

Optimal Portfolio Value at Risk Using Monte Carlo Simulation on the LQ45 Index Post-Covid-19

Niswa Nilhaya M.¹, Radian J. Situmeang^{2*}, Bobi F. Kuddi³

^{1,2,3}Statistics Study Program, Universitas Cenderawasih, Indonesia

*Corresponding author: radian.situmeang@gmail.com

*Submission date: 03 September 2025, Revision: 29 November 2025, Accepted: 07 April 2026

ABSTRACT

The LQ45 Index comprises 45 leading stocks on the Indonesia Stock Exchange (IDX), selected for high liquidity, large market capitalization, and strong fundamentals. Constructing an efficient portfolio is crucial for risk minimization through diversification. This study aims to form an optimal stock portfolio from the LQ45 index and estimate the maximum tolerable risk, or Value at Risk (VaR). The Single Index Model forms and validates the optimal portfolio via the Sharpe index, while Monte Carlo simulation measures VaR. This research contributes to the post-COVID-19 VaR literature by integrating portfolio optimization and risk measurement, tailored to Indonesia's market recovery. The data consists of weekly closing prices from January 1, 2022, to October 31, 2024. Market returns are based on the IHSG, and risk-free rates are derived from average SBI rates. From the initial 45 stocks, five form the optimal portfolio: Alamtri Resources Indonesia Tbk. (ADRO), Bank Rakyat Indonesia (Persero) Tbk. (BBRI), Medco Energi Internasional Tbk. (MEDC), Perusahaan Gas Negara Tbk. (PGAS), and United Tractors Tbk. (UNTR). This portfolio has an expected weekly return of 0.53%. A Monte Carlo simulation with 1000 iterations generates the return distribution. With an initial investment of Rp 100,000,000, the one-week VaR at a 95% confidence level is Rp 5,148,779.98. This indicates a 95% confidence that the maximum weekly loss will not exceed this amount.

KEYWORDS

Value at Risk, Monte Carlo, Single Index, LQ45.

1. INTRODUCTION

The capital market serves as a strategic platform connecting surplus fund holders (investors) and fund seekers (issuers) through long-term financial instruments such as stocks and bonds. In recent years, investor participation in the Indonesian capital market has significantly increased, with the number of investors rising from 1.6 million at the end of 2018 to 12.16 million by the end of 2023 [1]. Although the market offers profit potential, it is inherently associated with risks, primarily due to stock price fluctuations. To mitigate such risks, modern portfolio theory pioneered by Markowitz provides a fundamental framework emphasizing diversification to reduce risk without sacrificing expected returns [2].

Portfolio construction begins by identifying efficient portfolios, which are asset combinations that maximize returns for a given risk level or minimize risk for a given return. Subsequently, the optimal portfolio is selected from the set of efficient portfolios based on investors' risk preferences and investment goals [3]. One effective approach to establish an optimal portfolio is the Single Index model, which considers individual asset risk using extensive historical data to provide more accurate risk estimates and assist investors in managing market uncertainties [4, 5].

The COVID-19 pandemic caused unprecedented economic and capital market shocks globally. In Indonesia, the Composite Stock Price Index (IHSG) experienced extreme volatility and reached a low in March 2020 due to market panic. This led to significant capital outflows from both domestic and foreign investors and depreciation of the Rupiah. The post-pandemic

period (2022-2024) has seen economic recovery efforts and market adjustments, though uncertainties remain high due to macroeconomic factors such as inflation, interest rate hikes, and geopolitical issues [6, 7, 8, 9].

Risk measurement consolidates various market movement factors into a single, all-in-one metric [10], playing a vital role in volatile post pandemic market conditions. Traditional risk metrics such as variance or standard deviation have limitations, particularly under extreme or non-normal market conditions. Consequently, Value at Risk (VaR) has emerged as a comprehensive method capable of estimating potential maximum losses at a certain confidence level [10, 11]. Among VaR calculation methods, variance-covariance, Historical Simulation, and Monte Carlo Simulation, the latter is deemed more reliable as it accounts for exposure combinations and dynamic price changes, offering estimates closer to real market behavior [12]. This method can account for various combinations of exposures and risks, including nonlinear risks and price changes due to volatility. Consequently, it produces return estimates that are relatively close to real market conditions [13]. In addition, compared to advanced methods that focus on extreme return precision such as [10], this method actually offers return reality through a return data generation simulation.

Despite extensive research on Single Index and Monte Carlo simulation methods, there remains a gap in integrating both approaches, especially for estimating value at risk for LQ45 stock portfolios in the post-COVID-19 period. Irsan et.al [14] used variance-covariance methods and historical simulations to determine the VaR on LQ45 banking stocks, while Herlisa et.al [15] analyzes the optimal portfolio without measuring the risk. Some other studies [12, 16, 17, 18] have used Monte Carlo Simulations for VaR, but have not conducted optimal portfolio formation with Single Index Models in the post-COVID-19 period.

This study aims to bridge a research gap by integrating the Single Index model with Monte Carlo simulation to analyze optimal stock portfolios in the LQ45 index post-COVID-19 and subsequently measuring VaR. The findings aim to deliver a robust analytical model for measuring risk. The contribution of this research is to present a more relevant analytical model, while providing pragmatic quantitative guidance for investors in managing investment in the post pandemic era.

2. LITERATURE REVIEW

2.1 The LQ 45 Index: Representative of the Indonesian Market

The capital market is a system or place that connects parties with surplus funds (investors) and parties that require funds (issuers/companies or government) through trading financial instruments such as stocks, bonds, and other similar instruments. According to Law No. 8 of 1995 on Capital Markets, the capital market involves activities related to public offerings and trade of securities, public companies, and institutions and professions related to securities. The capital market has two main functions: as a channel to allocate funds efficiently from those with surplus funds to those in need, and as an opportunity for investors to obtain returns through long-term financial investments.

The Composite Stock Price Index (IHSG) is the main stock index in the Indonesia Stock Exchange (IDX) used to assess the overall performance of listed companies. It is calculated based on the weighted average prices of all publicly listed companies and serves as the primary indicator of the Indonesian stock market's condition as well as a benchmark for investors. IHSG is highly influenced by external factors, including global economic policy changes, international commodity price movements, and foreign capital flows. The IHSG positively correlates with increases in Gross Domestic Product (GDP) but is also highly sensitive to economic instability, such as high inflation and sharp fluctuations in exchange rates. Overall, the IHSG reflects not only national stock market conditions but also investor confidence in Indonesia's economic prospects [19]. According to the official IDX website (www.idx.co.id), there are currently 954 companies listed in the IHSG.

The LQ45 Index is chosen as the representative stock market proxy in this study because it consists of 45 top stocks characterized by high liquidity, large market capitalization, and strong fundamentals, significantly representing the overall movements of the Indonesian capital market, including the IHSG [9]. Unlike the SRI Kehati Index or the Jakarta Islamic Index, which are constructed based on environmental sustainability principles, and Sharia compliance, the LQ45 includes top-performing stocks selected based on trading activity and capitalization criteria without sectoral limitations. This broader coverage combined with higher liquidity makes LQ45 a more comprehensive market proxy. Studies also indicate a strong correlation between LQ45 and IHSG movements with positive impacts on the overall Indonesian stock market, making it a valid choice commonly used by institutional investors for portfolio construction. Therefore, LQ45 is seen as a more appropriate focus for this study to capture the risk-return dynamics of the Indonesian stock market in general compared with narrower indices like

SRI Kehati or Jakarta Islamic Index [20, 21].

2.2 Stock Returns and Risk

Stock returns represent the gains or losses an investor obtains from investing in a stock. Returns are categorized into expected returns and realized returns. Stock returns depend on price movement; positive market reactions such as acquisition announcements that trigger buying pressure produce positive returns. Conversely, negative reactions leading to selling pressure result in negative returns [22]. Calculation of stock realization return is as follows.

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (1)$$

$$E(R_i) = \mu_i = \frac{\sum_{t=1}^T R_{i,t}}{T} \quad (2)$$

where:

$R_{i,t}$: realization return of stock- i in period- t

$P_{i,t}$: stock price stock- i in period- t

$P_{i,t-1}$: stock price stock- i in period- $t-1$

$E(R_i)$: expected return of stock- i

T : The number of observation periods

Stock risk refers to the uncertainty or variability of returns that may cause investment outcomes to differ from expectations [23]. Managing and measuring risk is crucial in portfolio management. The three main widely used stock risk measures are Stock Beta, Standard Deviation, and Value at Risk (VaR). Beta (β) measures the sensitivity of a stock's return relative to the overall market return and represents systematic risk, which cannot be diversified away. A beta greater than 1 indicates higher sensitivity and volatility than the market, while beta less than 1 indicates lower volatility [24]. Standard Deviation (σ) measures total volatility or fluctuation of stock returns over a period, encompassing systematic and unsystematic risk reducible by diversification [24]. Value at Risk (VaR) estimates the maximum potential loss of a portfolio over a defined period at a given confidence level, serving as a key risk metric. VaR accounts for return distribution and dynamic volatility, thereby quantitatively capturing actual risk exposure [10].

Classically, financial theory often assumes hourly or daily stock returns follow a normal distribution, simplifying computations such as mean and variance, so VaR calculation based on these parameters [25]. However, Watorek et.al [26] shows that at very short intervals (seconds, minutes, daily), returns exhibit fat tails and deviate from normality. With longer intervals (weeks), return distributions approximate normality as autocorrelation diminishes and short-term memory effects vanish. This finding supports choosing weekly return intervals for this study's risk measurement because the normality assumption is more reasonable over that horizon.

2.3 Normal Distribution

The normal distribution is a theoretical probability distribution applicable to continuous random variables [27]. It is widely used in many fields, especially in statistics for sampling distributions of means and hypothesis testing. Even when the underlying population is not normally distributed, the sampling distribution of the mean tends to approximate normality. The assumption of normality generally underpins many statistical procedures.

The probability density function (pdf) of the normal distribution is given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (3)$$

where

x : data value

μ : mean

σ : standard deviation

In statistics, the normal distribution is a continuous probability distribution characterized by symmetry and two parameters, mean (μ) and variance (σ^2). The quantile at confidence level $(1 - \alpha)$ is the value below which a proportion α of the data fall. For the standard normal distribution, this quantile is denoted as $(Q_{(1-\alpha)})$ such that:

$$Q_{(1-\alpha)} = \mu + z_{(1-\alpha)}\sigma \quad (4)$$

where $z_{(1-\alpha)}$ is the z-score corresponding to the quantile $(1 - \alpha)$.

2.4 Multivariate Normal Data Generation

The understanding of the normal distribution of univariates as described earlier is a crucial foundation. However, in the context of portfolio management, we are not dealing with just one asset but with a set of assets that make up a portfolio. It is the shared behavior of a set of assets that needs to be modeled, where each asset not only has its own characteristics (mean and variance) but also has a correlation relationship with other assets (covariance).

Therefore, in order to simulate the behavior of a portfolio of LQ45 consisting of many stocks, we must move from the concept of a univariate normal distribution to a more complex one, i.e. a multivariate normal distribution. This distribution allows us to generate a set of random variables (stock returns) that are correlated with each other, so that the resulting simulation can represent the actual market dynamics. To be able to generate data from a multivariate normal distribution, a computational algorithm is needed. Commonly used algorithms utilize the decomposition of the covariance matrix and the transformation of independent normal variables. The following are the algorithmic steps to generate the multivariate normal data that will be applied in the Monte Carlo simulation in this study.

The algorithm for generating multivariate normal data is as follows:

1. Set distribution parameters. Define mean vector $\mu = [\mu_1, \mu_2, \dots, \mu_a]^T$ and covariance matrix $\Sigma \in \mathbb{R}^{a \times a}$
2. Decompose covariance matrix. Apply Cholesky decomposition $\Sigma = L \cdot L^T$ where L is a lower triangular matrix $a \times a$.
3. Generate standard normal matrix. Create matrix $Z \in \mathbb{R}^{a \times a}$ containing independent samples from $\mathcal{N}(0, 1)$
4. Transform data. Compute

$$X = Z \cdot L^T + \mu \quad (5)$$

5. Output : Matrix $X \in \mathbb{R}^{a \times a}$ follows a multivariate normal distribution $\mathcal{N}(\mu, \Sigma)$.

2.5 Normality Test for Return Data

In financial risk analysis, especially in calculating Value at Risk (VaR) using Monte Carlo simulation, it is critical to assume the portfolio returns follow a normal distribution. To validate this assumption, normality tests are conducted on the return data. The Kolmogorov-Smirnov (K-S) test is commonly utilized, comparing the empirical cumulative distribution function (ECDF) of sample data with the theoretical normal CDF.

H_0 : Sample returns are normally distributed.

H_1 : Sample returns are not normally distributed.

$$D_{count} = \max |S(x) - F(x)| \quad (6)$$

where $S(x)$ is the ECDF and $F(x)$ is the theoretical normal CDF. At significance level $\alpha = 5\%$, if $D > D^*(\alpha)$ (critical value), then H_0 rejected.

2.6 Risk Verification with Portfolio

Tested normality assumptions allow us to utilize the statistical properties of normal distributions in calculating risk. However, the focus of portfolio management is not on the risk and return of each asset individually, but rather on its combined performance. An investor holds a portfolio, and the overall risk of this portfolio is determined not only by the volatility of each asset, but also

by how the price movements relate between those assets. To calculate portfolio risk, we must first determine the return and variance of the portfolio. Here are the basic concepts and formulas for portfolio returns and variance that will be at the heart of risk verification. The return of a portfolio at time t is:

$$Rp_t = \sum_{i=1}^N w_i \cdot R_{it} \quad (7)$$

where Rp_t : portfolio return in period- t N : Number of asset in portfolio w_i : Weight of asset- i in the portfolio In vector notation:

$$\begin{aligned} Rp &= w_1 R_1 + w_2 R_2 + \dots + w_N R_N \\ &= [w_1 w_2 \dots w_N] \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_N \end{bmatrix} \\ &= w^T R \end{aligned} \quad (8)$$

The expected return of the portfolio is:

$$E(Rp) = \mu_p = \sum_{i=1}^N w_i \cdot \mu_i, \quad (9)$$

The variance of the portfolio return is:

$$\sigma_p^2 = \sum_{i=1}^N w_i^2 \sigma_i^2 + \sum_{j=1}^N w_j^2 \sigma_j^2 + 2 \sum_{i=1}^N \sum_{j=1}^N w_i w_j \sigma_{ij} \quad (10)$$

$$\sigma_{Rp} = \sqrt{\sigma_p^2} \quad (11)$$

Where σ_{ij} is the covariance between returns of assets i dan j .

2.7 Optimal Portfolio Using Single Index Model

The Single Index Model assumes that an asset's return is influenced only by overall market movements. When the market rises (indicating increased demand), stock prices also rise; conversely, a market downturn leads to price declines. Individual stocks have different sensitivities to market changes. This market sensitivity is measured by Beta [28].

The return of a security as well as the return of the market index can generally be explained by the relationship between the optimal portfolio containing assets at a high excess return to beta (ERB). Assets with low ERB will not be included in the optimal portfolio, so a cut-off-point is needed as the limit of the value of the ERB with high consideration. Single Index model expresses stock returns based on this "excess return to beta" (ERB) [29].

The steps to determine the optimal portfolio with the Single Index Model are:

1. Calculate realized returns ($R_{i,t}$) and expected returns ($E(R_i)$) for each stock
2. Calculate market returns and expected market returns based on the IHSG index.

$$RM_t = \frac{IHSG_t - IHSG_{t-1}}{IHSG_{t-1}} \quad (12)$$

$$E(RM) = \frac{\sum_{t=1}^T RM_t}{T} \quad (13)$$

where

RM_t : market return in period- t

$E(RM)$: expected of market return

3. Estimate stock alpha $\hat{\alpha}_i$ and $\hat{\beta}_i$ using covariance with market returns.

$$\hat{\alpha}_i = E(R_i) - (\hat{\beta}_i \cdot E(RM)) \quad (14)$$

$$\hat{\beta}_i = \frac{Cov(R_i, RM)}{\sigma_M^2} \quad (15)$$

where

$$Cov(R_i, RM) = \frac{1}{T-1} \sum_{t=1}^T (R_{i,t} - \bar{R}_i)(RM_t - \bar{RM})$$

4. Calculate residual variance $\sigma_{e_i}^2$, market variance σ_M^2 , and total stock risk σ_i^2 .

- (a) Residual Variance ($\sigma_{e_i}^2$)

$$\sigma_{e_i}^2 = \frac{\sum_{t=1}^T (R_{it} - (\hat{\alpha}_i + \hat{\beta}_i \cdot RM_t))^2}{T} \quad (16)$$

- (b) Market Variance (σ_M^2)

$$\sigma_M^2 = \frac{\sum_{t=1}^T (RM - E(RM))^2}{T} \quad (17)$$

- (c) Total stock risk (σ_i^2)

$$\sigma_i^2 = \hat{\beta}_i^2 \cdot \sigma_M^2 + \sigma_{e_i}^2 \quad (18)$$

5. Determine risk-free return (R_{BR}) from annual BI rate adjusted to weekly.

$$R_{BR} = (1 + r_{annual})^{\frac{1}{52}} - 1 \quad (19)$$

r_{annual} is the average annual interest rate of the BI Rate in the amount of 52 weeks in a year. The value of R_{BR} can be set at the weekly Bank Indonesia Certificate (SBI) interest rate in the study period, namely in 2022-2024.

6. Calculate excess return to beta (ERB) for each stock:

$$ERB_i = \frac{E(R_i) - R_{BR}}{\hat{\beta}_i} \quad (20)$$

7. Sort stocks descending by ERB, calculate temporary cutoff C_i .

$$C_i = \frac{\sigma_M^2 \sum_{j=1}^i A_j}{1 + \sigma_M^2 \sum_{j=1}^i B_j} \quad (21)$$

where

$$A_j = \frac{[E(R_j) - R_{BR}] \cdot \hat{\beta}_j}{\sigma_{e_j}^2} \quad (22)$$

$$B_j = \frac{\hat{\beta}_j^2}{\sigma_{e_j}^2} \quad (23)$$

8. Identify final cutoff C^* the last C_k where $ERB_i > C_k$

9. Compute weights w_i for selected stocks:

$$w_i = \frac{Z_i}{\sum_{i=1}^n Z_i} \quad (24)$$

where

$$Z_i = \frac{\hat{\beta}_i}{\sigma_{e_i}^2} (ERB_i - C^*) \quad (25)$$

Z_i is a measure of the risk contribution and profit potential of the stock in the portfolio. Stocks with negative Z_i will be eliminated.

10. Compute portfolio beta and alpha. Beta portfolio (β_p) is a measure that indicates the sensitivity or volatility of the portfolio to market movements. Alpha portfolio (α_p) is a measure to showing the difference in the actual return of the portfolio and the desired return based on market risk.

$$\beta_p = \sum_{i=1}^n w_i \cdot \hat{\beta}_i \quad (26)$$

$$\alpha_p = \sum_{i=1}^n w_i \cdot \hat{\alpha}_i \quad (27)$$

11. Calculate expected return $E(R_p)$ and variance of the portfolio (σ_p^2).

$$E(R_p) = \mu_p = \sum_{i=1}^N w_i \cdot E(R_i) \quad (28)$$

$$\sigma_p^2 = \beta_p^2 \cdot \sigma_M^2 + \left(\sum_{i=1}^N w_i \cdot \sigma_{e_i} \right)^2 \quad (29)$$

2.8 Sharpe Index

The Sharpe Index measures the performance of a portfolio based on total risk. The sharpe index is calculated by comparing the portfolio's risk premium (the difference between the average portfolio profit rate and the average risk-free interest rate) at the portfolio standard deviation (systematic risk and unsystematic risk). The Sharpe Index measures the extent to which the return on an investment exceeds the risk-free level, relative to the volatility or standard risk of the investment. Portfolio performance is said to be good when the value of the sharpe index is higher, which means the portfolio produces a greater return per unit of risk. As a benchmark, a sharpe value of more than 1 is considered good, more than 2 is good, and more than 3 is excellent. Based on equations (??), (8), and (17), the assessment of the performance of stock portfolios using the Sharpe index is [30]

$$Sharpe = \frac{\bar{R}_p - R_{BR}}{\sigma_{Rp}} \quad (30)$$

where $\bar{R}_p$ is an average of portfolio return.

2.9 Portfolio Value at Risk (VaR)

VaR is defined as the estimated maximum loss that may be experienced in the portfolio over a given period of time within this confidence level [31]. Therefore, there is a possibility that the losses experienced by the portfolio in this period can be smaller than the limit imposed on the VaR. However, investors can use the VaR value as a reference to determine the amount of risk target they want to take.

Technically, VaR is expressed as the quantile form of the return distribution (R_p^*). The quantile of portfolio return distribution can be obtained by $R_p^* = \mu_p + z_{(1-\alpha)} \cdot \sigma_p$. Then, VaR in the $(1 - \alpha)$ confidence level with holding times- t is formulated by

$$VaR_{(1-\alpha)} = W_0 R_p^* \sqrt{t} \quad (31)$$

where W_0 is initial stock investment.

2.10 Monte Carlo Simulation

The term Monte Carlo originated from the city of Monaco which was once a gambling center. This simulation was used by student statisticians to prove the well-known t-Student distribution. Monte Carlo simulation are different from conventional simulations because when choosing variables to be simulated, this simulation uses random and independent selection of variables.

Monte Carlo simulation is a method applied to study how random variations or errors affect the sensitivity, performance, or reliability of the system while being modeled. This method is included in the category of sampling methods because the inputs used are randomly selected based on probability distribution to collect samples from the actual population. Therefore, this model must choose the input distribution precisely on the available data [32].

Monte Carlo simulation are used to estimate future stock returns by estimating the average of various possible scenarios. The value of stock prices has characteristics that change over time with unexpected patterns, resulting in stock price movements being modeled for stochastic processes, which can also be grouped into stochastic processes of continuous time-time variables.

2.11 VaR Calculation with Monte Carlo

The VaR in the Monte Carlo simulation of the portfolio assumes that the return of the portfolio constituent assets follows a multivariate normal distribution. The basic algorithm when calculating VaR used in the Monte Carlo simulation, namely [33].

1. Estimate parameters of the multivariate normal distribution, such as mean vector and covariance matrix of portfolio assets based on historical data. The calculation of the mean return uses equation (1) and for the calculation of covariance uses the following equation.

$$Cov(R_i, R_j) = \frac{1}{T-1} \sum_{t=1}^T (R_{i,t} - \bar{R}_i)(R_{j,t} - \bar{R}_j) \quad (32)$$

2. Generate T random samples of assets return from multivariate normal distribution using parameters obtained from step-1.
3. Calculate portfolio return (R_{p_t}) of returns simulation obtained from step-2 using equation (7).
4. Determine the $(1 - \alpha)$ -quantile (R_p^*) of the empirical simulated portfolio returns.
5. Compute VaR for holding period t weeks using equation (12).
6. Repeat simulation step (2) to (5) for M times. Then we will get M portfolio VaR, namely $VaR_{(1-\alpha)}^{(1)}(t), VaR_{(1-\alpha)}^{(2)}(t), \dots, VaR_{(1-\alpha)}^{(M)}(t)$.
7. Calculate the average of M -VaR obtained to get overall estimates

$$\bar{VaR}_{(1-\alpha)}(t) = \sum_{m=1}^M \frac{VaR_{(1-\alpha)}^{(m)}(t)}{M} \quad (33)$$

3. METHODOLOGY

This study uses secondary weekly closing price data of stocks included consistently in the LQ45 Index from January 1, 2022, to October 31, 2024, obtained from www.investing.com. The research variable used in this study is the weekly closing price of the stock (P_{it}) as stated in **Table 1**. Weekly prices reflect the final transaction prices each week and serve as the basis for return calculations. With $t : 1, 2, \dots, 146$. Where i is an indexation for individual stocks observed in accordance with the list of companies in **Table 2**. There were twenty seven consistent companies that were members of the IDX and the LQ45 index during the research period.

Table 1. Research Variables

Research Variables	Definition	Unit
P_{it}	The closing price of the company's shares i at time t	Rupiah
IHSG _{t}	Composite stock price index at time t	Rupiah
BiRate	Bank Indonesia's annual interest rate	Percent

Table 2. The List of LQ45 Stocks Company Observed

Stock Code	Company Name
ADRO	Alamtri Resources Indonesia Tbk.
ANTM	Aneka Tambang Tbk.
ASII	Astra International Tbk.
BBCA	Bank Central Asia Tbk.
BBNI	Bank Negara Indonesia (Persero) Tbk.
BBRI	Bank Rakyat Indonesia (Persero) Tbk.
BBTN	Bank Tabungan Negara (Persero) Tbk.
BMRI	Bank Mandiri (Persero) Tbk.
BRPT	Barito Pacific Tbk.
CPIN	Charoen Pokphand Indonesia Tbk.
EXCL	XLSMART Telecom Sejahtera Tbk.
ICBP	Indofood CBP Sukses Makmur Tbk.
INCO	Vale Indonesia Tbk.
INDF	Indofood Sukses Makmur Tbk.
INKP	Indah Kiat Pulp & Paper Tbk.
INTP	Indocement Tunggal Prakarsa Tbk.
ITMG	Indo Tambangraya Megah Tbk.
JSMR	Jasa Marga (Persero) Tbk.
KLBF	Kalbe Farma Tbk.
MDKA	Merdeka Copper Gold Tbk.
MEDC	Medco Energi Internasional Tbk.
PGAS	Perusahaan Gas Negara Tbk.
PTBA	Bukit Asam Tbk.
SMGR	Semen Indonesia (Persero) Tbk.
TLKM	Telkom Indonesia (Persero) Tbk.
TOWR	Saran Menara Nusantara Tbk.
UNTR	United Tractors Tbk.
UNVR	Unilever Indonesia Tbk.

3.1 Data Analysis Methods

Data analysis was carried out in the single index method to obtain the portfolio optimally, then measured the VaR of the stock portfolio using Monte Carlo simulations, in calculation by using R Studio programs. The algorithm to be taken is:

1. Create matrix of LQ45 stock weekly closing price. Size of matrix is 147×28
2. Calculate the value of the return and expected return on the share price of each stock with the formula in equation (1) and (2)

3. Perform a normal-distributed return assumption test using the equation (6)
4. Calculate IHSG market return with the equation (13) and market expectations in the equation (14)
5. Calculate values $\hat{\alpha}_i$ using the equation (15) and $\hat{\beta}_i$ using the equation (17).
6. Calculating stock risk.
7. Determine the value of R_{BR} and ERB , where the value of R_{BR} and ERB is obtained from the formula in the equation (19) and (20).
8. Sorting stocks from the largest to the smallest ERB value.
9. Calculate the C_i value using the formula in equation (22).
10. Determining cut-off point (C^*)
11. Determining the stocks that qualify as the efficient stock, namely stocks with an ERB value greater than or equal to the ERB value at the cut-off point (C^*).
12. Calculating the weight (w_i) of the efficient stocks with positive z_i using equation (25).
13. Calculating the beta (β) and alpha (α) of a portfolio using equation (27) and (28).
14. Calculate the expected return of the portfolio using equation (9)
15. Calculate the portfolio risk using the formula in equation (29)
16. Measuring portfolio performance.
17. Perform a Monte Carlo simulation by first setting the parameter values for the variables (returns of the portfolio assets). The returns of the assets in the portfolio are assumed to be normally distributed.
18. Simulate the return values by generating random data 146 times using the parameters obtained in step (17).
19. The return value obtained in syntax (18) is used to calculate the portfolio return at time t in equation (32).
20. Finding the largest loss estimate at a confidence level $(1 - \alpha)$ is done by taking the α -quantile value from the empirical distribution of portfolio returns obtained from syntax (19), denoted by R_p^* .
21. Calculate the VaR value at the confidence level $(1 - \alpha)$ for the time period t precisely in equation (31). The VaR value obtained includes the maximum loss estimate that could potentially be experienced in the portfolio formed.
22. Repeating steps (18) to (21) for 1000 simulations reflects the various possible VaR values of the portfolio $Var^{(1)}(t), Var^{(2)}(t), \dots, V$
23. The mean VaR value is calculated from step (22)

$$\overline{VaR}_{(1-\alpha)}(t) = \sum_{m=1}^M \frac{VaR_{(1-\alpha)}^{(m)}(t)}{M}$$

is obtained in each simulation.

24. Interpreting the obtained VaR results.

4. RESULT & DISCUSSION

4.1 Descriptive Statistics

Figure 1 shows the distribution of LQ45 stocks based on expected return and standard deviation during the observation period. The majority of stocks are in the moderate risk range (standard deviation of 0.02–0.06) with expected returns between -0.002 and 0.002. MEDC stock stands out with the highest expected return of around 0.008 and high risk, while BRPT has the highest risk but low expected return. Conversely, stocks such as BBKA, IHSG, and ICBP show a stable profile with low risk and expected return.

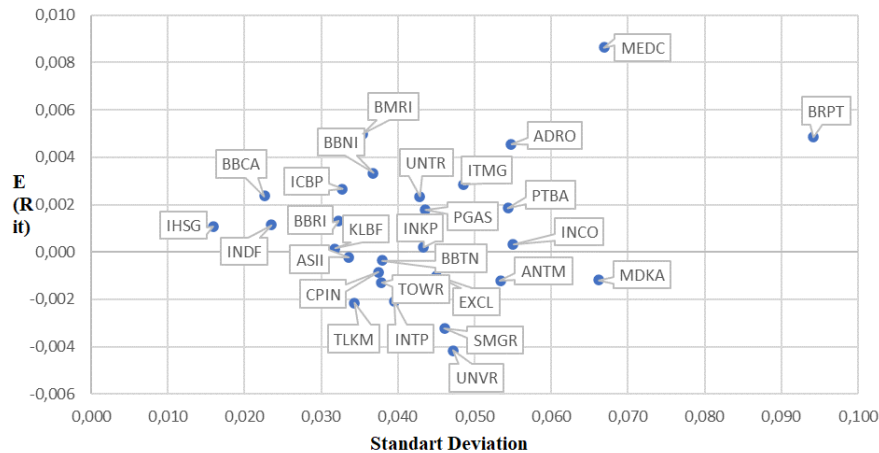


Figure 1. $E(R_i)$ and Standard Deviation of Return

4.2 Normality of Stock Return

The normality test on stock returns was carried out to ensure whether the stock return data used in this study was distributed normally. One of the methods applied is the Kolmogorov-Smirnov test. Based on the calculation of the results of the Kolmogorov-Smirnov test, it can be seen that of the 28 stocks tested, as many as 26 stocks have $D_{calculate}$ less than $D^*(\alpha) = 0.1126$, which means that the return data of these stocks is normally distributed. There are two stocks that are unusually distributed, namely BRPT ($D_{calculate} = 0.1780$) and JSMR with a value of ($D_{calculate} = 0.1219$). These results show that in general, the assumption of normality is met for most stocks in LQ45 index. However, it should be noted that the presence of unnormal stocks can have an impact on subsequent analysis, therefore BRPT and JSMR shares are not included in subsequent analysis.

4.3 Formation of an Optimal Portfolio

This section explains the steps for forming an optimal portfolio using the single index model approach. The process of determining the optimal portfolio in the single index model is carried out in several steps, namely:

1. Calculating market return, expected market return, $\hat{\alpha}_i$ dan $\hat{\beta}_i$. **Table 3** shows the results of calculating return market, expected return market, $\hat{\alpha}_i$, dan $\hat{\beta}_i$ for each stock in the study
2. Calculating residual variance (σ_{ei}^2), stock risk (σ_i^2) dan ERB_i . **Table 3** also shows the results of the calculations for residual variance (σ_{ei}^2), stock risk (σ_i^2), and ERB_i for each stock.

Table 3. $E(R_i)$, $\hat{\alpha}_i$, $\hat{\beta}_i$, σ_{ei}^2 , σ_i^2 , and ERB_i for all stocks

Stock	$E(R_i)$	$\hat{\beta}_i$	$\hat{\alpha}_i$	σ_{ei}^2	σ_i^2	ERB_i
ADRO	0.0046	0.0376	0.0045	0.0030	0.0030	0.0949
ANTM	-0.0012	0.2132	-0.0014	0.0028	0.0028	-0.0103
ASII	-0.0002	0.0125	-0.0002	0.0011	0.0011	-0.0973

Stock	$E(R_i)$	$\hat{\beta}_i$	$\hat{\alpha}_i$	σ_{ei}^2	σ_i^2	ERB_i
BBCA	0.0024	-0.0391	0.0024	0.0005	0.0005	-0.0356
BBNI	0.0033	-0.0635	0.0034	0.0014	0.0014	-0.0367
BBRI	0.0013	0.0030	0.0013	0.0010	0.0010	0.1110
BBTN	-0.0004	0.0898	-0.0005	0.0014	0.0014	-0.0151
BMRI	0.0050	-0.2257	0.0052	0.0012	0.0012	-0.0177
CPIN	-0.0009	-0.3227	-0.0005	0.0014	0.0014	0.0057
EXCL	-0.0010	-0.0252	-0.0010	0.0020	0.0020	0.0791
ICBP	0.0027	-0.3382	0.0030	0.0010	0.0010	-0.0049
INCO	0.0003	-0.0374	0.0004	0.0030	0.0030	0.0181
INDF	0.0012	-0.0361	0.0012	0.0006	0.0006	-0.0045
INKP	0.0002	-0.1248	0.0003	0.0019	0.0019	0.0063
INTP	-0.0021	-0.3006	-0.0018	0.0015	0.0015	0.0102
ITMG	0.0028	-0.0161	0.0029	0.0024	0.0024	-0.1152
KLBF	0.0001	-0.2306	0.0004	0.0010	0.0010	0.0037
MDKA	-0.0012	0.1076	-0.0013	0.0044	0.0044	-0.0203
MEDC	0.0086	0.4432	0.0082	0.0044	0.0044	0.0172
PGAS	0.0018	0.1014	0.0017	0.0019	0.0019	0.0077
PTBA	0.0019	-0.0483	0.0019	0.0030	0.0030	-0.0181
SMGR	-0.0032	-0.0845	-0.0031	0.0021	0.0021	0.0497
TLKM	-0.0022	0.0527	-0.0022	0.0012	0.0012	-0.0600
TOWR	-0.0013	0.2176	-0.0015	0.0014	0.0014	-0.0104
UNTR	0.0023	0.2634	0.0021	0.0018	0.0018	0.0051
UNVR	-0.0042	-0.5449	-0.0036	0.0022	0.0022	0.0094

Based on **Table 3**, each stock has a different expected return ($E(R_i)$), beta ($\hat{\beta}_i$), alpha ($\hat{\alpha}_i$), residual variance (σ_{ei}^2), stock risk (σ_i^2), and Excess Return to Beta (ERB_i). In terms of expected return, the stock with the highest value is UNVR (-0.0042), which shows the greatest potential for profit, while the lowest value is held by UNVR (-0.0042), which has the potential to incur losses. In terms of risk, MEDC and ADRO have the largest variance (0.0044 and 0.0030), while BBKA (0.0005) has the smallest risk.

Based on ERB_i , the variation between stocks is quite striking ERB_i measures the efficiency of returns relative to systematic risk (beta). The stocks with the highest values are BBRI (0.1110) and ADRO (0.0949), while the lowest are ITMG (-0.1152) and ASII (-0.0973).

Conceptually, the Expected Return Ratio, $E(R_i)$, describes the average expected return of a stock, while the Expected Risk Ratio ERB_i emphasizes the efficiency of returns relative to risk. In other words, the Expected Return Ratio $E(R_i)$ focuses on profit potential, while the Expected Risk Ratio $E(R_i)$ focuses on the balance between return and systematic risk.

3. Sorting stocks from the largest to the smallest ERB. The results of sorting stocks from the largest ERB_i to the smallest ERB_i can be seen in **Table 4**.
4. Calculate the values of A_j , B_j , and C_i . **Table 4** shows the results of calculating A_j , B_j , and C_i for each stock in the study.
5. Setting the final cut-off point value (C^*). The final cut-off point value (C^*) is the point at which the ERB value at the last moment is still higher than the C_i value. The (C^*) value is used as a limit to select which stocks are eligible to be candidates in the optimal portfolio. **Table 4** shows the results of determining the final cut-off point (C^*).

Table 4. The Results of Sorting the Largest to Smallest ERB_i , Calculating A_j , B_j , and C_i , and Determining C^*

Stock	ERB_i	A_j	B_j	C_i	Description
BBRI	0.1110	0.0009	0.0084	1.1803×10^{-43}	Efficient
ADRO	0.0949	0.0446	0.4700	5.7582×10^{-42}	Efficient
EXCL	0.0791	0.0248	0.3138	8.8942×10^{-42}	Efficient
SMGR	0.0497	0.1670	3.3612	3.0005×10^{-41}	Efficient
INCO	0.0181	0.0084	0.4608	3.1061×10^{-41}	Efficient
MEDC	0.0172	0.7654	44.3747	1.2780×10^{-40}	Efficient
INTP	0.0102	0.6005	58.6349	2.0369×10^{-40}	Efficient
UNVR	0.0094	1.3014	137.7506	3.6816×10^{-40}	Efficient
PGAS	0.0077	0.0420	5.4214	3.7346×10^{-40}	Efficient
INKP	0.0063	0.0528	8.3234	3.8014×10^{-40}	Efficient
CPIN	0.0057	0.4314	75.4328	4.3466×10^{-40}	Efficient
UNTR	0.0051	0.1959	38.1287	4.5942×10^{-40}	Efficient
KLBF	0.0037	0.1954	53.2748	4.8411×10^{-40}	Efficient
INDF	-0.0045	-0.0107	2.3513	4.8276×10^{-40}	Not Efficient
ICBP	-0.0049	-0.5427	109.7573	4.1417×10^{-40}	Not Efficient
ANTM	-0.0103	-0.1653	16.0349	3.9329×10^{-40}	Not Efficient
TOWR	-0.0104	-0.3476	33.2875	3.4935×10^{-40}	Not Efficient
BBTN	-0.0151	-0.0843	5.5947	3.3870×10^{-40}	Not Efficient
BMRI	-0.0177	-0.7285	41.1108	2.4664×10^{-40}	Not Efficient
PTBA	-0.0181	-0.0144	0.7911	2.4482×10^{-40}	Not Efficient
MDKA	-0.0203	-0.0536	2.6459	2.3804×10^{-40}	Not Efficient
BBCA	-0.0356	-0.1066	2.9935	2.2457×10^{-40}	Not Efficient
BBNI	-0.0367	-0.1095	2.9843	2.1073×10^{-40}	Not Efficient
TLKM	-0.0600	-0.1415	2.3586	1.9285×10^{-40}	Not Efficient
ASII	-0.0973	-0.0135	0.1389	1.9114×10^{-40}	Not Efficient
ITMG	-0.1152	-0.0128	0.1107	1.8953×10^{-40}	Not Efficient

Based on **Table 4**, which ranks the largest ERB to the smallest ERB , the calculation of A_j , B_j , and C_i , as well as the determination of C^* , shows that KLBF (Kalbe Farma Tbk) shares have a ERB value of 0.0037 and a C_i value of 4.8411×10^{-40} . This stock is the last one to be included in the portfolio, as after KLBF, the INDF stock has a value of -0.0045 for the ERB and 4.8411×10^{-40} for the C_i , and is categorized as inefficient. Therefore, the final cut-off point value is at the KLBF stock.

- Determining stocks that qualify as efficient stocks. Based on **Table 5**, the final cut-off point value for the (C_i) is set at KLBF stock, namely 4.8411×10^{-40} . Stocks with an ERB value greater than the C_i value are considered efficient and are selected as candidates for the optimal portfolio. Thus, there are 13 stocks that meet this criterion and are categorized as "Efficient" stocks. The selection of these stocks aims to maximize portfolio returns while considering systematic risk as reflected by each stock's beta.
- Forming an optimal portfolio by calculating the weight (w_i) and value Z_i . A negative value Z_i indicates that the stock is not optimal in terms of risk and return, so the stock should not be included in further calculations. This is to ensure that the portfolio only contains stocks that provide a positive return per unit of additional risk. As a result, only five of the thirteen stocks are included in the optimal portfolio. The stocks are BBRI, ADRO, MEDC, PGAS, and UNTR, where these five stocks will be included in the weight calculation (w_i) step. The results of the (w_i) and Z_i calculations for other stocks included in the optimal portfolio can be seen in **Table 5**.

Table 5. Calculation of w_i and Z_i for Fund Allocation Weights in the Optimal Portfolio

Stock Code	Z_i	w_i
BBRI	0.3153	0.0719
ADRO	1.1879	0.2707
MEDC	1.7270	0.3936
PGAS	0.4142	0.0944
UNTR	0.7439	0.1695

Table 5 also shows that only stocks with positive values for the Z_i are included in the optimal portfolio, because stocks with negative values for the Z_i are considered inefficient in terms of risk and return. MEDC stock has the highest value for the Z_i (1.7270), so it gets the biggest weight in the portfolio, which is 39.36%. Other efficient stocks like UNTR and ADRO also get big weights because they have high values of Z_i .

8. To see the performance of new portfolio, we need beta calculation (β_p), alpha portfolio (α_p), expected return portfolio ($E(R_p)$) and portfolio risk (σ_p^2). The results of those metrics can be seen in **Table 6**. The calculation results show that the

Table 6. Performance of the New Portfolio

Metric	Statistics
β_p	0.2390
α_p	0.0050
$E(R_p)$	0.0053
σ_p^2	0.0030

portfolio beta (β_p) is 0.2390, which indicates that this portfolio has low sensitivity to market changes and is defensive in nature, making it suitable for investors who avoid high risk. The portfolio alpha (α_p) of 0.0050 indicates positive portfolio performance because it is able to provide returns above market expectations. The portfolio's expected return of 0.53% per week reflects the average potential profit that investors can earn. Meanwhile, the portfolio's risk, as measured by variance (σ_p^2) is 0.0030, indicating relatively low volatility. Therefore, this portfolio not only provides positive returns but also keeps the level of risk under control. Thus, it can be concluded that the portfolio generated through the Single Index model approach and stock selection based on the cut-off point has successfully formed a portfolio with positive returns, low systematic risk, and performance efficiency through positive alpha. These results support that the approach used in this study is effective in forming an optimal portfolio.

9. A comparison between LQ45 and the optimal portfolio was then conducted to measure portfolio performance using the Sharpe Index, which is shown in **Table 7**. The average weekly portfolio return, when annualized, reached 27.5%

Table 7. Comparison of LQ45 and Optimal Portfolio

Metric	LQ45	Optimal Portfolio
Number of Stocks	45	5
$\bar{R}_p$	-0.0010	0.0046
σ_{R_p}	0.0183	0.0344
Sharpe Index	-0.0602	1.2061

(0.275). This value is much higher than Bank Indonesia's annual benchmark interest rate of 5.26%. This indicates that the portfolio has excellent investment performance, as it is able to provide a rate of return that far exceeds the risk-free rate. Thus, the portfolio's can be categorized as an optimal and promising portfolio for investment. The Sharpe ratio obtained confirms that the resulting portfolio is reliable.

4.4 VaR Calculation in Monte Carlo Simulation

The following is the calculation of Value at Risk for a stock portfolio using Monte Carlo simulation with the help of R Studio software. Determining VaR with Monte Carlo simulation is carried out in several stages as follows.

1. Calculating the initial parameters, namely the mean and covariance. The mean calculation results obtained the mean values for each stock, namely ADRO (0.0046), BBRI (0.0013), MEDC (0.0086), PGAS (0.0018), and UNTR (0.0023). Then, the triangle matrix of variance-covariance used for the simulation is.

$$\begin{pmatrix} 0.0030 & 0 & 0 & 0 & 0 \\ 0.0003 & 0.0010 & 0 & 0 & 0 \\ 0.0009 & 0.0001 & 0.0045 & 0 & 0 \\ 0.0007 & 0.0003 & 0.0009 & 0.0019 & 0 \\ 0.0014 & 0.0002 & 0.0010 & 0.0006 & 0.0018 \end{pmatrix}$$

2. Return generation for each stock for 146 observations based on mean and covariance. **Figure 2** is a line chart of the return

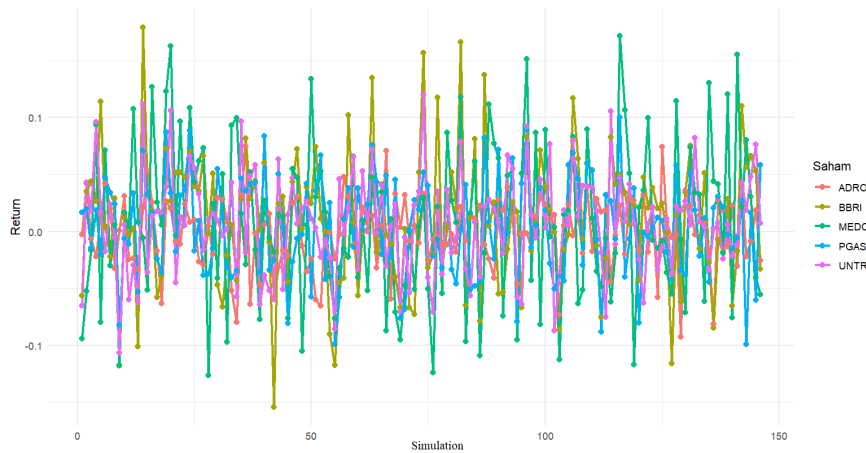


Figure 2. Weekly Return of assets from first Monte Carlo simulation

of 5 stocks based on mean and covariance values, where the red line represents ADRO stock, yellow represents BBRI stock, green represents MEDC stock, blue represents PGAS stock, and purple represents UNTR stock.

3. Calculate the weight multiplied by the return on stock generation. The results of the calculation of the weight multiplied by the return on generation are shown in **Table 8**.

Table 8. Results of Weight-Multiplied Return Calculations

t	BBRI	ADRO	MEDC	PGAS	UNTR	$R_{p,t}$
1	-0.004	-0.001	-0.037	0.002	0.011	-0.030
2	0.003	0.001	-0.021	0.002	-0.007	-0.012
3	0.003	-0.002	-0.007	-0.001	-0.003	-0.010
4	0.002	-0.006	0.037	0.002	-0.016	0.018
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
146	-0.002	-0.007	-0.022	0.006	-0.001	-0.027

4. Find the R^* . After obtaining the calculation w_i , multiply it by the return generated, then add up all the calculation results multiplied by the return generated to obtain the value $R_{p,t}$, which will be presented in the histogram in **Figure 3**. This

figure shows a histogram of the values of Rp_t which is the sum of the portfolio return multiplied by the w_i . It can be seen that the data distribution follows a symmetrical normal distribution pattern with a peak around zero. This means that most of the portfolio returns obtained from multiplying the w_i of the stock by the generated return are around the average, which is close to zero. This value is then used in determining the value of R_p^* . The 5% quantile (corresponding

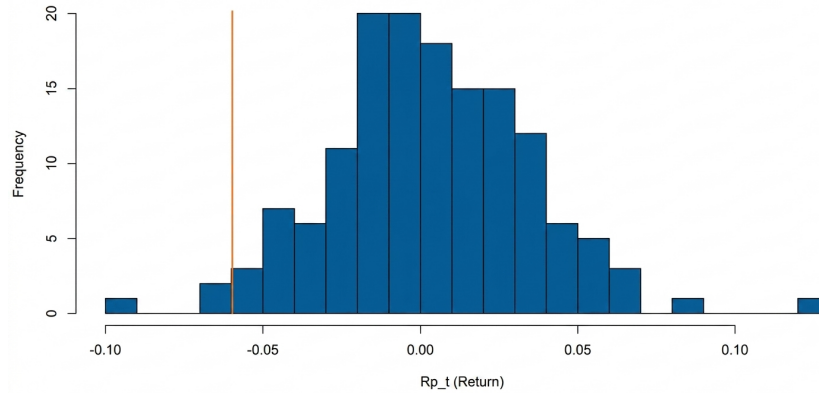


Figure 3. Distribution of the Return of the Portfolio(Rp_t) in the first simulation ($M=1$)

to $\alpha = 0.05$) was extracted from the empirical distribution of the simulated portfolio returns in the first Monte Carlo iteration ($M=1$), resulting in $R_p^* = -0,0626$.

5. Calculating VaR for the first simulation ($M1$). With initial fund $W_0 = Rp100,000,000$, $R_p^* = -0,0626$, and time adjustment factor $t = 1$ week.

$$\begin{aligned} VaR_{(1-\alpha)}(M) &= W_0 R_p^* \sqrt{t} \\ &= 100,000,000 (-0,0626) \sqrt{1} \\ &= -Rp6.260.000 \end{aligned}$$

Then, we obtain the portfolio VaR for the first simulation is $-Rp6,260,000$.

6. Repeat steps 1 to 5 for 1000 Monte Carlo simulations ($M=1000$). The results of the 1000 VaR simulations are shown in **Table 9**. Based on the results of 1000 Monte Carlo simulations, the average Value at Risk (VaR) value obtained

Table 9. Value at Risk (VaR) Calculation Results Using Monte Carlo Simulation

Monte Carlo (M)	$VaR_{1-\alpha}(M)$
1	Rp 6,260,000.00
2	Rp 4,624,714.06
3	Rp 4,999,431.83
4	Rp 6,350,541.62
$\vdots$	$\vdots$
1000	Rp 4,288,868.88
$\overline{VaR}$	Rp 5,148,779.98

was $-Rp5,148,779.98$, which means that at a confidence level of 95% , the portfolio has the potential to experience a maximum loss of around Rp 5.15 million in one period. **Figure 4** shows a histogram of the results of 1000 Monte Carlo simulations of weekly portfolio VaR at a 95% confidence level. The VaR value shows a symmetrical distribution following a normal distribution with the average simulation result centered at $-Rp 5,148,779.98$. This indicates a 95%

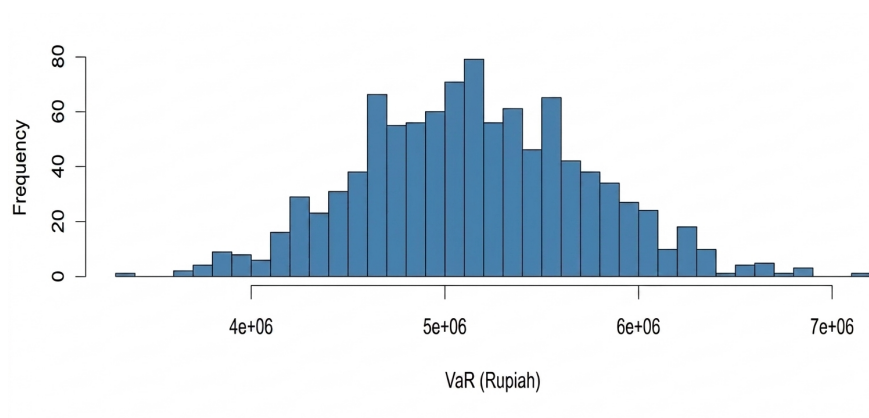


Figure 4. Histogram of 1000 VaR simulation

confidence that the investment loss from the portfolio containing ADRO, BBRI, MEDC, PGAS, and UNTR shares will not exceed IDR 5,148,779.98 within one week after October 27, 2024.

5. CONCLUSION

Based on the analysis results, we can conclude the following:

1. The portfolio consists of five stocks from the LQ45 index that meet the selected criteria, namely Alamtri Resources Indonesia Tbk. (ADRO), Bank Rakyat Indonesia (Persero) Tbk. (BBRI), Medco Energi Internasional Tbk. (MEDC), Perusahaan Gas Negara Tbk. (PGAS), and United Tractors Tbk. (UNTR).
2. The implementation of VaR measurement in the portfolio using Monte Carlo simulation resulted in an average VaR value of $-Rp5,148,779.98$ (a negative value indicates a loss) with an initial capital of $Rp100,000,000.00$, at a 95% confidence level for a one-week period. This means that there is a 95% confidence that the losses that investors may experience will not exceed $Rp5,148,779.98$ within a week after October 31, 2024. Conversely, the probability of a loss of $Rp5,148,779.98$ or more in a portfolio containing ADRO, BBRI, MEDC, PGAS, and UNTR stocks is 5%. For practical recommendations. Investors can utilize this portfolio composition as a defensive strategy in post-pandemic market conditions, while using the VaR figure of approximately 5.15 million from 100 million rupiah investment as a weekly loss threshold for risk management decisions. Regular portfolio rebalancing is recommended to maintain optimal risk-return characteristics.

This study is limited by its reliance on historical data and the normality assumption in Monte Carlo simulation. Future research could incorporate non-normal distributions, extend the analysis to other emerging markets, or examine the impact of additional macroeconomic variables on portfolio risk during recovery periods.

REFERENCES

- [1] O. J. K. (OJK), "Indonesian capital market statistics," <https://www.ojk.go.id>, diakses: 15 Desember 2024.
- [2] A. Chandra and J. Kho, "Calculation of value at risk of stock portfolios using the monte carlo simulation method," *JOM FMIPA*, vol. 1, no. 2, pp. 289–298, 2014.
- [3] S. Husnan, *Fundamentals of Portfolio Theory; Securities Analysis*, 5th ed. Yogyakarta: UPP STIM YKPN, 2015.
- [4] S. Febrianti and T. Apriani, "Listed on jii using the single index model," *Jurnal Ilmiah Ekonomi Islam*, vol. 7, no. 3, pp. 1895–1904, 2021.
- [5] A. Firdaus and D. F. Nadira, "Analysis of optimal portfolio formation using the single index model (case study: Lq45 stocks listed on the idx in 2012-2016)," *Journal of Economics*, vol. XXIII, no. 2, pp. 203–225, 2018, www.idx.co.id.

- [6] I. S. E. (IDX), “Annual report of the indonesia stock exchange 2023,” <https://www.idx.co.id>, diakses: 15 Desember 2024.
- [7] H. Saraswati, “The impact of the covid-19 pandemic on the stock market in indonesia,” *JAD: Dewantara Accounting & Finance Research Journal*, vol. 3, no. 2, 2020, <http://ejournal.stiedewantara.ac.id/index.php/JAD/issue/view/54>.
- [8] A. Herwany, E. Febrian, M. Anwar, and A. Gunardi, “The influence of the covid-19 pandemic on stock market returns in indonesia stock exchange,” *The Journal of Asian Finance, Economics and Business*, vol. 8, no. 3, pp. 39–47, 2021.
- [9] B. Mujib and I. R. Candraningrat, “Capital market reaction to covid-19 pandemic on lq45 shares at indonesia stock exchange (idx),” *American Journal of Humanities and Social Sciences Research*, no. 5, pp. 74–80, 2021, www.ajhssr.com.
- [10] R. J. Situmeang, “Application of extreme value theory in modeling investment risk in emerging markets,” *SAINTIFIK*, vol. 8, no. 2, pp. 204–212, Jul. 2022.
- [11] A. D. Adrianto and M. A. Khairunnisa, “Perhitungan value at risk (var) dengan metode historis dan monte carlo pada saham sub sektor rokok,” *Jurnal Riset Bisnis dan Manajemen*, vol. 11, no. 1, pp. 2580–9539, 2018, www.sahamoke.com.
- [12] E. Fitaloka, E. Sulistianingih, and H. Perdana, “Pengukuran value at risk (var) pada portofolio dengan simulasi monte carlo,” *Buletin Ilmiah Math. Stat. dan Terapannya (Bimaster)*, vol. 7, no. 2, pp. 141–148, 2018.
- [13] D. A. I. Maruddani and A. Purbowati, “Pengukuran value at risk pada aset tunggal dan portofolio dengan simulasi monte carlo,” *Media Statistika*, vol. 2, pp. 93–104, Dec. 2009.
- [14] M. Y. T. Irsan, E. Priscilla, and S. Siswanto, “Comparison of variance covariance and historical simulation methods to calculate value at risk on banking stock portfolio,” *Jurnal Matematika, Statistika dan Komputasi*, vol. 19, no. 1, pp. 241–250, Sep. 2022.
- [15] Herlisa, Arman, L. O. Saidi, L. Gubu, Ruslan, and Jufra, “Analisis portofolio optimum menggunakan metode simulasi monte carlo pada sepuluh saham lq45 terbaik di indonesia,” *Jurnal Jurusan Matematika FMIPA Universitas Halu Oleo*, vol. 3, no. 3, 2023, <http://jmks.uho.ac.id/index.php>.
- [16] D. C. Pradana, D. Asih, I. Maruddani, and H. Yasin, “Penggunaan simulasi monte carlo untuk pengukuran value at risk aset tunggal dan portofolio dengan pendekatan capital asset pricing model sebagai penentu portofolio optimal (studi kasus: Index saham kelompok sminfra18),” *Gaussian*, vol. 4, pp. 765–774, 2015, <http://ejournal-s1.undip.ac.id/index.php/gaussian>.
- [17] R. Lahi, A. Atti, M. A. Kleden, and R. D. Guntur, “Perhitungan risiko value at risk (var) aset tunggal menggunakan pendekatan metode simulasi monte carlo (studi kasus: Pt. indofood cbp sukses makmur tbk dan pt. astra international tbk),” *Jurnal Cakrawala Ilmiah*, vol. 2, no. 8, pp. 3297–3310, Apr. 2023.
- [18] W. Widiyatari, E. Sulistianingsih, and W. Andani, “Analisis value at risk portofolio saham lq45 dengan metode simulasi monte carlo control variates,” *Jurnal Matematika Murni dan Terapan*, vol. 17, no. 1, 2023, <http://ppjp.ulm.ac.id/journals/index.php/epsilon>.
- [19] M. Fakhrudin and M. S. Hadianito, *Perangkat dan Model Analisis Investasi di Pasar Modal*. Jakarta: Gramedia Pustaka Utama, 2001.
- [20] C. D. Polatikan, “Analisis komparasi risiko saham lq 45 dan non lq 45 pada beberapa sub sektor,” *Jurnal Riset Bisnis dan Manajemen*, vol. 3, no. 1, pp. 61–72, 2015.
- [21] A. Prasetyo, N. Vibriyanto, and R. Wulandari, “Comparison of volatility of jakarta islamic index with lq45 stock in indonesia,” *Jurnal Manajemen dan Organisasi*, vol. 15, no. 3, pp. 281–292, Sep. 2024.
- [22] F. N. Erawati, D. Angarani, and K. Hasan, “Analisis harga saham, return saham dan likuiditas saham sebelum dan sesudah akuisisi pada pt. semen indonesia,” in *Proceeding of National Conference on Accounting & Finance*, vol. 4, 2022, pp. 356–361.

- [23] H. N. Hawa, A. Fauzi, F. F. Putra, G. P. Naraya, G. V. Nazara, and I. A. Wa'afin, "Analisis risiko dan tingkat pengembalian dalam mengidentifikasi saham yang dimiliki investor," *Jurnal Pendidikan Siber Nusantara (JPSN)*, vol. 1, no. 4, 2023.
- [24] A. A. et al., *BUKU AJAR MANAJEMEN INVESTASI*. PT. Sonpedia Publishing Indonesia, 2024, www.buku.sonpedia.com.
- [25] E. F. Fama, "The behavior of stock-market prices," *The Journal of Business*, vol. 38, no. 1, pp. 34–105, 1965.
- [26] M. Wątopek, J. Kwapien, and S. Drozd, "Financial return distributions: Past, present, and covid-19," *Entropy*, vol. 23, no. 7, Jul. 2021.
- [27] M. I. Hasan, *Pokok - Pokok Materi Statistika 2 (Statistika Inferensif)*. Jakarta: PT Bumi Aksara, 2001.
- [28] Z. Zubir, *Manajemen portofolio: penerapannya dalam investasi saham*. Jakarta: Salemba Empat, 2011.
- [29] T. R. Adiningrum, R. R. Hidayat, and S. Sulasmiyati, "Penggunaan metode single index model dalam menentukan portofolio optimal tahun 2012-2015 (studi pada saham-saham yang terdaftar dalam indeks idx30 di bursa efek indonesia periode februari 2012-agustus 2015)," *Jurnal Administrasi Bisnis (JAB)*, vol. 38, no. 2, Sep. 2016.
- [30] J. Hartono, *Teori Portofolio dan Analisis Investasi*. Yogyakarta: BPFE Yogyakarta, 2017.
- [31] R. I. Wijayanti, "10 saham blue chip terbaik 2022, adro, antm, hingga hrum," <https://www.idxchannel.com/market-news/10-saham-blue-chip-terbaik-2022-adro-antm-hingga-hrum>.
- [32] S. Hamali, "Simulasi monte carlo dalam pengambilan keputusan di manajemen operasi," Manajemen BINUS University.
- [33] V. R. A. Priyantono, D. A. I. Maruddani, and I. T. Utami, "Analisis portofolio optimal menggunakan model indeks tunggal dan pengukuran value at risk dengan simulasi monte carlo (studi kasus: Exchange traded fund di bursa efek indonesia periode januari 2021 – juni 2022)," *Jurnal Gaussian*, vol. 12, no. 2, pp. 158–165, Jul. 2023.