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Implementation of Monte Carlo Simulation to Measure Value at Risk (VaR) in BNI Bank Stock Investments

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Abstract

This study applies the Value at Risk (VaR) method using Monte Carlo simulation to estimate the maximum potential loss in BNI stock investments. Daily closing prices of BNI stock for 2024 were analyzed to calculate returns and assess risk at confidence levels of 99%, 95%, and 90%. The Monte Carlo simulation, performed with 1,000 iterations, produced estimated maximum losses of approximately 9.7%, 7.4%, and 5.9% of the total investment for the respective confidence levels. These findings demonstrate that a higher confidence level corresponds to a larger potential loss, highlighting the usefulness of VaR combined with Monte Carlo simulation as a tool for evaluating and managing stock investment risk.

Keywords: *Investment risk, Monte Carlo simulation, Stock return, Value at Risk*

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1. Introduction

Along with the rapid advancement of technology, public access to various forms of investment has become increasingly convenient. Investment is an essential component of strategies for entering a new economic era, in which individuals commit to allocating a certain amount of money or other resources in the present with the expectation of obtaining greater returns in the future [1]. Stocks are one of the long-term financial instruments traded on the Indonesian capital market and remain a primary choice for many investors, as they offer attractive potential returns [2].

A stock price represents the value determined for each share traded in the capital market. It reflects the amount of money investors are willing to pay to acquire ownership of a particular share and emerges as a result of buy–sell transactions in the secondary market [3]. Among various price indicators, the closing price is often used as the main variable in stock price analysis and forecasting because it is generally more stable and less affected by temporary intraday fluctuations [4].

As a key pillar of the national economy, the banking sector functions as a trusted intermediary to ensure the smooth operation of payment systems for both individuals and organizations. PT Bank Negara Indonesia (Persero) Tbk (hereafter referred to as BNI) plays a crucial role in improving economic conditions and contributing to national development, a mandate strengthened by the enactment of Law No. 17 of 1968. BNI’s stock price exceeded the 6,000 level in 2024; however, at the beginning of 2025 it had corrected by 9.58% to around 4,120. Investment in BNI shares (BBNI) remains an attractive option for investors seeking bank stocks with stable and sustainable growth potential [5].

Value at Risk (VaR) is a widely used risk-measurement tool that quantifies the potential maximum loss of an investment portfolio over a specified time horizon and confidence level. By estimating the worst expected loss under normal market conditions, VaR helps investors assess and manage financial risk [6]. One approach to calculate VaR is the Monte Carlo simulation, which employs repeated random sampling to model a wide range of possible future price scenarios and generate a probabilistic distribution of returns. This method is especially valuable when the return distribution is complex or non-normal, as it captures market uncertainty more comprehensively than purely historical techniques [7]. Based on study [8] the risk assessment using the Value at Risk (VaR) method, the estimated losses are -5,871,809,812 at a 99% confidence level, -4,183,103,967 at 95%, and -3,195,086,406 at 90%. This indicates that investors are predicted to face a maximum loss of approximately 6% at the 99% confidence level, 4% at 95%, and 3% at 90% of their initial investment in BJTM shares—equivalent to IDR 5,871,809,812, IDR 4,183,103,967, and IDR 3,195,086,406, respectively. These results suggest that the confidence level is directly proportional to the risk: the higher the confidence level, the greater the potential loss investors may incur. Besides that [8] Using the Historical Simulation VaR at a 95% confidence level with an initial capital of IDR 10,000,000, CIMB Niaga stock showed the lowest risk (IDR 273,462), followed by BJB (IDR 303,154), MEGA (IDR 358,423), and Bukopin (IDR 470,246), while BSI had the highest risk (IDR 537,087). With the Monte Carlo method at the same confidence level, BJB had the lowest risk (IDR 334,731), followed by CIMB Niaga (IDR 348,783), MEGA (IDR 303,154), and Bukopin (IDR 484,728), with BSI again highest (IDR 642,237). During the portfolio optimization process, the largest weight was assigned to Bank OCBC NISP, resulting in an optimal portfolio VaR of –1.85% at the 95% confidence level, indicating a lower risk compared to investing in individual stocks.

2. Theoretical Reviews

2.1 Value at Risk

Value at Risk (VaR) is a measure that quantifies the level of risk based on the current position. It provides a way to evaluate risk using statistical techniques that are commonly applied in various engineering and technical fields. VaR is defined as the q-percent quantile of the total loss distribution. Value-at-Risk (VaR) and Expected Shortfall (ES) are two risk measures frequently used by financial institutions to manage market risk and extreme market movements [9]. VaR at level α is defined as the α-level quantile of the underlying portfolio's return distribution. VaR has been accepted as a standard measure of market risk for determining regulatory capital requirements. However, VaR does not provide information on the potential expected loss if losses exceed the VaR threshold, and therefore may not capture expected extreme risk, particularly for assets with wide-tailed return distributions [10]. VaR is the α-percentile of returns at a confidence level of $(1 - \alpha)$. For example, with 100 observations and a 95% confidence level ($\alpha = 5\%$), VaR corresponds to the sixth-worst return. The formula used to calculate VaR with the historical simulation method is as follows [11]:

$$VaR = \mu + (Z_{\propto} \times \sigma) \tag{1}$$

Where:

μ = Average Return

$Z_{\propto}$ = Z-Value of confidence level

σ = Standard deviation of returns

2.2 Monte Carlo Estimation

The Monte Carlo simulation can be defined as a statistical sampling technique used to estimate solutions to quantitative problems. The Monte Carlo method is a numerical analysis approach that involves random experimental sampling. One of the most popular inventory control simulation models is the Monte Carlo simulation [12]. The Monte Carlo simulation model is a form of probabilistic simulation in which the solution to a problem is derived through a randomization process. This random process incorporates the probability distribution of data variables collected from the observed data as well as the theoretical probability distribution [13]. Monte Carlo simulation is a simple and quick simulation method that can be done quickly using only a spreadsheet such as Microsoft Excel. The creation of a Monte Carlo simulation model is based on the probability obtained from historical data of an event and how often the event occurs, where [14]:

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i(x_{1i}, x_{2i}, \dots, x_{ni}) \tag{2}$$

Where:
N = Number of iterations
x_{1i} = Discrete random variable for single iteration i
X_i = Value of interest: {LCC, LCoE, Downtime, Lost Profist, Number of Activities}

2.3 Stock Return

A return is the result obtained from an investment, which can be in the form of a realized return—one that has already occurred—or an expected return, which has not yet occurred but is anticipated to happen in the future [15] . Historical returns also serve as a reference for estimating future expected returns and associated risks. The expected return represents the gain that investors anticipate receiving in the future, whereas the realized return reflects outcomes that have already materialized. The overall gain from an investment is commonly referred to simply as the total return. In a systematic form, the return can be expressed as follows. Calculate daily stock returns using the formula [16]:

$$R_i = \frac{D_t+(P_{t-P_{t-1}})}{P_{t-1}} \tag{3}$$

where:
$\boldsymbol{D_t}$ = Cash dividend paid during period *t*
$\boldsymbol{P_t}$ = Closing price of stock *i* at period *t* (current/last period)
$\boldsymbol{P_t}$ −1 = Closing price of stock *i* at period *t−1* (previous period)

3 Methods

3.1 Type of Research

This study is quantitative research aimed at implementing and obtaining predictions of maximum potential loss using Value at Risk (VaR) with a Monte Carlo simulation approach, utilizing the period January 1, 2024 – December 31, 2024

3.2 Object of Study

The object of this study is secondary data retrieved from finance.yahoo.com. The data consist of the historical closing prices of PT Bank Negara Indonesia (Persero) Tbk (BBNI) stock.

3.3 Research Variable

The research variable is the daily closing price of BBNI stock, which will be transformed into the daily stock return.

3.4 Research Procedure

The stages carried out to address the research questions are as follows:

1. Data Collection
   Download historical closing price data of BBNI stock from finance.yahoo.com.
2. Data Preparation
   Input the dataset into statistical software (e.g., R or Python) and perform data cleaning.
3. Computation of Stock Returns
4. Determination of Return Parameters
   Calculate the mean and standard deviation of the daily return series to obtain the key parameters for the return variable.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(R_i-\bar{R})^2}{n-1}} \tag{4}$$

5. Monte Carlo Simulation
   Perform a Monte Carlo simulation with 1,000 iterations to generate possible variations in future asset prices.

6. Value at Risk (VaR) Calculation based equation (1)
7. Determination of Maximum Loss
8. Calculate and interpret the maximum loss based on the obtained VaR value.

4 Results and Discussion

4.1 Stock Closing Price Return

The stock return is calculated to identify the daily pattern of price changes in the closing price of BNI shares. The results of these calculations are presented in Table 1.

Table 1. Return of BNI Stock Closing Price

Observation	Return
1	0,00448
2	-0,01786
3	-0,01364
4	0,06452
5	-0,00433
6	0,04348
7	-0,01667
8	0
…	…
52	-0,00229

The plot of the BNI stock closing-price returns is used to visualize the movement pattern of the returns over the study period. The return pattern is presented in Figure 1.

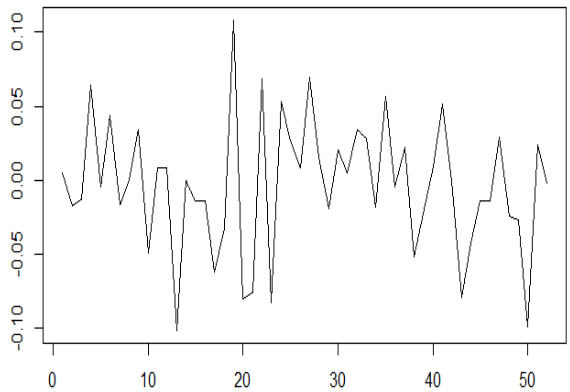

Figure 1. Plot of BNI Stock Closing-Price Returns

Figure 1 shows the movement pattern of BNI stock closing-price returns during the period January 1, 2024 – December 31, 2024. Based on Figure 1., the return values fluctuate over time. This fluctuation indicates high volatility, which is closely related to the potential risk associated with the stock.

4.2 Descriptive Analysis

A descriptive analysis was performed to obtain a general overview of the characteristics of the data to be analyzed. The results of the descriptive analysis of the BNI stock closing-price returns are presented in Table 2.

Table 2. Return of BNI Stock Closing Price

Minimum	Maximum	Mean	Deviation Standar
-0,101695	0,108137	-0,003755	0,045024

Based on Table 2, the minimum return of the BNI stock closing price is –0,101695 (–10,1695%), observed at the 13th observation, while the maximum return is 0,108137 (10,8137%), observed at the 19th observation. The average (mean) return of the closing price is –0,003755, with a standard deviation of 0,045024.

4.3 Monte Carlo Simulation

The first step in conducting the Monte Carlo simulation is testing the data distribution. The distribution test using the Lilliefors (Kolmogorov–Smirnov) test produced a p-value of 0.2864, which is greater than the significance level (α). Therefore, it can be concluded that the data follow a normal distribution. After confirming the distribution, the next step is to perform the Monte Carlo simulation. Monte Carlo simulation is a random-sampling–based method used to estimate the outcomes of a system by generating random data. In this study, the random data were generated from a normal distribution with the calculated mean and standard deviation as parameters.

The Value at Risk (VaR) calculation is performed to estimate the maximum potential loss that may occur in stock investment. The VaR estimation is carried out at several confidence levels: 99%, 95%, and 90%. The results for each confidence level are as follows:

1. VaR at the 99% Confidence Level

Using the Monte Carlo simulation at a 99% confidence level, the mean VaR is –0,097 (representing a maximum potential loss of 9,7%) with standard deviation 0f 0,017. The VaR histogram for the 99% confidence level is presented in Figure 2.

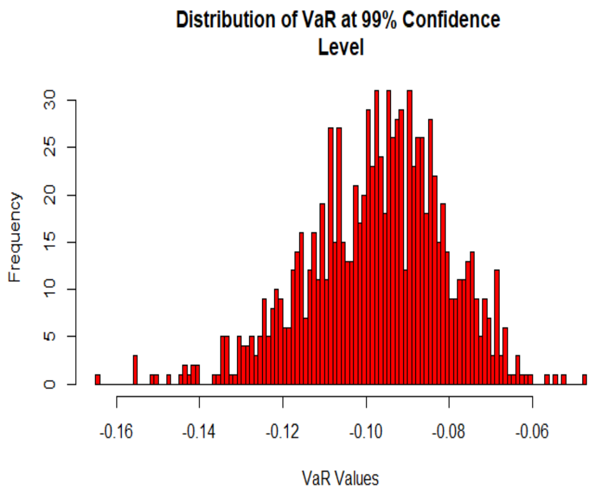

Figure 2. Histogram of VaR at the 99% Confidence Level

Based on Figure 2, the Monte Carlo simulation with 1,000 iterations produces the Value at Risk (VaR) at the 99% confidence level. The x-axis represents the VaR values (relative loss in percent), while the y-axis shows the frequency of each VaR value generated in the simulation. The histogram peaks around –

0,097, indicating that the simulation estimates a maximum potential loss of about 9,7% of the total investment with 99% confidence. Assuming an investment of IDR 100,000,000, the maximum expected loss is approximately IDR 9,700,000.

2. At the 95% Confidence Level

Using the Monte Carlo simulation at the 95% confidence level, the mean return is –0.074 and the standard deviation is 0,012. The histogram of VaR for the 95% confidence level is shown in Figure 3.

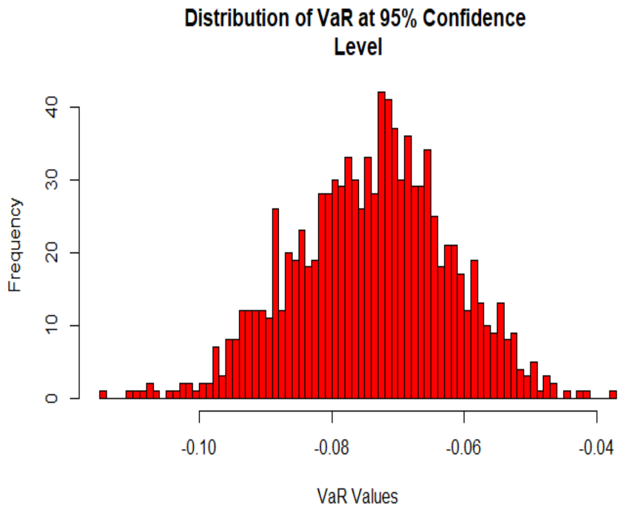

Figure 3. Histogram of VaR at the 95% Confidence Level

Based on Figure 3, the Monte Carlo simulation with 1,000 iterations provides the Value at Risk (VaR) at the 95% confidence level. The x-axis represents the VaR values (relative loss in percent), while the y-axis shows the frequency of each VaR value generated in the simulation. The histogram peaks around –0,074, indicating that the simulation estimates a maximum potential loss of about 7,4% of the total investment with 95% confidence. Assuming an investment of IDR 100,000,000, the maximum expected loss is approximately IDR 7,400,000.

3. At the 90% Confidence Level

Using the Monte Carlo simulation at the 90% confidence level, the mean return is –0.059 and the standard deviation is 0,010. The histogram of VaR for the 90% confidence level is shown in Figure 4.

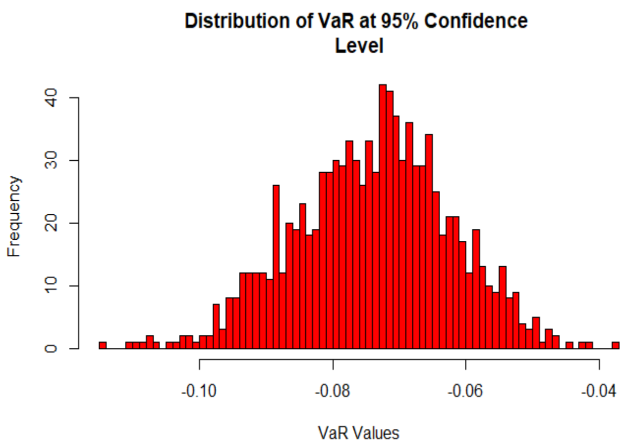

Figure 4. Histogram of VaR at a 90% Confidence Level

Based on Figure 4, the Monte Carlo simulation with 1,000 iterations shows the distribution of Value at Risk (VaR) at a 90% confidence level. The x-axis represents the VaR values (relative loss in percentage), while the y-axis indicates the frequency of each value occurring in the simulation. The peak of the histogram is around –0,059, indicating that the average simulation result estimates the maximum potential loss to be about 5.9% of the total investment with 90% confidence. Assuming a total investment of IDR 100,000,000, the estimated maximum potential loss at this confidence.

4. Conclusions

The Monte Carlo simulation of BNI stock returns effectively estimates Value at Risk (VaR) across multiple confidence levels. The results show maximum potential losses of about 9,7% at a 99% confidence level, 7,4% at 95%, and 5, 9% at 90%, indicating that risk increases with higher confidence levels. This confirms that VaR with Monte Carlo simulation provides a reliable measure for investors to anticipate and manage potential losses. Future research can extend this approach to diversified portfolios or different market conditions to enhance risk management strategies.

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