Calculating VaR in EU Candidate States

Saša Žiković*

Abstract

This paper examines whether VaR models that are created and suited for developed and liquid markets apply to the volatile and shallow financial markets of EU candidate states. To this end, several VaR models are tested on five official stock indexes from EU candidate states over a period of 500 trading days. The tested VaR models are: a historical simulation with rolling windows of 50, 100, 250 and 500 days, a parametric variance-covariance approach, a BRW historical simulation, a RiskMetrics system and a variance-covariance approach using GARCH forecasts. Based on the backtesting results it can be concluded that VaR models that are commonly used in developed financial market are not well-suited to measuring market risk in EU candidate states. Using some of the most widespread VaR models in these circumstances may result in serious problems for both banks and regulators.

Keywords: Abbreviations: EU, VaR, VCV, EWMA, Historical simulation, BRW, ARCH, GARCH

JEL: C22, C53, G15, G18

DOI: 10.2478/v10033-008-0003-y

1. Introduction

The impact of allowing banks to calculate their capital requirement for market risk based on their internal VaR models, as well as the impact of regulation changes on banks in less developed countries, has not been well studied. Even in the European Union, not all of the EU-15 member countries have systematically conducted research on the consequences and impact of these changes on their banking sectors. New EU member states and EU candidate states are even further behind in these issues. The group of EU candidate states is comprised of the following countries: Bulgaria, Romania, Croatia and Turkey. Bulgaria started its accession negotiations with the EU in February 2000, and closed the accession negotiations in June 2004. Romania, like Bulgaria, started its accession negotiations in February 2000, and closed the accession negotiations in December 2004. Both countries will become full EU members in January 2007. Croatia and Turkey started the accession negotiations on the same date, 03.10.2005.

Croatia is expected to become a full EU member in 2009. This is not the case with Turkey, which still has a long journey ahead of it. Although very different and unique in their own ways, when looking through a financial prism, these countries are similar in certain respects. The EU 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. When investing in these financial markets, banks and investment funds employ the same risk measurement models for measuring market

* Žiković: Faculty of Economics, University of Rijeka, Ivana Filipovića 4, Rijeka, Croatia, e-mail: sasa.zikovic@efri.hr

risk and forming provision as they do in developed markets. This means that risk managers presume equal or similar characteristics and behaviour in these markets to developed markets. Using VaR models that are created and suited for developed and liquid markets in developing markets raises concerns whether VaR models developed and tested in these financial markets apply to the volatile and shallow financial markets of EU candidate states. This paper therefore attempts to provide an answer to the question whether commonly used VaR models adequately capture market risk in the financial markets of EU candidate states. Employing VaR models in forming a bank's provisions that are not suited to developing markets can have serious consequences, resulting in big losses to banks' portfolios that could be undetected by the employed risk measurement models. Banks could also be penalized by the regulators via higher scaling factors when forming their market risk provisions due to the use of a faulty risk measurement model.

To this end, variance-covariance methods and historical simulation approaches are used to estimate VaR for official stock indexes from each of the EU candidate states over a period of 500 trading days. In the 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 briefly outlines the VaR approaches on which the calculations in this paper are based. Section 3 provides a brief description of the data used. Section 4 presents and explains the results. Section 5 offers a few concluding remarks.

2. Analyzed VaR Models

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:

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

where $F^{-1}(C)$ denotes the inverse of 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 $C \cdot N$ 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:

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

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 a daily historical time series of the returns of the relevant risk factors using equally weighted moving averages:

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

where the mean is often assumed to be zero, $\sigma_{ij,T}^2$ is variance (or covariance) at time T , $r_{i,t}$ and $r_{j,t}$ 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:

$$\sigma_{ij,t}^2 = \lambda \sigma_{ij,t-1}^2 + (1-\lambda) r_{i,t-1} r_{j,t-1} \quad 0 < \lambda < 1 \quad (4)$$

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 of volatility is a GARCH process:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i \sigma_{t-i}^2 \quad (5)$$

$$\varepsilon_t = \eta_t \sqrt{\sigma_t^2}$$

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_i 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 α is relatively high and β 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:

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

where $r_w((T+1)C)$ is taken from the set of ordered returns $\{r_w(1), r_w(2), \dots, r_w(T)\}$. 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, $r_t, r_{t-1}, \dots, r_{t-N+1}$, is associated

a weight, $\frac{1-\lambda}{1-\lambda^N}, \left(\frac{1-\lambda}{1-\lambda^N}\right)\lambda, \dots, \left(\frac{1-\lambda}{1-\lambda^N}\right)\lambda^{N-1}$ respectively.

The role of the term $\frac{1-\lambda}{1-\lambda^N}$ is simply to ensure that the

weights sum to 1, provided $0 < \lambda < 1$. After the probability weights are assigned, VaR is calculated based on the empirical cumulative distribution function of returns with the modified probability weights. To better understand the assumptions behind the BRW approach and its connection to historical simulation, BRW quantile estimator can be expressed as:

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

where $f_i(\lambda; N)$ are the weights associated with return r_i and $I(\cdot)$ 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 used in this paper.

3. Data and Methodology

For transitional economies such as those of EU candidate states, a significant problem for a serious and statistically significant analysis is the short histories of their market economies and active trading in financial markets. Because of the short time series of returns of individual stocks and their highly variable liquidity, it is practical to analyze the stock indexes of these countries. A 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 candidate states, nine VaR models are tested on the stock indexes of EU candidate states. The tested VaR models are: a historical simulation with rolling windows of 50, 100, 250 and 500 days, a parametric variance-covariance approach, a BRW historical simulation, a RiskMetrics system and a 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 pre-sample 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). The ACF, PACF and Ljung-Box Q-statistic test the presumption of IID in standardized innovations. If the tests do not discover autocorrelation in the standardized innovations employed, the ARMA model can be considered adequate. Squared standardized innovations are tested for autocorrelation and ARCH effects through ACF, PACF and Ljung-Box Q-statistic. The most parsimonious GARCH model based on the 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. The validity of the analyzed VaR models in EU candidate states is tested by the Kupiec test, the Christoffersen independence test,

the Blanco-Ihle test, the Lopez test, and the RMSE and MAPE measures.

Although there is an abundance of research papers dealing with VaR and market risk measurement and management, all of the existing VaR models have been developed and tested in mature, developed and liquid markets. Testing of VaR models in other, less developed or developing financial market is at best scarce. 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 clear positive trends over a longer time period. With the exception of the XU100 index, all of other indexes analyzed exhibit asymmetry and leptokurtosis. Based on performed tests of normality, it can be said with great certainty that these returns are not normally distributed. The tests employed show significant autocorrelation and ARCH effects in the squared returns of all the analyzed indexes. These phenomena violate normality assumption, as well as the IID assumption, which 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 the indexes tested at most of the confidence levels, use of historical simulation (especially based on shorter observation periods) is not recommendable in these markets.

4. Backtesting Results

Based on the ACF, PACF and Ljung-Box Q statistics of the returns and squared returns of analyzed stock indexes from EU candidate states given in tables V – IX, the presence of autocorrelation and heteroskedasticity in the data is obvious. All of the analysed indexes exhibit heteroskedasticity, with VIN, BBETINRM and SOFIX exhibiting autocorrelation in their 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 historical simulation and the BRW approach. This is very indicative for risk managers, because the elementary assumptions of many VaR models are not satisfied, meaning that VaR figures obtained for such models cannot be completely trusted. An ARMA-GARCH model performs a transformation of original return data to obtain independently and identically distributed observations. The ARMA-GARCH model successfully captured the dynamics of stock indexes from EU candidate states and produced standardized innovations that proved to be independently and identically distributed. In modelling conditional volatility, a basic GARCH (1,1) model was sufficient for all stock indexes. Estimated ARMA-GARCH parameters for stock indexes of EU candidate states are presented in Table I.

As can be seen from Table I, some of the tested indexes, such as 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. The majority of stock indexes are not even closely integrated, as is presumed by the EWMA volatility modelling that underlies the RiskMetrics model. The estimated GARCH parameters of stock indexes from EU candidate states point to the conclusion that VaR models based on simpler conditional volatility models, such as MA or EWMA, will underestimate or overestimate the true level of risk. The Kupiec test and Christoffersen independence test are usually used to identify VaR models that are acceptable to the regulators, and provide the desired level of safety to individual banks and, due to the contagion effect, to the entire banking sector. The results of the overall acceptance, according to the Kupiec and Christoffersen independence tests, of tested VaR models at 95% and 99% confidence levels and 10% significance level are presented in Tables II and III.

	Mean			Volatility		
	C	AR	MA	K	ARCH (α)	GARCH (β)
CROBEX	0.001014			1.06E -05	0.11082	0.8323
t-stat	(-1.26)			(21.32)	(11.43)	(93.44)
VIN	0.000278	0.145		1.25E -05	0.1405	0.78932
t-stat	(0.81)	(4.09)		(7.22)	(7.57)	(86.15)
BBETINRM	0.001409	0.1376		7.59E -06	0.17092	0.79299
t-stat	(4.39)	(4.37)		(3.77)	(6.55)	(28.76)
SOFIX	0.000403	0.75972	-0.62566	3.4E -06	0.14139	0.84515
t-stat	(4.31)	(4.31)	(-5.79)	(3.96)	(7.39)	(30.22)
XU100	0.001834			1.75E -05	0.070264	0.88758
t-stat	(3.83)			(1.02)	(7.72)	(53.03)

Table I - Estimated ARMA-GARCH parameters for stock indexes from EU candidate states

Model	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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

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

Model	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	Normal VCV	Risk Metrics	GARCH VCV
Kupiec test	5	4	3	1	3	2	4	4	2
Christoffersen IND test	5	4	2	1	3	0	1	3	1

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

From the data in Table II, it is clear that at a 95% confidence level, the tested VaR models perform very differently, with a majority of VaR models failing the Kupiec test and Christoffersen independence test for at least one stock index. VaR models that passed the Kupiec test across all the analyzed stock indexes are the GARCH VCV model, RiskMetrics system and both BRW models with $\lambda = 0.97$ and 0.99 . According to the Kupiec test, the worst performer out of all the tested VaR models is the HS 50 model, which failed the Kupiec test for four out of five stock indexes. The HS 50 model is followed by HS 500 with three failures. According to the Christoffersen independence test, the best performers are the HS 250 and both BRW models with $\lambda = 0.97$ and 0.99 . The worst performers are HS 50 and GARCH VCV. Overall, the best performers according to the Kupiec test and Christoffersen independence test at a 95% confidence level across stock indexes of EU candidate states are the BRW models with $\lambda = 0.97$ 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 for regulators is its performance at a 99% confidence level, as prescribed by the Basel Committee. According to the results obtained at a 99% confidence level, which are presented in Table III, all of the VaR models failed the Kupiec test for at least one stock index.

The situation is somewhat better with the Christoffersen independence test, where HS 250 and BRW model with $\lambda = 0.99$ both passed the test. The best performers according to the Kupiec test are the HS 500 model (one failure), the BRW model with $\lambda = 0.99$ and the GARCH VCV model (two failures). The worst performers according to the Kupiec test are the HS 50 model (five failures), followed by the HS 100, Normal VCV and RiskMetrics models, all of which failed the Kupiec test for four out of the five tested indexes. Overall, the best performer according to the Kupiec and Christoffersen independence tests at a 99% confidence level across stock indexes of EU candidate states is the HS 500 model, followed by the BRW model with $\lambda = 0.99$ and the GARCH VCV model. The superior performance of the HS 500 model at a 99% confidence level can be attributed to a presumed high volatility, which is a consequence of the long observation period of this model and the occurrence of extreme events in the observation period. The worst performer is the HS 50, followed by the HS 100 and RiskMetrics system.

When evaluating the VaR models analyzed according to other criteria, such as the Lopez test, Blanco-Ihle test, RMSE and MAPE, the situation is somewhat different. The best performing VaR models according to these criteria are presented in Table IV.

95%	CROBEX	VIN	BBETINRM	SOFIX	XU100
Lopez test	BRW $\lambda=0,97$	BRW $\lambda=0,99$	BRW $\lambda=0,99$	HS 100	BRW $\lambda=0,99$
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 $\lambda=0,97$	GARCH VCV
99%					
Lopez test	BRW $\lambda=0,99$	GARCH VCV	HS 250	HS 100	HS 500
Blanco -Ihle test	GARCH VCV	GARCH VCV	HS 250	BRW $\lambda=0,99$	GARCH VCV
RMSE	HS 50	HS 100	Normal VCV	Risk Metrics	Normal VCV
MAPE	BRW $\lambda=0,97$	GARCH VCV	BRW $\lambda=0,99$	HS 100	GARCH VCV

Table IV – Best performing VaR model for EU candidate states' stock indexes according to different criteria based on 500 trading days observation period

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

5. Conclusion

Based on the backtesting results, it can be concluded that the VaR models that are commonly used in developed financial market are not well suited for measuring market risk in EU candidate states. Tested at a 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 a 99% confidence level, was among the worst rated VaR models at a 95% confidence level. These findings bear very important implications that must be addressed by regulators and risk practitioners operating in EU candidate states. Risk managers have to start thinking

outside the frames set by their parent companies or else banks investing in these markets may find themselves in serious trouble, dealing with losses that they were not expecting. Contrary to widespread opinion, it is not enough to blindly implement the VaR models offered by various software companies. Every VaR software package that a bank is thinking about implementing should be rigorously tested and analyzed to see if it really provides a correct estimate of the true level of risk to which a bank will be exposed. National regulators have to take into consideration that simplistic VaR models widely used in some developed countries are not well suited for these illiquid and developing financial markets. The results obtained show that returns on indexes from EU candidate states are characterized by autocorrelation and heteroskedasticity, which considerably complicates VaR estimation and requires more complex, computationally and intellectually demanding VaR models. Before allowance is given to banks to use internal VaR models that are either purchased or developed in-house, national regulators should rigorously check and analyze the backtesting performance, as well as the theoretical framework of such models for any inconsistencies or unwanted simplifications. [E](#)

Appendix

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 0.486
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 19.486 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			

Table V - 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 0.159 0.159 37.888 0.000
2 -0.038 -0.085 40.073 0.000
3 0.032 0.050 41.576 0.000
4 0.078 0.081 50.190 0.000
5 0.012 -0.007 50.412 0.000
6 0.063 0.071 58.439 0.000
7 0.050 0.024 60.172 0.000
8 0.008 -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 -0.008 -0.012 71.487 0.000
16 0.012 0.005 71.725 0.000
17 -0.038 -0.047 73.740 0.000
18 0.017 0.031 74.188 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 51.198 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 51.283 0.000
7 -0.004 -0.004 51.293 0.000
8 0.008 0.010 51.398 0.000
9 0.008 0.007 51.444 0.000
10 0.001 -0.003 51.448 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 0.048 0.048 54.985 0.000
15 0.013 0.006 55.233 0.000
16 0.028 0.009 58.277 0.000
17 0.018 0.014 58.754 0.000
18 0.010 0.004 58.908 0.000
19 -0.003 -0.009 58.917 0.000
20 -0.005 -0.006 58.950 0.000			

Table VI - 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 0.112 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 0.008 -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 0.056 34.518 0.000
3 0.039 0.023 36.836 0.000
4 0.028 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 53.887 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 60.587 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			

Table VII - 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 -0.094	-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	99.786	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	119.89	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	240.83	0.000
		16 0.055	0.080	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

Table VIII - 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 0.001	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 0.068	0.085	525.00	0.000
		20 0.060	0.001	530.70	0.000

Table IX - 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.

CROBEX, VaR 95%, 500 days: 22.11.2004. - 2.1.2007.

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

CROBEX, VaR 99%, 500 days: 22.11.2004. - 2.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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

Table X - Backtesting results and diagnostics of 500 VaR forecasts for CROBEX index daily log returns, 95% and 99% confidence level, period 22.11.2004 - 2.1.2007**VIN, VaR 95%, 500 days: 5.11.2004. - 1.1.2007.**

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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: 5.11.2004. - 1.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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

Table XI - Backtesting results and diagnostics of 500 VaR forecasts for VIN index daily log returns, 95% and 99% confidence level, period 5.11.2004 - 1.1.2007

BBETINRM, VaR 95%, 500 days: 8.12.2004. - 3.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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: 8.12.2004. - 3.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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

Table XII - Backtesting results and diagnostics of 500 VaR forecasts for BBETINRM index daily log returns, 95% and 99% confidence level, period 8.12.2004 - 3.1.2007

SOFIX, VaR 95%, 500 days: 23.12.2004. - 1.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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: 23.12.2004. - 1.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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

Table XIII - Backtesting results and diagnostics of 500 VaR forecasts for SOFIX index daily log returns, 95% and 99% confidence level, period 23.12.2004 - 1.1.2007

XU100, VaR 95%, 500 days: 7.1.2005. - 4.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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: 7.1.2005. - 4.1.2007.

	HS 50	HS 100	HS 250	HS 500	BRW $\lambda=0,97$	BRW $\lambda=0,99$	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

Table XIV - Backtesting results and diagnostics of 500 VaR forecasts for XU100 index daily log returns, 95% and 99% confidence level, period 7.1.2005 - 4.1.2007

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