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Investment Portfolio Optimization using Mean-Semi Standard Deviation Model (Case Study: BBNI, BBCA, BMRI, TLKM, and ANTM)

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Abstract

This study aims to determine the optimal stock portfolio weight using the Mean-Semi Standard Deviation optimization model as an alternative to the more commonly used Mean-Variance model. This model considers downside risk which is more relevant to investor preferences in minimizing potential losses. The data used in this study are the daily closing prices of five stocks listed on the Indonesia Stock Exchange (BBNI, BBCA, BMRI, TLKM, and ANTM) during the period from December 7, 2023 to December 6, 2024. The optimization process is carried out using the Lagrange method to maximize the expected return of the portfolio with measurable risk, using the risk aversion parameter (ρ) as a control for risk preference. The results show that a portfolio with a value of ρ = 0.1 provides the highest return to risk ratio of 0.058556, with the largest portfolio weight allocated to BBCA shares. The implication of this study is that the Mean-Semi Standard Deviation model can be used as a better approach in managing stock portfolios in the Indonesian market, especially to reduce the risk of loss amid high market volatility.

Keywords: Investment portfolio, mean-semi standard deviation, indonesia stock exchange stocks, optimization, risk aversion.

1. Introduction

In the investment world, the stock market is one of the most popular financial instruments because of its high profit potential (Ghania et al., 2019). However, market volatility and stock price fluctuations do not cause significant risks for investors. Therefore, effective investment portfolio management is needed to maximize profits while minimizing risk (Mahmudah et al., 2024; Cunningham, 2024). Various mathematical approaches have been developed in portfolio theory since the introduction of the Mean-Variance Model by Harry Markowitz in 1952 (Goetzmann, 2023). This model is the basis for modern portfolio management by maximizing expected returns and minimizing variance as a measure of risk.

Although the Mean-Variance Model has become the dominant method in portfolio optimization, further research shows that this model has several limitations. One of the main criticisms of this model is the assumption that investment risk is only measured through return variance (Zhang, 2023). In practice, investors pay more attention to the risk of loss or potential loss than to holding returns in a positive direction (Hwang and Satchell, 2010). Therefore, several studies have introduced alternative models that are more sensitive to downside risk, such as the Mean-Semi Standard Deviation model used in this study.

The Mean-Semi Standard Deviation model offers a more realistic approach to measuring portfolio risk. This model considers semi-standard deviation, which is a deviation that only takes into account returns below the average, as a measure of risk. With this approach, the model is more in line with the risk preferences of investors who tend to avoid losses (Rigamonti and Lučivjanská, 2024).. In addition, the use of semi-standard deviation can provide a more stable portfolio solution in volatile market conditions.

Several previous studies have examined the application of the Mean-Semi Standard Deviation model in various contexts. For example, research conducted by Liu et al., (2024) shows that this model is more effective in managing the risk of loss than the Mean-Variance model. In addition, research by Qin et al., (2016) that semi-absolute deviation (which is related to the concept of semi-standard deviation) is a better tool for measuring downside risk than ordinary standard deviation, especially in asymmetric return distributions and surrounding situations. However, most of this research is still limited to the global market, while the application of this model in the Indonesian stock market is still rare.

In Indonesia, the stock market is growing with increasing participation of domestic investors, including from millennials (Indonesia Stock Exchange, 2024). However, the market decline influenced by economic, political, and social factors makes investment risk in the Indonesian stock market a challenge in itself (Zhong and Enke, 2017). Therefore, research is needed that can produce a portfolio optimization model that is more in line with the characteristics of the Indonesian stock market. This study contributes by applying the Mean-Semi Standard Deviation model to five leading stocks listed on the Indonesia Stock Exchange, namely BBNI, BBCA, BMRI, TLKM, and ANTM.

The purpose of this study is to develop a stock portfolio optimization model that considers the risk of a decline using the Mean-Semi Standard Deviation approach. This study will determine the optimal portfolio weight based on historical data on daily closing prices of stocks during a certain period, as well as provide a return to risk ratio generated by the portfolio formed. By using this approach, it is expected that an investment portfolio can be obtained that provides optimal returns with more measurable risks.

In addition, this study also aims to fill the research gap related to portfolio optimization in the Indonesian stock market. Most existing studies still use the Mean-Variance model as the main approach. Therefore, this study offers novelty in investment management portfolios by introducing a model that is more adaptive to the needs of investors in Indonesia.

The usefulness of this research is not only to provide theoretical contributions in the development of financial science, but also has practical implications for investors and investment managers in Indonesia. With the results of this study, it is expected that investors can make better investment decisions based on mathematically optimized portfolios. In addition, this research can also be a reference for the development of investment policies by financial institutions and capital market regulators.

This research is expected to provide new insights into portfolio risk management in the Indonesian stock market, especially in facing increasingly dynamic market challenges. By using a portfolio optimization model that considers downside risk, investors can be better prepared to face market fluctuations and minimize potential losses that can occur in stock investments.

2. Literature Overview

2.1. Markowitz Portfolio Optimization

Modern portfolio theory introduced by Harry Markowitz in 1952 uses the Mean-Variance Model to maximize portfolio returns by minimizing variance as a measure of risk (Goetzmann, 2023). However, in practice, investors are more concerned with downside risk, which is the potential for losses below the average return. Therefore, the Mean-Semi Standard Deviation Model was developed as a more conservative and relevant alternative in measuring risk.

The Mean-Semi Standard Deviation Model measures risk using semi-standard deviation, which only takes into account negative deviations from the average return. This approach is considered more realistic in the investment context because it better reflects the behavior of investors who tend to avoid losses rather than pursue high returns. In this model, the optimal portfolio is achieved by maximizing the expected return of the portfolio while minimizing semi-standard deviation as a measure of risk.

2.2. Risk Aversion Coefficient

In the Mean-Semi Standard Deviation Model, the parameter ρ is referred to as the risk aversion coefficient. This parameter reflects the investor's risk preference for the trade-off between return and risk. A higher value of ρ indicates that the investor is more conservative and tends to avoid risk, while a lower value of ρ reflects an investor's attitude that is more tolerant of risk. This risk aversion coefficient is used to control the portfolio weights allocated to various assets. In mathematical formulation, ρ affects the balance between maximizing returns and minimizing risk, which determines the optimal weight of each stock in the portfolio.

2.3. Mean-Semi Standard Deviation Portfolio Optimization Model

The Mean-Semi standard deviation portfolio optimization model can be formulated as follows:

$$\max\left\{\mu_p - \frac{\rho}{2}\sigma_p\right\} \tag{1}$$

with constraints:

$$\sum_{i=1}^{N} w_i = 1 \tag{2}$$

where:

- μ_p is the expected return of the portfolio
- σ_p is the semi standard deviation of the portfolio
- w_i is the portfolio weight for stock i
- ρ is the risk aversion coefficient

2.4. Mean-Semi Standard Deviation Portfolio Optimization Model Solution

The portfolio optimization equation above can be solved using the Lagrange method. The Lagrange function is formulated as:

$$L(w,\lambda) = \mu_p - \frac{\rho}{2}\sigma_p + \lambda\left(\sum_{i=1}^{N} w_i - 1\right) \tag{3}$$

portfolio Return Expectations:

$$\mu_p = \mathbf{w}^T\boldsymbol{\mu} \tag{4}$$

portfolio Standard Deviation:

$$\sigma_p = \sqrt{\mathbf{w}^T \Sigma \mathbf{w}} \tag{5}$$

calculate the first derivative of the Lagrange function with respect to w and λ:

$$\frac{\partial L}{\partial w} = \boldsymbol{\mu} - \rho\Sigma\mathbf{w} + \lambda\mathbf{e} = 0 \tag{6}$$

$$\frac{\partial L}{\partial \lambda} = \mathbf{e}^T\mathbf{w} - 1 = 0 \tag{7}$$

solving Systems of Linear Equations:
From the system of equations above, the optimal solution for portfolio weight $\mathbf{w}^*$ is obtained:

$$\mathbf{w}^* = \frac{(-2\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} - 2\lambda\boldsymbol{\Sigma}^{-1}\mathbf{e})}{(-2\mathbf{e}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} - 2\lambda\mathbf{e}^T\boldsymbol{\Sigma}^{-1}\mathbf{e})} \tag{8}$$

Where λ is a constant obtained from substituting back into the system of equations. While the covariance matrix (Σ) is calculated using the daily returns of each stock pair to measure the relationship between the returns of the two stocks:

$$\sigma_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left(r_{i,t} - \mu_i\right)\left(r_{j,t} - \mu_j\right) \tag{9}$$

2.5. Mathematical Properties of the Mean-Semi Standard Deviation Portfolio Optimization Model

This model has several important mathematical properties to ensure that the obtained solution is the maximum value:

1. Negative Definite Hessian Matrix:
   To ensure that the optimal solution is the maximum value, the Hessian matrix of the Lagrange function must be negative definite. The Hessian matrix is defined as the second derivative of the Lagrange function:

$$H = \frac{\partial^2 L}{\partial w^2} \tag{10}$$

2. Linearity and Convexity Properties:
   This model maintains linear properties in expected returns and quadratic properties in semi-standard deviations. Linearity in expected returns ensures that changes in portfolio weights provide proportional changes in portfolio returns. Meanwhile, convexity in semi-standard deviations indicates that risk increases in a more exponential manner.

3. Stability of Optimal Solutions:
   Since semi-standard deviations only take into account negative deviations, this model tends to provide more stable portfolio solutions in volatile market conditions. This is because downside risk is considered more significant than upside risk.

With these mathematical properties, the Mean-Semi Standard Deviation Model provides a more realistic and practical alternative to the Mean-Variance Model in the context of stock portfolio management.

3. Materials and Methods

3.1. Materials

Materials This study uses daily closing price data of five stocks listed on the Indonesia Stock Exchange (IDX), namely: BBNI (PT Bank Negara Indonesia Tbk), BBCA (PT Bank Central Asia Tbk), BMRI (PT Bank Mandiri Tbk), TLKM (PT Telkom Indonesia Tbk), and ANTM (PT Aneka Tambang Tbk).

The closing price data of stocks is taken from the Yahoo Finance website with a time period from December 7, 2023 to December 6, 2024. The data is used to calculate daily stock returns, covariance matrices, and other parameters needed in the Mean-Semi Standard Deviation portfolio optimization model.

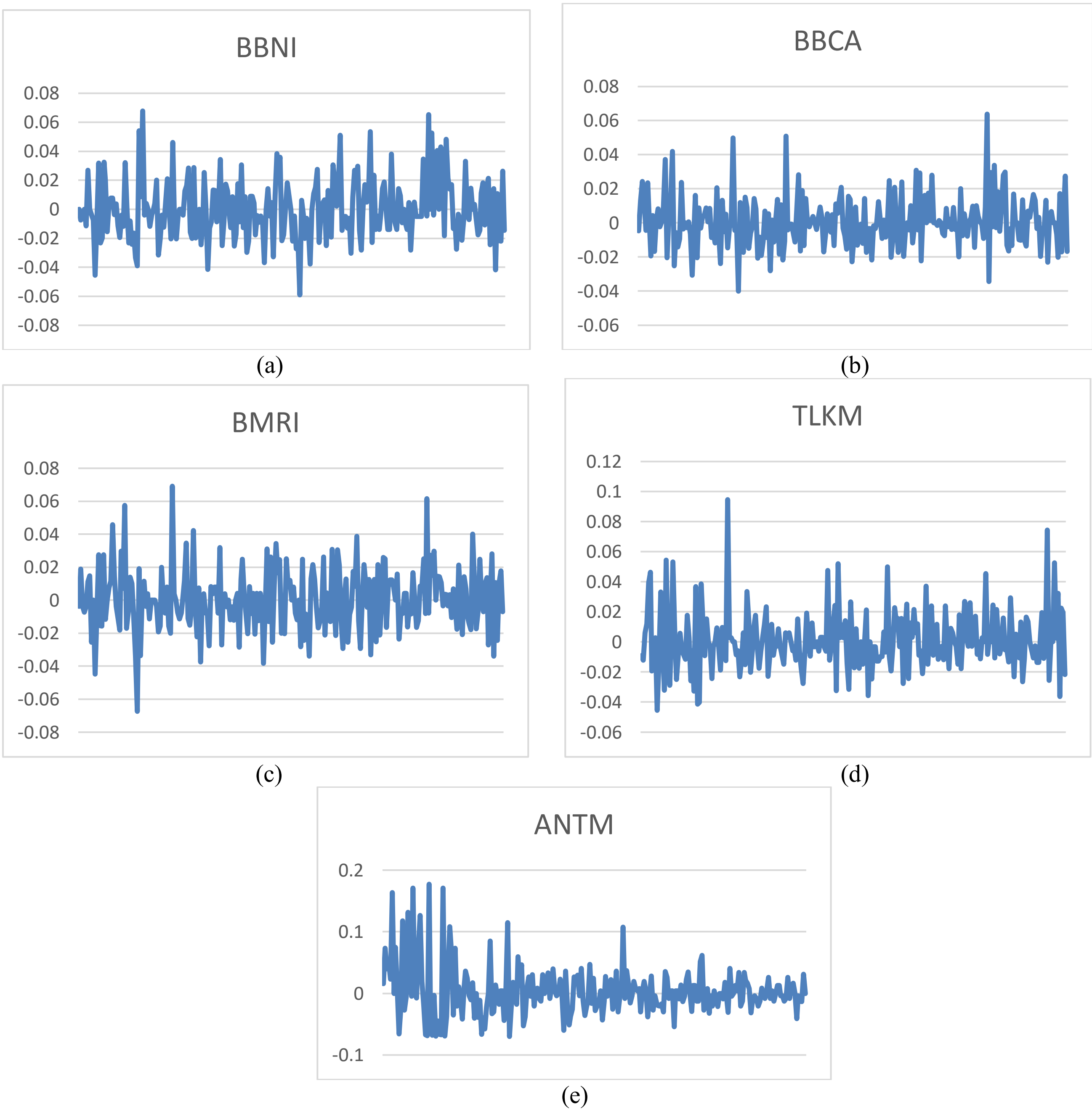

Figure 1: Data Return Plot (a. BBNI; b. BBCA; c. BMRI; d. TLKM; d. ANTM)

3.2. Methods

This study uses the Mean-Semi Standard Deviation portfolio optimization model to determine the optimal weights of five stocks listed on the Indonesia Stock Exchange. The data used in this study are the daily closing prices of BBNI, BBCA, BMRI, TLKM, and ANTM stocks, taken from the Yahoo Finance website with an observation period starting from December 7, 2023 to December 6, 2024. The data is processed to calculate the daily return of each stock, which is then used as a basis for calculating the expected return and portfolio risk.

The first stage in this study is to calculate the expected return and covariance matrix of the daily stock returns. The expected return is calculated as the average daily return during the observation period, while the covariance matrix is calculated to measure the relationship between the returns of each pair of stocks. This covariance matrix is very important in measuring portfolio risk because it reflects how stock returns fluctuate together, which contributes to the overall portfolio risk level.

After obtaining the expected return and covariance matrix, portfolio optimization is carried out using the Lagrange method. The Lagrange function is formulated by introducing Lagrange multipliers to handle the constraint that the total portfolio weight must be equal to 1. This optimization aims to maximize the expected return of the portfolio while minimizing the downside risk as measured by the semi-standard deviation. The risk aversion parameter (ρ) is used to control the risk preference of investors in this model. The last step is the evaluation of the optimal portfolio obtained by comparing the return to risk ratio (μ_p/σ_p) at various values of the parameter ρ. The calculation and optimization process is carried out using software such as Microsoft Excel to calculate daily returns, as well as Python or Matlab for calculating the covariance matrix, inverse matrix, and visualizing efficient surface graphs. This method is expected to provide an effective solution in managing stock portfolios by considering the downside risk that is more relevant to investors in the Indonesian stock market.

4. Results and Discussion

4.1. Expected Return and Covariance Matrix

The first step in portfolio optimization is to calculate the expected daily return of each stock to be included in the portfolio. Suppose there are five stocks with daily returns expressed as $r_{i,t}$ for the i-th stock at time t. The expected return of each stock is calculated using the formula:

$$\mu_i = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}$$

where:

- μ_i is the expected daily return of stock i
- T is the number of days in the observation period
- $r_{i,t}$ is the daily return of stock i at time t

Based on the data used in this study, the expected return vector (μ) for the five stocks is obtained as follows:

$$\mu = \begin{bmatrix} 0.00026 \\ 0.00062 \\ 0.00044 \\ 0.00102 \\ 0.00328 \end{bmatrix}$$

Next, the stock return covariance matrix is calculated to measure the relationship between the return fluctuations of each stock pair in the portfolio. The covariance matrix (Σ) is calculated using the formula:

$$\sigma_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left(r_{i,t} - \mu_i\right)\left(r_{j,t} - \mu_j\right)$$

The results of the covariance matrix calculation for the five stocks are as follows:

$$\Sigma = \begin{bmatrix} 0.00043 & 0.00016 & 0.00024 & 0.00013 & 0.00027 \\ 0.00016 & 0.00022 & 0.00014 & 0.00009 & 0.00008 \\ 0.00024 & 0.00014 & 0.00035 & 0.00011 & 0.00022 \\ 0.00013 & 0.00009 & 0.00011 & 0.00038 & 0.00021 \\ 0.00027 & 0.00008 & 0.00022 & 0.00021 & 0.00164 \end{bmatrix}$$

The inverse matrix of the covariance matrix (Σ^{-1}) is also calculated as part of the portfolio optimization process:

$$\Sigma^{-1} = \begin{bmatrix} 4375.57 & -1627.24 & -2038.37 & -342.57 & -323.68 \\ -1627.24 & 6959.26 & -1576.55 & -766.76 & 238.09 \\ -2038.37 & -1576.55 & 5123.83 & -280.43 & -238.94 \\ -342.57 & -766.76 & -280.43 & 3162.73 & -273.56 \\ -323.68 & 238.09 & -238.94 & -273.56 & 718.51 \end{bmatrix}$$

4.2. Portfolio Optimization Results

The portfolio optimization results show the optimal weights allocated to each stock for various values of the parameter ρ. The following table shows the results of the optimal weight allocation for certain values of ρ:

Table 1: Investment portfolio optimization results mean-semi standard deviation

ρ	BBNI	BBCA	BMRI	TLKM	ANTM	w^T e	μ_p	σ_p	μ_p/σ_p
0.1	**0.002014**	**0.550744**	**0.165699**	**0.256295**	**0.025248**	**1**	**0.000757**	**0.012936**	**0.058556**
0.2	0.002399	0.550605	0.165883	0.256204	0.02491	1	0.000756	0.012936	0.058471
0.3	0.002891	0.550427	0.166118	0.256087	0.024477	1	0.000755	0.012936	0.058362
0.4	0.003387	0.550249	0.166355	0.255969	0.024041	1	0.000754	0.012936	0.058252
0.5	0.003835	0.550087	0.16657	0.255862	0.023646	1	0.000752	0.012935	0.058152
0.6	0.004222	0.549947	0.166755	0.25577	0.023305	1	0.000751	0.012935	0.058066
0.7	0.00455	0.549829	0.166912	0.255692	0.023016	1	0.00075	0.012935	0.057994
0.8	0.004827	0.549729	0.167045	0.255626	0.022773	1	0.000749	0.012935	0.057932
0.9	0.005061	0.549645	0.167157	0.255571	0.022567	1	0.000749	0.012935	0.05788
1	0.00526	0.549573	0.167252	0.255523	0.022392	1	0.000748	0.012935	0.057836
1.1	0.005431	0.549511	0.167334	0.255483	0.022242	1	0.000748	0.012935	0.057798
1.2	0.005578	0.549458	0.167404	0.255448	0.022112	1	0.000747	0.012935	0.057765
1.3	0.005706	0.549412	0.167465	0.255417	0.021999	1	0.000747	0.012935	0.057737
1.4	0.005818	0.549371	0.167519	0.255391	0.0219	1	0.000747	0.012935	0.057712
1.5	0.005918	0.549336	0.167567	0.255367	0.021813	1	0.000746	0.012935	0.05769
1.6	0.006006	0.549304	0.167609	0.255346	0.021735	1	0.000746	0.012935	0.05767
1.7	0.006085	0.549275	0.167647	0.255327	0.021666	1	0.000746	0.012935	0.057653
1.8	0.006155	0.54925	0.16768	0.25531	0.021604	1	0.000746	0.012935	0.057637
1.9	0.006219	0.549227	0.167711	0.255295	0.021548	1	0.000745	0.012935	0.057623
2	0.006277	0.549206	0.167739	0.255281	0.021497	1	0.000745	0.012935	0.05761
2.1	0.00633	0.549187	0.167764	0.255269	0.02145	1	0.000745	0.012935	0.057598
2.2	0.006378	0.54917	0.167787	0.255257	0.021408	1	0.000745	0.012935	0.057588
2.3	0.006422	0.549154	0.167808	0.255247	0.021369	1	0.000745	0.012935	0.057578
2.4	0.006463	0.549139	0.167828	0.255237	0.021333	1	0.000745	0.012935	0.057569
2.5	0.006501	0.549125	0.167846	0.255228	0.0213	1	0.000745	0.012935	0.057561
2.6	0.006535	0.549113	0.167862	0.25522	0.021269	1	0.000744	0.012935	0.057553
2.7	0.006568	0.549101	0.167878	0.255212	0.021241	1	0.000744	0.012935	0.057546
2.8	0.006598	0.54909	0.167892	0.255205	0.021214	1	0.000744	0.012935	0.057539
2.9	0.006626	0.54908	0.167906	0.255198	0.02119	1	0.000744	0.012935	0.057533
3	0.006652	0.549071	0.167918	0.255192	0.021167	1	0.000744	0.012935	0.057527

Table 1 shows the results of investment portfolio optimization using the Mean-Semi Standard Deviation model with five stocks listed on the Indonesia Stock Exchange, namely BBNI, BBCA, BMRI, TLKM, and ANTM. The table contains the optimal weights allocated to each stock in the portfolio for various values of the risk aversion parameter (ρ). The results show that BBCA shares have the largest weight in the portfolio at almost all values of ρ, indicating that this stock is viewed as an asset that provides stable returns with lower risk compared to other stocks. In contrast, BBNI and ANTM shares have much smaller weights, indicating that both stocks tend to be more volatile or have higher downside risk.

In addition, the expected portfolio return (μ_p) and semi-standard deviation (σ_p) are relatively constant at various values of ρ, with the portfolio return hovering around 0.00075 and the portfolio risk around 0.01293. However, the return-to-risk ratio (μ_p/σ_p) shows a decrease as the value of ρ increases. This shows that the higher the investor's risk aversion preference, the lower the resulting portfolio efficiency. The highest return-to-risk ratio, which is 0.058556, is obtained at a value of ρ =0.1, indicating that a portfolio at a low risk aversion level provides the best balance between return and risk.

4.3. Interpretation of Portfolio Optimization Results Using Graphs

4.3.1. Efficient surface graph

The efficient surface graph illustrates the relationship between portfolio risk (σ_p) and expected portfolio return (μ_p) for various values of the risk aversion parameter (ρ). This graph shows how changes in the parameter ρ affect the portfolio composition and the level of optimality of the resulting portfolio. The efficient surface graph of the portfolio optimization results can be seen in Figure 2.

From the optimization results, it can be seen that a lower value of ρ produces a portfolio with a higher return to risk ratio. The graph shows that when investors have a lower risk preference (small value of ρ), they will choose a portfolio that has a more stable expected return with measurable risk. Conversely, if the value of ρ increases, the portfolio weight is more inclined to stocks with higher returns but with greater risk.

The efficient surface shows a concave shape that reflects the trade-off between return and risk. The concave part of the graph indicates that the portfolio at that point is the optimal portfolio that offers maximum return for a given level of risk. This graph confirms the basic principle in portfolio theory that greater risk tends to yield higher returns, but this trade-off can be managed by choosing optimal portfolio weights.

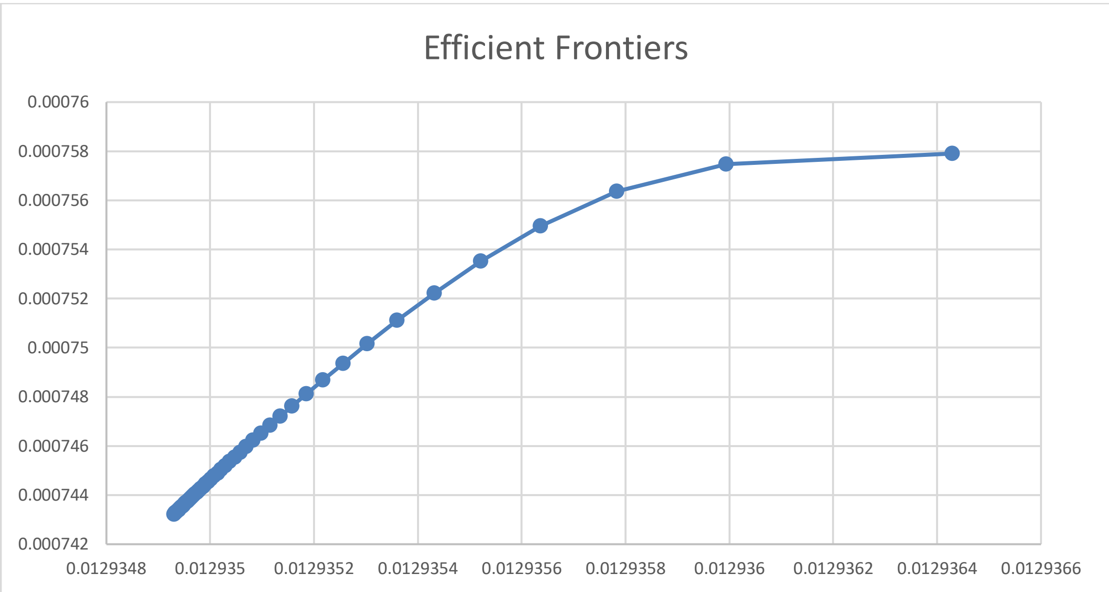

Figure 2: Efficient Frontiers Graph

4.3.2. Portfolio ratio chart

The portfolio ratio graph shows the relationship between the return to risk ratio (μ_p/σ_p) and the semi-standard deviation of the portfolio (σ_p). This graph provides important information about the efficiency of the resulting portfolio for various values of the parameter (ρ). The portfolio ratio graph resulting from the previous optimization can be seen in Figure 3.

The results of the graph show that the highest return to risk ratio is obtained at a value of $\rho = 0.1$, with a ratio value of 0.05856. This shows that portfolios formed with lower risk parameters tend to be more efficient in maximizing returns relative to the risk taken. The higher the value of ρ, the ratio decreases, which means that investors take greater risks without a significant increase in returns.

This graph also shows that changes in the value of ρ affect the distribution of portfolio weights. For example, for low values of ρ, the portfolio tends to diversify its weight more evenly among stocks with stable returns, while at higher values of ρ, the portfolio is more inclined towards stocks with higher returns but also more volatile.

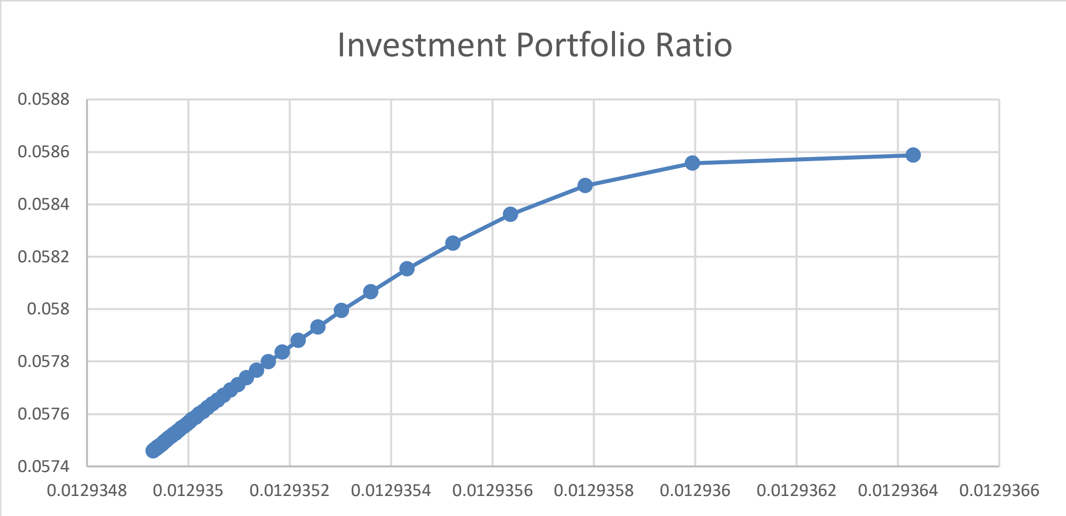

Figure 3: Investment Portfolio Ratio Graph

Overall, the efficient surface graph and portfolio ratio graph provide a clear visual representation of how the risk aversion parameter affects the asset allocation decision in a portfolio. From both graphs, it can be concluded that the optimal portfolio is generated at a low ρ value, indicating that the Mean-Semi Standard Deviation model can provide a more stable investment solution with measurable risk. This graph strengthens the argument that an approach that considers downside risk is more relevant for investors who prioritize stability in their investments, especially in a volatile market such as the Indonesia Stock Exchange.

5. Conclusion

This study has successfully applied the Mean-Semi Standard Deviation portfolio optimization model to determine the optimal investment weight allocation for five stocks listed on the Indonesia Stock Exchange, namely BBNI, BBCA, BMRI, TLKM, and ANTM. The optimization results show that the portfolio generated with a risk aversion parameter value of $\rho = 0{,}1$ provides the highest return to risk ratio (μ_p/σ_p), which is 0.058556. The optimal weight allocation at this risk aversion level is 0.550744 for BBCA, 0.165699 for BMRI, 0.256295 for TLKM, 0.002014 for BBNI, and 0.025248 for ANTM. These results indicate that BBCA shares have the largest contribution to the portfolio because they are considered to provide stable returns with lower downside risk compared to other shares. From the analysis results, it can be concluded that the Mean-Semi Standard Deviation model provides a more relevant alternative to managing portfolio risk compared to the traditional Mean-Variance model. This model pays more attention to downside risk, which is in accordance with investor preferences that tend to avoid losses rather than pursuing high profits. In the context of the Indonesian stock market, which is known to have high volatility, this model can help investors manage their portfolios better and minimize significant downside risks. This study also shows that the value of the risk aversion parameter (ρ) greatly affects portfolio composition. A lower ρ value produces a portfolio that is more efficient in maximizing returns with measurable risk, while a higher ρ value tends to produce a more conservative portfolio with a greater weighting on stocks that are considered safer.

As a recommendation for further research, it is recommended that the Mean-Semi Standard Deviation model be applied to a wider dataset, including stocks from different sectors, to see how this model works on various types of assets. Further research can also consider external factors that affect stock returns, such as interest rates, inflation, and global economic conditions. Additionally, the use of more sophisticated optimization methods, such as genetic algorithms or machine learning, can be explored to improve the accuracy and efficiency of the portfolio optimization process.

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