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VALUE AT RISK ANALYSIS ON BLUE CHIP STOCKS PORTFOLIO WITH GAUSSIAN COPULA

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ABSTRACT

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Value at Risk (VaR) is a risk measurement tool to calculate the estimated maximum investment loss with a certain confidence level and period. VaR calculations using financial data are often not normally distributed, so the copula method is used, which is flexible on the assumption of normality on stock return data. Previous research discussed Gaussian copula using stocks from the telecommunications sector. In this research, using Gaussian copula on Blue Chip stocks. Blue Chip stocks have a good reputation and have a stable growth rate so they have a lower risk. Therefore, the research objective is to analyze the VaR portfolio of Blue Chip stock with Gaussian copula. This research uses the daily stock closing prices of BBNI and BBTN from November 2, 2020 to October 27, 2022. The analysis results suggested that a VaR portfolio using Gaussian copula with a confidence level of 90%, 95%, and 99%, respectively are 2.24%, 2.88%, and 4.02%. The value shows the percentage of investment risk that may be obtained in the next one-day period. This result also indicates that the higher the confidence level, the greater the VaR.

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1. INTRODUCTION

Investment can be made in various ways, such as investing in gold bullion, collecting artwork, deposits, buying stocks in the capital market, etc. As one of the investment in the financial sector, stock can increase wealth through the return obtained, but can't be separated from the risk that will occur. Return and risk have a linear relationship, high return result in high risk that must be borne by investors. One of the ways to reduce risk is by investing in Blue Chip stocks. Blue Chip stocks are leaders in their sector, have stable earnings, and consistently pay dividends [1].

Portfolios are formed by combining two or more stocks to obtain investments that provide high return with low risk. Risk is defined as the chance of loss. Investment risk is a critical component and a concern for investors. The measurement tool used to calculate risk is Value at Risk (VaR). VaR is defined as an estimate of the maximum investment loss obtained during a certain period and confidence level under normal market conditions [2].

VaR calculation are often assumed to use normally distributed data. In reality, financial data is often not normally distributed. As a result, the resulting VaR analysis becomes inaccurate so the actual portfolio risk can be higher or lower than the estimated risk, causing an underestimation of the actual portfolio risk. Copula is one method that can describe the relationship between variables that is flexible on distribution assumptions [3]. Copulas are popular in modeling a joint distribution of several asset returns in finance [4]. Copula can overcome the non-linear relationship between variables and generate a multivariate joint distribution by combining their marginal distribution functions [5].

A copula approach is popular in modeling dependence, with the Gaussian copula being the most common copula choice. Gaussian copula and Student-t copula belong to the Elliptical copulas [6]. The Gaussian copula is based on the multivariate normal distribution, while the Student-t copula is based on the multivariate t-distribution. The Gaussian copula is superior to the Student-t copula, which is more complex to implement and requires the assumption of degrees of freedom in addition to the correlation matrix [7]. This research modeled the stocks using an Elliptical copulas, namely Gaussian copula. It then formed a portfolio and calculated the VaR of the portfolio. The method will be utilized to analyze the risk of PT Bank Negara Indonesia Tbk and PT Bank Tabungan Negara Tbk for the period of November 2, 2020, to October 27, 2022.

2. RESEARCH METHODS

2.1 Stock Return

Return is the profit or result obtained from an investment [6]. Return is the main reason investors invest because they make profit from their stocks. The stock return value for each period from the stock closing price can be calculated using **Equation (1)** [8].

$$R_t = \ln\left(\frac{S_t}{S_{t-1}}\right), \tag{1}$$

where R_t is the stock return value of the t period, S_t is the closing price of the stock in the t period, and S_{t-1} is the closing price of the stock in $t-1$ period.

2.2 Assumption Test

The data used will be tested first with several assumption tests, including a normality test, autocorrelation test, and heteroscedasticity test. The normality test is used to identify whether stock return are normally distributed or not using Kolmogorov-Smirnov (KS) with the following hypothesis [9]:

H_0 : stock return data is normally distributed

H_1 : stock return data is not normally distributed

Test statistics on the normality test uses **Equation (2)**

$$D_{count} = \sup|F(x) - S(x)|, \tag{2}$$

where $F(x)$ is the cumulative distribution of sample data and $S(x)$ is the cumulative distribution of normal distribution data.

Normality test criteria with a significance level of α, H_0 is rejected if the p-value of KS test $< \alpha$ or $D_{count} > D_{table}$.

The autocorrelation test identifies the existence of a correlation between the residuals of one observation and another using the Ljung-Box test. The Ljung-Box test tests the independence of residuals between lags with the following hypothesis [10]:

H_0 : $\rho_1 = \rho_2 = \cdots = \rho_K = 0$ (residuals white noise)

H_1 : There is at least one $\rho_k \neq 0, k = 1,2,3, \dots, K$ (residuals are not white noise)

The test statistics on the autocorrelation test use Equation (3)

$$Q = n(n + 2) \sum_{k=1}^{K} \frac{\hat{\rho}_k^2}{(n - k)}, \tag{3}$$

where n is the amount of data, K is the number of lags tested, and $\hat{\rho}_k^2$ is the autocorrelation of the residuals at the k-th lag.

Autocorrelation test criteria with significance level α, H_0 is rejected if p-value $< \alpha$ or $Q > X^2_{(\alpha,df)}$.

Heteroscedasticity test to determine whether the data has a very diverse variance that can produce unstable residuals using the ARCH LM test with the following hypothesis [11]:

H_0 : $\alpha_1 = \alpha_2 = \cdots = \alpha_k = 0$ (there is no ARCH effect in the residuals up to the k-th lag)

H_1 : There is at least one value $\alpha_i \neq 0, i = 1,2, \dots, k$ (there is an ARCH effect in the residuals up to k-th lag)

The test statistic on the heteroscedasticity test uses Equation (4)

$$LM = nR^2, \tag{4}$$

where n is the amount of data and R^2 denotes the coefficient of determination of α_t^2.

Heteroscedasticity test criteria with significance level α, H_0 is rejected if the p-value of ARCH LM test $< \alpha$ or $LM > \chi^2_{(\alpha,k)}$.

2.3 Gaussian Copula

Copulas are popular in modeling the joint distribution of multiple financial asset returns. Copulas can form multivariate distributions with different marginal distributions. Moreover, many different copulas can incorporate the data dependency structure [4]. Copula is one of the methods that can describe the relationship between variables that is not too strict on distribution assumptions [3].

One of the popularly used copula families is the Elliptical copulas. The Elliptical copulas family members are Gaussian copula and Student-t copula [6]. The Gaussian copula using the cumulative distribution function of the normal distribution can be formulated in Equation (5) [4]:

$$C_\rho^{Ga}(u, v) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right), \tag{5}$$

where Φ_ρ is a standard bivariate normal cumulative distribution function with correlation ρ, Φ^{-1} is the inverse of the standard normal cumulative distribution function, and $u, v \in [0,1]$. Since it uses a bivariate standard normal distribution, the Gaussian copula function can be written in Equation (6) [12]:

$$C_\rho^{Ga}(u, v) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi(1-\rho^2)^{\frac{1}{2}}} \exp\left\{-\frac{x^2 - 2\rho xy + y^2}{2(1-\rho^2)}\right\} dxdy. \tag{6}$$

2.4 Kendall's Tau Correlation and Gaussian Copula Parameter

Copulas define a measure of dependency or correlation between variables. Copulas measures non-linear correlation between variables [13]. The correlation of non-linearly correlated stock return can be calculated using Kendall's tau correlation without having to fulfill the normality assumption. Kendall's tau correlation is denoted as τ [4].

Suppose $\{(x_1, y_1), \ldots, (x_n, y_n)\}$ is a random sample of n observations of a vector (X, Y) of random variables. In the observations in the sample, there will be $\binom{n}{2}$ different pairs, namely (x_i, y_i) and (x_j, y_j) where each pair is either concordant or discordant. Observations (x_i, y_i) and (x_j, y_j) are said to be concordant if $(x_i - x_j)(y_i - y_j) > 0$ and said to be discordant if $(x_i - x_j)(y_i - y_j) < 0$. Let c denote the number of concordant pairs and d denote the number of discordant pairs. Furthermore, Kendall's tau correlation value can be calculated using Equation (7) [14].

$$\tau = \frac{c-d}{\binom{n}{2}} = \frac{c-d}{\frac{n(n-1)}{2}}. \tag{7}$$

The Kendall's tau correlation value obtained from Equation (7) is then subjected to a significance test to determine whether the value obtained has a significant correlation between variables with the following hypothesis [10].

$H_0 : \tau = 0$ (no correlation between variables)

$H_1 : \tau \neq 0$ (there is a correlation between variables)

The test statistics on the Kendall's tau correlation significance test use Equation (8):

$$Z_{count} = \sqrt{\frac{9n(n-1)}{2(2n+5)}}\,|\tau|, \tag{8}$$

Kendall's tau correlation significance test criteria with a significance level of α, H_0 is rejected if $Z_{count} > Z_{(\frac{\alpha}{2})}$ or p-value $< \alpha$.

The Kendall's tau correlation value that has been obtained is then used to calculate the parameters of the Gaussian copula. The value of the Gaussian copula parameter or the correlation coefficient value is calculated using Equation (9) [12]:

$$\rho = \sin\left(\frac{\pi\tau}{2}\right), \tag{9}$$

where ρ is the Gaussian copula parameter, τ is the Kendall's tau correlation, and π is 3.14.

2.5 Mean Variance Efficient Portfolio (MVEP)

Mean variance efficient portfolio (MVEP) is used to calculate the weight or proportion of each stock in the portfolio. MVEP calculation is done using Equation (10) [15]:

$$\boldsymbol{w} = \frac{\boldsymbol{\Sigma}^{-1}\boldsymbol{1}_N}{\boldsymbol{1}_N{}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{1}_N}, \tag{10}$$

where $\boldsymbol{w}$ is the stock weight, $\boldsymbol{\Sigma}^{-1}$ is the inverse of the variance-covariance matrix, and $\boldsymbol{1}_N$ is a one-vector with dimension $N \times 1$.

The variance-covariance matrix requires the variance value of each stock and the covariance value between stocks. The variance of each stock can be calculated using Equation (11) [16]:

$$\text{Var}(R_i) = s_i^2 = \frac{\sum_{t=1}^{n}(R_{i,t} - \overline{R_i})^2}{n-1}, \tag{11}$$

where s_i^2 is the variance of the i stock return, $R_{i,t}$ is the return of the i stock in t period, $\overline{R_i}$ is the average return of the i stock, and n is the amount of data.

Furthermore, the covariance between stocks can be calculated using **Equation (12) [16]**:

$$\mathrm{Cov}(R_1, R_2) = \frac{\sum_{t=1}^{n}\left(R_{1,t} - \overline{R_1}\right)\left(R_{2,t} - \overline{R_2}\right)}{n-1}, \tag{12}$$

where $R_{1,t}$ is the return of stock 1 in t period, $R_{2,t}$ is the return of stock 2 in t period, $\overline{R_1}$ is the average return of stock 1, $\overline{R_2}$ is the average return of stock 2, and n is the amount of data.

The variance-covariance matrix of a portfolio formed by two stocks can be written as **Equation (13)**:

$$\mathbf{\Sigma} = \begin{bmatrix} \mathrm{Var}(R_1) & \mathrm{Cov}(R_1, R_2) \\ \mathrm{Cov}(R_1, R_2) & \mathrm{Var}(R_2) \end{bmatrix}. \tag{13}$$

2.6 Value at Risk

Value at Risk (VaR) is defined as an estimate of the maximum investment loss obtained over a certain period of time under normal market conditions at a certain confidence level **[2]**. In addition, VaR limits the maximum loss a portfolio can bear at a given confidence level. A higher confidence level indicates a lower probability that the loss can be exceeded **[17]**. Therefore, there are three crucial variables in VaR: the amount of loss, period, and confidence level.

The drawback of VaR is that it cannot determine how much loss actually occurs and cannot definitively state the worst potential loss because there is a possibility that the actual loss could be worse. However, investors can use the VaR value as one of the benchmarks in determining how much risk is from an investment. The stages of calculating VaR using Gaussian copula parameters are as follows **[18]**:

a. Simulating the return value by generating random return data with Gaussian copula parameters as many as n data.

b. Calculate the portfolio return from the return that has been generated and the weights that have been obtained from the MVEP method using **Equation (14) [8]**:

$$Rp_t = \sum_{i=1}^{k} R_{i,t} w_i, \tag{14}$$

where Rp_t is the return of the portfolio of the t period, $R_{i,t}$ is the return of the i stock in t period, w_i is the weight of i stock in the portfolio, and i is the amount of stocks in the portfolio.

c. Calculate the VaR of the portfolio using **Equation (15) [8]**:

$$\mathrm{VaR}_{(1-\alpha)}(t) = V_0 R^* \sqrt{t}. \tag{15}$$

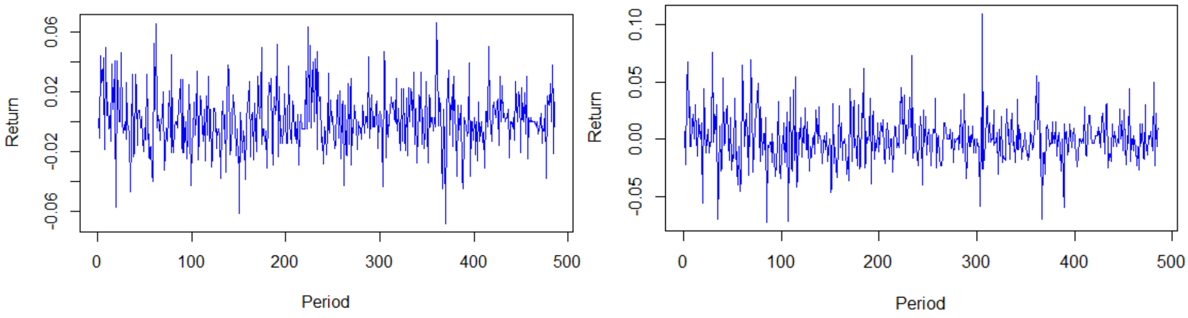
where V_0 is the initial investment fund of the portfolio, R^* is the value of α-quantile of the portfolio return distribution, and t is the period.

d. Repeat step (a) to step (c) as many as M times to reflect the various VaR possibilities as $VaR_1, VaR_2, \dots, VaR_M$

e. Calculate the average of the results from step (d) to stabilize the portfolio VaR value because the portfolio VaR value obtained from each simulation is different.

3. RESULTS AND DISCUSSION

The data used in this research are the daily stock closing price data for the banking sector stocks: PT Bank Negara Indonesia Tbk (BBNI) and PT Bank Tabungan Negara Tbk (BBTN). The data used is data for the period November 2, 2020, to October 27, 2022, obtained from www.finance.yahoo.com/. The first step is calculating each stocks closing price return value using **Equation (1)**. The plot of the closing price return of each stock is presented in **Figure 1**.



(a) **(b)**

Figure 1. Plot of Stock Closing Price Return, (a) Stock Return BBNI, (b) Stock Return BBTN

The next step is to calculate the descriptive statistics of the closing price return of each stock, namely the average value, standard deviation, skewness, and kurtosis. Descriptive statistics of the return of each stock can be seen in **Table 1**.

Table 1. Descriptive Statistics of Stock Closing Price Return

Stock	Mean	Standard Deviation	Skewness	Kurtosis
BBNI	0.0014	0.0198	0.2354	0.7487
BBTN	0.0002	0.0217	0.4583	2.4626

Table 1 shows that the average return of BBNI and BBTN stocks is positive, which means that both stocks tend to be profitable for investors. The standard deviation value of BBTN stock is greater than BBNI stock. This value indicates that BBTN stock have the potential to experience more significant losses than BBNI stock. The skewness value in both stocks is positive, showing a more long-tail slope to the right. In addition, the kurtosis value of both stocks is below three, which means that the kurtosis in both stocks has a flat taper.

3.1 Test of Normality, Autocorrelation, and Heteroscedasticity

Furthermore, assumption tests are carried out, including normality, autocorrelation, and heteroscedasticity tests. The normality test shows whether the data is normally distributed or not to anticipate price instability that may occur. The normality test used in this research is the Kolmogorov-Smirnov test. The normality test results are presented in **Table 2**.

Table 2. Kolmogorov-Smirnov Test BBNI and BBTN Stock Return

Stock	Kolmogorov Smirnov	
	D_{count}	*p-value*
BBNI	0.0801	0.0038
BBTN	0.0960	0.0002

In this research, the α value or significance level used is 5%. The p-value of both stocks is less than the value of α. In addition, the value of $D_{table(\alpha,486)}$ equals 0.0612, which is smaller or less than D_{count} both stocks. So, it can be concluded that H_0 was rejected for both stock return data, which means that the return of BBNI stock and BBTN stock return are not normally distributed.

After doing the normality test, the next step is to do the autocorrelation test. The autocorrelation test is a test that describes the relationship that occurs between the residuals of one observation and another observation. Strong autocorrelation can cause two unrelated variables to be related, so in order to detect the presence or absence of autocorrelation, the Ljung Box test was used in this research.

Table 3. Ljung-Box Test BBNI and BBTN Stock Return

Stock	Ljung-Box						
	Lag	**1**	**5**	**10**	**15**	**20**	**25**
BBNI	***p-value***	0.9374	0.3569	0.3078	0.3339	0.2428	0.3188
BBTN	***p-value***	0.7744	0.5406	0.5680	0.6254	0.4336	0.5563

Table 3 shows that the p-value on the lag return of BBNI and BBTN is greater than $\alpha = 0.05$. Thus, H_0 is accepted, which means that the return of BBNI stock and BBTN stock do not have autocorrelation.

The next test is the heteroscedasticity test. The heteroscedasticity test determines whether the variance inequality of the residuals of one observation to another. The heteroscedasticity test used in this research is the Lagrange Multiplier (LM) test, commonly referred to as the ARCH LM test.

Table 4. ARCH LM Test BBNI and BBTN stock Return

Stock	*p-value*
BBNI	0.172
BBTN	0.337

In **Table 4**, the p-value of the two stocks is greater than $\alpha = 0.05$. Thus, H_0 is accepted, which means that the return of BBNI stock and BBTN stock do not have heteroscedasticity properties. Therefore, that the analysis with BBNI stock and BBTN stock can be continued by calculating Kendall's tau correlation between stocks.

3.2 Gaussian Copula Parameters

Before finding the parameters of the Gaussian copula, the correlation value of Kendall's tau (τ) from BBNI and BBTN stock return data must be computed. The scatterplot in **Figure 2** shows that the stock return data of two stocks spread randomly, do not form a certain pattern, and do not spread following a straight line so there is a non-linear correlation. Non-linear correlation can be calculated using Kendall's tau (τ) correlation **[4]**.

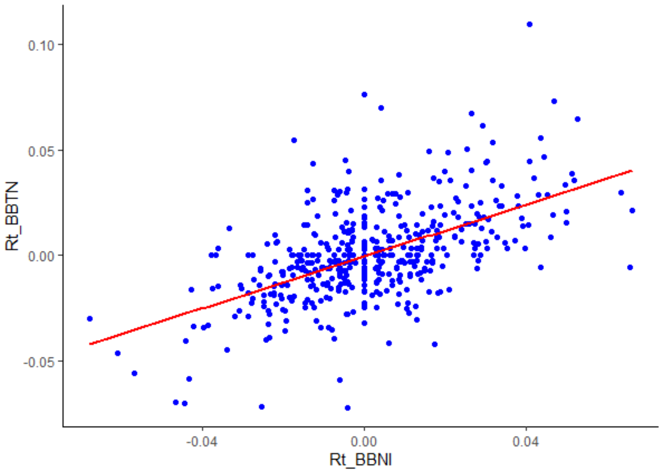


Figure 2. Scatterplot of BBNI and BBTN Stock Return

Correlation value τ can be calculated using **Equation (7)**. Using R Studio software version 2023.03.01 with significance level of 5%, the correlation value of τ is 0.3790 with a value Z_{count} of 12.375 is greater than $Z_{\left(\frac{\alpha}{2}\right)}$ of 1.96 and p-value $< 2.2 \times 10^{-16}$. The Kendall's tau correlation value of BBNI and BBTN stock return is positive, meaning that the two stocks in the portfolio move in the same direction and significantly affect each other. Next, the analysis is continued by calculating the Gaussian copula parameters based on **Equation (9)**.

$$\rho = \sin\left(\frac{\pi\tau}{2}\right) = \sin\left(\frac{\pi(0.3790)}{2}\right) = 0.5609$$

The value of the Gaussian copula parameter is obtained as 0.5609, which shows the correlation value or Gaussian copula parameter of the closing price return data of BBNI stock and BBTN stock. The Gaussian copula parameter is then used to generate new return data with Monte Carlo simulation.

3.3 Weight Calculation with MVEP

The portfolio in this research was formed from two stocks, BBNI and BBTN, which were calculated using the Mean Varian Efficient Portfolio (MVEP) method based on **Equation (10)**. Previously, the variance value of each stock was first sought with **Equation (11)** and the covariance value between the two stocks with **Equation (12)**.

$$\mathrm{Var}(R_1) = s_1^2 = \frac{\sum_{t=1}^{486}(R_{1,t} - 0.0014)^2}{486 - 1} = 0.000392$$

$$\mathrm{Var}(R_2) = s_2^2 = \frac{\sum_{t=1}^{486}(R_{2,t} - 0.0002)^2}{486 - 1} = 0.000474$$

$$\mathrm{Cov}(R_1, R_2) = \frac{\sum_{t=1}^{486}(R_{1,t} - 0.0014)(R_{2,t} - 0.0002)}{486 - 1} = 0.000242$$

After obtaining the variance and covariance values, a variance-covariance matrix can be formed based on **Equation (13)**, namely:

$$\mathbf{\Sigma} = \begin{bmatrix} 0.000392 & 0.000242 \\ 0.000242 & 0.000474 \end{bmatrix}$$

In the calculation of weights with MVEP, the inverse of the variance-covariance matrix ($\mathbf{\Sigma^{-1}}$) is required, so it is necessary to calculate the inverse of the variance-covariance matrix as follows:

$$\mathbf{\Sigma^{-1}} = \begin{bmatrix} 3733.69 & -1911.24 \\ -1911.24 & 3089.27 \end{bmatrix}$$

After obtaining the inverse of the variance-covariance matrix, then it can be calculated the weight of each stock with **Equation (10)**.

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \frac{\begin{bmatrix} 3733.69 & -1911.24 \\ -1911.24 & 3089.27 \end{bmatrix}\begin{bmatrix} 1 \\ 1 \end{bmatrix}}{\begin{bmatrix} 1 & 1 \end{bmatrix}\begin{bmatrix} 3733.69 & -1911.24 \\ -1911.24 & 3089.27 \end{bmatrix}\begin{bmatrix} 1 \\ 1 \end{bmatrix}} = \frac{\begin{bmatrix} 1822.45 \\ 1178.03 \end{bmatrix}}{[3000.48]}$$

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 0.607 \\ 0.393 \end{bmatrix}$$

From the calculation of the portfolio weight of two stocks using the MVEP method, the weight on BBNI is 0.607 or 60.7% of the proportion of BBNI stock in the portfolio and the weight on BBTN is 0.393 or 39.3% of the proportion of BBTN stock in the portfolio.

3.4 Value at Risk Portfolio

After obtaining the simulation result data, namely u and v using Gaussian copula parameters, the calculation of the return value of the simulated data is carried out where $R_{1,t} = \Phi^{-1}(u)$ and $R_{2,t} = \Phi^{-1}(v)$ states the inverse of the simulated data. The return value of the simulation results from data is used to calculate the portfolio return using **Equation (14)**, with the weight of BBNI stock in the portfolio (w_1) is 0.607 and the weight of BBTN stock in the portfolio (w_2) is 0.393. After obtaining the portfolio return value, it can be continued by calculating the VaR value of the portfolio with a confidence level of 90%, 95%, and 99% in a one day using **Equation (15)**. With a repetition of 1000 times from simulation to VaR calculation using R Studio software version 2023.03.01, the average of the VaR portfolio is presented in **Table 5**.

Table 5. Value of VaR Portfolio

	Confidence Level		
	90%	95%	99%
VaR	-2.24%	-2.88%	-4.02%

In Table 5, the average VaR of the portfolio from 1000 repetitions with a confidence level of 90%, 95%, and 99%, respectively is -2.24%, -2.88%, and -4.02%. VaR with a minus value indicates a loss. Suppose an investor makes an initial investment in a portfolio of Rp100,000,000 with a 90% confidence level. In that case, the maximum loss the investor will experience is Rp2,240,000 the next day.While at the 95% confidence level, the maximum loss that investors will be experienced is Rp2,880,000. At the 99% confidence level, the maximum loss will be experienced at Rp4,020,000. These results indicate that the higher the level of confidence in investing funds, the higher the investment risk that will be obtained and the capital allocation used to cover losses. This result is in line with VaR research conducted by [19] [20].

4. CONCLUSIONS

Based on the results of the analysis, the VaR using the Gaussian copula method on portfolios formed from stocks of PT Bank Negara Indonesia Tbk (BBNI) and PT Bank Tabungan Negara Tbk (BBTN) with a confidence level of 90%, 95%, and 99% respectively are 2.24%, 2.88%, and 4.02%. VaR values show the percentage of investment risk that may be obtained in the next one-day period. This value also indicates that the higher the confidence level, the greater the VaR value.

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