ECONOMETRIC MODELS USED FOR MANAGING THE MARKET RISK IN THE ROMANIAN BANKING SYSTEM

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Abstract

Taking into account that one of the most important factors which have caused the financial crisis was the bad risk management practices in banks we want to confirm the need to develop more efficient risk management practices. The fact that return distributions are characterized by time varying volatility poses some challenges in the estimation, especially in the period of severe financial crisis. In order to remedy this problem we propose the Extreme Value Theory as an alternative to VaR for quantifying the banks' exposures to interest rate risk. EVT models are more robust to fat-tailedness in the conditional distribution of returns and are preferred in the modeling of interest rate risk in periods with extreme variations. Finally, we assess the performance of the model analyzing the interest rate risk on the Romanian inter-bank market by measures that address its conservativeness, accuracy and efficiency, in the context of Basel II principles.

1. INTRODUCTION

Due to excessive portfolio exposures of banks, the joint evolution of exchange rates, interest rates, the evolvement of various financial instruments for market risk presents a critical issue for the banking system as well as for the supervising authorities. So the estimation and proper management of this has substantial consequences, by allowing an adequate capital allocation and, in the same time, ensuring financial stability.

This paper analyze interest rate risk behavior in periods characterized by extreme events and propose some EVT (Extreme Value Theory) models in order to quantify and manage the interest rate risk on the Romanian interbank market. It also shows that in ex-

treme volatility market conditions, like those from the beginning of financial crisis, EVT is better performing than VaR (Value at Risk).

Value at Risk has become a standard risk measure for banks, insurance companies, institutional investors and non-financial enterprises, recommended by the Basel Committee on Banking Supervision in quantifying the market risk. Since it received its first representation in July 1993 in the Group of Thirty Report, the technique has gone through significant refinement it originally appeared. Theoretical research was initiated by Jorion (1997), Dowd (1998), and Saunders (1999). Proponents of VaR believe it will replace or at least complement less standardized techniques such as Asset and Liability Management and Stress-testing. They also hoped that regulators, auditors, shareholders and management will finally be speaking a common language with respect to risk.

The VaR computed through historical simulation is based on the idea that the distribution of financial returns is normally distributed at monthly and larger horizons. But at shorter horizons and higher frequencies the return distributions tend to present non-normal features and are characterized by "fat-tails" (Fama, 1965). These are defined as tails that have a higher density than that which is predicted under the assumption of normality (Mandelbrot, 1963). These have important consequences on estimating VaR, because the normal distribution could underestimate the risk and the capital requirements needed to cover the losses that results, putting the bank into a risky position (Berkowits and O'brien, 2001). The solution found was to use other distributions which allow for a better modeling of larger movements than the normal distribution (like Pareto distribution ant Student t distribution). The recent studies propose to analyze only the distribution of extreme returns, instead of describing the behavior of all of the returns (Ferreira and Lopez, 2004; Burns, 2002; Rombouts and Verbeek, 2004).

Related to these studies is the EVT, introduced in finance by Embrechts (1997), although the basics were initiated by Fisher and Tippett (1928) when proposing the Generalized Extreme Value (GEV) distribution. The modeling of the financial variables through EVT was also studied by McNeil and Frail (2000), by Danielsson and De Vries (1997) which computed a model for calculating the VaR, taking into account the inconsistency of extreme values and by Huisman et al. (1997) which proposed a new estimator for the tail index. Bensalah (2000) found that EVT is performing better than VaR when analyzing the evolution of daily exchange rates of Canadian/U.S. dollars. Applying the EVT on the overnight borrowing and interest rates on Turkey, Gencay and Selcuk (2005) also came to this conclusion. Analyzing six major developed markets indices Gilli and Kellezi (2007) illustrated that EVT is better in modeling the tail related risk. LeBaron and Smanta (2004) applied EVT to construct statistical tests in order to estimate the level of „fattness" in the tails of emerging and developed markets. Using Monte Carlo methods and bootstrapping tests of pooled returns they found that emerging markets have fatter negative tails than the developed ones. Schaumburg (2010) proposed nonparametric quantile regression and EVT for computing Value at Risk.

The Value at Risk methodology has also been criticized in the last period by the financial authorities, because the majority of losses that banks have suffered have occurred from the trading book. Financial Service Authority (2009) highlighted that short-term observation periods and the assumption of normal distribution can lead to large underestimation of probability of extreme loss events. The Senior Supervisors Group (2010) also motivated the need for more adaptive risk management practices and the importance of supplementing VaR with other risk measures. After a study on eleven banks (2007) that are significant competi-

tors in the affected markets it was discovered that they identified weaknesses in their implementation of VaR and the calculations based on new market data ranged from about 30% to 80% higher compared with the calculations obtained using data sets reflecting earlier. Also they reported between two and sixteen back-testing exceptions, generated by much higher volatility that the historical data series implied.

In response to all these Basel Committee on Banking Supervision (BCBS) has adopted amendments to the Basel II Capital Accord and made changes to the market risk capital requirements. It also advised banks to use a stressed VaR measure using a one-year observation period. The major change is that the capital requirement for market risk will be the sum of the 10-day shock VaR currently required and the new stressed one-year VaR.

According with this, our paper deals with some risk management tools used by banks in order to quantify and manage their exposure to interest rate risk in periods characterized by extreme events. Section 2 presents the Value at Risk methodology, in accordance with the Basel II requirements. Section 3 describes the Extreme Value Theory and reviews the techniques used to model the distribution of the extreme data. In section 4 is presented a case study which analyzes the volatility of ROBOR (Romanian Interbank Offered Rate) and its impact on banks exposures. Section 5 concludes.

2.   VALUE AT RISK METHODOLOGY

Financial institutions have developed models for quantifying, comparing and aggregating the risk connected with different positions and portfolios. One of the most used methods is Value at Risk, which is defined as the expected maximum loss of a portfolio over some time period and for some level of probability. From a statistical point of view, VaR entails the estimation of the quantile of the returns' distribution. In other words, Value at Risk is the probability that returns or losses (ξ) are smaller than $-VaR$ over a period of time (T):

$$P_{VaR} = P(\xi < -VaR) = \int_{-\infty}^{-VaR} P_T \cdot \xi \cdot d\xi,$$

where P_T is the probability distribution of returns over the time horizon T.

Inputs to a VaR model include data on the bank on and off balance sheet positions and on respective interest rates, exchange rates, equity and commodity positions. The measurement parameters include a historical time horizon, a holding period and a confidence interval that allows for prudent judgments of the optimal level of protection. The Basel Committee recommends a holding period of 10 days trading, an historical observation period of a minimum of one year and a 99th percent confidence level. Due to these, providing accurate estimates is of crucial importance. If the underlying risk is not properly estimated, this may lead to a sub-optimal capital allocation with consequences on the profitability and the financial stability of the institutions.

In order to compute the VaR for a portfolio first we have to mark-to-market the portfolio and then to estimate the distribution of the portfolio's returns, which is a very challenging statistical problem. After this there could be applied three types of models for calculating VaR: parametric, non-parametric and semi-parametric. What makes the difference among them is related to the way they address the distribution problem. When the returns are normal, which is very rarely in practice, it is used the variance-covariance approach. When risk is recurrent VaR can be estimated by using historical time series and for

new situations it should be modeled through EWMA and GARCH models. When risk is sensitive to rare events it is preferred the Extreme Value Theory.

The main limitation of the VaR methodology is that the assumption of normal distribution can lead to large underestimation of the probability of extreme events, which affects the capital requirements. Also, the estimated distribution tends to fit central observations, while falling in fitting the extreme observations. The accuracy of VaR depends on how well the underlying markets have been simulated and how well each security has been modeled, because there exists a tremendous variability in current practices and different financial institutions perform each step with varying levels of accuracy.

3. ESTIMATING EXTREME EVENTS

In order to remedy the problem of the fat-tails, EVT has become more and more used by financial institutions because it doesn't make any assumption about the form of the distribution of financial returns. This approach is focused on the extreme events and states that in the case of a very large sample it converges toward a limit distribution. There are two approaches in identifying extremes in the data: block-maxima and excesses over a threshold. The first one, block-maxima approach, considers the maximum value the variables take in successive periods and the procedure consists in dividing the series of observations in blocks. The maximum value of each block constitutes the extreme value. This method is often used to analyze data with seasonality. The second approach, excess over a threshold, which has been used in the most recent applications, focuses on the values exceeding a given threshold.

The initial step in generating series by the **block-maxima method** is the Theorem of Fisher and Tippett (1928): Let (Xn) be a sequence of independent and identically distributed random variables. The maximum of the variables converges in law to the next distribution:

$$H_{(\xi,\mu,\sigma)} = \begin{cases} \exp\left\{-\left[1 + \xi(x-\mu)/\sigma\right]^{-1/\xi}\right\}, if \xi \neq 0 \\ \exp\left[-e^{-(x-\mu)/\sigma}\right] if \xi = 0 \end{cases},$$

where μ is a scalar, σ is the tendency and ξ indicates the thickness of the distribution's tail. The larger the ξ, the thicker the tail. If ξ is negative, the distribution corresponds to a Weibull type; if ξ is zero the distribution corresponds to a Gumbel type; when ξ is positive it corresponds to a Frechet distribution. The most used in modeling the financial series is the last one, because performs better in capturing the fat tails.

For a given probability p, the expression of VaR will be the following:

$$VaR_p = \begin{cases} \mu - \dfrac{\sigma}{\xi}\left(1 - \left(-\log\left(1 - \dfrac{1}{p}\right)\right)^{-\xi}\right), \xi \neq 0 \\ \mu - \sigma\log\left(-\log\left(1 - \dfrac{1}{p}\right)\right), \xi = 0 \end{cases}$$

The second approach, **excess over a threshold**, consists in determing the distribution of excesses over a chosen threshold, which can be approximated by a Generalized Pareto Distribution:

$$G_{(\xi,\beta)} = \begin{cases} 1 - \left(1 + \dfrac{\xi x}{\beta}\right)^{-1/\xi}, & if \, \xi \neq 0 \\ 1 - e^{-x/\beta}, & if \, \xi = 0 \end{cases},$$

where β is the tendency and ξ is the threshold, which should be large enough in order to satisfy the condition that permits its application and at the same time it should leave sufficient observations for the estimation. This approach is considered to be more efficiently and it is used by the most financial institutions.

So, the analytical expression of the VaR for a given probability p, could be defined as a function of GDP parameters:

$$VaR_p = u + \frac{\sigma}{\xi}\left(\left(\frac{n}{N_u}p\right)^{-\xi} - 1\right), \text{ where}$$

n is the threshold, n is the total number of observations and N_u is the observations above the threshold u.

4. ANALYZING EXTREME EVENTS ON THE ROMANIAN INTERBANK MARKET

In order do determine the VaR of a hypothetical portfolio of financial instruments in RON, VaR was calculated on daily data of ROBOR overnight published by the National Bank of Romania from 03.01.2007 to 30.06.2009. The observations on the interbank offered interest rates are available on a period longer than that we took in consideration, but we have considered that the recent observations provides a better estimation on the risk of the portfolio. Also, we divided the data into three samples: the first sample is from 04.01.2005 to 30.06.2009 (1.141 observations), the second sample is from 03.01.2007 to 30.06.2009 (633 observations) and the third sample is from 02.06.2008 to 30.06.2009 (273 observations), in order to highlight different behaviors in the pre-crisis period.
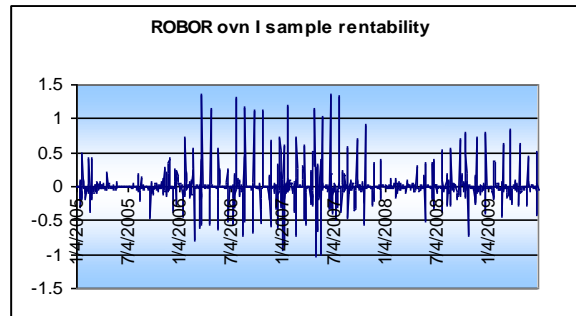
Source: authors' calculations
Figure no. 1a The daily evolution of rentabilities
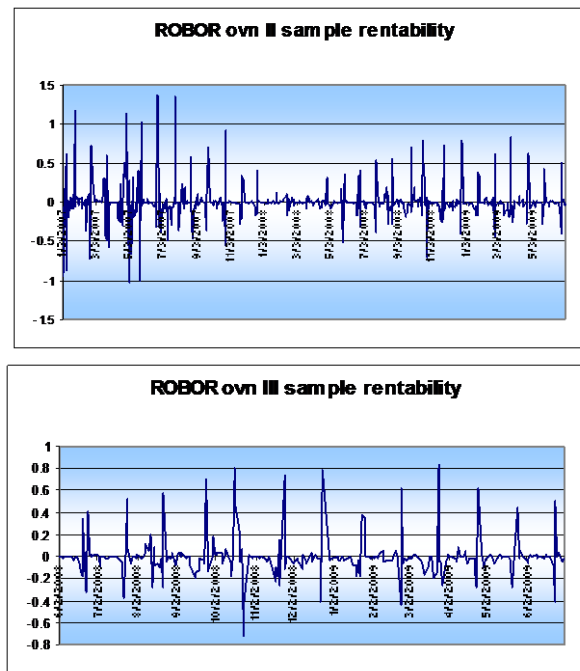
Source: authors' calculations
Figure no. 1b The daily evolution of rentabilities

The daily rentabilities (shown in the graphs below) were determined by logarithmation of the series of interbank offered rates and present a lot of extreme variations that took place on the monetary market. The Romanian Interbank Offered Rate for LEI has faced a period with extreme variations in the pre-crisis period from 17.10.2008 to 23.10.2008 when ROBOR overnight has reached a maximum of 57% because of the lack of liquidity in the Romanian banking system. From the beginning of 2009 it has decreased due to the Central Bank policy, which has reduced the level of main refinancing operation.

Applying the Jarque Berra Test we will observe that the normal hypothesis is rejected. The distributions are leptokurtic, more sharpen than the normal ones, for all of the samples, a fact shown by the kurtosis coefficient. Analyzing the skewness coefficient we will observe that the distributions are shifted to the left, compared with the normal distribution. Applying the ADF and the Philipe-Peron tests it will be observed that the series composed of the interest rates' values have one unit roots, which means that it is needed a first order differentiation in order to become stationary.

Table no. 1 The moments of the distributions

	ROBOR ovn I	**ROBOR ovn II**	**ROBOR ovn III**
Observations	1.141	633	273
Mean	-0.000469	0.000240	-0.000402
Median	0.000000	0.000000	0.000000
Maximum	0.514035	0.514035	0.514035
Minimum	-0.468803	-0.468803	-0.468803

	ROBOR ovn I	ROBOR ovn II	ROBOR ovn III
Std. Dev.	0.037123	0.047115	0.060703
Skewness	1.975164	1.762219	1.994071
Kurtosis	99.41499	68.43324	54.69923
Jarque-Bera	442682.1	113252.4	30584.14
Probability	0.000000	0.000000	0.000000

Source: authors' calculations

According to all these factors, the distribution of the rentabilities presents fat tails, which correspond to the extreme variations that took place on the money market. Using the historical simulation method can lead to an overestimation of VaR, especially that the method describes the maximum expected loss. Here appears the "volatility clustering" phenomena, which can be remedied by the heteroscedasticity models GARCH.

In order to eliminate the linear structure we propose some ARMA models studying the residuals' correlogram, for which the AIC and BIC criterions are minimum: ARMA(7) for the first sample, ARMA(5) for the second sample and ARMA(4) for the third sample. The remained residuals have a non-linear structure which was detected by the BDS test elaborated in 1987 by Brock, Dechert and Scheinkman, in order to check the stochastic non-linearity. The BDS test's values are strong, which sustains the rejection of the normal hypothesis.

This tendency reflects a degree of heteroscedasticity, which means that the present volatility depends on the previous volatility. Unless the data is filtered, this dependence will undermine the value of VaR. In order to eliminate the correlation between residuals we had to find some GARCH models. The best models identified were: GARCH(1,2), TGARCH, Orthogonal GARCH.

For expressing the current volatility as a function of past volatility, we have also used EWMA models, giving more importance to the recent data. Estimating the volatilities and the correlations through EWMA(0,94), EWMA(0,92) and EWMA(0,90) we have calculated VaR for more levels of the persistence parameter λ. We have seen that the closer the value λ to unity, the higher the risk.

For a better characterization of the extreme values found at the upper and lower tails we have applied the Extreme Value Theory, using the excess over a threshold method. In our study we have used the Generalized Pareto Distribution to represent the extreme values, after sorting the values and choosing the following thresholds: 0.5% and 1% and 5%. We have observed that the higher the threshold, the higher the risk.

Table no.2 VaR estimations

	ROBOR ovn I	ROBOR ovn II	ROBOR ovn III
VaR – HS	0,030	0,037	0,075
VaR – EWMA (0,94)	0,038	0,048	0,085
VaR – EWMA (0,92)	0,034	0,042	0,071
VaR – EWMA (0,90)	0,027	0,036	0,068
VaR – GARCH(1,2)	0,049	0,046	0,089
VaR – TGARCH	0,039	0,041	0,086
VaR – Ortogonal Garch	0,026	0,038	0,067
EVT (0.5%)	0,043	0,051	0,095
EVT (1%)	0,042	0,050	0,091
EVT (5%)	0,038	0,048	0,087

Source: authors' calculations

From the Table 2 we could see that for the first sample the GARCH (1,2) is the best, but for the second and for the third sample EVT (0.5%) performs better. In the pre-crisis period the EVT is followed by the EWMA (0.84), GARCH (1,2), the EWMA (0.92), TGARCH, Orthogonal Garch, Historical Simulation and EWMA (0,90). In the crisis period the most restrictive models in predicting VaR are EVT(0.5%), EVT (1%), GARCH (1,2), EVT (5%), TGARCH, EWMA and Historical Simulation. Taking into consideration the whole database (sample I) the GARCH method performs better, followed by EVT(0.5%) and EVT(1%). Analyzing the all three samples the results confirm what the BCBS proposed – using a shorter data sample for the periods characterized by extreme variations. In our case, using the first sample, with 1.141 observations could lead to the underestimation of risk.

In order to test the post efficiency of the methodologies we have used the back-testing, by simulating the stress scenarios for the least 245 days. We have applied the quadratic loss function approach, calculating how many times the VaR has been exceeded. The best methods, which are in the minimum risk zone (which means that VaR has been exceeded for no more that 4 times), are the EVT models, followed by the GARCH models and EWMA models (medium safety zone). The method that failed mostly in accurately estimating the risk is the Historical Simulation method.
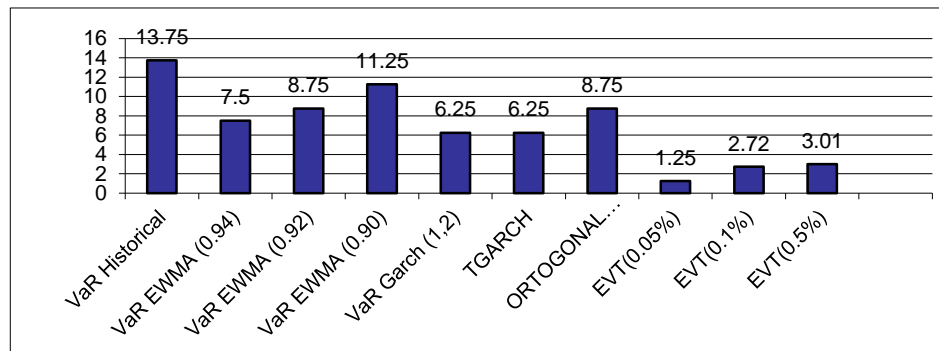
Source: authors' calculations
Figure no. 2 Back-testing - the quadratic loss function approach

5. CONCLUSIONS

We confirmed our hypothesis that only advanced VaR models such as Extreme Value Theory can adequately measure the interest rate risk for the overnight ROBOR and satisfy the BCBS criteria in periods characterized by extreme events. Also, in forecasting VaR for exposures to interest rate risk in crisis periods it should be used a shorter sample of data, the most recent one, in order to capture the large movements on the market. With regard to accuracy, the risk managers should be concerned with whether the model's ex-post performance is compatible with the theoretically desired level, applying permanently back-testing criteria.

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