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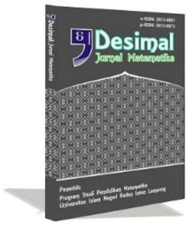

Unlocking market insight: Forecasting PT Bank Central Asia Tbk stock prices with ARIMA-GARCH analysis

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ABSTRACT

Stock prices are very important financial assets and accurate forecasting of stock price movements is of great value in making investment decisions. This research methodology begins with the analysis of historical data of BBCA stock prices. The ARIMA (Autoregressive Integrated Moving Average) model is used to capture trends and patterns of stock price fluctuations that occur over time. This model is then improved with the application of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to measure changes in volatility and heteroskedasticity in stock prices. The data used in this study includes the daily share price of BBCA in the period 1 October 2021 - 30 October 2023, obtained from reliable data sources. This research aims to develop an effective forecasting model for the stock price of PT Bank Central Asia Tbk (BBCA) using a combination of ARIMA and GARCH models. The results of the study show that the closing price of shares of PT Bank Central Asia Tbk (BBCA) contains elements of heteroskedasticity. The best model obtained is ARIMA (0,1,1)-GARCH (6,0). The MAPE value obtained is 0.9610548.

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INTRODUCTION

In the past few years, the financial sector has experienced rapid fluctuations. For example, the stock price index tends to be unstable over time or always change over time (heteroscedastic) (Yolanda et al., 2017). In Indonesia, investors often focus on the Jakarta Composite Index (IHSG) when investing in the Indonesian Stock Exchange (BEI). The movement of JHSG is influenced by many factors such as interest rates, global economy, energy prices, political stability and many more (Blanchard, 2017; Febriyanto, 2016). Bank Central Asia Tbk (BBCA) is one of the leading private banks on BEI with stable profit growth. Its stock, as a blue chip, shows liquid price stability like other banking sector stocks (BBRI, BMRI, and BBNI), but still experienced a significant increase after a sharp drop in price (Sabbat, 2020). Until September 2023, BBCA's market capitalization reached Rp1,077.02 trillion, accounting for 10.47% of the total Indonesian capital market. In the world of equity investing, an understanding of risk management is important, as certain factors can affect the value of stocks.

Faced with this problem, predictive analytics can make decisions based on considerations of what is expected to happen when the decision is executed. Therefore, stock return forecasting plays an important role in projecting future price developments and stock returns. In this research, the Autoregressive Integrated Moving Average - Generalized Autoregressive Conditional Heteroskedasticity (ARIMA-GARCH) method is the main focus. This is because, the advantage of the ARIMA-GARCH method in modeling time series by taking into account the ARIMA characteristics of the trend component and the conditional heteroskedasticity nature of using GARCH to overcome fluctuations in financial data, such as the BBCA stock price. The ARIMA-GARCH method is more suitable for data with high volatility or heteroskedasticity in the residual data, so that the forecasting results are more accurate. (Azmi & Syaifudin, 2020).

Some studies sometimes have problems with ARIMA model residuals showing heteroskedasticity in variance. One of the solutions to overcome this problem is to apply the ARIMA-GARCH method. Previous research on commodity price forecasting has proven that the ARIMA-GARCH method is effective with a lower AIC value than ARIMA alone (Azmi & Syaifudin, 2020). Some other studies such as Toki Carbon Company's stock price forecast using the ARCH/GARCH model conclude that the ARCH/GARCH method has a high level of accuracy in making forecasts (Faydian et al., 2021).

Research on stock price forecasting using the ARIMA-GARCH method has been carried out by many previous researchers. One of them is a study on the application of the ARIMA-GARCH model to predict the stock price of BRI bank. The results of the study show that there is a tendency of heteroskedasticity in BRI bank share prices with the best model being ARIMA(2,1,1,)-GARCH(2,2) and the coefficient of determination reaching 99.91% (Yolanda et al., 2017). Furthermore, PT Verena Multi Finance Tbk share price index forecasting with ARIMA and ARCH-GARCH modeling methods has also been carried out. Based on the results of the analysis using ARCH-GARCH forecast, the value of the stock price index is 102.4 with a forecast error rate of 22.9971% (MAPE) and the best ARIMA model (0,1,1) (Fitriyani et al., 2021). In addition, another study predicts the stock price of PT Unilever Indonesia, the results show that the most optimal model found is ARIMA (1,0,1)-GARCH (1,2) (Utami et al., 2023).

The main objective of this research is to make a significant contribution to improve BBCA stock price forecasting using a combined ARIMA-GARCH approach. Therefore, it is hoped that this research can serve as an effective tool for investors to make informed decisions, maximize investment returns, and reduce risk in the stock market.

METHOD

The stock price data used in this study was obtained from the website https://finance.yahoo.com/quote/BBCA.JK?.tsrc=fin-srch and is secondary data. For this study, the variable used is Adjusted Close, which is the closing price of the stock that has been adjusted to take into account certain changes that may affect the stock price temporarily. The data used is daily data for the period from October 2021 to October 2023. The software used in this research is RStudio. The steps used in this research are:

1. Input daily stock data of PT Bank Central Asia Tbk for the period October 2021 to October 2023 into RStudio.
2. To identify the problem, ADF test, ACF test and PACF test are used to test the stability of the data. If the data is non-stationary, differentiation of the data is carried out.
3. If the data is stationary, proceed by estimating the ARIMA (p, d, q) model, then fitting the model first.
4. Perform diagnostic tests for significant ARIMA (p, d, q) models including normality tests, autocorrelation tests and homoscedasticity tests.
5. If heteroskedasticity is present, then proceed with the ARCH/GARCH model.
6. Estimate the GARCH (p, q) model and perform model attachment tests and diagnostics.
7. After obtaining the best ARIMA (p, d, q) −GARCH (p, q) model, forecasting is carried out and the forecasting error value is calculated using the model that has been obtained.

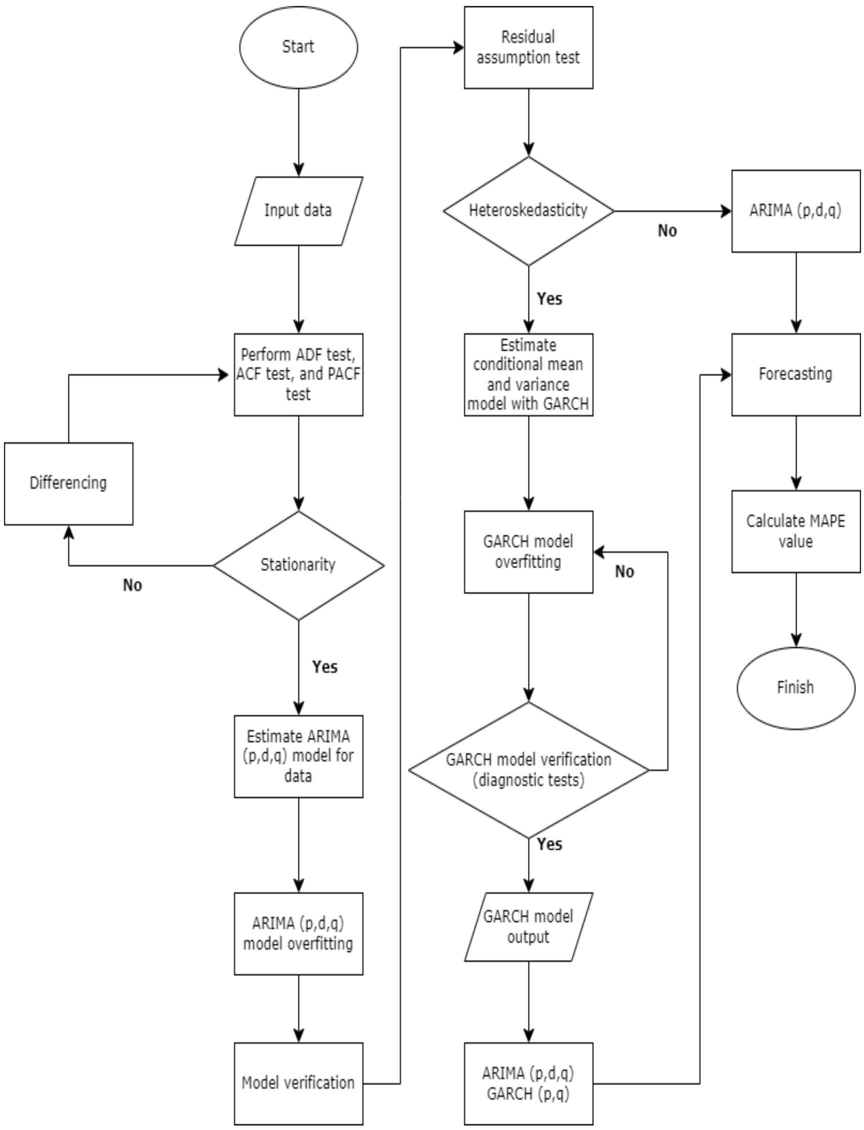

Figure 1. Research flow chart

2.1 Stationarity of Data

The stability of the data can be seen through the Autocorrelation graph (ACF) of the data. If the ACF graph drops rapidly to zero, usually after the second or third lag, the data can be considered stationary. Non-stationary data can be recognized by the presence of trends in the data, which are seen through fluctuations up and down over time. In non-stationary data with a trend, the Autocorrelation Function (ACF) graph will show a significant value in the initial lag, which then gradually decreases (Makridakis, 1988).

1. Dickey-Fuller Unit Root Test (ADF)

The Augmented Dickey-Fuller (ADF) test is one of the methods commonly used to test the stability of data by checking the presence of a unit root in the following model or equation. (Mustapa & Ismail, 2019; Rosadi, 2011).

$$X_t = \alpha + \delta_t + \rho X_{t-1} + \sum_{j=1}^{k} \emptyset_j X_{t-1} + e_t \quad (1)$$

where X_t is the value of variable X at time t, α and δ are the estimation parameters and e_t as white noise error, and:

$$\rho = \sum_{j=1}^{k} \alpha_j - 1 \, , \emptyset = \sum_{i=1}^{k} \alpha_i$$

2. Box-Cox Transformation

The Box-Cox transformation is one of the techniques used to make non-stationary data in variance, stationary. In its mathematical representation, the Box-Cox transformation can be formulated as follows (Aswi & Sukarna, 2006).

$$Z_t^{(\lambda)} = \frac{Z_t^{(\lambda)} - 1}{\lambda} \quad (2)$$

where λ as the transformation parameter.

3. Autocorrelation Function (ACF)

Autocorrelation is the correlation between a variable and that variable with a lag of 1, 2, 3 or more periods, for example X_t and X_{t-1}. The autocorrelation coefficient for lags $1, 2, 3, \ldots, k$ with many observations n, can be found using the formula r_{xy}. The X_t data are assumed stationary, if the two mean values X_t and X_{t-k} can be assumed equal and the two variance or standard deviation values can be measured once using all known X_t data, as follows.

$$r_k = \frac{\sum_{t=1}^{n-k}(X_t - \bar{X})(X_{t+k} - \bar{X})}{\sum_{t=1}^{n}(X_t - \bar{X})^2} \quad (3)$$

with r_k as the autocorrelation coefficient at lag-k, j =0, 1, 2, ...,k, k is the time difference, n is the number of data, $\bar{X}$ is the average of the observations, X_t is the value of time t observation and X_{t+k} is time t + k observation, k = 1, 2, 3, ... (Makridakis, 1988).

4. Partial Autocorrelation Function (PACF)

The partial autocorrelation function (PACF) is a set of partial autocorrelations for various lags, denoted by (φ_{kk};j =1,2,3,...,k) representing the partial autocorrelation for lag k. The partial autocorrelation function is used to measure the degree of association between X_t and X_{t-k}, when the influence of time lags 1, 2, 3, ..., k-1 is considered separately (Makridakis, 1988), bellow is the formula for the variance φ_{kk}.

$$Var(\varphi_{kk}) \approx \frac{1}{N} \quad (4)$$

2.2 Diagnostic Tests

Diagnostic tests are conducted to assess how well the model fits the observed data and whether the model meets the necessary assumptions. Some of the diagnostic tests carried out in this study are as follows:

1. Error Normality Test

The residual normality test is used to assess whether the error follows a normal distribution. This can be done through normal probability plots or the Jarque-Bera test. The residuals that are in the range of the diagonal line show a distribution that is close to normal, while those that are not, show a different distribution (Rosadi, 2011). The following is the formula for the Jarque-Bera test (Kabasarang et al., 2012).

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (5)$$

where n being the sample size, S is skewness and K is kurtosis.

2. Homoscedasticity Test (Error)

The homoscedastic test assesses whether the error variance is constant (homoskedastic) or changing (heteroscedastic). Heteroskedasticity, which can be detected through a non-random pattern in the residual plot or the relationship of the residual plot with the independent variable (Rosadi, 2011). The homoscedasticity test in this study uses the ARCH-LM test with the following equation (Wulandari, 2020):

$$L = T \times R^2 \quad (6)$$

where T is the number of observations, R^2 is the coefficient of determination of the regression model ε_t^2 and q is the number of influencing observations.

2.3 ARIMA-GARCH Models

The ARIMA model is the result of transforming a non-stationary ARMA model into a stationary model by differentiation, which is commonly used in time series data analysis. In contrast, GARCH is a more general and flexible process, evolving from ARCH, which allows for a wider lag structure. Like the evolution from the autoregressive model to the ARMA model, the development from ARCH to GARCH has the same impact, allowing a simpler description in various situations of time series analysis (Milniadi & Adiwijaya, 2023; Wijoyo, 2016).

1. Autoregressive Integrated Moving Average

The Autoregressive Integrated Moving Average (ARIMA) model involves AR process, difference process (I) and MA. It can be said that non-stationary data is added to the ARMA process mixture, then the ARIMA (p, d, q) model is obtained (Deviana et al., 2021; Zolfaghari & Gholami, 2021).

$$\phi_p(B)(1-B)^d Y_t = c + \theta_q(B)e_t \quad (7)$$

with c as the costant, e_t as the error in period t, $(1-B)^d$ is the d-order differencing process, $\phi_p(B)$ is $(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ which is the backward step operator for AR and $\theta_q(B)$ is $(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ which is the backward step operator for MA.

2. ARCH-GARCH

The ARCH method was introduced by Engle in 1982 to deal with uncertainty in financial data. Later, it developed into GARCH developed by Bollerslev in 1986. The GARCH model is used to describe the volatility dynamics of order (p, q) data, showing the dependence of the variance on past information and certain patterns (Rosadi, 2011).

$$var(y_t|\ni_{t-1}) = E(\varepsilon_t^2|\ni_{t-1}) = \sigma_t^2 \quad (8)$$

with:

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \alpha_i \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_j \sigma_{t-i}^2 \quad (9)$$

where σ_t^2 is the conditional volatility at time t, ω is a parameter represents the constant component of volatility, α_i is a parameter that control the effect of conditional volatility from the residuals at the previous time (ε_{t-j}^2), β_j is a parameter that controls of volatility conditional on the volatility at the previous time (σ_{t-i}^2), p is the order of the autoregressive (AR) component and q is the order of the Moving Average (MA) component.

The coefficients of the GARCH(p, q)model are as follows:

1) $\omega > 0$
2) $\alpha_i \geq 0$ for $i = 1, 2, \ldots, p$
3) $\beta_j \geq 0$ for $j = 1, 2, \ldots, q$
4) $\sum_{j=1}^{p} \sum_{i=1}^{q} (\alpha_i + \beta_j) < 1$

Condition 4 is required for the model to be stationary while conditions 1, 2, 3 are required for $\sigma_t^2 > 0$ (Haque & Shaik, 2021; Rosadi, 2011).

2.4 Measurement of Forecasting Error

The measurement of the error in forecasting is done by comparing the forecast results with the reality that occurs. The optimal forecasting technique is the forecasting technique that produces the least error. The Mean Absolute

Percentage Error (MAPE) is the average value of all percentage errors between the actual data and the estimated data. Here is the formula for MAPE:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|X(t) - F(t)|}{X(t)} \quad (10)$$

where X_t is the actual data, F_t is the forecasting data and n is the amount of data.

RESULTS AND DISCUSSION

In this study, the first identification will be done with the ARIMA model, followed by the residual analysis of the ARIMA model to identify the presence of heteroscedasticity. If a heteroskedasticity problem is found, then the modeling will continue using GARCH.

The following is a graph of daily stock price fluctuations of PT Bank Central Asia Tbk (BBCA). Figure 2 is a graph of the adjusted closing price (Adjusted Closing) of PT Bank Central Asia Tbk (BBCA) shares taken during the period 1 October 2021 to 30 October 2023. The graph shows that there is high volatility from July 2022 to September 2022. In addition, adjusted closing data for shares of PT Bank Central Asia Tbk (BBCA) still looks up and down (volatile). This shows trends so the data should be stabilized in mean and variance before model estimation or forecasting is carried out.

Furthermore, the stationarity test is conducted using the unit root test. Based on the hypothesis test, the results of the unit root test can be seen as follows:

H_0 : PT Bank Central Asia Tbk stock contains unit root (data is not stationary)

H_1 : PT Bank Central Asia Tbk stock do not contain unit roots (stationary data)

Based on the results of the Dickey-Fuller value output $= -2.5733 > -2.875330 =$ Mackinon's Critical Value or P-value $= 0.3356 > 0.05 = \alpha$, it fails to reject H_0, which means that PT Bank Central Asia Tbk (BBCA) stock price contains a unit root or the data is not stationary on average.

Then a Box-Cox transformation was performed to normalize the data. Data can be said to be stationary at variance if the value of $\lambda \geq 1$ (Wei, 2006). Based on the results obtained using RStudio software, the lambda value is 1. So, it can be interpreted that the stock price data of PT Bank Central Asia Tbk (BBCA) has been stationary in variance.

After conducting the unit root test and getting the result that PT Bank Central Asia Tbk (BBCA) share price data is not stationary on average. The next step is to look at the correlogram of the ACF and PACF

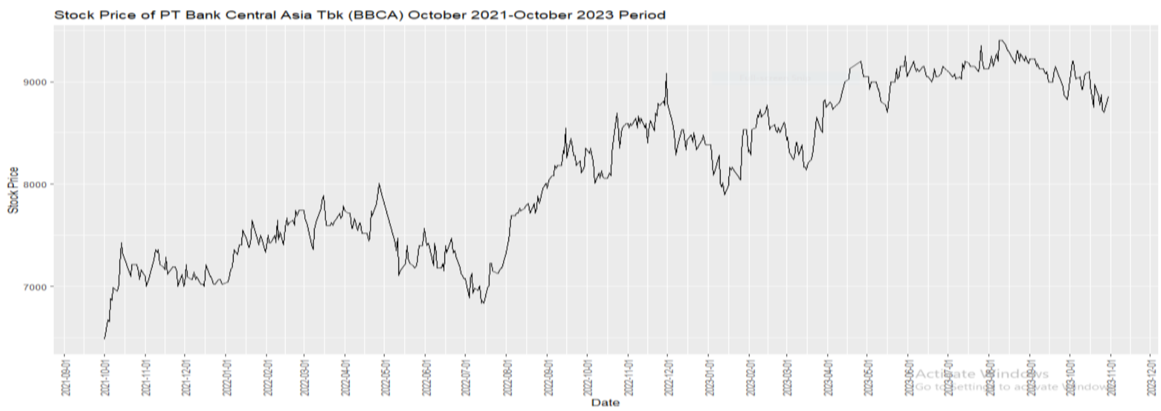

Figure 2. Time series plot of closing stock price data

As shown in Figure 3, the ACF plot decreases slowly, so it can be concluded that the stock price data of PT Bank Central Asia Tbk (BBCA) is still not stationary and needs to be differentiated. Meanwhile, PACF plots that show some significant lags or unclear patterns indicate the presence of trend components that have yet to be addressed.

To use data series in forecasting with ARIMA modeling, it is necessary to assume that the mean and variance of the data series are stationary. If the data is not stationary, it is necessary to perform differentiation or transformation. Based on the difference results obtained that Dickey-Fuller value $= -8.5811 < -2.875330 =$ Mackinon Critical Value or P-value $= 0.01 < 0.05 = \alpha$, then reject H_0, meaning the data is stationary on average.

Identification of ARIMA modeling data series can be done by looking at ACF and PACF plots. The following ACF and PACF plot results were obtained.

Based on Figure 3 the ACF plot shows that there is 1 lag out which means it contains a moving average or MA(1). While the PACF plot shows there is 1 lag out which means it contains autoregressive or AR(1). So the main model obtained is ARIMA (1,1,1). Furthermore, to find out the best ARIMA model, model overfitting is run around the main model including ARIMA (1,1,0) and ARIMA (0,1,1).

Model estimation is performed by selecting the best ARIMA model determined using the Akakike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The following is the result of calculating the AIC and BIC values.

Table 1. AIC value of ARIMA models

Models	AIC	BIC
ARIMA (1,1,1)	6128.63	6141.31
ARIMA (1,1,0)	6126.55	61355.01
ARIMA (0,1,1)	6126.55	6135

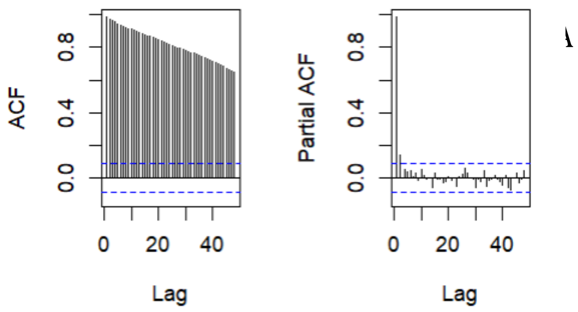

Figure 3. ACF and PACF plots of BBCA before stationary

Based on Table 1. it can be seen in this study that the model with the smallest AIC and BIC value is the ARIMA (0,1,1) model where the AIC value is 6126.55 and the BIC value is 6135.

Before using GARCH modeling, the first step is to identify whether there is heteroskedasticity in the observed data. The results of the ARCH-LM test are based on the following hypothesis tests:

H_0 : There is no ARCH/GARCH effect on BCA bank (homoscedastic)

H_1 : There is an ARCH/GACR effect on BCA bank (heteroscedastic)

Based on the results of the ARCH-LM test on the BCA bank share price using the Lagrange-Multiple test, the p-value is below 0.05 which means rejecting H_0 or there is an ARCH-GARCH effect

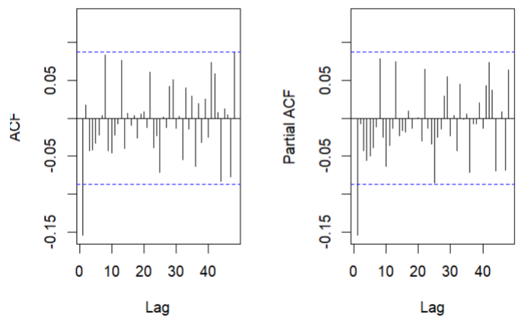

Figure 4. ACF and PACF plots of squared residuals of ARIMA(0,1,1) model

(heteroskedasticity). So it can be concluded that the BCA bank share price data with the ARIMA (0,1,1) model contains elements of heteroscedasticity, so the ARCH-GARCH model will be estimated because it has elements of heteroskedasticity.

The stage in identifying the GARCH(p,q) model is to look at the ACF plot and the PACF plot of the residual squared ARIMA model (0,1,1). Below is the ACF plot and the PACF plot of the squared residuals of the ARIMA(0,1,1) model.

In Figure 5. it can be seen that the ACF plot is cut at lag 3 and 6. Similarly, the PACF plot is cut at lag 3 and 6. Therefore, twelve GARCH (p,q) models can be formed. Here are some alternative GARCH conjecture models that can be used:

1. Model 1: GARCH (6,1)
2. Model 2: GARCH (6,0)
3. Model 3: GARCH (5,1)
4. Model 4: GARCH (5,0)
5. Model 5: GARCH (4,1)
6. Model 6: GARCH (4,0)
7. Model 7: GARCH (3,1)
8. Model 8: GARCH (3,0)
9. Model 9: GARCH (2,1)
10, Model 10: GARCH (2,0)
11. Model 11: GARCH (1,1)
12. Model 12: GARCH (1,0)

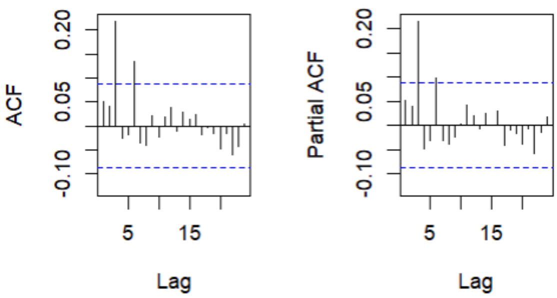

Figure 5. ACF and PACF plots of GARCH (p,q)

Based on the GARCH conjecture model that has been formed before, the next step is to determine the best model that will be used to predict the stock price index of PT Bank Central Asia Tbk. In determining the best ARCH-GARCH conjecture model, it can be seen from the model that has the smallest AIC value. Here are the AIC values generated in this model can be seen in the table.

Table 2. AIC value of GARCH models

Models	AIC	Models	AIC
GARCH (6,1)	12.07726	GARCH (3,1)	12.09174
GARCH (6,0)	**12.07504**	GARCH (3,0)	12.08767
GARCH (5,1)	12.09869	GARCH (2,1)	12.09154
GARCH (5,0)	12.09413	GARCH (2,0)	12.10308
GARCH (4,1)	12.09541	GARCH (1,1)	12.08974
GARCH (4,0)	12.09147	GARCH (1,0)	12.10644

Based on **Table 2**, it can be seen in this study that the GARCH model with the smallest AIC value is the GARCH (6,0) model where the AIC value is 12.07504.

The last stage is to evaluate the ARIMA-GARCH model that has been obtained. This research focuses on the closing price forecast of PT Bank Central Asia Tbk shares for the next 5 days. The following is the forecast of the closing price of PT Bank Central Asia Tbk shares:

Table 3. The predicted closing price of PT Bank Central Asia Tbk stock

Period	Prediction	Actual
October 31, 2023	8830.513	8512.29
November 1, 2023	8832.724	8366.37
November 2, 2023	8832.724	8609.58
November 3, 2023	8832.724	8658.22
November 6, 2023	8832.724	8804.14

Based on Table 3, it can be seen that the forecast results have approached the actual value of the daily closing price data of PT Bank Central Asia Tbk shares. The plot of the closing price prediction of PT Bank Central Asia Tbk shares on Figure 6.

Based on Figure 6. it can be seen that the forecast results have an upward trend. This means that the stock price of PT Bank Central Asia Tbk in the next 5 periods has increased. Furthermore, to determine the accuracy of the prediction results, the

MAPE value is calculated. The MAPE value of PT Bank Central Asia Tbk stock closing price prediction is 0.9610548, so the ARIMA (0,1,1) - GARCH (6,0) model can be said to be used to predict the next few days.

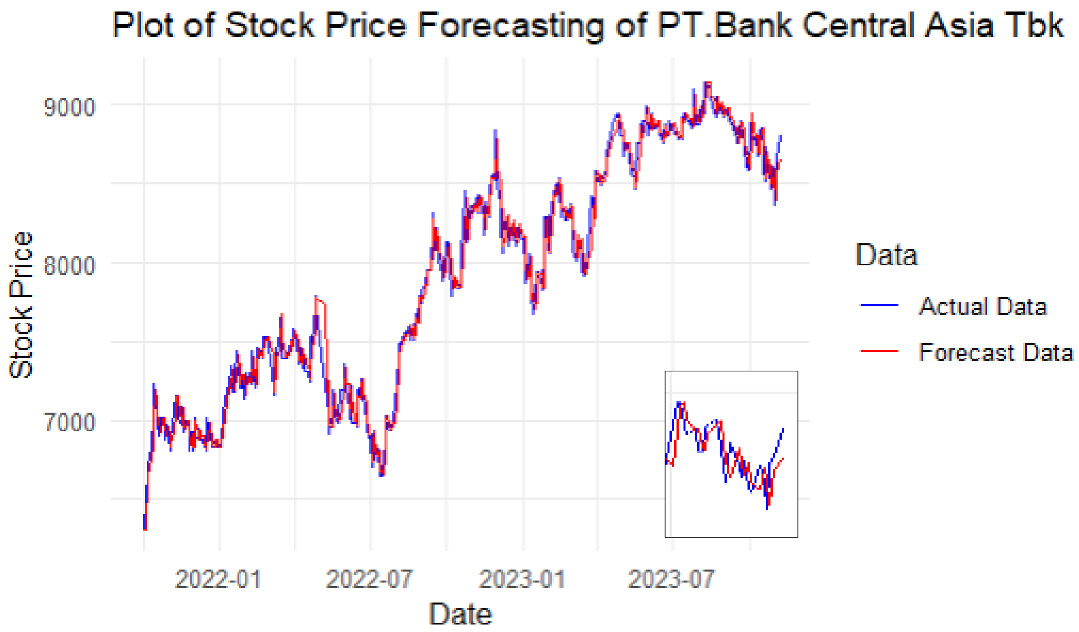

Figure 5. Plot of predicted closing price of PT Bank Central Asia Tbk stock

The difference between this research and the previous research with the title Application of ARIMA-GARCH Model to Forecast BRI Bank stock price is the selection of the time series model by looking at the smallest AIC and SIC values. in this study using the same modeling which is ARIMA-GARCH and the resulting difference in the selection of time series models is seen from the smallest AIC and BIC values.

CONCLUSIONS AND SUGGESTIONS

The ARIMA(0,1,1) – GARCH(6,0) model can predict the closing price of PT Bank Central Asia Tbk shares well. This model was chosen because it had the smallest AIC and BIC values. In addition, the forecast results state that the closing price of PT Bank Central Asia Tbk shares on 31 October 2023 to 6 November 2023 has increased. With the resulting MAPE value of 0.9610548, the ARIMA (0,1,1)-GARCH (6,0) model can be said to be good at predicting the closing share price of PT Bank Central Asia Tbk.

For further research, it is recommended to compare the ARIMA-GARCH method with linear regression, neural network, or ensemble methods. The aim is to evaluate whether the ARIMA-GARCH combination consistently provides more accurate forecasts than the mentioned methods.

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