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Portfolio Optimization across Various Types of Variance-Covariance Matrices Using The Sequential Quadratic Programming (SQP)

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ABSTRACT

This study analyzes stocks provided in LQ45 index and compares the performance of ten stocks with highest expected returns between Danantara and non-Danantara groups. The data are used to estimate parameters for optimization. The Markowitz model is employed to construct portfolios based on risk and expected return, requiring the derivation of a variance-covariance matrix. This matrix is compared with those generated by the Single Index Model (SIM) and Constant Correlation Model to evaluate differences among approaches. The nonlinear optimization problem is solved using Sequential Quadratic Programming (SQP). At an expected return of 0.2597%, all matrices allocate weights to a single stock, while setting it to zero changes portfolio proportions without altering the Sharpe ratio.

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1. Introduction

The dynamics of the financial market, which are shaped by uncertainty in monetary policy, geopolitical tensions, and shifts in global sentiment, require investment decisions to be made with greater discipline and on the basis of rigorous risk measurement. The Financial Services Authority (OJK) reported that, at the close of trading in 2025, the Indonesia Composite Index (IHSG) stood at 8,644.26, representing an increase of 22.10% compared with the closing level in

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2024. OJK also recorded that market capitalization exceeded IDR 15,810 trillion, reflecting a 28.16% increase relative to 2024. In addition, OJK reported strong growth in retail investors throughout 2025, with an additional 5.34 million new investors, bringing the total number of investors to approximately 20.2 million Single Investor Identification (SID) accounts, of which 79% were from individuals under the age of 40 (OJK, 2025). KSEI further recorded that, by the end of December 2025, the total number of SID accounts had reached 20,347,147 (Kustodian Sentral Efek Indonesia, 2025). This growth has broadened market participation while simultaneously increasing the need for portfolio strategies capable of balancing returns and risks in a measurable manner, particularly when investment decisions are made by investors with heterogeneous levels of financial literacy and risk tolerance.

From a theoretical perspective, the need can be explained by the Markowitz model, which positions portfolio selection as a trade-off between expected return and risk. Portfolio return is defined as the weighted average of asset returns, whereas portfolio risk is determined not only by the variance of each individual asset but also by the relationships among assets as summarized in the variance-covariance matrix. This foundation suggests that the quality of a portfolio solution is highly dependent on how the variance-covariance matrix is constructed. Sun et al. (2019) emphasized that portfolio risk measurement in many models depended on variance and inter-stock relationships represented by the variance-covariance matrix. This argument connects investors' practical needs with the technical demands of research, because the accuracy of the variance-covariance matrix directly influenced the portfolio weights selected (Sun et al., 2019).

In practice, variance-covariance matrices derived from historical data are often estimated using sample covariance. However, this approach may yield unstable values when the number of stocks is large or the available data period is limited. Neffelli (2018) argued that risk-based portfolio weights may still vary due to misspecification in sample covariance, indicating the need to explore alternative matrices with more structured characteristics (Neffelli, 2018). Similarly, Nguyen et al. (2022) showed that a shrinkage-based covariance approach can improve portfolio selection in high-dimensional cases by reducing the instability inherent in sample covariance estimates (Nguyen et al., 2022). These findings highlight the importance of comparing several methods for constructing variance-covariance matrices within a unified analytical framework.

One of the most frequently used forms of simplification is the Single Index Model (SIM). It is employed because it simplifies the relationships among stocks through a single market factor. Neffelli (2018) included SIM as one of the target matrices that can be used to construct a covariance matrix that is more structured than sample covariance (Neffelli, 2018). Research on LQ45 stocks in Indonesia has also applied the single-index model to construct an optimal portfolio, indicating that the SIM approach remains relevant in the context of domestic stock market data. This connection provides a basis for examining whether the simplification of covariance structure can still produce reasonable portfolio weights over a more recent data period.

Another alternative is the Constant Correlation model, which simplifies the correlations among stocks by assuming that they are relatively uniform, and then constructs the covariance matrix from the variance of each stock and the common correlation coefficient. Neffelli (2018) also included the constant correlation

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approach as a target in the construction of a more stable matrix (Neffelli, 2018). Devita et al. (2024) applied the constant correlation model to construct an optimal portfolio and calculate expected shortfall risk for stocks in the IDX30 index, suggesting that this approach has practical relevance to the characteristics of the Indonesian market (Devita et al., 2024). This discussion leads to an important question, namely whether such a simplification of correlation remains sufficiently reliable when the data exhibits rapid changes in volatility.

The next stage is to formulate the portfolio optimization problem by defining an optimization objective that captures the trade-off between return and risk. One approach is to formulate the problem as a multi-objective optimization model, in which expected return is maximized while portfolio risk is minimized simultaneously, producing a set of Pareto-optimal portfolios (Mustika et al., 2021). Alternatively, conflicting objectives can be combined into a single performance measure. Among such formulations, the Sharpe ratio is one of the most widely used performance measures in portfolio optimization because it evaluates the excess return earned for each unit of portfolio risk.

Mousavi & Michailidis (2025) defined the Sharpe ratio as the ratio between the average excess return and the standard deviation of excess return over the same period, such that a higher ratio indicates greater additional return for each unit of risk borne by the investor. In practice, the problem of maximizing the Sharpe ratio almost always requires constraints, particularly the constraint that the sum of portfolio weights equals one and the constraint that portfolio weights are non-negative so that the portfolio is long-only. The ratio form of the objective function, together with the presence of constraints, places this problem within the domain of constrained nonlinear optimization.

Consequently, an optimization algorithm capable of handling constrained nonlinear problems is required. One such method is Sequential Quadratic Programming (SQP). Joshy & Hwang (2024) explained that SQP solves constrained nonlinear optimization problems by formulating and solving a sequence of quadratic subproblems iteratively, making SQP suitable for problems that require strict satisfaction of constraints (Joshy & Hwang, 2024). The SQP method is also appropriate for the present study because a consistent optimization procedure is required when comparing several forms of variance-covariance matrices.

This study examines the portfolio optimization problem through a comparison of variance-covariance matrices. The standard variance-covariance is compared to SIM-based covariance and constant correlation using the SQP approach as the optimization framework. The study uses stocks included in the LQ45 index because the index consists of 45 highly liquid stocks and reflects company size measured on the basis of the proportion of shares outstanding and publicly tradable (free float), while also applying a clear selection methodology. The stocks are then classified according to the needs of the analysis into Danantara, companies belong to governmental institution, and non-Danantara groups, so that the comparison of portfolio outcomes would be more informative. Preliminary calculations on the data show that the risk of each stock and the relationships among stocks can differ substantially. Therefore, differences in the method used to construct the variance-covariance matrix may alter portfolio weights, portfolio risk values, and performance ratio outcomes. The novelty of this study lies in the uniform comparison of these three matrix approaches within a single SQP-based constrained optimization framework using recent Indonesian stock market data.

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2. Method

This study uses daily closing price stock data from companies included in the LQ45 index, as the index comprises 45 stocks characterized by relatively large market capitalization, high liquidity, and periodic selection by the Indonesia Stock Exchange (Indonesia Stock Exchange, 2024). The stocks were classified into Danantara and non-Danantara groups based on various variance-covariance matrices so that the portfolio analysis using Sharpe ratio and SQP could compare risk and return behavior across groups more clearly.

2.1. Risk-Free Interest Rate Conversion

In this study, the Bank Indonesia policy rate (BI 7-Day Reverse Repo Rate) is used as a proxy for the risk-free rate because Bank Indonesia officially publishes the benchmark interest rate and its applicable period. It requires to convert the monthly interest rate, denoted by i, into a daily interest rate, denoted by c, for each policy period using the compound interest formula

$$c = (1+i)^{\frac{1}{m}} - 1 \tag{1}$$

where m denotes the number of days in one conversion period.

2.2. Return Measurement

Daily returns as the basis for the analysis reflect relative changes in value and facilitate comparisons across stocks with different price levels. The log return of stock i on day t is calculated using the formula based the closing price $P_{t,i}$ as (Benninga & Mofkadi, 2022; Erawati et al., 2022)

$$r_{t,i} = \ln\left(\frac{P_{t,i}}{P_{t-1,i}}\right). \tag{2}$$

2.3. Mean Return and the Excess Return Matrix

The next step is to construct the mean return and centered return data so that the variance-covariance matrix can be developed consistently. The mean return for each stock $E[r_i]$ is written as follows

$$E\left[r_i\right] = \frac{1}{n}\sum_{t=1}^{n} r_{t,i} \tag{3}$$

where $r_{t,i}$ denotes the return of stock i at day t while n denotes the number of observation days in the dataset (Benninga & Mofkadi, 2022; Sun et al., 2019). The excess return matrix A is defined as the difference between daily return and the mean return of each stock which is formulated as

$$A = \begin{bmatrix} r_{11} - E[r_1] & \cdots & r_{1n} - E[r_n] \\ \vdots & \ddots & \vdots \\ r_{t1} - E[r_1] & \cdots & r_{tn} - E[r_n] \end{bmatrix}. \tag{4}$$

2.4. Variance-Covariance Matrix

Accordingly, the variance-covariance matrix is obtained as follows (Benninga & Mofkadi, 2022)

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$$S = \frac{A^T \cdot A}{n-1}. \tag{5}$$

The denominator $n-1$ is applied because sample covariance requires degrees of freedom in order to produce an unbiased estimator for a finite sample size.

2.5. Alternative Variance-Covariance Matrices

This study compares standard matrix, i.e. Eq. (5), with two other matrices, namely the Single-Index Model (SIM), and Constant Correlation, Shrinkage. These two alternatives were selected because each provides a different approach to estimate sample covariance.

1. Single-Index Model (SIM)
   This study models stock returns as a combination of market effects and stock-specific components through the following regression
   $$\tilde{r}_i = \alpha_i + \beta_i r_m + \varepsilon_i \tag{6}$$
   where r_m denotes the return of the benchmark market index, β_i represents the sensitivity of stock i to market movements, and ε_i denotes the residual term. The SIM covariance matrix (Benninga & Mofkadi, 2022) is then constructed by
   $$(\sigma_{ij})_{\text{sim}} = \begin{cases} \sigma_m^2 \beta_i \beta_j, & i \neq j \\ \sigma_i^2, & i = j \end{cases} \tag{7}$$
   where σ_m^2 denotes the variance of market returns, β_i is formulated as
   $$\beta_i = \frac{Cov(r_i, r_m)}{\sigma_m^2}.$$
2. Constant Correlation
   This study constructs a correlation matrix under the assumption that correlations among stocks are relatively uniform. The average correlation, denoted by $\bar{\rho}$, is calculated from pairwise stock correlations, and the covariance matrix is then formed as follows (Devita et al., 2024)
   $$(\sigma_{ij})_{\text{cc}} = \begin{cases} \rho \sigma_i \sigma_j, & i \neq j \\ \sigma_i^2, & i = j \end{cases} \tag{8}$$
   for $i \neq j$, where $s_i$denotes the standard deviation of the return of stock i.

2.6. Portfolio Performance and Risk Measures

The expected portfolio return is calculated (Benninga & Mofkadi, 2022) as

$$E(r_p) = \sum_{i=1}^{n} w_i \bar{r}_i \tag{9}$$

where w_i denotes the weight of the i-th stock and $\bar{r}_i$ denotes the mean return of the i-th stock. Hence, the portfolio variance is

$$\text{Var}(r_p) = w^T S w \tag{10}$$

while the portfolio standard deviation is given by $\sigma_p = \sqrt{w^T S w}$.

Before counting the proportion w, we have to solve linear system

$$Sz = E[\boldsymbol{r}] - c\mathbf{1} \tag{11}$$

where $E[\boldsymbol{r}]$ is an expected return vector and $\mathbf{1}$ is a vector of ones. The weights are then normalized as

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$$w_i = \frac{z_i}{\sum_{j=1}^{n} z_j}. \tag{12}$$

2.7. Envelope Portfolio

An envelope portfolio consists of risky assets giving the lowest variance of return among all portfolio containing the equal expected return (Benninga & Mofkadi, 2022). For two arbitrary envelope portfolios, assume $x = (x_1, x_2, \dots, x_n)$ and $y = (y_1, y_2, \dots, y_n)$, there is another envelope governed by

$$\phi = ax + (1-a)y \tag{13}$$

where a is a constant.

2.8. Sharpe Ratio

This study maximizes the portfolio Sharpe ratio using the following expression

$$\Theta(w) = \frac{E(r_p) - c}{\sigma_p} \tag{14}$$

with

$$E(r_p) = w^T R,$$

$$\sigma_p = \sqrt{w^T S w}.$$

where $E(r_p)$ denotes the expected portfolio return, R denotes expected return vector for stocks, σ_p denotes portfolio risk, and c denotes the daily risk-free rate (Benninga & Mofkadi, 2022; Xu, 2025).

2.9. Sequential Quadratic Programming (SQP)

Sequential Quadratic Programming (SQP) is one of the most widely used methods for solving constrained nonlinear optimization problems. The main idea of SQP is to approximate the original nonlinear optimization problem at each iteration by a quadratic programming (QP) subproblem constructed from the Lagrangian function and the linearization of the constraints (Berahas et al., 2025; Winston, 2022)

Consider the constrained nonlinear optimization problem

$$\min_{x \in \mathbb{R}^n} f(x)$$

subject to

$$h(x) = 0$$

where $f: \mathbb{R}^n \to \mathbb{R}$ is the objective function and $h: \mathbb{R}^n \to \mathbb{R}^m$ denotes the constraint functions. The associated Lagrangian function is defined as

$$L(x, \lambda) = f(x) + \sum_{i=1}^{m} \lambda_i h_i(x),$$

with λ representing the Lagrange multipliers.

At iteration k, SQP constructs a quadratic approximation of the objective function together with a linear approximation of the constraints, leading to the following QP subproblem

$$\min_d \nabla f(x^k) d + \frac{1}{2} d^T \nabla_x^2 L(x^k, \lambda^k) d$$

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subject to

$$h\left(x^k\right)+\nabla h\left(x^k\right)d=0,$$

where $d = x^{k+1} - x^k$ denotes the search direction. The solution of the QP subproblem is then used to update the decision variables iteratively until convergence is achieved. SQP algorithm is particularly suitable for constrained portfolio optimization because it can efficiently handle nonlinear objective functions while maintaining strict satisfaction of the portfolio constraints.

3. Results and Discussion

3.1. Data

The stock data from companies are included in the LQ45 index over the observation period from 18 October 2024 to 31 December 2025. Daily closing price data were obtained from Yahoo Finance through its historical data download facility, allowing the study to construct consistent price time series and calculate returns for each stock. The problem is classified the sample stocks into two categories, namely Danantara stocks and non-Danantara stocks which both of those are limited to 10 highest stock returns. At the initial stage, the data presentation displays stocks in the Danantara and non-Danantara category in Table 1 as a representation of the expected return used in the portfolio analysis.

As it seen in Table 1, the non-Danantara cluster has non-negative expected return for all top ten highest return over observed period, but it is different on Danantara one which has only three stocks with positive return. The top return of both groups is ANTM and BRPT with return 0.2314% and 0.4073% respectively. In the other side, BMRI has return -0.01194% which is the lowest in Danantara category while MEDC has slightly more than zero at 0.0106% as the lowest in another category.

Table 1. Expected Return of Stock in Danantara and non-Danantara Group

Danantara		non-Danantara	
Stock	**Return**	**Stock**	**Return**
PGAS	0.0787%	ADMR	0.0304%
BBNI	-0.0898%	ASII	0.1080%
BMRI	-0.1194%	BRPT	0.4073%
BBRI	-0.1070%	INCO	0.0797%
BBTN	-0.0854%	INKP	0.0115%
TLKM	0.0404%	JPFA	0.1703%
JSMR	-0.1217%	MBMA	0.0189%
ANTM	0.2314%	MEDC	0.0106%
PGEO	-0.0062%	UNTR	0.0345%
PTBA	-0.0972%	UNVR	0.0383%

3.2. Daily Interest Rate Conversion

This study employs the BI 7-Day Reverse Repo Rate as a proxy for the risk-free rate, as Bank Indonesia sets this benchmark policy rate and publishes its revisions periodically. The time unit of the interest rate is aligned with the daily stock return data to ensure that the risk-free adjustment in the portfolio model is applied consistently. Bank Indonesia provides official statistical information on the benchmark interest rate, as in Table 2, indicator together with its effective dates (Indonesia Bank, 2026).

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Table 2 shows interest rate issued by Bank Indonesia over interval period. In the interval October 16th, 2024 until November 20th, 2024, the interest rate is 6.00%. There are 25 business days in that period so that by using Eq. 1, the daily interest rate is 0.2333%. For the other periods, the same process is applied to obtained other results.

Table 2. Daily Interest Rate

Date	Days	Interest Rate	Daily Interest Rate
16/10/2024	25	6.00%	0.2333%
20/11/2024	19	6.00%	0.3071%
18/12/2024	18	6.00%	0.3242%
15/01/2025	23	5.75%	0.2433%
19/02/2025	20	5.75%	0.2799%
19/03/2025	24	5.75%	0.2332%
23/04/2025	20	5.75%	0.2821%
21/05/2025	19	5.50%	0.2822%
18/06/2025	19	5.50%	0.2822%
16/07/2025	25	5.25%	0.2049%
20/08/2025	19	5.00%	0.2571%
17/09/2025	25	4.75%	0.1858%
22/10/2025	20	4.75%	0.2323%
19/11/2025	19	4.75%	0.2445%
17/12/2025	10	4.75%	0.4651%
02/01/2026	-	4.75%	-

3.3. Envelope Portfolio

An envelope portfolio can be generated through two envelope portfolios. Based on Eq. 11 and 12 which is the standard model, we assume the first one, x portfolio, is calculated with $c = 0$ while the other, y portfolio, is obtained where $c = 0.2597\%$ is the mean of daily rate from Table 2. The result both of x and y portfolio for Danantara and non-Danantara stocks can be seen at Table 3. Only x portfolio at Danantara group has proportion less than -1 and more than 1.

Table 3. Danantara and non-Danantara Portfolio

Danantara		non-Danantara	
x	y	x	y
-1.287	0.002	0.009	0.042
-0.549	-0.069	0.618	0.181
0.892	0.210	0.540	0.234
0.759	0.120	0.105	-0.0157
0.001	0.006	-0.146	0.152
1.398	0.001	0.390	0.041
-0.653	0.341	-0.098	0.062
-1.095	-0.122	-0.221	0.382
-0.035	0.064	-0.113	0.323
1.569	0.445	-0.084	0.067

In case of Danantara, the weight of x yields risk at 5.823% and expected return at -0.842% while the weight of y yields risk at 1.856% and expected return at 0.349%. In the other hand, x and y portfolio of non-Danantara results pairs of risk and expected return at $(2.676\%, 0.349\%)$ and $(1.846\%, -0.308\%)$ respectively as

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it seen at Figure 1.

By functioning Eq. 13 with constant a lying on interval $[-3,3]$, the envelope, set of all envelope portfolio, can be plotted as pair of risk σ and expected return μ as in Figure 1. In Danantara case, it provides narrower feasible region, inside convex plot, than non-Danantara does. It affects the choices of number of portfolios. The envelope of Danantara also has the lowest risk at 1.284% with expected return at -0.318%. On the other side, the non-Danantara one has slightly higher the lowest risk at 1.378% with higher expected return at -0.045%.

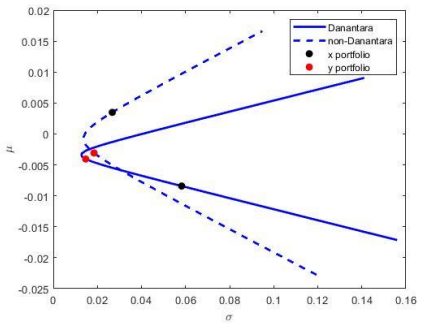
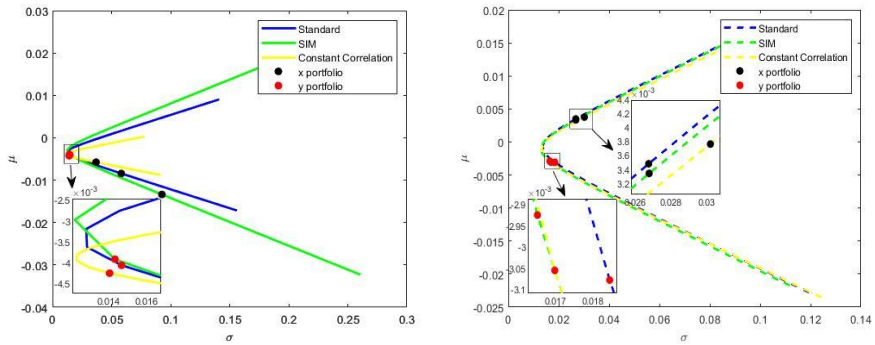


Figure 1. The Envelope of Danantara and non-Danantara

In Figure 2 (a), SIM provides wider region while constant correlation model provides narrower region than the standard does. SIM affects the original envelope expand, but constant correlation affects the original one shrink. Both the alternatives impact to lower risk on the lowest risk on each enveloped compared with the original, but SIM gives higher expected return while constant correlation gives lower one. It is quite different in Figure 2 (b), it is almost nothing to change unless small movement from the original envelope caused by both two alternative matrices.



(a) (b)

Figure 2. Comparison Three Variance-Covariance Matrices on The Envelope of (a) Danantara and (b) non-Danantara

3.4. SQP Optimization

To determine the optimal portfolio, the Sequential Quadratic Programming (SQP) algorithm is used to maximize the Sharpe ratio, which measures the excess return per unit of portfolio risk. In this study, the SQP implementation was performed using the 'fmincon' function available in MATLAB software. Since the MATLAB 'fmincon' solver is designed for minimization problems, the negative Sharpe ratio is adopted as the objective function. In other words, the optimized objective

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function is

$$\min\left(-\frac{w^T R - c}{\sqrt{w^T S w}}\right)$$

subject to

$$\sum_{i=1}^{n} w_i = 1,$$

$$w_i \geq 0.$$

The initial point for the SQP algorithm is taken from the envelope portfolio generated by each covariance estimation method. Consequently, different covariance matrices employ different initial portfolios. In Eq. (15), S represents the covariance matrix. Three different variance-covariance matrices obtained from the standard model, the Single Index Model (SIM), and the Constant Correlation model are used. Therefore, six optimization problems are solved, corresponding to the three covariance estimation methods applied to each of the two stock groups.

When the risk-free rate c is set to 0.2597%, the SQP optimization produced the same optimal portfolio for all three matrices methods. In the Danantara stock group, the optimal portfolio allocates all investment to the eighth stock ($w_8 = 1$), resulting in a Sharpe ratio of -0.864%, a risk of 3.275%, and an expected return of 0.231%,. In contrast, the optimal portfolio for the non-Danantara stock group allocates all investment to the third stock ($w_3 = 1$), with a Sharpe ratio of 3.738%, a risk of 3.949%, and an expected return of 0.407%. These results indicate that the optimal portfolio for the non-Danantara stock group outperforms than that of the Danantara stock group, as reflected by its higher Sharpe ratio.

Table 4. Optimal Portfolio on The Danantara Stock for The Three Covariance Approaches

Matrix	Standard	SIM	CC
w_1	0.381	0.428	0.375
w_2	0	0	0
w_3	0	0	0
w_4	0	0	0
w_5	0	0	0
w_6	0.007	0	0
w_7	0	0	0
w_8	0.621	0.572	0.625
w_9	0	0	0
w_{10}	0	0	0
$E[r_p]$	0.172%	0.166%	0.174%
σ	2.296%	2.158%	2.341%
$\Theta(w)$	-0.864%	-0.864%	-0.864%

When the risk-free rate, c, is assumed to be zero, the optimization results obtained using the SQP method for the three covariance estimation methods across the two stock groups (Danantara and non-Danantara) are presented in Table 4 and Table 5. Comparing the two stock groups, the non-Danantara portfolio consistently outperforms the Danantara portfolio. Specifically, the non-Danantara portfolio achieves a positive Sharpe ratio of 3.738%, whereas the Danantara

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portfolio produces a negative Sharpe ratio of -0.864%. This finding suggests that, under the assumption of a zero risk-free rate, the non-Danantara stocks provide a more favorable return-to-risk trade-off regardless of the covariance estimation method employed.

Table 5. Optimal Portfolio on The non-Danantara Stock for The Three Covariance Approaches

Matrix	Standard	SIM	CC
w_1	0	0	0
w_2	0.352	0.311	0.344
w_3	0.383	0.397	0.411
w_4	0	0	0
w_5	0	0	0
w_6	0.265	0.292	0.245
w_7	0	0	0
w_8	0	0	0
w_9	0	0	0
w_{10}	0	0	0
$E[r_p]$	0.239%	0.245%	0.246%
σ	1.965%	2.036%	2.104%
$\Theta(w)$	3.738%	3.738%	3.738%

4. Conclusions

Overall, the envelope of Danantara has lower expected return than the one of non-Danantara at the same risk. It also provides lower risk, but provides lower expected return at the lowest risk of the envelope compared with the envelope of non-Danantara. In Danantara case, SIM establishes larger feasible area and expands, but constant correlation establishes smaller one and shrinks.

In implementing the SQP, when c equal to 0.2597% is applied, all of three approach matrices lead to weight to the eighth stock with Sharpe ratio -0.864% in Danantara stock group, but in case of non-Danantara group, it allocates weight to the third stock with Sharpe ratio 3.738%. In addition, the Sharpe ratio for Danantara and non-Danantara group is not altered for three various matrices when $c = 0$. In the contrary, the weight on both Danantara and non-Danantara are slightly scattered when c is equal to 0.

Author Contributions

Lutfi Mardianto: Conceptualization, Methodology, Validation, Software, Writing - original draft; **Mira Mustika:** Validation, Software, Writing - review & editing; **Eristia Arfi**: Supervision, Validation; **Ramanda Ditra Kristian:** Data curation, Software, Writing - review & editing, **Nayla Nurul Aisyah:** Data curation, Resources; **Prismahardi Aji Riyantoko**: Software, Supervision, Validation.

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Declaration of Competing Interest

There is no conflict of interest in writing this article.

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