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ARIMA-GARCH Markov switching method for forecasting the share price of PT. Bank Rakyat Indonesia (Persero) Tbk.

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ABSTRACT

Shares are financial instruments that represent a small ownership in a company and give the holder the right to receive dividends and participate in the company's decisions. The Covid-19 pandemic is also believed to have a major impact on the world stock market, so it is also important to analyze stock price fluctuations before and after the outbreak. One of the suitable methods for predicting stock price volatility is ARIMA-GARCH Markov Switching. The data used is secondary data from PT. Bank Rakyat Indonesia (PERSERO) Tbk. From January 2, 2019 to November 30, 2023. PT stock price data forecast. Bank Rakyat Indonesia (PERSERO) Tbk. Using ARIMA-GARCH Markov Switching method, the best model is ARIMA(2,1,2) GARCH(1,1) and the forecast value obtained is 5280.935; 5275.403; 5276.776; 5279.255; 5275,760 for 5 periods and divided into 2 regimes, namely the first regime with data that has low volatility and the second regime with data that has high volatility.

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INTRODUCTION

The COVID-19 pandemic that has hit the world since the beginning of 2020 has had an extraordinary global social, economic and health impact. This pandemic not only affects human physical health because the virus spreads so quickly and requires serious treatment, but also drastically changes the order of social life and human behavior such as working from home, the occurrence of an economic crisis, and the amount of unemployment (Kurman, 2020). The effects related to this make people scramble to continue to earn enough income to support life as before the COVID-19 epidemic (WHO, 2020). An interesting aspect to study is the fluctuation in activities and phenomena during this epidemic, compared to the period before the epidemic. The stock market, also known as the equity market, is one of the main components of the financial system that facilitates the trading of shares or equity of publicly listed companies. The stock market is one of the main aspects of the global financial system that has a major impact on the economy, business and investment (Syamsir, 2008). Stock trading is the process of buying and selling shares or ownership in companies listed on a stock exchange. In the stock market, stock prices are determined by the interaction between supply and demand. Factors that affect stock prices include the company's financial performance, growth expectations, macroeconomic conditions, news or events that affect a particular company or industry, and market sentiment that is influenced by investors' emotions and perception (OJK, 2017). Drastic changes in consumption patterns, business closures and travel restrictions affect corporate performance, which in turn affects the stock market. Bank shares are financial instruments that represent ownership or part ownership in a bank or financial institution listed on the stock market (IDX, 2023). Bank stocks are one of the most important assets in the financial world and play an important role in driving the global economy. The banking sector is the backbone of the global financial system. Banks are the primary intermediaries that collect funds from account holders and provide credit to individuals, businesses and governments. Banks also play a role as guardians of economic stability by regulating money supply through monetary policy and managing financial risks (Lestari, 2017). Therefore, bank shares are a mirror of the health and economic performance of a country.

Bank Rakyat Indonesia (Persero) Tbk. shares are an interesting subject in the world of investment in the Indonesian stock market. Bank Rakyat Indonesia (BRI) is one of the leading banks in Indonesia that has an important role in supporting the national economy and the development of the banking sector. BRI stock is one of the most traded financial instruments on the Indonesia Stock Exchange (IDX), and its performance can provide valuable insight for investors, market analysts and other stakeholders. (Zaenal & Dewi, 2019). Research on BRI shares have significant relevance in understanding the role of the bank in the Indonesian economy and how the movement of its share price can provide insight into the dynamics of the stock market. Moreover, discussing the impact of an epidemic on the stock market is very interesting because the epidemic provides a vivid illustration of how an unexpected external event can drastically change market dynamics. In addition, this study can provide insight into the market's ability to adapt to extreme events and how government policies and financial authorities affect market stability. An understanding of the market's response to the outbreak can help investors, companies and policymakers plan better strategies to deal with similar crises in the future.

Forecasting is one of the important elements in decision making in various fields, and the ability to predict changes in time series data (Hadyan, 2020) . Forecasting is one of the important elements in decision making in various fields, and the ability to predict changes in time series data (Hadyan, 2020). The ARIMA (AutoRegressive Integrated Moving Average) model has become one of the most commonly used forecasting methods. This model makes it possible to overcome both stationary and non-stationary nature of time series data. However, in financial and investment markets, asset prices often show high volatility and unstable behavior. In addition, the forecast of asset price fluctuations is also the main focus of investors and traders, especially when considering risk management in investment portfolios. The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is a commonly used tool for modeling heteroskedastic volatility in financial data. Furthermore, in situations where time series undergo structural changes, such as periods of economic crisis or changes in economic policy, flexible forecasting models are required to accommodate such changes. (Wijoyo, 2016). The Markov Switching (MS) model is an approach that allows for structural changes in time series. Combining ARIMA, GARCH and Markov Switching in one forecasting model (ARIMA-GARCH Markov Switching) can provide a strong ability to predict changes in financial data, especially when the volatility fluctuates and the structure changes. Therefore, research on forecasting using ARIMA-GARCH Markov Transformation is important in facing complex forecasting challenges in financial and economic contexts. This research aims to explore and develop forecasting methods using ARIMA-GARCH Markov Switching to deal with uncertainty and structural change in time data, with particular emphasis on applications in the stock market of Bank Rakyat Indonesia (BRI).

This study aims to comprehensively explore BRI stock price fluctuations in the period before and after the COVID-19 pandemic, and to implement the ARIMA-GARCH Markov Conversion model to predict BRI stock prices in the future. By analyzing the behavior of BRI stock prices before and after the pandemic, this research aims to provide a more comprehensive picture of the impact of the pandemic on the capital market. Through the application of complex forecasting models such as ARIMA-GARCH Markov Switching, another objective of this study is to test the effectiveness of the model in predicting future BRI stock price fluctuations, so that it can provide a deeper understanding of stock price movement patterns and help. investors in making smarter investment decisions. It is hoped that the results of this study will not only make a meaningful academic contribution to the understanding of the capital market and forecasting methodology, but will also have significant practical implications for researchers, related agencies, and readers interested in stock investment, especially in the face of uncertain economic situations, such as the COVID-19 outbreak.

The ARIMA-GARCH Markov Switching Model was conducted to look at the volatility of LQ45 stocks with the GARCH Markov Switching approach by comparing the AIC and BIC values in the GARCH and Markov Switching GARCH results (Ermanely, 2023). In addition, ARIMA GARCH modeling has been used in a study titled ARIMA GARCH Model in predicting PT Jasa Marga (Persero) Share Prices until the best modeling is obtained (Putri et al., 2021). Also BRI stock price forecasts were studied which used ARIMA and produced accurate forecasts (Lilipaly et al., 2014) and the ARIMA GARCH method which produced the best model (Yolanda et al., 2017). Furthermore, the Markov switching method has been used in research predicting the banking crisis in Indonesia with the Markov Switching VAR approach (Rusydiana et al., 2021). Based on previous studies, we tried to apply the ARIMA-GARCH Markov Conversion Method to predict the share price of PT Bank Rakyat Indonesia. In particular, to see forecast numbers using ARIMA-GARCH and to see high and low volatility regimes in stock prices using Markov Switching.

METHOD

This study uses daily data on the share price of PT Bank Rakyat Indonesia (Persero) Tbk, especially the adjusted closing variable or the closing price of the stock that has been adjusted (adjusted) to accommodate changes that may affect the stock price in the January range. 2, 2019 to November 30, 2023 through the website www.ir-bri.com.

In the stationarity test for stock price data of PT Bank Rakyat Indonesia

(Persero) Tbk, we use the Augmented Dickey-Fuller (ADF) test and the Boxcox Test. The Augmented Dickey-Fuller (ADF) test is a statistical method used to test for stationarity in time series data. Data are said to be stationary if their mean and variance are constant over time and there is no strong autocorrelation between different lags. This test aims to identify whether time series data is stationary by testing the null hypothesis that the data has a unit root (non-stationary data assumption). The general form of the ADF Test is as follows:

$$\Delta Z_t = \beta_1 + \beta_2 t + \delta Z_{t-1} + \alpha_1 \Delta Z_{t-1} + \alpha_2 \Delta Z_{t-2+\cdots+} \alpha_2 \Delta Z_{t-2} + \alpha_t$$

In the ADF test, the t-statistic is calculated and compared to the corresponding critical value. If the t-statistic is smaller than the critical value, then the null hypothesis is rejected, indicating stationary data. Conversely, if the t-statistic is greater than the critical value, the null hypothesis fails to be rejected, indicating that the data are not stationary. Regression models for ADF tests involve changes in time series data and previous lags.

The Boxcox test is a statistical method used to transform data so that the distribution approximates a normal distribution. This transformation is particularly useful when the data has non-constant variance or a distribution that deviates from normality. By transforming the data, the Box-Cox test can help correct heteroscedasticity and non-normality problems, allowing for more valid and accurate statistical analysis.

$$y' = \begin{cases} \dfrac{y^\lambda - 1}{\lambda} & if\ \lambda \neq 0 \\ \log(y) & if\ \lambda = 0 \end{cases}$$

Where y' is the transformed data, y^λ is the original data, and λ is the transformation parameter controlling the degree of transformation.

ARIMA has a strong theoretical foundation and is flexible for modeling trending, seasonal or fluctuating time series. ARIMA combines three main components: autoregression (AR), variance component (Integrated) and moving average (MA) (Sari, 2019). The equation of this model can be explained by the following expression

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} \epsilon_t + \emptyset_1 \epsilon_{t-1} + \emptyset_2 \epsilon_{t-2} + \emptyset_q \epsilon_{t-q}$$

The ARIMA model includes three parameters p, d and q. Autoregressive (AR), Moving Average (MA) and differentiation (I) models work together when the time series used is non-stationary assuming p is the order of AR which is the autoregressive term, d is the order of I which is the non-seasonal difference and q is the order of MA which is the amount of forecast error left in the forecast equation (Fualt, 2022).

The tests used for ARIMA modeling are Z test, Ljung-Box test and Langrange Multiplier Test. The Z-test was used to see if there was a significant effect of the variables in the best Arima model. The Z test is used to test a hypothesis about a population parameter (such as the mean) using a normal distribution. This test is appropriate when the sample size is large (more than 30) and the population variance is known.

$$Z = \frac{\bar{x} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

where $\bar{x}$ is the sample mean, μ is the population mean value, σ is the population standard deviation, n is the sample size.

The Ljung-Box test is a method for testing the presence of autocorrelation in a time series up to a certain number of lags. The statistical value calculated is Q, which follows a chi-squared distribution.

$$Q = n\left(\sum_{k=1}^{m} \frac{\hat{r}_k^2}{n-k}\right)$$

where n is the sample size, m is the number of lags tested, and $\hat{r}_k^2$ is the autocorrelation at lag.

The Lagrange Multiplier test (LM test) is a statistical method used to test whether certain parameters in a statistical model satisfy certain restrictions or constraints.

$$LM = nR^2$$

with the null hypothesis being that there is no ARCH effect and the Alternative Hypothesis being that there is an ARCH effect. n is the number of residual data and is the coefficient of determination in the regression model.

The GARCH model of order (p, q) states that the variance of y_t is conditional on past information and will follow the form of (Christian Francq, 2019)

$$var(y_t | \ni_{t-1}) = E(\varepsilon_t^2 | \ni_{t-1}) = \sigma_t^2$$

With $\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_i \varepsilon_{t-1}^2 \sum_{i=1}^{q} \beta_j \sigma_{t-1}^2$

If $q = 0$ then it has Engle GARCH model, if $p = q = 0$ then it has a white noise model with variance. In the GARCH (p, q) model, the ε_t^2 process is expressed as follows $\varepsilon_t^2 = \sqrt{\sigma_t v_t}$, σ_t is the root of σ_t^2 and v_t is an independent and identically distributed process which is often assumed to be N(0,1) standard normal distribution. The coefficients of the GARCH (p, q) model are as follows

$$\alpha_i \geq 0 \; for \; i = 1,2,3, \dots, p$$
$$\beta_j \geq 0 \; for \; i = 1,2,3, \dots, p$$
$$\sum_{j-1}^{p} \sum_{i=1}^{q} (\alpha_i + \beta_j) < 1$$

In the Markov Switching model, there are several possible states or regimes in the system, and switching between these regimes occurs randomly based on a certain probability distribution. As the system changes from one regime to another, the behavior and parameters that describe the system may also change significantly. Suppose the state space is discrete such that at time t, the sequence can be in state i, with $i = 1,2, \dots, N$. The transition probabilities for the Markov chain are as follows

$$P_{ij} = \Pr(S_t = j | S_{t-1} = i)$$

where P_{ij} is the probability that the sequence at time $t - 1$ is in state i will be in state j at one time unit later, i.e. at time t with a one-step transition probability matrix as follows. (Widaad, 2016) :

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{12} & p_{22} & \cdots & p_{1N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix}$$

with

$$\sum_{j=1}^{N} p_{ij} = p_{11} + p_{12} + \cdots + p_{iN}$$
$$= 1 \; for \; i = 1,2, \dots, N$$

The work steps are contained in the following flowchart

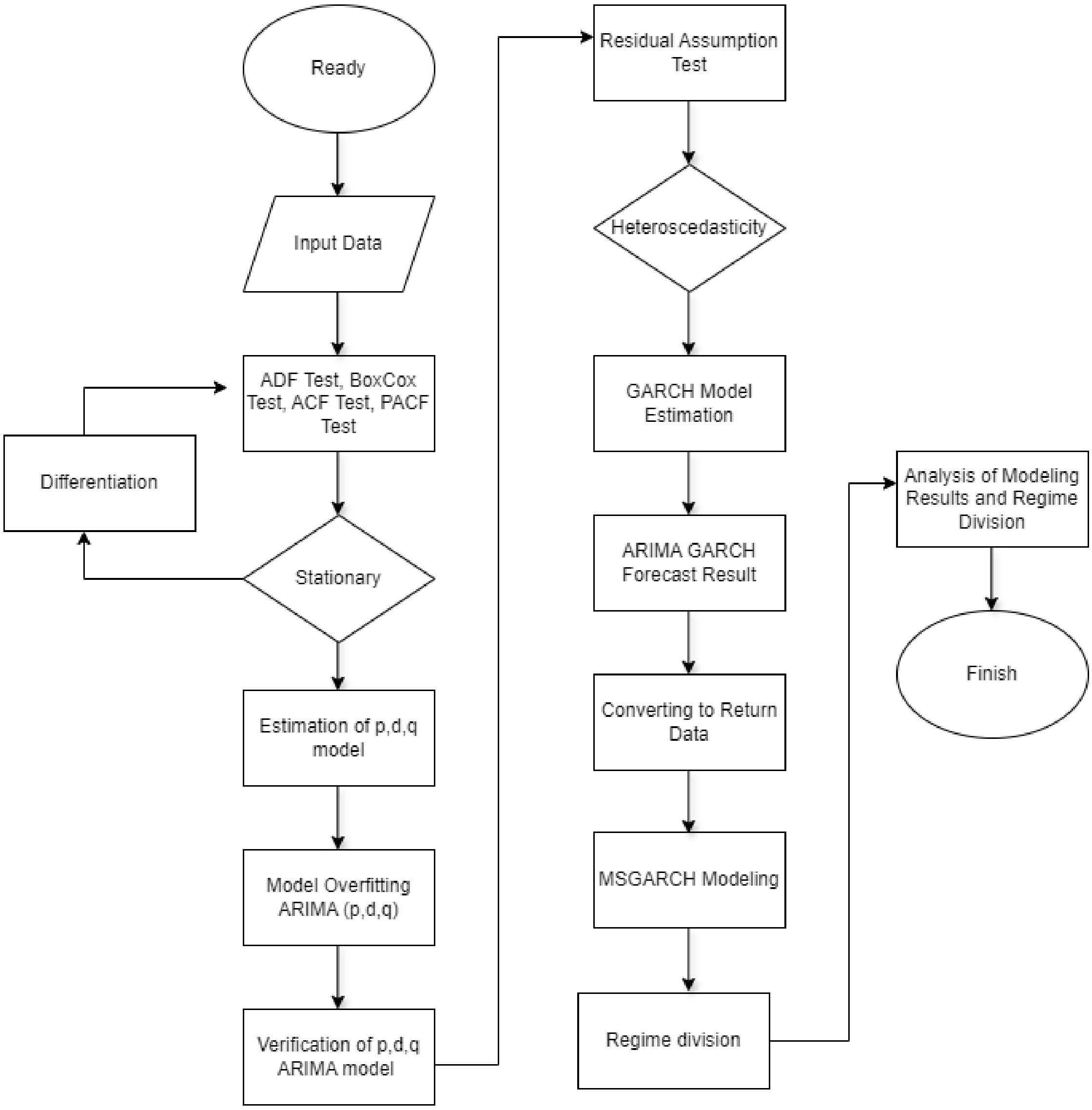

Figure 1. Flowchart

This research stage starts with data input and then tests ADF Test, Boxcox Test, ACF and PACF Test to determine data stationarity. If the data is not stationary then differentiation is carried out until the data is proven to be stationary. Next, estimate, overfit and validate the model until you get the best ARIMA model. Additionally, residual assumption tests were conducted to determine heteroskedasticity in the data. If the data is proven to contain heteroscedasticity, GARCH modeling is continued until obtaining the best forecast results. Furthermore, to proceed to Markov Switching, the data is converted to return data, then MSGARCH modeling, regime partitioning, and analysis of the modeling and regime partitioning results.

RESULTS AND DISCUSSION

The steps taken by plotting the BRI Stock Price time series data are aimed at seeing that the data pattern has trends, seasonal components and stationary data. The daily data plot of BRI share prices from 2 January 2019 to 30 November 2023 can be seen in Figure 2.

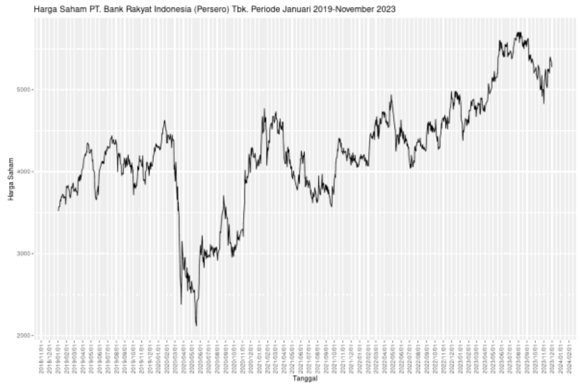

Figure 2. Plot of BRI Share Price January 2019-November 2023

Based on Figure 1, it is known that the daily plot of BRI Stock has an upward and downward trend at certain times and the data does not fluctuate around the middle value and is not constant over time. The lowest and highest values of BRI Stock Price data are 2117 and 5700, respectively. While the average value is 4227. This shows that the daily data of BRI Stock is not static to the mean value and variance.

To find out that the BRI Stock data has not moved to the mean value, testing was conducted using the ADF and BoxCox tests. In the Augmented Dickey-Fuller (ADF) test, the null hypothesis (H_0) states that the time series data has a unit root, meaning the data is non-stationary. The alternative hypothesis (H_1) states that the time series data does not have a unit root, meaning that the data is stationary. To evaluate the results of the ADF test, we need to consider the ADF value (test statistic) and the p value. The combination of a negative ADF value and a low p value is a strong indication that the time series data is stationary. However, if the ADF value is negative but the p value is high, the data may not be stationary. ADF test results obtained ADF values vary from -2.64 to -2.43 at lags 0 to 6, while p values range from 0.305 to 0.396 which is greater than $\alpha = 0.05$. So, it can be concluded that the data failed to reject the null hypothesis which means that the data contains a unit root or is not stationary to the mean. Furthermore, the stationarity test is conducted on the variance using the BoxCox Test, the Box-Cox Test is a transformation method used to transform the data to make it closer to a normal distribution. This test tests various values of the parameter λ to determine the most suitable transformation. In the Box-Cox test, the null hypothesis states that transformation is not necessary because the data are already close to a normal distribution; mathematically, this means that the value of λ is 1. On the other hand, the alternative hypothesis states that lambda values other than 1 are more appropriate, meaning that the data needs to be transformed to be closer to a normal distribution. The resulting λ value from our data is 1, so it can be concluded that the data fails to reject the null hypothesis, which means that the stock price data is stationary in terms of variance. Since the stock data are not stationary at the mean, differencing and retesting using the ADF test is performed. This results in ADF values ranging from -36.3 to -13.0 at lags 0 to 6, and a p value of 0.01 less than α = 0.05. It can be concluded that the differenced data reject the null hypothesis, which means that the data are stationary to the mean.

The first step in identifying an ARIMA model is to look at the ACF and PACF values from the R Studio output in the following figure.

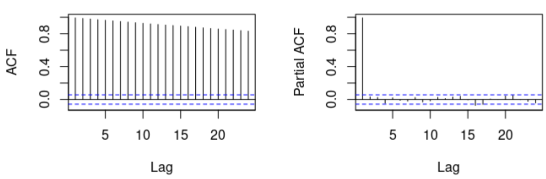

Figure 3. ACF and PACF Value of BRI Stock Price Data

Based on Figure 2, the ACF plot shows there is 1 lag out, meaning it contains Moving Average or MA(1) and the PACF shows there are 2 lag outs, meaning it contains AutoRegressive or AR(2). Therefore, the main model obtained is ARIMA (2,1,1). Furthermore, to find the best ARIMA model, overfitting was performed around the model and the resulting AIC and BIC values are provided in table 1.

Table 1. AIC and BIC Values in ARIMA Modeling

Model	AIC Value	BIC Value
ARIMA(1,1,2)	13823.84	13844.2
ARIMA(2,1,1)	13823.31	13843.67
ARIMA(1,1,1)	13825.59	13840.86
ARIMA(1,1,0)	13824.26	13834.44
ARIMA(0,1,1)	13824.05	13834.23
ARIMA(0,1,0)	13824.95	13830.04
ARIMA(2,1,2)	13821.01	13846.46
ARIMA(1,1,2)	13823.84	13844.2
ARIMA(2,1,1)	13823.31	13843.67
ARIMA(1,1,1)	13825.59	13840.86
ARIMA(1,1,0)	13824.26	13834.44

From Table 1, the best ARIMA model is determined through the smallest AIC value, so the best ARIMA model is ARIMA (2,1,2). Next, for the verification process of the best ARIMA model which aims to ensure that the built model is in accordance with the assumptions and data used, the Z-test and L-Jung-Box Test are carried out. The Z-test was used to test the significance of the coefficients in the ARIMA model and the results are provided in Table 2.

Table 2. Z-Test Result

	Estimation	Sd Error	Z-value	Pr(>Z)
Ar1	-0.99307	0.11131	-8.9216	< 2.2e-16
Ar2	-0.78344	0.16266	-4.8165	1.461e-06
Ma1	0.94861	0.12374	7.6659	1.775e-14 ***
Ma2	0.72296	0.18248	3.9618	7.439e-05 ***

Based on Table 2, testing using the Z-test has a null hypothesis (H_0), that is, the coefficient of the variable in the model is equal to zero (not significant), which means that the variable does not have a significant effect in the model, while the alternative hypothesis (H_1), that is variable coefficients in the model are different from zero (significant). Based on the test results, it shows that all the coefficients in the best model have a very high level of significance (very small p-value). This shows that each variable (Ar1, Ar2, Ma1, Ma2) has a meaningful and significant influence on the results of the model. All coefficients have very low p-values indicating that they are all highly statistically significant. This shows that the ARIMA model has important coefficients and significantly affects the behavior of the data.

Next, the L-JungBox Test is performed to test whether there is a residual pattern in the ARIMA model The resulting P value for the Ljung-Box test is $0.2259 > 0.05$ which means there is no significant correlation in the ARIMA residual. model at the 95% confidence level. This indicates that we cannot reject the null hypothesis that the model residuals are independent or have no significant autocorrelation at the tested lags. The results of the L-JungBox test show that the ARIMA(2,1,2) model handles the data well and leaves no significant autocorrelation in the residuals. This is an indicator that the model has modeled the data well enough, so the model is reliable for further analysis and prediction. The degrees of freedom (df) used in this test is 236, while the number of lags used is 240. The model has 4 degrees of freedom which corresponds to the number of parameters in the ARIMA(2,1,2) model. Overall, these results provide confidence that the ARIMA(2,1,2) model captures the patterns in the data well, and the residuals show no significant patterns.

Furthermore, the best ARIMA model, obtained which is ARIMA(2,1,2), was tested for heteroscedasticity using the Portmanteau-Q test and the Lagrange-Multiplier test. In the Portmanteau-Q test, the null hypothesis states that there is no significant autocorrelation in the model residuals at various lags, while the alternative hypothesis states that there is significant autocorrelation in the model residuals. The test results show very small p-values (0) at various orders (4, 8, 12, 16, 20, 24), thereby rejecting the null hypothesis and accepting the alternative hypothesis. This indicates that there is significant autocorrelation in the residuals of the model, indicating that the residuals are not independent at various lags. In the Lagrange-Multiplier test, the null hypothesis states that there is no significant heteroscedasticity (ARCH effect) in the residual model, while the alternative hypothesis states that there is significant heteroskedasticity (ARCH effect) in the residual model. The test results show a very small p-value (0.00e+00) at various orders (4, 8, 12, 16, 20, 24), thus rejecting the null hypothesis and accepting the alternative hypothesis. This indicates the presence of significant heteroscedasticity in the residuals of the model, indicating that the variability of the residual's changes over time. Therefore, the results of both tests indicate the presence of significant heteroscedasticity in the residual ARIMA model, so the test is continued to the GARCH model. The best GARCH modeling on the BRI Stock data is assumed to be GARCH (1,1). Next, to see the results of forecasting or forecasting BRI Stock Price Data with ARIMA (2,1,2) and GARCH (1,1), the following results were obtained

Table 3. ARIMA GARCH Forecasting Results

Date	**Forecast Result**
1 December 23	5280.935
4 December 23	5275.403
5 December 23	5276.776
6 December 23	5279.256
7 December 23	5275.760

Based on Table 3, there are forecasting values for BRI Stock Price Data for the next 5 periods, namely on December 1, 2023, December 4, 2023, December 5, 2023, December 6, 2023, and December 2023, namely 5280,935; 5275,403; 5276,776; 5279,256; and 5275,760.

Before introducing the Markov Transform, the data is converted to return data. The return data is the difference between successive values divided by the previous value, which can be expressed mathematically a $R_t = \frac{P_t - P_{t1}}{P_{t-1}}$, where R_t is the return data at time t, P_t is the price at time t, and P_{t-1} is the price at the previous time. Converting stock price data to returns has several important benefits. First, returns normalize the data and make it more measurable and comparable, overcoming large fluctuations in stock prices. Second, returns tend to have more stable variance, facilitating model analysis. Third, returns allow analysis of the stock's performance relative to the initial investment, providing a clear picture of the stock's performance. In addition, returns are directly related to risk and volatility, important in financial analysis, and allow comparison between investment instruments relatively unaffected by initial price differences. Using return data allows for more effective modeling and analysis, including in Markov Switching models, because return data reflects relative changes in stock prices and helps identify patterns of change.

GARCH Markov Switching is a powerful tool in financial market analysis that helps in understanding market volatility and making better decisions in the context of investment and risk management. The state of high and low volatility undergoes structural changes with the presence of regime 1 and regime 2 in the BRI stock price data. The order chosen to estimate this GARCH Markov Switching model is based on the order of the previous GARCH model, so that the Markov Switching GARCH (1,1) model is obtained.

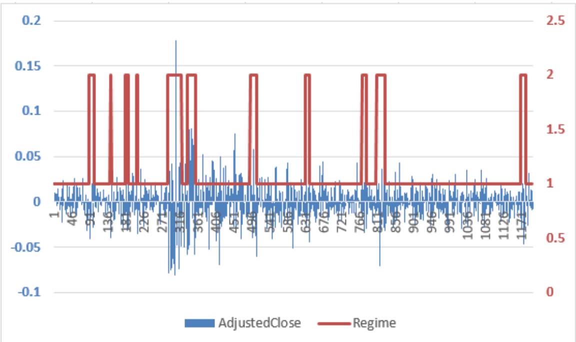

Figure 4. State 1 and 2 Division Result

Based on Figure 3, the red plot is the division of regimes 1 and 2, while the blue plot is the return data plot. The probability values show that the second regime is more representative of high volatility, while the first regime tends to be low volatility. To estimate the GARCH Markov Switching (1,1) model to show the probability that the regime will change to another regime in the next period, the results of the transition matrix are obtained using Rstudio software and the resulting matrix

$$P = \begin{bmatrix} 0.9696 & 0.0304 \\ 0.1149 & 0.8851 \end{bmatrix}$$

The P matrix explains that 96.96% of the data remains in regime 1 in the next period if it is currently in regime 1. It shows that regime 1 is very stable and tends to last. A probability of 3.04% indicates that the data will shift to regime 2 in the next period if it is in regime 1 and this indicates that the transition from regime 1 to regime 2 is relatively rare. A probability of 11.49% indicates that the data will switch to regime 1 in the next period if it is currently in regime 2 and this indicates that a transition from regime 2 to regime 1 is more likely than vice versa. A probability of 88.51% shows that the data will remain in regime 2 in the next period if it is in regime 2. This shows that regime 2 is also quite stable, although not as strong as regime 1. From this transition matrix, it can be concluded that regime 1 is very stable, with a very low probability of switching to regime 2. Meanwhile, regime 2 is also relatively stable, but is more likely to switch to regime 1 than vice versa. In the distribution of regimes 1 and 2, the length of the regime period is shown in Table 4.

Table 4. Period Length

Regime	Period Length
1	2 January - 14 May 2019
2	15 May - 10 June 2019
1	11 June - 2 August 2019
2	5 August - 7 August 2019
1	8 August- 25 September 2019
2	26 September - 4 October 2019
1	7 October - 4 November 2019
2	5 November - 7 November 2019
1	08 November 2019 - 26 February 2020
2	27 February- 17 April 2020
1	20 April 2020 - 11 May 2020
2	12 May 2020 - 16 June 2020
1	17 June 2020 - 7 January 2021
2	8 January - 1 February 2021
1	2 February - 3 August 2021
2	4 August - 19 August 2021
1	20 August 2021 - 23 February 2022
2	24 February - 15 March 2022
1	16 March - 19 April 2022
2	20 April - 2 June 2022
1	3 June 2022 - 18 October 2023
2	19 October - 6 November 2023
1	7 November - 29 November 2023

Table 4 produces 12 periods of regime 1 and 11 periods of regime 2, from the duration of the period it can be seen that the period in regime 1 tends to be longer than regime 2.

Furthermore, to show the probability that the model will be in each regime in the long run, the result of the Stable Probability in condition 1 is 0.7905 and in condition 2 is 0.2095. So, the probability of the regime 1 state will be in the long run.

The difference between this research and the previous research with the title LQ45 Stock Volatility Model with Markov Switching Garch Approach (Ermanely, 2023) is that in the previous research, the best model was selected for the GARCH and MS GARCH models by comparing the smallest AIC results. and BIC values, and the resulting conclusion that the best model that can be used in modeling the LQ45 stock data is the MS GARCH model. With the MS GARCH model, the smallest variance model is obtained. A small variance will cause the volatility of LQ45 shares to be small, which means that the data volatility changes will be smaller, so the risk that will be obtained when investing in LQ45 shares will also be smaller. In this study using the same modeling which is GARCH MS and the resulting differences in regimes 1 and 2 based on the volatility and duration of each regime.

CONCLUSIONS AND SUGGESTIONS

The stock price data of PT Bank Rakyat Indonesia (Persero) Tbk produces the best ARIMA model is ARIMA (2,1,2) and it is assumed that the best GARCH model is GARCH (1,1). The value of the forecast result using ARIMA GARCH is 5280.935; 5275.403; 5276.776; 5279.255; 5275.760 for the next 5 periods. Furthermore, the analysis is carried out using markov switching and it is known that the regime condition 1 is the data with low volatility, and the regime condition 2 is for the high volatility data. Share price data of PT Bank Rakyat Indonesia (Persero) Tbk. from January 2, 2019 to November 30, 2023 there are 11 state 1 or low volatility regimes and 11 state 2 or high volatility regimes. In Indonesia, the COVID-19 pandemic is expected to occur from March 2, 2020 to June 21, 2023, during that time period, there will be 6 state regime 1 and 6 state regime 2. This is quite stable, but it is possible. seen for the beginning of the COVID-19 pandemic period is quite long in state 2, meaning that the fluctuations or fluctuations in stock prices are quite drastic and last quite a long time.

Recommendations for further research in order to further explore the related factors that divide the 2 regimes with high and low volatility which is expected to be a true reflection of the increase and decrease in share prices of PT Bank Rakyat Indonesia (Persero) Tbk.

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