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ENHANCING STOCK PORTFOLIO PERFORMANCE USING MARKOV-SWITCHING MODELS AND CANDLESTICK PATTERNS FOR LONG-TERM INVESTMENT

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ABSTRACT

Islamic stocks in Indonesia face challenges in portfolio management due to the limited number of issuers and low diversification. The change in market regime from bullish to bearish makes the portfolio more vulnerable, especially since some investors do not understand the concept of portfolio and the importance of determining optimal asset weighting. In addition, the allocation strategy used tends to be static and minimizes the utilization of sharia-based technical analysis, making investment decisions less responsive to market dynamics. This study aims to compare the performance of two portfolio allocation algorithms, which integrate Markov-switching models and Heiken Ashi candlestick patterns for trend identification, respectively. The research method used is a quantitative approach with experimental techniques or computational simulations that aim to test the performance of the algorithm in producing optimal portfolio weights. The portfolio model developed is an extension of the Markowitz model with two different integration approaches, namely the Markov-switching model and the Heiken Ashi candlestick pattern. Portfolio weight optimization on each algorithm is performed using the Generalized Reduced Gradient (GRG) method. The Markov-switching model is a time series model used to identify changes in the average market regime. In contrast, the Heiken Ashi pattern is used to detect trend changes in stock price movements. The time series data used consists of daily stock prices of Islamic stocks listed in the Jakarta Islamic Index (JII) during the period January 2019 to August 2022, obtained from the Indonesia Stock Exchange (IDX). This study finds that the Markowitz model integrated with the Markov-switching model is able to effectively identify market regimes and improve efficiency in portfolio weight optimization. These findings provide valuable insights for Islamic equity investors in their risk mitigation efforts while helping to align expected returns with long-term investment strategies that are adaptive to bullish and bearish market conditions.

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1. INTRODUCTION

Investment is the activity of investing in valuable assets to obtain profits, both in the short and long term, by considering two important aspects: time and risk [1]. In Indonesia, the development of stock investment shows an increasing trend, characterized by the emergence of various conventional stocks and stocks based on Sharia principles. One of the indices containing sharia stocks is the Jakarta Islamic Index (JII), which is part of the Composite Stock Price Index (IHSG) [2]. Like other stocks in the IHSG, Islamic stocks in the JII also experience market dynamics, including bullish and bearish periods, especially during the COVID-19 pandemic. For example, there was a significant surge in Islamic stocks in the pharmaceutical sector [3], an increase in ANTM's share price due to increased demand for gold [4], and a decline in share prices due to foreign investor sell-offs [5].

Islamic stocks in Indonesia face various challenges in portfolio management, mainly due to the limited number of issuers and low level of diversification compared to conventional stocks. It leaves investors with little room to form a balanced portfolio, making them more vulnerable to market risk. This vulnerability is further increased when there is a change in the market regime from bullish to bearish conditions, where the portfolio value can decrease significantly if not managed adaptively. Unfortunately, some investors still do not understand the basic concepts of portfolios, including the importance of optimal asset weighting in maintaining a balance between risk and return. In addition, the allocation strategies used are generally static and do not take into account real-time market dynamics. The low utilization of technical analysis based on sharia principles, such as candlestick patterns or other trend indicators, also makes investment decisions less responsive to market changes, thus risking untimely and unprofitable decisions.

The profit or loss earned from an investment is referred to as return, while the deviation between actual return and expected return is known as investment risk. A portfolio is a collection of securities or stocks that are combined and treated as a single asset. One of the common problems in portfolio management is that many investors still use allocation strategies with equal weights for each asset, which can increase the overall risk level. To overcome this, a portfolio allocation algorithm is needed that can help investors in a more optimal decision-making process. Portfolio Theory itself was developed from the mean-variance model by Markowitz, which aims to minimize portfolio risk at a fixed rate of return through an efficient frontier approach [6]. Portfolio weight optimization is generally done using Excel's Solver software with the Generalized Reduced Gradient (GRG) algorithm. However, this approach has limitations in dealing with market dynamics that have two regimes, namely bullish and bearish market conditions. A bullish market describes a period when investment confidence and activity increase, along with the expectation of future price increases (capital gains), which usually occur even before an economic recovery takes place. A bearish market, on the other hand, is a period of generally declining stock prices that reflects a shift from investor optimism to widespread pessimism or fear.

In previous studies, various methods have been used to solve problems in portfolio Theory, such as the applied single index model [7], fuzzy selection [8], hybrid Monte Carlo simulation [9], and the Bayesian approach in the Markowitz model [10]. However, most of these studies have not considered dynamic market conditions, such as the existence of bullish and bearish periods, so the resulting portfolios tend to be less applicable in real market conditions. One approach that has been done is to use the finite discrete-time Markov chain method to divide the Markowitz model into several discrete periods [11], but this approach also does not accommodate the existence of the two market regimes. Another study has identified bull and bear periods using a regime-switching model known as the Markov transition model [12]. Furthermore, this model is further developed in the form of equations that represent market dynamics more generally [13].

The objectives of this study are to: a) present descriptive statistics that describe the characteristics of Islamic stock data used in portfolio formation; b) compare the performance of two portfolio allocation algorithms, namely an algorithm that integrates the Markov-Switching model and an algorithm that utilizes the Heiken Ashi Candlestick pattern in the process of identifying market trends; and c) produce optimal portfolio weights based on the best model, which can minimize risk and adjust asset allocation to bullish and bearish market conditions. This research uses a quantitative approach with experimental techniques or computational simulations designed to test the performance of algorithms in generating optimal portfolio weights. The portfolio model developed is an extension of the classic Markowitz model but with a more adaptive approach through the integration of two different analytical methods, namely the Markov-switching model and the Heiken Ashi candlestick pattern. The Markov-switching model is used as a time series analysis tool that is able to identify dynamic market regime changes, such as transitions from bull to bear conditions or vice versa, by paying attention to shifts in average values within a certain period. Meanwhile, the Heiken Ashi pattern is utilized to detect trend changes in stock price movements by presenting a smoother and clearer visualization than conventional candlesticks, making it easier to interpret market direction. Portfolio weight optimization in each algorithm is performed using the Generalized Reduced Gradient (GRG) method, which is known to be effective in solving nonlinear programming problems and producing optimal solutions in asset distribution. The combination of these approaches is expected to create a portfolio allocation model that is not only mathematically efficient but also responsive to the changing dynamics of the stock market.

This study offers a new approach to identifying bull and bear market regimes in the context of portfolio management by utilizing visual patterns from candlestick charts that represent opening, closing, high, and low prices [14] and can signal changes in market trends [15]. The Heiken Ashi pattern, a popular variation of the Japanese candlestick, was chosen for its ability to filter out short-term fluctuations and indicate a clearer trend direction [16]. The optimization algorithms of these two approaches are implemented through syntactic programming using the open-source software R. Within the framework of portfolio Theory, this research refers to the Markowitz model that formulates portfolio weights in the form of nonlinear programming, and the optimization process is performed using the generalized reduced gradient method [17][18]. Although various approaches have been developed, the best portfolio is generally obtained based on one main criterion, which is to minimize portfolio risk for an expected level of return [17].

This research provides meaningful benefits for academics and the wider community. For academics, this study is a scientific contribution to the development of a more adaptive modern portfolio Theory by integrating the Markov-switching model and Heiken Ashi candlestick pattern as an innovative approach to stock market analysis. These findings can be used as a basis for the development of further research in the fields of finance, economics, and data science, especially those related to sharia-based investment and capital market dynamics. For the public, especially individuals involved or interested in investment, this research presents a portfolio allocation strategy that is more responsive to changes in market conditions so that it can improve financial literacy and help make investment decisions that are smarter, safer, and in accordance with Sharia principles.

Many investors do not understand the pattern of stock movements in bull and bear periods, making them vulnerable to losses due to inappropriate investment decisions. This condition highlights the need for an adaptive portfolio weight allocation algorithm that can adjust asset allocation strategies according to changing market dynamics. Therefore, this research is important to develop as an effort to present quantitative analysis-based solutions that can assist investors in making more precise and measurable decisions.

2. RESEARCH METHODS

2.1 Research Design

This research conducts a comparative analysis of two portfolio allocation algorithms that integrate the Markov-switching model and the Heiken Ashi candlestick pattern, respectively. Both algorithms are implemented using the R programming language, which is an open-source statistical computing software [19]. The approach used is a quantitative approach by applying the algorithms to historical stock price data to evaluate their effectiveness in optimizing portfolio allocation under different market conditions, namely when the market is in the bullish and bearish phases.

Within the framework of the Markowitz model, portfolio selection is based on two main parameters, namely, the expected portfolio return and the portfolio risk level. Mathematically, this portfolio Theory is formulated through three main components: portfolio return (R_t), expected portfolio return (μ_R), and portfolio risk (σ_R), each of which is calculated based on a combination of asset weights and variance-covariance between assets in the portfolio [17].

$$R_t = \sum_{a=1}^{N} w_a r_{a,t} \ ; \quad t = 1,2,\dots,n, \tag{1}$$

$$\mu_R = E[R_t] = \sum_{a=1}^{N} w_a \mu_a \,, \tag{2}$$

$$\sigma_R = \sqrt{var[R_t]} = \sqrt{\sum_{a=1}^{N}\sum_{b=1}^{N} w_a w_b \sigma_{ab}}\,, \tag{3}$$

Where N represents the number of stocks in the portfolio, while n represents the number of observations or stock price data used, in this study, the best portfolio is determined based on one main optimization criterion, namely minimizing portfolio risk while maintaining the desired level of expected return [17]. The criterion is formulated in the form of a nonlinear programming equation as follows:

$$\begin{aligned} &\text{minimize } f(w) = \sigma_R = \sqrt{\sum_{a=1}^{N}\sum_{b=1}^{N} w_a w_b \sigma_{ab}} \\ &\text{Constraints: } \mu_R = \sum_{a=1}^{N} w_a \mu_a \geq \mu_0 \\ &\sum_{a=1}^{N} w_a = 1 \\ &w_a \geq 0\ ;\ a = 1,2,\dots,N. \end{aligned} \tag{4}$$

The Generalized Reduced Gradient (GRG) algorithm is a refinement of the reduced gradient algorithm designed to solve nonlinear optimization problems with constraints. GRG is the best coefficient optimization method among other methods in Excel's Solver software for nonlinear programming [20]. In the context of inequality-shaped constraints, nonlinear programming can be formulated in the following general form [18]:

$$\begin{aligned} &\text{Minimize } f(x) \\ &\text{Constraints}: a_{k*} \leq g_{k*}(x) \leq b_{k*} \quad ; k^* = 1,2,3,\dots,K^* \\ &\qquad h_k(x) = 0 \quad ; k = 1,2,3,\dots,K\ . \\ &\qquad x_i^{(L)} \leq x_i \leq x_i^{(U)} \quad ; i = 1,2,\dots,M \end{aligned} \tag{5}$$

Inequality constraints a < b changes into

$$h_{k*}(x) = g_{k*}(x) - b_{k*} + x_{M+k*} = 0, \tag{6}$$

where x_{M+k*} is the slack variables for k*, whereas inequality constraints $g_{k*}(x) \geq b_{k*}$ also changes into Eq. (6)

$$h_{k*}(x) = g_{k*}(x) - a_{k*} - x_{M+k*} = 0, \tag{7}$$

where x_{M+k*} is the surplus variable for k* .

The Markov-switching model is a method used to handle regime-switching problems, where stock returns are modeled using first-order autoregressive (AR(1)) by incorporating state changes (s_t) that are considered constant in each regime [12]. In general, this model can be extended to a p-order autoregressive (AR(p)) form, where changes in state (s_t) affect the overall structure of the model [13] so that the stock return model can be represented as follows:

$$r_t = \begin{cases} \varphi_{0,1} + \sum_{i=1}^{p} \varphi_{i,1} y_{t-i} + \varepsilon_t & ;\ s_t = 1 \\ \varphi_{0,2} + \sum_{i=1}^{p} \varphi_{i,2} y_{t-i} + \varepsilon_t & ;\ s_t = 2 \end{cases} \tag{8}$$

which can be solved in simple forms, into

$$r_t = \varphi_{0,St} + \sum_{i=1}^{p} \varphi_{i,s_t} y_{t-i} + \varepsilon_t\ , \varepsilon_t \sim N(0, \sigma_{St}^2) \tag{9}$$

The observation data can be identified and divided based on filtering probability [12]:

$$\xi_{j,t} = P(s_t = j|\ \Omega_t; \theta) = \frac{\sum_{i=1}^{2} p_{ij}\, \xi_{j,t-1}\, \eta_{jt}}{f(y_t|\Omega_{t-1}; \theta)}. \tag{10}$$

Filtering probability may differ if the series follows a bullish or bearish period.

2.2 Data Source

The population in this study includes all stocks that comply with Sharia principles in Indonesia. The samples used are stocks listed in the Jakarta Islamic Index (JII) during the COVID-19 pandemic period. Data was obtained from PT TICMI, a subsidiary of the Indonesia Stock Exchange (IDX). A random sampling technique was used to select stocks from the historical database. The dataset used is secondary data in the form of daily stock prices, covering the period from January 2019 to August 2022.

2.3 Research Variables

This study uses four main variables in the stock price data, namely the opening price, highest price, lowest price, and closing price. All of these variables are continuous data measured on a ratio scale. The stocks selected for analysis include TLKM, ADRO, UNTR, EMTK, KLBF, and ANTM. The closing price (c_t) is used as the basis for calculating stock returns (r) over n observations by the return calculation formula presented in Eq. (11).

$$r_t = log\left(\frac{C_t}{C_{t-1}}\right), i = 1,2, \dots , n$$

2.4 Data Analysis

The portfolio allocation process using the Markov-switching model is carried out through several systematic stages. The first step is to enter the closing price data of all stocks analyzed, then calculate the return for each stock and calculate the portfolio return with equal weights. Next, the Markov-switching model parameters are estimated on the portfolio return using the built-in package in R software, namely MSwM. The results of this estimation are used to obtain the filtering probability as described in Eq. (10). Based on these probabilities, the stock return regime is determined, and all stock returns are divided into two regimes. For each regime, the correlation matrix between stock returns, as well as the expected return and covariance matrix of the overall stock variance, are calculated. Next, the identification of the suitability regime, whether it is a bear or bull period, based on the results of the correlation, average, and standard deviation of the stocks. Portfolio weight optimization for each regime (w_{s_t})) is carried out with the Generalized Reduced Gradient (GRG) algorithm through several sub-steps, such as determining the initial value of the portfolio weight (w), calculating the objective function $f(w)$ and constraint function $h(w)$, and their derivatives $\nabla f(w)$ and $\nabla h(w)$, then continuing with the weight update through iteration until it meets the convergence criteria. Calculating gradient function $\nabla \tilde{f}(w^{(r)}) = \nabla \bar{f}(w^{(r)}) - \nabla \hat{f}(w^{(r)})J^{-1}C$. If $\left\|\nabla \tilde{f}(w^{(r)})\right\| \le \varepsilon_1$ is accomplished, thus the iteration step stop; but if $\left\|\nabla \tilde{f}(w^{(r)})\right\| \le \varepsilon_1$ is not accomplished, thus calculating $\bar{d} = (-\nabla \tilde{f})^T$, $\hat{d} = -J^{-1}C\ \bar{d}$, and $d = (\hat{d}, \bar{d})^T$. Minimizing $f(x^{(r)} + \alpha\ d)$ considering α value. Let $\alpha^{(r)}$ present optimization α, thus calculating $w^{(r+1)} = w^{(r)} + \alpha^{(r)}d$; and then the process be repeated again. After obtaining the optimal weight for each regime (w_{s_t}), the calculation of the final weight of the portfolio (w_a), expectation return portfolio (μ_R), and risk portfolio (σ_R) based on w_a. And then, and the results of calculating w_a, μ_R, and σ_R is carried out.

Candlestick patterns are known to be difficult to implement in algorithms and programming due to the complexity of their shapes and interpretations. Therefore, this research uses the Heiken Ashi (HA) candlestick pattern as a more structured alternative to be implemented computationally. The portfolio allocation process with the HA pattern begins by entering the closing, opening, highest, and lowest price data of all stocks analyzed. Next, the return of each stock and the aggregate value of the closing, opening, highest, and lowest prices of the portfolio with equal weights are calculated. Based on these data, HA values were calculated: HA closing price was obtained from the average of open price, close price, low price, and high price, HA opening price was calculated from the average between HA opening and closing prices in the previous period, HA high price was determined from the maximum value between the current high price, HA opening, and HA closing, while HA low price was taken from the minimum value of the three components. Determination of candle type is done with the criteria: candles are categorized as bullish if close HA > open HA and bearish if otherwise. Based on this classification, the stock return data is divided into two regimes, namely Regime 1 and Regime 2. For each regime, the portfolio weight (w_{s_t}) is optimized using the Generalized Reduced Gradient (GRG) algorithm. Next, the portfolio weights of each regime are displayed, and the final portfolio weights are calculated. Calculating expectation return portfolio (μ_R) and risk portfolio (σ_R) based on w_a. Showing the results of calculating w_a, μ_R, and σ_R.

3. RESULTS AND DISCUSSION

In this paper, the dataset used is in the form of daily stock price time series data, which includes the opening price, highest price, lowest price, and closing price of selected Islamic stocks in Indonesia, with a time span from January 2019 to August 2022. In the process of portfolio formation, the stocks are first screened using Stock Screener criteria for the Jakarta Islamic Index (JII) group and must meet good fundamental requirements, namely having Market Capitalization ≥ 50,000 billion rupiah and Return on Assets (ROA) ≥ 5%. In addition, the selected stocks must also have a historical pattern that does not show a monotonous downward trend. Based on these specifications, six stocks from the JII group were selected for analysis, namely TLKM, ADRO, UNTR, EMTK, KLBF, and ANTM. The following shows a time series plot of the closing prices of these stocks that show a historical pattern with an upward trend.

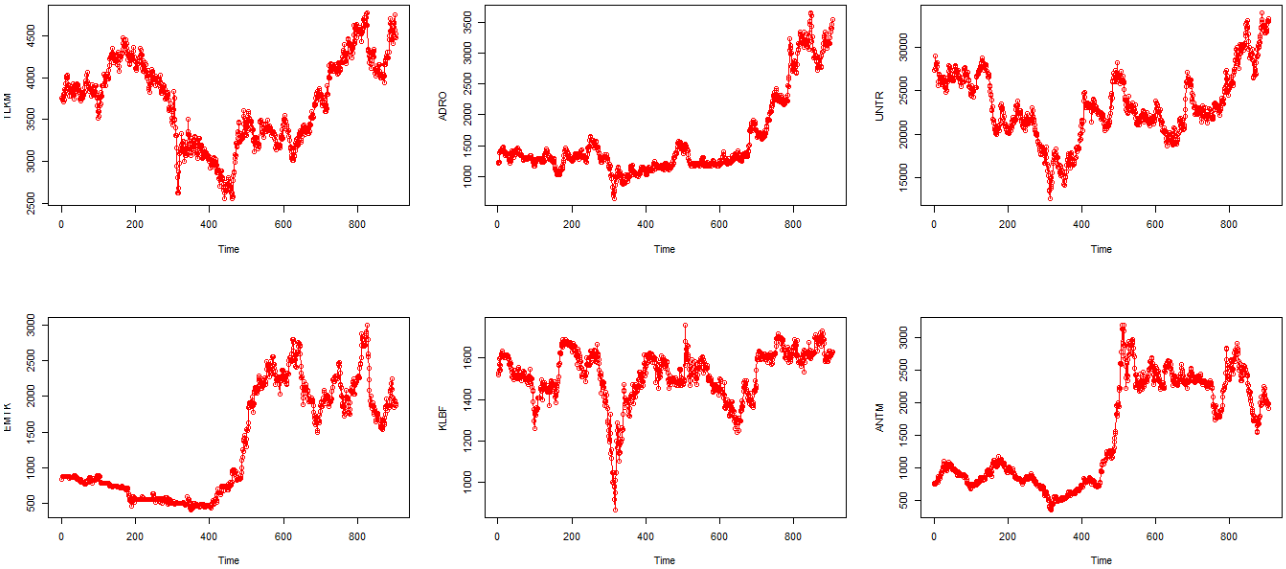

Figure 1. Time Series Plots for the Closing Prices of TLKM, ADRO, UNTR, EMTK, KLBF, and ANTM Stocks
(*Source: The figure was generated using R (version 3.4.1)*)

On an upward trend, investors tend to have high confidence in the potential for future gains (capital gains). Fig. 1 shows that some stock closing prices show a historical pattern with an upward trend, although, in the final period, there are indications of a downward trend. This pattern of price movement reflects the phenomenon of bullish and bearish market cycles, which are characterized by fluctuating increases and decreases in stock prices over some time. In the last week, August 31, 2022, the weekly closing prices for the six stocks were: TLKM by 4,480, ADRO by 3,540, UNTR by 33,325, EMTK by 1,900, KLBF by 1,630, and ANTM by 1,985.

Based on the results shown, it can be synthesized that the upward trend of stock price movements reflects market optimism, where investors have high confidence in the potential for future profits (capital gains). This phenomenon is often associated with bull market conditions, a period when stock prices generally move up in response to positive sentiment, good fundamental performance, or expectations of strengthening economic growth. However, as illustrated in Fig. 1, while most stock prices exhibit an uptrend pattern over their historical period, there are indications of a downturn at the end of the period, which could lead to a transition to bearish conditions, i.e., a period when stock prices tend to decline due to weakening market sentiment or economic pressures. This cyclical change reflects the non-static dynamics of the capital market, where various external and internal factors, such as changes in economic policy, issuer performance, and global conditions, strongly influence stock prices. The weekly closing price data as of August 31, 2022, shows the actual position of the six stocks (TLKM, ADRO, UNTR, EMTK, KLBF, and ANTM), which can be used as a reference for further analysis regarding the return and risk of each stock. These prices are an important basis for building an investment portfolio, especially in identifying the transition moment between bullish and bearish phases to determine the return and risk of each stock.

This closing price dataset is then used to calculate stock returns mathematically $r_t = \ln(P_t / P_{t-1})$ with $t = 1,2,\ldots,n$. A visualization of the return time series plot, as well as a summary of the descriptive statistics of the data, are shown in Fig. 2 and Table 1.

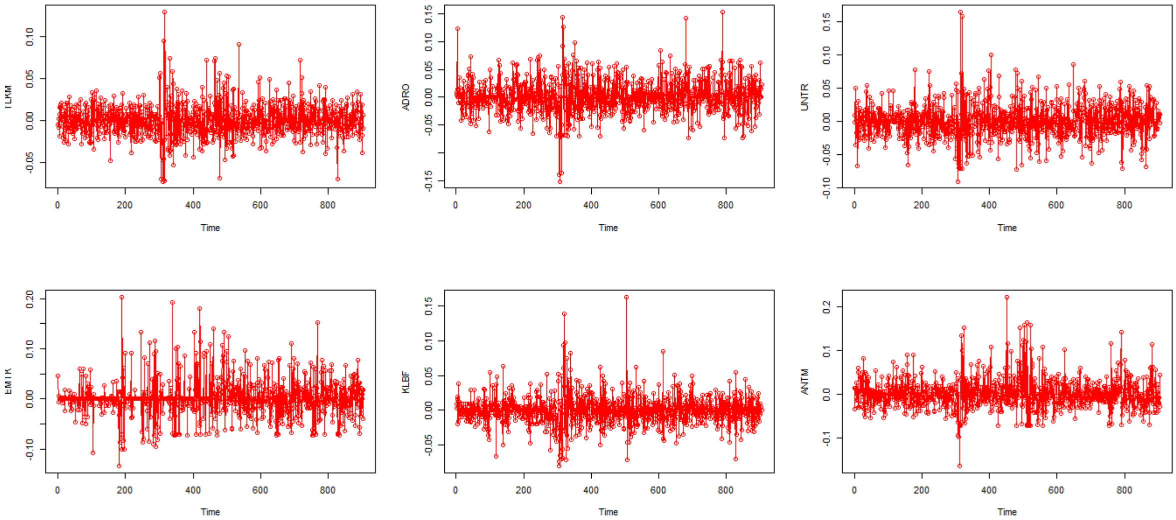

Figure 2. Time Series Plot for the Return of TLKM, ADRO, UNTR, EMTK, KLBF, and ANTM Stocks
(*Source: The figure was generated using R (version 3.4.1)*)

Table 1. Summary of Descriptive Statistics from Return Shariah Stocks.

Stocks	Observation	Expectation Return	Standard Deviation
TLKM	904	0.02%	0.0196
ADRO	904	0.12%	0.0306
UNTR	904	0.02%	0.0259
EMTK	904	0.09%	0.0368
KLBF	904	0.01%	0.0215
ANTM	904	0.11%	0.0351

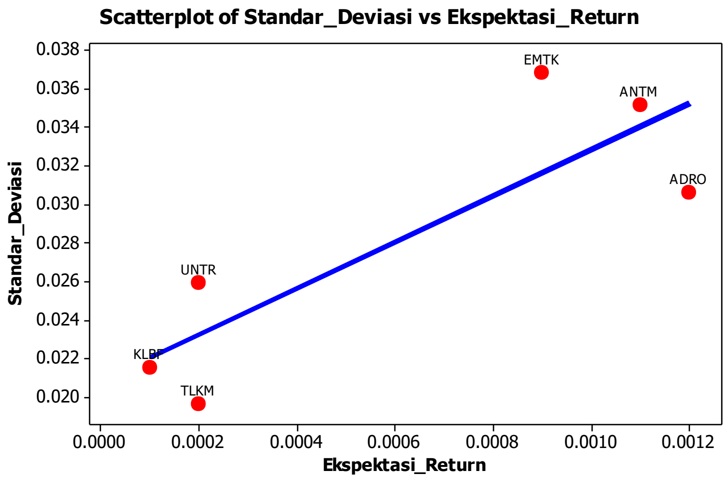

Figure 3. Scatter Plot with Regression for the Closing Prices of TLKM, ADRO, UNTR, EMTK, KLBF, and ANTM Stocks
(*Source: The figure was generated using R (version 3.4.1)*)

Based on the output of Table 1 and Fig. 3, the highest expected return is given by ADRO stock of 0.12% with a risk level (standard deviation) of 0.0306. In contrast, the lowest expected return is shown by KLBF stock at 0.01%, with a risk of 0.0215. EMTK stock shows the highest risk among the entire sample, while the lowest risk is owned by TLKM stock. These results indicate that the descriptive statistical characteristics of the six stocks are in line with economic Theory, which states that higher potential returns are usually accompanied by greater risk. However, this Theory does not always apply consistently to certain market conditions, such as during bullish or bearish periods. It should be noted that the descriptive statistics in Table 1 are general and do not identify stock characteristics based on these market conditions. Based on Fig. 3, there is a clustering of stocks into two categories: stocks with relatively low expected return and risk (KLBF, TLKM, and UNTR) and stocks with relatively high expected return and risk (EMTK, ANTM, and ADRO).

The results presented in Table 1 and Fig. 3 provide important insights into the relationship between return and risk of the six stocks studied. ADRO stock occupies the highest position in terms of expected return (0.12%) but also has a relatively high risk (standard deviation 0.0306), while KLBF stock shows the lowest expected return (0.01%) with a lower risk (0.0215). It suggests a positive relationship between return and risk, which is in line with the basic principles of financial economic Theory, namely high risk, high return. However, a deeper synthesis reveals that the Theory is general and may not necessarily apply consistently in all market conditions. In this context, it is worth considering that the descriptive statistical data used is still aggregate, not considering segmentation based on market phases such as bullish (uptrend) or bearish (downtrend), which can dynamically affect risk and return characteristics. Fig. 3 shows the clustering of stocks based on the risk-return profile. KLBF, TLKM, and UNTR stocks form a group with lower risk and return, suitable for conservative investors who prioritize stability. In contrast, EMTK, ANTM, and ADRO are in the group with higher risk and return, appealing to aggressive investors who pursue greater profit potential despite having to face higher market volatility. This discussion emphasizes the importance of segmentation in portfolio analysis. Categorizing stocks based on their return and risk characteristics allows investors to be more strategic in constructing a portfolio that suits their investment profile and objectives. In addition, this approach opens up opportunities to implement dynamic portfolio strategies, such as market regime-based allocation, which will be further analyzed in the study using Markov Switching models.

Using one optimization criterion, which is to minimize the portfolio risk for the expected return level, the results of the portfolio optimization algorithm comparison are summarized in Table 2. The table presents the implemented portfolio weights from three approaches: Markov-Switching model with AR(1), Markov-Switching model with AR(2), and Heiken Ashi candlestick pattern.

Table 2. Summary of the Results of Comparing Algorithm of Optimization Portfolio

Methods		**MSwM-AR(1) Model**	**MSwM-AR(2) Model**	**Candlestick Pattern**
unconditional portofolio weights (upw)	TLKM	4.98%	4.81%	20.12%
	ADRO	17.64%	0.46%	11,90%
	UNTR	2.35%	19.44%	13.32%
	EMTK	35.88%	36.13%	26.23%
	KLBF	12.88%	12.73%	27.21%
	ANTM	26.27%	26.43%	1.22%
Expectation Return		0.08%	0.07%	0.05%
Standard Deviation		0.0206	0.0200	0.0159

Table 2 shows that the three methods compared produce relatively similar minimum portfolio risk (standard deviation), which is close to 0.02. On the other hand, the portfolio with the highest expected return is obtained from the MSwM-AR(1) model, which is 0.08%. In general, the Markov-switching model approach shows superior performance compared to other methods. Next, the detailed results of the MSwM-AR(1) model as the best-performing model are shown.

The results in Table 2 show that the three portfolio optimization methods compared produce relatively similar minimum risk levels, with a standard deviation close to 0.02, indicating the ability of all methods to control portfolio risk at a low level. However, what distinguishes their performance is the level of expected return generated. In this case, the MSwM-AR(1) (Markov Switching with Autoregressive order 1 model excels with the highest expected return of 0.08%, making it the most optimal model among the three approaches tested. Synthesized, these results show that the Markov-switching model is able to adjust the portfolio strategy to the dynamics of changing market regimes, making it more adaptive than static methods. The model is not only able to identify shifts in market conditions between bullish and bearish but also contextually optimize portfolio weights according to the characteristics of the prevailing regime. It makes the Markov-switching approach particularly relevant in volatile and non-stationary market environments. In other words, while all models can reduce risk, only the Markov-switching approach (specifically MSwM-AR(1)) consistently delivers higher expected returns without significantly compromising risk stability.

Therefore, these results support the utilization of regime-based dynamic models as a superior framework in long-term portfolio optimization, especially in the face of high market uncertainty.

In the Markov-switching approach, the identification of the feasibility of regimes to represent Bullish and Bearish market conditions is done by considering the correlation between stock returns, expected return, and standard deviation of each stock. When the portfolio return regime is applied (with equal weights) to all stock returns, lower inter-return correlations, higher expected stock returns, and lower standard deviations characterize Bullish market periods. Conversely, Bearish market periods are characterized by higher correlations between returns, lower expected returns, and higher standard deviations. The details of the correlation output between stock returns for each regime are presented below:

Table 3. Correlation Among Return Stocks Based on Regime MSwM-AR(1)

No.	Stock (i)	Stock (j)	Correlation Regime 1	Correlation Regime 2
1	TLKM	ADRO	0.1741*	0.6112*
2	TLKM	UNTR	0.1920*	0.5703*
3	ADRO	UNTR	0.4836*	0.7127*
4	TLKM	EMTK	-0.0407	0.1811
5	ADRO	EMTK	0.0210	0.1877
6	UNTR	EMTK	-0.0484	0.0949
7	TLKM	KLBF	0.1896*	0.5045*
8	ADRO	KLBF	0.1123*	0.3737*
9	UNTR	KLBF	0.1305*	0.4344*
10	EMTK	KLBF	-0.0323	0.2828
11	TLKM	ANTM	0.1910*	0.5934*
12	ADRO	ANTM	0.3158*	0.5959*
13	UNTR	ANTM	0.2495*	0.5695*
14	EMTK	ANTM	0.0911	0.2434*
15	KLBF	ANTM	0.1352*	0.2829*

* Significant for α of 1% (P-value < 1%).

Based on the output of Table 3, it is found that all correlation values between stock returns in regime 2 are greater than the correlation values in regime 1. This finding indicates that Regime 1 represents a bullish market period, while Regime 2 reflects a bearish market period. To corroborate this conclusion, additional descriptive statistical analysis was conducted, specifically on the expected return and standard deviation of each stock return included in regime 1 (n_1 = 790) and regime 2 (n_2 = 114).

Table 4. Descriptive Statistics Return Stock Based on Regime MSwM-AR(1)

Stock	Expectation Return Regime 1	Expectation Return Regime 2	Standard Deviation Regime 1	Standard Deviation Regime 2
TLKM	0.04%	-0.11%	0.0166	0.0338
ADRO	0.15%	-0.09%	0.0270	0.0490
UNTR	0.04%	-0.10%	0.0223	0.0434
EMTK	-0.02%	0.83%	0.0347	0.0486
KLBF	0.02%	-0.08%	0.0172	0.0404
ANTM	-0.01%	0.92%	0.0278	0.0662

Based on the descriptive statistics output in Table 4, all stock returns show that the expected return in regime 1 is higher than the expected return in regime 2. In addition, the standard deviation in regime 1 is consistently lower than that in regime 2. These findings reinforce the conclusion that Regime 1 represents a bullish market period, while Regime 2 reflects a bearish market period, as visualized in Fig. 4.

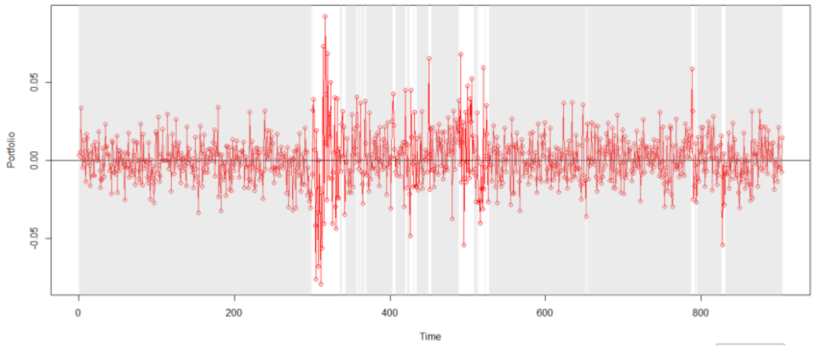

Figure 4. Time Series Plot from Return Portfolio with Dark Area for Regime 1 (Bullish market period) based on MSwM-AR(1)
(*Source: The figure was generated using R (version 3.4.1)*)

The results shown in Table 3 and Table 4 provide a strong basis for identifying the characteristics of two market regimes, namely Regime 1 as a bullish period and Regime 2 as a bearish period. The higher inter-stock return correlation in Regime 2 indicates that during bearish periods, stock movements tend to be more synchronized or coordinated, which is a common feature when markets are under stress-stocks tend to fall together. In contrast, the lower correlation in Regime 1 indicates a natural diversification among stocks, which generally occurs when the market is in a positive or bullish condition. Furthermore, the results from Table 4 corroborate these findings through descriptive statistical analysis: all stocks show higher expected returns in Regime 1 and lower risk (standard deviation) compared to Regime 2. This pattern is highly consistent with finance Theory, which states that during a bull market, investors are more optimistic, volatility decreases, and returns increase. Conversely, in a bear market, uncertainty increases, so volatility rises and expected returns decrease. In synthesis, the Markov-switching-based approach successfully captures the dynamic structure of the market by distinguishing between two regimes based on empirical data. It is an added value in portfolio management strategies as it allows investors to adapt asset allocation based on the ongoing market phase rather than just based on aggregate data that could be misleading. By recognizing market conditions through indicators such as correlation, return, and risk between regimes, investment decisions become more responsive and strategic and reduce the possibility of large losses when the market reverses.

Portfolio optimization is carried out to meet the optimization criteria, namely minimizing portfolio risk against the desired level of expected return. The expected return value (μ_0) used as a reference in regime one is obtained from the average of all expected returns in regime one, as listed in Table 4. In contrast, the value for regime two (μ_0) is calculated from the average of all expected returns in regime 2. Alternatively, users can also use the expected return value (μ_0) in regime 1 of 0.0004 (0.04%) and in regime 2 of 0.0023 (0.23%). Based on these values, the output is obtained in the form of portfolio weights for regime 1, regime 2, and unconditional portfolio weight (*upw*), as shown in Table 5.

Table 5. Portfolio Weights Based on MSwM-AR(1) and GRG Method

Stocks	**Portofolio Weights Regime 1**	**Portofolio Weights Regime 2**	**Unconditional Portofolio Weights (upw)**
TLKM	34.08%	0%	4.98%
ADRO	3.83%	20%	17.64%
UNTR	16.09%	0%	2.35%
EMTK	11.83%	40%	35.88%
KLBF	29.69%	10%	12.88%
ANTM	4.49%	30%	26.27%
Expectation Return	0.03%	0.58%	0.08%
Standard Deviation	0.0112	0.0386	0.0206

In Table 5, the resulting portfolio shows an expected return of 0.08% with a portfolio standard deviation of 0.0206. This result reflects a more realistic estimation of return and risk in the face of both Bearish and Bullish market conditions. This finding also indicates that the portfolio is able to achieve minimum risk with an acceptable level of return. These values are then used as the basis for descriptive statistical analysis of the portfolio formed.

The results shown in Table 5 illustrate that the portfolio formed through the Markov-switching model approach, taking into account both bullish and bearish market conditions, can produce an efficient combination of return and risk. With an expected return of 0.08% and a portfolio standard deviation of 0.0206, this portfolio reflects a realistic allocation strategy that is responsive to market dynamics. This finding indicates that despite extreme market fluctuations between bullish and bearish conditions, the model that considers regime change can keep risk at a minimum level without significantly compromising potential returns. It is very important in portfolio management practice as static approaches that ignore market cycles tend to provide biased or misleading risk-return estimates. In terms of synthesis, these results show that the integration between the regime-based statistical approach and portfolio optimization criteria provides advantages in producing more informative investment decisions. The resulting return and risk estimate not only reflect aggregate historical performance but also anticipate changes in market conditions. In other words, this approach increases the adaptive ability of the portfolio, making it more responsive to changes in market direction, as well as more robust in the face of economic uncertainty.

4. CONCLUSION

The results show that the Markov-switching model-based portfolio approach is able to effectively capture the cyclical market dynamics between bullish and bearish phases. The model not only identifies market regime shifts based on historical stock return data but also provides more realistic and adaptive portfolio risk and return estimates than static methods. The portfolios generated with this model exhibit an optimal combination of competitive expected return (0.08%) and minimum risk (0.0206) and accommodate different stock characteristics for different types of investors. The clustering of stocks based on the risk-return profile, as well as the correlation analysis results between stocks in each regime, also support the model's ability to develop a more precise asset allocation strategy. The findings confirm that the combination of a regime-based statistical approach and dynamic portfolio optimization is a superior strategy for making long-term investment decisions amid market uncertainty.

Based on the findings, it is recommended that investors and financial practitioners consider using regime-based dynamic models, such as MSwM-AR(1), in portfolio construction strategies, especially in volatile and non-stationary market conditions. The use of this model can be further enhanced by integrating advanced optimization methods, such as genetic algorithms, convex optimization, or hybrid approaches, to obtain higher portfolio efficiency and flexibility to market changes. In addition, further research needs to expand the scope of stock data and observation period so that the validity of the model can be tested more broadly, as well as consider external factors such as macroeconomic policies or global sentiment that may affect the transition between regimes. The development of an early warning system based on regime change is also a promising potential in supporting proactive portfolio risk management.

Author Contributions

Denny Nurdiansyah: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft, Supervision, Final approval of the manuscript. Agus Sulistiawan: Writing – review & editing, Conceptualization, Theoretical Framework, Writing – Review and Editing, Supervision, Final approval of the manuscript. Both authors were actively involved in academic discussions and have jointly agreed on the content of the final manuscript.

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Declarations

The authors declare that they have no conflict of interest related to this study.

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