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Article

Application of Threshold Generalized Autoregressive Conditional Heteroscedastic (TGARCH) Model in Forecasting the LQ45 Stock Price Return

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Abstract. Economics is one of the most important fields for a country. One of the activities that illustrate the importance of the economy in a country is an investment. Investment activities, especially stock investment, are included in the capital market activities that various age groups currently carry out. Stocks are generally known to have high-risk, high-return characteristics. Therefore we need a way to minimize losses in investing. This study uses time series analysis theory to analyze LQ45 stock data.The data used is the closing price of PT. Bank Central Asia, Tbk. obtained from finance.Yahoo.com. The results of this study indicate that the return of daily closing price data of PT. Bank Central Asia, Tbk. during the period 2017-2021, there are heteroscedasticity and asymmetric shocks, so variations of the ARCH/GARCH model are needed to obtain accurate forecasting results. One suitable model is Threshold GARCH (TGARCH). The results of this study indicate that the suitable forecasting model for the data is the MA(3)-TGARCH(1,1) model. The model produces forecasts with an accuracy rate based on MAPE of 0.895% for the next seven days

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1. Introduction

Economics is one of the most important fields for a country. One of the activities that illustrate the importance of the economy in a country is capital market activities that various age groups currently carry out. The capital market is for different long-term products that can be traded. The capital market instruments traded include stocks, bonds, mutual funds, exchange-traded funds (ETFs), and various other derivative products. Investment is an activity related to the withdrawal of resources (funds) used for the procurement of capital goods at this time, and with capital goods, new product flows will be generated in the future. In stock investing, an investor expects a level of profit from the results of his investment, which is called stock return. To reduce stock investment losses, it's necessary to make stock predictions [1-3].

Stock prediction has been done by many researchers using various models and methods. Khan and Alghulaiakh has done prediction of Netflix stock starting from 7 April 2015 to 7 April 2020 using ARIMA model. Challa et al.[4] has done forecasts the return and volatility dynamics of S&P BSE Sensex and S&P BSE IT indices of the Bombay Stock Exchange using ARIMA model. Monika et al.[5] has done rainfall prediction in Bandung City using ARIMA-ARCH model. Rita et al.[6] has done analyze seasonal pattern of stock return using ARCH-GARCH model. Endri at al.[7] has done prediction of Indonesian stock market volatility using GARCH model. Emenogu et al.[8] has done investigates the volatility of the stock price of Total Nigeria Plc using nine variants of GARCH models. Sunday et al.[9] has done Modelling the Efficiency in Nigeria Inflation Rate using TGARCH model.

The ARIMA model has a constant variance, so the ARIMA model cannot capture the heteroscedasticity of stock price returns which have a high level of volatility. The ARCH/GACRH model can overcome the problem of heteroscedasticity but has a weakness in capturing the asymmetric phenomena of good news and bad news on volatility. In some financial cases, there is a difference in the amount of volatility in the return value, which is called asymmetry. The asymmetry occurs in the form of a negative or positive correlation between the current return value and future volatility [10-12]. The negative correlation between the return value and changes in volatility is the tendency of volatility to decrease when returns increase, and conversely, the tendency of volatility to increase returns decreases. This study uses a variation of the ARCH/GARCH model, namely the TGARCH (Threshold-GARCH) model, to see whether the model contains an asymmetric effect [13-15].

2. Literature Review

2.1 Stock Return

Stock return is the profit individuals, agencies, or companies receive from the investments made. The return of a stock can be calculated using the following equation [16]:

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

Where,

r_t : return value at time t

P_t : stock price at time t

P_{t-1} : stock price at time $(t-1)$.

2.2 Stationary Data

One way to check the stationarity of a data can be done by using the Augmented Dickey Fuller (ADF) unit root test [17]. The ADF test hypothesis is as follows:

$H_0 : \delta = 0$ (there is a unit root, the data is not stationary)

$H_1 : \delta < 0$ (no unit root, data is stationary)

Statistics test,

$$\hat{\tau} = \frac{\hat{\delta}}{se(\hat{\delta})} \tag{2}$$

Where,

$\hat{\delta}$: parameter estimate value of δ

$se(\hat{\delta})$: standar error of $\hat{\delta}$.

The test criteria, reject H_0 if $\hat{\tau} > t_{kritis}$ or $p - value <$ significant value α, it means the data is stationary, accept H_0 in other ways.

2.3 Box-Jenkins Model

Table 1. Box-Jenkins Model

Name Model	Equation Model
Autoregressive (AR) Model	$Z_t = c + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + e_t$
Moving Average (MA) Model	$Z_t = \mu + e_t - \theta_1 e_{t-1} - \theta e_{t-2} - \cdots - \theta_q e_{t-q}$
Model Autoregressive Moving Average (ARMA) Model	$Z_t = c + \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$
Model Autoregressive Integrated Moving Average (ARIMA) Model	$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B) e_t$,

Where,

c : a constant

ϕ_i : AR parameter model ($i = 1,2,3,..,p$)

θ_i : MA parameter model ($i = 1,2,3,..,q$)

e_{t-q} : error value at time to $(t-q)$

B : back shift operator

$(1-B)^d Z_t$: stationary time series at the d difference (differencing operator)

$\boldsymbol{p}$: AR model order

$\boldsymbol{q}$: MA model order

$\boldsymbol{d}$: differencing order

2.4 Parameter of Box Jenkins Model Estimation

One way to estimate the parameters of the Box-Jenkins model is the Maximum Likelihood Estimation method. The probability function can be written as follows [18] :

$$L(\theta) = f(x_1, x_2, \dots, x_n; \theta) = \prod_{i=1}^{n} f(x_i; \theta) \tag{3}$$

The log of the likelihood function is:

$$l(\theta) = \log L(\theta) = \log \prod_{i=1}^{n} f(x_i; \theta) = \sum_{i=1}^{n} \log f(x_i; \theta) \tag{4}$$

The value of θ which can be obtained by means of $\frac{\partial(\log L(\theta))}{\partial\theta} = 0$.

2.5 Box Jenkins Model Diagnostics

For checking whether the residual assumptions in the model have been met for the assumption of white noise using the Ljung-Box test [19]. White Noise test with the hypothesis used are:

$H_0: \rho_1 = \rho_2 = \cdots = \rho_k = 0$ (non-autocorrelated residual / white noise)

H_1: there is at least one $\rho_k \neq 0$ (autocorrelated residual / not white noise)
Test Statistics,

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\rho_k^2}{n-k} \tag{6}$$

The test criteria, reject H_0 if $Q > \chi^2_{table}$ or $p - value < \alpha = 0.05$, accept H_0 in other ways.

2.6 Best Box-Jenkins Model Selection

Determination of the better or most optimum model is by looking at the AIC (Akaike Information Criterion) value in the model. The best model is the model that has the smallest AIC value. The equation for determining the AIC value as follows [20]:

$$\text{AIC} = 2k - 2\ln \hat{\sigma}_a^2, \tag{7}$$

Where, k is number of parameters.

2.7 Heteroscedasticity Effect Test

To identify whether in a time series data there is a heteroscedasticity effect or not, the Lagrange Multiplier Test can be used [21]. The hypotheses used are:
$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$ (there is no Heteroscedasticity effect)
H_1: there is at least one $\alpha_i \neq 0$ (there is a Heteroscedasticity effect)

Test Statistics,

$$LM = nR^2 \ , \tag{8}$$

where, R^2 is the coefficient of determination in the model.
The test criteria, reject H_0 if $LM > \chi^2_{\alpha,k}$ or $p - value < \alpha$ which means that there is a Heteroscedasticity effect, accept H_0 in other ways.

2.8 Generalized Autoregressive Conditional Heteroscedastic (GARCH)

The GARCH(p,q) model is an extension of the ARCH(p) model, this model was developed by Bollerslev and Taylor (1986). The GARCH(p,q) model is formulated as follows [22]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}\alpha_i e_{t-i}^2 + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2 \ , \tag{9}$$
$$e_t = \sigma_t \epsilon_t$$

where $e_t \sim N(0, \sigma_t^2)$.
$\omega, \alpha_i, \beta_j$: parameter model
e_t : residual at time t
σ_t^2 : residual variance at time t

2.9 Asymmetric Effect

The asymmetric nature is the difference in price increases or decreases in prices, commonly referred to as leverage effects. The asymmetric effect is the tendency of decreasing and increasing the level of volatility when returns increase and vice versa. One way to test the asymmetric effect is to model the time series data into a GARCH model and then test whether the model has an asymmetric effect by looking at the correlation between the lag residual ($\boldsymbol{e_{t-k}}$) and the squared residual ($\boldsymbol{e_t^2}$) using cross correlation. If a bar exceeds the standard deviation, the cross-correlation value is significantly different from zero, which means that it has an asymmetric effect on volatility [23].

2.10 Threshold Generalized Autoregressive Conditional Heteroscedastic (TGARCH)

The TGARCH model was introduced by Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994). The TGARCH(p,q) model can be formulated as follows [24]:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\, e_{t-i}^2 + \sum_{i=1}^{p} \gamma_i N_{t-i}\, e_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{10}$$

with,

$\alpha_i, \gamma_i, \beta_j$: parameter model

γ_i : leverage effect

$$N_{t-i} = \begin{cases} 1, & a_{t-i} < 0 \\ 0, & a_{t-i} \geq 0 \end{cases}.$$

2.11 Determination of Forecasting Accuracy

Forecasting attempts to predict future conditions by testing past conditions. Forecasting carried out is expected to minimize the value of forecasting errors that can be measured by mean error (ME), mean absolute error (MAE), mean absolute percentage error (MAPE), mean squared error (MSE), and root mean squared error (RMSE) [25-27]. In this study using Mean Absolute Percent Error (MAPE) with the following formula:

$$\text{MAPE} = \frac{\sum_{t=1}^{n} \left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\%}{n} \quad . \tag{11}$$

According to Lewis (1982) in Lawrence[28], the MAPE criteria in the level of forecasting accuracy are explained as follows:

Table 2. Value of MAPE

MAPE	Description
MAPE $\leq$ 10%	Forecasting ability is very accurate
10% $<$ MAPE $\leq$ 20%	Forecasting ability is accurate
20% $<$ MAPE $\leq$ 50%	Forecasting ability is quite accurate
MAPE $>$ 50%	Forecasting ability is not accurate

3. Results Methods

In this research, the data source used stock price data of PT Bank Central Asia Tbk. daily stock price data for five years, starting from 1 January 2017 to 31 December 2021. Data obtained from YahooFinance web. Based on the description above, this research using ARIMA-TGARCH model for predicting stock returns of PT Bank Central Asia Tbk. This research is expected to overcome the problem of asymmetric nature in the financial case.

Research Implementation

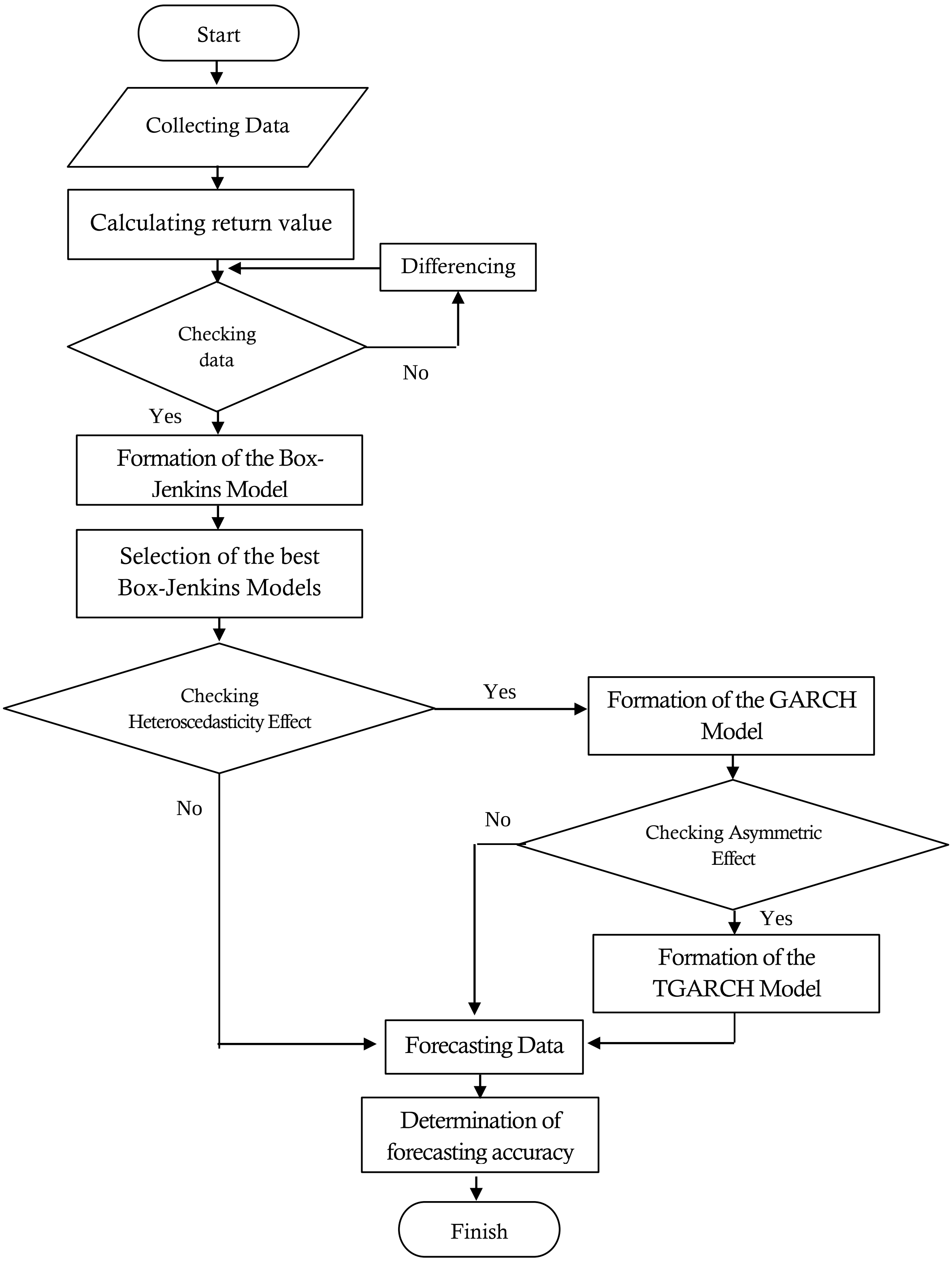

Figure 1. Flowchart of research implementation

4. Results and Discussion

4.1 Descriptive analysis

The data used in this research is the daily closing price of PT Bank Central Asia Tbk. starting from January 1, 2017 to December 31, 2021. The data plot is presented in Figure 1.

Figure 2. Plot of BBCA's Stock Closing Price

Based on Figure 2, it can be seen that each stock data fluctuates and has high volatility. It's known that the data is not stationary because the plot shows an uptrend and a downtrend. Because the BBCA data is not stationary, the differencing process will be done by finding the return value. The return value of BBCA's daily closing price is as follows:

$$r_1 = \ln\left(\frac{P_2}{P_1}\right) = \ln\left(\frac{3155}{3100}\right) = 0.017586$$

In the same way it can be calculated to obtain a BBCA return of 1061. The plot of return is presented in Figure 3.

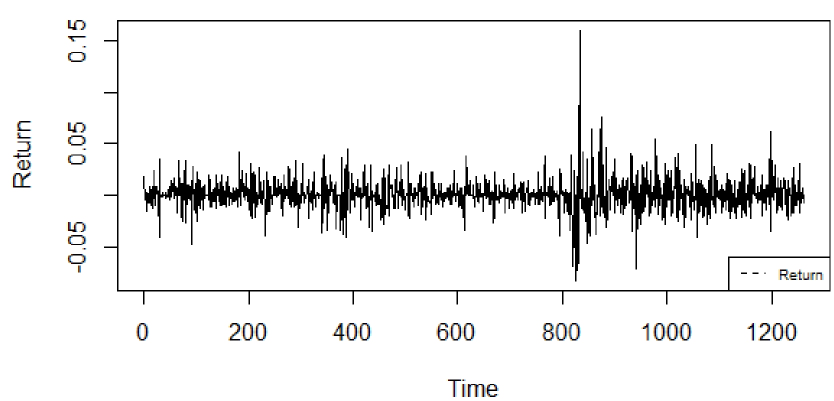

Figure 3. Plot of BBCA's Stock Price Return

Based on Figure 3, it can be seen that the movement of returns fluctuates from year to year. In financial or financial theory, this event is called clustering volatility, a condition where the direction of time series data tends to rise or fall drastically and suddenly under certain conditions or circumstances.

4.2 Data Stationary Test

To ensure stationary, we can use the ADF test presented in Table 3.

Table 3. ADF Test Results from BBCA Stock Price Return Data

Stationary Test	$p-value$ $(\alpha = 0.05)$
Augmented Dickey Fuller	0.01

Based on Table 3, obtained $p-value = 0.01$ less than the test level $\alpha = 0.05$, so the decision to reject H_0 means that the return data is stationary.

4.3 Formation of the Box-Jenkins Model

Identification of the Box-Jenkins model can be seen based on the ACF and PACF plots. The plot results are presented in Figure 4 and Figure 5.

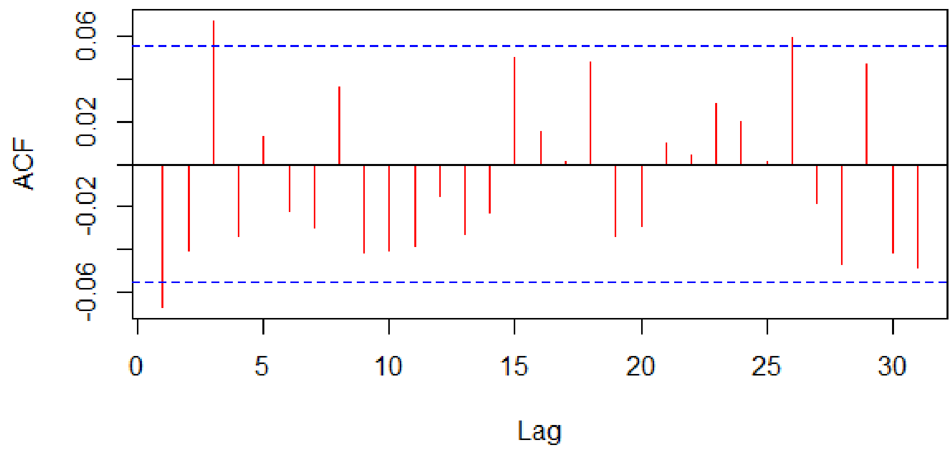

Figure 4. Plot of ACF BBCA's Return Stock Price

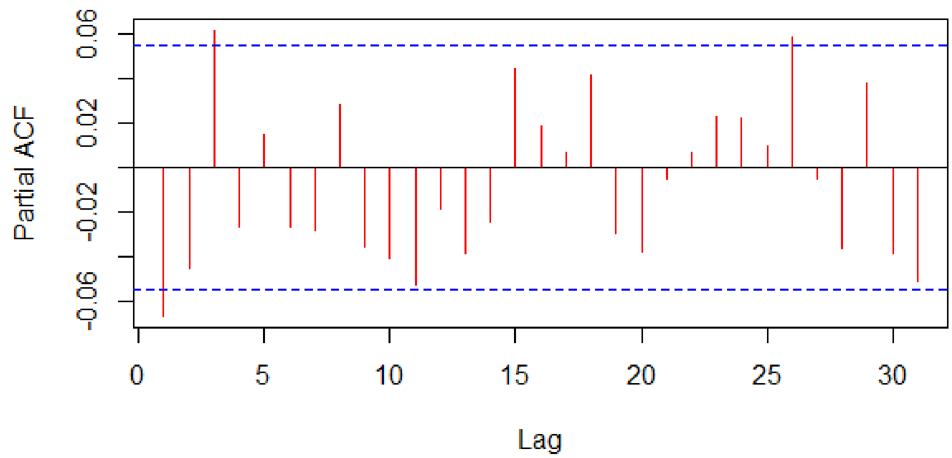

Figure 5. Plot of PACF BBCA's Reurn Stock Price

Based on Figure 4 and Figure 5, the ACF plot is interrupted at lags 1 and 3, the model formed from the ACF plot is MA(1) and MA(3), then the PACF plot is interrupted at lags 1 and 3, the model formed from the PACF plot is AR(1) and AR(3). After obtaining the prospective model, parameter estimation and parameter significance tests are carried out, which are presented in Table 4.

Table 4. Estimation and Formation Results of Box-Jenkins Model Parameters

Model	Parameter	Parameter Estimation	*p-value*	White Noise	AIC
AR(1)	Intercept	0.00067912	0.9145	Yes	-6959.08
	ϕ_1	-0.06666739			
AR(3)	Intercept	0,00067899	0.9534	Yes	-6962.46
	ϕ_1	-0,06689178			
	ϕ_2	-0,04121806			
	ϕ_3	0,06141449			
MA(1)	Intercept	0.00067905	0.9348	Yes	-6959.55
	θ_1	0.07189250			
MA(3)	Intercept	0.00067905	0.942	Yes	-6962.33
	θ_1	-0.06307210			
	θ_2	-0.04028932			
	θ_3	0.06653538			
ARMA(1,1)	Intercept	0.00067204	0.9397	Yes	-6958.05
	ϕ_1	0.17608913			
	θ_1	-0.24709708			
ARMA(1,3)	Intercept	0.00067834	0.9937	Yes	-6961.40
	ϕ_1	-0.34456577			
	θ_1	0.27980404			
	θ_2	-0.06115911			
	θ_3	0.05387566			
ARMA(3,3)	Intercept	0.00069388	0.7003	Yes	-6959.76
	ϕ_1	-0.36345336			
	ϕ_2	0.45281801			
	ϕ_3	0.61153894			
	θ_1	0.30964262			
	θ_2	-0.51426482			
	θ_3	-0.56359915			

A good Box-Jenkins model is a model that fulfils the assumption that the residuals are white noise or non-autocorrelated residuals. A test is carried out using the Q-Ljung Box test to determine whether the residual is white noise. Based on Table 4, all the candidates for the Box-Jenkins model meet the white noise assumption (no autocorrelation residue). Then the selection of the best Box-Jenkins model can be seen from the model that has the smallest AIC value. The model that has the smallest AIC value is the MA(3) model, so it can be concluded that the best Box-Jenkins model is the MA(3) model.

4.4 Heteroscedasticity Effect Test

Testing the effect of heteroscedasticity was carried out using the Lagrange Multiplier test which is presented in Table 5.

Table 5. Identification Results of the Effect Heteroscedasticity in Box-Jenkins Model

Model	Heteroscedasticity test	*X-Squared*	*p-value*	Description
MA(3)	*Lagrange Multiplier*	16.577	4.671×10^{-5}	There is a heteroscedasticity effect

Based on Table 5, the results of the Lagrange Multiplier test show that the $p - value = 0.0004671$ is smaller than the level $\alpha = 0.05$. So the MA(3) model has a heteroscedasticity effect.

4.5 Formation of the GARCH Model

The parameter estimation results for the GARCH(p,q) model are presented in Table 6.

Tabel 6. Estimate and Formation Results of GARCH Model Parameters

Model	Parameter	Parameter Estimation	AIC
MA(3)-GARCH(1,1)	Intercept	0.001004	-5.7588
	θ_1	-0.145670	
	θ_2	-0.066756	
	θ_3	0.001279	
	ω	0.000013	
	α_1	0.101980	
	β_1	0.834965	
MA(3)-GARCH(1,2)	Intercept	0.001004	-5.7572
	θ_1	-0.145648	
	θ_2	-0.066766	
	θ_3	0.001338	
	ω	0.000013	
	α_1	0.101843	
	β_1	0.834989	
	β_2	0.000002	
MA(3)-GARCH(2,1)	Intercept	0.000999	-5.7573
	θ_1	-0.145015	
	θ_2	-0.067030	
	θ_3	0.001476	
	ω	0.000014	
	α_1	0.094760	
	α_2	0.012237	
	β_1	0.824721	
MA(3)-GARCH(2,2)	Intercept	0.000989	-5.7565
	θ_1	-0.144198	
	θ_2	-0.068761	
	θ_3	0.005493	
	ω	0.000025	
	α_1	0.091036	
	α_2	0.099150	
	β_1	0.000000	
	β_2	0.687480	

Based on Table 6, the best GARCH model is selected by looking at the smallest AIC value. The best GARCH model is MA(3)-GARCH(1,1) because the parameters contained in the model have the smallest AIC value is -5.7588.

4.6 Asymmetric Effect Test

To find out whether the data is asymmetrical or not, it is tested by cross-correlation between e_t^2(squared residual) and e_{t-p}(lag residual) which will be presented in Figure 5.

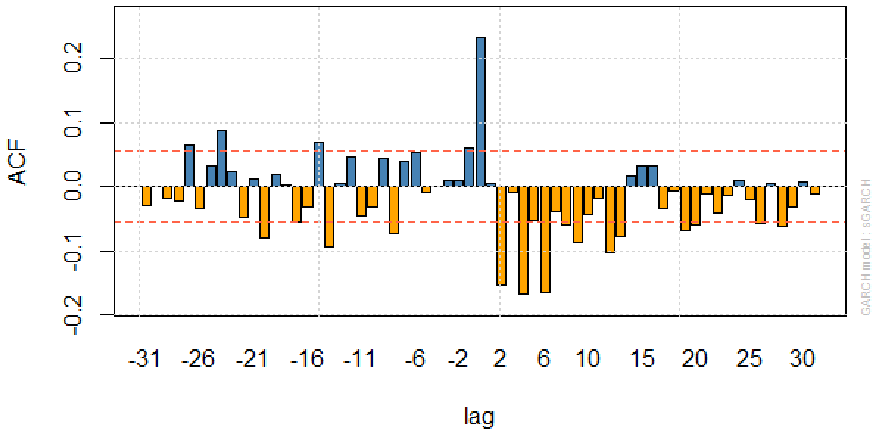

Figure 6. Cross-Correlation result of squared residual with residual lag

Based on Figure 6, some bars exceed the Bartlet line, which means there is an asymmetric effect on the BBCA closing price return data, so the GARCH model cannot be used. Overcoming the model that has asymmetrical conditions can be done with the Threshold GARCH (TGARCH) model.

4.7 Formation TGARCH Model

The parameter estimation results for the TGARCH(p,q) model are presented in Table 7.

Table 7. Estimate and Significance Test Results of TGARCH Model Parameters

Model	Parameter	Parameter Estimation	AIC
MA(3)-TGARCH(1,1)	Intercept	0.000659	-5.7777
	θ_1	-0.134855	
	θ_2	-0.062073	
	θ_3	-0.000623	
	ω	0.000831	
	α_1	0.093171	
	β_1	0.873729	
	γ_i	0.591583	
MA(3)-TGARCH(1,2)	Intercept	0.000659	-5.7761
	θ_1	-0.134851	
	θ_2	-0.062077	
	θ_3	-0.000622	
	ω	0.000831	
	α_1	0.093177	
	β_1	0.873712	
	β_2	0.000010	
	γ_1	0.591597	
MA(3)-TGARCH(2,1)	Intercept	0.000679	-5.7764
	θ_1	-0.133300	
	θ_2	-0.059947	
	θ_3	0.002312	
	ω	0.000923	
	α_1	0.088969	
	α_2	0.019384	
	β_1	0.827759	
	γ_1	0.355507	
	γ_2	0.999979	

	Intercept	0.000688	
	θ_1	-0.132903	
	θ_2	-0.060804	
	θ_3	0.002550	
	ω	0.001033	
MA(3)-TGARCH(2,2)	α_1	0.102366	-5.7750
	α_2	0.021936	
	β_1	0.627291	
	β_2	0.177384	
	γ_1	0.361320	
	γ_2	0.999978	

Based on Table 8, the best TGARCH model is selected by looking at the smallest AIC value. The best TGARCH model is MA(3)-TGARCH(1,1) because the parameters contained in the model have the smallest AIC value of -5.7777. The equation of the MA(3)- TGARCH(1,1) model is as follows:

$$r_t = 0.000659 - 0.134855a_{t-1} - 0.062073a_{t-2}$$
$$\sigma_t^2 = 0.000831 + (0.093171 + 0.591583\mathrm{N}_{t-1})a_{t-1}^2 + 0.873729\sigma_{t-1}^2 \tag{13}$$
$$N_{t-i} = \begin{cases} 1, & a_{t-i} < 0 \\ 0, & a_{t-i} \geq 0 \end{cases}$$

3.8 Forecasting Accuracy Calculation

After getting the best model for BBCA returns, then evaluate the accuracy of the MA(3)-TGARCH(1,1) forecasting model that has been formed with BBCA return observation data using MAPE (Mean Absolute Percent Error), which is presented in Table 8.

Table 8. Evaluation Results of MA(3)-TGARCH(1,1) Model with MAPE

Period	*Return* Actual	*Return Forecast*	$\left\lvert\frac{Z_t - \hat{Z}_t}{Z_t}\right\rvert \times 100\%$
3 Januari 2022	0.003418807	0.0013214	0.613490876 %
4 Januari 2022	0.010186845	0.0007644	0.924962049 %
5 Januari 2022	0.006734032	0.0006603	0.901945821 %
6 Januari 2022	0.003350087	0.0006593	0.803199134 %
7 Januari 2022	0.023141529	0.0006593	0.971510093 %
10 Januari 2022	-0.006557401	0.0006593	1.10054289 %
11 Januari 2022	0.013072082	0.0006593	0.949564268 %
	$\sum_{t=1}^{n}\left\lvert\frac{Z_t - \hat{Z}_t}{Z_t}\right\rvert \times 100\%$		6.265215131 %
	MAPE		0.895030733 %

Based on Table 8, the results of forecasting the model with MAPE have a value of 0.895030733%. Referring to Table 2 that the MA(3)-TGARCH(1,1) forecasting model is said to have very good forecasting ability.

5. Conclusion

The data used in this research is the daily stock return of PT. Bank Central Asia Tbk. By conducting the analysis, including ACF, PACF, heteroscedasticity, and asymmetric effect of the collected data, we obtained the proper model for forecasting is MA(3)-TGARCH(1,1). The level of accuracy of forecasting the return value of PT. Bank Central Asia Tbk. with the model MA(3)-TGARCH(1,1) for the next seven periods using MAPE obtained 0.895030733% said to have outstanding forecasting ability.

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