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Portfolio Analysis to Determine the Optimal Expected Return and Minimal Risk for Lq45 Companies Listed on the Indonesian Stock Exchange

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Keywords
optimal portfolio; single index model; lq45 shares; diversification of investments; systematic risks

Abstract
Indonesia's growing capital market provides investors with diverse opportunities; however, differences in stock returns and risks require systematic portfolio selection. This study aimed to identify LQ45 stocks that formed an optimal portfolio and determine their investment proportions during 2021–2025 using the Single Index Model. A quantitative descriptive approach was employed using secondary data obtained from the Indonesia Stock Exchange and Bank Indonesia, including monthly closing stock prices, Composite Stock Price Index (CSPI) data, and the BI Rate. Stocks were selected through purposive sampling and analyzed based on expected return, beta, residual variance, Excess Return to Beta (ERB), Cut-Off Point, and fund allocation proportion. The findings identified eight stocks as optimal portfolio constituents, namely ASII, TLKM, TOWR, PGAS, UNTR, ANTM, UNVR, and MEDC, with a Cut-Off Point value of 0.01335. PGAS achieved the highest ERB value of 6.4313, indicating the highest return efficiency relative to systematic risk. However, ASII received the largest portfolio allocation at 19%, followed by TLKM at 17%, TOWR at 15%, PGAS and UNTR at 14% each, ANTM at 8%, UNVR at 7%, and MEDC at 6%. The study concluded that the Single Index Model effectively generated a diversified, rational, and risk-conscious investment portfolio for Indonesia's post-pandemic market and provided practical allocation guidance for investors and investment managers seeking efficient investment decisions.

INTRODUCTION

Indonesia's capital market has experienced rapid development over the past decade and has increasingly become a major investment instrument for both public and institutional investors. The increase in the number of issuers, ease of access to trading through digital platforms, and availability of real-time market information have expanded investor participation in stock investment activities. However, this growth has also increased the complexity of investment decision-making, as investors are faced with a wider range of stock alternatives with varying return and risk characteristics. Research shows that information quality, financial literacy, and the use of investment information systems play important roles in improving the accuracy of investment decisions, while behavioral biases among investors remain one of the causes of suboptimal investment decisions (Dwitayanti et al., 2023; Wicaksono et al., 2024). Therefore, a systematic and quantitative investment analysis approach is needed to ensure that investment decisions are not based solely on subjective preferences but also consider the balance between potential returns and associated risks (Barua & Sharma, 2023).

In the context of the Indonesian capital market, the LQ45 index is one of the most widely used benchmarks for investment references because it consists of companies with large market capitalizations and high liquidity levels. The inclusion of stocks in the LQ45 index does not automatically indicate that all stocks have the same level of investment efficiency. Sandi et al. (2025) showed that only a small proportion of LQ45 stocks met optimal portfolio criteria after considering the relationship between return and risk. Similar findings were reported by Suhandi et al. (2025), who found that most LQ45 stocks remained below the Capital Market Line, indicating that they were unable to provide returns commensurate with the risks borne by investors. This condition demonstrates that stock selection within a leading index still requires an objective selection process through the formation of an optimal portfolio.

Theoretically, rational investment decisions are not oriented toward selecting the best individual stocks but rather toward forming asset combinations capable of generating maximum returns at a certain level of risk. This principle is the foundation of Modern Portfolio Theory (MPT), introduced by Markowitz (1952), which emphasizes that diversification is the primary mechanism for reducing unsystematic risk. In its development, this theory became the basis for various modern portfolio optimization models, including the Capital Asset Pricing Model and various risk-based asset allocation approaches (Sharpe, 1964; Boyd et al., 2024). Thus, investment efficiency is determined more by the quality of portfolio composition than by the performance of individual stocks.

Although the Markowitz Model serves as the primary foundation of portfolio theory, its application to a large number of stocks faces challenges due to the need to calculate complex covariance matrices. To overcome these limitations, Sharpe (1963) developed the Single Index Model, which simplifies the optimization process by using a single market index as a representation of systematic factors. This model requires only estimated returns, beta coefficients, residual variance, and market returns, making it more computationally efficient without eliminating the essence of optimal portfolio formation. Several studies have also demonstrated that the Single Index Model can generate portfolios with competitive risk-return characteristics compared with the mean-variance approach, particularly in emerging markets (Boyd et al., 2024).

The effectiveness of the Single Index Model has been demonstrated in various Indonesian stock indices, with relatively consistent findings indicating its ability to identify efficient stocks as optimal portfolio constituents. Putri et al. (2025) identified seven optimal stocks in the IDX30 index with an expected return of 2.99%, while Kusy and Alyssa (2025) reported eight optimal stocks in the IDX-MES BUMN 17 index that generated higher returns than the market. Research by Devi et al. (2025) on IDX Value30 and Widodo (2023) on LQ45 also showed that the number of selected stocks and fund allocation proportions varied according to index characteristics and observation periods. These findings confirm that the Single Index Model is context-dependent, as the optimal portfolio composition is strongly influenced by market dynamics and observation periods.

This state-of-the-art review shows that most previous studies have focused on optimal portfolio formation during the pre-pandemic period or the early stages of economic recovery. Putra et al. (2022) demonstrated that the COVID-19 pandemic caused significant changes in abnormal returns of LQ45 stocks due to increased market uncertainty. Tobing et al. (2024) examined portfolio formation using the CAPM approach during the post-pandemic period. At the international level, Hatemi-J et al. (2019) developed risk-adjusted return-based portfolio optimization, while Colapinto and Mejri (2024) showed that modern portfolio optimization research has shifted toward integrating risk factors, asset allocation, and more adaptive quantitative approaches. Studies specifically evaluating the efficiency of LQ45 stocks during the 2021–2025 economic normalization period using the Single Index Model remain relatively limited.

Based on the development of the literature, a clear research gap exists in three aspects. First, most Indonesian studies have used relatively short observation periods or focused only on crisis phases, making them insufficient to describe LQ45 stock behavior during a more stable economic recovery period. Second, previous research has generally stopped at identifying optimal stocks without providing a comprehensive analysis of investment proportions based on Excess Return to Beta (ERB) and the Cut-Off Point. Third, limited research has integrated post-pandemic macroeconomic dynamics, such as interest rate normalization and changes in leading sectors, into the evaluation of LQ45 portfolio efficiency. This gap highlights the need for research that provides new empirical evidence regarding optimal portfolio composition under market conditions that differ from those examined in previous studies.

Changes in macroeconomic conditions during the 2021–2025 period further strengthen the urgency of this research. Interest rate policy normalization, inflationary pressures, domestic consumption recovery, and changes in the performance of the energy, telecommunications, and automotive sectors have the potential to alter the return and risk characteristics of LQ45 stocks. Candy and Winardy (2018) showed that macroeconomic variables significantly influence LQ45 stock returns. Therefore, reassessing the efficiency of LQ45 stocks during the post-pandemic period is important to ensure that investment decisions remain aligned with current market conditions.

Based on the identified research gap, the novelty of this study lies in analyzing the formation of an optimal LQ45 stock portfolio during the 2021–2025 period using the Single Index Model by integrating five main indicators: expected return, beta, Excess Return to Beta (ERB), Cut-Off Point (C*), and fund allocation proportion. Unlike previous studies that generally only identified optimal stocks or compared optimization methods, this study produces a complete portfolio composition along with the investment weights of each stock, thereby providing more applicable information for investors in developing asset allocation strategies. Thus, this study not only contributes empirical evidence to the portfolio optimization literature in Indonesia but also expands understanding of the relevance of the Single Index Model during the economic normalization period.

Based on this background, this study aimed to identify the stocks forming an optimal portfolio within the LQ45 index during the 2021–2025 period and determine the investment proportions that produce the most efficient combination of returns and risks using the Single Index Model. The results of this study are expected to provide theoretical contributions to the development of modern portfolio studies and serve as a practical reference for investors and investment managers in making more rational and risk-based investment decisions.

METHOD

Research Design

This study employed a quantitative empirical approach to construct an optimal stock portfolio using the Single Index Model. The research analyzed the relationship between expected returns and stock risks to identify investment alternatives that provided optimal returns with minimal risk. The descriptive-quantitative research design was applied based on historical capital market data.

Populations, Samples, and Data Sources

The research population is all companies that are members of the LQ45 index on the Indonesia Stock Exchange (IDX) during the 2021–2025 period. The sample is determined using the purposive sampling technique, which is the selection of samples based on certain criteria so that the analyzed stocks meet the characteristics of optimal portfolio formation.

These criteria include companies that are consistently listed in the LQ45 index during the observation period, have *an expected return* value greater than the risk-free return rate, have a market beta value greater than zero, and have an *Excess Return to Beta* (ERB) value greater than or equal to the *Cut-Off Point* value (C*). Stocks that meet all these criteria are designated as optimal portfolio formation candidates.

Table 1. Criteria for Determining Research Samples

Yes	Sample Criteria
1	The company is listed in the LQ45 index for the period 2021–2025
2	Have *an expected return* greater than the risk-free return (Rf)
3	Have a beta value (β) greater than zero
4	Has an ERB value ≥ *Cut-Off Point* (C*)

The data used is secondary data obtained from official publications of the Indonesia Stock Exchange and Bank Indonesia. The research data includes IDX *Monthly Statistics* for the 2021–2025 period, the monthly closing price of individual stocks, the monthly Composite Stock Price Index (JCI) as the basis for calculating market returns, the monthly BI Rate as a proxy for risk-free returns, as well as beta correction and alpha stock data used in the formation of an optimal portfolio.

Variable measurement

This study uses portfolio *expected return* as the main variable in the formation of an optimal portfolio, while the analysis component consists of individual stock returns, market returns, risk-free returns, beta, alpha, residual variance, *Excess Return to Beta* (ERB), *Cut-Off Point* (C*), fund proportion, portfolio risk, and expected portfolio return. All variables were measured on a ratio scale using monthly stock price data during the observation period.

Table 2. Operationalization of Research Variables

Variable	Indicator	Scale
Individual stock returns	Monthly closing price changes	Ratio
Expected return	Average stock return	Ratio
Market returns	Monthly JCI changes	Ratio
Risk-free returns	Monthly BI Rate	Ratio
Beta (β)	Systematic risk of stocks	Ratio
Residual variance	Unsystematic risk	Ratio
Excess Return to Beta	The difference of return to Rf divided by beta	Ratio
Cut-Off Point (C*)	Portfolio selection limit value	Ratio
Proportion of funds	Investment weight per share	Ratio

Data Analysis Techniques

Data analysis was carried out using the Single Index Model developed by Sharpe to simplify the formation of optimal portfolios. This model was chosen because it is able to identify efficient stocks through the relationship between returns, systematic risk, and market returns so as to result in a combination of investments with the maximum expected return at a certain level of risk. The analysis process is carried out in stages starting from the calculation of returns to the formation of an optimal portfolio.

Determination of the Optimal Portfolio

The first stage is to calculate the return of individual stocks using changes in the monthly closing price of each stock. Individual returns are calculated by the following equation:

$$R_i = \frac{P_t - P_{t-1}}{P_{t-1}}$$

With is the return of individual shares, is the stock price of the current period, and is the stock price of the previous period. Furthermore, market returns are calculated based on changes in the Composite Stock Price Index (JCI), then the expected stock return is obtained from the average individual return during the research period. Risk-free returns are calculated using the average monthly BI Rate. Stocks are only defended in the analysis process if they have an expected return greater than the risk-free return, thus providing a positive premium return to investors. $R_i P_t P_{t-1}$

The next stage is to calculate stock beta, alpha, and residual variance as a measure of systematic risk and unsystematic risk. Beta values are used to measure the sensitivity of a stock's return to market movements, while residual variance indicates risks derived from company-specific factors. Stocks with positive beta values are maintained because they have a direct relationship with market conditions and produce ERB values that are worth further analysis. After the beta is obtained, the Excess Return to Beta (ERB) value is calculated as the basis for the stock rating. The ERB is calculated using the following equation:

$$ERB_i = \frac{E(R_i) - R_f}{\beta_i}$$

With is the expected return of the stock, is a risk-free return, and is a beta stock. A higher ERB value indicates that stocks provide a greater excess return against each systematic risk unit. $E(R_i) R_f \beta_i$

The next stage is to determine the Cut-Off Point (C*) as the limit for the selection of stocks that form the portfolio. The C* value is obtained through the accumulation of components A and B from all stocks that have been sorted based on the highest ERB value. Stocks with an ERB value greater than or equal to a C* value are designated as optimal portfolio members, while stocks with an ERB value below C* are excluded from the portfolio candidates.

After the optimal shares are selected, a calculation of the proportion of funds (Wi) is carried out to determine the investment weight of each share. The amount of the proportion of funds is calculated based on the Z value of each security so that the total investment weight amounts to 100%. The equations used are:

$$W_i = \frac{Z_i}{\sum Z_i}$$

is the proportion of the i share fund and is the weighting value obtained from the difference between the ERB and the Cut-Off Point. $W_i Z_i$

3.6 Research Analysis Flow

Overall, the research analysis procedure is carried out systematically starting from data collection to portfolio performance evaluation. This stage ensures that only stocks that meet the efficiency criteria based on the Single Index Model are selected as optimal portfolio builders.

Table 3. Stages of Analysis for Optimal Portfolio Formation

Stages	Analysis Output
1	Calculating individual stock returns
2	Calculating market returns (JCI)
3	Calculating expected return on stocks
4	Calculating risk-free (Rf) returns
5	Calculating beta, alpha, and residual variance

6	Calculating Excess Return to Beta (ERB)
7	Determining the Cut-Off Point (C*)
8	Selecting portfolio candidate stocks
9	Calculating the proportion of funds per share
10	Calculate the alpha, beta, risk, and expected return of the portfolio

RESULTS AND DISCUSSION

Portfolio Formation Stock Description

The selection results show that there are 8 stocks that meet all the criteria for optimal portfolio formation, namely having an expected return greater than the risk-free rate, positive beta, and an ERB value that meets the Cut-Off Point limit. The eight stocks come from various sectors, forming a diversified portfolio.

Table 4. Optimal Portfolio Formation Stocks

Yes	Stock Code
1	UNTR
2	TLKM
3	MEDC
4	TOWR
5	ANTM
6	UNVR
7	PGAS
8	ASII

Results of Risk and Return Indicator Calculation

The initial stage of analysis results in the beta value, residual variance, and expected return of each stock. Beta describes the systematic risk of each stock, while residual variance indicates the unsystematic risk inherent in each issuer.

Table 5. Beta, Variance, and Expected Return of Stocks

Code	Beta	Variance	Expected Return
UNTR	0.0894	0.001755	0.00238
TLKM	1.0000	0.001499	0.00200
MEDC	0.0570	0.003834	0.00737
TOWR	0.0131	0.001796	-0.00228
ANTM	0.0189	0.003183	0.00329
UNVR	0.0177	0.003708	-0.00042
PGAS	0.0438	0.001727	0.00251
ASII	0.0080	0.001269	0.00148

Based on Table 5, MEDC shares have the highest expected return of 0.00737, while UNVR and TOWR show negative expected returns. Nevertheless, all stocks still meet the analysis stage because the final selection process is determined through the ERB and *Cut-Off Point values.*

Stock Selection Based on Excess Return to Beta (ERB)

The Excess Return to Beta (ERB) value is used as a basis to determine the efficiency of each stock against the systematic risks borne by investors. The higher the ERB value, the greater the excess return obtained for each unit of risk.

Table 6. Excess Return to Beta (ERB) Value Rating

Ratings	Code	ERB Value
1	PGAS	6.4313
2	MEDC	3.5809
3	TOWR	2.9916
4	ANTM	2.8698
5	UNVR	1.2451
6	UNTR	0.5795
7	ASII	0.2892
8	TLKM	0.0915

The calculation results show that PGAS is the stock with the highest ERB value (6.4313), followed by MEDC (3.5809) and TOWR (2.9916). This value shows that the three stocks provide the highest relative return advantage compared to their systematic risks.

Cut-off Point Determination

The stock selection process is carried out using the Cut-Off Point (C*) value obtained from the accumulation of A and B values on each security. The calculation results result in a value of C* = 0.01335, which is the minimum limit of accepting shares into the optimal portfolio.

Table 7. Cut-Off Point Determination Results

Indicator	Value
Market return variance	0.000383
Cut-Off Point (C*)	0.01335
Number of selected shares	8 Shares

All eight stocks have an ERB value greater than the Cut-Off Point value, so all are designated as optimal portfolio members.

Optimal Portfolio Composition

After the optimal stock is determined, the next step is to calculate the proportion of funds (weight allocation) on each stock. The investment weight is obtained based on the Zi value so that the total fund allocation is 100%.

Table 8. Optimal Portfolio Fund Proportion

Code	Weight	Percentage
ASII	0.1918	19%
TLKM	0.1661	17%
TOWR	0.1515	15%
PGAS	0.1445	14%
UNTR	0.1396	14%
ANTM	0.0770	8%
UNVR	0.0705	7%
MEDC	0.0589	6%
Total	1.0000	100%

Table 8 shows that ASII's shares received the largest allocation of funds at 19%, followed by TLKM at 17%, while MEDC received the smallest proportion of investment at 6%.

Visualization of Portfolio Composition

The composition of the investment weights in eight stocks is presented in Figure 1 to provide an overview of the proportion of funds in the optimal portfolio.

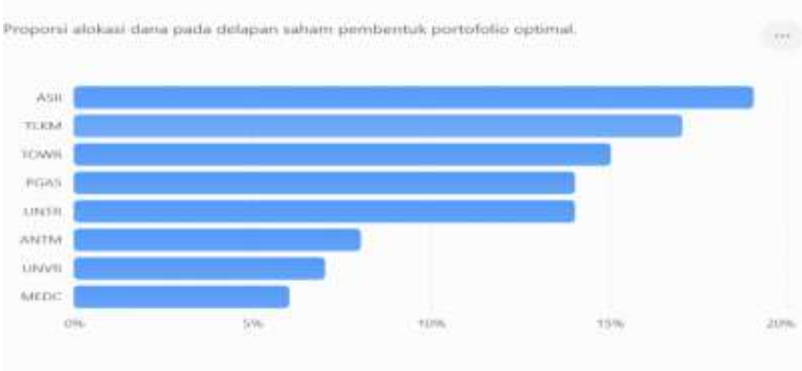

Figure 1. Optimal Portfolio Weight Distribution

The visualization shows that the investment allocation is relatively spread across eight stocks, with the largest concentration being ASII, TLKM, TOWR, PGAS, and UNTR which cumulatively make up 79% of the total portfolio. The formation of the portfolio using the Single Index Model resulted in eight optimal stocks with a Cut-Off Point value of 0.01335. PGAS shares have the highest ERB value as an indicator of return on risk efficiency, while ASII has the largest proportion of funds in the portfolio with a weight of 19%, followed by TLKM (17%) and TOWR (15%). These results are the basis for evaluating and discussing portfolio efficiency in the next section.

Optimal Portfolio Formation Yields Eight Efficient Stocks

The results of the study show that the application of the Single Index Model has succeeded in forming an optimal portfolio consisting of eight LQ45 stocks. These findings show that portfolio formation is not done by including all stocks in the index, but rather through a selection process that produces the most efficient combination of stocks based on the relationship between expected return and systematic risk.

These findings support Modern Portfolio Theory which states that rational investors should choose a combination of assets that are able to maximize returns at a certain level of risk, rather than choosing stocks with the highest returns individually (Markowitz, 1952). Sharpe (1963) then simplified the approach through the Single Index Model so that portfolio formation becomes more computationally efficient while still producing solutions that are close to the mean–variance model.

The results of this study are also consistent with the development of contemporary literature which shows that the Single Index Model remains a competitive optimization method in emerging markets. Boyd et al. (2024) assert that although various modern optimization approaches have evolved, the Markowitz–Sharpe framework is still the main foundation in institutional portfolio construction. In addition, Colapinto and Mejri (2024) through a bibliometric study found that modern portfolio optimization is still dominated by the development of Markowitz theory as the basis for various asset allocation models.

Excess Return to Beta as an Indicator of Investment Efficiency

The results show that PGAS has the highest Excess Return to Beta (ERB) value, making it the most efficient stock based on the systematic return to risk ratio. The value of ERB reflects the amount of excess return received by investors for each beta unit, so it is the main indicator in the stock selection process in the Single Index Model (Sharpe, 1963). Theoretically, beta is a systematic measure of risk that cannot be eliminated through diversification, while excess return is the compensation that investors expect for that risk (Sharpe, 1964). Therefore, the use of ERB provides a more comprehensive measure of efficiency than looking at individual returns alone because it has integrated the dimension of market risk.

This finding is in line with Yuliani and Achsani (2017) who show that the stocks with the highest ERB value are consistently the optimal portfolio members in the Jakarta Islamic

Index. Similar results were also reported by Albuquerque et al. (2023), who found that the formation of a portfolio based on a covariance matrix and risk estimation resulted in more stable performance when the selection process considered the relationship between return and risk simultaneously.

Diversification Across Sectors Lowers Portfolio Risk

The optimal portfolio consists of stocks from the automotive, telecommunications, energy, infrastructure, mining, consumer goods, and heavy equipment sectors. The composition shows that diversification is carried out across sectors so that company-specific risks can be reduced without eliminating potential investment returns. Diversification is a key principle in modern portfolio theory which states that unsystematic risk can be suppressed through a combination of assets with different characteristics (Markowitz, 1952). Brinson et al. (1986) show that asset allocation has a much greater contribution to portfolio performance than individual securities selection, so that the distribution of investments across sectors is an important factor in the formation of efficient portfolios.

The results of this study are also strengthened by Hatemi-J et al. (2019), who show that portfolio optimization based on risk-adjusted return results in more effective diversification than an evenly distributed fund strategy. Thus, the existence of eight stocks from various sectors reflects the implementation of diversification that is oriented towards risk efficiency, not on the number of assets alone.

Fund Proportions Reflect Risk and Return Optimization

ASII obtained the largest investment weight of 19%, while MEDC, which has a relatively high return, actually obtained the smallest weight of 6%. These findings suggest that investment weights are not determined by individual returns, but are the result of optimization that considers beta, residual variance, and Cut-Off Point simultaneously. In the Single Index Model, the proportion of funds is calculated using the Zi value so that each stock gains weight based on its contribution to the overall efficiency of the portfolio (Sharpe, 1963). Hammer and Phillips (1992) explained that this mechanism results in a more stable allocation of funds because the residual risk of each stock is also taken into account in the optimization process.

These findings are consistent with the research of Yuan et al. (2025) who developed a multifactor-based Black–Litterman optimization model. The study shows that the optimal investment weight is the result of the interaction between estimated returns, risks, and systematic factors so that the stocks with the highest returns do not necessarily get the largest proportion of investment. This reinforces that the decision to allocate funds is a multivariate optimization process, not just a ranking of returns.

Relevance of the Single Index Model in the Indonesian Capital Market

The results of the study prove that the Single Index Model is still relevant to be applied to the Indonesian capital market for the 2021–2025 period. The model is able to generate efficient portfolios through relatively simple analysis procedures, making it feasible to use as an alternative optimization method for individual investors and investment managers.

Recent developments in the literature show that portfolio optimization has evolved, Bertsimas et al. (2012) assert that modern optimization models still depart from the Markowitz mean–variance framework as its mathematical foundation. Boyd et al. (2024) also concluded that for more than seven decades, Markowitz's theory was still the dominant paradigm in institutional portfolio construction.

This study is expected to make an empirical contribution by showing that the Markowitz–Sharpe framework remains effective in emerging markets such as Indonesia, especially in post-economic market conditions characterized by interest rate changes and relatively high volatility.

Practical Implications for Investors

From a practical perspective, the results of the study show that an investment strategy based on the Single Index Model is able to produce a more rational portfolio composition than intuitive stock selection. Investors obtained fund allocation guidelines of 19% in ASII, 17% in TLKM, 15% in TOWR, 14% in PGAS, 14% in UNTR, 8% in ANTM, 7% in UNVR, and 6% in MEDC so that investments are spread across several sectors with different risk characteristics.

These results are in line with Black and Litterman (1992) who stated that investment decisions should be oriented towards asset allocation, not just individual stock selection. In addition, Barua (2023) shows that the combination of market information and risk estimation can improve the quality of investment decisions because it produces a portfolio with better risk-adjusted returns. The application of the Single Index Model can be a practical alternative for Indonesian investors in compiling efficient portfolios based on historical market data.

CONCLUSION

The study concluded that the Single Index Model successfully identified eight LQ45 stocks as components of the optimal portfolio for the 2021–2025 period: ASII, TLKM, TOWR, PGAS, UNTR, ANTM, UNVR, and MEDC. With a Cut-Off Point value of 0.01335, PGAS recorded the highest Excess Return to Beta (ERB) value, indicating the highest return efficiency relative to systematic risk. Nevertheless, ASII received the largest portfolio allocation because the portfolio weights were determined jointly based on expected return, beta, residual variance, and the Cut-Off Point value. The resulting allocations were 19% for ASII, 17% for TLKM, 15% for TOWR, 14% each for PGAS and UNTR, 8% for ANTM, 7% for UNVR, and 6% for MEDC. This cross-sector composition demonstrated that the Single Index Model remained effective for constructing a diversified and risk-conscious portfolio in Indonesia's post-pandemic capital market.

Future research should evaluate portfolio performance using out-of-sample data and compare realized returns with relevant benchmarks, such as the LQ45 Index and the Composite Stock Price Index (CSPI), using risk-adjusted performance measures, including the Sharpe, Treynor, and Jensen indices. Researchers should also compare the Single Index Model with other portfolio optimization approaches, such as the Markowitz Model, Black–Litterman Model, and multifactor models, while incorporating transaction costs, liquidity constraints, macroeconomic variables, and varying market conditions. Furthermore, subsequent studies should apply rolling observation periods and robustness tests to examine whether the selected stocks and portfolio weights remain stable over time. Future research should also verify the consistency between the stated selection criterion of expected returns exceeding the risk-free rate and the inclusion of stocks with negative expected returns.

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