Estimation of confidence level for Value-at-Risk: statistical analysis

Abstract. The paper investigates the problem of estimation of the confidence level for Value-at-Risk to get the minimum VaR portfolio with a predefined level of expected return. The equation which describes the relation between the confidence level and the rate of the expected return depends on the unknown parameters of distribution of asset returns which should be estimated. The classical sample estimators for unknown parameters are used. The author has examined the properties of the estimator for the confidence level in considerable detail. Under the assumption that the asset returns are multivariate, we find the asymptotic distribution of the estimator for the confidence level. Moreover, we extend this result to the case of elliptically contoured distributed asset returns. Based on the distributional properties, the confidence interval for the confidence level for VaR is constructed and the test procedure whether the resulting portfolio is statistically different from the global minimum variance portfolio is provided. Using a simulation study, we demonstrate that our results give a good approximation even in the case of moderate sample sizes \( n = 250, n = 500 \) not only in the case of normally distributed asset returns, but also when asset returns follow the elliptically countered distribution. We have concluded that investors can use the results of the paper with regard to all sectors of the economy.

We used monthly asset returns of five stocks included into Dow Jones Index, namely: McDonald’s, Johnson&Johnson, Procter&Gamble, AT&T, and Verizon Communications from 01 October 2010 to 01 September 2015 to give numerical illustration of our fundamental results.

Keywords: Portfolio Selection Problem; Value-at-Risk; Variance; Expected Return; Sample Estimator; Risk Measure

JEL Classification: G11; G17; C13

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1. Introduction

To divide the wealth between assets in order to get the maximum expected return and the minimum risk is the main goal of the investor. Diversification is a basic tool for risk sharing between the financial elements used in the investment process and the consequent reduction in the overall level of risk. One of the most popular methods of application of diversification in financial activity is the use of portfolios. At the first glance, it may seem that because of risk reduction the total return of portfolio should also become smaller. But the main point in portfolio construction is that this process does not always lead to a decrease in income in spite of the fact that the total risk of the portfolio becomes smaller. This is archived by using different models of portfolio optimisation.
2. Brief Literature Review

The first model of portfolio optimisation was described by Markowitz in 1952 (Markowitz, 1952). In his work, Markowitz proposed to construct an optimal portfolio by minimising portfolio risk for a fixed level of expected return or, equivalently, by maximizing portfolio expected return for a given level of risk. To measure the portfolio risk Markowitz took the portfolio variance. All optimal, according to Markowitz, portfolios lie on the parabola in the variance space and the hyperbola in mean standard deviation space (Merton, 1972). This set is known as the efficient frontier. The portfolios which belong to this frontier are called efficient by Markowitz. According to Markowitz, the portfolio is efficient if and only if its expected return cannot be increased without increasing its variance or its variance cannot be decreased without decreasing its expected return. It means that an investor who uses Markowitz’s method for portfolio construction should choose a suitable portfolio only among the efficient portfolios.

The theory developed by Markowitz has one serious drawback. Portfolio variance is not a good risk measure. It may happen that high returns increase the variance. The better risk measures are based on either positive values of losses or negative values of returns. Such measures are known as downside risk measures (Krokhmal et al., 2011). The example of such measures is quantile-based measures. The most popular of each is the so-called Value-at-Risk (VaR). The VaR is nowadays recommended as a standard tool for banking supervision (Basc, committee on banking supervision, 2001). The VaR shows the maximal level of losses with the probability α. The quantity α is known as a confidence level. The values for α which are usually chosen are 0.9; 0.95; 0.99; 0.999.

The VaR framework for portfolio construction was considered in (Alexander and Baptista, 2002; Bodnar et al., 2002; Rockafellar et al., 2006a, 2006b; Kilianova and Pflug, 2009). For example, a theoretical background for the portfolio VaR minimisation is presented in (Alexander and Baptista, 2002). It is shown that the minimum VaR portfolio is efficient by Markowitz. In (Bodnar et al., 2002), the problem of parameter uncertainty for the minimum VaR portfolio is taken into account and the exact and asymptotic distributions of the characteristics of the minimum VaR portfolio are found. In spite of the fact that VaR minimization is very popular for portfolio construction it can happen that the expected return of the minimum VaR portfolio is smaller than the desirable level. This problem is on a par with the problem of parameter uncertainty. This problem is on a par with the problem of the sharp ratio maximisation when the VaR is chosen as the portfolio risk measure (Bodnar and Zabolotskyy, 2013). It is shown that a portfolio with the maximum Sharpe ratio can be constructed as the minimum VaR portfolio. But it is also proved that such a portfolio is very risky. For another risk measures such investigation is provided in (Rockafellar et al., 2006a, 2006b). In (Zabolotskyy and Bilyi, 2014), the relation between the expected return of the minimum VaR portfolio and the VaR confidence level is considered. Unfortunately, the investor has no possibility to use this finding in the portfolio construction process because it depends on unknown parameters of the asset return process andΣ. These quantities have to be estimated. We make use of the sample estimators. Let X1, X2,...,Xn be independent realisations of the vector of asset returns. The sample estimators are expressed as

\[ \bar{\mu} = \frac{1}{n} \sum_{i=1}^{n} X_i, \quad \hat{\Sigma} = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{\mu})(X_i - \bar{\mu})' \]

Replacing the unknown parameters μ and Σ in (4) by their estimators (5) we get an estimator of α0

\[ \hat{\alpha}_0 = \hat{\phi} \left( \sqrt{\hat{\mu}' \hat{\phi}^{-1} \hat{\phi} \hat{\mu}} \right) \]

The expected return of portfolio with the weight vector w is the mean of X1(t), i.e. R = E (X1(t)) = w' μ. The variance of the portfolio is equal to \( \sigma^2 = w' \Sigma w \). The VaR at the confidence level α (VaRα) of the portfolio with the weight vector w is equal to the rate of return such that \( \Phi(X_1 < \text{VaR}_\alpha) = 1-\alpha \). The optimisation problem of the portfolio VaR minimisation (Alexander and Baptista, 2002) is given by

\[ \text{VaR}_\alpha \rightarrow \min \text{subject to } w_1 = 1 \]

It should be noted that the short sales are allowed, i.e. we do not use the condition \( w_i \geq 0, i = 1,...,n \) in (1). If we additionally assume that the vector of asset returns \( X_1 \) is multivariate normally distributed, then the problem (1) can be rewritten in the following form:

\[ z_\alpha \sqrt{\mathbf{w}' \Sigma \mathbf{w}} - \mathbf{w}' \mu \rightarrow \min \text{subject to } \mathbf{w}' \mathbf{1} = 1 \]

where \( z_\alpha \) is the \( \alpha \)-quantile of the standard normal distribution. If we additionally denote

\[ w_{\text{VaR}} = \mathbf{w}_{\text{opt}} + z_\alpha \sqrt{\mathbf{w}_{\text{opt}}' \Sigma \mathbf{w}_{\text{opt}}} \]

then the solution to problem (2) can be written as follows:

\[ w_{\text{VaR}} = w_{\text{opt}} + \frac{z_\alpha \sqrt{\mathbf{w}_{\text{opt}}' \Sigma \mathbf{w}_{\text{opt}}}}{\sqrt{\mathbf{1}' \mathbf{w}_{\text{opt}}}} \]

It may happen that the expected return \( R_{\text{VaR}} \) of the minimum VaR portfolio with the weights \( w_{\text{VaR}} \) at confidence level \( \alpha \) is smaller than the desirable value. In this situation, the investor can decrease the confidence level to get larger expected return. In (Zabolotskyy and Bilyi, 2014) it is shown that if the investor is interested in the minimum VaR portfolio with the expected return equal to \( R_i \), then she/he should choose the confidence level equal to

\[ \alpha_i = \phi \left( \sqrt{\mathbf{w}_{\text{opt}}' \Sigma \mathbf{w}_{\text{opt}}} \right) \]

The expression (4) cannot be used in practice because it depends on the unknown parameters of the asset returns process \( \mu \) and \( \Sigma \). These quantities have to be estimated. We make use of the sample estimators. Let \( X_1, X_2,...,X_n \) be independent realisations of the vector of asset returns. The sample estimators are expressed as

\[ \hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} X_i, \quad \hat{\Sigma} = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \hat{\mu})(X_i - \hat{\mu})' \]

Replacing the unknown parameters \( \mu \) and \( \Sigma \) in (4) by their estimators (5) we get an estimator of \( \alpha_0 \)

\[ \hat{\alpha}_0 = \hat{\phi} \left( \sqrt{\hat{\mu}' \hat{\Sigma}^{-1} \hat{\mu}} \right) \]

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Our aim is to investigate the distributional properties of the sample estimator of \( \alpha_0 \) (6). These properties are heavily dependent on the distributional properties of the vector of asset returns \( \mathbf{X} \).

**Normally distributed asset returns**

We assume that the vector of asset returns \( \mathbf{X} \) is multivariate normally distributed with the mean vector \( \mathbf{\mu} \) and the covariance matrix \( \Sigma \). This assumption is criticised in financial literature because the returns with high frequency (daily, hourly, ...) do not satisfy this assumption in practice. However, the assumption of normality is relevant to monthly return (Fama, 1976). Taking into account that our aim is to get first theoretical results about distributional properties of the vector of asset returns \( \mathbf{X} \), we assume that the vector of asset returns \( \mathbf{X} \) is multivariate normally distributed with the mean vector \( \mathbf{\mu} \) and the covariance \( \Sigma \).

The asymptotic distribution of sample estimator (6) is presented in Theorem 1.

**Theorem 1.** Let us form a portfolio within \( k \) assets. Let \( \mathbf{X} \) be the \( k \)-dimensional vector of asset returns and \( \mathbf{X}_t - \mathcal{N}(\mathbf{\mu}, \Sigma) \). Let \( \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_t \) be independent realizations of the vector of asset returns and \( \mathbf{\mu} \) and \( \mathbf{\Sigma} \). Then, the asymptotic distribution of sample estimator of \( \alpha_0 \) (6) is given by:

\[
\sqrt{n}(\hat{\alpha}_n - \alpha_0) \sim \mathcal{N}(0, \sigma_n^2),
\]

with

\[
\sigma_n^2 = \frac{\hat{\varphi}(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right],
\]

where \( I, s, \Delta \) are given in (7) and \( \varphi \) is the density of the standard normal distribution.

**Proof.** From the delta method (DasGupta, 2008; Bodnar et al., 2009) and denoted by the symbol \( \rightarrow \) convergence in distribution we get:

\[
\sqrt{n} \left( \frac{\hat{\mathbf{R}}_{\mathbf{C}} - \mathbf{R}_{\mathbf{C}}}{\mathbf{V}_{\mathbf{C}}} \right) \rightarrow \mathcal{N}(0, \Sigma_{\mathbf{C}}).
\]

Using the application of the delta method and (10) we get,

\[
\sqrt{n}(\hat{\alpha}_n - \alpha_0) \sim \mathcal{N}(0, \sigma_n^2),
\]

where

\[
\sigma_n^2 = \frac{\varphi(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right],
\]

This leads to:

\[
\frac{\partial \hat{\mathbf{R}}_{\mathbf{C}}}{\partial \mathbf{R}_{\mathbf{C}}} = \frac{1}{I} \left( \frac{\partial \hat{\mathbf{R}}_{\mathbf{C}}}{\partial \mathbf{V}_{\mathbf{C}}} \frac{\partial \mathbf{V}_{\mathbf{C}}}{\partial \mathbf{R}_{\mathbf{C}}} \right),
\]

Inserting the derivatives in (11) we get the statement of the theorem. The theorem is proved.

The straightforward use of the result of Theorem 1 is impossible because the variance \( \sigma_n^2 \) depends on the unknown parameters of the asset return distribution \( \mathbf{\mu} \) and \( \Sigma \). The investor can estimate these parameters using the sample estimators (5). Then, the estimator of \( \sigma_n^2 \) will have the following form:

\[
\hat{\sigma}_n^2 = \frac{\varphi(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right].
\]

The correctness of the estimator (12) is provided by the next theorem.

**Theorem 2.** Under conditions of Theorem 1, by \( n \rightarrow \infty \) the estimator (12) almost surely converges to its true value of \( \sigma_n^2 \):

\[
\sigma_n^2 = \frac{\varphi(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right].
\]

**Proof.** The theorem follows directly from the proof of Theorem 1 and the continuous mapping theorem (DasGupta, 2008).

The results of Theorems 1 and 2 make it possible to construct (1-f)-confidence interval for \( \alpha_0 \):

\[
\left[ \hat{\alpha}_n - \frac{\varphi(t)}{\sqrt{n}} \varphi(t) \Delta; \hat{\alpha}_n + \frac{\varphi(t)}{\sqrt{n}} \varphi(t) \Delta \right].
\]

The confidence interval (13) allows us to test the hypothesis whether the confidence level \( \alpha_0 \) significantly differs from 1 or, in other words, whether the minimum VaR portfolio with the confidence level \( \alpha_0 \) significantly differs from the global minimum variance portfolio. To test this, it is enough to check whether the interval (13) contains 1. If it is so, then with the confidence level (1-f) minimum VaR portfolio and the global minimum variance portfolio are statistically identical.

**Elliptically contoured distributed asset returns**

We extend the obtained results to the case of elliptically contoured distributed asset returns. We assume that the vector of asset returns \( \mathbf{X} \) is elliptically contoured distributed with \( \mathbf{E}(\mathbf{X}) = \mathbf{\mu} \) and \( \mathbf{V}(\mathbf{X}) = \Sigma \).

The \( k \)-dimensional vector \( \mathbf{Y} \) is elliptically contoured distributed if its characteristics function is given by:

\[
E(\exp(i\mathbf{\alpha}^\top \mathbf{Y})) = \exp(i\mathbf{\alpha}^\top \mathbf{\mu}) \psi(\mathbf{\alpha}^\top \Sigma \mathbf{\alpha})
\]

where \( \mathbf{\Delta} = \Sigma \). The function \( \psi \) is known as the characteristic generator of the elliptical distribution. This class of distributions contains the multivariate normal distribution, the multivariate t-distribution, the multivariate Laplace distribution, the multivariate symmetric stable distribution among others. The distributions from this class are often used in financial literature (Gupta et al., 2013, DasGupta, 2008, Chamberlain, 1983, Berk, 1997).

Under this assumption, we get:

\[
\alpha_0 = F \left( \frac{\hat{\varphi}(s) - \frac{1}{2} I^2 \hat{V}_{\mathbf{C}} - s}{\left( \mathbf{R}_{\mathbf{C}} - \mathbf{R}_{\mathbf{C}} \right)} \right),
\]

where \( F \) denotes the univariate marginal distribution function of the elements in \( \mathbf{X} \) and \( \varphi = (\varphi(0)/2)^2 \).

**Theorem 3.** Let us form another portfolio within \( k \) assets. Let \( \mathbf{X} \) be the \( k \)-dimensional vector of asset returns and \( \mathbf{X} \) is an elliptically contoured distributed asset return with \( \mathbf{E}(\mathbf{X}) = \mathbf{\mu} \) and \( \mathbf{V}(\mathbf{X}) = \Sigma \) and the characteristic function given in (14). Let \( \mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_t \) be independent realizations of the vector of asset returns and \( \mathbf{\mu}, \mathbf{\Sigma} \). Then, the asymptotic distribution of the sample estimator of \( \alpha_0 \) is given as follows:

\[
\sqrt{n}(\hat{\alpha}_n - \alpha_0) \sim \mathcal{N}(0, \sigma_n^2),
\]

with

\[
\sigma_n^2 = \frac{\varphi(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right],
\]

where \( I, s, \Delta \) are given in (7), \( \delta = \varphi(0)/\varphi(0) \) and \( I \) is the univariate marginal density function of the elements in \( \mathbf{X} \).

**Proof.** The proof is similar to the proof of Theorem 1 taking into account the fact that in the case of elliptically contoured distributed asset returns we have:

\[
\sqrt{n} \left( \frac{\hat{\mathbf{R}}_{\mathbf{C}} - \mathbf{R}_{\mathbf{C}}}{\mathbf{V}_{\mathbf{C}}} \right) \rightarrow \mathcal{N}(0, \Sigma_{\mathbf{C}}),
\]

where

\[
\sigma_n^2 = \frac{\varphi(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right],
\]

with

\[
\sigma_n^2 = \frac{\varphi(t)}{I^2} \left[ \frac{s}{2\Delta} \left( 2I^2 \hat{V}_{\mathbf{C}}(1+s) + \hat{V}_{\mathbf{C}} \Delta + (2\Delta - \delta)^2(2+s) \right) \right],
\]

where \( I, s, \Delta \) are given in (7), \( \delta = \varphi(0)/\varphi(0) \) and \( I \) is the univariate marginal density function of the elements in \( \mathbf{X} \).
Numerical illustration

In this section we analyse the finite sample properties of \( \tilde{\alpha}_0 \). We choose monthly asset returns of five \( (k=5) \) stocks included into Dow Jones Index (McDonald’s, Johnson & Johnson, Procter & Gamble, AT&T, Verizon Communications) from October 2010 to 01 September 2015. Estimating from the data the mean vector \( \mu \) and covariance matrix \( \Sigma \) and using these estimators we can calculate the expected returns of the global minimum variance portfolio and the minimum VaR portfolio with the confidence level \( \alpha=0.95 \). \( R_{GMV}=0.387 \) and \( R_{VaR}=0.428 \). We construct 12 confidence intervals (for confidence levels \( (1-\beta) \) from \( (0.9; 0.95; 0.99) \) and sample sizes \( n \) from \( (120; 250; 500; 1000) \)) for the confidence level for VaR to get the expected return \( R_0 \) equal to 0.428. The results are presented in Table 1. We observe that minimum VaR, \( \tilde{\alpha}_0 \), portfolio is statistically identical for all sample sizes and for all confidence levels if compared to the global minimum variance portfolio.

The largest values for the confidence level for VaR for which the minimum VaR portfolio significantly differs from the global minimum variance portfolio with a probability of 0.95 can be found by equating the upper bound of the 0.95-confidence interval \( (13) \) to 1 (for different values of \( n \)). The results are presented in Table 2. We observe that the portfolios are very risky in all the cases.

We further compare the asymptotic densities of the sample estimator of \( \tilde{\alpha}_0 \) (6) from Theorem 1 and Theorem 3 with the exact ones. For the presentation of the results of Theorem 3 we choose the multivariate \( t \)-distribution with 5 degrees of freedom. The results of the simulation study are based on \( 10^3 \) independent repetitions and are presented in Figure 1. For the desired level of the expected return we choose \( R_0=2R_{VaR,0.95} \). This finding illustrates that the finite sample density of \( \sqrt{n}(\tilde{\alpha}_0 - \alpha_0) \) can be well approximated by a normal distribution and the resulting approximation performs very well for moderate sample sizes in spite of the fact that the convergence to the limit distribution is a little bit slower in the case of \( t \)-distributed asset returns.

5. Conclusion

The minimum VaR portfolios are very popular not only in financial literature but also from a practical perspective. They give a simple interpretation of the optimal portfolio and its risk. The dependency of these portfolios on the confidence level gives additional information about the portfolio risk. A higher confidence level implies more reliable results. However, increasing the confidence level we decrease the expected return of the minimum VaR portfolio. It may happen that the level of the expected return is smaller than the desirable value. By choosing the smaller confidence level the investor can increase the expected return of the minimum VaR portfolio.

### Table 1: Confidence intervals for \( \tilde{\alpha}_0 \) with \( R_0=0.428 \)

<table>
<thead>
<tr>
<th>( n=120 )</th>
<th>( n=250 )</th>
<th>( n=500 )</th>
<th>( n=1000 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower bound</td>
<td>0.9</td>
<td>0.95</td>
<td>0.99</td>
</tr>
<tr>
<td>Upper bound</td>
<td>-0.77</td>
<td>-1.10</td>
<td>-1.75</td>
</tr>
</tbody>
</table>

Source: Own research

### Table 2: The largest values for the confidence level \( \tilde{\alpha}_0 \) for which the minimum VaR portfolio significantly differs from the minimum variance portfolio with a probability of 0.95

<table>
<thead>
<tr>
<th>( n=120 )</th>
<th>( n=250 )</th>
<th>( n=500 )</th>
<th>( n=1000 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence level ( \alpha )</td>
<td>0.64</td>
<td>0.66</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Source: Own research

Fig. 1: Exact and asymptotic densities of \( \sqrt{n}(\tilde{\alpha}_0 - \alpha_0) \) for \( n \) from \( (120, 250, 500, 1000) \) in the case of normally distributed asset returns (left) and in the case of elliptically contoured distributed asset returns (right)

Source: Own research
References

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