THE MARKET RISK ANALYSIS BY QUANTIFICATION METHOD

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Abstract

In this article, the authors aimed to establish the concrete econometric ways in which market risk can be determined and based on the calculated parameters can be estimated.

This study starts from the concrete situation of the occurrence of market risk which is obvious in the conditions in which they appear disturbed from one period of time to another. Through the data available to them, the authors identified and highlighted the advantages of the quantification method, in fact the only method to establish in concrete terms a system of equations on the basis of which to obtain the parameters, which can then be used in estimating market developments in the context of risk.

The article comprises a series of calculation relations, some data being introduced in these relations and established, then in equations to underlie the calculations performed. The article has a more theoretical character because it starts from the specialized literature and ensures the implementation of a generally valid method of quantification.

Keywords: *risk, market, capital, estimation, parameters, methods.*

Classification JEL: *F14, F37*

1. Introduction

In order to allocate capital, assess the solvency and measure the profitability of different business units, ranging from individual traders to the entire organization, risk managers and regulators quantify the magnitude and probability of possible changes in the value of a portfolio, for different forecast horizons. This process is often called market risk measurement, which is a subset of the risk management function. All models with several regimes assume that the dynamics of profitability in each regime is described by normal distributions. This implies that for two-state models there are only two levels of volatility. but this is not in line with empirical evidence and is in contrast to GARCH models, for which volatility can take any positive value. In the case of normal distribution, VaR is proportional to the standard deviation and is a consistent measure. If another distribution is used, VaR loses its coherence. Thus, the VaR resulting from the combination of two portfolios may be greater than the sum of the risks of the individual portfolios. According to the method used, the portfolio of an intermediary is expressed as a linear combination of several hundred risk factors whose covariance matrix is updated daily using historical data.

Having become a well-established way of measuring risk, the VaR method is applied differently, depending on the portfolio to be assessed. The approaches used to calculate the value at risk can be divided into two groups depending on whether the assessment is local or total.

The parametric method of calculating the value at risk has the advantage of being able to be implemented very easily, because it involves simple matrix multiplication operations. On the other hand, the criticisms brought to this model aim mainly at the weak approach of the extreme financial events that are found in the distribution queues followed by the returns of the financial assets.

The Monte Carlo simulation method is a general problem-solving technique that estimates the value at risk by randomly generating trajectories for future values of market variables and using nonlinear valuation models to estimate portfolio value changes in each scenario.

In the case of a wide variety of financial instruments and products traded on the market, their mapping can be simplified by breaking down the instruments into a small number of basic instruments, such as: spot positions on the exchange rate, positions in shares, zero-coupon bonds, futures / forward positions.

2. Literature review

Aebi, Sabato and Schmid (2012) sought to identify whether corporate governance mechanisms related to risk management are associated with better bank performance during the financial crisis. Aizenman (2010) analyzed the need for external debt management policy in emerging markets in situations of financial crisis. Ameur and Prigent (2010) studied the optimal design of structured finance portfolios within the rank-dependent utility. Angelelli, Mansini and Speranza (2008) analyzed two linear programming models to solve the portfolio selection problem. Anghelache and Anghel (2019) analyzed a series of portfolio selection and management models. Baule (2010) addressed a number of issues regarding the optimal portfolio selection of the small investor, taking into account risk and transaction costs. Beltratti and Stulz (2012) studied the factors that generated the poor performance of banks during the credit crunch. Chaudhury (2010) addressed the practical issues facing a bank in designing and implementing an operational risk model. Chen (2008) used goal programming to establish a new portfolio selection model. Guidolin and Hyde (2010) examined whether and how simple VARs can produce empirical portfolio rules. Liu, Wang, and Qiu (2003) analyzed an average variation model for portfolio selection with transaction costs, while Zhai et al (2018) proposed a medium risk model for portfolio selection in an uncertain environment.

3. Methodology, data, discussions, results

The commercial and investment banks, as well as capital market intermediaries, hold complex securities portfolios, whose values depend on exogenous variables, such as interest rates or the exchange rate. According to the BIS, market risk is the risk that the value of balance sheet and off-balance sheet positions will be adversely affected by movements in the capital and interbank markets, exchange rate changes and commodity prices. Thus, it is considered that the main components of market risk are capital risk, interest rate risk, currency risk and the risk of changes in commodity prices.

According to the Risk Management - A Practical Guide (1999), in addition to market risk, the price of financial instruments may also be influenced by the following residual risks: difference risk, underlying risk, specific risk and volatility risk:

- The difference risk is the potential loss caused by changes in spreads between two instruments. For example, there is a risk of a difference between corporate and government bonds.
- The underlying risk is the potential loss due to price differences between equivalent instruments, such as futures, bonds and swaps.
- The specific risk refers to the specific risk of the issuer. For example, there is the risk of holding a portfolio of shares versus a futures contract. We specify that according to the evaluation model of CAPM actions, the specific risk is entirely diversifiable.
- The volatility risk is defined as the potential loss of a derivatives portfolio due to volatility fluctuations. In general, portfolios that contain short positions in options decrease in value if the volatility of the underlying asset increases.

In order to determine the total risk of financial instruments, the market risk is summed with the residual risks:

Market risk	+	Residual risks	=	Total risk
capital risk		*risk of difference*		
interest rate risk		*basic risk*		
currency risk		*specific risk*		
risk of changes in commodity prices		*the risk of volatility*		

The risk is especially important in economics and finance. Therefore, the determination of optimal portfolios is calculated based on portfolio risk. This is a cause for concern for investors as they face changing risks on a daily basis. Generally speaking, risk is associated with the probability that a financial investment will result in losses.

In recent decades, as a result of rapid movements in financial markets and the proliferation of financial derivatives, many companies have built up highly complex portfolios, comprising both cash and financial derivatives. Due to the high degree of complexity of financial products, as well as the large number of transactions with various derivatives, the degree of market risk coverage for companies' portfolios changes. Although many risk quantification models are built, most of them are quite complicated and not easy to understand by the Executive Management of Financial Intermediaries. Therefore, portfolio managers need quantitative risk measurement, which a manager can briefly report on the level of risk supervision and management and trading operations.

Markowitz's mean-variance model is fundamental to the modem theory of the portfolio. Markowitz's idea is that agents aim to optimally select efficient mid-variance portfolios. Concrete studies include determining the optimal structure of the portfolio, measuring the gains from diversification with market assets and evaluating the performance of the portfolio.

At the end of the 1980s, Value at Risk (VaR) was introduced and used as a measure of the risks of traded portfolios. The VaR model is also used by other financial institutions and non-financial corporations. After the concept of VaR was introduced by JP Morgan, it became widely used in a short period of time and received widespread recognition from other financial structures. The development was driven by the amendments to the Basel Accord, which required banks to raise capital for protection against market risk, although the use of VaR models was conditioned by certain qualitative and quantitative standards. VaR has become the recognized standard approach for measuring market risk and one of the most important and widely used methods of risk quantification.

VaR describes losses that may occur over a period of time, at a given confidence level, as a result of exposure to market risk. The appealing simplicity of the VaR concept has led to its adoption as an elementary risk measure for financial entities involved in large commercial operations, but also for retail banks, insurance companies, institutional investors and non-financial enterprises.

Initially, the Basel Accord provided for a standardized approach according to which all institutions were required to adopt certain limits in the calculation of VaR for the calculation of capital requirements, but also as a component part of the risk management process in the bank.

Subsequently, the Basel Accord was amended to allow financial intermediaries to use internal models for determining VaR and capital requirements.

The predominant approaches to VaR calculation are based on a linear approximation of portfolio risk and involve a normal price distribution. The VaR measurement for a portfolio is based on a model that analyzes changes in asset prices and a model for calculating the sensitivity of derivative prices.

There are several methods for estimating VaR, the best known being the historical simulation method or the Monte-Carlo simulation method.

According to other opinions, there are four groups of ways to calculate VaR, namely historical simulations, parametric models, extreme value theory and quantum-based regression approaches. In the literature, two aspects are more important to calculate VaR, namely the validity of the normality assumption regarding the return of an asset or portfolio, including the study of extreme events and clusters of volatility and the assumption of non-linearity of assets.

Several empirical analyzes have been prepared to prove the non-normality of financial returns. Some authors have proposed the use of thicker-tailed distributions than the normal distribution, such as the Pareto distribution, the Student-t distribution, or the Student-t skewed distribution.

There are several schemes for the joint distribution of monthly shares and bond yields.

Due to the complex implications of developing risk management models, they have recently received special attention from practitioners and regulators, with analyzes focusing heavily on the VaR method. VaR is widely used as a risk management tool by staff in treasuries, dealers, fund managers, financial institutions and regulators. In addition, the idea of reducing market risk was rediscovered through VaR, becoming one of the most popular measures.

There are a number of theoretical and practical difficulties associated with using VaR as a measure of market risk. From a financial point of view, the axiom of sub-additivity means that a merger does not create additional risk. Due to the lack of sub-additivity, VaR is inefficient in identifying credit risk generating elements and fails to indicate the severity of the economic consequences of exposure to rare events. It is possible for VaR to maintain its status as a prominent practice, as it measures operational activity much more easily than most other risk measures.

The study also provides other evidence to support a relaxation of the sub-additivity hypothesis, including evidence from utility theory, psychology, and the study of extreme events in the case of VaR.

When an agent faces a VaR constraint at the initial time, in a continuous time model, the agent may select a higher risk exposure than he would have chosen in the absence of this constraint. For these reasons, a number of researchers propose the use of CVaR rather than VaR.

Although CVaR is less used in finance, it is widely used in insurance. CVaR is a very good measure of risk because it is consistent, convex and stable, and most methods used to estimate VaR can also be applied to calculate CVaR.

The advantages of CVaR over VaR, as a risk mitigation measure, have led to the development of an extensive literature exploring the use of CVaR in portfolio optimization.

The problem of selecting the portfolio of an agent who is subject to the constraint of not losing more than a fixed fraction of the maximum gain achieved up to that point is another situation. Usually, in an economy with two assets (one risky and one risk-free), the optimal portfolio involves investing a sum in risky assets, which is a constant fraction of the difference between: current wealth and expected income. Cvitanic and Karatzas (1995) extend this result to the case where there are several risky assets.

Assuming that the loss is a function that depends on a number of parameters (for example, the loss of a portfolio is often a function that depends on the interest rate and volatility of assets) it follows that VaR and CVaR specific to losses are functions of these parameters. The partial derivatives of these functions are called VaR and CVaR sensitivities, providing information on how changes in these parameters affect the value of the resulting risk measures. These sensitivities are useful in managing risk, verifying model adequacy, and solving stochastic optimization problems.

If the parameters of the loss model are controllable, ie risk managers can adjust these parameters, their sensitivities can be used for risk management. For example, if the parameters are percentages of the total value of the portfolio allocated to different financial assets, their sensitivities can be used to adjust the value of the portfolio to ensure that its VaR or CVaR is below a certain level. given. if the parameters are not controllable their sensitivities are measures of adequacy of the model.

In addition, in any loss models there are constants that are subject to estimation errors. In these models some constants can be estimated from historical data. If the sensitivity to a particular parameter is high, it can be concluded that the information about that parameter is valuable. Because there are often errors in the specifications of a parameter, it may be necessary to reconsider the model, and therefore VaR or CVaR may change significantly depending on a small specification error.

When VaR and CVaR are used in stochastic optimization, their sensitivities represent partial derivatives. If the slope calculation is known, nonlinear optimization algorithms, such as the quasi-Newton method, can be applied to solve optimization problems.

Functions that quantify losses specific to derivative portfolios are often nonlinear interest rate and volatility functions, and objective functions, constraints from convex stochastic optimization problems, can also be nonlinear.

Therefore, sensitivity estimators for CVaR are needed that can be applied to nonlinear loss functions. In addition, the performance of the kemel estimator is sensitive to kemel function choices and bandwidth. In the likelihood ratio method, the density of the loss function is differentiated. This applies on a larger scale than disturbance analysis. However, estimators often have large variances.

An additional problem is that VaR is difficult to optimize when using complex parametric distributions. It becomes difficult to solve as a function of portfolio positions and can expose multiple local extremes, making it difficult to determine the optimal mix of positions and a special mix on VaR. In addition, VaR does not provide any information on the extent of losses exceeding the quantified threshold. By contrast, the CVaR tries to quantify the losses that could be encountered in extreme situations. This is because the CVaR for a portfolio is the loss that an agent expects to bear, given that the loss is equal to or greater than the VaR of the portfolio.

Therefore, one of the most used risk estimation methods is VaR.

Given the position of the portfolio in relation to each risk factor, but also the assumption that the value of the portfolio is normally distributed, VaR can be generated in one day, with a 95% confidence level.

The VaR method was successful due to the importance given to it by the Basel Accord in the 1996 amendment. This amendment recommends that central banks use VaR to quantify the minimum capital limit required for a credit institution to protect itself. against market risk.

Under the agreement, CBSB set a time horizon of 10 days and a 99% confidence interval for the market risk of a trading book. For credit risk, VaR is calculated for a time horizon of 1 year with a confidence level of 99.9%. Therefore, the values of the two parameters may vary depending on different situations. In practice, it is assumed that the changes in the value of the portfolio follow a normal distribution in the time horizon considered, and the average change in the value of the portfolio is zero, given by the relation:

$$VaR = \sigma N^{-1}(\alpha) \qquad (1)$$

where α represents the confidence level, σ is the volatility of the portfolio over the considered time horizon, and $N^{-1}(\alpha)$ is the inverse of the distribution function of the standard normal distribution. As can be seen, regardless of the time horizon chosen, the VaR at a certain confidence interval is proportional to σ. For ease of calculation and in the event that changes in market factors are normally distributed, VaR for one day is constant over the time horizon and if there are no serial correlations, portfolio managers begin their analysis with VaR determination at one day, after which use the following formula:

$$VaR_{Nzile} = VaR_{1zi}\sqrt{N} \qquad (2)$$

There are various extensions and method variants for VaR, which reflect a wide range of applications and issues for which the VaR conceptual framework can be used. Thus there may be: Incremental VaR, is a measure that provides guidance on how the addition of a new position could have an impact on the VaR portfolio. In other words, incremental VaR is the change in value of

VaR associated with the addition of a new position in the portfolio. Marginal VaR is a measure of how VaR changes if we increase the position by an additional unit of the underlying risk factor. Relative VaR is a measure of how the VaR for the analyzed portfolio differs from a VaR for a benchmark portfolio. In other words, the relative VaR is the difference between the VaR for the analyzed portfolio and the VaR for the benchmark. (This is a very popular risk measure in asset management).

Cash Flows at Risk (FNLR) and Earnings at Risk (CLR)**:** VaR describes a general class of probabilistic models that measure the risk of loss. However, the same mechanism can be applied to assess the uncertainty of the value for other settings, regardless of how the value is defined. The element that is actually measured can be adapted to suit the circumstances in which the method is applied.

In this context, FNLR and CLR are also probabilistic models, developed from statistical analysis. FNLR is a reasonable choice for non-financial corporations that are concerned with managing the inherent risks of cash flows and not with changes in market values. Usually, the time horizon is much longer in FNLR calculations compared to VaR. For example, a company might be interested in distributing quarterly cash flows for the next 12 quarters and how those distributions are affected by transactions in financial instruments.

- Before calculating the VaR, it is necessary to specify three parameters: the confidence level, the time horizon and the base currency.

a) confidence level

The confidence levels are generally between 90% and 99%. RiskMetrics Group (1999) assumes a 95% confidence level as a reference system, but gives users the flexibility to choose other levels. Thus, it is recommended to choose several confidence levels (eg 95% and 99%) and horizons and forecast (eg one day and one year).

b) time horizon

In general, active financial intermediaries consistently use a 1-day forecast horizon for the VaR analysis of all market risk positions. For banks, it simply does not make sense for the market risk to be projected for a much longer period, as trading positions can change very quickly from one day to the next. On the other hand, investment managers often use a 1-month forecast horizon, while corporations can make quarterly or even annual market risk forecasts.

c) base currency

The base currency for calculating VaR is usually a company's reporting currency. For example, Bank of America uses the US dollar to calculate and report its global risks, while the United Bank of Switzerland uses the Swiss franc.

In practice, several methods of VaR calculation are used, the best known being: the parametric method, the historical method and the Monte Carlo simulation. In the process of establishing the VaR calculation method, various elements are analyzed, such as: the financial instruments on which it can be applied, the accuracy of risk measures, including the statistical assumptions on which they are based, implementation requirements, necessary IT systems and ease of communication of results to users.

Local valuation methods, such as parametric VaR, measure risk by valuing the portfolio once, at baseline, and using first- and second-order derivatives to determine changes in value. They assume the existence of normal distributions for risk factors, being suitable for portfolios exposed to limited sources of risk. Total valuation methods measure the risk of the portfolio by determining its value in different scenarios. These methods can be implemented by historical simulation or Monte-Carlo simulation.

This classification implies a fundamental compromise between speed and accuracy. The speed of determining the value at risk is important for large portfolios that are exposed to numerous risks, which implies a large number of correlations. For these, the recommended method is the parametric one. However, in the case of portfolios with components that do not respect linearity, accuracy becomes more important.

The parametric VaR method is known in the literature as analytical VaR, linear VaR, variance-covariance method, Greek-Normal VaR or Delta Normal VaR.

According to the parametric VaR method, the distribution of the analyzed series is normal and requires the calculation of the coefficients of variance and covariance. The method also aims to determine the distribution of all possible values of a portfolio for the specified time period and to determine the VaR for each distribution, depending on the specified confidence level. Once the distribution of potential portfolio profits and losses has been identified, the properties of the standard normal distribution are used to determine the loss that will be achieved.

In order to determine the VaR, using the parametric method, the following steps are also performed:

• identification of risk factors affecting the portfolio

• determining the volatility of each element of the portfolio in the case of each risk factor

• calculation of the standard deviation of changes in risk factors and correlation coefficients, based on historical data

• estimating the standard deviation for the portfolio value by multiplying the sensitivities with the standard deviations calculated at the previous stage

• approximation of VaR to the established confidence level.

In the case of a portfolio of n assets, the return is calculated as follows:

$$R_p = \sum_{i=1}^{n} w_i R_i \;<=>\; \Delta R_p = \sum_{i=1}^{n} w_i \Delta R_i \qquad (3)$$

where: w_i represents the weights of each asset in the portfolio.

Given that the portfolio yield is a linear combination of normally distributed variables, it follows that this also follows a normal distribution. In order to determine the value at risk, the average and variance (dispersion) of the changes in the portfolio return must be determined., ΔR_p.

Thus, the relation of the average has the following form:

$$\mu_p = \sum_{i=1}^{n} w_i \mu_i \qquad (4)$$

For the calculation of the dispersion, the volatilities of each asset *i* in the portfolio σ_i, are defined, as well as the correlation coefficients between the returns on asset *i* and asset j ($\rho_{i,j}$). Thus, the variance of the portfolio return will be:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1} \rho_{i,j} w_i w_j \sigma_i \sigma_j = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j<i} \rho_{i,j} w_i w_j \sigma_i \sigma_j \qquad (5)$$

Using the matrix form, the variance of the portfolio returns can be written as follows:

$$\sigma^2(R_p) = w^T \sum w \qquad (6)$$

where $\sum$ represents the variance-covariance matrix $(\sigma_{i,j})_{i,j=\overline{1,n}}$ estimated for the considered time horizon.

The VaR calculated at a 99% confidence interval and a time horizon of N days will be:

$$VaR = 2{,}33 \sigma_p \sqrt{N} \qquad (7)$$

The standard deviation corresponding to the change over *N* days is $\sigma_p \sqrt{N}$, and a probability of 99% is associated with a coefficient $\alpha = 2{,}33$.

This method inadequately quantifies nonlinear risks. Thus, in the case of options, the asymmetries of the distributions are not captured by the delta-normal method. Also, the use of the covariance matrix in the calculation algorithm represents a limitation of the parametric model because this implies stable and constant correlations between the risk factors.

The method of historical simulation, from a conceptual point of view, is the easiest method of calculating the value at risk. However, from the implementation point of view, the VaR calculated by the historical simulation method requires a significantly longer period of time than in the case of the parametric method. To estimate the distribution of the portfolio, followed by the actual changes in the value of the portfolio, the daily historical changes in assets are used in a direct manner. In essence, the approach involves using historical asset returns to build a distribution of potential profits and losses in their portfolio and then the VaR is identified.

The distribution of the future income series is constructed by evaluating the portfolio according to the percentage changes of the relevant risk factors for each of the last N periods. The use of real historical price changes in order to calculate hypothetical profits and losses is the characteristic feature of historical simulations and the source of the name of this method.

In general, a one-day time horizon, a 99% confidence interval, and historical data from the last 500 days are used for the VaR calculation using the historical simulation method. Thus, the following steps are followed:

• identification of risk factors that may affect the value of the portfolio
• obtaining the formula that expresses the market value of the portfolio;
• collecting data on changes in risk factors in the last 500 days;
• identifying 500 alternative scenarios for what may happen the next day with risk factors;
• calculating the change in value (profit or loss) of the portfolio for each scenario (thus resulting in a distribution of daily changes);
• ordering profits and losses according to market marking, from the highest profit to the lowest loss;
• estimating the first percentile of the distribution (being 500 days, it is the 5th of the worst results).

This value represents the VaR estimate.

For this method to become more realistic, Attikouris (2005) considers that in the case of at least three steps, their developments need to be more efficient. First, in step 1 there are chances that there will be more risk factors. They must be identified and included in the market value formula of the components of the portfolio. Second, in step 2 the historical values of all risk factors must be collected, taking into account that the sample is synchronized. It is very important to mark the market profits and losses for each asset in the portfolio and then add them up for each period before ordering them from the highest value to the lowest. Therefore, the ordering process in step 4 must be performed for the entire portfolio and not individually for each asset. The VaR calculation thus aims to capture any correlation between the historical values of the risk factors and to eliminate the need for explicit assumptions.

An advantage of this method is that it does not make any assumptions about the distribution of profitability, because it uses the empirical distribution obtained from the analysis of past data. Being an intuitive method, historical simulation is the most used method of determining the value at risk, having the advantage of being easy to implement if the necessary historical data are available. Also, for the VaR calculation it is not necessary to assume that the changes of the risk factors follow a normal distribution, being allowed also non-linear evaluation methods. Perhaps the most important advantage of this method is that the historical simulation can take into account the particularities of the distribution queues and, as it is not based on valuation models, eliminates the model risk.

Among the disadvantages of the VaR calculation method through historical simulations, the most representative are:

• there is enough historical data to calculate VaR, which is not true for all assets (using a short historical series leads to appreciable errors);

• predicts the future evolution of asset prices based on the past, in contradiction with theoretical models that consider asset prices to be Markov-type processes (no important new events are considered, or on the contrary, some events are considered to recur);

• can become burdensome for portfolios with more complicated structures, using certain simplifications that lead to the loss of the benefits offered by the total evaluation.

The Monte Carlo simulation method is named after the famous city in the state of Monaco, where the primary attraction is given by gambling. Although this method has a number of similarities to historical simulation, the major difference is that in this method a statistical distribution is chosen that is considered appropriate to capture or approximate possible changes in risk factors, as opposed to the method of historical simulations where the Nl hypothetical profits and losses were generated according to the values of the risk factors for N periods.

In addition, the clear advantages over the first two methods of determining the value at risk are that Monte Carlo simulations capture the nonlinear effects of risk factors and can generate a very large number of scenarios. However, compared to the parametric method, the speed of implementation of Monte Carlo simulations can be 1000 times slower. Regarding the comparison with the method of historical simulations, in this case it is necessary the hypothesis of a normal distribution for the risk factors.

For the Monte Carlo simulation method, the steps are as follows:

• evaluating the portfolio at current market value and obtaining the formula that expresses the market value of the portfolio;

• the determining the specific distribution for the profitability of the risk factors and estimating the parameters of that distribution. The ability to choose an appropriate distribution is the distinguishing feature of the Monte Carlo method from the other two methods, because within them the distribution of changes in risk factors is specific as part of the method;

• the calculation of each market variable at the end of the day, using random changes

• the revaluation of the portfolio at the end of the day;

• determining a random variation of the portfolio value.

The last four steps of the method are repeated to build a distribution for portfolio value changes. After identifying the shape of the distribution, the VaR is calculated as the corresponding percentile in this distribution.

This method is considered to be the most appropriate method of calculating VaR, because it incorporates the analysis of a variety of exposures, while presenting the necessary flexibility to take into account the particularities of the distribution queues, the variation of volatility over time and extreme events. At the same time, the results of the simulation of a multitude of scenarios, allow the analysis of an expected loss that exceeds the value at risk determined within the model. Also, the people responsible for the design of the risk management system are free to decide which distribution will be used to describe the possible future changes in the values of the risk factors. Assumptions that these possible future changes in risk factors will occur are based on past changes, which are considered sufficient for model builders to choose any distribution they deem appropriate to approximate past changes in risk factors.

However, like the other methods, the Monte Carlo simulation has some limitations, namely:

• the calculation speed

• if the valuation of assets at a certain date involves another simulation, the method will represent a simulation in the simulation, which becomes very difficult to implement frequently; also, the implementation of this method involves high costs in terms of the configuration of the necessary systems.

• model risk; because the Monte Carlo simulation is based on stochastic processes specific to risk factors and on certain valuation models for some financial assets, there is a risk that these models may be wrong.

The methodologies presented, the P / L of the portfolio were derived from the P / L of the individual positions and it is considered that direct modeling of each position is possible. Practitioners design positions based on a small number of risk factors - a process called risk factor mapping. There are a number of main reasons for mapping, namely: the unavailability of historical data for certain positions and the size of the variance-covariance matrix of risk factors may become too large.

In the case of a portfolio of n instruments, n volatilities and correlation coefficients result, which corresponds to a number of n factors and n (n-1) / 2 correlation coefficients, which corresponds to a number of n (n-1) / 2 factors and mapping drastically reduces computational requirements.

All three approaches to estimating VaR have something to offer and can also be used together to build a more robust VaR model. For example, a parametric approach can be used to manage risk during a trading day, while an approach based on historical simulations can be used to provide Risk Photography at the end of a trading day.

4. Conclusions

VaR is a general statistical measure of market risk quantification, which is used to assess the risk for all assets in a portfolio. VaR is defined as the loss for the worst case scenario, at a specific confidence level, over a period of time.

There are three major methodologies for calculating VaR, each with unique characteristics. Parametric VaR is a simple and fast method, but it is inaccurate for non-linear positions. There are also two simulation methodologies, that of historical simulations and the Monte Carlo simulation method. They also manage to capture the risks with a non-linear evolution and to offer a complete distribution of the potential results, but with a greater calculation effort. Before calculating the VaR, three parameters must be specified: the confidence level, the time horizon and the base currency.

Financial instruments are subject to both market and residual risk. The four basic components of market risk are interest rates, capital risk, risk of changes in commodity prices and currency risk. Residual risk includes spread, core risk, specific risk and volatility risk.

Because the VaR method faces a number of limitations related to the property of sub-additivity or the fact that it is a statistical measure of market risk under normal market conditions, the researchers proposed the use of CVaR rather than VaR. This method represents the expected loss given by a loss greater than the VaR for a certain value. Several types of optimization problems have been proposed for the calculation of the optimal CVaR. It has been shown that when the optimization problem is approximated by a Monte Carlo simulation, it is equivalent to a linear programming problem and can be solved by a standard linear programming method.

In addition, for the situation in which it is desired to increase the number of scenarios and generate a higher number of prices for the next period, it is necessary to build an optimal problem over several periods.

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