagreeing in many things, all researchers are united in the opinion that there does not exist a single approach, or a single VaR model that is optimal in all the markets and all situations. According to published research, VaR models based on moving average volatility models seem to perform the worst. Otherwise, there is no straightforward result, and it is impossible to establish a ranking among the models. The results are very sensitive to the type of loss functions used, the chosen probability level of VaR, the period being turbulent or normal etc. Some researchers also find a trade-off between model sophistication and uncertainty. A famous study by Berkowitz, O'Brien (2002) examines the VaR models used by six leading US financial institutions. Their results indicate that these models are in some cases highly inaccurate: banks sometimes experienced high losses much larger than their models predicted, which suggests that these models are poor at dealing with fat tails and extreme events. Their results also indicate that banks' models have difficulty dealing with changes in volatility. In addition, a comparison of banks' models with a simple univariate parametric GARCH model indicates that the latter gives roughly comparable coverage of high losses, but also tends to produce lower VaR figures and is much better at dealing with volatility changes. These results suggest that the banks' structural models embody so many approximations and other implementation compromises that they lose any edge over much simpler models such as GARCH. Their findings could also be interpreted as a suggestion that banks would be better off ditching their structural risk models in favour of GARCH models. Similar findings are also reported by Lucas (2000) who finds that sophisticated risk models based on estimates of complete variance-covariance matrices fail to perform much better than simpler univariate VaR models that require only volatility estimates. Lehar, Scheicher, Schittenkopf (2002) find that more complex volatility models (GARCH and Stochastic volatility) are unable to improve on constant volatility models for VaR forecast, although they do for option pricing. Wong, Cheng, Wong (2002) conclude that while GARCH models are often superior in forecasting volatility, they consistently fail the Basel backtest. Several papers investigate the issue of trade-off in model choice; for example Caporin (2003) finds that the EWMA compared to GARCH-based VaR forecast provides the best efficiency at a lower level of complexity. Bams, Wielhouwer (2000) draw similar conclusions, although sophisticated tail modelling results in better VaR estimates but with more uncertainty. Supposing that the data-generating process is close to be integrated, the use of the more general GARCH model introduces estimation error, which might result in the superiority of EWMA. Guermat, Harris (2002) show that EWMA-based VaR forecasts are excessively volatile and unnecessarily high, when returns do not have conditionally normal distribution but fat tail. This is because EWMA puts too much weight on extremes. According to Brooks and Persand (2003), the relative performance of different models depends on the loss function used. However, GARCH models provide reasonably accurate VaR. Christoffersen, Hahn, Inoue (2001) show that different models (EWMA, GARCH, Implied Volatility) might be optimal for different probability levels. Harmantzis, Miao, Chien (2006) praise the EVT approach for dealing with extreme returns, which are characteristic for transitional market. Marinelli C., d'Addona S., Rachev S. T. (2006) find that EVT approach, although quite appealing for its theoretical justification in terms of the theorems of Gnedenko and Balkema and de Haan, and because it applies to a large class of returns distributions, presents some potentially difficult issues when applied in practice. For instance, using the POT approach it is necessary to subjectively choose a specific threshold. Their empirical analysis does not uniquely identify the best approach to calculating VaR. However, it definitely provides evidence that α–stable laws outperform the so-called block maxima method of EVT approach. Their empirical results conflict with a similar analysis presented in Harmantzis, Miao, Chien (2006).

Although there is an abundance of research papers dealing with VaR and market risk measurement and management, all of the existing VaR models are developed and tested in mature, developed and liquid markets (see Manganelli, Engle, 2001 and Alexander, 2001). Testing VaR models in other, less developed or developing stock markets is at best scarce (e.g. Parrondo, 1997, Santoso, 2000, Sinha, Chamu, 2000, Fallon, Sabogal, 2004, Valentinyi-Endrész, 2004, Žiković, 2006a, 2006b, Žiković, Bezić, 2006). Žiković, Bezić (2006) investigated the performance of historical simulation VaR models on stock indexes of the EU candidate states. CROBEX (Croatia), SOFIX (Bulgaria), BBETINRM (Romania) and XU100 (Turkey) indexes all show a clear positive trend in a longer time period. With the exception of XU100 index all of other analysed indexes exhibit asymmetry, leptokurtosis and based on performed tests of normality. It can be said with great certainty that these returns are not normally distributed. Employed tests show significant autocorrelation and ARCH effects in the squared returns of all the analysed indexes. These phenomena violate the normality assumption, as well as the IID assumption that is a necessary requirement for the proper implementation of historical simulation. Results point to the conclusion that even though historical simulation provided correct unconditional coverage for tested indexes at most of the confidence levels, use of historical simulation (especially based on shorter observation periods) is not recommendable in these markets. Generally speaking, VaR literature is extremely scarce with research papers dealing with quantitative VaR model comparison or volatility forecasting in the stock markets of EU transitional countries.

3. Tested VaR models and methodology

The VaR approach is attractive to practitioners and regulators because it is easy to understand and it provides an estimate of the amount of capital that is needed to support a certain level of risk. Another advantage of this measure is the ability to incorporate the effects of portfolio diversification. Many banks and other financial institutions now base their assessment of financial risk and risk management practices on VaR or plan to do so in the future. VaR reduces the risk associated with any portfolio to just one number, the expected loss associated with a given probability over a defined holding period. VaR for a given probability *C* can be expressed as:

$$VaR_c = F^{-1}(C) \qquad (1)$$

where $F^{-1}(C)$ denotes the inverse of the cumulative probability distribution of the changes in the market value of a portfolio. Thus, losses greater than the estimated VaR should only occur with the probability *1-C*, i.e. the "tail events", should on average, occur *C*N* times in every *N* trading days.

The variance-covariance approach assumes that the risk factors that determine the value of the portfolio are multivariate normally distributed, which implies that changes in the value of a portfolio are normally distributed. Since the normal distribution is fully described by its first two moments, the VaR of a portfolio is essentially a multiple of the standard deviation. VaR under the variance-covariance approach is given by:

$$VaR = -\alpha\sqrt{w'\Sigma w} \qquad (2)$$

where w is a vector of absolute portfolio weights, w' is its transpose, Σ denotes a variance-covariance matrix and α is a scaling factor. The variances and covariances are usually estimated from daily historical time series of the returns of the relevant risk factors using equally weighted moving averages:

$$\sigma^2_{ij,T} = \sum_{t=T-n}^{T-1} \frac{r_{i,t} r_{j,t}}{n} \qquad (3)$$

where the mean is often assumed to be zero, $\sigma^2_{ij,T}$ is variance (or covariance) at time T, ri,t and rj,t are returns and n is the number of observations, i.e. the window length, used to calculate the variances and covariances. Another frequently used estimator is the exponentially weighted moving average (EWMA), which is used in RiskMetrics methodology. In contrast to equally weighted moving averages, the exponentially weighted moving average weights current observations more than past observations in calculating conditional variances (covariances). The EWMA estimator in its recursive form is given by:

$$\sigma^2_{ij,t} = \lambda\sigma^2_{ij,t-1} + (1-\lambda) r_{i,t-1} r_{j,t-1} \qquad (4)$$

Parameter λ determines the exponentially declining weighting scheme of the observations. One difference between the two estimators is that the equally weighted moving average does not account for time-dependent variances, whereas the exponentially weighted moving average does. A more sophisticated parametric estimator is an ARMA-GARCH process:

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$
$$\varepsilon_t = \eta_t \sqrt{\sigma_t^2} \qquad (5)$$
$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

where $\eta_t \sim IID\ N(0,1)$

In a GARCH model ε_t denotes a real-valued discrete-time stochastic process whose conditional distribution is assumed to follow a specific probability distribution (Gaussian, Student's T, etc.). The sizes of the parameters α and β determine the short-run dynamics of the resulting volatility time series. Large GARCH lag coefficients β indicate that shocks to conditional variance take a long time to die out, so volatility is persistent. Large GARCH error coefficients α mean that volatility reacts intensely to market movements, meaning that if alpha is relatively high and beta is relatively low, volatilities tend to be spiky.

The second approach used in this paper is historical simulation. In contrast to parametric methods, no specific distributional assumptions about the individual market risk factors, i.e. returns, are made, and no variances or covariances have to be estimated. Instead, it is only assumed that the distribution of the relevant market returns is constant over the sample period. Historical simulation VaR can be expressed as:

$$HS - VaR_{T+1|T}^{C} \equiv r_w((T+1)C) \qquad (6)$$

where $r_w(T+1)C)$ is taken from the set of ordered returns $\{r_w(1), r_w(2),..., r_w(T)\}$. The BRW approach developed by Boudoukh, Richardson and Whitelaw (1998), combines RiskMetrics and historical simulation methodologies, by applying exponentially declining weights to past returns of the portfolio. Each of the most recent N returns of the portfolio, r_t, rt_{-1}, ..., r_{t-N+1}, is associated a weight, $\frac{1-\lambda}{1-\lambda^N}, \left(\frac{1-\lambda}{1-\lambda^N}\right)\lambda, ..., \left(\frac{1-\lambda}{1-\lambda^N}\right)\lambda^{N-1}$ assigned, VaR is calculated based on the empirical cumulative distribution function of returns with the modified probability weights. The basic historical simulation method can be considered as a special case of the more general BRW method in which the decay factor (λ) is set equal to 1. To better understand the assumptions behind the BRW approach and its connection to historical simulation, BRW quantile estimator can be expressed as:

$$\hat{q}_{t+1,C} = \sum_{j=t-N+1}^{t} r_j I\left(\sum_{i=1}^{N} f_i(\lambda;N) I(r_{t+1-i} \leq r_j) = C\right) \qquad (7)$$

where $f_i(\lambda; N)$ are the weights associated with return r_i and $I(\bullet)$ is the indicator function. If $f_i(\lambda; N) = 1/N$ BRW quantile estimator equals the historical simulation estimator. Boudoukh, Richardson and Whitelaw in their paper set λ equal to 0.97 and 0.99, the same coefficients are used in this paper.

4. Analysed data set

For transitional economies such as those of EU new member and candidate states a significant problem of a serious and statistically significant analysis is a short history of market economy and active trading in the stock markets. Because of the short time series of returns of individual stocks and their highly variable liquidity, it is practical to analyse the stock indexes of these countries. Stock index can be viewed as a portfolio of selected securities from an individual country. In this paper, the performance of selected VaR models is tested on stock indexes from Croatia: Zagreb stock exchange (CROBEX) and Varazdin stock exchange (VIN), Bulgaria (SOFIX), Romania (BBETINRM) and Turkey (XU100). To answer which VaR models adequately capture the market risk in the stock markets of the EU new member and candidate states, nine VaR models are tested on the stock indexes. The tested VaR models are: historical simulation with rolling windows of 50, 100, 250 and 500 days, parametric variance-covariance approach, BRW historical simulation, RiskMetrics system and variance-covariance approach using GARCH forecasts. VaR models are calculated for a one-day holding period at 95% and 99% coverage of the market risk. To secure the same out-of-the-sample VaR backtesting period for all of the tested indexes, the out-of-the-sample data sets are formed by taking out 500 of the latest observations from each index. The rest of the observations are used as presample observations needed for VaR starting values and volatility model calibration.

When employing the ARMA-GARCH VCV model, the goal is to capture the dynamic of the data generating process of the return series so that the standardised innovations are independently and identically distributed (IID). Presumption of IID in standardised innovations is tested by ACF, PACF and Ljung-Box Q-statistic. If the tests do not discover autocorrelation in the standardized innovations employed the ARMA model can be considered as adequate. Squared standardised innovations are tested for autocorrelation and ARCH effects also through ACF, PACF and Ljung-Box Q-statistic. The most parsimonious GARCH model based on Akaike and Schwartz information criterion that passes the tests of autocorrelation and ARCH effects in the squared standardized innovations is chosen to describe the volatility dynamics of the return series. Validity of the analysed VaR models in EU new member and candidate states is tested by Kupiec test, Christoffersen independence test, Blanco-Ihle test, Lopez test, RMSE and MAPE measures.

5. Backtesting results

Based on the ACF, PACF and Ljung-Box Q statistics of the returns and squared returns of analysed stock indexes from EU new member and candidate states, given in tables 1 - 5, the presence of autocorrelation and heteroskedasticity in the data is obvious.

Table 1: ACF, PACF and Ljung-Box Q test for mean adjusted returns and squared returns for CROBEX index in the period 24.10.2000 - 2.1.2007.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.050	-0.050	3.7330	0.053
		2	-0.013	-0.016	3.9878	0.136
		3	-0.012	-0.013	4.1928	0.241
		4	0.050	0.048	7.8910	0.096
		5	-0.038	-0.033	10.009	0.075
		6	-0.003	-0.005	10.019	0.124
		7	0.002	0.001	10.023	0.187
		8	0.010	0.007	10.174	0.253
		9	0.020	0.025	10.799	0.290
		10	0.001	0.003	10.801	0.373
		11	-0.032	-0.032	12.377	0.336
		12	-0.022	-0.026	13.109	0.361
		13	0.009	0.005	13.237	0.430
		14	0.019	0.020	13.779	0.466
		15	0.024	0.029	14.630	0.478
		16	-0.011	-0.008	14.825	0.537
		17	0.028	0.025	16.011	0.523
		18	-0.011	-0.010	16.192	0.579
		19	0.047	0.046	19.466	0.427
		20	0.002	0.012	19.472	0.491

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.317	0.317	150.06	0.000
		2	0.193	0.103	205.75	0.000
		3	0.185	0.110	257.00	0.000
		4	0.065	-0.039	263.40	0.000
		5	-0.001	-0.050	263.40	0.000
		6	-0.008	-0.017	263.50	0.000
		7	0.023	0.040	264.27	0.000
		8	0.003	0.001	264.28	0.000
		9	0.022	0.024	265.01	0.000
		10	0.009	-0.014	265.13	0.000
		11	-0.009	-0.019	265.26	0.000
		12	-0.010	-0.009	265.42	0.000
		13	0.008	0.021	265.52	0.000
		14	-0.004	-0.004	265.54	0.000
		15	0.035	0.044	267.40	0.000
		16	0.021	-0.005	268.07	0.000
		17	-0.007	-0.025	268.14	0.000
		18	0.006	0.001	268.19	0.000
		19	0.002	0.001	268.20	0.000
		20	-0.013	-0.008	268.47	0.000

Source: Author's calculations

Table 2: ACF, PACF and Ljung-Box Q test for mean adjusted returns and squared returns for VIN index in the period 24.10.2000 - 1.1.2007.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.159	0.159	37.888	0.000
		2	-0.038	-0.065	40.073	0.000
		3	0.032	0.050	41.576	0.000
		4	0.076	0.061	50.190	0.000
		5	0.012	-0.007	50.412	0.000
		6	0.063	0.071	56.439	0.000
		7	0.050	0.024	60.172	0.000
		8	0.006	-0.004	60.229	0.000
		9	0.045	0.047	63.296	0.000
		10	0.068	0.044	70.325	0.000
		11	0.025	0.007	71.289	0.000
		12	0.008	0.004	71.389	0.000
		13	0.005	-0.009	71.422	0.000
		14	-0.001	-0.009	71.424	0.000
		15	-0.006	-0.012	71.487	0.000
		16	0.012	0.005	71.725	0.000
		17	-0.036	-0.047	73.740	0.000
		18	0.017	0.031	74.168	0.000
		19	0.012	-0.004	74.389	0.000
		20	0.011	0.010	74.576	0.000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.031	0.031	1.4092	0.235
		2	0.182	0.181	51.196	0.000
		3	0.001	-0.009	51.198	0.000
		4	0.005	-0.029	51.231	0.000
		5	-0.002	0.000	51.237	0.000
		6	-0.004	0.000	51.263	0.000
		7	-0.004	-0.004	51.293	0.000
		8	0.008	0.010	51.396	0.000
		9	0.006	0.007	51.444	0.000
		10	0.001	-0.003	51.446	0.000
		11	0.001	-0.001	51.447	0.000
		12	-0.003	-0.002	51.458	0.000
		13	0.013	0.014	51.732	0.000
		14	0.046	0.048	54.965	0.000
		15	0.013	0.006	55.233	0.000
		16	0.026	0.009	56.277	0.000
		17	0.018	0.014	56.754	0.000
		18	0.010	0.004	56.906	0.000
		19	-0.003	-0.009	56.917	0.000
		20	-0.005	-0.006	56.950	0.000

Source: Author's calculations

Table 3: ACF, PACF and Ljung-Box Q test for mean adjusted returns and squared returns for BBETINRM index in the period 24.10.2000 - 3.1.2007.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.112	0.112	18.917	0.000
		2	-0.020	-0.033	19.495	0.000
		3	-0.013	-0.007	19.752	0.000
		4	-0.026	-0.024	20.743	0.000
		5	0.002	0.007	20.749	0.001
		6	0.048	0.046	24.232	0.000
		7	0.063	0.053	30.211	0.000
		8	-0.003	-0.014	30.222	0.000
		9	0.017	0.023	30.659	0.000
		10	-0.020	-0.022	31.277	0.001
		11	0.019	0.028	31.830	0.001
		12	0.019	0.011	32.387	0.001
		13	0.018	0.012	32.883	0.002
		14	0.040	0.035	35.304	0.001
		15	0.006	-0.000	35.367	0.002
		16	-0.032	-0.031	36.904	0.002
		17	0.014	0.024	37.188	0.003
		18	-0.057	-0.067	42.135	0.001
		19	0.021	0.035	42.792	0.001
		20	0.054	0.039	47.289	0.001

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.133	0.133	26.781	0.000
		2	0.072	0.055	34.518	0.000
		3	0.039	0.023	36.836	0.000
		4	0.026	0.014	37.845	0.000
		5	0.032	0.024	39.400	0.000
		6	0.053	0.044	43.639	0.000
		7	0.082	0.068	53.867	0.000
		8	0.014	-0.012	54.170	0.000
		9	0.010	-0.002	54.335	0.000
		10	0.013	0.007	54.605	0.000
		11	0.027	0.021	55.746	0.000
		12	0.023	0.011	56.527	0.000
		13	0.017	0.003	56.948	0.000
		14	0.043	0.033	59.819	0.000
		15	0.022	0.010	60.567	0.000
		16	0.040	0.031	63.055	0.000
		17	0.093	0.079	76.190	0.000
		18	0.034	0.004	77.947	0.000
		19	0.017	-0.003	78.398	0.000
		20	0.008	-0.005	78.506	0.000

Source: Author’s calculations

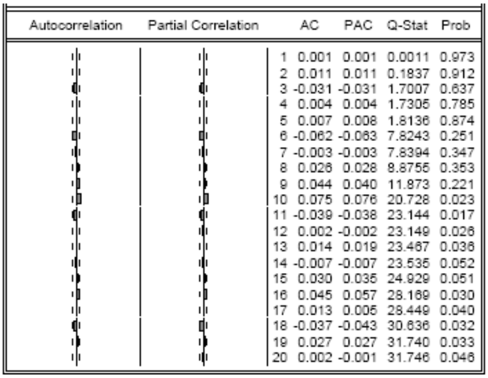
Table 4: ACF, PACF and Ljung-Box Q test for mean adjusted returns and squared returns for SOFIX index in the period 24.10.2000 - 1.1.2007.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.094	-0.094	13.529	0.000
		2	0.061	0.052	19.149	0.000
		3	-0.066	-0.056	25.795	0.000
		4	0.016	0.003	26.210	0.000
		5	0.004	0.012	26.233	0.000
		6	0.030	0.028	27.649	0.000
		7	-0.071	-0.067	35.431	0.000
		8	0.063	0.051	41.601	0.000
		9	-0.066	-0.047	48.185	0.000
		10	0.035	0.012	50.041	0.000
		11	-0.069	-0.055	57.445	0.000
		12	0.049	0.032	61.142	0.000
		13	0.038	0.057	63.415	0.000
		14	-0.008	-0.017	63.519	0.000
		15	-0.002	0.005	63.527	0.000
		16	0.057	0.057	68.614	0.000
		17	-0.043	-0.028	71.524	0.000
		18	0.030	0.004	72.950	0.000
		19	-0.013	0.011	73.230	0.000
		20	-0.013	-0.024	73.482	0.000

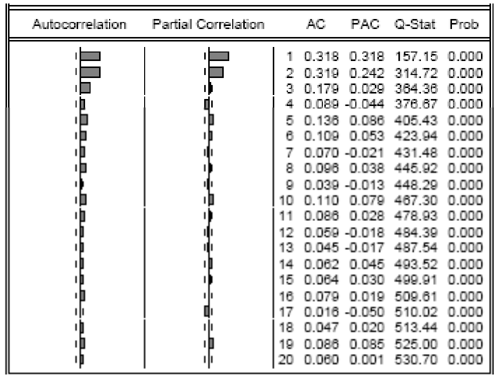
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.255	0.255	98.816	0.000
		2	0.025	-0.043	99.766	0.000
		3	0.016	0.022	100.17	0.000
		4	-0.003	-0.012	100.18	0.000
		5	0.018	0.023	100.67	0.000
		6	0.019	0.009	101.25	0.000
		7	0.085	0.084	112.42	0.000
		8	0.068	0.026	119.57	0.000
		9	0.009	-0.015	119.69	0.000
		10	-0.004	-0.003	119.71	0.000
		11	0.137	0.150	148.50	0.000
		12	0.232	0.173	230.89	0.000
		13	0.059	-0.044	236.21	0.000
		14	0.046	0.040	239.43	0.000
		15	0.028	0.002	240.63	0.000
		16	0.055	0.060	245.36	0.000
		17	0.001	-0.032	245.36	0.000
		18	0.025	0.020	246.34	0.000
		19	0.002	-0.059	246.35	0.000
		20	0.006	0.004	246.40	0.000

Source: Author’s calculations

Table 5: ACF, PACF and Ljung-Box Q test for mean adjusted returns and squared returns for XU100 index in the period 24.10.2000 - 4.1.2007.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0011	0.973
		2	0.011	0.011	0.1837	0.912
		3	-0.031	-0.031	1.7007	0.637
		4	0.004	0.004	1.7305	0.785
		5	0.007	0.008	1.8136	0.874
		6	-0.062	-0.063	7.8243	0.251
		7	-0.003	-0.003	7.8394	0.347
		8	0.026	0.028	8.8755	0.353
		9	0.044	0.040	11.873	0.221
		10	0.075	0.076	20.728	0.023
		11	-0.039	-0.038	23.144	0.017
		12	0.002	-0.002	23.149	0.026
		13	0.014	0.019	23.467	0.036
		14	-0.007	-0.007	23.535	0.052
		15	0.030	0.035	24.929	0.051
		16	0.045	0.057	28.169	0.030
		17	0.013	0.005	28.449	0.040
		18	-0.037	-0.043	30.636	0.032
		19	0.027	0.027	31.740	0.033
		20	0.002	-0.001	31.746	0.046



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.318	0.318	157.15	0.000
		2	0.319	0.242	314.72	0.000
		3	0.179	0.029	364.36	0.000
		4	0.089	-0.044	376.67	0.000
		5	0.136	0.086	405.43	0.000
		6	0.109	0.053	423.94	0.000
		7	0.070	-0.021	431.48	0.000
		8	0.096	0.038	445.92	0.000
		9	0.039	-0.013	448.29	0.000
		10	0.110	0.079	467.30	0.000
		11	0.086	0.028	478.93	0.000
		12	0.059	-0.018	484.39	0.000
		13	0.045	-0.017	487.54	0.000
		14	0.062	0.045	493.52	0.000
		15	0.064	0.030	499.91	0.000
		16	0.079	0.019	509.61	0.000
		17	0.016	-0.050	510.02	0.000
		18	0.047	0.020	513.44	0.000
		19	0.086	0.085	525.00	0.000
		20	0.060	0.001	530.70	0.000

Source: Author's calculations

It is clear that all of the analysed indexes exhibit heteroskedasticity, with VIN, BBETINRM and SOFIX indexes also exhibiting autocorrelation in the returns. This finding is troubling for VaR models based on normality assumption, as well as for the nonparametric and semi-parametric approaches that are based on the IID assumption, such as the historical simulation and BRW approach. This is very indicative for risk managers, because elementary assumptions of many VaR models are not satisfied, meaning that VaR figures obtained for such models cannot be completely trusted.

Transformation of original return data to obtain independently and identically distributed observations is performed by fitting an ARMA-GARCH model. ARMA-GARCH model successfully captured the dynamics of stock indexes from EU new member and candidate states and produced standardised innovations that proved to be independently and identically distributed. In modelling conditional volatility basic GARCH (1,1) model was sufficient for all stock index. Estimated ARMA-GARCH parameters for stock indexes of EU new member and candidate states are presented in Table 6.

Table 6: ARMA-GARCH parameters for stock indexes from EU new member and candidate states

	Mean			Volatility		
	C	AR	MA	K	GARCH	ARCH
CROBEX	0			1.06E-05	0.8323	0.11082
VIN	0	0.145		1.25E-05	0.78932	0.1405
BBETINRM	0.00141	0.13760		7.59E-06	0.79299	0.17092
SOFIX	0.0004	0.75972	-0.62566	3.40E-06	0.84515	0.14139
XU100	0.00183			0	0.88758	0.070264

Source: Author's calculations

As can be seen from Table 6, some of the tested indexes like VIN and BBETINRM show unusually low persistence in volatility but are very reactive to volatility, which will make VaR forecasts based on GARCH volatility spiky. Majority of stock indexes is not even closely integrated as is presumed by EWMA volatility modelling that is underlying the RiskMetrics model. The estimated GARCH parameters of stock indexes from EU new member and candidate states point to the conclusion that VaR models based on simpler conditional volatility models, such as MA or EWMA underestimate the true level of risk. Backtesting results and diagnostics of 500 VaR forecasts for analysed stock indexes, at 95% and 99% confidence level, are presented in tables 10-14, in the appendix.

Kupiec test and Christoffersen independence test are usually used to identifying VaR models that are acceptable to the regulators, and provide the desired level of safety to individual banks and, due to contagion effect, to the entire banking sector. The results of the overall acceptance, according to Kupiec and Christoffersen independence test, of tested VaR models at 95% and 99% confidence levels and 10% significance level are presented in Tables 7 and 8.

Table 7: Number of VaR model failures according to Kupiec and Christoffersen independence test, tested on five EU new member and candidate states' stock indexes, 500 observations, at 95% confidence level

Model	HS 50	HS 100	HS 250	HS 500	BRW λ=0.97	BRW λ=0.99	Normal VCV	Risk Metrics	GARCH VCV
Kupiec test	4	2	2	3	0	0	1	0	0
Christoffersen IND test	4	1	0	2	0	0	1	1	3

Source: Author's calculations

Table 8: Number of VaR model failures according to Kupiec and Christoffersen independence test, tested on five EU new member and candidate states' stock indexes, 500 observations, at 99% confidence level

Model	HS 50	HS 100	HS 250	HS 500	BRW λ=0.97	BRW λ=0.99	Normal VCV	Risk Metrics	GARCH VCV
Kupiec test	5	4	3	1	3	2	4	4	2
Christoffersen IND test	5	4	0	1	3	0	1	3	1

Source: Author's calculations

From the data in Table 7, it is clear that at 95% confidence level, tested VaR models perform very differently with a majority of VaR models failing Kupiec test and Christoffersen independence test for at least one stock index. VaR models that passed the Kupiec test across all the analysed stock indexes are the GARCH VCV model, RiskMetrics system and both BRW models with λ = 0.97 and 0.99. The worst performer according to Kupiec test, out of the tested VaR model is the HS 50 model, which failed the Kupiec test for four out of five stock indexes. HS 50 model is followed by HS 500 with three failures. According to Christoffersen independence test the best performers are the HS 500 and both BRW models with λ = 0.97 and 0.99. The worst performers are HS 50 and HS 100 models. Overall, the best performers according to Kupiec and Christoffersen independence test at 95% confidence level across stock indexes of EU new member and candidate states are the BRW models with λ = 0.97 and 0.99. The worst performers are the HS 50 and HS 500 models. Although it is very informative to look at VaR model performance at different confidence levels, the true test of VaR model acceptability to regulators is its' performance at 99% confidence level, as prescribed by the Basel Committee. According to results obtained at 99% confidence level, presented in Table 8, all of VaR models failed Kupiec test for at least one stock index. Situation is somewhat better with Christoffersen independence test where HS 250 and BRW model with λ = 0.99 both passed the test. The best performers according to Kupiec test are the HS 500 model (one failure), BRW model with λ = 0.99 and GARCH VCV model (two failures). The worst performers according to Kupiec test, out of the tested VaR model, are the HS 50 model (five failures), followed by HS 100, Normal VCV and RiskMetrics model, all of which failed the Kupiec test for four out of five tested indexes. Overall, the best performer according to Kupiec and Christoffersen independence test at 99% confidence level across stock indexes of EU new member and candidate states is the HS 500 model, followed by BRW model with λ = 0.99 and GARCH VCV model. The superior performance of HS 500 model at 99% confidence level can be attributed to a presumed high volatility, which is a consequence of a long observation period of this model and occurrence of extreme events in the observation period. The worst performer is the HS 50 followed by HS 100 and RiskMetrics system.

When evaluating analysed VaR models according to other criteria, such as Lopez test, Blanco-Ihle test, RMSE and MAPE the situation is somewhat different. Best performing VaR model according to these criteria are presented in Table 9.

Table 9: Best performing VaR model for EU new member and candidate states' stock indexes according to different criteria based on 500 trading days observation period

95%	CROBEX	VIN	BBETINRM	SOFIX	XU100
Lopez test	BRW λ=0.97	BRW λ=0.99	BRW λ=0.99	HS 100	BRW λ=0.99
Blanco-Ihle test	GARCH VCV	GARCH VCV	GARCH VCV	GARCH VCV	GARCH VCV
RMSE	HS 250	HS 500	HS 500	Risk Metrics	Risk Metrics
MAPE	Risk Metrics	Risk Metrics	Risk Metrics	BRW λ=0.97	GARCH VCV
99%					
Lopez test	BRW λ=0.99	GARCH VCV	HS 250	HS 100	HS 500
Blanco-Ihle test	GARCH VCV	GARCH VCV	HS 250	BRW λ=0.99	GARCH VCV
RMSE	HS 50	HS 100	Normal VCV	Risk Metrics	Normal VCV
MAPE	BRW λ=0.97	GARCH VCV	BRW λ=0.99	HS 100	GARCH VCV

Source: Author's calculations

Rankings from Table 9 show that different models are predominant depending on the confidence level used for the analysis. According to Lopez and Blanco-Ihle test BRW models and GARCH VCV model are constantly among the best performing VaR models for both confidence levels. HS models and RiskMetrics system are often among the best performers according to RMSE measure.

6. Conclusion

Based on the backtesting results it can be concluded that VaR models that are commonly used in developed stock markets are not well suited for measuring market risk in EU new member and candidate states. Tested at 99% confidence level the best performers for these markets are the HS 500 model, BRW model and GARCH VCV model. At the same time HS 500, which was the best VaR model at 99% confidence level, was among the worst rated VaR models at 95% confidence level. These findings bear very important implications that have to be addressed by regulators and risk practitioners. Risk managers have to start thinking outside the frames set by their parent companies or else investors present in these markets may find themselves in serious trouble, dealing with losses that they were not expecting. Contrary to the widespread opinion, it is not enough to blindly implement the VaR models that are being offered by various software companies. Every VaR software package that a bank is thinking about implementing should be rigorously tested and analysed to see if it really provides a correct estimate of the true level of risk a bank is exposed to.

National regulators have to take into consideration that simplistic VaR models that are widely used in some developed countries are not well suited for these illiquid and developing stock markets. These results show that returns on indexes from EU new member and candidate states are characterised by autocorrelation and heteroskedasticity, which considerably complicates VaR estimation and requires more complex, computationally and intellectually demanding VaR models. For these reasons, it is imperative that before allowance is given to banks to use internal VaR models that are either purchased or developed in-house, national regulators should rigorously checks and analyse the backtesting performance as well as the theoretical framework of such model for any inconsistencies or unwanted simplifications.

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Testiranje popularnih VaR modela u novim članicama i zemljama kandidatima za članstvo u EU[1]

Saša Žiković[2]

Sažetak

Utjecaj izračuna kapitalnih rezervi za banke putem internih VaR modela, kao i utjecaj ostalih zakonskih promjena u području upravljanja rizicima, nažalost, nije uopće istražen u tranzicijskim zemljama. Rad istražuje da li su VaR modeli koji su stvoreni i prilagođeni za razvijena tržišta kapitala, primjenjivi i na turbulentnim tržištima kapitala novih članica i zemalja kandidata za članstvo u EU (Bugarska, Rumunjska, Hrvatska i Turska). U radu je testirano devet VaR modela na pet dioničkih indeksa iz novih članica i zemalja kandidata za članstvo u EU. Rezultati testiranja ukazuju na to da VaR modeli, koji se uobičajeno koriste na razvijenim tržištima kapitala, nisu uspješni u mjerenju tržišnog rizika u novim članicama i zemljama kandidatima za članstvo u EU. Izneseni rezultati istraživanja ukazuju na veoma važne činjenice koje moraju biti uzete u obzir od strane svih regulatornih institucija i osoba koje se bave upravljanjem rizicima. Menadžeri zaduženi za upravljanje rizicima moraju početi razmišljati izvan okvira zadanih od strane njihovih matičnih kompanija ili će se tvrtke koje investiraju na ovim tržištima naći u ozbiljnim problemima, suočeni s gubitcima za koje nisu spremni. Nacionalni regulatori trebaju uzeti u obzir da jednostavni VaR modeli, koji su u širokoj primjeni u pojedinim razvijenim zemljama ne odgovaraju nelikvidnim i razvijajućim tržištima kapitala.

Ključne riječi: *nove članice i zemlje kandidati za članstvo u EU, dionički indeksi, upravljanje rizicima, tržišni rizik, GARCH*

JEL klasifikacija: *C22, C53, G15, G18, G20*

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APPENDICES

Table 10: Backtesting results and diagnostics of 500 VaR forecasts for CROBEX index daily log returns, 95% and 99% confidence level, period 22 Nov. 2004 - 2 Jan. 2007

CROBEX, VaR 95%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	35	29	21	17	27	22	20	17	11
Frequency of failures	0.07	0.058	0.042	0.034	0.054	0.044	0.04	0.034	0.022
Kupiec test (p value)	0.019643	0.17647	0.75905	0.94408	0.29612	0.6879	0.82115	0.94408	0.99886
Christoffersen IND test (p value)	0.11774	0.10028	0.008682	0.016105	0.23115	0.012682	0.044012	0.60145	0.23191
Lopez test	10.168	4.1685	-3.8463	-7.8737	2.1302	-2.8711	-4.8825	-7.9232	-13.962
Blanco-Ihle test	16.344	14.549	11.479	8.4001	11.556	9.2428	7.8082	6.196	2.0484
RMSE	0.013789	0.014141	0.013655	0.014224	0.014733	0.01421	0.015144	0.014625	0.017295
MAPE	2.404	1.7082	2.384	3.2469	1.7681	2.1347	2.5436	1.5935	3.1097
Average VaR	-0.01296	-0.0135	-0.01373	-0.01478	-0.01424	-0.01431	-0.01541	-0.0146	-0.01819

CROBEX, VaR 99%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	11	13	8	2	7	6	8	6	2
Frequency of failures	0.022	0.026	0.016	0.004	0.014	0.012	0.016	0.012	0.004
Kupiec test (p value)	0.005208	0.000646	0.06711	0.87661	0.13232	0.23708	0.06711	0.23708	0.87661
Christoffersen IND test (p value)	0.01859	0.039413	0.004139	0.89904	0.078954	0.05405	0.10917	0.70234	0.89904
Lopez test	6.06	8.0494	3.0305	-2.9957	2.0337	1.0178	3.0188	1.018	-2.9959
Blanco-Ihle test	4.262	2.9231	1.5147	0.14551	1.9843	0.86425	0.81733	0.92024	0.14484
RMSE	0.018073	0.018682	0.02211	0.026437	0.025755	0.023221	0.021632	0.02128	0.02505
MAPE	1.1596	1.2369	1.2618	0.82793	0.42145	1.0175	1.1696	0.72319	0.50125
Average VaR	-0.01812	-0.01881	-0.02264	-0.02776	-0.02345	-0.0239	-0.02245	-0.02114	-0.02572

Source: Author’s calculations

Table 11: Backtesting results and diagnostics of 500 VaR forecasts for VIN index daily log returns, 95% and 99% confidence level, period 5 Nov. 2004 - 1 Jan. 2007

VIN, VaR 95%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	29	26	28	31	21	25	23	26	16
Frequency of failures	0.058	0.052	0.056	0.062	0.042	0.05	0.046	0.052	0.032
Kupiec test (p value)	0.17647	0.36861	0.23168	0.09445	0.75905	0.44706	0.61007	0.36861	0.96571
Christoffersen IND test (p value)	0.0238	0.046153	0.017199	0.000244	0.058758	0.03444	0.09888	0.73711	0.53106
Lopez test	4.2758	1.2276	3.2391	6.2525	-3.7946	0.20739	-1.8202	1.1708	-8.8887
Blanco-Ihle test	26.419	17.518	18.553	19.674	16.063	14.324	12.064	12.972	5.663
RMSE	0.016097	0.016169	0.016493	0.015882	0.017003	0.016703	0.018443	0.020107	0.021361
MAPE	1.3691	1.6035	2.7606	2.9751	1.3541	2.2145	2.3416	1.3416	1.7481
Average VaR	-0.01365	-0.01431	-0.01449	-0.01386	-0.01502	-0.01517	-0.01715	-0.01687	-0.01942

VIN, VaR 99%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	15	10	8	6	11	7	9	11	4
Frequency of failures	0.03	0.02	0.016	0.012	0.022	0.014	0.018	0.022	0.008
Kupiec test (p value)	6.15E-05	0.013244	0.06711	0.23708	0.005208	0.13232	0.031102	0.005208	0.56039
Christoffersen IND test (p value)	0.007142	0.18573	0.60964	0.70234	0.23191	0.65537	0.14477	0.23191	0.7993
Lopez test	10.121	5.0927	3.0862	1.0755	6.0782	2.0711	4.0767	6.0618	-0.95086
Blanco-Ihle test	6.968	4.2621	3.8453	3.1788	3.3796	2.8325	3.4061	2.8499	1.6071
RMSE	0.024701	0.023815	0.02448	0.023857	0.024015	0.025248	0.025515	0.028251	0.029803
MAPE	1.9975	1.0399	1.2244	1.0299	0.95262	0.97506	1.4688	1.4289	0.86284
Average VaR	-0.02297	-0.02336	-0.02435	-0.02402	-0.02354	-0.02513	-0.02522	-0.02485	-0.02746

Source: Author's calculations

Table 12: Backtesting results and diagnostics of 500 VaR forecasts for BBETINRM index daily log returns, 95% and 99% confidence level, period 8 Dec. 2004 - 3 Jan. 2007

BBETINRM, VaR 95%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	37	33	31	39	27	24	21	26	26
Frequency of failures	0.074	0.066	0.062	0.078	0.054	0.048	0.042	0.052	0.052
Kupiec test (p value)	0.007661	0.045412	0.09445	0.002701	0.29612	0.52865	0.75905	0.36861	0.36861
Christoffersen IND test (p value)	0.17911	9.46E-05	2.9E-05	0.000337	0.060759	0.000439	0.000937	0.046153	0.58221
Lopez test	12.48	8.5026	6.478	14.605	2.4008	-0.57729	-3.6177	1.3599	1.374
Blanco-Ihle test	26.754	27.65	23.224	37.522	18.484	19.176	16.153	16.135	14.728
RMSE	0.023917	0.024443	0.023342	0.022677	0.025717	0.024351	0.026743	0.02643	0.02731
MAPE	1.8479	3.5237	3.8005	4.793	1.7905	3.2145	4.0299	1.4489	2.2519
Average VaR	-0.02165	-0.02288	-0.02274	-0.02123	-0.02453	-0.024	-0.02681	-0.02534	-0.02618

BBETINRM, VaR 99%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	16	14	7	11	12	9	9	9	10
Frequency of failures	0.032	0.028	0.014	0.022	0.024	0.018	0.018	0.018	0.02
Kupiec test (p value)	1.73E-05	0.000206	0.13232	0.005208	0.001901	0.031102	0.031102	0.031102	0.013244
Christoffersen IND test (p value)	0.096153	0.054505	0.078954	0.23191	0.28312	0.14477	0.14477	0.56529	0.18573
Lopez test	11.245	9.2492	2.1804	6.2374	7.2322	4.1867	4.2327	4.1948	5.2031
Blanco-Ihle test	9.4729	8.8584	4.5077	7.0397	7.322	4.7247	6.7585	5.9299	5.3488
RMSE	0.042161	0.039568	0.046639	0.044536	0.042127	0.048852	0.037796	0.037812	0.038305
MAPE	1.7007	1.591	0.71571	1.2519	1.2643	0.68579	0.98504	0.92519	0.95511
Average VaR	-0.03771	-0.03659	-0.04656	-0.04505	-0.04048	-0.04846	-0.03866	-0.03673	-0.03672

Source: Author’s calculations

Table 13: Backtesting results and diagnostics of 500 VaR forecasts for SOFIX index daily log returns, 95% and 99% confidence level, period 23 Dec. 2004 - 1 Jan. 2007

SOFIX, VaR 95%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	34	24	26	20	24	19	19	24	11
Frequency of failures	0.068	0.048	0.052	0.04	0.048	0.038	0.038	0.048	0.022
Kupiec test (p value)	0.03026	0.52865	0.36861	0.82115	0.52865	0.87277	0.87277	0.52865	0.99886
Christoffersen IND test (p value)	0.001066	0.000439	0.000134	0.000551	0.12501	0.000312	0.003747	0.025213	0.48129
Lopez test	9.2176	-0.8244	1.2156	-4.8015	-0.84663	-5.8359	-5.8445	-0.84951	-13.924
Blanco-Ihle test	24.12	16.437	19.544	14.522	15.286	13.682	10.563	17.069	4.4519
RMSE	0.014062	0.013605	0.014465	0.013894	0.014703	0.014214	0.015095	0.01342	0.015093
MAPE	2.4589	1.5711	4.3192	4.3616	1.0399	2.818	3.7955	1.3092	2.9352
Average VaR	-0.01193	-0.01239	-0.01348	-0.01408	-0.0131	-0.0135	-0.01498	-0.01255	-0.01529

SOFIX, VaR 99%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	12	5	4	4	6	3	7	14	5
Frequency of failures	0.024	0.01	0.008	0.008	0.012	0.006	0.014	0.028	0.01
Kupiec test (p value)	0.001901	0.38404	0.56039	0.56039	0.23708	0.73638	0.13232	0.000206	0.38404
Christoffersen IND test (p value)	0.44186	0.75037	0.7993	0.7993	0.70234	0.84892	0.078954	0.004504	0.75037
Lopez test	7.0817	0.024583	-0.98231	-0.97978	1.0323	-1.9912	2.0671	9.065	0.02986
Blanco-Ihle test	7.2067	2.4055	0.87132	0.66356	2.7474	0.43187	3.1911	4.8128	1.2068
RMSE	0.020971	0.023927	0.029184	0.032718	0.0248	0.029247	0.021376	0.019542	0.021869
MAPE	1.5187	0.34913	0.78055	1.0299	0.37656	0.67082	0.79551	2.1571	0.7606
Average VaR	-0.01912	-0.02258	-0.02876	-0.03383	-0.02351	-0.02907	-0.02169	-0.01853	-0.02163

Source: Author's calculations

Table 14: Backtesting results and diagnostics of 500 VaR forecasts for XU100 index daily log returns, 95% and 99% confidence level, period 7 Jan. 2005 - 4 Jan. 2007

XU100, VaR 95%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	39	34	32	31	25	25	36	30	19
Frequency of failures	0.078	0.068	0.064	0.062	0.05	0.05	0.072	0.06	0.038
Kupiec test (p value)	0.002701	0.03026	0.066371	0.09445	0.44706	0.44706	0.012425	0.13085	0.87277
Christoffersen IND test (p value)	0.097731	0.025703	0.002596	0.009505	0.000737	0.005742	0.002539	0.00657	0.032264
Lopez test	14.359	9.336	7.2902	6.3006	0.28061	0.25821	11.361	5.3356	-5.7839
Blanco-Ihle test	17.595	14.06	10.885	11.215	11.726	9.3979	14.646	15.18	7.6577
RMSE	0.023501	0.025414	0.025295	0.025237	0.025591	0.025967	0.023484	0.023468	0.025581
MAPE	2.4913	2.6459	3.0175	3.6234	1.5711	1.7606	3.9252	1.6309	1.5312
Average VaR	-0.02483	-0.0275	-0.02798	-0.02806	-0.0278	-0.02871	-0.02596	-0.02549	-0.02848

XU100, VaR 99%, 500 days

	HS 50	HS 100	HS 250	HS 500	BRW λ=0,97	BRW λ=0,99	Normal VCV	Risk Metrics	GARCH VCV
Number of failures	11	13	8	7	11	8	10	11	8
Frequency of failures	0.022	0.026	0.016	0.014	0.022	0.016	0.02	0.022	0.016
Kupiec test (p value)	0.005208	0.000646	0.06711	0.13232	0.005208	0.06711	0.013244	0.005208	0.06711
Christoffersen IND test (p value)	0.23191	0.002719	0.10917	0.078954	0.23191	0.10917	0.011969	0.000842	0.60964
Lopez test	6.1327	8.1268	3.1058	2.0866	6.1063	3.0858	5.126	6.1412	3.0833
Blanco-Ihle test	4.5552	3.6683	2.7865	2.1665	3.0075	2.1693	3.6259	4.4323	2.0435
RMSE	0.036097	0.037329	0.036397	0.040116	0.038654	0.040892	0.034312	0.034982	0.03782
MAPE	1.1746	1.9651	1.0524	1.2868	1.5985	1.0524	1.5511	1.3865	0.9601
Average VaR	-0.03694	-0.03896	-0.03935	-0.04285	-0.04061	-0.04325	-0.03728	-0.03677	-0.04028

Source: Author's calculations