ADVANTAGES AND LIMITATIONS OF VAR MODELS USED IN MANAGING MARKET RISK IN BANKS

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1. Introduction

Value-at-Risk (VaR) is a risk management methodology, which has been greeted with extensive focus in recent years from both academic researchers and practitioners. VaR provides a statistical quantification of the different components of risk into a single quantitative indicator.

Value at Risk measures the maximum probable loss which may occur for a portfolio in a certain period of time and a confidence interval (Jorion, 2001). Faced with a simple conceptual definition, the implementation of VaR can be achieved by various methods, which share a common procedural approach.

The outcomes of various approaches differ considerably, even if the models are based on the same basic notions, large differences are to be found regarding the use of data, the estimation procedures of the volatility and corelations. Not all VaR methodologies are based on portfolio approach, certain VaR estimation methods are built using historical simulation or some more complex approaches, eg Monte Carlo simulation method.

Implementing the VaR model is currently considered a goal of risk management , until now Basel II. offered banks the opportunity to design their own internal models to estimate risk, currently, Basel III requires that the models used by banks enhance the quality and quantity of capital of banks.

2. Methodology

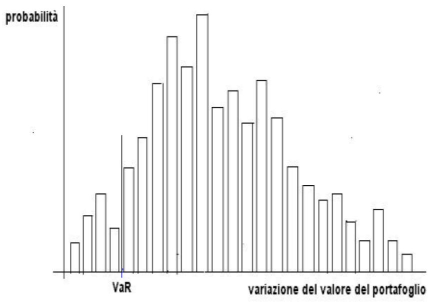
Value at Risk (VaR) is a statistical method for measuring the risk of a portfolio, so the potential maximum expected loss of the portfolio is represented for a given time horizon and a predefined confidence level.

Thus, if we consider a probability such as *c%* (*c* representing the confidence level) and a period of time in days *t*, VaR is the measurement of the loss expected to be exceeded only with a probability *(1-c)%* in t days in the future.

The choice of *c* and t are subjective, depending on the confidence level *c,* which defines the degree of protection against the risks due to the various factors of the market movements. Typical values for *c* are 99%, 97.5%, or 95%, the choice can be be relevant or not depending on the purpose for which VaR is calculated. So if VaR is used as an absolute measure of risk or a unit of comparison (ie. comparing the risk between different portfolios), *c* is only a scale factor. Of course, the higher the choosen confidence level is, the greater is the ability to reduce the losses by VaR (the level that is unlikely to be exceeded expected by the maximum loss).

Also the period of time t usually varies in from 1 or 2 days to 10 days ,or even a month. The underlying assumption is that the composition of the portfolio remains constant over the period of time considered, so the choice of time horizon should depend on the frequency with which the portfolio is subject to manipulation and the time required for the liquidation of the portfolio.

The definition of of VaR can be be easily illustrated from a graphical point of view. Suppose that the change in the portfolio, ΔW is defined as $\Delta W = W_0 - W_t$, where W_0 stands for the initial value of the portfolio, while W_t for the value of the portfolio at the end of time horizon chosen.



Probability distribution of the portfolio value changes of ΔW (Source: Pederzoli, Ch., Torricelli, C., (1999))

In the chart above, starting from left (where the greatest losses can be found), the individual probability values areadded until they reach a cumulative probability of (1-c)%, resulting a VaR which separates the normal, expected value losses from the exceptional losses.

There are several methods for calculating VaR, characterized by different assumptions and different procedures, but a basic model can be identified, with common elements to all methods, including (Jorion, 2001)):

- identifying the relevant risk factors, namely the factors affecting the market value of the portfolio;
- estimating the probability distribution for the rate of returns for risk factors;
- determining the probability distribution of portfolio yields in terms of profit and loss based on previous estimates;
- determine VaR as the maximum loss at a level of probability of c%;

The common goal of all methods is to obtain an estimation of the probability distribution for the rate of returns, or rather to capture the changes in the portfolio value.

The Parametric models are those models which are based on variance-covariance approach, in this paper we present the following ones:

- The normal portfolio VaR
- Asset-Normal VaR
- Beta-Normal VaR

When using parametric models, it is assumed that financial assets in the trading book of the bank follows a known theoretical distribution, so VaR will be calculated based on the parameters of that distribution. Banks used most common parameters that vary over time, paying attention to recent observations and ignoring those in the distant past. The main advantage of these methods is that they perform a full characterization of the distribution yields, leading also to improved performance.

The normal portfolio VaR

To calculate VaR, we consider only the total portfolio value, Π, and the volatility of portfolio return бΠ without decomposing it into its components. Assumptions regarding the daily rates of return are:

- Independent;
- The expected value is zero;
- Distributed by the normal law of distribution

At a confidence level of 1% for N days, the VaR will be equal to Π * -2.33 * бΠ.

Asset-Normal VaR

The portfolio is divided into its components and it is assumed that the daily return are normally distributed. In this case in the calculation of VaR we have to take into account the volatility and the correlations between returns.

The assumptions underlying the model are:

- The portfolio is composed from *n* assets;
- Changes in the portfolio value depend linearly from the variations of the n assets;
- The probability distribution of the portfolio yields follow the normal distribution and are independent;
- Variance portfolio includes correlations between profitability;

Portfolio return and volatility are obtained from:

$$\frac{d\Pi}{\Pi} = \sum_{i=1}^{n} \omega_i R_i \ ,$$

$$\sigma_n = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} \omega_i \omega_j \sigma_i \sigma_j \rho_{ij}} \quad .$$

Where σ_i reprezents the volatility of asset *i*, while σ_j stand for the volatility of asset *j*, ρ_{ij} beeing the correlation between them. This model has also a limit, because when the portfolio is composed of several securities, it is necessary to calculate all the correlations between the assets.

Beta-Normal VaR

It aims to simplify the variance-covariance matrix needed to compute the VaR of the portfolio of shares. Therefore we consider Sharpe's model in which the yields of the securities comprising the portfolio are influenced by the market index return. Sharpe's method determines the selection of a set of efficient portfolios at each level of risk, maximizing the expected profitability, without indicating an optimal portfolio for each investor.

$$R_{j,t} = \alpha_j + \beta_j \cdot R_{M,t} + \varepsilon_{j,t},\ j = \overline{1,N}.$$

Given the assumptions of the econometric model, the elements from the the variance-covariance matrix of the rate of returns will have the expressions:
The anticipated rate of returns:

$$E(R_j) = \alpha + \beta \cdot E(R_M)$$

The variance of the rate of returns:

$$V(R_{j,t}) = \beta_j^2 V(R_{M,t}) + V(\varepsilon_{j,t})$$

$$\leftrightarrow \sigma^2(R_j) = \beta_j^2 \cdot \sigma^2(R_M) + \sigma^2(\varepsilon_j)$$

The covariance between the title i and title j

$$\operatorname{cov}(R_i, R_j) = E\left[\left(R_i - E(R_i)\right)\left(R_j - E(R_j)\right)\right]$$

$$= \beta_i \beta_j \rho^2(R_M)$$

The variance-covariance matrix can be written in the following form:

$$\Omega = \sigma^2(R_M) \cdot BB^{'} + E$$

Where E represents the diagonal matrix of the variance of the residuals $\sigma^2(\varepsilon_i)$, while *B* is the vector of Beta,and *B'* represents the transposed matrix.

Risk management models require a quantitative estimation of risk associated with a financial position, therefore we used these techniques to estimate the volatility:

- Moving averages
- The GARCH(1,1) model
- The Risk Metrics model

Moving averages

a) Simple (Standard Deviation)

$$\rho = \sqrt{1/n \sum_{i=0}^{n-1} r_{t-i}^2}$$

b) Weighted (EWMA)

Exponentially Weighted Moving Average variance was calculated as a weighted average of the variable percentage of the historical series squared returns, using a constant weighting λ (decay factor), 0 <λ <1, indicating the "degree of permanence" of past observations.

$$\sigma^2 = (1-\lambda) \cdot r_{t-1}^2 + \lambda \cdot \sigma_{t-1}^2$$

Each time series corresponds to one such factor that minimizes the average error optimal λ) quadratic prediction of the variance, (ε_{t+1}), where:

$$\varepsilon_{t+1} = r_{t+1}^2 - \sigma_{t+1}^2$$

Thus, lambda is obtained minimizing the expression:

$$\tau_i = \sqrt{1/T \sum \left(r_{t+1}^2 - \sigma_{t+1}^2(\lambda)\right)^2}$$

We consider a time interval consisting in T days, and based on the historical evolution of the prices, the yields are calculated (r_{t+j} ,where $j \geq 1$) for each day in this time period. After that, the volatility iterations are written, and then through successive attempts the value of the degradation factor is searched so that it minimizes τ from the formula above. The disadvantage lies in the choice of lambda.

The GARCH (1,1) Model

It was proposed by T. Bollereslev in 1986, and it is a part of a broader class of GARCH (q, p) models. It enjoys a great popularity among practitioners because of its relative similarity to Engel's model. The variance is obtained by: $\sigma_t^2 = \gamma \cdot V + \alpha \cdot r_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$,

where $\gamma + \alpha + \beta = 1$.

The forecast suggests that the variance is based, in this case, on the most recent observation of return on assets and on the last calculated value of the variance. The general GARCH (q, p) calculates the expected variance based on past *q* observations and the most recent p estimated variances. (Campbell,J., Lo, A., MacKinley, C., 1997).

The Risk Metrics model

It is based on the assumption that the rate of returns follow a normal distribution law and the VaR is calculated by the EWMA method.

In this model the variance and covariance are determined using a weighted moving average exponential model. The biggest advantage of this model is the speed at which it reacts to the unexpected market movements. The volatility equation can be described as follows:

$$\sigma_t^2 = (1-\lambda) \cdot \sum_{t=1}^{n} \lambda^2 \cdot (R_t - \mu)^2$$

Where σ_t^2 represents the standard deviation, R_t the yields at the moment t, while μ stands fot the average value of the distribution *n* is the time horizon, and λ the exponential factor that captures the persistence of volatility, with values between 0 and 1. So 1**-** λ λ is a parameter that captures the shock absorption of the market volatility. The RiskMetrics department uses a value of 0.94 in order to estimate the daily volatility and a value of 0.97 for monthly estimates.

Taking into account the above, the volatility of asset *i* at time *t* can be written as follows:

$$\sigma_{i,t} = \sqrt{\frac{1-\lambda}{1-\lambda^n} \sum_{j=0}^{n} \lambda^j \cdot r_{i,j}}$$

And the correlation between the returns can be built in the same manner:

$$\sigma_{12,t}^2 = (1-\lambda) \sum_{j=1}^{T} \lambda^{j-1} \left(r_{1t} - \overline{r_1}\right)\left(r_{2t} - \overline{r_2}\right)$$

From the non-parametric models or rather those based on simulation models used to determine VaR in this paper we present the following ones:

- Historical Simulation Method
- Filtred Historical Simulation Method
- Monte Carlo Simulation Method

In the case of simulation-based approaches it is necessary to construct a range of hypothetical future values of portfolio profitability, which combined with relative frequencies gives us the shape of the probability distribution of future portfolio returns and losses. So using the distribution obtained the level of VaR can be read considering a certain confidence level.

There are two types of procedures that can be used to create hypothetical probability distributions, one based on historical data simulation, and another that provides random data generation.

a) *Historical Simulation Method*

a1) Historical Simulation *(HS)*

In this approach, the value of VaR of a portfolio is estimated by creating a series of hypothetical returns for a portfolio. This are obtained by running the portfolio with real historical data and calculating changes that had occurred in each period.

a2) Historical simulation with bootstrapping (HS BOOT)

So far we have assumed that the period for calculating VaR is the same as the frequency of historical data, which in practice is not always true. Solving this problem comes along with bootstrapping method's. Bootstrapping in practice means that instead of using every return included in the sample of historical returns only once, a large number of N values will be extracted from the sample values (and the extracted values will be reintroduced each time into the sample, so the same return will be twice chosen or more). In this case, VaR is calculated based on a random causal extraction, following the normal law, with 10,000 values from the series of the portfolio rate of returns series from the classical historical simulation.

b) Filtred Historical Simulation Method

b1) Filtered Historical Simulation (FHS)

By using this method greater weights are given to the most recent yields, and therefore to the recent market volatility, this feature is not considered by the classical historical simulation.

VaR is calculated based on a filtered time series of return obtained by :

- GARCH volatility estimates for each asset in the portfolio;
- calculating the scaled returns for each asset in the portfolio, which are obtained by dividing the returns to the GARCH volatility;
- calculating the filtered returns for each asset in the portfolio, by multiplicating the scaled returns with the predicted Garch volatility obtained for t +1.

b2) Filtered Historical Simulation with bootstrapping (FHS BOOT)

In the case of this method Value at Risk is obtained from a random extraction of 10,000 values from the filtered return series obtained by classical historical simulating.

b3) Clasic Filtered Historical Simulation (FHS BIS)

VaR is calculated based on the historical rates of return of the portfolio, which is considered as a single asset obtained by:

- GARCH volatility estimates for the portfolio as a single asset.
- calculating the scaled returns for each asset in the portfolio, which are obtained by dividing the returns to the GARCH volatility;
- calculating the filtered returns for the portfolio, by multiplicating the scaled returns with the predicted Garch volatility obtained for t +1. In this way the distribution of the yields is consistent with both past and current simulated volatility, and if the GARCH model was estimated correctly, the returns are identical and independently distributed.

b4) Filtered Historical Simulation with bootstrapping (FHS BIS BOOT)

VaR is obtained based on a casual extraction of 10.000 values from the the filtered return series obtained by classical historical simulating, considering the portfolio as a single asset.

c) Monte Carlo Simulation

In the case of the Monte Carlo simulation the yields of the bank's trading book are obtained by generating different scenarios for the considered risk factors, and then calculating the value of the portfolio under these conditions. By extracting a random sample from the probability distribution that describes the behavior of a probabilistic variable, the simulation model reproduces the random nature of the uncontrollable variable. Monte Carlo method is used most often when we need to calculate the expected value of a function f (x), with the given density probability distribution ψ(x):

$$\nu = E_{\Psi(x)}\left[f_{(x)}\right] = \int f_{(x)}\psi_{(x)}dx^n$$

The value sought through this method is as it follows: $m_s = \sqrt[s]{\int f_{(x)}\psi_{(x)}dx^n}$

Regarding the validation of models we use VaR back-testing and we determined the number of times, and as the VaR limit was exceeded and thus two approaches:

- *The binary loss function approach:* - k factor that helps determine capital adequacy. The test can be described as follows:

$$T_i = \begin{cases} 1, loss_i < VaR_i \\ 0, loss_i \geq VaR_i \end{cases}$$

- *The quadratic loss function approach:*- are used to compare different VaR models and consists of the following test:

$$T_i = \begin{cases} 1 + \left(\Delta P_t - VaR_t\right)^2, \Delta P_t < VaR_i \\ 0, \Delta P_t \geq VaR_i \end{cases}$$

where P is the loss of the portfolio. The test result is: $T = \sum_i T_i$

Following the results of back-testing the area of risk will be determined in which the bank is located, and on that basis the value of "k" will be determined, from the formula of the capital requirement for market risk. As a bank will record multiple exceedances of VaR, the more it will move toward the major risk area and accordingly will be penalized.

The maximum number of errors of the VaR on a short period of time horizont, namely 250 days, accepted by the Basel Committee is 4, otherwise the VaR model is not appropriate. BCBS defines the following risk areas:

- Safe risk area: up to four errors of VaR;
- Medium risk area: between four and nine errors of the VaR;
- Major risk area: ten errors of the VaR.

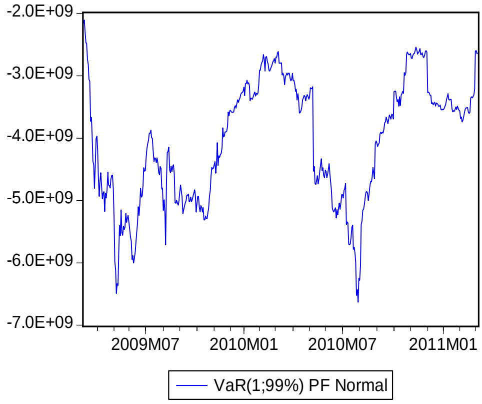
3. Empirical findings

The statistical data used in this study consist of the daily stock closing prices of 6 shares, which were extracted from http://bvb.ro/. The sample period is between 14.02.2008-03.03.2011, where we considered a theoretical portfolio of a bank which would consist of the securities Erste Group Bank, SIF Banat-Crişana, SIF Moldova, SIF Transilvania, SIF Muntenia, SIF Oltenia. We calculate VaR (1, 99%) of the portfolio for all working days from 03.03.2009 to 03.03.2011. Based on these rates the logarithmic daily price changes were calculated using the formula: $r_t = \ln\left(S_t / S_{t-1}\right)$.

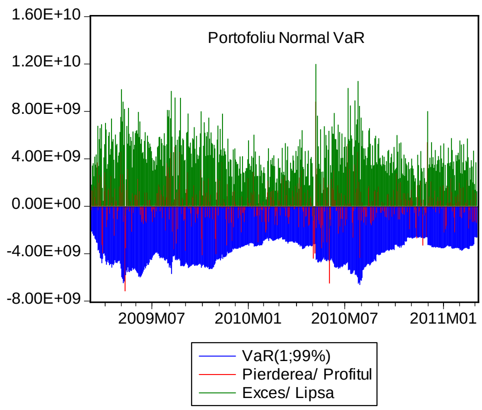
Non parametric VaR calculation methods

The normal portfolio VaR

To calculate VaR, we consider only the total portfolio value, П, and the volatility of portfolio return бП without decomposing it into its components, EBS and SIF. Then we calculate the VaR given that the confidence level is 99% and within one day, in the form бП * -2.33 * П. (6)



The evolution of Normal Portfolio VaR (1,99%)



Normal Portfolio VaR

(Source: own processing)

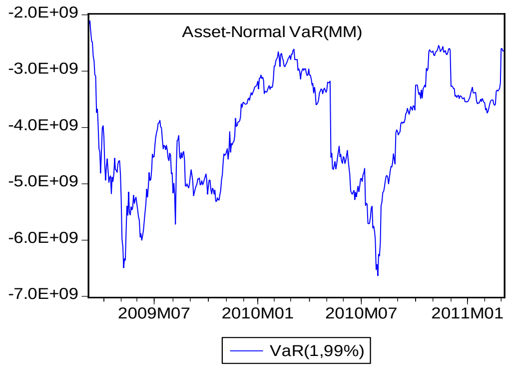
From the chart above we can see that in most cases the loss / profit for the owner of the portfolio is covered by VaR, its value being much more greater than the face value of the portfolio.

Asset Normal VaR

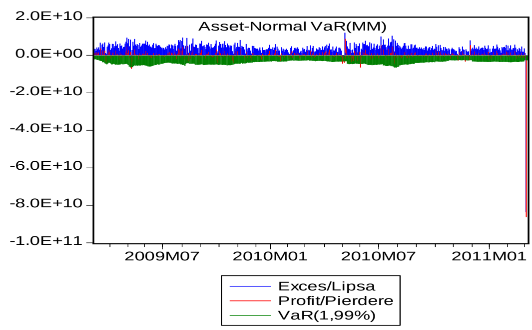
The portfolio is divided into components, namely the EBS and SIF titles. We assume that the daily returns of the security are normally distributed. In this case the calculation of VaR will take into account the volatility of the titles EBS and SIF, but also the correlations between them.

The assumptions of the underlying model are:

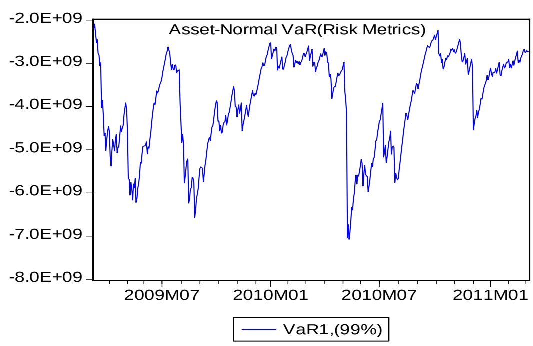
- The portfolio is composed of two assets: EBS and SIF;
- Changes in the value of the portfolio depend linearly of the variations of the titles EBS and SIF;
- The rate of returns of the titles EBS and SIF follow a normal distribution and are independent;
- The variance of the portfolio includes the correlations between the rate of returns of the titles EBS and SIF.



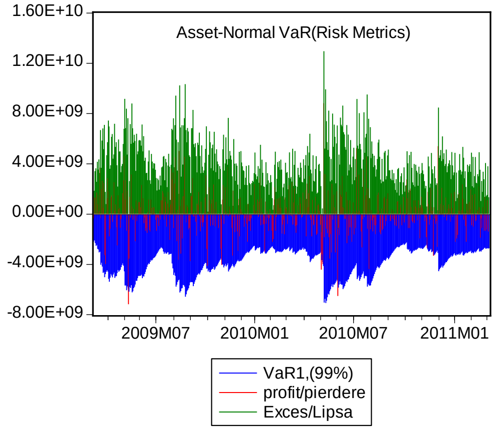
The evolution of VaR(1,99%) Asset Normal VaR(MM)



Asset Normal VaR(MM)

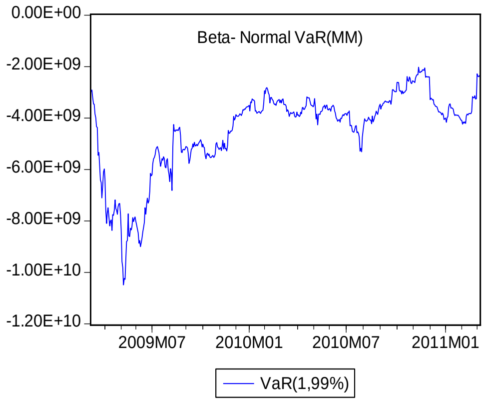


The evolution of VaR (1,99%) Asset Normal VaR (Risk Metrics)

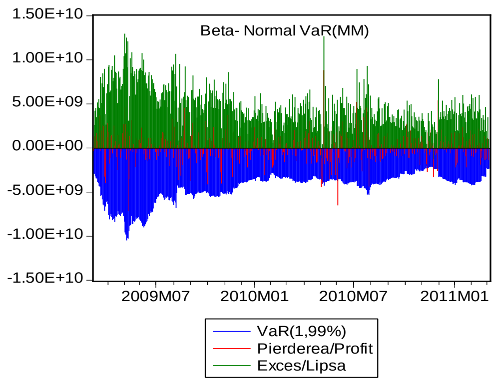


Asset Normal VaR(Risk Metrics)
(Source: own processing)

Beta Normal VaR

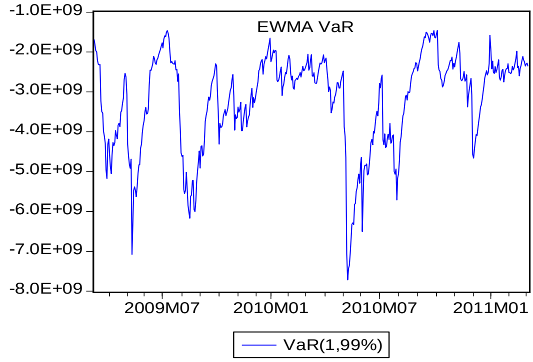


The evolution of Beta Normal VaR(MM)

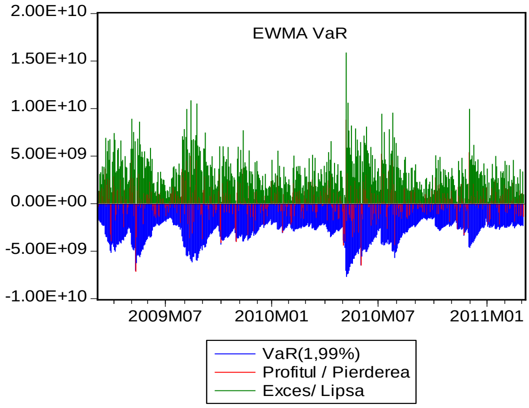


Beta Normal VaR(MM)
(Source: own processing)

EWMA VaR

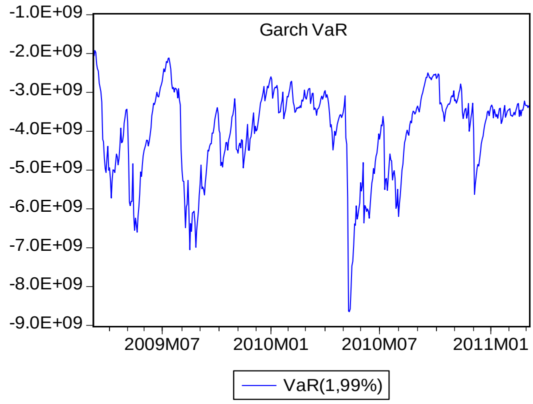


The evolution of EWMA VaR

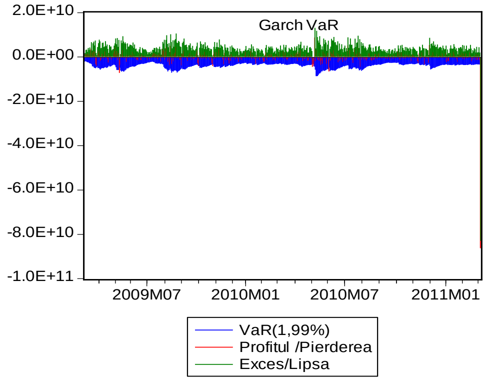


EWMA VaR
(Source: own processing)

GARCH VaR

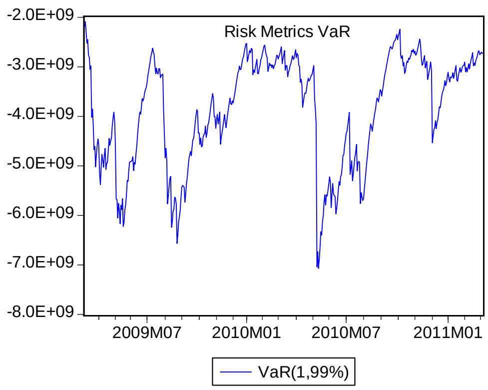


The evolution of GARCH VaR

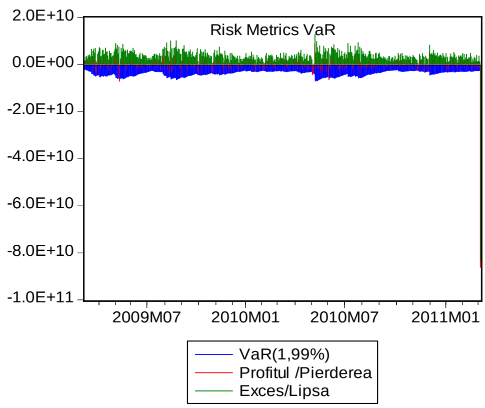


GARCH VaR
(Source: own processing)

Risk Metrics VaR



The evolution of Risk Metrics VaR



Risk Metrics VaR
(Source: own processing)

Performance evaluation of VaR models

To test the effectiveness the back-testing technique was used, by simulating the last 504 days of stress scenarios. We used quadratic approach procedure, determining how many times in this time interval VaR was exceeded, but also the linear approach procedure by which we could see the value of average error and average excess.

The results of back-testing
(The binary loss function approach and the quadratic loss function approach)

Nr. errors	Average error	Average excess
1. *Normal Portfolio* **VaR**		
6	-917.378.236	4.267.798.239
2.Asset-Normal VaR(MM)		
8	-176.655.453	4.280.300.514
3.Asset-Normal VaR(Risk Metrics)		
8	-10.334.090	4.091.219.802
4.Beta-Normal VaR(MM)		
5	-12.043.148	4.688.855.562
5.VaR Garch		
6	-9.236.371	4.168.446.233
6. VaR Risk Metrics		
8	-10.330.808	4.026.222.001
7. VaR EWMA		
5	-1.469.100	3.360.634.074

(Source: own processing)

Regarding the parametric models implemented in the bank's stock portfolio, we can observe that all the models used are at the medium risk area. The number of errors is between 5 and 9 to a sample of 504 daily data. From the table above we can see that it is very important to determine the linear approach of losses. We can have the same number of errors / overrun in terms of size but in the case of some models, the average error is significantly higher and different as compared to others.

The most representative models for determining the Value at Risk in the quadratic approach are the Beta-Normal VaR and EWMA, while in the linear approach the EWMA, GARCH models stand out, with the Risk Metrics and Asset Normal models with very similar values.

Therefore we should not accept a model based only on the number of errors / overruns, but rather we should take into account the average error, which is a more relevant indicator.

Non parametric models
(The approach based on simulation)

This approach is intended to generate scenarios and simulate models based on the historical returns of the theoretical portfolio of the bank.. In the case of BOOT HS, VaR is calculated based on a casual extraction of 10,000 values from the rate of returns of the portfolio from HS.

The results of classical historical simulation and bootstrapping

	HS	**HS BOOT**
N=1	-13,263%	-10,141%
VaR(99%)	- 9.785.027.077	- 7.597.358.685

((Source: own processing)

We can observe from the table above that the values are quite close in terms of probable maximum loss of the portfolio.

***VaR calculation with* the Filtered Historical Simulation**

For the Filtered Historical Simulation FHS, Value at Risk is calculated based on the filtered rate of returns of the portfolio, while in the case of BOOT FHS VaR was calculated based on 10,000 casual extractions from the filtered return of the series of the portfolio.

The results of filtred historical simulation and with bootstrapping

	FHS	**FHS BOOT**
N=1	-3,341%	-3,349%
VaR(99%)	- 2.588.661.588	- 2.594.336.441

(Source: own processing)

Drawing a parallel between the results obtained by the classical simulation method and by bootstrapping, we can see that the potential loss in the last case is much lower.

The results of filtred historical simulation for the portfolio considereted unique asset and with bootstrapping

	FHS BIS	**FHS BIS BOOT**
N=1	-4,317%	-4,264%
VaR(99%)	- 3.328.941.248	- 3.288.563.176

(Source: own processing)

By calculating Value at Risk we could notice that the maximum probable loss given the confidence interval varies in terms of simulating methods based on filtered. Greater loss is recorded when we consider the portfolio as a single asset, and do not decompose it into its components, in this case the two titles. When using bootstrapping technique the values are quite close to those of the classical *Filtered* historical simulation method, namely the classical *Filtered* historical simulation method which consider the portfolio as a single asset.

***VaR calculation with* the Monte Carlo Simulation**

The method is flexible and can be applied to all types of portfolios, but requires a higher computing power and the careful selection of valuation models for financial assets in the portfolio composition.

Monte Carlo Simulation

	Monte Carlo
N=1	- 5,692%
VaR(99%)	- 4.484.145.747

(Source: own processing)

Regarding the non parametric models for calculating Value at Risk, we could notice the period under consideration that both the classical filtered simulation and bootstrapping methods were those with the lowest value, followed by higher values of VaR for historical simulation.

4. Conclusions

Despite its limits, VaR is one of the most popular methods used to measure and prevent the manifestation of market risks. In an attempt to capture this risk, we used non-parametric models, based on simulation to calculate VaR, but also parametric models, with theire advantages and disadvantages, but also models for calculating the volatility and correlations. In order to implement a successful VAR estimation, the accuracy of this depends on the portfolio return distribution. Although the normal distribution is the easiest to use in practice, it may lead to an underestimation of the risk and capital allocation, because in the reality the data series have elongated tails corresponding to extreme market movements. It is appropriate to identify specific Value at Risk models for each portfolio, but we must never forget that each of these models has its own advantages and disadvantages, that relate to the probable maximum loss to a certain degree of confidence.

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