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Global financial crisis and VaR performance in emerging markets: A case of EU candidate states - Turkey and Croatia*[1]

Saša Žiković[2], *Bora Aktan*[3]

Abstract

We investigate the relative performance of a wide array of Value at Risk (VaR) models with the daily returns of Turkish (XU100) and Croatian (CROBEX) stock index prior to and during the ongoing financial crisis. In addition to widely used VaR models, we also study the behaviour of conditional and unconditional extreme value theory (EVT) and hybrid historical simulation (HHS) models to generate 95, 99 and 99.5% confidence level estimates. Results indicate that during the crisis period all tested VaR model except EVT and HHS models seriously underpredict the true level of risk, with EVT models doing so at a higher cost of capital compared to HHS model.

Key words: *financial crisis, emerging markets, Value at Risk, extreme value theory, hybrid historical simulation*

JEL classification: *G24, C14, C22, C52, C53*

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2 *Assistant Professor, University of Rijeka, Faculty of Economics, I. Filipovića 4, 51000 Rijeka, Croatia. Scientific affiliation: banking, risk management, quantitative modelling. Phone: +385 51 355 139. E-mail: szikovic@efri.hr*

3 *Assistant Professor, Yasar University, Faculty of Economics and Administrative Sciences, Universite Caddesi, No. 35-37, 35100 Bornova, Izmir, Turkey. Scientific affiliation: quantitative finance, optimisation, risk management. Phone: +90 (232) 411 5000. E-mail: bora.aktan@yasar.edu.tr*

1. Introduction

Current financial crisis although looking catastrophical from current viewpoint is by no means a unique event. Extraordinary events such as the US stock market crash of October 1987, the breakdown of the European Monetary System in September 1992, the turmoil in the bond market in February 1994 and the financial crisis in Asia-Pacific starting from 1997 were all extraordinary events in their time and as such present a central issue in finance and particularly in risk management and financial regulation. From a regulatory point of view, the capital put aside by a bank has to cover the largest loss such that it can stay in business even after a great market shock. Therefore, how to deal with the extreme events is paramount in risk management. This topic is even more crucial in emerging markets with its' inherent abrupt changes in volatility regimes. The fundamental difference between emerging and developed markets reflected in lower liquidity, frequent internal and external shocks (inflation, depreciation of local currency, credit rating changes, etc.) as well as higher degree of insider trading causes the markets to be more volatile and deviate more from the normal distribution which makes accurate risk estimation more problematic and estimation models that assume normal distribution less reliable in emerging markets. Although different in many aspects, Turkey and Croatia have a common denominator being both Mediterranean emerging economies and EU candidate states. This means that they are both subject to similar processes of adaptation to EU regulation and both are seen as an interesting investment opportunity for international hedge funds looking to diversify their portfolio. Being one of the largest and fastest growing as well as profitable emerging markets, Istanbul Stock Exchange (ISE) is an appropriate testing area for many researchers and as such has been the subject of many papers measuring risk in term of Value-at-Risk (VaR) both individually Eksi et. al. (2005), Cifter et. al. (2007), Alper et. al. (2007) and in a group of emerging markets, Gencay and Selcuk (2004), Maghyereh and Al-Zoubi (2006). Eksi et. al. (2005) test a variety of VaR models and conclude that EVT is theoretically more appropriate for calculating risk measures yet all models are found equivalent according to Lopez backtest results while EVT is found superior to GARCH model according to Kupiec test. Cifter et. al. (2007) argue that financial markets in Turkey experience sudden and severe volatility movements due to lack of depth in the market and that is the reason why traditional VaR models are not capable of identifying such volatility movements in Turkey. One of the papers which tests a wide range of models is Alper et. al. (2007). They compare the performances of eight filtered EVT models with those of GARCH and FIGARCH models on XU100 index. The backtesting results indicate that EVT models perform better than the competing parametric models. Using daily returns, Gencay et. al. (2003) compare the performance of EVT to other methods like GARCH, VCV and Historical simulation. Results indicate that GARCH, and GPD models are preferable for most quantiles. Gencay and Selcuk (2004) use VCV, Historical simulation and EVT models to calculate VaR in nine emerging markets including Turkey. VaR measures estimated by EVT are found to be more accurate in higher quantiles. They find that left and right tails of return distributions in these countries differ significantly meaning that that one should be careful when using assumption of symmetry. Maghyereh and Al-Zoubi (2006) investigate performance of a range of models to estimate VaR in seven Middle East and North Africa (MENA) countries. Results indicate that EVT models perform better in five of the MENA stock markets excluding Turkey and Morocco, where the best model is the skewed-t APARCH model. Measuring of market risk on Croatian Zagreb Stock Exchange (ZSE) has not been as extensively studied as ISE. Žiković (2006) analyses the benefits of using time weighted historical simulation (BRW approach) and obtains much better results than by using plain historical simulation. Jurun et. al. (2007) conclude that using assumption of heavy tailed distribution, such as Student's t-distribution in GARCH models, it is possible to forecast market risk much more precisely than under normality assumption. Žiković (2007a, b) tests a wide range of VaR models on transitional markets of 2004 and 2007 EU new member states as well as EU candidate states (Croatia and Turkey). Findings show that widespread VaR models do not fare well in volatile and shallow markets of transitional countries. Žiković (2007b) develops a new semi parametric approach for calculating VaR based on GARCH volatility updating and nonparametric bootstrapping. The new method provided superior conditional coverage compared to a wide array of VaR models. There is some degree of ambiguity in the results of papers related to which method performs better and to the distribution characteristics of both ISE and ZSE returns. The only consistency can be seen in the fact that in most of the paper where EVT approach is tested, conditional or unconditional, it proved to be one of the best models for both Turkish and Croatian market.

The goal of this paper is to test the performance of a wide array of VaR models in the midst of a global financial crisis in emerging countries, particularly EU candidate states (Turkey and Croatia). In the paper we test the hypothesis that only realistic and theoretically sound VaR models such as EVT and HHS, can adequately measure equity risk in stated developing economies in times of crisis. To the best of our knowledge this is the first extensive study of VaR model performance in EU candidate states under the increased market stress of current financial crisis. Contribution of this paper is the empirical investigation and tail risk assessment of a wide array of VaR models during the time of increased market stress in emerging countries and around the world. VaR models that are analyzed in this paper are: Normal simple moving average (VCV) VaR, RiskMetrics system, historical simulation with rolling windows of 250 and 500 days, BRW (time weighted) simulation with decay factors of 0.97 and 0.99, RiskMetrics system augmented with GARCH type volatility forecasting, unconditional EVT approach using Generalized Pareto distribution (GPD), conditional quantile EVT approach and Hybrid Historical simulation (HHS). The rest of the paper is organized as follows: Section 2 presents a brief description of tested VaR models with emphasis on EV and HHS models. Section 3 gives the description of the analyzed data and statistical characteristics of Turkish and Croatian stock market. Findings and backtesting results are presented and discussed in section 4. Section 5 concludes.

2. Value-at-risk models

Let (X_t, $t \in Z$) be a strictly stationary time series representing daily observations of the log return on a financial asset price. The dynamics of X is given by:

$$X_t = \mu_t + \sigma_t Z_t \tag{1}$$

where the innovations Z are IID with zero mean, unit variance and marginal distribution function F_z(z). Assume that μ_t and σ_t are measurable with respect to ψ_{t-1} (information set about the return process available up to time *t-1*). Let F_x(x) denote the marginal distribution of (X_t) and for a horizon *hp* let $F_{X_{t+1}+\ldots+X_{t+hp}|\psi_t}(x)$ denote the predictive distribution of the return over the next *hp* days, given information set up to and including day *t*. Looking from a tail events perspective for 0 < *cl* <1, unconditional $VaR_{cl}(X)$ is a quantile of the marginal distribution denoted by:

$$VaR_{cl}(X) = \inf\{x \in R : F_X(x) \geq cl\} \tag{2}$$

and conditional $VaR_{cl}^t(X)$ is a quantile of the predictive distribution for the return over the next *hp* days denoted by:

$$VaR_{cl,hp}^t(X) = \inf\left\{x \in R : F_{X_{t+1}+\ldots+X_{t+hp}|\psi_t}(x) \geq cl\right\} \tag{3}$$

From the perspective of 100*cl*% best cases, VaR at the 100(1-*cl*)% confidence level is defined as the upper 100*cl* percentile of the loss distribution. Following Artzner et al. (1999), VaR is defined at the 100(1-*cl*)% confidence level ($VaR_{cl}(X)$) as:

$$VaR_{cl}(X) = \sup\{x \mid P[X \geq x] > cl\} \tag{4}$$

where sup{x | A} is the upper limit of *x* given event *A*, and sup{x | P[X ≥ x] > cl} indicates the upper 100*cl* percentile of loss distribution.

In recent years extreme value theory (EVT) has become very popular in risk management since it provides a framework for theoretically sound estimation of extreme (rare) events from historical data. A widely accepted method of using EVT in finance is based on modelling the behaviour of extreme values above a high cut-off level, usually referred to as peaks over threshold (POT) approach. An exceedence of the threshold *u* occurs when a realization is higher than the threshold, $X_t > u$ for any *t* in *t* = 1, 2,..., *n*. An excess over *u* is defined by $y = X_i - u$. Provided a high threshold *u*, the probability distribution of excess values of *X* over threshold *u* can be defined as:

$$F_u(y) = P(X - u \leq y \mid X > u) \tag{5}$$

which represents the probability that the value of X exceeds the threshold u by at most an amount y given that X exceeds the threshold u. The excess distribution above the threshold u as the conditional probability can be defined as:

$$F_u(y) = \frac{P(X - u \le y \mid X > u)}{P(X > u)} = \frac{F(y+u) - F(u)}{1 - F(u)}, \qquad y > 0 \tag{6}$$

Since $x = y + u$ for all exceedences, the following representation holds provided that $X>u$:

$$F(x) = [1 - F(u)]F_u(y) + F(u) \tag{7}$$

Balkema, de Haan (1974) show that for sufficiently high threshold u, the distribution function of the excess observations may be approximated by the Generalized Pareto distribution (GPD). As the threshold u gets larger, the excess distribution $F_u(y)$ converges in limit to the GPD, which is defined as:

$$G_{\xi,\sigma,\mu}(x) = \begin{cases} 1 - \left(1 + \xi \dfrac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}} & if \quad \xi \ne 0 \\ 1 - e^{-(x-\mu)/\sigma} & if \quad \xi = 0 \end{cases} \tag{8}$$

$$x \in \begin{cases} [\mu, \infty] & if \quad \xi \ge 0 \\ [\mu, \mu - \sigma/\xi] & if \quad \xi < 0 \end{cases}$$

where ξ is the shape parameter, σ is the scale parameter, and μ is the location parameter. In order to estimate the tails of the loss distribution we use the result from asymptotic theory that for a sufficiently high threshold u, Fu(y) ≈ Gξ,β(u)(y). An approximation of *F(x)*, for *X>u*, can be obtained from equation (7):

$$F(x) = [1 - F(u)]G_{\xi,\sigma,u}(x - u) + F(u) \tag{9}$$

An estimate of *F(u)* can be obtained non-parametrically by means of the empirical cumulative distribution function:

$$\hat{F}(u) = (n-k)/n \tag{10}$$

where k represents the number of exceedences over the threshold u and n number of observations. By substituting equation (9) into equation (10), the following estimate for *F(x)* is obtained:

$$\hat{F}(x) = 1 - \frac{k}{n}\left(1 + \hat{\xi}\frac{x-u}{\hat{\sigma}}\right)^{-\frac{1}{\hat{\xi}}} \text{ given that } G_{\xi,\sigma,u}(x) = 1 - \left(1 + \xi\frac{x-u}{\sigma}\right)^{-\frac{1}{\xi}} \quad (11)$$

Where $\hat{\xi}$ and $\hat{\sigma}$ are the maximum likelihood estimators of ξ and σ. This equation can be inverted to obtain a quantile of the underlying distribution, which is actually VaR. For $cl \geq F(u)$ VaR is calculated as:

$$VaR_{cl} = q_{cl}(F) = u + \frac{\sigma}{\xi}\left(\left(\frac{1-cl}{\overline{F}(u)}\right)^{-\xi} - 1\right) = u + \frac{\sigma}{\xi}\left(\left(\frac{1-cl}{k/n}\right)^{-\xi} - 1\right) \quad (12)$$

Unfortunately, this approach is plagued by an important problem and that is the estimation of tail index and connected to it the decision about the suitable cut-off level. In this paper the value of cut-off has been chosen as the value which minimizes Anderson-Darling statistic as proposed by Coronel-Brizio and Hernandez-Montoya (2005). The use of the Anderson-Darling statistic is due to the fact that the corresponding weighting function puts more weight in the tails of the distribution. A plot of cut-off value versus Anderson-Darling statistic is used, for finding the value of the cut-off which minimizes the Anderson-Darling statistic. Under the assumption that a tail of the distribution follows a Pareto law, the asymptotic distribution of the Anderson-Darling statistic is known and we can use this distribution as a reference to determine an estimate of the cut-off using a statistical approach. VaR models that are analyzed in the paper are already standard VaR models used in academic literature and practice. Since their description can be found in numerous academic papers and books we will not elaborate the details of every model since this is not in the scope of this paper.

The HHS model tested in this paper, based on the modification of recursive bootstrap procedure volatility updating, was developed by Žiković (2007b). The HHS model is based on the modification of recursive bootstrap procedure developed by Freedman, Peters (1984) and Hull, White (1998) volatility updating. This is why the model does not impose any theoretical distribution on the data since it uses empirical distribution of the return series. Two main problems with empirical data are heteroskedasticity and autocorrelation. In order to correctly implement bootstrapping the data series should not posses these characteristics, meaning that it should be IID. In modelling of residuals the following general specification is used:

$$r_t = \varphi(x) + \varepsilon_t, \quad \varepsilon_t \sim (0, \sigma_t)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{13}$$

$$z_t = \varepsilon_t / \sigma_t$$

where φ is some functional form (usually ARMA), x is a vector of explanatory variables (observed at time t or lagged), ε_t is the disturbance term with zero mean and standard deviation σ_t, which follows a GARCH process. Based on the general specification the HHS model can be implemented in the following manner:

Autocorrelation is removed by fitting an ARMA(p,q) model to historical returns:

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$$

$$\varepsilon_t = \eta_t \sqrt{\sigma_t^2} \qquad \eta_t \sim IID\ N(0,1) \tag{14}$$

GARCH(p,q) model is fitted to the obtained residuals:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{15}$$

To obtain standardized residuals $\{z_t\}$, residuals $\{\varepsilon_t\}$ are divided by conditional GARCH(p,q) volatility forecasts:

$$z_t = \varepsilon_t / \sigma_t \tag{16}$$

Under the GARCH hypothesis the set of standardized residuals are IID and therefore suitable for bootstrapping. Standardized residual returns $\{z_t\}$ are bootstrapped to obtain a standardized historical time series Θ. Since bootstrapping is applied to IID residuals results are unbiased:

$$z = \{z_1, z_2, \ldots, z_t\}\ z_i \in \Theta \tag{17}$$

After obtaining the bootstrapped standardized residuals the calculation of VaR is straightforward. A modification of Hull-White (1998) framework of volatility updating the standardized residuals $\{z_t\}$ is used to scales them by the latest GARCH volatility forecast ($\hat{\sigma}_{t+1}$) to obtained a series of historical residuals that have been updated by forecasted volatility to reflect the current market conditions $\{\hat{Z}_{t+1}\}$.

$$\hat{z}_{t+1} = z_t \times \hat{\sigma}_{t+1} \tag{18}$$

Simulated returns $\hat{r}_{t+1}$ are obtained by using updated bootstrapped residuals $\{\hat{Z}_{t+1}\}$:

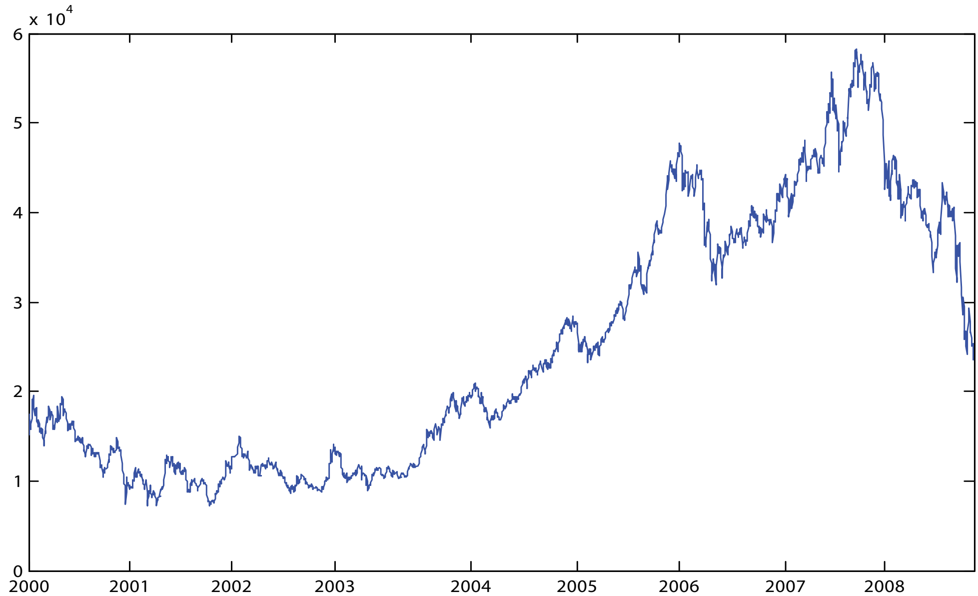
$$\hat{r}_{t+1} = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i+1} + \sum_{i=1}^{q} \theta_i \hat{z}_{t-i+1} + \hat{z}_{t+1} \tag{19}$$

VaR can be approximated from $G(.; t;N)$, the empirical cumulative distribution function of $\{\hat{r}_t\}$ based on return observations $\hat{r}_{t-1},...,\hat{r}_{t-N}$. VaR can also be calculated by applying a smooth density estimator such as kernel. By modelling VaR to reflect the current market conditions through nonparametric bootstrapping we can choose between letting the observation period freely grow with the passing of time, resulting in slightly more conservative VaR estimates, which are resilient to extreme events or setting the length of the observation period arbitrary, allowing the VaR estimates to be less conservative but also less attuned to extreme events. Length of the observation period is purely arbitrary but should in no case be shorter than three years of daily data.

3. Data and preliminary analysis

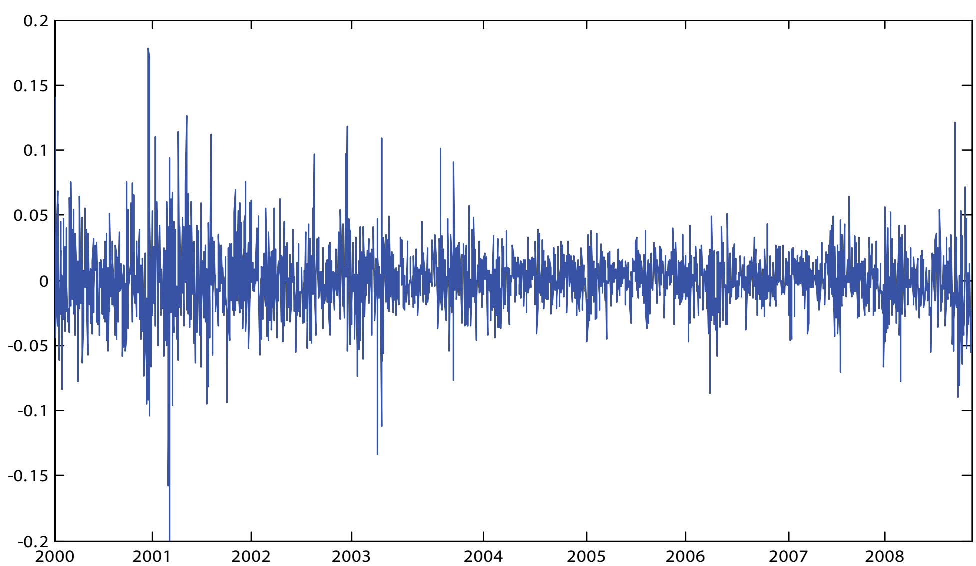
Data used in the analyses of VaR models is the daily log returns series from Turkish XU 100 and Croatian CROBEX index. The returns are collected from Bloomberg web site for the period 01.01.2000 - 03.11.2008, which includes the latest US sub prime mortgage crisis and its effects on global stock markets. The calculated VaR figures are for a one-day ahead horizon and 95, 99 and 99.5 percent confidence levels. To secure the same out-of-the-sample VaR backtesting period for all of the tested stock indexes, the out-of-the-sample data sets are formed by taking out 1,000 of the latest observations from each stock index. For CROBEX index 1,000 trading days covers the period from 21.09.2004 and for XU100 index from 17.11.2004. The rest of the observations are used as presample observations needed for VaR starting values and volatility model calibration. Data from both stock indexes shows significant autoregression and heteroskedasticity. In the case of XU 100 index ARMA(2,2) model and in the case of CROBEX index ARMA(1,1) model had to be used to remove the autoregression from the data. In order to capture the dynamics of data generating process and the presence of "leverage effect" in the XU 100 index, EGARCH model with Student's t distribution was used. In the case of CROBEX index where no "leverage effect" was found GARCH representation with GED distribution was used. Graphical representation of levels and daily changes for both indexes in the analysed period is given in figures 1 to 4.

Figure 1: XU 100 index values, period 03.01.2000 – 03.11.2008



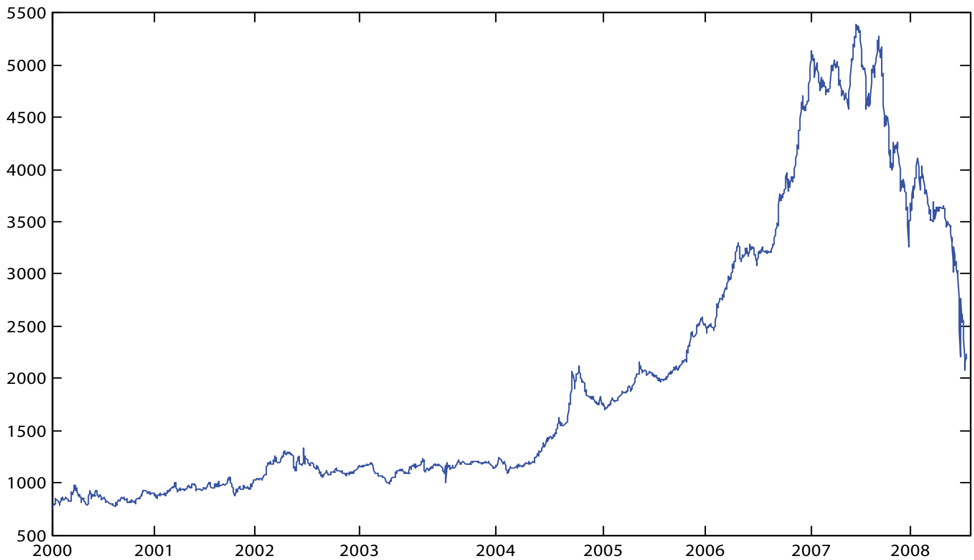
Source: Bloomberg

Figure 2: XU 100 index returns, period 03.01.2000 – 03.11.2008



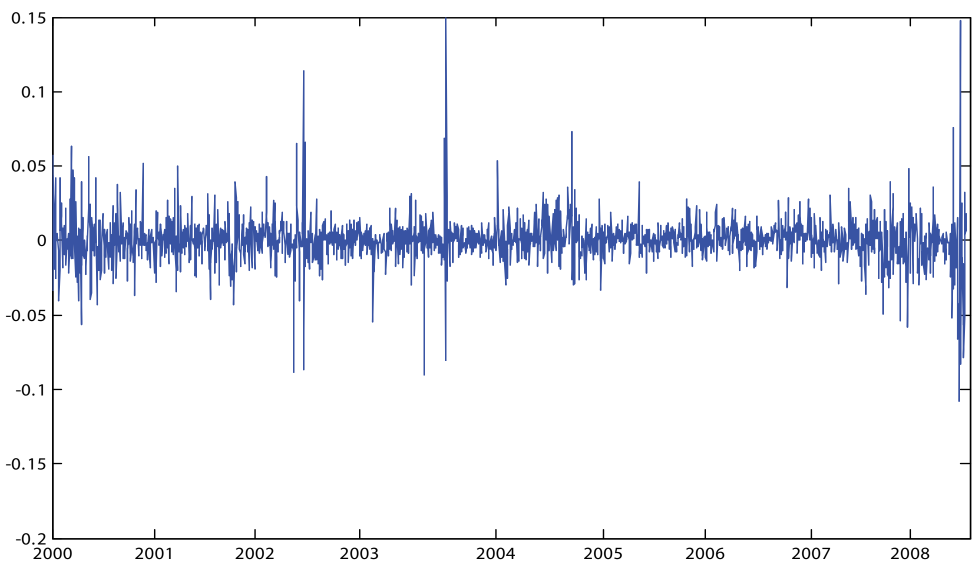
Source: Bloomberg

Figure 3: CROBEX index values, period 03.01.2000 – 03.11.2008



Source: Bloomberg

Figure 4: CROBEX index returns, period 03.01.2000 – 03.11.2008



Source: Bloomberg

Summary of descriptive statistics for XU 100 and CROBEX index returns is presented in table 1.

Table 1: Summary descriptive statistics for XU 100 and CROBEX index returns for the period 04.01.2000 - 03.11.2008 and 1.000 backtesting days up to 03.11.2008.

XU 100	04.01.2000 - 03.11.2008	17.11.2004 - 03.11.2008	CROBEX	04.01.2000 - 03.11.2008	22.09.2004 - 03.11.2008
Descriptive statistics					
Mean	0,00028	0,00023	Mean	0,00048	0,00046
Median	0,00050	0,00050	Median	0,00038	0,00068
Minimum	-0,19979	-0,09014	Minimum	-0,10764	-0,10764
Maximum	0,17774	0,12127	Maximum	0,14979	0,14779
St.Dev.	0,02641	0,01950	St.Dev.	0,01530	0,01515
Skewness	0,08604	-0,19202	Skewness	0,47346	0,16354
Kurtosis	8,97	6,00	Kurtosis	18,82	19,25
Normality tests					
Lilliefors	3.276,87	381,52	Lilliefors	22.493,69	11.020,51
(p value)	0,00	0,00	(p value)	0,00	0,00
Shapiro Wilk/Francia	0,062	0,051	Shapiro Wilk/Francia	0,105	0,118
(p value)	0,00	0,00	(p value)	0,00	0,00
Jarque-Bera	0,940	0,969	Jarque-Bera	0,842	0,837
(p value)	0,00	0,00	(p value)	0,00	0,00
Unit Root tests					
ADF (AR + drift)	-32,763	-21,865	ADF (AR + drift)	-33,646	-22,169
P-P (AR + drift)	-47,135	-29,625	P-P (AR + drift)	-45,747	-28,563

Source: Author's calculations

Returns from both indexes are stationary but far from being normally distributed. They are both leptokurtic, especially CROBEX index and skewed. XU 100 index is negatively skewed during the last 1,000 days although when looking at the entire sample period it has a slight positive skew. CROBEX index has a pronounced positive skew, although it has noticeably decreased in the last 1,000 days. Time varying volatility, skewness and kurtosis all complicate the measurement of risk and a priori indicate that classical VaR models will have a hard time forecasting the true level of risk an investor is faced with. Given these characteristics, VaR models using heavy tailed and asymmetric distributions, especially those based on EV approach should be more capable of capturing the true level of risk since they focus on the tail regions of the return distribution.

For proper implementation of EVT models, estimation of the tail index parameter is crucial, which again is directly linked to cut-off value, over which returns are considered to be extreme. We determined the cut-off value by using Coronel-Brizio and Hernandez-Montoya (2005) procedure. The same procedure of estimating the cut-off value was also performed on IID innovations required for the implementation conditional quantile EVT-GARCH model. GPD estimation results are presented in table 2.

Table 2: Maximum likelihood estimates of shape and scale parameter of the GPD for the XU 100 and CROBEX index negative returns and innovations, period 04.01.2000 - 03.11.2008

	Returns			Innovations		
XU 100	estimate	se	threshold value	estimate	se	threshold value
Tail index	0,0045	0,0770	3,2421	0,0282	0,1028	1,5905
Sigma	1,6381	0,1781		0,6026	0,0864	
	Returns			Innovations		
CROBEX	estimate	se	threshold value	estimate	se	threshold value
Tail index	0,2576	0,0937	1,5356	0,0310	0,0768	1,1436
Sigma	0,8847	0,1046		0,5963	0,0638	

Source: Author's calculations

Tail index of XU 100 index is not significantly different from zero implying that its' empirical left tail belongs to Gumbel domain of attraction. This means that modelling of the left tail of XU 100 index by Student's t, lognormal, gamma or exponential distribution would be more appropriate then using the Pareto distribution. This characteristic of XU 100 index left tail could result in overly conservative VaR estimates when using unconditional GPD or conditional quantile EVT model. CROBEX index has a higher tail index belonging to Fréchet domain of attraction and it does not even have a finite fourth moment since the estimated tail index is greater than 0.25. High value of the estimated tail index for the left tail makes CROBEX index a good candidate for EVT VaR models as it indicates that Croatian stock market experienced extreme crashes over the recent period.

4. Backtesting methodology and results

All of the analyzed VaR models are tested in several ways to determine their statistical characteristics and ability to adequately measure market risk in the analyzed markets. First employed test is the Kupiec test, a simple expansion of the failure rate, which is prescribed by Basel Committee on Banking Supervision. The second test is the Christoffersen (IND) independence test which tests whether VaR exceedences are IID. Christoffersen unconditional (UC) test and conditional (CC) test are also calculated but in authors' opinion they provide a somewhat distorted image of the relative performance of VaR models. Since Christoffersen UC test is distributed as chi-square with one degree of freedom, deviations from the expected value of the test that occur on the conservative side (i.e. number of exceedences is lower than the excepted value) are treated more severely, a characteristic that is not compatible with regulators desire to increase the safety of the banking system.

Kupiec and Christoffersen independence (IND) test backtesting results, at 5% significance level, for tested VaR models at 95, 99 and 99.5% confidence level are presented in table 3.

Table 3: Kupiec and Christoffersen independence (IND) test backtesting results at 95, 99 and 99.5% confidence levels, period 1,000 trading days up to 03.11.2008

VaR models	Kupiec test						Christoffersen IND test					
	XU 100			CROBEX			XU 100			CROBEX		
	95%	99%	99,5%	95%	99%	99,5%	95%	99%	99,5%	95%	99%	99,5%
HS 250									+			
HS 500									+			
BRW λ=0,97	+							+	+			
BRW λ=0,99	+								+			
Normal VCV												
Risk Metrics				+								
GARCH RM	+			+			+	+	+		+	+
HHS	+	+	+	+	+	+	+	+	+		+	+
EVT GARCH	+	+	+	+	+	+	+	+	+	+	+	+
GPD	+	+	+	+	+	+	+	+	+		+	+

Grey areas mark VaR models that satisfy Kupiec/Christoffersen IND test for the selected stock index and confidence level, at 5% significance level.

Source: Author's calculations

In the case of XU 100 index Kupiec test results shows that at high quantiles (99 and 99.5%) only EVT models and HHS model satisfy the Basel criteria while all other tested models fail. At 95% confidence level EGARCH-t model and BRW simulation also passed the test. It is interesting to see that widespread models such as historical simulation, VCV and RiskMetrics model do not predict the true level of risk even at this low quantile. Christoffersen (IND) test gives similar results with EGARCH-t model passing the test along with EVT and HHS models. The rest of the models besides failing the basic Kupiec test also fail the independence test, meaning that their failures are not even IID i.e. they tend to cluster which makes them completely unusable in these circumstances.

In the case of CROBEX situation is similar for both Kupiec and independence test, where again, at higher quantiles, only EVT and HHS models passed. The only striking difference in case of the CROBEX index is the failure of independence test at 95% for both GPD and HHS models, with only conditional EVT model passing the test.

The results are very consistent and indicative in pointing to the conclusion that when taking into the testing period the latest global financial crisis only EVT and HHS models perform satisfactory for the tested stock indexes, while other more widespread VaR models tend to seriously underpredict the true level of risk. Since EVT and HHS models satisfy the Kupiec and independence test for higher quantiles it is useful to know which model gives the closest fit to the true level of risk and which models could be the most acceptable by financial institutions regarding the average VaR values they forecast.

Table 4: Lopez test ranking of competing VaR models, period 1,000 trading days up to 03.11.2008

VaR models	XU 100			CROBEX		
	95%	99%	99,5%	95%	99%	99,5%
HS 250	14,86	8,25	5,17	26,86	15,28	13,18
HS 500	13,87	11,27	3,15	34,04	14,36	11,23
BRW λ=0,97	7,73	12,29	11,22	13,50	13,19	14,13
BRW λ=0,99	6,76	6,21	5,15	13,65	11,17	6,08
Normal VCV	16,85	16,34	15,24	22,77	19,36	14,29
Risk Metrics	13,75	11,29	14,21	4,52	11,25	12,19
GARCH RM	-3,47	5,15	5,09	-2,62	5,12	6,08
HHS	-12,61	-5,98	-4,00	5,47	4,11	2,05
EVT GARCH	-21,67	-5,97	-3,00	-25,78	-6,96	-2,98
GPD	-37,76	-5,96	-3,99	-37,69	-5,96	-3,99

Source: Author's calculations

Table 5: Average VaR values at 95, 99 and 99.5% confidence levels, for VaR models which satisfied Kupiec test at 5% significance level, period 1,000 trading days up to 03.11.2008

VaR models	XU 100			CROBEX		
	95%	99%	99,5%	95%	99%	99,5%
HS 250						
HS 500						
BRW λ=0,97	2,94					
BRW λ=0,99	2,94					
Normal VCV						
Risk Metrics				1,86		
GARCH RM	3,03			2,15		
HHS	3,38	5,63	6,52	1,96	3,03	3,71
EVT GARCH	3,66	5,80	6,75	2,47	3,93	4,58
GPD	4,85	7,53	8,69	3,92	7,71	9,90

Source: Author's calculations

When looking at the Kupiec, independence and Lopez test performance of non EVT models is far worse than reported by other studies in these field, which is a natural consequence of increased market stress and occurrence of high loses that cannot be accounted for by classical VaR models. The magnitude of losses that occurred in these markets under the parametric models using normality assumption are expected to occur once in a thousand years and in the historical simulation models periods of such high volatility and extreme losses simply fell out of the observation sample. For the XU 100 index the only models that overpredict the amount of risk are the EVT and HHS models. Other tested models seriously underpredict the true level of risk. Overprediction of EVT models can be explained by the fact that XU 100 index left tail falls into Gumbel domain of attraction and as such Pareto distribution is too fat tailed for it, but at the same time it is still to fat tailed for classical VaR models to capture it. Similar results are obtained for CROBEX index although based on the tail index parameter one would expect a better fit of Pareto distribution to the empirical data. Excluding the HHS model which slightly underpredicts the risk, but within acceptable bounds, and has the smallest Lopez statistic, performance of other VaR models is even worse than in the case of XU 100 index. Consistency of VaR forecasts of different models is clearly visible since; in general, VaR models that underpredict the risk at 95% confidence level do so also at 99 and 99.5% levels. The same applies to EVT models and their constant overprediction of risk, although this phenomenon is less pronounced for conditional quantile EVT approach. Although EVT models successfully capture extreme movements in the analyzed indexes in the case of unconditional EVT approach the price in capital was quite high. Average VaR at 99% confidence level for the GPD model is 7.53% in the case of XU 100 index and 7.71% in the case of CROBEX index. Superiority of the conditional quantile EVT approach over the unconditional one can be seen in the difference of average VaR values, which at the 99% confidence level is 29.9% in the case of XU 100 index and 96.4% for CROBEX. Similar results are present at 99.5% confidence level with the difference between the two being 28.8% for XU 100 and 116.1% for CROBEX. Out of the tested VaR models the only non EVT model that satisfies backtesting criteria is the HHS and at the same time is has the lowest average VaR value at 99 and 99.5% confidence levels. At 99.5% for XU 100 index the difference between the HHS and unconditional EVT model is 33.3% and for CROBEX index the difference is 166.7%. As the backtesting results show HHS presents a viable alternative to EVT models, since out of the ten tested models, it is the only non EVT model that satisfies the backtesting criteria but does so at a significantly lower cost compared to EVT models.

5. Conclusion

We investigated the relative performance of an array of VaR models on daily stock market returns from Turkey and Croatia in a dynamic setting. Results for Turkish XU 100 index and Croatian CROBEX index are similar in that Kupiec test shows that at high quantiles (99 and 99.5%) only EVT models and HHS model satisfy the Basel criteria. The rest of the tested models besides failing the basic Kupiec test also fail the independence test, meaning that their failures are not even IID i.e. they tend to cluster which makes them completely unusable in these circumstances and markets. We confirmed our hypothesis that only advanced and theoretically sound VaR models such as EVT and HHS, can adequately measure equity risk on Turkish and Croatian equity markets in times of crisis. The results are very consistent and indicative in pointing to the conclusion that when taking into the testing period the latest global financial crisis only EVT and HHS models perform satisfactory for the tested stock indexes, while other more widespread VaR models tend to seriously underpredict the true level of risk. VaR models that underpredict the risk at 95% confidence level do so also at 99 and 99.5% levels. The same applies to EVT models and their constant overprediction of risk, although this phenomenon is less pronounced for conditional quantile EVT approach. The main limitation of our study is the fact that we have only entered into the current global financial crisis and only after its passing will we be able to claim for certain if even the EVT and the hybrid model performed satisfactory or not. One of the main directions for future research is the inclusion of a wider sample of transitional and emerging countries over a longer period and across a wider spectrum of risk coverage. The findings for Turkish XU 100 index are similar to some degree with findings of Gencay, Selcuk (2004), Maghyereh, Al-Zoubi (2006) and Alper et. al. (2007). Same as in these papers the EVT models satisfy the backtesting criteria but at the same time they are seriously over predicting the true level of risk. As the backtesting results show HHS model presents a viable alternative to EVT models, since out of the ten tested VaR models, it is the only non EVT model that satisfies the backtesting criteria but does so at a significantly lower cost of capital compared to EVT approaches.

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Globalna financijska kriza i uspješnost VaR-a na brzorastućim tržištima: Primjer zemalja kandidata za EU članstvo – Turska i Hrvatska[1]

Saša Žiković[2], Bora Aktan[3]

Sažetak

U ovom radu istražujemo uspješnost širokog spektra modela rizične vrijednosti (VaR) na uzorku dnevnih prinosa na turski XU100 i hrvatski CROBEX dionički indeks u razdoblju netom prije i tijekom trenutne svjetske financijske krize. Uz primjenu standardno korištenih VaR modela, u ovom radu ispitujemo i ponašanje kondicionalnih i nekondicionalnih VaR modela koji se temelje na teoriji ekstremnih vrijednosti (EVT), kao i VaR model hibridne povijesne simulacije (HHS). Analizirani modeli su korišteni kako bi se generirale procijene 95, 99 i 99.5% razine vjerojatnosti. Dobiveni rezultati ukazuju na zaključak da za vrijeme trajanja kriznog razdoblja svi testirani VaR modeli, s izuzetkom VaR modela temeljenih na teoriji ekstremnih vrijednosti te hibridne povijesne simulacije, značajno podcjenjuju stvarnu razinu rizika na analiziranim tržištima. Iako oba modela daju ispravne rezultate, EVT modeli to čine uz znatno viši trošak kapitala nego što je to slučaj kod HHS modela.

Ključne riječi: *financijska kriza, brzorastuća tržišta, rizična vrijednost, teorija ekstremnih vrijednosti, hibridna povijesna simulacija*

JEL klasifikacija: *G24, C14, C22, C52, C53*

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[2] *Docent, Sveučilište u Rijeci, Ekonomski fakultet, I. Filipovića 4, 51000 Rijeka. Znanstveni interes: bankarstvo, upravljanje rizicima, kvantitativno modeliranje. Tel: +385 51 355 139. E-mail: szikovic@efri.hr*

[3] *Docent, Sveučilište Yasar, Fakultet ekonomskih i administrativnih znanosti, Universite Caddesi, No. 35-37, 35100 Bornova, Izmir, Turska. Znanstveni interes: kvantitativne financije, optimizacija, upravljanje rizicima. Tel: +90 (232) 411 5000. E-mail: bora.aktan@yasar.edu.tr*

Appendices

Table A1: Backtesting results and diagnostics of 1.000 VaR forecasts for XU100 and CROBEX index daily log returns, 99.5% confidence level, period 1,000 trading days up to 03.11.2008

XU 100 index	HS 250	HS 500	BRW l=0.97	BRW l=0.99	VCV	Risk Metrics	GARCH RM	HHS	EVT GARCH	GPD
Number of failures	10	8	16	10	20	19	10	1	2	1
Frequency of failures	0,01	0,008	0,016	0,01	0,02	0,019	0,01	0,001	0,002	0,001
Kupiec test (p value)	0,013	0,068	0,000	0,013	0,000	0,000	0,013	0,960	0,876	0,960
Christoffersen UC test (p)	0,049	0,216	0,000	0,049	0,000	0,000	0,049	0,029	0,126	0,029
Christoffersen IND test (p)	0,653	0,719	0,253	0,653	0,006	0,004	0,653	0,964	0,929	0,964
Christoffersen CC test (p)	0,129	0,436	0,000	0,129	0,000	0,000	0,129	0,091	0,309	0,091
Lopez test	5,167	3,153	11,216	5,151	15,243	14,209	5,086	-4,000	-2,996	-3,993
Blanco-Ihle test	3,509	3,023	5,596	3,073	5,539	5,409	1,596	0,001	0,052	0,079
RMSE	0,049	0,050	0,049	0,054	0,042	0,044	0,046	0,065	0,004	0,003
MAPE	0,789	0,730	1,159	0,730	1,550	1,449	0,705	0,500	0,500	0,500
Average VaR (%)	5,15	5,23	5,01	5,56	4,47	4,48	4,75	6,52	6,75	8,69
CROBEX index	HS 250	HS 500	BRW l=0.97	BRW l=0.99	VCV	Risk Metrics	GARCH RM	HHS	EVT GARCH	GPD
Number of failures	18	16	19	11	19	17	11	7	2	1
Frequency of failures	0,018	0,016	0,019	0,011	0,019	0,017	0,011	0,007	0,002	0,001
Kupiec test (p value)	0,000	0,000	0,000	0,005	0,000	0,000	0,005	0,133	0,876	0,960
Christoffersen UC test (p)	0,000	0,000	0,000	0,020	0,000	0,000	0,020	0,398	0,126	0,029
Christoffersen IND test (p)	0,039	0,023	0,004	0,004	0,049	0,002	0,621	0,753	0,929	0,964
Christoffersen CC test (p)	0,000	0,000	0,000	0,001	0,000	0,000	0,060	0,666	0,309	0,091
Lopez test	13,179	11,233	14,131	6,083	14,285	12,187	6,084	2,048	-2,976	-3,991
Blanco-Ihle test	4,843	6,043	4,801	2,298	7,782	5,699	2,598	1,387	0,510	0,088
RMSE	0,032	0,039	0,041	0,040	0,027	0,033	0,037	0,042	0,003	0,003
MAPE	1,366	1,304	1,198	0,791	1,365	1,260	1,009	0,763	0,500	0,500
Average VaR (%)	3,08	3,78	3,63	3,83	2,75	2,98	3,36	3,71	4,58	9,90

Source: Author’s calculations

Table A2: Backtesting results and diagnostics of 1.000 VaR forecasts for XU100 and CROBEX index daily log returns, 99% confidence level, period 1,000 trading days up to 03.11.2008

XU100 index	HS 250	HS 500	BRW l=0.97	BRW l=0.99	VCV	Risk Metrics	GARCH RM	HHS	EVT GARCH	GPD
Number of failures	18	21	22	16	26	21	15	4	4	4
Frequency of failures	0,018	0,021	0,022	0,016	0,026	0,021	0,015	0,004	0,004	0,004
Kupiec test (p value)	0,007	0,001	0,000	0,026	0,000	0,001	0,048	0,971	0,971	0,971
Christoffersen UC test (p)	0,022	0,002	0,001	0,079	0,000	0,002	0,139	0,030	0,030	0,030
Christoffersen IND test (p)	0,039	0,008	0,091	0,023	0,004	0,008	0,499	0,858	0,858	0,858
Christoffersen CC test (p)	0,009	0,000	0,001	0,016	0,000	0,000	0,266	0,094	0,094	0,094
Lopez test	8,252	11,270	12,293	6,206	16,343	11,292	5,148	-5,979	-5,975	-5,963
Blanco-Ihle test	5,788	6,012	7,921	4,657	8,597	8,238	3,103	0,284	0,407	0,493
RMSE	0,041	0,042	0,045	0,047	0,037	0,039	0,041	0,055	0,004	0,002
MAPE	0,984	1,185	1,228	0,853	1,521	1,068	0,629	0,778	0,794	0,774
Average VaR (%)	4,39	4,47	4,58	4,87	4,03	4,03	4,29	5,63	5,80	7,53

CROBEX index	HS 250	HS 500	BRW l=0.97	BRW l=0.99	VCV	Risk Metrics	GARCH RM	HHS	EVT GARCH	GPD
Number of failures	25	24	23	21	29	21	15	14	3	4
Frequency of failures	0,025	0,024	0,023	0,021	0,029	0,021	0,015	0,014	0,003	0,004
Kupiec test (p value)	0,000	0,000	0,000	0,001	0,000	0,001	0,048	0,082	0,990	0,971
Christoffersen UC test (p)	0,000	0,000	0,000	0,002	0,000	0,002	0,139	0,231	0,009	0,030
Christoffersen IND test (p)	0,003	0,002	0,014	0,008	0,001	0,008	0,499	0,528	0,893	0,009
Christoffersen CC test (p)	0,000	0,000	0,000	0,000	0,000	0,000	0,266	0,399	0,033	0,003
Lopez test	15,276	14,364	13,185	11,173	19,361	11,249	5,122	4,115	-6,960	-5,960
Blanco-Ihle test	8,415	11,384	7,278	5,261	11,265	8,576	4,185	3,992	1,025	0,519
RMSE	0,027	0,026	0,034	0,031	0,025	0,030	0,033	0,034	0,002	0,002
MAPE	1,688	1,642	1,117	1,368	1,957	1,276	0,909	0,883	0,756	1,022
Average VaR (%)	2,64	2,70	3,10	3,00	2,47	2,68	3,03	3,03	3,93	7,71

Source: Author's calculations

Table A3: Backtesting results and diagnostics of 1.000 VaR forecasts for XU100 and CROBEX index daily log returns, 95% confidence level, period 1,000 trading days up to 03.11.2008

XU100 index	HS 250	HS 500	BRW l=0.97	BRW l=0.99	VCV	Risk Metrics	GARCH RM	HHS	EVT GARCH	GPD
Number of failures	64	63	57	56	66	63	46	37	28	12
Frequency of failures	0,064	0,063	0,057	0,056	0,066	0,063	0,046	0,037	0,028	0,012
Kupiec test (p value)	0,021	0,028	0,139	0,172	0,011	0,028	0,688	0,969	1,000	1,000
Christoffersen UC test (p)	0,051	0,069	0,320	0,393	0,027	0,069	0,557	0,048	0,001	0,000
Christoffersen IND test (p)	0,002	0,000	0,004	0,001	0,000	0,001	0,222	0,599	0,204	0,130
Christoffersen CC test (p)	0,001	0,000	0,010	0,002	0,000	0,001	0,399	0,124	0,001	0,000
Lopez test	14,856	13,871	7,728	6,762	16,853	13,750	-3,471	-12,609	-21,672	-37,760
Blanco-Ihle test	30,300	30,258	27,485	25,457	30,383	29,424	16,095	10,573	8,857	4,947
RMSE	0,027	0,027	0,028	0,027	0,026	0,027	0,028	0,031	0,002	0,002
MAPE	2,780	2,728	1,501	1,728	2,938	1,583	1,442	1,899	2,405	4,262
Average VaR (%)	2,88	2,90	2,94	2,94	2,83	2,80	3,03	3,38	3,66	4,85

CROBEX index	HS 250	HS 500	BRW l=0.97	BRW l=0.99	VCV	Risk Metrics	GARCH RM	HHS	EVT GARCH	GPD
Number of failures	76	83	63	63	72	54	47	55	24	12
Frequency of failures	0,076	0,083	0,063	0,063	0,072	0,054	0,047	0,055	0,024	0,012
Kupiec test (p value)	0,000	0,000	0,028	0,028	0,001	0,253	0,634	0,210	1,000	1,000
Christoffersen UC test (p)	0,000	0,000	0,069	0,069	0,003	0,566	0,660	0,475	0,000	0,000
Christoffersen IND test (p)	0,000	0,000	0,005	0,000	0,000	0,000	0,000	0,000	0,603	0,000
Christoffersen CC test (p)	0,000	0,000	0,004	0,000	0,000	0,000	0,001	0,000	0,000	0,000
Lopez test	26,864	34,036	13,497	13,655	22,767	4,521	-2,620	5,472	-25,783	-37,692
Blanco-Ihle test	44,871	57,424	28,880	32,580	37,388	27,687	16,914	23,606	8,251	7,848
RMSE	0,018	0,017	0,020	0,019	0,019	0,021	0,023	0,022	0,001	0,001
MAPE	3,635	4,915	1,767	2,414	3,577	2,370	3,049	2,704	3,121	4,587
Average VaR (%)	1,60	1,53	1,85	1,73	1,71	1,86	2,15	1,96	2,47	3,92

Source: Author's calculations