Available online at www.sciencedirect.com

ScienceDirect

Procedia Economics and Finance 24 (2015) 18 – 24

Procedia Economics and Finance

www.elsevier.com/locate/procedia

International Conference on Applied Economics, ICOAE 2015, 2-4 July 2015, Kazan, Russia

The history and ideas behind VaR

Peter Adamko[a,]*, Erika Spuchľáková[b], Katarína Valášková[b]

[a]*Department of Quantitative Methods and Economic Informatics, Faculty of Operations and Economic of Transport and Communications, University of Žilina, Univerzitná 1, 010 26 Žilina, Slovakia*

[b,c]*Department of Economics, Faculty of Operations and Economic of Transport and Communications, University of Žilina, Univerzitná 1, 010 26 Žilina, Slovakia*

Abstract

The value at risk is one of the most essential risk measures used in the financial industry. Even though from time to time criticized, the VaR is a valuable method for many investors. This paper describes how the VaR is computed in practice, and gives a short overview of value at risk history. Finally, paper describes the basic types of methods and compares their similarities and differences.

Selection and/or peer-review under responsibility of the Organizing Committee of ICOAE 2015.
Keywords: Value at risk; VaR; risk modeling; volatility;

1. Introduction

The risk management defines risk as deviation from the expected result (as negative as well as positive). Typical indicators of risk are therefore statistical concepts called variance or standard deviation. These concepts are the cornerstone of the amount of financial theories, Cisko and Kliestik (2013). Despite the existence of these concepts, it was necessary to develop an indicator that would be able to cope with the complexity of financial derivatives.

One possibility is the Value at Risk (VaR). Value at Risk gives a single number representing the most you could lose with a given level of confidence. The definition of VaR implies that it is necessary to choose two parameters, namely holding period and confidence level.

Holding time may be a day, ten (business) days or a month, but it may also be longer periods. Confidence level depends mainly on the purpose of the use of VaR. If the aim is to ensure a low probability of insolvency or high

* Corresponding author. Tel.: +421-415-133-270; fax: +421-415-131-527.
E-mail address: peter.adamko@fpedas.uniza.sk

Selection and/or peer-review under responsibility of the Organizing Committee of ICOAE 2015.
doi:10.1016/S2212-5671(15)00607-3

rating chosen confidence level can be up to 99.9%. For regulatory purposes is typically used daily confidence level of VaR in the range 99% to 95%, that means realized losses exceeded the level of confidence approximately 2 to 12 times a year.

For example, VaR equals $1,000,000 with horizon one day and confidence level 95% means we are 95% confident that no losses will be higher than $1,000,000 for a period of one day. In statistical terms the VaR can be thought of as a quantile (in this case 95%) of the returns distribution of the portfolio held over a period of time (in this case one day), Hull (2011), see Fig. 1.

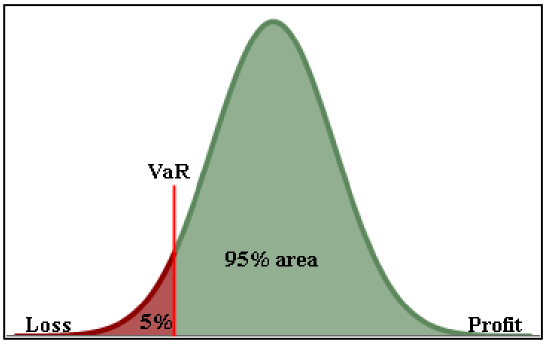

Fig. 1. graphical representation of example of VaR.

There are several aspects that should be mentioned. VaR does not include distribution of potential losses occurring in rare cases exceeding VaR, Misankova et al. (2014). VaR does not specify the maximum size of the loss and even size less probable losses. Relying only on the VaR could lead to the use of very dangerous and risky business strategies. VaR is only an estimate and not precisely defined value, Kollar and Bartosova (2014).

2. History of VaR

The first attempts to measure risk and thus express potential losses in the portfolio, are attributed to Francis Edgeworth and dates back to 1888. He made important contributions to the statistical theory, advocating the use of data from past experience as the basis for estimating future probabilities.

History of the VaR continued in 1945, when Dickson H. Leavens created a work that is considered the first mention of VaR It was a simple example of a portfolio that included ten government bonds. He suggested that either the bond reaches maturity in the amount of $1,000 or agreed conditions are not met and become so worthless. He furthermore assumed that the bonds are independent of each other. He attempts to measure the value of the portfolio. In his work, he did not use name value at risk. He repeatedly mentioned "the spread between the likely profit and loss" and that most likely mean standard deviation, which is used to measure risk and is an important part VaR.

In the 1952 Harry Markowitz, who was awarded the Nobel Prize in Economics in 1990 for his pioneering research in the area of portfolio theory, and independently three months later Arthur D. Roy proposed VaR indicators, which were surprisingly similar, Kollar (2014). Both were trying to find a way which could be optimized profit at a given level of risk. In their proposals played an important role covariance, but VaR indicators differed significantly. Roy and Markowitz expressed conjectures about how it should be specified a probability distribution. To calculate VaR by Roy was necessary to know the vector of average incomes respectively losses and variance-covariance matrix of risk factors. These had to be estimated on the basis of historical data. To calculate VaR by Markowitz was sufficient to know the variance-covariance matrix. Both assumed that for their calculation is necessary to combine statistical techniques with the sound judgment of experts.

During the 70th to 80th years were created many new financial products. This represented a new challenge for modeling of risk. New financial products have no history, through which could be estimated risks at least approximately, Gavlakova and Kliestik (2014). One option was to find approximately similar financial products and try to derive the risk from them. For example, the abolition of the monetary system in 1971 has resulted in a foreign exchange forward market. These new challenges stimulated the development of an easily understandable and reliable indicator of risk.

In 1971, Bernard Lietaer developed a model that focuses on the risk of exchange rate fluctuations. The topic has been high on the agenda because after the Second World War, most currencies began to devalue at some point, Jaros et al. (2014). His model was a solution; it shrunk the impact of the conversion risk. It was a special modeling of devaluation, which helped to optimize the protection strategy (hedging), Misankova and Kocisova (2014). In the Lietaer work was probably for the first time used the Monte Carlo method.

Although the first publications about predecessors of VaR date back to the 20th century, the credit for the use of current VaR attributed mainly to US investment bank JP Morgan. Its chairman, Dennis Weatherstone asked for something simple, but something that would cover the whole spectrum of risks faced by the bank for the next 24 hours. Bank developed, using Markowitz portfolio theory, the VaR. But at that time it was called 4:15 report. The origin of the name "Value at risk" is unknown. In the 90s has been also used names "dollars at risk", "capital at risk", "income at risk", "earnings at risk", "money at risk", Holton (2002).

In 1994, J. P. Morgan published a technical document of this system. This was followed by the mass acquisition of the system by many institutions. VaR was popularized as the risk measure of choice among investment banks looking to be able to measure their portfolio risk for the benefit of banking regulators. When the German Government in June 1974 had to bail out the Herstatt Bank and this has turned into the international crisis, thus, even in the same year initiative was created by members of the G10 and Luxembourg, who founded the Basel Committee on Banking Supervision (BCBS). The BCBS has set global standards to promote banking sector stability. According to the Basle Committee, the VaR methodology can be used by financial institutions to calculate capital charges in respect of their financial risk. There was also approved the use of banks' own proprietary VaR.

3. Methods

Although VaR represents very simple and clear concept, its measurement is a difficult statistical problem. There are many methods for calculation of the VaR. Methods have different conditions, different input data which are necessary for the calculation and different complexity of the calculations. Moreover, each of the methods can be applied in various ways. Although various models for the calculation of VaR use different methodologies, all retain the same general structure, which can be summarized in the following steps:

- The calculation of the present value of the portfolio (Mark-to-Market Value), which is a function of the current values of market factors (interest rates, exchange rates and so on).
- An estimation of the distribution of changes in the portfolio. This step is the main difference among the VaR methods.
- The calculation of the VaR

VaR calculation can be done in different ways. Traditionally, there are three:

- Historical simulation.
- Analytical method
- Monte Carlo simulation.

Some authors divide the methods into two groups:

- Delta method (different variants of the analytical method)
- Monte Carlo methods (simulation methods, including historical simulation)

Other authors divide them into four groups:

- Parametric (GARCH and RiskMetrics)
- Nonparametric (historical and hybrid models)
- Semi-parametric (Extreme Value Theory and CAViaR)
- Monte Carlo methods.

VaR calculated by individual methods may vary significantly.

There are different approaches used to compute Value at Risk, even though, there are nowadays numerous variations within each approach.

3.1. Analytical method VaR

Analytical VaR has also other names such as Variance-Covariance VaR, Parametric VaR Linear VaR or Delta Normal VaR. This method was introduced in the RiskMetrics™ system. After selecting the parameters for the holding period and confidence level is possible to calculate 1-day VaR by a simple formula:

$VaR(\alpha) = \sigma N^{-1}(\alpha)$ [%] or $VaR(\alpha) = V\sigma N^{-1}(\alpha)$ [e.g. €]

where
α is the level of confidence,
σ is the standard deviation of changes (volatility) in the portfolio over a given time horizon,
V is the market value of the position, and
N^{-1} is the inverse function of the standard normal cumulative distribution.

A prerequisite for the use of this formula is the assumption that the change in the value of the portfolio is subject to normal distribution, and the average change in the portfolio's value is zero.

Calculation of the 10-day VaR may seem problematic, because if the institution uses a historical VaR calculation method, the number of ten-day intervals over 1-2 years is so low that it could lead to the problem of small sample size. Achieving representative features of a normal distribution would require the use of aged data from the previous 5-6 years, which is also not very desirable.

Therefore, the Basel standards propose to use the so-called square root of time rule. Assuming a normal distribution and independence of daily returns, it is possible to calculate the T-day VaR by multiplying the 1-day VaR by the square root of T, where T represents the new holding period.

Why Basel standards propose square root of time rule? At the very basic level, VaR measures the standard deviation of returns. We calculate standard deviation, as the difference of individual data points from their mean and square it, before taking the square root. So while taking the square root of the variance we are also taking the square root of time.

However, this practice always misestimates the VaR measure since it assumes that the data is independent and identically distributed. This is a very restrictive assumption and is seldom seen in the financial markets. Also, if volatility changes over time, or there are jumps, time scaling will be inaccurate.

Analytical VaR of a portfolio of several assets is somewhat more complex. We need calculate VaR of each asset from the portfolio. But the overall VaR of a portfolio of 2 or more assets is not a simple sum of the individual VaR. It is necessary to know the relationship (correlation, ρ) between every two assets in the portfolio, Buc and Kliestik (2013). Positive/negative correlation means that both assets move in the same/opposite direction, 0 means they are random. Formula (1) shows how calculate analytical VaR for a portfolio of n assets.

$$VaR^2 = x \cdot \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1n} \\ \rho_{21} & 1 & \cdots & \rho_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \rho_{n1} & \rho_{n2} & \cdots & 1 \end{pmatrix} \cdot x^T \quad (1)$$

Where
$x = (VaR_1, VaR_2, \dots, VaR_{n-1}, VaR_n)$ - The vector of VaR of each asset in portfolio.
ρ_{ij} - The correlation between the i^{th} and j^{th} asset.

Steps to calculate:

- Assume distribution.
- Compute the VaR (using the distributional assumptions) of each asset in the portfolio.
- Compute correlation of each pair of assets.
- Compute overall VaR

Advantages:

- Historical data not needed.
- The simplicity of the application (even for VaR for a period longer than one day, thanks to the rule square root of time).

Weaknesses:

- The method is not ideal for a non-linear profile of financial instruments.

3.2. The method of historical simulation VaR

The historical method applying current weights to a time-series of historical asset returns. This return does not represent an actual portfolio, but rather reconstructs the history of a hypothetical portfolio using the current position. If asset returns are all normally distributed, the VAR obtained under the historical-simulation method should be the same as that under the analytical method.

This method consists in the assumption that the past will be repeated. Profits and losses are sorted by size from the largest loss at one end to highest profit at the other end of the distribution. Then we choose from the end of losses the pre-set percentage. Although this distribution reminds normal distribution, it is not a perfect, even with a large number of observations. In practice, it tends to have a higher average value of the distribution. Also, common financial data has a fat tail, which means that the probability of extremely large positive as well as extremely large negative values is higher than in the normal distribution. Ignoring this phenomenon can be very dangerous.

Steps to calculate:

- Calculate daily changes in price.
- Apply each change to actual price.
- Sort results ascending (ranking).
- Select n^{th} worst percentile.

Advantages:

- Simplicity and general applicability of the method, easy to implement.
- It is not necessary to calculate the correlation or standard deviation.
- Stress scenarios can be incorporated quite easily.
- The method is not assuming a normal distribution of changes in the portfolio.
- The simple choice of the time horizon – the horizon of measurement corresponds to the length of time holding.
- Directly gives the worst result (possible losses are simulated directly on the historical scenarios).

Weaknesses:

- High demands for historical data, regulators generally impose 1 year of data as a minimum.
- Short data series might not capture all the required changes.
- Too long data series may have events not relevant to present market conditions.
- If an event did not occur in the sample period so it cannot be predicted.
- Changes from volatilities of the underliers can take long time before they take an effect.
- Recent observations have the same weight as observations from the distant past.

Slight improvement of the historical method is the application of bootstrap methods. The bootstrap method is nonparametric randomization that from the existing distribution creates a so-called pseudo-observation. In this way, it is possible to increase the size of the sample and preserve its original characteristics, for example, fat tails, etc.

3.3. The method of Monte Carlo

However, there are cases that cannot be met by previous methods. An example is a portfolio that is characterized by fat tails, a portfolio that is too heterogeneous, or historical data are not available. In such case can be applied to the Monte Carlo method, Kollar and Kliestik (2014).

This method based on the assumption that the risk factors that affect the value of the portfolio are managed by a random process. The random process is simulated many times (e.g., 10,000 times). The result is a simulated distribution of profit and loss (P / L).

The more simulations, the resulting distribution is more accurate. Monte Carlo method is based on the assumption that the share price (or value of the total portfolio) is governed by a geometric Brownian motion.

Steps to calculate:

- Generate random scenarios.
- Revaluate portfolio under scenarios.
- Sort results ascending (ranking).
- Select n^{th} worst percentile.

The advantages:

- It is the most comprehensive approach to the calculation of VaR
- It allows to model volatility change over time, as well as the change in average yields, fat tails.
- The ability to include non-linear exposure risk, vega (kappa) risk (implied volatilities of the underliers)

Weaknesses:

- Computational complexity - the reason for the large number of risk factors and "roads"
- High financial cost (with respect to human capital and intellectual development)
- The risk of model: assumptions allocation risk factors play a key role

Monte Carlo method is the most used method presently. Computers are becoming more powerful every year, the software becomes simpler for the user - and that is what plays in favour of VaR Monte Carlo simulations.

4. Conclusion

VaR's attractiveness lies in the fact that it is very simple to calculate; it is well known and commonly used as a tool of risk management. VaR exists in many forms, and that means great flexibility. VaR is usable for any types of assets.

But VaR has to also faced criticism. The resulting VAR is only as good as the inputs and assumptions. Different methods lead to different results. VaR may give a false sense of security, that there is tendency underestimate the worst results. VaR does not give any information about the severity of losses beyond the VaR level. But as Dennis Weatherstone, former CEO, JP Morgan said: “VaR gets me to 95% confidence. I pay my Risk Managers good salaries, to look after the remaining 5%.”

Acknowledgements

The contribution is an output of the science project VEGA 1/0656/14 - Research of Possibilities of Credit Default Models Application in Conditions of the SR as a Tool for Objective Quantification of Businesses Credit Risks.

References

Buc, D., Kliestik, T., 2013. Aspects of statistics in terms of financial modelling and risk, Proceeding of the 7th International Days of Statistics and Economics, Prague, 215-224.

Cisko, S., Kliestik, T., 2013. Financny manazment podniku II, EDIS Publishers, University of Zilina, Zilina, pp. 775

Dengov, V.V., Melnikova, E.P., 2012. Adverse selection on credit markets: the analysis of the empirical research results, Proceedings of the 7th international conference on currency, banking and international finance. 27 and 28 September 2012, Bratislava, Slovenska Republika., 38-52.

Gavlakova, P., Kliestik, T., 2014. Credit Risk Models and Valuation. In: 4th International Conference on Applied Social Science (ICASS 2014), Information Engineering Research Institute, Singapore, Advances in Education Research, 51, 139-143.

Holton, G., A., 2003. Value-at-Risk: Theory and Practice. Academic Press.

Hull, J. C., 2011. Options, Futures, and Other Derivatives (8th ed.). Prentice Hall.

Jaros, J., Melichar, V., Svadlenka, L., 2014. Impact of the Financial Crisis on Capital Markets and Global Economic Performance. In: 18th International Conference on Transport Means, Kaunas Lithuania, 431-434.

Kollar, B., 2014. Credit Value at Risk and options of its Measurement. In: 2nd international conference on economics and social science (ICESS 2014), Information Engineering Research Institute, Advances in Education Research, 61, 143-147.

Kollar, B., Bartosova, V., 2014. Comparison of Credit Risk Measures as an Alternative to VaR. In: 2nd International Conference on Social Sciences Research (SSR 2014), Advances in Social and Behavioral Sciences Volume, 5, pp. 167.

Kollar, B., Kliestik T., 2014. Simulation approach in credit risk models, In: 4th International Conference on Applied Social Science (ICASS 2014), Information Engineering Research Institute, Advances in Education Research, 51, 150-155.

Misankova, M., Kocisova, K., Frajtova-Michalikova, K., Adamko, P., 2014. CreditMetrics and Its Use for the Calculation of Credit Risk. 2nd International Conference on Economics and Social Science (ICESS 2014), Information Engineering Research Institute, Advances in Education Research, 61, 124-129.

Misankova M., Kocisova K., 2014. Theoretical Framework of Merton's Model. In: 4th International Conference on Applied Social Science (ICASS 2014), Information Engineering Research Institute, Singapore, Advances in Education Research, 51, 557-562.