Value at Risk prediction: the failure of RiskMetrics in preventing financial crisis. Evidence from Romanian capital market

Dumitru-Cristian Oanea\textsuperscript{a*}, Gabriela Anghelache\textsuperscript{b}

\textsuperscript{a,b}The Bucharest University of Economic Studies, 6, Piata Romana, 1st district, Bucharest 010374, Romania

Abstract

Financial markets are not perfect and the risk cannot be totally eliminated, that’s why risk reduction became more and more important for the financial markets, since the 2008 financial crisis.

The most commonly used tool for risk measure is Value at Risk, being considered a crucial milestone, because it shows the maximum loss in the value of a portfolio asset.

The first comprehensive market risk management methodology was developed by JP Morgan in 1994, and was called RiskMetrics, which become extremely popular due to its easy implementation.

This paper analyzes the capacity of RiskMetrics in forecasting the high volatility during the financial crisis for the financial Romanian market and to see if there is some differences regarding the value of decay factor estimated based on squared error loss, the RiskMetrics approach, and the values obtain from implementing the check error loss function in estimating the decay factors. We found that in the case of BET and BET-FI, the RiskMetrics estimations underestimate the decay factor, by attaching a lower weight to the most recent variance. Moreover, we proved that RiskMetrics model was good enough to forecast the volatility on Romanian financial market during the financial crisis period, only if we estimate the decay factor based on check error loss function.

© 2015 The Authors. Published by Elsevier B.V.

Selection and peer-review under responsibility of the Faculty of Economics and Business Administration, Alexandru Ioan Cuza University of Iasi.

Keywords: RiskMetrics; correlation; financial instrument; financial crisis; financial market; risk prediction; decay factor estimated.

* Corresponding author. Tel.: +40-747-812305.
E-mail address: oanea.cristian@gmail.com.
1. Introduction

Even if Value at Risk concept and methodology was analyzed by many researchers, we cannot find a constant basic definition of Value at Risk in the literature. As is presented in Wilson (1998), each institution has a unique name for its Value at Risk (e.g. J.P. Morgan’s Value at Risk – VaR and Daily Earnings at Risk – DEaR, Bankers Trust Capital at Risk – CaR, other institution’s Dollars at Risk – DaR and Money at Risk – MaR), so each of them has a unique technical implementation, having three common elements: the maximum loss, a given probability and time horizon.

Over time, Value at Risk became institutionalized, due to fact that Basel Committee imposed to all banks to use this tool for performing regulatory capital calculations.

This paper is organized as follows: section 2 reviews the literature on Value at Risk estimation, section 3 describes the methodology and data used and through section 4 we present our results. Finally, we emphasise the main conclusions of this paper.

2. Literature review

Even if, Value at Risk is used by many financial and non financial investors, this tool has some limitations. Linsmeier and Pearson (2000) states that the VaR estimates do not capture all information searched by an investor in order to manage the risk. Furthermore, Beder (1995) emphasize several types of risks (liquidity risk, personnel risk, political risk, regulatory risk) which are not captured by Value at Risk.

There are three ways of computing Value at Risk: variance-covariance approach (used by RiskMetrics model), historical simulation and Monte Carlo simulation. Of course all these approaches have some drawbacks. Sollis (2009) is stated that variance-covariance approach underestimates VaR, due to distribution assumption, historical simulation can be altered sample size and Monte Carlo simulation approach may suffer by incorrect distribution assumption.

First step in computing VaR is represented by volatility’s estimation. The first model used to compute VaR was ARCH model, proposed by Engle (1982), and further generalized by Bollerslev (1986) into a GARCH model, which was improved over time.

There is a lot of research which compare Exponentially Weighted Moving Average (EWMA) performance with different types of ARCH/GARCH models in forecasting volatility. According to Hull (2008) the main advantage of EWMA is represented by relatively little data needs to be stored. Furthermore, Tse (1991) and Tse and Tung (1992) emphasize the fact that EWMA model over performed ARCH models in estimating the risk for Japanese and Singaporean financial markets.

But not all authors proved that EWMA is the best model in forecasting the volatility. Regarding this, Hammoudeh et al. (2011) found that GARCH-t model over perform EWMA in estimating the risk involved in commodities market. Moreover, Degiannakis et al. (2011) proves that ARCH framework is better in estimating risk compared to RiskMetrics model.

Furthermore, several researchers as McMillan and Kambouroudis (2009), and Pafka and Kondor (2001) emphasized the fact that the RiskMetrics performance in forecasting the risk directly depends on the choice of the significance level (of 90%, 95% or 99%).

There are some papers as Fan et al. (2004) and Gonzalez-Riviera et al. (2007), which stated that decay factor’s value is not necessary equal with 0.94, value imposed by RiskMetrics methodology for daily data.
3. Methodology

3.1. The model

One day continuously compounded returns - \( r_t \), are defined as:

\[
    r_t = \ln \left( \frac{P_t}{P_{t-1}} \right), \quad t = 1, \ldots, T
\]  

(1)

The following stochastic process is described by the RiskMetrics model:

\[
    r_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t
\]  

(2)

where \( z_t \) is an independent and identically distributed Gaussian random variables with \( E[z_t] = 0 \) and \( V[z_t] = 1 \), \( \mu_t = E[r_t | I_{t-1}] \) and \( \sigma_t^2 = E[\varepsilon_t^2 | I_{t-1}] \); ( \( \mu_t \equiv 0 \ \forall t \) - RiskMetrics assumption). The conditional variance estimation is based on exponentially weighted moving average model (EWMA), where \( \lambda \in (0, 1) \) is the decay factor:

\[
    \sigma_t^2(\lambda) = (1 - \lambda) \sum_{i=1}^{t-1} \lambda^{t-i-1} r_{t-i}^2
\]  

(3)

Based on RiskMetrics methodology, relation (3) is well approximated by:

\[
    \sigma_t^2 = \lambda \sigma_{t-1}^2 + (1 - \lambda)r_{t-1}^2
\]  

(4)

J. P. Morgan (1996) chooses 0.94, the most appropriate value for decay factor (one day continuously compounded returns). During the time, RiskMetrics have improved the assumption regarding to the error term. If the initial assumption from 1994 stated that the error term was Normal distributed, later in 2006, it was assumed that the residuals follow a Student-\( t \)-distribution with 5 degrees of freedom (Zumbach, 2006). This improvement was made due to the existence of fat tails in the data.

Based on (4) we are able to estimate the volatility, and further the total risk of a financial instrument. Further for measuring the total risk we use Value at Risk, defined as conditional \( \alpha \)-percentile:

\[
    \text{VaR}_\alpha \equiv q_{\alpha, t} = k_{\alpha} \sigma_t(\lambda)
\]  

(5)

where \( k_{\alpha} \) is either the conditional normality - \( \phi^{-1}(\alpha) \) or conditional Student-\( t \) - \( H^{-1}(\alpha)\sqrt{(\nu - 2)/\nu} \) with \( \nu \) - degree of freedom parameter.

The goal of this paper is to see if the RiskMetrics model is good enough to forecast the volatility during the financial crisis for Romanian financial market. In order to achieve this, we use the rolling window method for back testing.

The analysis uses daily financial data starting with January 1st, 2001 until December 31st, 2012. Based on the rolling window methodology, we divided the total sample in two subsamples: in-sample (ante-financial crisis period) and out-of-sample (financial crisis period). Officially, financial crisis started in September 15th 2008, when Lehman Brothers filed for Chapter 11 bankruptcy protection.
First step is represented by the empirical estimation of the decay factor through two types of functions: squared error loss function and check error loss function.

The first way of estimating decay factor is represented by minimizing the squared error loss function for the conditional variance:

$$\hat{\lambda}_i = \arg\min_{\lambda \in (0,1)} \frac{1}{T-M} \sum_{j=1}^{T-M} [\sigma_j^2(\lambda) - r_j^2]^2$$

(6)

The second way of estimation is represented by the methodology proposed by Gonzalez-Riviera et al. (2007), through which they emphasize the purpose of VaR, and they determine the decay factor by minimizing the check error loss function:

$$\rho_\alpha(e_j) = \begin{cases} \alpha \cdot e_j & e_j \geq 0 \\ (\alpha - 1) \cdot e_j & e_j < 0 \end{cases}, \text{ where } e_j = r_j - VaR_{j,\alpha}$$

(7)

Similarly, in this paper we will estimate the decay factor based on formula below:

$$\hat{\lambda}_i = \arg\min_{\lambda \in (0,1)} \frac{1}{T-M} \sum_{j=1}^{T-M} \rho_\alpha(e_j)$$

(8)

Having all values for the decay factors, we are able now to compute the volatility and further the Value at Risk, for each financial index, based on three models:

- **RM1** - RiskMetrics model (decay factor equals 0.94) based on two types of return distribution: Normal distribution (RiskMetrics-1994) and Student-t distribution (RiskMetrics-2006)
- **RM2** - decay factor is estimated based on squared error loss function, considering both Normal distribution and Student-t distribution
- **RM3** - decay factor is estimated based on check error loss function, under Normal distribution and Student-t distribution

Moreover, we are interested to check the models’ accurateness, to see if they are able to predict the risk. To achieve this objective we will use the conditional coverage test, developed by Christoffersen (1998), who adapted the log-likelihood testing framework of Kupiec into a better form, which take into account the conditional coverage.

First we define the $I_i$ – indicator variable such as:

$$I_i = \begin{cases} 1 & r_i < VaR_i \\ 0 & r_i \geq -VaR_i \end{cases}$$

(9)

The conditional coverage test proposed by Christoffersen is given by:

$$LR_{CC} = -2 \ln \left( \frac{(1-\alpha)^{n_0} \alpha^{n_1}}{(1 - \hat{\alpha}_{01})^{n_0} \hat{\alpha}_{01} (1 - \hat{\alpha}_{11})^{n_0} \hat{\alpha}_{11}} \right) \sim \chi^2(2)$$

(10)
where, \( n_{ij} \) is the number of observation with value \( i \) followed by \( j \), 

\[ \pi_{ij} = \Pr(I_t = i \mid I_{t-1} = j) \ (i, \ j=0,1), \]

\[ \hat{x}_{01} = n_{01} / (n_{00} + n_{01}) , \quad \hat{x}_{11} = n_{11} / (n_{01} + n_{11}) . \]

### 3.2. Data and descriptive statistics

We applied RiskMetrics model on Romanian stock market data for Value at Risk estimation. Three market indices namely, BET, BET-C and BET-FI, were selected for analysis, in order to allow enough data for estimating the volatility. We used daily data starting with January 4th, 2001 until December 28th, 2012. All the data were obtained from Bucharest Stock Exchange web site.

<table>
<thead>
<tr>
<th>Index</th>
<th>( n )</th>
<th>Mean</th>
<th>St. deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>BET</td>
<td>2992</td>
<td>0.0007</td>
<td>0.0171</td>
<td>-0.52</td>
<td>9.81</td>
</tr>
<tr>
<td>BET-C</td>
<td>2992</td>
<td>0.0005</td>
<td>0.0158</td>
<td>-0.67</td>
<td>10.51</td>
</tr>
<tr>
<td>BET-FI</td>
<td>2992</td>
<td>0.0009</td>
<td>0.0258</td>
<td>-0.08</td>
<td>8.28</td>
</tr>
</tbody>
</table>

Descriptive statistics of daily returns expressed in percentages are presented in Table 1. All indices have a positive average return for the period 2001 - 2012. The highest value of 0.09% is recorded by BET-FI, which seems to be the most profitable market segment over the analyzed period. Based on standard deviation, investors had the lowest risk if they had chosen to invest in BET-C and highest risk if they invested in BET-FI. The financial data present negative skewness and excess kurtosis (higher than 8). More information regarding each index are found in

Analyzing data from Table 2, results that all indices are positively correlated. The highest correlation of 0.9525 is recorded between BET and BET-C, and the lowest one between BET-C and BET-FI.

<table>
<thead>
<tr>
<th>Index</th>
<th>BET</th>
<th>BET-C</th>
<th>BET-FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>BET</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BET-C</td>
<td>0.9525</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>BET-FI</td>
<td>0.6910</td>
<td>0.6876</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

We want to check if the financial crisis had a significant impact on the Romanian financial market. In order to achieve this, we computed the mean returns and standard deviation for BET, BET-C and BET-FI crisis period and for a period of four years before crisis, to have symmetry in the data.

The graphic results are represented in Fig. 1, where there are two main clusters: period before crisis and crisis period. We can see that the Romanian financial market was highly affected by financial crisis. Regarding this, the average return decreased during financial crisis and average volatility increased.

![Fig. 1. Average return and standard deviation before crisis and crisis period](image)
Moreover, we want to see if these differences between two periods are statistically significant, that’s why we performed a t-test, according to Table 3. These results show that the financial crisis had a significant influence over the Romanian financial market, on both mean returns and volatility, with a higher influence on their volatility.

Table 3. Paired sample differences test

<table>
<thead>
<tr>
<th></th>
<th>Mean returns</th>
<th>Mean standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-test value</td>
<td>4.155</td>
<td>-5.211</td>
</tr>
</tbody>
</table>

*,** - the null hypothesis of equality for the two period is rejected at 5%, respectively 10% significance level

4. Results

First we want to see if there are differences regarding the value of decay factor estimated based on squared error loss and the check error loss function.

We use a simply grid search in estimating $\lambda$ for both loss functions mentioned above. First 250 daily observations will be used for obtaining the initial value for conditional variance. This value will be used to compute all variances based on relation (4). This process is repeated for all 99 values of $\lambda \in [0.01; 0.02; \ldots; 0.99]$ in order to choose the value which minimizes the error loss function used in estimation process.

There are differences between the estimates obtained with squared error loss function and those obtained with check error loss function. Lambda’s estimates provided by squared error loss function are presented on Fig. 2 and lambda’s estimates provided by check error loss function are presented in Appendix in figures 3 and 4.

Table 4. Decay factor estimates

<table>
<thead>
<tr>
<th>Index</th>
<th>Squared error loss function</th>
<th>Check loss function</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\hat{\lambda}_F$</td>
<td>$\hat{\lambda}_{T,0.01}$</td>
</tr>
<tr>
<td>BET</td>
<td>0.89</td>
<td>0.93</td>
</tr>
<tr>
<td>BET-C</td>
<td>0.88</td>
<td>0.91</td>
</tr>
<tr>
<td>BET-FI</td>
<td>0.87</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Legend: The table presents decay factor estimates for the full sample period. The bold-font values indicate the largest discrepancies (larger than 4%) between the estimates provided by the squared error loss function and those based on the check loss function.

Based on estimation results of $\lambda$ for the full sample period presented in Table 4, we can see the tendency of RiskMetrics’ estimations to underestimate the decay factor, in BET and BET-FI case. The opposite situation is obtain in BET-C’s case, because RM model attaches a higher weight of 0.88, compared to value computed based on check error loss function of 0.84 (Normal distribution with $\alpha = 0.10$).

Fig. 2. Lambda Estimates based on squared error loss function
We investigate the out-of-sample performance of VaR forecast for the three types of RiskMetrics models: RM\(_1\) (decay factor equals 0.94), RM\(_2\) - decay factor is estimated based on squared error loss function and RM\(_3\) - decay factor is estimated based on check error loss function.

We started with the estimation of conditional variance, and thus the VaR for BET, BET-C and BET-FI, based on the three models presented above. In the end we check if the models used in these estimations are accurate and able to predict the risk, based on conditional coverage test, presented in Table 5. All the estimations for Value at Risk are represented in figures 5 – 10 from Appendix.

Based on the results presented in Table 5, we can see that the best model, which was able to predict the risk for all indices, is represented by RM\(_3\) model, which estimates the volatility by determining the decay factor through the check error loss function. This model is accepted for BET, BET-C and BET-FI under Normal distribution at \( \alpha = 0.05 \), and only for BET-C and BET-FI under Student-t distribution at \( \alpha = 0.01 \). The other two types of models were capable to predict the risk only for BET-FI under Normal distribution at \( \alpha = 0.10 \) and \( \alpha = 0.05 \) (only for RM\(_2\)) and Student-t distribution at \( \alpha = 0.01 \) (for both RM\(_1\) and RM\(_2\)).

<table>
<thead>
<tr>
<th>Index</th>
<th>RM(_1) MODEL</th>
<th>Normal distribution</th>
<th>Student-t distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.05</td>
<td>0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>RM(_2) MODEL</th>
<th>Normal distribution</th>
<th>Student-t distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.05</td>
<td>0.01</td>
</tr>
<tr>
<td>BET-C</td>
<td>9.401</td>
<td>11.102</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>RM(_3) MODEL</th>
<th>Normal distribution</th>
<th>Student-t distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.05</td>
<td>0.01</td>
</tr>
<tr>
<td>BET</td>
<td>3.232</td>
<td>3.045</td>
</tr>
<tr>
<td>BET-FI</td>
<td>4.632</td>
<td>2.978</td>
</tr>
</tbody>
</table>

Legend: Critical values for \( \chi^2 \) are 4.605 (90%), 5.991 (95%) and 9.210 (99%). The bold-font values indicate that the model is accepted.

5. Conclusions

The paper improves available literature by emphasizing the RiskMetrics performance on Romanian financial market over the last financial crisis. We used daily financial data starting with January 1\(^{st}\), 2001 until December 31\(^{st}\), 2012 for three indices: BET, BET-C and BET-FI. We start the study with the empirical estimation of the decay factor through two types of functions: squared error loss function (RiskMetrics’ methodology) and check error loss function (Gonzalez-Riviera et al. (2007) methodology).

Regarding the decay factor estimation, we obtained similar results as in the Fan et al. (2004) paper. In the case of BET and BET-FI, the RiskMetrics estimations underestimate the decay factor, by attaching a lower weight to the most recent variance. In the case of BET-C, we obtained that the RiskMetrics model overestimates the decay factor, by attaching a higher weight to recent variance. Moreover, we wanted to see if the RiskMetrics model was good enough to forecast the volatility on Romanian financial market during the financial crisis period.
Based on the results presented on Table 5, we can see that there are some differences between out-of-sample performances of VaR forecasts estimated based on check error loss function and squared error loss function. We see that the RM$_3$ model was able to predict the risk under Normal distribution at 0.05 confidence level for all indices, while the RM$_1$ and RM$_2$ models were able to predict the risk only for BET-FI. So investors may gain in the predictability ability of RiskMetrics, by estimating the decay factor using the check error loss function. These results are opposite with the analysis’ findings of Gonzalez-Riviera et al. (2007), who do not find significant differences between the decay factor estimations.

References


Appendix

Fig. 3. Lambda estimates based on check error loss function under Normal distribution

Fig. 4. Lambda estimates based on check error loss function under Student-t distribution

Fig. 5. Value at Risk Estimates based on RM1 model under Normal distribution

Fig. 6. Value at Risk Estimates based on RM1 model under Student-t distribution
Fig. 7. Value at Risk Estimates based on RM2 model under Normal distribution

Fig. 8. Value at Risk Estimates based on RM2 model under Student-t distribution

Fig. 9. Value at Risk Estimates based on RM3 model under Normal distribution

Fig. 10. Value at Risk Estimates based on RM3 model under Student-t distribution