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Comparative Portfolio Optimization on LQ100 Using Classical, Robust, and Mean–Variance Methods

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Abstract

Investment in the Indonesian capital market has grown significantly, surpassing 18 million investors as of August 2025. This study compares five portfolio optimization methods—Classical Mean–Variance, Fast Minimum Covariance Determinant (FMCD), Robust S-Estimator, Robust Constrained M (CM) Estimator, and Mean–Value at Risk (Mean–VaR)—using LQ100 constituent stocks. Daily closing data from January 2023 to December 2024, selecting ten stocks with the highest Sharpe ratios to construct the portfolio. Each model was optimized under various levels of risk aversion and evaluated through backtesting from January to August 2025. Using an initial capital of Rp 100 million, the results indicate that while robust estimators such as FMCD and CM provide greater stability during market volatility, the Classical Mean–Variance model with moderate risk aversion ($\gamma = 25$) yields the most profitable and well-diversified portfolio composition, with the largest allocations in AMMN.JK (20.36%), BSSR.JK (19.65%), and JPFA.JK (9.22%). The backtesting results in a total projected profit of approximately Rp 13.7 million over eight months. These findings confirm that the Classical Markowitz framework remains a reliable and efficient approach for portfolio allocation in the Indonesian stock market, especially for moderately risk-averse investors seeking a balance between diversification and return stability.

Key words: *Portfolio optimization, Mean–Variance, Robust Estimator, Mean Value at Risk, Sharpe Ratio.*

1. Background

Investing in financial markets has grown rapidly in recent years. According to data from the Indonesia Stock Exchange (IDX), by August 2025 the number of capital market investors had surpassed 18 million, reaching exactly 18,012,665 single investor identifications (SIDs). In just six months, the figure rose by around 3,141,026, showing strong momentum in market participation. Of this total, stock investors accounted for 7,558,552 SIDs, including 1,177,108 new investors. This growth not only reflects the rising public interest in investment but also demonstrates greater confidence in Indonesia's economy and capital markets, supported by improving financial literacy and the increasing recognition of investment as a means of building wealth and supporting long-term economic development [1].

However, investing inherently involves a trade-off between return and risk, as stock prices can fluctuate rapidly, even within minutes or seconds. For this reason, investors require a solid understanding of both the markets and the companies they intend to invest in, as well as an appropriate investment strategy. One of the most widely recognized strategies to balance risk and return is the construction of an investment portfolio. A portfolio is defined as a collection of two or more securities, such as stocks, bonds, options, or warrants, selected by an investor over a certain period and under specific conditions. The main objective of portfolio formation is to allocate capital optimally across available risky assets in the market to achieve a favorable balance between risk and return. By diversifying across assets with uncorrelated returns (idiosyncratic risks), investors can reduce overall portfolio volatility without sacrificing expected returns [2].

The foundation of portfolio optimization can be traced back to the pioneering work of Markowitz (1952), who introduced the mean–variance (MV) model [2]. This model recommends the use of two statistical measures from historical stock returns mean as a representation of expected return and variance as a representation of risk—to construct an optimal portfolio. The fundamental idea of the MV framework is that expected returns and the variance–covariance matrix must be estimated from data; however, estimation errors are inevitable. Several studies, including Chopra and Ziemba (1993) and Ceria and Stubbs (2006), have shown that the optimal portfolio derived from the MV model is highly sensitive to changes in its input parameters, namely the mean vector and variance–covariance matrix [3], [4].

To overcome these challenges, researchers have developed robust portfolio optimization approaches designed to reduce the impact of estimation errors. Robust portfolio models employ alternative estimation techniques that are less sensitive to outliers and non-normal data distributions. For example, the Robust Fast Minimum Covariance Determinant (FMCD) estimator is widely applied to obtain resistant estimates of the mean vector and covariance matrix in the presence of outliers [5]. The Robust S-Estimates method minimizes the effect of outliers and residual dispersion, producing more stable parameter estimates [6]. The Robust Constrained M (CM) Estimator further addresses the high sensitivity of classical estimators, leading to improved portfolio stability [7]. These advancements illustrate that robust methods can provide more reliable portfolio allocations under uncertain and volatile market conditions. In addition, the Mean Value at Risk (Mean–VaR) approach extends beyond variance-based risk by incorporating downside risk at a specified confidence level, allowing investors to manage potential losses from extreme market movements [8]. These advancements offer more reliable portfolio allocations under uncertain and volatile market conditions.

In the context of the Indonesian capital market, the LQ100 index is one of the most prominent stock indices, consisting of 100 leading issuers with high liquidity and credibility. While robust portfolio models have been developed to address the limitations of the classical approach, their relative performance may vary across markets and time periods. Therefore, this study aims to empirically compare both classical and robust methods within the context of the Indonesian stock market. In this study, ten stocks from the LQ45 index will be selected based on their Sharpe ratios, representing those with the most attractive risk–return profiles [9]. The portfolio weights of these selected stocks will then be optimized using five different methods: the classical mean–variance approach, Robust FMCD, Robust S-Estimates, Robust CM Estimator, and Mean Value at Risk. The primary objective of this research is to compare these portfolio optimization methods and determine which approach provides the most effective balance between maximizing returns and minimizing risks. The findings are expected to contribute to both the academic literature and practical investment strategies, particularly in the context of emerging markets such as Indonesia.

2. Research Methodology

This research employs a quantitative and simulation-based design using secondary data analysis. The main focus is on constructing and evaluating stock portfolios derived from the LQ100 index during the period from January 2023 to December 2024. The methodological approach emphasizes the estimation of portfolio returns, risks, and performance under both classical and robust statistical frameworks. Robust statistical methods are designed to provide reliable estimation of location and dispersion in the presence of outliers and deviations from normality, which are commonly observed in financial return data [18]. In the context of portfolio optimization, robust approaches have been increasingly adopted to improve portfolio stability and risk estimation under data contamination and non-normal return behavior [20]. Prior studies have shown that portfolio construction can be preceded by stock grouping techniques, such as time series clustering using the K-Medoid algorithm with Dynamic Time Warping (DTW) distance, to capture similarity patterns among asset returns before optimization [14]. However, this study focuses directly on portfolio optimization using robust estimation methods, as robust estimators have been shown to improve the stability and reliability of optimal portfolio formation in the presence of outliers and non-normal return distributions [15].

Before outlining the research procedures, it is important to clarify the distinction between the concepts of an efficient portfolio and an optimal portfolio. An efficient portfolio is defined as a portfolio that lies on the efficient frontier, meaning that for a given level of risk it provides the maximum expected return, or conversely, for a given level of expected return it minimizes the level of risk [2]. The efficient frontier thus represents the set of portfolios that are not dominated by any other portfolio in terms of the risk–return trade-off [21]. In contrast, an optimal portfolio refers to a specific portfolio chosen from the efficient frontier based on the investor's objectives and risk preferences. For instance, an investor who seeks to maximize risk-adjusted performance may select the portfolio with the highest Sharpe ratio, while a more risk-averse investor might prefer the portfolio with the lowest volatility, also known as the minimum variance portfolio [11]. In other words, while there may be many efficient portfolios, only one (or a few) becomes optimal depending on the chosen decision criterion.

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In this study, two optimization criteria are applied to determine the optimal portfolio: (1) maximizing the Sharpe ratio, which reflects risk-adjusted return, and (2) minimizing portfolio volatility, which emphasizes risk reduction. Both optimization approaches are tested across five portfolio estimation models, namely the Classical estimator, the Fast Minimum Covariance Determinant (FMCD), the S-estimator, the CM-estimator, and the Mean-Value at Risk (Mean-VaR). The resulting portfolios are subsequently subjected to backtesting to assess their out-of-sample performance in early 2025.

2.1. Data Collection

The data used in this study consist of daily closing prices of all stocks included in the LQ100 index, obtained from Yahoo Finance, covering the period from January 1, 2023 to December 31, 2024. Daily closing prices are chosen because they represent the most common benchmark in financial markets to capture the fair value of a security at the end of each trading day. Although closing prices do not occur exactly 24 hours apart, financial research often treats them as equally spaced observations for the sake of statistical modeling [12].

2.2. Research Procedures

2.2.1. Data Processing

The first stage of data processing is the calculation of daily stock returns for each company in the LQ100 index. A return is the gain or loss that an investment generates over time, representing the fundamental measure of performance in portfolio analysis [11]. Returns in this study are computed using the logarithmic return formula [12].

$$r_{it} = ln\left(\frac{P_{it}}{P_{i,t-1}}\right) \tag{1}$$

where r_{it} denotes the return of stock i at the time t, P_{it} is the closing price of stock i at the time t, and $P_{i,t-1}$ is the closing price of stock i at the time $t-1$. The use of logarithmic return is preferred because it ensures additivity over time and is widely adopted in empirical finance research. After obtaining daily returns, the next step is the measurement of volatility, which is expressed as the standard deviation of returns. The volatility of stock i is calculated using the following formula [19]:

$$\sigma_i = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}(r_{it} - \bar{r}_i)^2} \tag{2}$$

where σ_i is the volatility of stock i, $\bar{r}_i$ is the mean return of stock i, and n represents the number of observations. This measure captures dispersion of returns and reflects the risk associated with each stock. To evaluate risk-adjusted performance, the Sharpe Ratio is calculated for each stock [9]:

$$SR_i = \frac{\bar{r}_i - r_f}{\sigma_i} \tag{3}$$

where SR_i is denotes the Sharpe Ratio of stock i , $\bar{r}_i$ is the mean return of stock i, σ_i is the standard deviation of return stock i, and r_f represents the risk-free rate, proxied in this study by the average Bank Indonesia policy rate (BI Rate) during 2023—2024, which is 6%. From the Sharpe Ratio ranking, the 10 stocks with the highest Sharpe Ratios were selected to be included in the subsequent portfolio optimization and analysis.

2.2.2. Construction of Statistical Matrices

After identifying the 10 stocks with the highest Sharpe Ratios, the next step is the construction of statistical matrices that will serve as the main input for portfolio optimization. At this stage, two fundamental components are derived, namely the mean return vector (μ) and the covariance matrix (Σ). The mean return vector represents the expected return of each selected stock, calculated as the average of its historical daily returns, and is expressed in the following form:

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$$\mu = \begin{bmatrix} \overline{r_1} \\ \overline{r_2} \\ \vdots \\ \overline{r_{10}} \end{bmatrix} \tag{4}$$

where $\bar{r}_i$ denotes the mean daily return of stock i. The second statistical component is the covariance matrix Σ, which summarizes both the variance of individual stock returns (represented along the diagonal) and the covariance between pairs of stocks (represented in the off-diagonal elements). The symmetric 10 x 10 matrix is expressed as follows:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \mathrm{Cov}(r_1, r_2) & \dots & \mathrm{Cov}(r_1, r_{10}) \\ \mathrm{Cov}(r_2, r_1) & \sigma_2^2 & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{Cov}(r_{10}, r_1) & \mathrm{Cov}(r_{10}, r_2) & \dots & \sigma_{10}^2 \end{bmatrix} \tag{5}$$

Thus, the mean return vector provides information about the expected profitability of each stock, while the covariance matrix reflects both the individual risks and the interdependencies among the selected stocks. These matrices form the foundation for subsequent optimization of portfolio weights.

2.2.3. Portfolio Weight Optimization

2.2.3.1. Portfolio Weight Optimization

The Mean-Variance (MV) portfolio model, introduced by Markowitz (1952), aims to construct an optimal portfolio based on the trade-off between expected return and risk, represented respectively by the mean and variance of asset returns. The optimization problem is formulated as:

$$\Sigma \max_{\boldsymbol{w}} \boldsymbol{w}'\boldsymbol{\mu} - \frac{\gamma}{2}\boldsymbol{w}'\Sigma\boldsymbol{w} \tag{6}$$

subject to $\boldsymbol{w}'\boldsymbol{e} = 1$

where:

- $\boldsymbol{w}$ = vector of portfolio weights
- $\boldsymbol{\mu}$ = vector of expected returns
- $\sum$ = covariance matrix of asset returns
- $\boldsymbol{e}$ = vector of ones
- $\boldsymbol{\gamma \geq 0}$ = risk aversion coefficient

The MV model assumes investors are risk-averse, meaning they prefer portfolios that maximize expected utility $E(U)$. By expanding the utility function $U(W_0(1 + R_p))$ using a second-order Taylor series, it can be shown that maximizing expected utility is equivalent to maximizing:

$$A = \mu_p - \frac{1}{2}\gamma\sigma_p^2 \tag{7}$$

where $\mu_p = \boldsymbol{w}'\boldsymbol{\mu}$ and $\sigma_p^2 = \boldsymbol{w}'\sum\boldsymbol{w}$.

Using the Lagrange multiplier method, the optimal portfolio weights are derived as:

$$w = \frac{1}{2}(\Sigma^{-1} - \Sigma^{-1}e(e'\Sigma^{-1}e)^{-1}e'\Sigma^{-1})\boldsymbol{\mu} + e(e'\Sigma^{-1}e)^{-1} \tag{8}$$

This solution shows that the optimal portfolio weights depend on the expected returns and the covariance matrix of asset returns. According to Elton and Gruber (2014), an efficient portfolio provides the highest expected return for a given level of risk or the lowest risk for a given expected return [21]. Thus, the MV framework enables investors to determine the efficient frontier and select portfolios that maximize expected utility based on their

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individual risk preferences.

2.2.3.2. The Fast Minimum Covariance Determinant (FMCD)

If the historical return data used in the formation of a classical Mean-Variance (MV) portfolio are not normally distributed and contain outliers, the resulting classical MV portfolio becomes ineffective. This occurs because classical estimators of the mean vector and covariance matrix are highly sensitive to outliers and deviations from normality, leading to unreliable estimates. Therefore, it is necessary to develop statistical procedures that remain stable even in the presence of outliers and when the data do not follow a normal distribution. The use of robust covariance estimators in portfolio optimization has been widely studied to address the sensitivity of classical mean–variance models to outliers and non-normal return distributions. In the context of stock portfolio construction, the Fast Minimum Covariance Determinant (FMCD) estimator has been shown to produce more stable mean and covariance estimates, leading to improved portfolio robustness [17].

In this study, robust estimation methods are employed to estimate the mean vector and covariance matrix. The FMCD estimator, in particular, is based on the C-Step theorem [5].

According to this theorem, given a dataset of size n, a subsample H_1 of size $h$is drawn. The sample statistics for this subset are defined as follows:

$$\hat{\mu}_1 = \frac{1}{h}\sum_{i \in H_1} r_i \tag{9}$$

$$\hat{\Sigma}_1 = \frac{1}{h}\sum_{i \in H_1} (r_i - \hat{\mu}_1)(r_i - \hat{\mu}_1)' \tag{10}$$

If $|\ \hat{\Sigma}_1\ | > 0$, then the Mahalanobis distance for each observation i can be expressed as:

$$d_i = (r_i;\ \hat{\mu}_1, \hat{\sum}_1) \tag{11}$$

Next, a new subset H_2 is selected, consisting of the h observations with the smallest distances d_i, that is:

$$\{d_1(i) \mid i \in H_2\} = \{(d_1)_1, (d_1)_2, \dots, (d_1)_h\} \tag{12}$$

with $(d_1)_1 \leq (d_1)_2 \leq \ldots \leq (d_1)_n$.

Using subset H_2, the new estimates of the mean and covariance are recalculated as in equations (9) and (10). The determinant of the covariance matrix satisfies the following condition:

$$|\ \hat{\Sigma}_2\ | \leq |\ \hat{\Sigma}_1\ | \tag{13}$$

Equality holds ($\hat{\mu}_1 = \hat{\mu}_2$ and $\hat{\Sigma}_1 = \hat{\Sigma}_2$) when convergence is reached. A robust estimator with a high breakdown point aims to find a subset of h observations from a total of n that yields the smallest determinant of the covariance matrix.

Given data $r_1, r_2, \ldots, r_n$consisting of n observations and p variables, the MCD estimator is a pair $(\hat{\mu}, \hat{S})$, where $\widehat{S}$ is a positive definite symmetric matrix of dimension $p \times p$, calculated from a subsample of size h using the formulas:

$$\hat{\mu} = \frac{1}{h}\sum_{i \in H} r_i \tag{14}$$

$$\hat{S} = \frac{1}{h}\sum_{i \in H} (r_i - \hat{\mu})(r_i - \hat{\mu})' \tag{15}$$

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In 1999, Rousseeuw and Van Driessen proposed the FAST-MCD method, a computationally efficient enhancement of the classical MCD, making it feasible for large datasets ($n > 20$). The Fast-MCD algorithm, also known as the C-Steps (Concentration Steps) method, iteratively focuses on the $h$observations with the smallest Mahalanobis distances. The updated covariance matrix S_2 obtained in each iteration is "more concentrated," meaning it has a smaller determinant than the previous S_1, leading to a more robust and stable estimate of the covariance structure.

2.2.3.3. The S-Estimator

The S-Estimator was first introduced by Rousseeuw and Yohai (1984) as a robust estimation method designed to compute the mean vector and covariance matrix that remain stable in the presence of outliers and non-normal data distributions. The main idea is to find a pair $(\hat{\mu}, \hat{\Sigma})$ that minimizes the determinant of the covariance matrix $|\Sigma|$ subject to a specific loss function constraint. This approach was later extended by Davies (1987) and Lopuhaa (1989) to achieve greater theoretical efficiency and stability.

Mathematically, the S-estimator is defined as the pair $(\hat{\mu}, \hat{\Sigma})$ that minimizes $|\Sigma|$ subject to the constraint

$$\frac{1}{n}\sum_{i=1}^{n} \rho\left(\sqrt{(r_i - \mu)'\Sigma^{-1}(r_i - \mu)}\right) = b_0 \tag{16}$$

where $\rho(\cdot)$ is a loss function, and b_0 is a constant that controls the degree of robustness. When the underlying data distribution is unknown, $b_0$is typically chosen as $E\{\rho(\|r\|)\}$.

To obtain the S-estimator, Davies (1987) derived the following system of estimating equations:

$$\frac{1}{n}\sum_{i=1}^{n} u(d_i)(r_i - \mu) = 0 \tag{17}$$

$$\frac{1}{n}\sum_{i=1}^{n} pu(d_i)(r_i - \mu)(r_i - \mu)' - v(d_i)\Sigma = 0 \tag{18}$$

where

$$d_i = (r_i - \mu)'\Sigma^{-1}(r_i - \mu), \psi(d_i) = \frac{\partial \rho}{\partial d_i}$$

$$u(d_i) = \frac{\psi(d_i)}{d_i}, v(d_i) = \psi(d_i)d_i - \rho(d_i) + b_0$$

Equations (17) and (18) are solved iteratively until $\hat{\mu}$ and $\hat{\Sigma}$ converge. The S-estimator thus seeks a measure of location and dispersion that minimizes the overall scale of the data while maintaining a controlled average loss defined by ρ.

In practice, the estimation process begins with initial values μ_0 and Σ_0, which are usually obtained from classical estimates or from componentwise medians. These initial values are used to compute the robust Mahalanobis distances d_i, after which the functions $\rho(d_i)$ and $\psi(d_i)$ are evaluated to update $\hat{\mu}$ and $\hat{\Sigma}$. The process is repeated until the estimates become stable.

This robust estimation approach produces a covariance matrix that is more consistent in the presence of extreme observations in the data. As a result, portfolio optimization based on the robust covariance matrix $\hat{\Sigma}_S$ tends to reflect a more realistic risk structure. In other words, the S-Estimator helps maintain the stability of mean and covariance estimates against the influence of outliers that frequently occur in financial or economic return data.

2.2.3.4. The CM-Estimator

The CM-Estimator was introduced by Kent and Tyler (1996) as an extension of the robust estimation framework that combines the global robustness of S-estimators with the local robustness properties of M-estimators. While the M-estimator performs well in terms of efficiency and has a bounded influence function, it suffers from a low breakdown point, meaning it is sensitive to extreme outliers. To overcome this limitation, the CM-estimator was developed to achieve both high efficiency and high breakdown robustness, making it stable under various data contamination scenarios.

Let $\{r_i, i = 1, \ldots, n\}$ be a random sample in $\mathbb{R}^p$, and let $\mathcal{P}_p$ denote the set of all $p \times p$ symmetric positive definite matrices. The CM-estimator of location $\hat{\mu} \in \mathbb{R}^p$ and scatter $\hat{\Sigma} \in \mathcal{P}_p$ is defined as the pair $(\hat{\mu}, \hat{\Sigma})$ that minimizes the following objective function:

$$Q(\mu, \Sigma;\ r) = \frac{1}{n}\sum_{i=1}^{n} \rho(d_i) + \frac{1}{2} log|\Sigma| \tag{19}$$

subject to the constraint

$$\frac{1}{n}\sum_{i=1}^{n} \rho(d_i) \leq \epsilon\rho(\infty), \tag{20}$$

where $d_i = (r_i - \mu)'\Sigma^{-1}(r_i - \mu)$, $\rho(\cdot)$ is a loss function, and ϵ represents the breakdown point, i.e., the proportion of contamination (outlier observations) the estimator can tolerate before it breaks down. A higher breakdown point implies greater robustness of the estimator. When $\rho(\cdot)$ is differentiable, the CM-estimates of location and scatter are obtained by solving the following system of equations:

$$\sum_{i=1}^{n} \psi(d_i)(r_i - \mu) = 0, \tag{21}$$

$$\Sigma = \frac{p\sum_{i=1}^{n} \psi(d_i)(r_i - \mu)(r_i - \mu)'}{\sum_{i=1}^{n} W(d_i)}, \tag{22}$$

and either

$$\frac{1}{n}\sum_{i=1}^{n} W(d_i) = p, \tag{23}$$

or equivalently,

$$\frac{1}{n}\sum_{i=1}^{n} \rho(d_i) = \epsilon\rho(\infty), \tag{24}$$

where $\psi(d) = 2\rho'(d)$ and $W(d) = d\psi(d)$. Equations (21)–(23) apply when the constraint (20) is expressed as an inequality, while (21)–(24) are used when the constraint is written as an equality. These equations represent the critical points of the objective function $Q(\mu, \Sigma; r)$.

In practice, the CM-estimator refines both location and covariance estimates by down-weighting the influence of extreme observations through the loss function $\rho(d_i)$. Observations that lie far from the data receive smaller weights in the estimation process, thus reducing their effect on the resulting mean and covariance matrix.

2.2.3.5. The Mean-Value at Risk (Mean-VaR)

Value at Risk (VaR) is one of the most widely used risk measures in portfolio management due to its intuitive interpretation and computational simplicity. However, VaR has been criticized for lacking coherence properties, particularly subadditivity, which may lead to misleading risk assessments in diversified portfolios. To address

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these limitations, Acerbi and Tasche (2002) introduced Expected Shortfall (ES) as a coherent and theoretically sound alternative to VaR, capable of capturing tail risk more effectively [10]. Despite these criticisms, VaR remains widely applied in portfolio optimization frameworks due to its interpretability and tractability. Several studies have proposed Mean–VaR–based optimization models as an alternative to the classical mean–variance approach, particularly in financial markets characterized by non-normal return distributions and downside risk concerns [16].

In the Mean–VaR (Value at Risk) framework, investors determine the optimal portfolio weights w_i for each asset to achieve a balance between expected return and risk minimization [13]. Let $E(R_i)$ denote the expected return of asset i, and Σ the covariance matrix of asset returns. The weight vector is $w = [w_1, w_2, \dots, w_n]'$ with the full investment constraint $e'Tw = 1$, where e is the vector of ones.

The portfolio returns, expected return, and variance are given respectively by:

$$R_w = w'R, \qquad E(R_w) = w'\mu, \qquad \text{and} \qquad Var(R_w) = w'\Sigma w \tag{25}$$

In the Mean–VaR model, portfolio risk is measured using Value at Risk (VaR), defined as:

$$Var(R_w) = z_\alpha \sqrt{w'\Sigma w} - w'\mu \tag{26}$$

where z_α is the critical value from the standard normal distribution corresponding to the confidence level α. The optimization problem aims to maximize expected return while minimizing risk (VaR), expressed as:

$$\max_w (w'\mu - z_\alpha \sqrt{w'\Sigma w}), \qquad subject\ to \qquad e'Tw = 1 \tag{27}$$

This is a constrained optimization problem, which can be solved using the Lagrange multiplier method. The Lagrangian function is formulated as:

$$\mathcal{L}(w, \lambda) = w'\mu - z_\alpha \sqrt{w'\Sigma w} + \lambda(1 - e'Tw) \tag{28}$$

and the optimal portfolio weights $\hat{w}$ are obtained from the first-order conditions:

$$\frac{\partial \mathcal{L}}{\partial w} = 0, \qquad \frac{\partial \mathcal{L}}{\partial \lambda} = 0 \tag{29}$$

The resulting vector $\hat{w}$ represents the optimal proportion of investment in each asset that minimizes Value at Risk for a given level of expected return and confidence level α. This Mean–VaR approach provides a more realistic risk measure compared to traditional mean–variance models, especially in financial markets with non-normal return distributions.

2.2.4. Optimization Criteria

The optimization criterion employed in this study is the Sharpe Ratio, which measures the performance of a portfolio by considering the trade-off between return and risk. The Sharpe Ratio is formulated as:

$$S = \frac{E[R_p - R_f]}{\sigma_p} \tag{30}$$

where:

- $E[R_p]$: expected return of the portfolio,
- R_f: risk-free rate,
- σ_p: standard deviation of the portfolio return.

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The objective of the optimization process is to maximize S, that is, to find the portfolio weight vector $\mathbf{w}^*$ that yields the highest ratio of return to risk:

$$\mathbf{w}^* = arg \max_{w} \frac{E[w'r] - R_f}{\sqrt{w'\Sigma w}} \tag{31}$$

To analyze the sensitivity of the models to different levels of risk aversion, several values of the risk-aversion parameter (γ) are tested:

$$\gamma \in \{0.5, 1.0, 2.0, 5.0, 10.0, 15.0, 20.0, 25.0, 30.0, 35.0, 40.0, 45.0, 50.0\}$$

Each γ value is applied across the five portfolio models to evaluate the changes in performance and stability of the optimal portfolio based on the maximum Sharpe Ratio.

2.2.5. Backtesting Simulation

The simulation process followed several key stages:

1. Stock Selection
   Ten stocks were selected from the LQ100 index based on their highest Sharpe Ratios, calculated using daily closing prices from January 1, 2023 to December 31, 2024. This step ensured that only stocks with the best risk-adjusted returns were included in the portfolio construction process.

2. Portfolio Model Evaluation
   The selected ten stocks were then used to construct portfolios under five different optimization models. For each model, various risk-aversion levels were tested:
   $$\gamma \in \{0.5, 1.0, 2.0, 5.0, 10.0, 15.0, 20.0, 25.0, 30.0, 35.0, 40.0, 45.0, 50.0\}$$
   The optimal γ for each model was determined as the one that yielded the highest Sharpe Ratio, representing the most efficient balance between return and risk.

3. Simulation Period
   The backtesting period was set from January to August 2025, with the portfolio assumed to be purchased on January 2, 2025. Portfolio performance was monitored at the end of each month, reflecting real-world investment conditions where periodic revaluation occurs.

4. Performance Evaluation
   For each of the five optimized portfolios, the monthly returns were calculated based on the observed price changes of the constituent stocks. The final performance metric was the total portfolio return at the end of August 2025. The best-performing portfolio was identified as the one achieving the highest cumulative return by the end of the simulation period.

3. Result and Discussion

In line with the rapid growth of Indonesia’s capital market participation, this study empirically analyzes portfolio optimization using selected LQ100 stocks. As investors continuously balance risk and return, the analysis compares how different optimization methods manage this trade-off. The process begins with a descriptive review of stock returns and volatilities to illustrate basic risk–return dynamics, followed by identifying the ten best-performing stocks based on their Sharpe Ratios as the foundation for portfolio construction. Portfolio weights are then determined using five approaches: Mean-Variance, Robust FMCD, Robust S-Estimator, Robust CM-Estimator, and Mean-VaR, under varying risk-aversion levels. Simulations compare their performance in terms of risk-adjusted returns and minimum volatility. The results highlight the relative effectiveness of classical, robust, and risk-based portfolio models under volatile market conditions, offering practical insights for investors seeking more reliable strategies in the Indonesian stock market.

After calculating returns and volatilities for all 96 stocks in LQ100 constituents, stocks are ranked by Sharpe Ratio (return per unit of risk). **The ten highest-Sharpe stocks are selected as the optimized portfolio’s core**, as summarized in Table 1.

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Table 1. Top 10 Stocks Based on Sharpe Ratio

Rank	Stock	Sharpe Ratio	Avg. Return (%)	Risk (Std Dev, %)	P-value Normalitas
1	AMMN.JK	2.37127	0.00491	0.0313	0.0000
2	SSIA.JK	1.72141	0.00385	0.03335	0.0000
3	BSSR.JK	1.4201	0.00136	0.01263	0.0000
4	TOTL.JK	1.39194	0.00243	0.02509	0.0000
5	RAJA.JK	1.36129	0.00393	0.04308	0.0000
6	DEWA.JK	1.04649	0.00272	0.0377	0.0000
7	SILO.JK	0.95099	0.00214	0.03188	0.0000
8	BRIS.JK	0.89374	0.00158	0.02388	0.0000
9	JPFA.JK	0.78755	0.00132	0.02187	0.0000
10	MAPA.JK	0.76392	0.00158	0.02792	0.0000

Table 1 ranks the top 10 LQ100 stocks by their Sharpe Ratios, which measure return earned per unit of risk. A higher ratio indicates superior risk-adjusted performance. **AMMN.JK records the highest Sharpe Ratio** (2.37) with an average return of 0.49% and volatility of 3.13%, **followed by SSIA.JK, BSSR.JK, TOTL.JK, and RAJA.JK**. These stocks are considered relatively efficient and attractive for portfolio inclusion compared to those with lower ratios.

In addition, the normality test shows P-values of 0.000 for all stocks, indicating that returns deviate significantly from normal distribution. This suggests the classical mean–variance assumption may not fully apply, reinforcing the need for robust estimation methods that are less sensitive to outliers and fat-tailed returns.

Using these Top 10 stocks as the investable universe, portfolio optimization is conducted under five approaches: Mean-Variance, Robust FMCD, Robust S-Estimator, Robust CM-Estimator, and Mean-VaR to minimize sensitivity to estimation error. For each method, optimal weights are computed across different risk-aversion parameters (γ), where lower γ emphasizes returns and higher γ focuses on risk control. Tables 2–6 summarize the resulting optimal portfolios

Table 2. Portfolio Weights under the Classical Model

γ	AMMN.JK	SSIA.JK	BSSR.JK	TOTL.JK	RAJA.JK	DEWA.JK	SILO.JK	BRIS.JK	JPFA.JK	MAPA.JK
0.5	48.9422	25.2786	0.0000	0.0000	25.7792	0.0000	0.0000	0.0000	0.0000	0.0000
1.0	49.4574	25.6142	0.0000	0.0000	24.9284	0.0000	0.0000	0.0000	0.0000	0.0000
2.0	71.8066	19.4646	0.0000	0.0000	8.7288	0.0000	0.0000	0.0000	0.0000	0.0000
5.0	52.1520	27.1075	0.0000	3.0630	17.6775	0.0000	0.0000	0.0000	0.0000	0.0000
10	34.6803	20.2698	6.9555	11.8057	14.4694	4.2363	3.4800	2.0822	2.0208	0.0000
15	26.3685	15.7164	11.3366	12.3061	9.8030	3.7749	5.0105	5.6384	6.5018	3.5438
20	22.2013	13.4222	13.5433	12.5415	7.5312	3.5570	5.7593	7.4051	8.7305	5.3086
25	20.3615	9.9676	19.6504	12.6056	8.5947	3.0603	4.4791	6.9648	9.2214	5.0946
30	16.6791	7.7840	29.6058	11.4533	5.9143	3.1395	4.2185	6.3263	9.6101	5.2691
35	15.0602	6.8707	31.6009	11.1459	5.3833	2.9775	4.1449	6.8482	10.4360	5.5325
40	14.1727	6.2656	33.2911	10.9875	4.9309	2.4812	3.9668	7.2165	11.0418	5.6460
45	13.0693	6.9325	35.1393	9.7698	5.0248	1.6656	4.6507	7.2078	10.3061	6.2342
50	12.3156	6.5007	36.3743	9.6015	4.7080	1.6053	4.6292	7.3123	10.6355	6.3174

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Table 3. Portfolio Weights under the Robust FMCD Model

γ	AMMN.JK	SSIA.JK	BSSR.JK	TOTL.JK	RAJA.JK	DEWA.JK	SILO.JK	BRIS.JK	JPFA.JK	MAPA.JK
0.5	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5.0	76.5534	14.0349	0.0000	0.0000	0.0000	0.0000	14.7492	6.4630	0.0000	2.9486
10	47.7639	16.2350	0.0000	0.0000	0.0000	0.0000	11.8291	12.9916	0.0000	11.1803
15	42.2970	14.7871	4.5444	0.0000	0.0000	0.0000	13.3425	12.7608	1.5899	10.6783
20	34.2625	13.1370	9.3200	3.1297	0.0000	0.0000	13.8766	12.3044	3.7716	10.1983
25	29.1383	12.0089	12.6394	5.1767	0.0000	0.0000	14.1028	12.0101	5.1080	9.8158
30	26.1804	11.1136	15.3321	6.3280	0.0000	0.0000	14.2513	11.7951	5.6544	9.3451
35	21.1387	11.6534	26.0383	3.5817	0.4211	0.0000	13.6865	12.2767	2.4497	8.7540
40	19.0863	10.7043	29.8134	4.3996	0.5307	0.0000	12.9358	11.4078	2.9239	8.1982
45	17.5377	9.8736	32.5187	5.2354	0.5555	0.0000	12.3223	10.7519	3.4334	7.7716
50	16.0563	9.1734	35.0002	5.9182	0.8747	0.0000	11.7474	10.3908	3.5301	7.3089

Table 4. Portfolio Weights under the Robust S-Estimator Model

γ	AMMN.JK	SSIA.JK	BSSR.JK	TOTL.JK	RAJA.JK	DEWA.JK	SILO.JK	BRIS.JK	JPFA.JK	MAPA.JK
0.5	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	59.7003	0.0000	40.2997	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
15	43.4600	0.0000	56.5400	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20	28.4187	0.0000	71.5813	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
25	13.8560	0.0000	86.1440	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	0.0000	0.0000	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
35	0.0000	0.0000	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
40	0.0000	0.0000	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
45	0.0000	0.0000	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	0.0000	0.0000	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5. Portfolio Weights under the Robust CM-Estimator Model

γ	AMMN.JK	SSIA.JK	BSSR.JK	TOTL.JK	RAJA.JK	DEWA.JK	SILO.JK	BRIS.JK	JPFA.JK	MAPA.JK
0.5	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2.0	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5.0	82.5674	0.0000	0.0000	0.0000	14.5435	2.889	0.0000	0.0000	0.0000	0.0000
10	64.8348	6.5539	3.7783	0.0000	12.0937	3.3958	9.4795	5.1789	0.0000	3.6761
15	41.0176	7.2154	9.4762	3.4744	9.4114	1.8417	11.4127	7.2689	2.7226	6.1590
20	32.4407	7.6889	11.8573	6.2000	7.6911	1.2738	12.1354	8.0175	5.3160	7.3722
25	27.3338	7.9689	13.1955	7.7807	6.7741	1.0740	12.509	8.4595	6.8294	8.0752
30	26.1363	6.7822	18.5879	6.5931	7.0888	2.2068	12.4551	7.4195	4.656	8.4206
35	24.0577	6.2234	20.3340	7.5482	7.4369	2.7621	12.5407	7.4932	5.398	6.2190
40	19.9622	6.6544	31.7477	6.4477	5.6592	2.2149	11.2772	6.1942	3.4387	6.8099
45	18.0724	6.4182	33.1923	7.2816	5.2228	1.7838	10.9079	6.6261	4.2967	6.1980
50	17.1175	5.9507	34.3426	7.9539	5.0472	1.2457	10.7902	6.6419	4.8613	6.0490

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Table 6. Portfolio Weights under the Mean Value at Risk (Mean-VaR) Model

γ	AMMN.JK	SSIA.JK	BSSR.JK	TOTL.JK	RAJA.JK	DEWA.JK	SILO.JK	BRIS.JK	JPFA.JK	MAPA.JK
0.5	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
1	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
2	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
5	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
10	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
15	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
20	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
25	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
30	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
35	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
40	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
45	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540
50	20.2967	15.6059	4.6244	9.3512	15.9374	10.5930	8.0553	5.5629	4.4191	5.5540

While the previous tables show how portfolio weights change across models and risk-aversion levels (γ), investors ultimately seek portfolios with the best performance. Therefore, this study selects the portfolio with the highest Sharpe Ratio for each method as the most efficient in risk-adjusted terms. This comparison reveals which optimization approach offers superior returns per unit of risk. The recommended portfolios are presented in Table 7.

Table 7. Recommended Portfolios with the Highest Sharpe Ratio Across Models

Model	Gamma	Expected Return	Volatility	Sharpe Ratio	Effective_N
CM-Estimator	40.0	0.6387	0.1287	45.758	57.220
FMCD	35.0	0.6696	0.1349	45.924	59.021
Classic	25.0	0.7016	0.1771	36.801	75.656
S-Estimator	1.0	0.8630	0.3686	2.060	1.000
Mean-Var	25.00	0.7016	0.1771	36.801	75.656

Table 7 summarizes the portfolios with the highest Sharpe Ratios across the optimization methods. Each model: Classical, Mean–Variance, FMCD, S-Estimator, and CM-Estimator produces its own optimal allocation at a given risk-aversion level (γ). All methods yield efficient risk-adjusted returns, though expected return and volatility differ. Some portfolios achieve higher returns with slightly more volatility, while others emphasize stability with moderate Sharpe Ratios. Overall, these results show that different optimization techniques can generate distinct yet effective allocations, giving investors alternatives based on their risk and robustness preferences.

To assess real-world applicability, a backtest simulation applies the optimal weights from each model to actual stock price movements. The analysis focuses on portfolios with the highest Sharpe Ratios, as they represent the most efficient allocations for each method. Comparing realized performances reveals whether theoretically optimal portfolios under mean–variance and robust frameworks maintain their efficiency in real market conditions.

Figure 1 illustrates the backtesting results of the Classical Mean–Variance portfolio (γ = 25), showing its initial allocation and monthly profit–loss trends over January–August 2025.

Figure 1. Backtest Simulation of the Classical Mean–Variance Portfolio
Source: Author's computation using Google Colab (2025)

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The Classical portfolio (γ = 25) exhibits a balanced diversification, allocating the largest weights to AMMN.JK (20.4%), BSSR.JK (19.7%), and TOTL.JK (12.6%), with moderate exposures to SSIA.JK (10.0%), JPFA.JK (9.2%), and RAJA.JK (8.6%). Smaller proportions are held in BRIS.JK (7.0%), MAPA.JK (5.1%), SILO.JK (4.5%), and DEWA.JK (3.1%). Despite this balance, the portfolio recorded losses in early 2025, most notably in March (≈ Rp

–16.4 million) and February (≈ Rp –13.0 million), before rebounding strongly in June (+17.3 million) and July (+13.7 million). Overall, while temporarily affected by sectoral volatility, the Classical model maintained solid diversification and recovered effectively, demonstrating consistent risk-return efficiency under moderate risk aversion (γ = 25).

Figure 2 illustrates the backtesting results of the FMCD (Robust) portfolio (γ = 25), showing the initial asset composition and monthly profit–loss dynamics during January–August 2025.

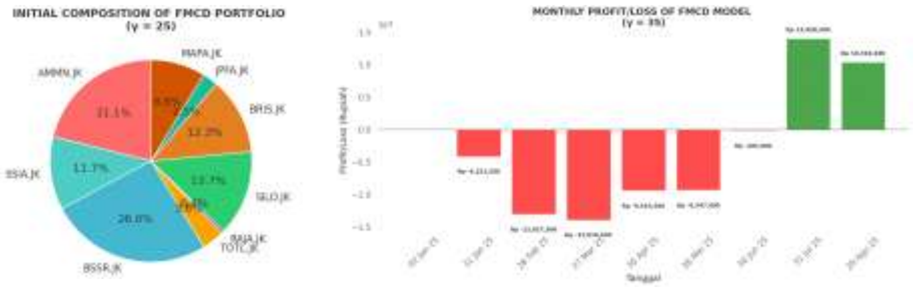

Figure 2. Backtest Simulation of the FMCD Portfolio
Source: Author's computation using Google Colab (2025)

The FMCD portfolio (γ = 25) shows a moderately concentrated structure, dominated by BSSR.JK (26.0%) and AMMN.JK (21.1%), with additional exposure to SILO.JK (13.7%), BRIS.JK (12.3%), and SSIA.JK (11.7%). Smaller allocations include MAPA.JK (8.8%), TOTL.JK (3.6%), JPFA.JK (2.5%), and RAJA.JK (0.6%). This composition reflects a focus on mining and energy sectors, offering high return potential but increased risk. During early 2025, the portfolio experienced drawdowns in February–May (up to Rp –13.9 million) before stabilizing in June and rebounding strongly in July (+13.9 million) and August (+10.3 million). Overall, despite its higher concentration, the FMCD model demonstrated robust recovery and competitive returns once markets stabilized, though periodic rebalancing could further strengthen risk control.

Figure 3 presents the backtesting results of the S-Estimator (Robust) portfolio (γ = 1), illustrating its fully concentrated allocation in AMMN.JK and the corresponding monthly profit–loss performance throughout January–August 2025.

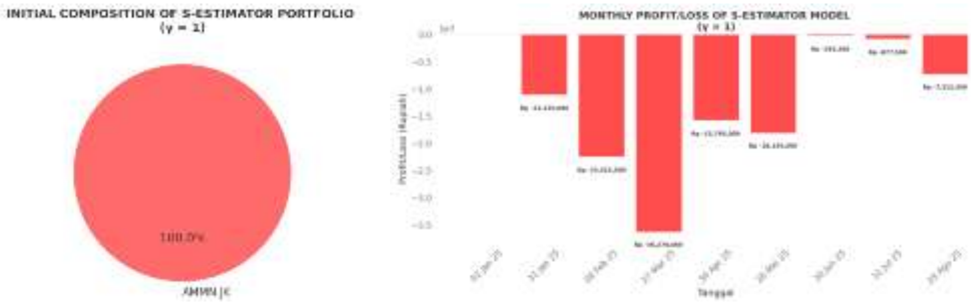

Figure 3. Backtest Simulation of the S-Estimator Portfolio

Source: Author's computation using Google Colab (2025).

The S-Estimator portfolio (γ = 1) is fully concentrated in AMMN.JK, with 100% allocation to a single asset and no diversification. This structure exposes the portfolio to extreme volatility, magnifying both gains and losses. Backtest results show sustained declines through early 2025, with major drawdowns in March (≈ Rp –36.3 million), February (≈ Rp –22.1 million), and April (≈ Rp –15.8 million). Minor recoveries in June and July were insufficient to offset earlier losses, leaving overall performance deeply negative. The model's lack of diversification severely undermines its resilience, highlighting that single-asset exposure even in strong-performing stocks offers poor stability compared to diversified portfolios.

Figure 4 displays the backtesting results of the CM-Estimator (Robust) portfolio (γ = 15), showing its diversified allocation across ten assets and the corresponding monthly profit–loss movements during January–August 2025.

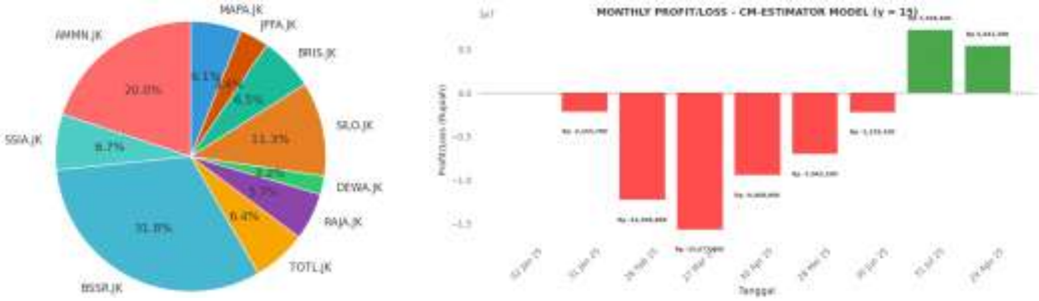

Figure 4. Backtest Simulation of the CM-Estimator Portfolio
Source: Author's computation using Google Colab (2025)

The CM-Estimator portfolio is relatively well diversified compared to other robust models, with major holdings in BSSR.JK (31.8%), AMMN.JK (20.0%), and SILO.JK (11.3%). Smaller allocations are spread across SSIA.JK, TOTL.JK, BRIS.JK, MAPA.JK, RAJA.JK, JPFA.JK, and DEWA.JK. The backtest shows consecutive losses from January to June—peaking in March (≈ Rp –15.7 million)—before recovering in July (+7.3 million) and August (+5.4 million). Although the cumulative result remained slightly negative, the CM-Estimator proved more resilient than the S-Estimator due to its broader diversification. However, exposure to cyclical resource stocks such as BSSR.JK and AMMN.JK contributed to early volatility. Overall, the model balances robustness and diversification effectively, though limiting concentration and periodic rebalancing could further improve stability.enhance portfolio stability under changing market conditions

Figure 5 presents the backtesting results of the Mean–Value at Risk (Mean–VaR) portfolio (γ = 25), illustrating its diversified allocation and monthly profit–loss pattern throughout January–August 2025.

Figure 5. Backtest Simulation of the Mean–Value at Risk Portfolio
Source: Author's computation using Google Colab (2025)

The Mean–Value at Risk (Mean–VaR) portfolio (γ = 25) is well balanced across ten assets, with the largest allocations in AMMN.JK (20.4%) and BSSR.JK (19.7%), followed by TOTL.JK (12.6%), SSIA.JK (10.0%), and RAJA.JK (8.6%). Smaller portions are held in JPFA.JK, BRIS.JK, SILO.JK, DEWA.JK, and MAPA.JK. This structure aligns with the Mean–VaR framework's focus on limiting downside risk while maintaining return potential. Backtesting reveals a high-risk, high-return trajectory: early losses peaked in March (≈ Rp –16.6 million) but were followed by strong recoveries in June–August, culminating in a net profit by period end. Overall, the Mean–VaR model effectively balances upside capture and tail-risk control, offering a robust alternative to classical optimization in volatile markets.

4. Conclusion

This study aims to identify the most effective portfolio optimization method among the Classical and four advanced approaches, Robust FMCD, Robust S-Estimates, Robust CM Estimates, and Mean Value at Risk, using Indonesian stocks listed in the LQ100 index. Following a pre-weight computation based on the highest Sharpe ratio, ten stocks were selected to construct the portfolio: AMMN.JK, SSIA.JK, BSSR.JK, TOTL.JK, RAJA.JK, DEWA.JK, SILO.JK, BRIS.JK, JPFA.JK, and MAPA.JK. The results of the weight computation across the five methods and varying levels of risk aversion indicate that the optimal balance between risk and return differs among the models. These optimal weights were subsequently applied in backtesting, utilizing actual market volatility and stock price movements. Assuming an investment initiated in early January 2025 and held for eight months until

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August 2025, the backtesting results reveal that the S-Estimator method yields the weakest performance because it is characterized by a single stock allocation, resulting in a projected capital loss due to stock price depreciation. Conversely, among the five evaluated methods, the Classical approach yields the most profitable and well-diversified portfolio composition. Under a moderate risk aversion level ($\gamma = 25$), this method allocates the largest weights to AMMN.JK (20.36%), BSSR.JK (19.65%), and JPFA.JK (9.22%), with moderate allocations to TOTL.JK (12.61%), RAJA.JK (8.59%), and BRIS.JK (6.96%), and smaller exposures across MAPA.JK, SILO.JK, and DEWA.JK. The backtesting outcomes further demonstrate that, over the eight-month investment horizon, the Classical portfolio exhibits a consistent recovery following early-year drawdowns and achieves a total projected profit of approximately Rp 13,727,400. Overall, these findings affirm that the Classical Markowitz model remains a reliable and effective framework for portfolio allocation within the Indonesian stock market, particularly for moderately risk-averse investors seeking optimal diversification and sustainable returns. Furthermore, the comparative evaluation across all models highlights key insights into their practical applications. The Robust FMCD model, while statistically more resistant to outliers, tends to concentrate heavily in the mining and energy sectors, primarily on BSSR.JK (26.0%) and AMMN.JK (21.1%), leading to higher sectoral exposure. It demonstrates strong recovery performance in July--August but remains vulnerable to early-year volatility, making it suitable for more aggressive investors who can tolerate temporary drawdowns. The Robust CM-Estimator model offers a more balanced diversification, with major allocations to BSSR.JK (31.8%) and AMMN.JK (20.0%). Despite experiencing initial losses, it exhibits a steady recovery in later months, positioning it as a viable choice for conservative investors seeking robust returns with adequate risk management. The Mean–Value at Risk (Mean–VaR) approach, provides a well-diversified structure similar to the Classical model but with better control over downside risk, effectively capturing returns while limiting tail losses. In summary, while robust estimation methods enhance stability under data uncertainty, the Classical Mean–Variance approach remains the most effective and profitable model in this study. For conservative investors, the CM-Estimator and Mean–VaR models offer safer alternatives emphasizing risk mitigation. In contrast, for more aggressive investors, the Classical and FMCD approaches may yield higher returns with manageable volatility. However, the findings also underline the importance of maintaining diversification, as excessive concentration—such as observed in the S-Estimator model—can significantly increase portfolio risk under volatile market conditions.

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