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IDX30 Stock Portfolio Optimization Using the Mean-Semivariance Method

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ABSTRACT: Mean-semivariance is a portfolio optimization method developed from the mean-variance method. Mean-semivariance method is free from assumptions and this method measures portfolio risk by using semivariance and semideviation. IDX30 is an index that measures the price performance of the best stocks in Indonesia. IDX30 is composed of 30 stocks with relatively large market capitalization, high liquidity, and good fundamentals. Stocks that have consistently been included in the IDX30 for five years (2018-2022) are optimized using the mean-semivariance method. The optimal portfolio is formed by allocating the weight of each stock to get the smallest risk. Based on the calculation, the optimal portfolio with the best performance is a portfolio composed of ADRO, ICBP, and PGAS stocks, with the Sharpe index of 0.083507. The weight for each stock in this portfolio is 16.1039% for stocks of PT Adaro Energy Indonesia Tbk (ADRO), 57.5554% for stocks of PT Indofood CBP Sukses Makmur Tbk (ICBP), and 26.3407% for stocks of PT Perusahaan Gas Negara Tbk (PGAS).

KEYWORDS: Portfolio, Mean-Semivariance, IDX30

1. INTRODUCTION

Modern developments require humans to innovate, including innovating in utilizing income. People must be good at managing their income to make it useful not only in the present but also in the future. One way to maximize the benefits of income is to invest. Investment is a commitment of a certain amount of funds or other resources made in the present, to get a certain amount of profit in the future (Tandelilin, 2010). Through investment, investors will obtain profits or benefits from future increases in asset prices.

Investments can be made in the capital market. The capital market is a market that sells various financial instruments also known as long-term securities, whether in the form of debt or private capital, whether issued by the government, public authorities, or private companies (Husnan, 1998). The activity of buying and selling financial instruments (securities) occurs in a place known as the stock exchange. According to Law of the Republic of Indonesia Number 8 of 1995 concerning Capital Markets chapter 1 verse 5, securities include debt recognition letters, commercial securities, stocks, bonds, proof of debt, participation units in collective investment contracts, futures contracts on securities, and any derivatives of securities. One of the financial market instruments that is very popular and is the choice of investors is stocks. This is because stocks are able to provide very attractive profits (Sudarmanto et al., 2021). Darmadji and Fakhruddin (2001) stated that stocks are a sign of ownership or participation of an individual or group in a limited liability company.

To maximize profits (returns) and minimize risks, investors can diversify. Through diversification, investors are ordered not only to invest in one asset, but to invest in several assets. Diversification is carried out by forming an optimal portfolio. The optimal portfolio is obtained by selecting the best portfolio among a collection of efficient portfolios.

Markowitz (1959) is one of the inventors of the portfolio formation method by emphasizes the relationship between risk and return. Markowitz introduced the mean-semivariance method which is a development of the mean-variance method. This method is almost the same as mean-semivariance, only this method is free from all kinds of assumptions. Mean-semivariance uses semivariance as a measure of risk.

Several previous studies related to portfolio formation using the mean-semivariance method have been carried out, including by Entrisnasari (2015), Pandi (2020), Chrisnadewi (2021), and Kumar et al. (2022). Entrisnasari (2015) forms a mean-semivariance portfolio involving stocks that are members of the Jakarta Islamic Index (JII). In that research, the selection of stocks to make up the portfolio was carried out by looking at the return and risk of the stocks of the stocks as a whole without looking at the relationship between the stocks. According to Husnan (1998), the effectiveness of risk reduction is partly caused by the correlation coefficient of the stocks used to form the portfolio. Therefore, in this research, the correlation coefficient was also calculated to select stocks that make up the portfolio. Pandi (2020) forms a portfolio using the mean-variance and mean-semivariance methods. This research shows that the return generated from the mean-semivariance portfolio is better than the mean-variance portfolio. This research also shows that the risk of a mean-semivariance portfolio is smaller than a mean-variance portfolio for the same level of return. In addition, the performance of the portfolio with Sharpe and Sortino ratios shows that the performance of the mean-semivariance portfolio is better than the mean-variance portfolio. This supports the need to carry out research again using the mean-semivariance method. Chrisnadewi (2021), forms a mean-semivariance portfolio involving stocks that are members of PEFINDO25. In this research, portfolio performance was not calculated. So in this research, the performance of the portfolio formed was calculated. Kumar et al. (2022) applied mean-variance and mean-semivariance portfolio optimization techniques on stocks listed on the South Pacific Stock Exchange, Fiji. The results of this study show that the rate of return and standard deviation of mean-semivariance analysis are lower when compared with mean-variance analysis. Meanwhile, the Sharpe ratios resulting from the mean-semivariance analysis are greater than the mean-variance.

IDX30 is one of the stock indexes in Indonesia. IDX30 was published by the Indonesian Stock Exchange on April 23, 2012. Reported on the IDX Indonesia Stock Exchange website (http://www.idx.co.id), IDX30 is an index that measures the price performance of 30 stocks with high liquidity, large market capitalization, and supported by good company fundamentals.

Based on the explanation above, this research involves the mean-semivariance method to form an optimal portfolio. This method is free from all kinds of assumptions. The stocks used to form this portfolio are stocks listed on the IDX30 index. The selected portfolio will be the optimal portfolio with the best performance.

2. LITERATURE REVIEW

2.1 Return and Expected Return

The profits obtained through investment are known as returns. In this research, stock return calculations were carried out using continuously compounded returns. Let P_t be the closing price of an asset at time *t* without dividends and P_{t-1} be the closing price of an asset at time *t-1*, then the return value R_t can be calculated by:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

$E(R_i)$ or expected return is a rate of return that is the investor's hope for the investment made.

$$E(R_i) = \frac{1}{N}\sum_{t=1}^{N} R_t \tag{2}$$

where, *N* is the number of return observations (Mustakini, 2003).

2.2 Portfolio

Risk is the possible difference between the expected return and the actual return received (Tandelilin, 2010). The greater the difference between the two, the greater the investment risk. Statistically, the level of risk can be determined based on the size of the data distribution deviation. Two measures of data distribution are commonly used to represent risk, variance, and standard deviation. Variance and standard deviation are measures of the magnitude of the distribution of a variable's data relative to its average value. The greater the distribution of returns from an investment, the higher the risk level of that investment (Tandelilin, 2010).

To minimize risk, investors could diversify by compiling a portfolio. This means that investors do not invest in just one asset but rather invest in many assets. According to Sunariyah (2000), a portfolio is defined as a combination of assets invested and owned by investors, both individuals and institutions.

An efficient portfolio is a portfolio that is able to provide maximum profits with a certain risk, or a portfolio that is able to provide minimum risk with a certain level of profit (Husnan, 1998). In this study, the expected portfolio return is expected to be positive. It can be obtained by choosing stocks that have a positive expected return value. The optimal portfolio is obtained by finding the weight or proportion of each share with a function. This function provides a combination of weights that is able to produce a minimum risk level.

2.3 Correlation

Correlation is a value that shows the direction and strength of the relationship between two or more variables (Sugiyono, 2014). The direction of the relationship is expressed by positive values and negative values, while the strength of the relationship between variables is expressed by the magnitude of the correlation coefficient which ranges from -1 to 1. A value of 0 for the correlation coefficient means no relationship between the variables. The following table is a guide to interpreting the correlation coefficient.

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Table 1. Correlation Coefficient Interpretation Guide

Coefficient Interval	Relationship Level
0.00 – 0.199	Very low
0.20 – 0.399	Low
0.40 – 0.599	Medium
0.60 – 0.799	Strong
0.80 – 1.000	Very strong

* This table also applies to negative values in different directions.

Let $b_t = X_t - Y_t$ where X_t is the t-th data belonging to variable X and Y_t is the t-th data belonging to variable Y, then the value of the Spearman correlation coefficient (ρ) of two variables totaling N data is as Equation (3) (Sugiyono, 2014).

$$\rho = 1 - \frac{6 \sum {b_t}^2}{N(N-1)} \quad (3)$$

The lower the correlation coefficient, the more effective the reduction of risk. This means that the less there is a relationship between securities, the lower the portfolio risk (Husnan, 1998).

2.4 Optimizing Portfolio

2.4.1 Mean-Semivariance

Mean-semivariance is a method developed from mean-variance which was introduced by Harry Markowitz in 1959. Unlike mean-variance, mean-semivariance does not need special assumptions. Forming a portfolio with mean-semivariance uses the mean or expected value as a measure of profit and replaces variance with semivariance as a measure of risk. Semivariance is the squared average that is calculated in periods when the return value is smaller than a certain threshold. Thus, the observation periods when the return value is above a certain threshold will be given a value of 0 (Marmer & Ng, 1993). Semivariance is a particularly useful measure of downside risk because it considers return as risky only if they are below some reference return (Markowitz, et al., (2020).

Let R is the realized portfolio return and c is $E(R)$ or can also a constant, then the semivariance (S^2) is:

$$S^2 = E\{[Min(0, R - c)]^2\} \quad (4)$$

Markowitz (1959) estimates portfolio semivariance with the following formula:

$$S_p^2 = \frac{1}{T} \sum_{k=1}^{K} (w_i R_{ik})^2 \quad (5)$$

The square root of the semivariance calculation is the semideviation value.

The semivariance of a portfolio with benchmark B between securities i and j is formulated as follows:

$$S_{pB}^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j S_{ijB} \quad (6)$$

where $$S_{ijB} = \frac{1}{T} \sum_{k=1}^{K} (R_{ik} - B)(R_{jk} - B) \quad (7)$$

The portfolio mean-semivariance is not easy to derive because the cosemivariance matrix is endogenous and not symmetric. This endogenous matrix means that changes in weights affect the period when the portfolio underperforms the benchmark, thereby affecting the elements of the cosemivariance matrix (Estrada, 2008).

Hogan and Warren (1974) also define cosemivariance between securities i and j as follows:

$$S_{ijB}^{HW} = E\{(R_i - R_f).Min(R_j - R_f, 0)\}$$
$$= \frac{1}{T} \sum_{t=1}^{T} [(R_{it} - R_f).Min(R_{jt} - R_f, 0)] \quad (8)$$

The semivariance formulated by Hogan and Warren still has weaknesses, these weaknesses are:

1. Benchmark returns are limited to the risk-free rate and cannot be changed using other benchmarks.
2. $S_{ijB}^{HW} \neq S_{jiB}^{HW}$. These characteristics will provide formal boundaries (the cosemivariance matrix is not symmetric) and intuitive boundaries (the interpretation of the contribution of securities i and j to portfolio risk is unclear).

Estrada (2008) finally found a solution and was able to overcome the shortcomings of the previous proposal. Estrada defines the semivariance of the return of security i with benchmark (B) using the following equation:

$$S_{iB}^2 = E\{[Min(R_i - B, 0)]^2\}$$
$$= \frac{1}{T} \sum_{t=1}^{T} [Min(R_{it} - B, 0)]^2 \quad (9)$$

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Estrada (2008) also defines the semivariance between securities *i* and *j* using a benchmark (*B*) like the following equation:

$$S_{ijB} = E\{Min(R_i - B, 0).Min(R_j - B, 0)\}$$
$$= \frac{1}{T}\sum_{t=1}^{T}\left[Min(R_{it} - B, 0).Min(R_{jt} - B, 0)\right] \quad (10)$$

This formula is able to produce symmetric cosemivariance, $S_{ijB} = S_{jiB}$, and exogenous. In addition, the benchmark (*B*) in this definition can be changed according to the investor's wishes.

Based on the mean-semivariance portfolio risk function in Equation (6), a portfolio optimization model can be constructed as follows:

Minimize $\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j S_{ijB}$

subject to

$\sum_{i=1}^{n} w_i R_i = R_p$; $\sum_{i=1}^{n} w_i = 1$; $0 \le w_i \le 1,\ i = 1,2,\dots,n$

2.4.2 Stock Weight Calculation

The semivariance-cosemivariance matrix, which is originally asymmetric and endogenous, is able to change to be symmetric and exogenous through a heuristic approach. The goal of mean-semivariance is the same as mean-variance, minimizing risk based on a certain expected return. This is the same as optimizing the weight $\boldsymbol{w} = [w_1, w_2, \dots, w_N]^T$ with the objective of minimizing the risk (semivariance) of the portfolio. The weighting vector $\boldsymbol{w}$ must be limited by two constraints, so that the portfolio formed has minimum semivariance ($\boldsymbol{w}^T\boldsymbol{\Sigma}_{\mathbf{sv}}\boldsymbol{w}$) (Zivot, 2016). These constraints are:

1. $\boldsymbol{w}^T\boldsymbol{\mu} = \boldsymbol{\mu}_{\boldsymbol{p}}$
2. $\boldsymbol{w}^T\mathbf{1}_{\boldsymbol{N}} = 1$ (the sum of the weights of the portfolio is one)

where, $\boldsymbol{w}^T$ is the transpose value of $\boldsymbol{w}$; $\boldsymbol{\mu}_{\boldsymbol{p}}$ is a vector of portfolio expected returns; $\mathbf{1}_{\boldsymbol{N}}$ is a vector with dimensions $N \times 1$.

Portfolio optimization can be completed using the Lagrange method. The Lagrange method is able to transform constrained optimization problems into unconstrained optimization problems (Manik et al., 2018). The Lagrange function with two multipliers is as follows:

$$L = \boldsymbol{w}^T\boldsymbol{\Sigma}_{sv}\boldsymbol{w} + \lambda_1(\boldsymbol{\mu}_{\boldsymbol{p}} - \boldsymbol{w}^T\boldsymbol{\mu}) + \lambda_2(\mathbf{1} - \boldsymbol{w}^T\mathbf{1}_{\boldsymbol{N}}) \quad (11)$$

where, λ_1 is the Lagrange multiplier for the $\boldsymbol{w}^T\boldsymbol{\mu} = \boldsymbol{\mu}_{\boldsymbol{p}}$, and λ_2 is the Lagrange multiplier for the $\boldsymbol{w}^T\mathbf{1}_{\boldsymbol{N}} = \mathbf{1}$. To obtain a solution for the optimal value of $\boldsymbol{w}$ by minimizing semivariance, the Lagrange function is derived partially with respect to $\boldsymbol{w}$, $\frac{\partial L}{\partial \boldsymbol{w}} = 0$ dan $\frac{\partial^2 L}{\partial \boldsymbol{w}^2} > 0$.

$$\Leftrightarrow \frac{\partial}{\partial \boldsymbol{w}}\left[\boldsymbol{w}^T\boldsymbol{\Sigma}_{\mathbf{sv}}\boldsymbol{w} + \lambda_1(\boldsymbol{\mu}_{\boldsymbol{p}} - \boldsymbol{w}^T\boldsymbol{\mu}) + \lambda_2(\mathbf{1} - \boldsymbol{w}^T\mathbf{1}_{\boldsymbol{N}})\right] = 0$$
$$\Leftrightarrow 2\boldsymbol{\Sigma}_{\mathbf{sv}}\boldsymbol{w} - \lambda_1\boldsymbol{\mu} - \lambda_2\mathbf{1}_{\boldsymbol{N}} = 0$$
$$\Leftrightarrow \boldsymbol{\Sigma}_{\mathbf{sv}}\boldsymbol{w} = \frac{1}{2}(\lambda_1\boldsymbol{\mu} + \lambda_2\mathbf{1}_{\boldsymbol{N}})$$
$$\Leftrightarrow \boldsymbol{w} = \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}(\lambda_1\boldsymbol{\mu} + \lambda_2\mathbf{1}_{\boldsymbol{N}})$$

The second side is multiplied by $\mathbf{1}_{\boldsymbol{N}}{}^T$, yield

$$\Leftrightarrow \mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{w} = \frac{1}{2}\mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}(\lambda_1\boldsymbol{\mu} + \lambda_2\mathbf{1}_{\boldsymbol{N}})$$

Since $\mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{w} = 1$, then

$$\Leftrightarrow 1 = \frac{1}{2}\mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}(\lambda_1\boldsymbol{\mu} + \lambda_2\mathbf{1}_{\boldsymbol{N}})$$
$$\Leftrightarrow 2 = \mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}(\lambda_1\boldsymbol{\mu} + \lambda_2\mathbf{1}_{\boldsymbol{N}})$$
$$\Leftrightarrow 2 = \mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\lambda_1\boldsymbol{\mu} + \mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\lambda_2\mathbf{1}_{\boldsymbol{N}}$$
$$\Leftrightarrow \mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-\mathbf{1}}\lambda_2\mathbf{1}_{\boldsymbol{N}} = 2 - \mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\lambda_1\boldsymbol{\mu}$$
$$\Leftrightarrow \lambda_2 = \frac{2 - \lambda_1\mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\boldsymbol{\mu}}{\mathbf{1}_{\boldsymbol{N}}{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_{\boldsymbol{N}}}$$

After substitution, we get

$$\boldsymbol{w} = \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}(\lambda_1\boldsymbol{\mu} + \lambda_2\mathbf{1}_{\boldsymbol{N}})$$

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$$= \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\left(\lambda_1\boldsymbol{\mu} + \left(\frac{2-\lambda_1\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\boldsymbol{\mu}}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}\right)\mathbf{1}_N\right)$$
$$= \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\lambda_1\boldsymbol{\mu} + \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\left(\frac{2\mathbf{1}_N-\lambda_1\mathbf{1}_N{}^T\,\Sigma_{sv}{}^{-1}\boldsymbol{\mu}\mathbf{1}_N}{\mathbf{1}_N{}^T\,\Sigma_{sv}{}^{-1}\mathbf{1}_N}\right)$$
$$= \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\lambda_1\boldsymbol{\mu} + \frac{\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N} - \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\left(\frac{\lambda_1\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\boldsymbol{\mu}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}\right)$$
$$= \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\lambda_1\boldsymbol{\mu} - \frac{1}{2}\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\left(\frac{\lambda_1\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\boldsymbol{\mu}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}\right) + \frac{\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}$$
$$= \frac{1}{2}\lambda_1\left(\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\boldsymbol{\mu} - \frac{\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\boldsymbol{\mu}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}\right) + \frac{\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}\mathbf{1}_N}$$

In a portfolio with efficient semivariance, no restriction on the portfolio mean, or $\lambda_1 = 0$. Thus, the mean-semivariance portfolio weight is calculated by the formula:

$$\boldsymbol{w} = \frac{\boldsymbol{\Sigma}_{sv}{}^{-1}\mathbf{1}_N}{\mathbf{1}_N{}^T\boldsymbol{\Sigma}_{sv}{}^{-1}\mathbf{1}_N} \tag{12}$$

where, $\boldsymbol{\Sigma}_{\mathbf{sv}}{}^{-1}$ is the inverse value of the semivariance-cosemivariance matrix.
Proof that the Lagrange function is a minimum function is shown in Equation (13).

$$\frac{\partial^2}{\partial \boldsymbol{w}^2}[2\boldsymbol{\Sigma}_{sv}\boldsymbol{w} - \lambda_1\boldsymbol{\mu} - \lambda_2\mathbf{1}_N] > 0 \tag{13}$$
$$2\boldsymbol{\Sigma}_{sv} > 0$$

provided that the matrix $\boldsymbol{\Sigma}_{\mathbf{sv}}$ is a positive definite matrix. The $\boldsymbol{w}$ value obtained will provide minimal risk compared to other $\boldsymbol{w}$ values.

2.5 Portfolio Performance

Portfolio performance can be evaluated using the Sharpe index. The Sharpe index calculation is based on the concept of the capital market line which is used as a benchmark. The Sharpe Index is calculated by dividing the portfolio risk premium by its standard deviation (Tandelilin, 2010). The Sharpe Index is the ratio of compensation to total risk which is the sum of systematic risk and unsystematic risk. The following is the formula for $\hat{S}_p$ or Sharpe index:

$$\hat{S}_p = \frac{\bar{R}_p - \overline{RF}}{\sigma_{TR}} \tag{14}$$

where, $\bar{R}_p$ is the portfolio return, $\overline{RF}$ is the average risk-free rate of return over the observation period, and σ_{TR} is the standard deviation of portfolio returns over the observation period. The greater the Sharpe index of a portfolio, the better the performance of that portfolio.

3. DATA AND METHODOLOGY

The data used in this research is daily closing price data of 15 stocks included in the IDX30 index for five consecutive years and data of the Composite Stock Price Indeks as the benchmark. This data can be accessed via the Yahoo Finance website (http://finance.yahoo.com). The stock closing price data used is data from the period 1 January 2022 to 31 December 2022 with a total of 246 data. Apart from that, the BI 7-Day Repo Rate value is used as the risk-free rate which is accessed via the Bank Indonesia website (www.bi.go.id). The following are the processing stages on the data to form an optimal portfolio:

1. Collect the daily closing price data of selected stocks from the period 1 January 2022 to 31 December 2022.
2. Calculate the return value from the closing price of the stock.
3. Look for the expected return value of each selected stock.
4. Selecting securities by eliminating stocks that have negative expected returns.
5. Calculate the correlation coefficient between stocks and select stocks that have a negative correlation coefficient.
6. Form a combination of portfolio stocks.
7. Calculate the semivariance value of each stock.
8. Calculate the cosemivariance value between stocks.
9. Form a semivariance-cosemivariance matrix.
10. Calculate the weight for each share.
11. Calculate portfolio returns.
12. Calculate the expected return and semideviation of the portfolio.
13. Calculate the portfolio performance of the portfolio.
14. Choose the optimal portfolio that has the best portfolio performance.

4. RESULTS AND DISCUSSION

4.1 Stock Selection

4.1.1 Expected Return

Portfolio formation begins with calculating the return of each stock of the candidate of the prospective portfolio using Equation (1). Then, calculate the expected return for each stock. Stocks with negative expected return values will be eliminated. This is because a negative value means that the stock causes losses in the future. Based on Equation (2), the results of the expected return calculation are obtained as in Table 2.

Table 2. Expected Return

Stock Code	Expected Return
ADRO	0.001980
ANTM	-0.000672
ASII	-0.000018
BBCA	0.000631
BBNI	0.001290
BBRI	0.000682
BMRI	0.001396
ICBP	0.000604
INDF	0.000299
KLBF	0.001040
PGAS	0.000934
SMGR	-0.000413
TLKM	-0.000443
UNTR	0.000726
UNVR	0.000430

Based on Table 2, the expected return of ANTM, ASII, SMGR and TLKM stocks is negative. Therefore, these stocks are removed from the list of stocks for potential portfolio composition. Stocks with positive expected returns will proceed to the next analysis.

4.1.2 Correlation Coefficient

The stock selection process is also carried out by checking out the correlation coefficient between stocks. The correlation coefficient calculation is carried out to determine the direction of the relationship and the strength and weakness of the relationship between stocks. Stocks that have a negative relationship direction and a positive relationship direction with low and very low relationship levels will be selected to form the portfolio. The results of calculating the correlation coefficient using Equation (3) are presented in Table 3.

Table 3. Correlation Coefficient between Stocks

	ADRO	BBCA	BBNI	BBRI	BMRI	ICBP	INDF	KLBF	PGAS	UNTR	UNVR
ADRO	1.000	0.106	0.131	0.176	0.221	-0.028	0.075	0.063	0.378	0.527	0.008
BBCA	0.106	1.000	0.441	0.425	0.354	0.118	0.169	0.210	0.166	0.153	0.198
BBNI	0.131	0.441	1.000	0.536	0.475	0.116	0.003	0.152	0.209	0.159	0.196
BBRI	0.176	0.425	0.536	1.000	0.427	0.110	0.011	0.103	0.180	0.138	0.150
BMRI	0.221	0.354	0.475	0.427	1.000	0.149	0.031	0.173	0.180	0.172	0.193
ICBP	-0.028	0.118	0.116	0.110	0.149	1.000	0.337	0.183	-0.006	-0.043	0.260
INDF	0.075	0.169	0.003	0.011	0.031	0.337	1.000	0.203	0.106	0.004	0.210
KLBF	0.063	0.210	0.152	0.103	0.173	0.183	0.203	1.000	0.129	0.139	0.205
PGAS	0.378	0.166	0.209	0.180	0.180	-0.006	0.106	0.129	1.000	0.349	0.038
UNTR	0.527	0.153	0.159	0.138	0.172	-0.043	0.004	0.139	0.349	1.000	0.042
UNVR	0.008	0.198	0.196	0.150	0.193	0.260	0.210	0.205	0.038	0.042	1.000

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Based on the correlation coefficient, the stocks that meet the criteria (have a negative relationship direction and have a positive relationship direction with low relationship levels) are ADRO, ICBP, PGAS and UNTR. These stocks are then formed into 5 portfolio combinations as follows:

1) Portfolio 1, consisting of ADRO, ICBP, PGAS and UNTR.
2) Portfolio 2, consisting of ADRO, ICBP and PGAS.
3) Portfolio 3, consisting of ADRO, ICBP and UNTR.
4) Portfolio 4, consisting of ICBP, PGAS, UNTR.

4.2 Semivariance-Cosemivariance Matrix

Portfolio formation using the mean-semivariance method is carried out by forming a semivariance-cosemivariance matrix. After calculating the semivariance for each stock using Equation (9) and calculating the cosemivariance between stocks using Equation (10), the semivariance-cosemivariance matrix for each portfolio is obtained as follows:

Portfolio1

$$\mathbf{\Sigma_{sv}} = \begin{bmatrix} 0.00026270 & 3.93099e-05 & 0.00010119 & 0.00014935 \\ 3.93099e-05 & 0.00012905 & 4.16884e-05 & 3.39768e-05 \\ 0.00010119 & 4.16884e-05 & 0.00019474 & 7.86120e-05 \\ 0.00014935 & 3.39768e-05 & 7.86120e-05 & 0.00019016 \end{bmatrix}$$

Portfolio 2

$$\mathbf{\Sigma_{sv}} = \begin{bmatrix} 0.00026270 & 3.93099e-05 & 0.00010119 \\ 3.93099e-05 & 0.00012905 & 4.16884e-05 \\ 0.00010119 & 4.16884e-05 & 0.00019474 \end{bmatrix}$$

Portfolio 3

$$\mathbf{\Sigma_{sv}} = \begin{bmatrix} 0.00026270 & 3.93099e-05 & 0.00014935 \\ 3.93099e-05 & 0.00012905 & 3.39768e-05 \\ 0.00014935 & 3.39768e-05 & 0.00019016 \end{bmatrix}$$

Portfolio 4

$$\mathbf{\Sigma_{sv}} = \begin{bmatrix} 0.00012905 & 4.16884e-05 & 3.39768e-05 \\ 4.16884e-05 & 0.00019474 & 7.86120e-05 \\ 3.39768e-05 & 7.86120e-05 & 0.00019016 \end{bmatrix}$$

4.3 Stock Weight

The semivariance-cosemivariance matrix is then used to calculate the weight of each stock for each portfolio. Based on calculations using Equation (12), the weight values for stocks from each portfolio are obtained as in Table 4.

Table 4. Stock Weight for Each Portfolio

Portfolio	Stock Code	Weight
1	ADRO	0.022514
	ICBP	0.516257
	PGAS	0.213251
	UNTR	0.247977
2	ADRO	0.161039
	ICBP	0.575554
	PGAS	0.263407
3	ADRO	0.083242
	ICBP	0.606325
	UNTR	0.310433
4	ICBP	0.517801
	PGAS	0.218712
	UNTR	0.263488

4.4 Summary of Portfolio

The weight value is used to calculate portfolio returns. The calculation is carried out by multiplying the weight value by the related stock return. Table 5 is brief data on the returns for each portfolio. The expected return value of each portfolio is positive. This means that an investor who invests capital in these portfolios will get a profit or gain in the future.

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Table 5. Summary of Portfolio Return Data

Portfolio	Minimum	Median	Expected Return	Maximum
1	-0.032235	0.000469	0.000736	0.050851
2	-0.031589	0.001052	0.000912	0.051013
3	-0.038506	0.001283	0.000756	0.047728
4	-0.032952	0.000241	0.000708	0.051921

4.5 Risk of Portfolio

An investor should focus on the risks of the portfolio that has been compiled. In the mean-semivariance method, the portfolio risk value can be determined by looking at the semivariance and semideviation values. The smaller the semivariance and semideviation values, the smaller the risk of the portfolio. Portfolio semivariance is calculated using Equation (6), while semideviation is the result of the square root of semivariance. The results of semivariance and semideviation calculations are presented in Table 6.

Table 6. Semivariance and Semideviation

Portfolio	Semivariance	Semideviation
1	0.00008482	0.00920989
2	0.00009158	0.00957000
3	0.00009206	0.00959501
4	0.00008489	0.00921362

4.6 Portfolio Performance

Portfolio performance can be measured using the Sharpe index as shown in Equation (14). The portfolio performance gets better if the Sharpe index calculation results are bigger. The Sharpe index calculation for each portfolio is presented in Figure 1. The portfolio with the best performance is Portfolio 2. This is because the Sharpe index value belonging to Portfolio 2 has the greatest value.

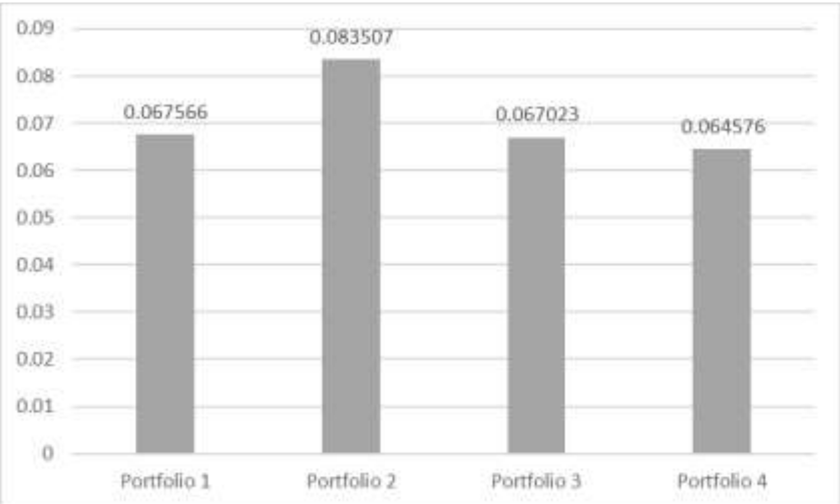

Figure 1. The Sharpe Index of the Portfolios

5. CONCLUSIONS

The optimal portfolio is formed by allocating the weights to produce the smallest risk. The analysis that has been carried out shows that the optimal portfolio with the best performance is portfolio 2, since it has the largest Sharpe index value of 0.083507. Portfolio 2 is a portfolio formed from a combination of stocks owned by PT Adaro Energy Indonesia Tbk (ADRO), PT Indofood CBP Sukses Makmur Tbk (ICBP), and PT Perusahaan Gas Negara Tbk (PGAS) with weights of 16.1039%, 57.5554%, and 26.3407% respectively.

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