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AN EXAMINATION OF THE GREEN STOCK PORTFOLIO IN CONNECTION WITH THE 2024 INDONESIAN REPUBLIC PRESIDENTIAL GENERAL ELECTION

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ABSTRACT

The presidential election of the Republic of Indonesia occurs on a frequency of once every five years. The present work investigated the impact of the 2024 Presidential Election on the performance of the optimal stock portfolio constructed by K-Means Clustering during the first phase of stock selection. Subsequently, the portfolio will be evaluated using two distinct approaches, namely Mean Absolute Deviation (MAD) and Mean-Variance Efficient Portfolio (MVEP). Both techniques were employed to construct several portfolios throughout three time periods: before the Presidential Election (13 August 2023 to 13 February 2024) and after the Presidential Election (15 February to 15 April 2024 and 20 April 2024 to 20 May 2024). This was done by implementing a mechanism to manage the allocation of shares in order to optimize the portfolio. The analyzed data is historical data on daily green stock closing prices indexed on the SRI-KEHATI index. A portfolio was constructed and subsequently evaluated for its performance using the Sharpe Index. The findings of this study suggest that the upcoming 2024 general election for the presidency of the Republic of Indonesia had a favorable impact on the Indonesian capital market, particularly for stocks that are indexed by SRI-KEHATI. This criterion was proposed based on the observation that the average Sharpe ratio index for Period II and Period III exceeds the average Sharpe ratio index for Period I (prior to the election day). The most optimal portfolio examined in this study was the MVEP portfolio, mostly composed of assets in the primary consumer products industry, with a Sharpe ratio of 0.53586. Furthermore, the performance of portfolios in period III (after the election result release) was far superior to that of other portfolios examined in previous periods.

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1. INTRODUCTION

Financial markets exhibit a high degree of sensitivity to both political and economic fluctuations. Transitions in government often lead to modifications in regulatory legislation, which can influence the financial performance of companies and the value of stocks [1]. Numerous scholars have undertaken studies on the influence of elections as a significant political event in several countries worldwide.

An analysis of the factors affecting the performance of Indonesian stock investment portfolios was conducted by [2]. The analysis was conducted under the methodology of literature review. The research findings indicate that the election may lead to political instability due to concerns among investors regarding the predicted economic strategies of the new government.

A study conducted by [3] examined the influence of elections on the volatility of the Indonesian stock market and projected the closing value of IHSG in the year of the elections, 2024, using GARCH simulation. Statistical analysis revealed a strong positive correlation between political months and the IHSG value. More precisely, the IHSG score is 743.53 points higher in months experiencing political events compared to months without such occurrences.

The research undertaken by [1] investigated the impact of the reaction of the 2016 stock market to the outcomes of the 2016 presidential election. In order to investigate the impact of numerous independent variables, including interest rates, polling variables, and the VIX index, on the daily stock return in the United States, the researchers utilized linear regression analysis. The estimated findings revealed that there was no statistically significant correlation between market returns and opinion polls that showed a preference for one candidate over another. However, fundamental statistical analysis suggests that the market exhibited better performance when Trump was ahead of Clinton in polls.

Argantha et al. conducted an investigation of the abnormal returns identified in 44 stocks listed on the LQ45 Index to investigate the stock market reaction to Indonesia's General Election Events in 2019 [4]. The findings of the study, which demonstrate a significantly unusual return on elections and election announcements, suggest that crucial information is revealed during election events that provoke reactions in the stock market. A study conducted in 2024 by Crane et al. examined the empirical data from US Presidential Elections to ascertain the true impact of markets on politics. The study concluded that examining the fluctuation in stock market participation at the county level revealed that market performance influenced election results. In times of robust market performance, counties that exhibit greater levels of engagement are more likely to endorse the current government in comparison to counties with lower levels of participation [5].

The study conducted by [5] examined the reaction of the stock market to changes in the political and economic conditions in Spain. The data analysis suggests that the uncertainty generated by a change in the party affiliation of an incumbent is connected to the short-term negative market response to the general elections. Moreover, it is unrelated to both industry features and firm size.

Prior scholarship has not yet investigated the influence of presidential elections on capital markets, specifically in relation to the performance of asset portfolios. The objective of this study is to examine the creation of optimal portfolios by utilizing the Mean Absolute Deviation (MAD) and Mean-Variance Efficient Portfolio (MVEP) techniques on green stocks indexed by SRI-KEHATI. The analysis will focus on the time period before and after the 2024 general election for the presidency of the Indonesia Republic. Mean Value at Risk (MVEP) and Mean Absolute Deviation (MAD) are statistical techniques used in financial statistics to determine the proportion of stocks that form an ideal portfolio. Both methodologies have been extensively utilized in several studies, including those by [6], [7], [8], [9], and [10].

2. RESEARCH METHODS

This work will present a fundamental theory of K-Means Clustering, which will be used to classify stocks indexed by SRI-KEHATI. Once the stocks used to construct portfolios have been classified, the allocation of stocks for each portfolio is determined using the Mean-Variance Efficient Portfolio (MVEP) and Mean Absolute Deviation (MAD). Therefore, this part also includes a concise overview of the MVEP and MAD.

2.1 K-Means Clustering

The K-Means Clustering Analysis is a technique that uses the algorithm provided as follows:

1. The initial step is to ascertain the desired number of clusters, denoted as k.

   The determination of the number of clusters k necessitates consideration of several factors, encompassing both theoretical and conceptual dimensions, which might be suggested to establish the cluster number. The Elbow Method is employed in this study to ascertain the cluster number. On the Elbow Method, the optimal number of clusters is obtained by minimizing the difference between the values of the first and second clusters on the graph. A comprehensive explanation of the procedures can be found in [11].

2. Construct the initial cluster center point (k centroid) via random selection.

   The initial centroid is chosen at random from the objects comprising the k cluster. In order to determine the subsequent centroid cluster, Equation (1) can be utilized.

$$v = \frac{\sum_{i=1}^{n} x_i}{n};\ i = 1, 2, 3, \cdots, n. \tag{1}$$

   In the cluster, v represents a centroid of the cluster, x_i denotes i_{th} object, and n represents the number of objects/the number of objects that are members of the cluster.

3. Quantify the distance between each object and the centroid in every cluster using the Euclidean Distance method, which is defined as Equation (2).

$$d(x, y) = \|x - y\| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{2}$$

   where $i = 1, 2, 3, \cdots, n$; x_i is the i-th object of x, y_i is the i_{th} object of y, and n is the total number of objects. Each object is assigned to the centroid that has the nearest distance.

   Carry out the iteration steps first and then determine the new position for the centroid. Repeat step 3 if the new centroid positions are not identical. The convergence verification process is carried out by checking the comparison between the group assignment matrix in the previous iteration and the group assignment matrix in the current iteration. If both are identical, the K-Means Cluster Analysis algorithm is considered to have converged. However, if there is a difference, it indicates that the algorithm has not reached convergence, and therefore, the next iteration needs to be carried out [9]. K-Means Clustering has been utilized to classify stocks in several research such as [12], [6], [13], and [7].

2.2 Mean-Variance Efficient Portfolio

In forming a portfolio, an investor will try to maximize the expected return by minimizing a certain level of risk. This is what investors consider when choosing an optimal portfolio. One way to form an optimal portfolio is MVEP. MVEP is defined as an investment portfolio that provides optimal returns for a certain level of risk, so that the portfolio weighting using MVEP is formulated using Equation (3) [14].

$$\boldsymbol{w} = \frac{\Sigma^{-1} \mathbf{1}_N}{\mathbf{1}_N^T \Sigma^{-1} \mathbf{1}_N}. \tag{3}$$

In Equation (3), $\boldsymbol{w}$ is the weight or proportion of stock, $\boldsymbol{\Sigma^{-1}}$ is the inverse matrix of the variance-covariance of stock returns, $\mathbf{1}_N$ is a vector whose elements are all one (with dimension N×1), and $\mathbf{1}_N^T$ is the transpose of $\mathbf{1}_N$ [6].

Forming an optimal portfolio using MVEP requires a calculation of variance-covariance matrices generated from a variance and covariance stock return written as follows:

$$\sum = \begin{bmatrix} S_1^2 & S_{R_1R_2} \\ S_{R_1R_2} & S_2^2 \end{bmatrix} \tag{4}$$

where Σ is a variance-covariance matrix, $S_{R_1R_2}$ is the covariance between the first stock return and the second stock return, S_1^2 is the variance of the first stock return, and S_2^2 is the variance of the second stock return.

2.3 Mean Absolute Deviation

The concept of a MAD portfolio is the absolute value of the difference between the return and the expected return of each stock over a specified period. The absolute value of the difference between return and expected return is given in **Equation (5) [6]** .

$$m_{it} = \left|R_{i(t)} - E(R_i)\right|. \tag{5}$$

The average of m it is the MAD value of each stock that can be calculated by **Equation (6)**.

$$MAD_i = \sum_{t=1}^{T} \frac{m_{it}}{T} \tag{6}$$

The simplex method can be used to solve the linear program optimization on the MAD Portfolio to calculate the investment weight of each stock. The equation can be expressed as follows **[15]**:

Minimize

$$\sigma(W) = (MAD)_1 w_1 + (MAD)_2 w_2 + \cdots + (MAD)_n w_n \tag{7}$$

with constraint

$$E(R_1)w_1 + E(R_2)w_2 + \cdots + E(R_n)w_n \geq R_{min} \tag{8}$$
$$w_1 + w_2 + \cdots + w_n = 1 \tag{9}$$
$$0 \leq w_i \leq u_i, \text{for } i \; = \; 1,2, \ldots, n \tag{10}$$

where $\sigma(W)$ is a portfolio risk, R_{min} is a minimum return rate portfolio, w_1 is the amount of investment weight of the i_{th} stock, and u_i is the maximum weight of i_{th} stock. An expected return portfolio for a stock portfolio may offer an overview of the expected return on investment in stocks. Then, the expected return of stock can be quantified by **Equation (11) [15]**.

$$E(R_p) = \sum_{i=1}^{n} w_i \cdot E(R_i) \tag{11}$$

where $E(R_p)$ is the expected return of the stock portfolio.

The writing method in this study is a literature study conducted by investigating theories that support the K-Means Clustering, MVEP, and MAD analysis through several journals. This study also contains a case study that uses secondary data, namely daily data from the closing price of stocks indexed by SRI-KEHATI. SRI-KEHATI is one of 44 stock indices in the Indonesia Stock Exchange (IDX). The SRI-KEHATI stock index is an index that measures the stock price performance of 25 listed companies that have a good performance in encouraging sustainable businesses and have an awareness of the environment, social, and good corporate governance, also known as Sustainable and Responsible Investment (SRI). The SRI-KEHATI index was launched and managed in collaboration with the Indonesian Biodiversity Foundation (Yayasan KEHATI).

The data was accessed from http://www.finance.yahoo.com. The analyzed data is divided into three periods. The first period is from 13 August 2023 to 13 February 2024 (6 months before the general election for the president of Indonesia Republic in 2024). The second period is between 15 February and 15 April 2024 (two months after the general election for the president of Indonesia Republic in 2024). Then, the third period is from 20 April 2024 to 20 May 2024 (one month after the winner announcement of the general election for president of Indonesia Republic in 2024).

The following are the number of stages carried out in this study:

1. Collecting closing price data for stocks, which is regularly indexed by SRI-KEHATI in the three analyzed periods.
2. Determining the optimal k value using the Elbow method.
3. Conducting non-hierarchical cluster analysis of K-Means Clustering.
    a. Determining the initial centroid
    b. Calculating the distance of the object to the centroid using the Euclidean distance.
    c. Grouping objects based on the minimum distance.
    d. Evaluating objects that move to other clusters.

e. Determines a new centroid when an object is found to have changed clusters.

4. Forming a portfolio from the cluster results.
5. Calculating the Expectation, Variance, and Variance-Covariance Matrix of the closing stock price return.
6. Calculating the stock weight using the MVEP and MAD.
7. Calculating the expected return of the portfolio and the Variance (Risk) of the portfolio based on the results of steps 4, 5, and 6.
8. Calculating the Sharpe ratio of portfolios based on the results of step 7. The best portfolio for each period is the portfolio that has the highest Sharpe ratio among the portfolios.

3. RESULTS AND DISCUSSION

3.1 Portfolio of Stocks Indexed by SRI-KEHATI in The First Period of Analysis

In this section, stocks indexed by SRI-KEHATI were listed based on their consistency over the last two periods in the stock index (before the first analyzed period, from 13 August 2023 to 13 February 2024). The 22 stocks that were selected based on stock consistency are tabulated in **Table 1**.

Table 1. The Selected Stocks Indexed by SRI-KEHATI for Period I

No	Ticker Code of Stock	The Company Name
1	BBCA	PT Bank Central Asia Tbk
2	BBNI	PT Bank Negara Indonesia Tbk
3	BBTN	PT Bank Tabungan Negara Indonesia
4	BMRI	PT Bank Mandiri Tbk
5	DSNG	PT Dharma Satya Nusantara Tbk
6	ICBP	PT Indofood CBP Sukses Makmur Tbk
7	INCO	PT Vale Indonesia
8	INDF	PT Indofood Sukses Makmur Tbk
9	INTP	PT Indocement Tunggal Prakarsa TBK
10	JPFA	PT Japfa Comfeed Indonesia TBK
11	JSMR	PT Jasa Marga Tbk
12	KLBF	PT Kalbe Farma Tbk
13	SILO	PT Siloam International Hospitals Tbk
14	SMGR	PT Semen Indonesia Tbk
15	SSMS	PT Sawit Sumbermas Sarana Tbk
16	TINS	PT Timah Tbk
17	TLKM	PT Telkom Indonesia Tbk
18	UNVR	PT Unilever Indonesia Tbk
19	WIKA	PT Wijaya Karya Tbk
20	BBRI	PT Bank Rakyat Indonesia Tbk
21	ANTM	PT Aneka Tambang Tbk
22	AUTO	PT Astra Otoparts Tbk

Then, the log-returns of the analyzed stock prices are calculated to observe the expected return of the analyzed stocks. The expected return of the stocks is provided in **Table 2**. BBNI, BBRI, ICBP, INTP, KLBF, SMGR, TLKM, and UNVR are eliminated and are not provided in **Table 2** because of their negative expected return. Meanwhile, WIKA was also excluded from the next analysis because of a suspension from the Indonesian Stock Exchange on 18 December 2023. WIKA has postponed the principal payment of the Wijaya Karya Sustainable Sukuk Mudharabah I Phase 1 of 2020 Series A, which matures on 18 December 2023.

The stocks having positive log returns will be candidates to get in a portfolio constructed by mixing the method of K-Means Clustering and the two methods (MVEP and MAD), enabling the construction of the optimal stock portfolio. In the first period of analysis, not all stocks produce a positive expected return. This condition is indicated in Table 2. The first and the third columns in Table 2 are the Ticker Code of Stock (TCO), while the second and the fourth columns are the expected return of each asset (TER).

Table 2. The Expected Return of Analyzed Stocks Indexed by SRI-KEHATI for The First Period

TCO	TER	TCO	TER
ANTM	-0,00208	JSMR	0,00202
AUTO	-0,00339	WIKA	-0,00379
BBCA	0,00032	JPFA	-0,00201
BBNI	0,00197	BBRI	0,00049
BBTN	0,00027	SILO	0,00053
BMRI	0,00134	KLBF	-0,00180
DSNG	-0,00116	SMGR	-0,00087
ICBP	-0,00002	SSMS	-0,00082
INCO	-0,00369	TINS	-0,00354
INDF	-0,00084	TLKM	0,00031
INTP	-0,00207	UNVR	-0,00231

Based on Table 2, eight stocks will be candidate assets comprising a portfolio, namely BBCA, BBNI, BBTN, BMRI, JSMR, BBRI, SILO, and TLKM. The eight stocks will be clustered using K-Means Clustering. In this research, the optimal cluster number is determined by the Elbow Method.

The first step in grouping the stocks is constructing a Euclidean Matrix where the elements are given in Table 3.

Table 3. The Elements of Euclidean Matrix for The Analyzed Stock in Period I

TCO	BBCA	BBNI	BBRI	BBTN	BMRI	JSMR	SILO	TLKM
BBCA	0.00000	45398.168	41780.416	88442.288	34802.981	52244.938	78093.928	60083.288
BBNI	45398.168	0.000	4994.259	43290.824	10820.765	7291.696	32932.407	15082.495
BBRI	41780.416	4994.249	0.000	46707.256	0.000	11035.410	36442.528	18373.934
BBTN	88442.288	43290.824	46707.256	0.000	53723.445	36512.212	10596.910	28400.250
BMRI	34802.981	10820.765	7340.480	53723.445	0.000	17704.788	43402.522	25410.126
JSMR	52244.938	7291.696	11035.410	36512.212	17704.788	0.000	26164.457	8598.647
SILO	78093.928	32932.407	36442.528	10596.910	43402.522	26164.457	0.000	18167.930
TLKM	60083.288	15082.495	18373.934	28400.250	25410.126	8598.647	18167.930	0.000

After constructing the Euclidean matrix, the optimal number of clusters is established using the Elbow Method. Based on Figure 1, it can be concluded that the optimal number of clusters for this case is three. Next, the stocks that will be cluster centers are specified. For this research, the cluster center (centroid) for each cluster is BBCA for Cluster 1, BBNI for Cluster 2, and BBRI for Cluster 3.

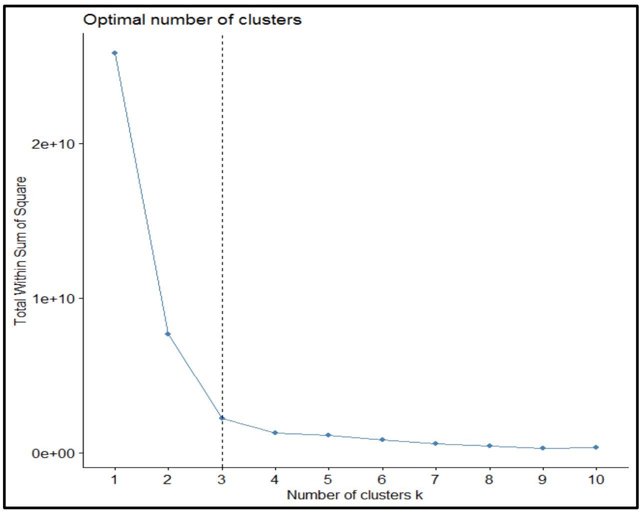


Figure 1. The Number of Optimal Clusters for Period I Using the Elbow Method

The next step is to determine the initial group of clusters by finding the closest distance to the center of the cluster. This quantification is carried out by utilizing the distance between the closing prices of each stock, with the analyzed period from 13 August 2023 to 13 February 2024. For each stock, the data will then be compared to see the level of homogeneity of characteristics among the stocks.

Next, the Euclidean distance value is used to group stocks into clusters. Euclidean distance is calculated on all data by applying **Equation (2)**. The results of the calculation are provided in **Table 4**. The fourth column of **Table 4** gives the closest distance (TCD) to the corresponding centroid.

Table 4. Grouping of Stock Based on Euclidean Distance on Three Clusters (Iteration 1)

TCO	C1	C2	C3	TCD	Cluster
BBCA	0	4750	3675	0	1
BBNI	4750	0	1050	0	2
BBRI	3725	975	0	0	3
BBTN	8000	3250	4280	3250	2
BMRI	3500	1250	200	200	3
JSMR	5630	870	1875	870	2
SILO	7260	2510	3565	2510	2
TLKM	5480	720	1815	720	2

Table 4 shows the results of calculating the Euclidean distance with 3 clusters that have similar characteristics in each of the grouped stocks, where each stock is grouped based on the similarity of its characteristics to the nearest centroid. The analysis results show that the stocks will be situated in clusters based on the closest centroid; for example, a stock that is closest to centroid 1 (C1) will be situated in cluster 1, and so on for the next cluster.

The next stage is to re-determine the centroid by calculating the average of each similar cluster to obtain a new centroid. **Equation (1)** can be used in the process of re-determining the centroid. The new centroid results for this iteration are not presented here for brevity. After the new centroid is obtained, the next step is to find out the results of the stock grouping listed in **Table 5**.

Table 5. Grouping of Stock Based on Euclidean Distance on Three Clusters (Iteration 2)

TCO	C1	C2	C3	TCD	Cluster
BBCA	0	6220	3575	0	1
BBNI	4750	1470	1150	1150	3
BBRI	3725	2445	100	100	3
BBTN	8000	1780	4380	1780	2
BMRI	3500	2720	100	100	3

TCO	C1	C2	C3	TCD	Cluster
JSMR	5630	600	1975	600	2
SILO	7260	1040	3665	1040	2
TLKM	5480	750	1915	750	2

In **Table 5**, BBNI moved from cluster 2 to cluster 3. So, a new centroid was re-determined, and the next iteration was carried out. On the third iteration, there are no stocks moving into another cluster, so the iteration process is stopped. The results of the clustering of eight stocks using K-Means Clustering for the final iteration are given in **Table 6**.

Table 6. Grouping of Stock Based on Euclidean Distance on Three Clusters (Iteration 3)

TCO	C1	C2	C3	TCD	Cluster
BBCA	0	6587.5	3958.33	0	1
BBNI	4750	1837.5	766.67	766.67	3
BBRI	3725	2812.5	283.33	283.33	3
BBTN	8000	1412.5	3996.67	1412.5	2
BMRI	3500	3087.5	483.33	483.33	3
JSMR	5630	967.5	1591.67	967.5	2
SILO	7260	672.5	3281.67	672.5	2
TLKM	5480	1117.5	531.67	1117.5	2

For cluster one, there is only one stock, namely BBCA. This does not meet the requirements for forming a stock portfolio. This condition happened because the stocks grouped into clusters do not have enough homogeneity with one of the stocks, which in this case is BBCA. This does not mean that BBCA stock is a stock that has poor performance because, in forming the portfolio using K-Means Clustering, only groups of stocks that have the same characteristics are included in a cluster. K-Means Clustering does not consider whether or not the stocks are appropriate for investors to invest in.

After forming portfolios, the proportion of assets in each portfolio is specified using two methods, namely MVEP and MAD. Using MVEP, the proportion or weight of investment for each asset in Portfolio I and Portfolio II can be obtained by employing **Equation (3)**.

Table 7. Weight of Assets Comprising Each Portfolio for Period I Using MVEP

Portfolio	TCO	Weight
I	BBTN	0.335803
	JSMR	0.047845
	SILO	0.056059
	TLKM	0.560292
II	BBRI	0.269472
	BMRI	0.349870
	BBNI	0.380657

Using MAD, the proportion of each asset constructing a portfolio can also be identified. The MAD method has a purpose similar to the MVEP, namely, to minimize the risk of investment. MAD is started by calculating the minimum return of the portfolio using **Equation (7)**. The minimal returns are given in **Table 8**.

Table 8. The Minimal Return of Portfolio

Portfolio	Minimal Return	Portfolio	Minimal Return
I	0.00078409	II	0.01052289

Then, the constraint functions are formed as provided in **Table 9**.

Table 9. The Constraints Function Related to Portfolios

Portfolio I
a. The first constraint
$0.00027443w_1 + 0.00202434w_2 + 0.00052777w_3$ $+0.00030982w_4 \geq 0.00078409$
b. The second constraint
$w_1 + w_2 + w_3 + w_4 \; = 1$
c. The third constraint
$w_i \leq 30\%;\; i = 1,2,3,4$
Portfolio II
a. The first constraint
$0.00197298w_5 + 0.00048471w_6 + 0.00133939w_7$ ≥ 0.01052289
b. The second constraint
$w_5 + w_6 + w_7 \; = 1$
c. The third constraint
$w_i \leq 40\%\,;\, i = 5,6,7$

Then, the quantification MAD value is conducted, where the results are suggested in **Table 10**.

Table 10. MAD Value for Each Asset

TCS	MAD Value
BBCA	0.00769324
BBNI	0.01025410
BBRI	0.01112331
BBTN	0.00961771
BMRI	0.01019125
JSMR	0.01631030
SILO	0.02163089
TLKM	0.00897566

Next, the objective function is specified for each portfolio as follows

The objective function of Portfolio I:

$$\sigma(w_1) \; = 0.00961771w_1 + 0.016310w_2 + 0.02163089w_3 \; + 0.00897566w_4$$

The objective function of Portfolio II:

$$\sigma(w_2) \; = 0.01025410w_5 + 0.01112331w_6 + 0.01019125w_7$$

After all the components needed to determine the investment weight using the MAD method are known, the next step is to find the investment weight for each stock. The investment weight calculation is obtained by minimizing the objective function with previously established constraints. The investment weight results of the portfolio formed are presented in **Table 11**.

Table 11. **Weight of Assets Comprising Each Portfolio for Period I using MAD**

Portfolio	TCS	Weight
I	BBTN	0.30000
	JSMR	0.30000
	SILO	0.10000
	TLKM	0.30000
II	BBRI	0.20000
	BMRI	0.40000
	BBNI	0.40000

Based on **Table 7** and **Table 11**, the expected-return portfolios, the risk portfolios, and the Sharpe index measuring the performance of portfolios for each method can be quantified. The results of quantifications are provided in **Table 12**.

Table 12. **The Performance Assessment of Portfolios using MVEP and MAD in Period I**

Portfolio	Method	Risk Portfolio	Expected Return Portfolio	Sharpe Ratio
I	MVEP	0.00008	0.00039	0.04075
	MAD	0.00084	0.01263	0.06612
II	MVEP	0.00013	0.00135	0.11938
	MAD	0.01040	0.00142	0.13668

Based on **Table 12**, it can be concluded that the best portfolio for period I is Portfolio II, constructed by MAD, because the value of the Sharpe ratio of the portfolio is higher than the value of the ratio of other portfolios in Period I. It means that for every 1% of risk faced by the investor, the corresponding portfolio II will provide a profit of 13.668% compared to risk-free investments, in this case, government securities.

3.2 Portfolio of Stocks Indexed by SRI-KEHATI in The Second and Third Periods of Analysis

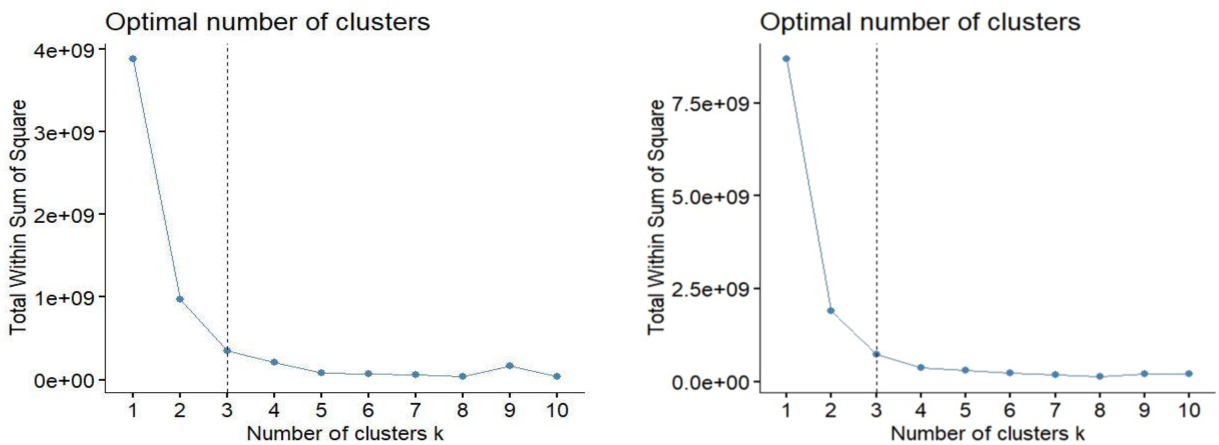
In the second and third periods of analysis, K-Means clustering is conducted to group stocks listed in **Table 13**.

Table 13. **The Expected Return of Analyzed Stocks Indexed by SRI-KEHATI for The Second Period and The Third Period**

Period	Ticker Code of Stock	The Expected Return	Ticker Code of Stock	The Expected Return
II	ANTM	0.00475	JSMR	0.00343
	AUTO	-0.00150	KLBF	-0.00010
	BBCA	-0.00114	SILO	0.00351
	BBNI	-0.00421	SMGR	-0.00451
	BBRI	0.00398	SSMS	0.00168
	BBTN	0.00032	TINS	0.01624
	BMRI	-0.00245	TLKM	-0.00660
	DSNG	0.00616	UNVR	-0.00420
	ICBP	-0.00420	WIKA	-0.00479
	INCO	0.00280	AALI	-0.00022
	INDF	-0.00117	DRMA	-0.00686
	INTP	-0.00107	EMTK	-0.00387
	JPFA	0.00282		

Period	Ticker Code of Stock	The Expected Return	Ticker Code of Stock	The Expected Return
III	ANTM	-0.00342	JSMR	-0.00453
	AUTO	-0.00028	KLBF	0.00493
	BBCA	-1.2E-17	SILO	-0.00065
	BBNI	-0.00267	SMGR	-0.01336
	BBRI	-0.00501	SSMS	0.00027
	BBTN	-0.00441	TINS	-0.00169
	BMRI	-0.00341	TLKM	-0.00290
	DSNG	-0.00043	UNVR	0.00700
	ICBP	0.00426	WIKA	-0.02631
	INCO	0.00874	AALI	-0.00368
	INDF	0.00112	DRMA	-0.00087
	JPFA	0.01398	EMTK	0.01087
	INTP	-0.00593		

The Elbow Method in this research is used to determine the number of optimal clusters. Based on the result of The Elbow Method given in Figure 2 (a) and Figure 2 (b), it can be concluded that the number of optimal clusters in period II and period III successively is three.



(a) **(b)**

Figure 2. The Number of Optimal Clusters Using the Elbow Method (a) for Period II, (b) for Period III

For Period III, the number of clusters decreased to two because one cluster resulted from the Elbow Method, which only consisted of one stock, namely PT Indofood CBP Sukses Makmur Tbk (ICBP). The clustering process for Period II and Period III involves three iterations times to obtain stocks in a condition where there are no stocks moving to another cluster. The clustering constructed three stock portfolios for period II and two stock portfolios for period III are given in Table 14. For Portfolio I**, there are BBCA, BMRI, and INDF. Portfolio II** comprises AUTO, INCO, JSMR, and SILO. Portfolio III** is constructed by ANTM, BBTN, DSNG, JPFA, SSMS, and TINS. Meanwhile, for period III, the stocks constructing portfolio I*** are JPFA, KLBF, SSMS, UNVR, and EMTK, while the stocks comprising portfolio II*** are INCO and INDF.

Table 14. Portfolio Constructed by K-Means Clustering for Periods II and III

Period	Portfolio	Stocks
II	I**	BBCA, BMRI, INDF
	II**	AUTO, INCO, JSMR, SILO

Period	Portfolio	Stocks
	III**	ANTM, BBTN, DSNG, JPFA, SSMS, TINS
III	I***	JPFA, KLBF, SSMS, UNVR, EMTK
	II***	INCO, INDF

After constructing portfolios by clustering, the weight of each asset forming each portfolio is then determined by MVEP and MAD. Because the processes are similar to those conducted in Section 3.1, the detailed processes are not provided here for brevity.

Table 15. The Weight of Stocks Obtaining by MVEP and MAD for The Second and The Third Period

Period	Portfolio	Ticker Code of Stocks	MVEP's Weight	MAD's Weight
II	I**	BBCA	0.10281	0.27332
		BMRI	0.48932	0.40000
		INDF	0.40785	0.32668
	II**	AUTO	0.32409	0.26036
		INCO	0.02695	0.13964
		JSMR	0.36049	0.30000
		SILO	0.28848	0.30000
	III**	ANTM	0.02975	0.00000
		BBTN	0.09368	0.20000
		DSNG	0.20799	0.20000
		JPFA	0.43257	0.20000
		SSMS	0.22323	0.20000
		TINS	0.01276	0.20000
III	I***	JPFA	0.18988	0.20000
		KLBF	0.43724	0.20000
		SSMS	0.25629	0.20000
		UNVR	0.13798	0.20000
		EMTK	-0.02139	0.20000
	II***	INCO	0.12533	0.50000
		INDF	0.87467	0.50000

Table 15 indicates the results of the analysis of MVEP and MAD for the three portfolios in period II and the two portfolios in period III. Table 15 also indicates the performance of each portfolio by the value of the Sharpe ratio. Based on Table 15, the expected-return portfolios, the risk portfolios, and the Sharpe ratio measuring the performance of portfolios for each method can be quantified. The quantifications are provided in Table 16.

Then, Table 16 provides a summary of the Sharpe ratio for the analyzed portfolios constructed by MVEP and MAD for comparison purposes. Based on Table 16, it can be noted that for Period II, the best performance portfolio is Portfolio II**, generated from MVEP, with a Sharpe ratio of 0.39210. The best portfolio consists of ANTM, BBTN, JPFA, SILO, and SSMS, in which ANTM represents the metal and mineral mining sector, BBTN represents the financial sector, JPFA and SSMS represent the primary consumer goods sector, and SILO represents the health sector. Meanwhile, the worst portfolio performance for Period II was indicated by Portfolio II**, which was developed by MAD because the portfolio has the lowest Sharpe ratio among other Sharpe ratio Portfolios for Period II.

Table 16. The Performance Assessment of Portfolios using MVEP and MAD in Period I, Period II, and Period III

Period	Stocks Constructing the Portfolio	Portfolio	Method	Sharpe Ratio
I	BBTN, JSMR, SILO, TLKM	I	MVEP	0.04075
		I	MAD	0.06612
	BBNI, BBRI, BMRI	II	MVEP	0.11938
		II	MAD	0.13668
		Mean of the Sharpe Ratio		**0.10739**
II	INCO, JSMR	I**	MVEP	0.17936
		I**	MAD	0.16515
	ANTM, BBTN, JPFA, SILO, SSMS	II**	MVEP	0.39210
		II**	MAD	0.13958
	DSNG, TINS	III**	MVEP	0.35746
		III**	MAD	0.31939
		Mean of the Sharpe Ratio		**0.25884**
III	JPFA, KLBF, SSMS, UNVR, EMTK	I***	MVEP	0.53586
		I***	MAD	0.35860
	BBNI, BMRI	II***	MVEP	0.16049
		II***	MAD	0.24795
		Mean of the Sharpe Ratio		**0.32573**

Table 16 indicates that the performance of the stock portfolio with regard to the mean of sharpe ratio for Period III (20 April 2024 to 20 May 2024) is the best among the performance of the stock portfolio for Periods I, II, and III. The best portfolio analyzed in this research is the MVEP portfolio, which was mostly constructed in the primary consumer goods sector with a Sharpe ratio of 0.53586. Furthermore, the performance of portfolios in period III (after the announcement of the election result) is prominent among other analyzed portfolios in other periods. Therefore, it can be summarized that Indonesia's stock market indicates an increase in performance after the election. This means that the Indonesian capital market, especially stocks indexed by SRIKEHATI, was positively impacted by the General Election for President of the Indonesia Republic in 2024, even after the announcement of the election winner.

4. CONCLUSION

Based on the results of analyses, it can be concluded that there is a positive effect of the winner announcement of the general election for president of the Republic of Indonesia in 2024 on the capital market in Indonesia, especially for stocks indexed by SRI-KEHATI. This condition was suggested by the mean of the Sharpe ratio index for Period II and Period III, which is greater than the mean of the Sharpe ratio index for Period I. The best portfolio analyzed in this research is portfolio I***, which was mainly constructed of the primary consumer goods sector in the period after the announcement of the election winner, namely period III.

AUTHOR CONTRIBUTIONS

Evy Sulistianingsih: Conceptualization, Data curation, Methodology, Supervision, Validation, Visualization, Writing - Original Draft, Writing - Review and Editing. Shantika Martha: Data curation, Project administration, Software, Supervision, Validation. Wirda Andani: Data curation, Methodology, Software, Validation. Hendri Agustono: Formal analysis, Visualization. Rifki Pebriyandi: Formal analysis, Visualization. Risky Gunawan: Formal analysis, Visualization. Cinta Priscillia Maharani: Formal analysis, Visualization. All authors discussed the results and contributed to the final manuscript.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest to report study.

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