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The Application of the ARIMA-GARCH Model in Return Forecasting and Stock Volatility Analysis of PT. Bank Rakyat Indonesia TBK.

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A B S T R A C T

Investment is a strategy to optimize future returns, particularly common in the banking sector due to its close ties to economic conditions and strong fundamentals. PT Bank Rakyat Indonesia Tbk. (BBRI) is frequently analyzed for its high liquidity and strategic financial role. However, the volatile nature of BBRI's stock price often leads to heteroscedasticity in return data. While ARIMA is widely used for forecasting based on historical trends, it is less effective in handling fluctuating variances. To address this, the ARIMA-GARCH model is applied, combining ARIMA for mean modeling and GARCH for capturing time-varying volatility. This study uses maximum likelihood estimation to forecast BBRI's return and volatility over the in-sample period from January 1, 2021 to January 1, 2025, and out-sample period from January 3 to February 19, 2025. The ARMA([1,4],[1,4])-GARCH(1,1) model was found to be appropriate in dealing with heteroscedasticity. Forecast accuracy, measured using sMAPE, yielded 157,03% for return and a great forecast of volatility proven with visual comparison between actual and forecast data.

Keywords: Stock Price, Return, Volatility, Forecasting, ARIMA, GARCH

1. INTRODUCTION

Investment is the placement of funds to obtain future profits, and stocks are a popular choice because of their high returns even though they are accompanied by great risks [1]. Liquid stocks such as BBRI, which reflect the dynamics of the national banking sector, offer yield stability (Suratna et al., 2020). BBRI's share price, which rose from IDR 90 in 2003 to IDR 5,850 in 2024, then fell to IDR 3,450 in 2025, shows high volatility. This volatility, which reflects investment risk, can be measured by standard deviations [2]. Volatility is a time-lapse data with an analysis method that is often used, namely the Autoregressive Integrated Moving Average (ARIMA) statistical method.

The ARIMA method developed by Box and Jenkins in 1970 is used to forecast future values based on historical data through three main components: AR, I, and MA. This model assumes homogeneity, but financial data often show heteroscedasticity due to high volatility, thus reducing the accuracy of the model [3]. To address this, Engle in 1982 introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, which was later refined by Bollerslev in 1986 into Generalized Autoregressive Conditional Heteroscedasticity (GARCH), which was more flexible at greater lags and more efficient in handling variance fluctuations in financial data.

The GARCH model allows volatility to depend not only on previous volatility events but also on the overall variability of previous periods. Thus, the GARCH model can capture more persistent volatility effects than ARCH, which only considers the effects of previous squared errors.

Previous research has also proven the accuracy of the ARIMA-GARCH model. In their research, Putri et al., (2021) about the stock price forecasting of PT. Jasa Marga (Persero) uses the ARIMA(1,1,1)-GARCH(2,2) model to prove that ARIMA-GARCH is very good in overcoming the problem of heterogeneity of the Mean Absolute Percentage Error (MAPE) value of 1.5647. Research using the ARCH/GARCH method was also conducted by Widayanti et al. (2023) for a case study of the return and volatility of the cryptocurrency Bitcoin using the ARIMA(1,0,[4])-GARCH(1,1) model as the best model with the smallest AIC of -1.4263 which cures the effect of asymmetry on the residual model.

Based on the description above, the author is encouraged to research the application of the ARIMA-GARCH model to forecast the daily return and volatility of PT. The purpose of this study is to see whether there is a heteroskepticism problem, find out the mean and variance models, the best models in the specified period, and forecast the next 19 periods on BBRI stock return data.

2. Literature Review

Shares are a sign of participation or ownership of a person or entity in a company or limited liability company [4]. The profits that investors get by buying or owning shares are, dividends and capital gains. Shareholders have the right to receive dividends as well as participate in decision-making through voting rights in the general meeting of shareholders [4].

Tandelilin [1] defines stock *return* as the difference between the selling price and the purchase price of shares expressed in the form of a percentage, which reflects the profit or loss that investors get from the investment. *Stock returns* can be calculated daily, weekly, monthly, and yearly. The shorter the period, the *return calculation* should be used using a geometric model that can be calculated with the following formula:

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

with Y_t is the *value of the return* at time *T*, is the stock price of the P_t *period T*, and P_{t-1} is the stock price of the previous period.

Time series analysis, according to Sugiarto and Harijono [5], is a statistical method used to identify the probabilistic pattern or structure of a phenomenon to project future events. This approach generally utilizes historical data Yt-1 and Yt current data to generate accurate predictions.

Time series data is said to be stationary if the average and variance are constant, there is no trend element in the data, and there is no seasonal element. According to Wei [6] for stationary processes Zt has the following 3 properties:

1. $E(Z_t) = \mu$, constant for all t
2. $\text{Var}(Z_t) = E(Z_t - \mu)^2 = \sigma^2$, constant for all t
3. $\text{Cov}(Z_t, Z_{t+k}) = E[(Z_t - \mu)(Z_{t+k} - \mu)] = \gamma_k$, constant for all t and $k \neq 0$ and γ_k is autocovariance at lag k

The ADF test is used to test the stationarity of data in mean. According to Wei [6], the model in the ADF test for testing the serial correlation between residual and can be expressed in the general form of autoregressive processes as follows:

$$\Delta Z_t = \beta_1 + \beta_2 t + \delta Z_{t-1} + \alpha_1 \Delta Z_{t-1} + \alpha_2 \Delta Z_{t-2} + \cdots \alpha_1 \Delta Z_{t-2} + a_t \quad (2)$$

where ε_t is a process in which white noise is normally distributed $\text{N}(0, \sigma^2)$ and $\Delta Z_{t-1} = (Z_{t-1} - Z_{t-2})$

Hypothesis:
$\text{H}_0 : \delta = 0$ (there is a unit root or non-stationary time sequence data)

$\text{H}_1 : \delta < 0$ (there is no unit root or stationary time sequence data)

Significance Level: α

Test Statistics: $t = \frac{\hat{\delta}}{SE(\hat{\delta})}$

Test criteria:

H_0 rejected if ADF < Dickey Fuller critical value or p-value $< \alpha$

Wei [6] explains that the Box-Cox transformation is a power transformation in the response. Box-Cox takes into account the class of single-rank transformations, which λ can be ranked on the response variable Z_t, so that the transformation becomes Z_t^λ, which λ is the parameter that needs to be guessed [10].

According to Makridakis et al. [7], the term autocorrelation is used to describe the association or mutual dependence between the value of the same periodic series in different periods. Autocorrelation at lag k, is defined as follows:

$$\rho_k = \frac{\text{kov}(Z_t, Z_{t-k})}{[\text{Var}(Z_t) \cdot \text{Var}(Z_{t-k})]^{1/2}} = \frac{\gamma_k}{\gamma_0} \quad (3)$$

According to Makridakis et al. [7] the measure of partial autocorrelation is used to show the magnitude of the relationship between the current value of a variable and the value of the previous variable of the same variable (values for various time delays) by assuming that the influence of all other time delays is constant. Partial autocorrelation is defined as follows:

$$\emptyset_{kk} = \frac{\begin{vmatrix} 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-2} & \rho_1 \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-3} & \rho_2 \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & \rho_1 & \rho_k \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-2} & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-3} & \rho_{k-2} \\ \vdots & \vdots & \vdots & & \vdots & \vdots \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & \rho_1 & 1 \end{vmatrix}}$$

In general, there are 3 time-series models, namely *the Autoregressive* (AR) model, the Moving Average (MA) model, and the homogeneous non-stationary model Autoregressive Integrated Moving Average (ARIMA). Wei [6] explains that the general form of a p-order autoregressive process (AR(p)) is:

Autoregressive (AR) Model

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + a_t \quad (4)$$

with Y_t is the data on the time sequence t, ϕ_p is the parameter of the autoregressive model, and $a_t$is the residual value.

Moving Average (MA) Model

$$Y_t = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \quad (5)$$

with Y_t is the data at the time sequence *t*, θ_q is the parameter of the moving average model, and a_t is the residual value at *the time t*

Autoregressive Moving Average (ARIMA) Model

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)a_t \quad (6)$$

with, $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_P B^P$ and $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$

Subset *Autoregressive Moving Average* (ARIMA) Model

A subset model is a detailed part of a more general or generalized ARMA model, not described as a whole, which can be thought of as a collection of parts of the ARMA model. Tarno [8] in his research, exemplifying the representation of the ARMA subset ($[p, m]$,$[q, n]$) can be arranged as follows:

$$\left(1 - \phi_p B - \phi_m B^m\right)Y_t = (1 - \theta_q B - \theta_n B^n)a_t \quad (7)$$

with, *p*, *q*, *m*, and *n* are the lag pieces via the ARMA model ($[p, m]$, $[q, n]$)

To determine the orders p and q in the ARIMA (p, d, q) model using ACF and PACF graphs. There are several guidelines in estimating the ARIMA model from a time series data described by Wei [6] related to the ACF and PACF plots that have been summarized in Table 1.

Table 1. Model estimation based on ACF and PACF plots

Type	ACF	PACF
AR(p)	It drops exponentially forming a sine wave.	Cut off after lag p.
MA(q)	Cut off after lag q.	It drops exponentially or forms a sine wave.
ARMA (p,q)	Fast drop after lag (q-p)	Fast drop after lag (p-q)

The parameter estimation used is *maximum likelihood estimation* (MLE). According to Wei [6], MLE estimation is an estimate of parameters that maximize the probability function, based on certain statistical methods. In the ARMA(p,q) model, *the maximum likelihood* method can be applied to estimate parameters ϕ_p and θ_q by solving the derivative of the log-likelihood function $\frac{\partial l}{\partial \phi_p} = 0$ [9]. The following is the procedure for the parameter significance test performed individually for the ARIMA model:

Hypothesis:

For the AR(p) Model

$H_0: \phi_i = 0$ (the parameter is not significant to the model)

$H_1: \phi_i \neq 0$ (the parameter is significant to the model) with $i = 1,2, \ldots, p$

For the MA(q) Model

$H_0: \theta_i = 0$ (the MA parameter is not significant to the model)

$H_1: \theta_i \neq 0$ (the MA parameter is significant to the model) with $i = 1,2, \ldots, q$

the Significance Level: α

Test Statistics:

For the AR(p) Model.

$$t = \frac{\hat{\phi}_i}{SE(\hat{\phi}_i)} \quad (8)$$

For the MA(q) model

$$t = \frac{\hat{\theta}_i}{SE(\hat{\theta}_i)} \quad (9)$$

Test Statistics:

H_0 is rejected if $|t| > t_{(\alpha/2, n-1)} p < \alpha$

The basic assumption is that the residual is white noise which means that there is no correlation between residual (independent) with a mean equal to 0 and constant variance [6]. The error independence test is used to find out if the error between lags is independent, meaning that there is no error correlation between lags. The test used is the Q-Ljung-Box test with the following hypothesis:

Hypothesis:

$H_0: \rho_1 = \rho_2 = \cdots = \rho_k = 0$ (independent error)

H_1 : at least one $\rho_k \neq 0$ (non-independent error)

Significance Level: α

Test Statistics:

$$Q = n(n+2)\sum_{k=1}^{K} (n-k)^{-1}\hat{\rho}_k^2 \quad (10)$$

Q distributes $\chi^2_{(\alpha,K-m)}$ with n : a lot of data, $\hat{\rho}_k$: autocorrelation error lag to- k, $\mathrm{m} = \mathrm{p} + \mathrm{q}$

Test statistics:

H_0 rejected if $Q > \chi^2_{(\alpha,K-m)}$ or $p - value < \alpha$.

The normality test aims to test whether the error of the model follows the normal distribution. One way to test the assumption of normality of a data is to use the Kolmogorov-Smirnov test.

Hypothesis:
H_0 : normal distributed error

H_1 : normal distributed error

Significance Level: Test Statistics:α

$$D = \sup_{a_t} |S(a_t) - F_0(a_t)| \quad (11)$$

Rejection Criteria:

H_0 is rejected if the value $D > K_{(1-\alpha);n}$ or $p - value < \alpha$.

According to Engle, this test is necessary to know that there are no cases of heteroscedasticity in the residual model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_n a_{t-n}^2 \quad (12)$$

Hypothesis
H_0: $a_1 = a_2 = \cdots = a_n = 0$ (no ARCH/GARCH effect)

H_1: At least one value $a_i \neq 0$, with $i = 1,2,\ldots,n$ (there is an ARCH/GARCH effect)

Test Statistics

$$LM = \frac{(SSR_0 - SSR_1)/k}{SSR_1/(n-2k-1)} \quad (13)$$

with $SSR_0 = \sum_{t=k+1}^{n}(a_t^2 - \overline{\omega})^2$; $\overline{\omega} = \frac{\sum_{t=1}^{n} a_t^2}{n}$; $SSR_1 = \sum_{t=k+1}^{n} w_t^2$,

with:

k : the number of lags tested

n : many observations

$\overline{\omega}$: average sample of a_t^2

w_t^2 : residual squares at time ke $-$ t

The Test Statistics are rejected if the value $LM > \chi^2_{(\alpha;m)}$ or $p -$ value $< \alpha$.

The *Autoregresive Conditional Heteroscedasticity* (ARCH) and *Generalized Autoregresive Conditional Heteroscedasticity* (GARCH) model, ARCH is one of the econometric models introduced by Engle in 1982 and later developed by Bollerslev in 1986 into the GARCH model. In its development, the ARCH-GARCH model became the mainstay for the analysis of time sequences in the capital market. The general form of the ARCH(m) model is as follows [3]:

$$a_t = \sigma_t \epsilon_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_m a_{t-m}^2 \quad (14)$$

with:

α_0 : Constanta Components

α_m : parameter ARCH

α_{t-m}^2 : residual squares at the time to *t-m*

σ_t^2 : residual variance at the time to t

ϵ_t is an independent random variable and identical to mean 0 and variant 1, in the ARCH model the parameters must meet $\alpha_0 > 0, \alpha_i \geq 0$, with $i = 1,2,\ldots,m$. While the general form of the GARCH model (m, s) is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \quad (15)$$

With ϵ_t is a random variable that is independent and identical to mean 0 and variance 1, $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$ and $\sum_{i=1}^{m} \sum_{j=1}^{s} (\alpha_i + \beta_j) < 1$. β_j is a GARCH parameter and σ_{t-j}^2 is the square of the residual variance in time $t-j$ [3].

The parameter significance test is carried out after the estimated value of each parameter is obtained to find out whether it is suitable for use. The parameter significance test on the GARCH model includes α_0, α_i and β_j.

Testing of each of the parameters can be done as follows,

Hypothesis

$H_0 : \forall\alpha_0 = 0,\ \alpha_a = 0,\ \beta_b = 0,\ a = 1,2,\dots,v,\ b = 1,2,\dots,w$ (parameters are not significant to the model)

$H_1 : \exists\alpha_0 \neq 0$ or $\alpha_a \neq 0$ or $\beta_b \neq 0,\ a = 1,2,\dots,v,\ b = 1,2,\dots,w$

(significant parameters to the model)

Significance level: $\alpha = 5\%$

Test Statistics:

$$t = \frac{\hat{\theta}}{SE(\hat{\theta})}\ ,\ , \in \{\alpha_0, \alpha_a, \beta_b \mid a = 1,2,\dots,v,\ b = 1,2,\dots,w\} \qquad (16)$$

Rejection Criteria:

H_0 rejected if the value $|t_{hitung}| > t\left(\frac{a}{2}; n-k\right)$ or value $p-value < \alpha$, with n as the number of observations and k are many parameters estimated.

Forecasting can generate several suitable models, so the best model selection criteria are required. This selection is usually based on residual statistics from the estimated model or forecasting errors [6]. One of the commonly used criteria is Akaike's Information Criterion (AIC). The model with the smallest AIC is the best model [6].

$$AIC(M) = n \text{ In } \hat{\sigma}_e^2 + 2M \qquad (17)$$

3. Research and Methods

The data used in this study is secondary data on the closing *price* of shares with a daily time period starting from January 1, 2021 to January 1, 2025 with a total of 968 data. Daily stock closing price data was obtained www.finance.yahoo.com. The data analysis in this study was carried out with the help of R-Studio software. The stages in the data analysis of this research are:

1. Dividing the data into two parts, namely in-sample to form a model and out-sample to measure accuracy.
2. In-sample data is processed by calculating the return from the closing price of the stock.
3. Perform a stationariness test on the mean and variance; if it is not stationary in the mean, differentiating is performed, and if it is not stationary in the variance, a Box-Cox transform is performed.
4. Identify the suspect model using ACF and PACF plots.
5. Estimating and testing the significance of parameters on the ARIMA model.
6. Conducting a model assumption test, through normality tests and residual independence tests.
7. Determining the best ARIMA model based on the smallest AIC value
8. Perform LM tests on the best model residues to detect symptoms of heteroskepticism. If no symptoms of heteroskepticism are found, the data can be continued with ARIMA, and the modeling is completed. If symptoms of heteroskepticism are found, then modeling is continued with ARIMA-GARCH.
9. Perform parameter estimation tests on the ARIMA-GARCH model.
10. Perform LM tests on the best ARIMA-GARCH models to ensure the residual variance has been constant.
11. Perform volatility and return forecasting of the best model to test the accuracy of the model.

4. Result

The data used is secondary data on the daily closing price of shares from PT. Bank Rakyat Indonesia Tbk. (BBRI) from January 1, 2021 to January 1, 2025. The data shows quite volatile fluctuations with the maximum share price at Rp. 6400,- and the minimum price at Rp. 3373,- per share shown in Figure 1.

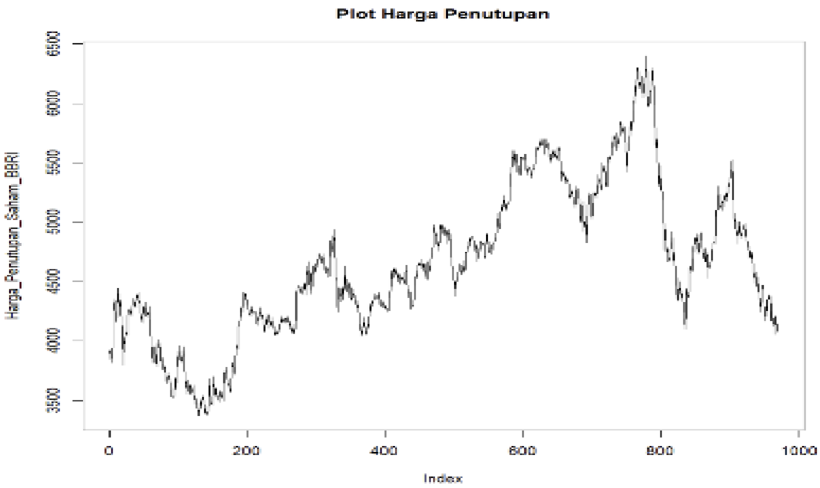

Figure 1. Plot Timeline of BBRI stock closing price.

It can be seen in Figure 1 that BBRI shares have fluctuated. This allows BBRI's share price to increase in the next period. The following is the plot *of* BBRI stock returns that fluctuate from time to time in Figure 2.

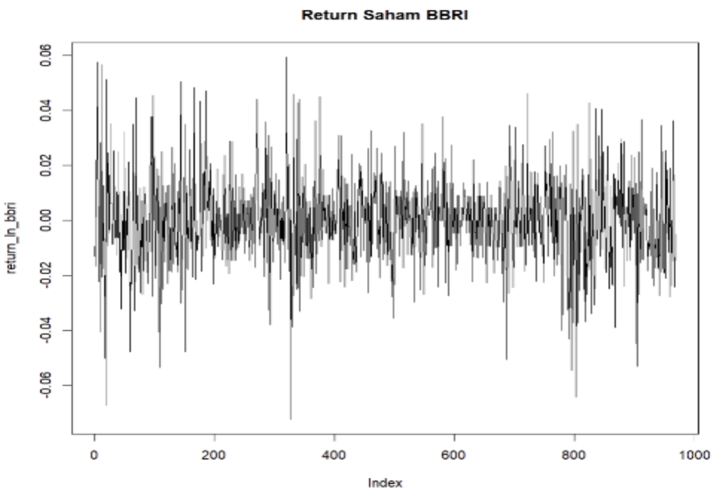

Figure 2. Plot of BBRI Stock Return Runtime

Figure 2 shows the plot of the BBRI stock *return* timeline and shows that there is *volatility clustering*, which is a process when high volatility in one period will occur cyclically in the next period and vice versa. This is often called a case of heteroskepticism and can be solved with the ARCH/GARCH model.

BBRI share return *data* is analyzed using descriptive statistics to find out an overview of *the return* data presented in Table 2.

Table 2. Descriptive Statistics *of* BBRI Stock Return

Statistics	**Value**
n	968
Mean	0.000042
Variance	0.000285
Standard Deviation	0.016869
Maximum	0.059466
Minimum	-0.072372

Based on the stationarity test through *R-Studio software*, it was obtained that BBRI stock return data was stationary both in *mean* and variant through the *Box-Cox* test and *the Augmented Dickey Fuller test*. Furthermore, the ARIMA model is estimated through the ACF and PACF plots.

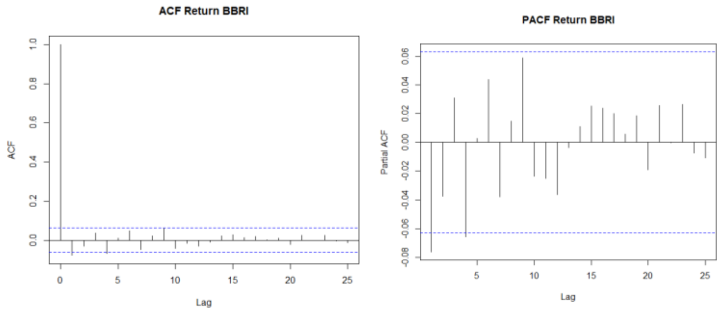

Figure 3. Plot of ACF and PACF *Return* of BBRI Shares.

Based on Figure 3. Tentative model for *Return* BBRI shares are ARMA(1,0), ARMA([4],0), ARMA([1,4],0), ARMA(0,1), ARMA(0,[4]), ARMA(0,[1,4]), ARMA(1,1), ARMA(1,[4]), ARMA([4],1), ARMA([4],[4]), ARMA(1,[1,4]), ARMA([4],[1,4]), ARMA([1,4],1), ARMA([1,4],[4]), ARMA([1,4],[1,4]). All of these conjecture models are then proceeded to parameter estimation tests. The model with significant parameters is continued to the model assumption test, with a gradual approach, namely the residual normality test, the residual independence test, and the non-heteroskepticism test.

The residual normality test uses *the Kolmogorov-Smirnov method* to find out whether the residual model is normally distributed or not, the result is obtained that in almost all models ARIMA is not normally distributed. According to Pincheira (2019) if the number of observations is quite large, then the assumption of normality is not always necessary in time series analysis, especially if the goal is to obtain the best linear predictors.

The residual independence test uses *the Ljung-Box* method to identify whether the residual models are correlated with each other or not, the result is obtained that *the alleged BBRI stock return model does not have a residual correlation between lags so that it can be continued to the non-heteroskepticism test.*

The Non-Heteroskedasticity test or better known as *the Lagrange Multiplier* (LM) test is a test of the presence of *heteroskedacticity elements*. This test is used to detect the presence or absence of ARCH/GARCH effects on the residual ARIMA model, the results are obtained that all models have ARCH/GARCH effects in the residual, so that they can be continued to the ARIMA-ARCH/GARCH model.

Table 3. Conclusion of the AIC Test and Score of the ARIMA Model

Model Assumption	Parameter Significance Test	Residual Normality Test	Residual Independence Test	AIC
ARMA (1.0)	Significant	Abnormal Distribution	No Autocorrelation	-5158,884
ARMA ([4],0)	Significant	Abnormal Distribution	No Autocorrelation	-5157,934
ARMA ([1,4],0)	Significant	Abnormal Distribution	No Autocorrelation	-5161,224
ARMA (0.1)	Significant	Abnormal Distribution	No Autocorrelation	-5159,271
ARMA (0,[4])	Significant	Normally Distributed	No Autocorrelation	-5157,761
ARMA (0,[1,4])	Significant	Abnormal Distribution	No Autocorrelation	-5161,175
ARMA (1,1)	Insignificant	Abnormal Distribution	No Autocorrelation	-5157,844
ARMA (1,[4])	Significant	Abnormal Distribution	No Autocorrelation	-5161,029
ARMA ([4],1)	Significant	Abnormal Distribution	No Autocorrelation	-5161,546
ARMA ([4],[4])	Insignificant	Abnormal Distribution	No Autocorrelation	-5156,802

Model Assumption	Parameter Significance Test	Residual Normality Test	Residual Independence Test	AIC
ARMA (1,[1,4])	Insignificant	Abnormal Distribution	No Autocorrelation	-5159,185
ARMA ([4],[1,4])	Insignificant	Abnormal Distribution	No Autocorrelation	-5159,978
ARMA ([1,4],1)	Insignificant	Abnormal Distribution	No Autocorrelation	-5159,647
ARMA ([1,4],[4])	Insignificant	Abnormal Distribution	No Autocorrelation	-5159,289
ARMA ([1,4],[1,4])	Significant	Abnormal Distribution	No Autocorrelation	-5161,717

The results of all model assumption tests are presented in Table 3. Models whose parameters are significant, the residues are normally distributed and do not correlate with other residuals, then the selection of the best model is continued through the smallest AIC value. The best model for BBRI stock returns is the ARMA([1,4],[1,4]) model with an AIC of -5.3844.

The model that still has the ARCH/GARCH effect can then be continued with the ARIMA-GARCH model. After modeling, the GARCH model is then tested for parameter significance, and the best model is searched through the smallest AIC. This best ARIMA-GARCH model is expected to be able to overcome the variance in it. Through the significance test of the smallest GARCH and AIC parameters, the results were obtained that the best model is ARMA([1,4],[1,4])-GARCH(1,1) presented in Table 4.

Table 4. Significance Test and AIC of the ARIMA-GARCH Model

Type	Parameter Significance Test	AIC
ARMA ([1,4],[1,4]) – GARCH (1,1)	Significant	-5,3884
ARMA ([1,4],[1,4]) – GARCH (1,2)	Insignificant	-5,3863
ARMA ([1,4],[1,4]) – GARCH (2,1)	Insignificant	-5,3864
ARMA ([1,4],[1,4]) – GARCH (2,2)	Insignificant	-5,3844

The best ARIMA-GARCH was then tested again by LM to find out whether it was able to overcome the symptoms of heteroskepticism or not, and the failed model was rejected because of the value $H_0 LM = 13{,}23 < \chi^2_{(0{,}05;12)} = 21.02607$ or indicated that the symptoms of heteroskepticism could be treated with the ARIMA([1,4],[1,4])-GARCH(1,1)-GARCH(1,1) model in the $p - value = 0{,}3525 > \alpha = 0{,}05$ *daily return* data of BBRI shares. The ARIMA([1,4],[1,4])-GARCH(1,1) model was then used in forecasting *returns* and volatility for the next 19 periods. The data from the forecast results is shown in Table 5.

Table 5. Return and Volatility Forecasting Results

Period	Forecasting *Return*	Volatility Forecasting
03/01/2025	-0,049419477	0,01712
04/01/2025	0,01842019	0,01710
07/01/2025	0,019671112	0,01708
08/01/2025	-0,002035134	0,01706
09/01/2025	-0,026502188	0,01705

Period	**Forecasting *Return***	**Volatility Forecasting**
10/01/2025	0,015977441	0,01703
11/01/2025	-0,000126939	0,01702
14/01/2025	0,008339824	0,01700
15/01/2025	-0,02772119	0,01699
16/01/2025	0,002104262	0,01697
17/01/2025	0,039927673	0,01696
18/01/2025	0,031547123	0,01695
21/01/2025	-0,001127152	0,01694
22/01/2025	-0,030265894	0,01693
23/01/2025	-0,005567087	0,01691
24/01/2025	0,014552294	0,01690
25/01/2025	-0,015610145	0,01689
31/01/2025	-0,017064679	0,01688
01/02/2025	-0,013198353	0,01687

Based on Table 5. The results of forecasting returns and volatility using the ARMA([1,4],[1,4])-GARCH(1,1) model were obtained for the next 19 periods. The results of this forecast are then compared with *out-sample* data to be compared in finding *the sMAPE value.* Based on the calculation of sMAPE obtained 157.034% in excellent return forecasting and volatility forecasting, as evidenced by *sMAPE* < 10% and visual comparison of data between forecasting data and actual data, shown in Figure 5.

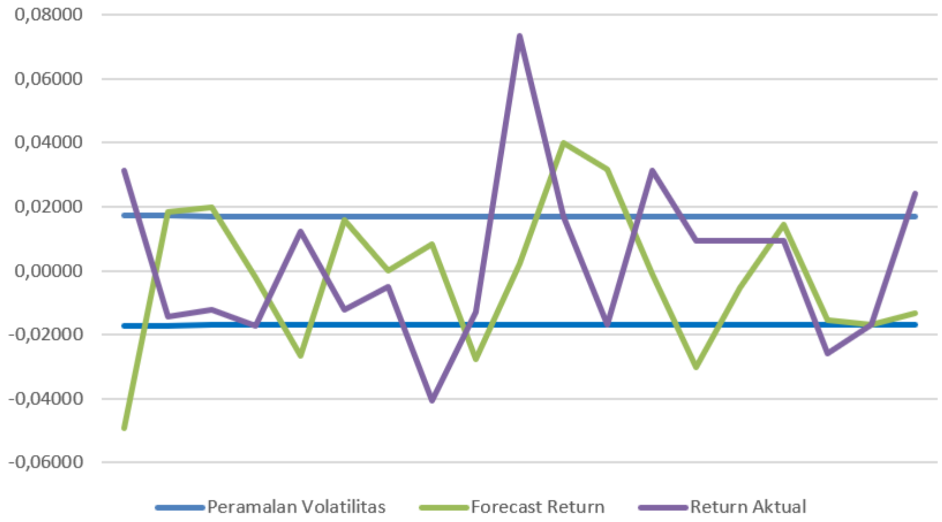

Figure 5. Forecast Results ARMA([1,4], [1,4])-GARCH(1,1)

Based on Figure 5, a good volatility forecasting volatility forecast, characterized by a volatility forecasting plot that follows most of the return fluctuations in BBRI's daily stock returns and volatility patterns seen in actual data. So it can be concluded that the forecasting model is able to capture and describe well the volatility that occurs in the data.

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5. Conclusion

The results of the study show that there is a heteroskepticism problem in the BBRI share price return data which is shown by the results of the insignificant homoskedactitis assumption test in all the ARIMA models formed. This proves that high volatility can indicate the existence of a heteroskepticism effect. The ARCH/GARCH modeling is used to solve the problem of heteroskepticism in the data. Through parameter significance test and LM test on the alleged ARIMA-GARCH model, it was found that the best model is the ARIMA([1,4],[1,4])-GARCH(1,1) model with an AIC value of -5.3884 with the following equation: $\hat{Y}_t = 0{,}448327Y_{t-1} - 0{,}658217Y_{t-4} + 0{,}502108a_{t-1} - 0{,}625038a_{t-4} + a_t$ with

$$a_t \sim iidN(0, \sigma^2)$$

and,

$$\hat{\sigma}_t^2 = 0{,}000011 + 0{,}062076a_{t-1}^2 + 0{,}898221\sigma_{t-1}^2$$

References

Tandellin, E. (2017). Capital Markets: Portfolio Management and Investments. Yogyakarta: Kanisius.

Laila, A. N., Anindita, R., & Koerniawati, T. (2017). Analysis of vegetable price volatility in East Java. Journal of Agricultural Economics and Agribusiness, 1(2), 144–154.

Tsay, R. S. (2010). Analysis of financial time series (3rd ed.). New York: John Wiley & Sons.

Suratna, Hendro, W., & Tri, W. (2020). Stock Investment. LPPM National Development University "Veteran" Yogyakarta.

Sugiarto and Harijono. (2000). Business forecasting. Jakarta: PT. Gramedia Pustaka Utama.

Wei, W. W. (2006). Time series analysis univariate and multivariate methods (2nd ed.). New York: Pearson.

Makridakis, S., Wheelwright, S. C., and McGee, V. E. (1999). Forecasting Methods and Applications (Volume 1). Jakarta: Erlangga.

Tarno. (2013). A combination of ARIMA subset modeling procedures and outlier detection for time-series data prediction. Proceedings of the National Seminar on Statistics, Diponegoro University 2013, 583–592.

Lo, M. S. (2003). Generalized autoregressive conditional heteroscedastic time series models. Spanyol: Simon Fraser University.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (1970). Time series analysis: Forecasting and control. San Francisco: Holden Day.