Forecasting Stock Price PT. Indonesian Telecommunication with ARCH-GARCH Model

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Article Info	ABSTRACT
	This research discusses the modeling of time series using R software, focusing on forecasting the stock price of PT. Indonesian telecommunications with ARCH-GARCH model. The data used daily closing data on stock prices from January 6, 2020, to January 6, 2021 was obtained from the website www.finance.yahoo.com. The goal is to find out the best model arch-garch on PT. Indonesian telecommunications to find out the results of stock price forecasting the next day using the ARCH-GARCH model. The best model was ARIMA (2,1,3). The results of the ARCH-LM test showed the data contained heteroskedasticity effects or ARCH elements. The research models proposed in this study are ARCH (1) and ARCH-GARCH (1,1). The smallest AIC and BIC values of these two models are ARCH-GARCH (1,1) which is the best model for forecasting the stock price of PT. Indonesian telecommunications for the next 10 days. The study attempts to conduct stock price forecasting with the ARCH-GARCH model. The result of the forecasting of the share price of PT. Indonesian telecommunications from January 07, 2021 to January 20, 2021 respectively except for holidays is IDR 3374.884, IDR 3379.617,IDR 3378.305, IDR 3376.610, IDR 3380.050, IDR 3376.372, IDR 3379.071, IDR 3377.964, IDR 3377.515, IDR 3379.002. Forecasting results are close to factual data for forecasting the next 10 days so that they can be taken into consideration in investing by investors.

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A. INTRODUCTION

The position of supply and demand for shares in the Indonesian capital market makes shares have a selling price. The higher the demand, the stock price will increase, and the higher the supply the stock price will decrease. The movement of stock prices in Indonesia is volatile, meaning it can go up or down, therefore it is necessary to do modeling and predictions to determine conditions and prepare strategies to deal with stock price declines or spikes (Prasetya et al., 2020).

Information in finance such as stock indices is usually very random and has large volatility or variable error that is not constant (heteroscedasticity). The model that can be used to test the efficiency of the weak form of the capital market with heteroscedasticity is the ARCH-GARCH model. The ARCH (Autoregressive Conditional Heteroskedasticity) model was originally introduced by Engle which was developed to respond to the case of volatility in financial data. The basic concept of the ARCH model is the residual variance depending on the past square. Then this method was developed into GARCH (Generalized Autoregressive Conditional Heteroskedasticity) by Bollerslev, the use of the GARCH model on time series data experiencing heteroscedasticity is very useful in increasing efficiency because the dependence of most of the past volatility can be reduced. In this modeling, the residual variance does not only depend on the square of the past residual but also the variance of the past residual (Juliana et al., 2019).

Several studies that apply the ARCH-GARCH model include: (Bakhtiar et al., 2021) research uses the GJR-ARCH model in analyzing price data and measuring share price losses using AVAR as a measuring tool to assess the worst losses experienced by

investors. (Larasati et al., 2016) research using the GARCH model in predicting the price of nine staple foods to increase in 2015. In this study, the best GARCH model was used for analysis and research, and predicted the volatility of 9 staple foods or other studies that had a heteroscedasticity effect. (Arumningtyas et al., 2021) research analyzed using the ARIMAX-GARCH approach and using VaR to measure risk. The results showed that the major loss in investing using the ARIMAX-GARCH method was estimating VaR. (Angraeny, 2019) research uses the ARCH-GARCH model to analyze and forecast the value of Indonesia's exports. Using the help of the Eviews software. From the forecast results, it was found that the value of Indonesian exports increased and decreased from one month to the next. The research of (Bilondatu et al., 2019) with ARCH (1) and GARCH (1,1) models gives an indication that the forecasting results are close to factual data.

PT. Indonesian Telecommunications is the largest telecommunications company in Indonesia and is one of the largest state-owned enterprises owned by the government where all levels of society know it through its telecommunications products. PT. Indonesian Telecommunications is listed as a grade A stock on the Indonesian stock exchange, it is also included in the LQ45 list which contains the 45 most liquid on the stock. as a material consideration in investing by investors (Heriyanto, 2022). Increasing need for planning in business and economic activities, so that accurate predictions of future conditions continue to be a necessity. Modern time series analysis processes are based on statistical modeling and weight calculations that are possible with today's computers and software, such as the R program (Krispin, 2019). The growth of computing technology supports the development of various procedures and forecasting methods to predict future conditions that will answer these needs (Firdaus, 2020). Until the author is interested in doing Forecasting Stock Price PT. Indonesian Telecommunications With the ARCH-GARCH Model. Based on the above background, the purpose of this research is to get the best model of ARCH-GARCH at PT. Indonesian Telecommunications and Estimating the share price of PT. Indonesian Telecommunications the next day using the ARCH-GARCH Model.

B. LITERATURE REVIEW

1. Time Series Analysis

Time series analysis is an analysis based on time-oriented or chronological data or observations on the observed variables. This analysis is very useful in data whose changes are influenced by time or previous observations. In its development time series analysis is widely used in several fields such as economics, finance, transportation, and many more. To create a model suitable for data forecasting, there are several stages of the process in time series analysis, namely: data stationarity, parameter estimation, model specification, model checking, unit root testing, and forecasting (Prasetya et al., 2020).

2. ARIMA (Autoregressive Integrated Moving Average)

The ARIMA model or commonly referred to as the Box-Jenkins method is a model formed from two estimation models, namely the Autoregressive (AR) and Moving Average (MA) models. The Autoregressive (AR) model is a model that illustrates that the dependent variable that produces accurate short-term forecasts is influenced by the dependent variable itself in the previous period and the current error (error) or residual, in general, the AR (p) model can be written as:

$$r_t = \phi_0 + \sum_{1-i}^{p} \phi_1 r_{t-1} + a_t \tag{1}$$

Information:

r_t	=	dependent variable
p	=	Positive integer
ϕ_0	=	constant
$\phi_1, \ldots, \phi_p$	=	coefficient of the first autoregressive parameter to p
$r_{t-1}, \ldots, r_{t-p}$	=	Returns the past time, the independent variable which is the lag value of the dependent variable
a_t	=	Residual (white noise)

The moving average model is a model that states the dependence of observations (r_t) with a continuous error value from period t to $t - q$. Where $MA(q)$ can be written as follows:

$$r_t = C_0 + \sum_{1-i}^{p} \theta_i a_{t-1} + a_t \tag{2}$$

Information:

$$q \quad = \quad \text{Positive integer}$$
$$C_0 \quad = \quad \text{constant}$$
$$\theta_1, \ldots, \theta_q \quad = \quad \text{Moving Average parameter coefficient to 1 to } q$$
$$a_t \quad = \quad \text{Residual at time } t$$

Meanwhile, for non-stationary data, reduction or reduction is carried out until the data is stable and stationary. The ARIMA model (p, d, q) has the following formula:

$$\phi_p(B)(1 - B)^d Z_t = \theta_0 + \theta_q(B)a_t \tag{3}$$

Where,

$$\phi_p(B) = (1 - \phi_1 B - \cdots - \phi_p B^p)$$
$$\phi_q(B) = (1 - \phi_1 B - \cdots - \phi_q B^q)$$

Information:

$$(1 - B)^d \quad = \quad \text{differencing non-seasonal on order } d$$

To estimate the time series data model used, the ARIMA Box Jenkins procedure is needed. The ADF (Augmented Dickey-Fuller) test was used to test the stationarity of the data. By hypothesis

$$H_0 : \delta > 0.05 \quad = \quad \text{or not stationary}$$
$$H_0 : \delta < 0.05 \quad = \quad \text{or stationary}$$

$$\Delta Z = \delta Z_{t-1} + u_t \tag{4}$$

$$\tau^* = \frac{\widehat{\delta}}{s.e(\widehat{\delta})} \tag{5}$$

If the value of $|\tau^*|$ is greater than the critical value of ADF with n degrees of freedom and significance level then H_0 is rejected, which can indicate that it has been corrected or the data is stationary. If the data is not stationary, then differencing is carried out until the data is stationary (Soeksin and Fatanah, 2020).

The ACF and PACF correlograms are used to estimate the ARIMA model, after which this model can be tested to estimate and test the significance of the parameters. The autocorrelation function (ACF) proves how the realization of the variable at time t relates to the realization of the variable discussed at some point in the future. ACF can be calculated by the following formula:

$$\tau S| = +\frac{E[y_t - E(y_t)][y_{t-s} - E(y_{t-s})]}{E[y_t - E(y_t)]^2} = \frac{\gamma_s}{\gamma_0}; s = 0, 1, 2, \ldots \tag{6}$$

The model selected from the estimation/estimation results can be AR(p), MA(q), ARMA(p,q), or ARIMA (p, d, q) models. Then the model obtained from the estimation results is then tested to get the best model based on several criteria. Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), and Hannan Quinn Criterion (HQIC). The order that has the smallest data value is the order that has the smallest value of the information criteria. There are no very superior information criteria, here we can use multiple criteria (orders selected by several information criteria) (Yusup and Purqon, 2015).

3. Arima Model Verification

Model verification is carried out to find out whether the model fits the observation data. The model verification includes the residual independence test and the residual normality test. A Residual independence test was conducted to see if there was a residual correlation between lags. The hypothesis for the residual independence test is: (Widyantomo et al., 2018).

$$H_0 : \quad = \quad \text{There is no residual correlation between lags}$$
$$H_1 : \quad = \quad \text{There is a residual correlation between lag}$$

The level of significance used is $\alpha = 0.05$, with test statistics:

$$Q = n(n + 2) \sum_{k=1}^{m} (n - k)^{-1} p_k^2 \tag{7}$$

The test criteria are H_0 is accepted if the probability value is $\geq \alpha$ dan H_1 is accepted if the probability value is $< \alpha$.

The normality of the residuals was checked by the Jarque-Bera test measuring the difference between the skewness and kurtosis of the data from a normal distribution and included a measure of variance. The hypotheses for the residual normality test are:

$H_0 :$ = Residuals are normally distributed

$H_1 :$ = Residual distribution is not normal

With significance level $\alpha = 0.05$ and test statistics:

$$JB = N - K/6(S^2 + 1/4(k-3)^2) \tag{8}$$

Where:

JB = Jarque-bera

K = Kurtosis

S = Skewness

k = The number of estimated coefficients

n = Number of observations

The test criteria are H_0 accepted if the probability value $\geq \alpha$ dan H_1 is accepted if the probability value is $< \alpha$.

4. ARCH-GARCH

a. ARCH

The ARCH model is commonly used in modeling financial time series. The Autoregressive Conditional Heteroscedastic (ARCH) model is now commonly used to describe and predict changes in the volatility of financial data according. This Autoregressive Conditional Heteroscedastic (ARCH) model is used to overcome non-constant errors in time series data. The ARCH model was first introduced by Engle in 1982 (Bilondatu et al., 2019).

ARCH is the first model to provide a systematic framework for volatility modelling (Tsay, 2010). The basic concept of the ARCH model is that the residual variance depends on the square of the past residual. ARCH with order m (ARCH M) is model with the following equation (Tsay, 2010):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \alpha_{t-1}^2 + \cdots + \alpha_m \alpha_{t-m}^2 \tag{9}$$

Where:

σ_t^2 = residual variance value

α_0 = constant value

α_{t-1}^2 = last residual square

α_1 = constant value to $= (1, 2, \ldots)$

It is assumed that the model formed is ARCH (1), so to predict $t + 1$ is as follows:

$$\sigma_{t+1}^2 = \alpha_0 + \alpha_1 \alpha_t^2 \quad \text{(Juliana et al., 2019)} \tag{10}$$

b. GARCH

GARCH is a process with a more general class, which can be used for a much more flexible lag structure. The GARCH method can be used for modeling heteroscedasticity data without eliminating the heteroscedasticity nature. In this modeling, the residual variance does not only depend on the square of the past residual but also the past residual variance. The general form of the GARCH model with the order m,s: (Tsay, 2010)

$$\sigma_t^2 = \alpha_0 + \alpha_i \alpha_{t-1}^2 + \sum_{j=1}^{S} \beta_j \sigma_{t-j}^2 \tag{11}$$

Where:

σ_t^2 = t-th data variance

α_0 = constant

α_j = ARCH Parameters

β_j = GARCH Parameters

α_{t-1}^2 = Residual to $t - i$

It is assumed that the model formed is GARCH (1,1) then to predict t + 1 the formula is (Tsay, 2010).

$$\sigma_{t+1}^2 = \alpha_0 + \alpha_1 \alpha_t^2 + \beta_1 \beta_t^2 \quad \text{(Juliana et al., 2019)} \tag{12}$$

Order identification on GARCH can also be done by looking at the ACF and PACF patterns from the time series data (Azmi and Syaifudin, 2020).

5. Lagrange Multiplier Test (ARCH-LM Test)

The Lagrange Multiplier test is also often referred to as the ARCH-LM. This test is used to detect the effect of heteroscedasticity of the data, and the test also shows the effect of ARCH which is the subject of this study. Therefore, this study will use the heteroscedasticity test or the Lagrange Multiplier test (ARCH-LM test) to test the heteroscedasticity and the effect of ARCH. The test that can overcome the heteroscedasticity problem that can overcome the variance that is not constant in the time series developed by Engle is called the ARCH-LM test. The main idea of this test is that the residual variance is not only a function of the independent variable but depends on the residual squared in the previous period. Here are the steps in testing the ARCH effect:

Hypothesis:

$H_0 : \quad = \quad \alpha_0 = \alpha_1 = \ldots = \alpha_p = 0$ (There is no ARCH-GARCH effect in the residual)

$H_1 : \quad = \quad$ there is at least one $\alpha \neq 1$ for $i = 1, 2, \ldots p$ (there is an ARCH-GARCH effect in the Residual)

Test Statistics

$$F = \frac{\dfrac{(SSR_0 - SSR_1)}{p}}{\left(\dfrac{SSR_1}{(T - 2p - 1)}\right)} \tag{13}$$

Where:

$$SSR_0 = \sum_{t=p+1}^{T} (\varepsilon - \omega)^2$$

$$\omega = \frac{\sum_{t=1}^{T} \varepsilon_t^2}{T}$$

$$SSR_1 = \sum_{t=p+1}^{T} W_t^2$$

with:

$\alpha \quad = \quad$ Significance level (0.05)
$p \quad = \quad$ Number of independent variable
$W_t^2 \quad = \quad$ Least square residual
$\omega \quad = \quad$ The average of T

Decision H_0 rejected if $F_{hit} > X_p^2(\alpha)$ or $p - value < \alpha$

6. Akaike Information Criterion (AIC) Test

AIC is an information standard that provides a measure of the information that can be found between the balance and measure of model goodness and model specifications. Models are used to select the best model. To get the best model, it can be seen from the smallest AIC value. The AIC formula is as follows:

$$AIC = \left(e^{\frac{2k}{n}}\right) \left(\frac{\sum e_i^2}{n}\right) = \left(e^{\frac{2k}{n}}\right) \left(\frac{SSE}{n}\right) \tag{14}$$

Where:

$SSSE \quad = \quad$ Sum square error $= \sum e_i^2$
$\quad \quad = \quad \sum \left(\widehat{Z}_I - Z_i\right)^2$
$K \quad = \quad$ Number of parameters in the model
$n \quad = \quad$ Number of sample observations $\quad$ (Ermawati et al., 2018)

7. Forecasting

As the demand for business planning and economic activity increases, so does the need for accurate predictions of future conditions. The development of computing technology has led to the development of various forecasting methods and techniques to predict future conditions that can meet these needs (Firdaus, 2020).

C. RESEARCH METHOD

The data required is the daily closing data of PT. Telekomunikasi Indonesia starting from January 2020 to January 2021 was obtained from the website www.finance.yahoo.com. The variable used in this study is the daily closing data variable for the stock price of PT. Telekomunikasi Indonesia (Z_t). The closing stock price is considered the most accurate assessment of stock to assess changes in stock prices from time to time.

In building the ARCH-GARCH method, a methodology is needed, namely the stages carried out in the use of the ARCH-GARCH model. The steps for implementing the ARCH-GARCH, method are as follows:

1. Make data tabulation.
2. Check the stationary of the data.
3. Identify the ARIMA model.
4. Estimation of model parameters and selection of the best model.
5. Verify the model.
6. Heteroscedasticity Test.
7. Parameter estimation and selection of the best ARCH/GARC model.
8. Verify the best model.
9. Do Forecasting.

D. RESULTS AND DISCUSSION

The data used in this study is the daily historical data closing the stock price of PT. Telekomunikasi Indonesia from 06 January 2020 to 06 January 2021 which was obtained online through finance.yahoo.com.

1. Stationery Test

Time series data cannot be separated from the stationarity test of the data to be studied. Therefore, a stationary test was carried out. Data testing can still be done by looking at the data graph and by going through the unit root test statistic test using the Augmented Dickey-Fulller (ADF) method. Based on the closing data of PT. Telekomunikasi Indonesia then obtained a time series plot as shown in Figure 1 below:
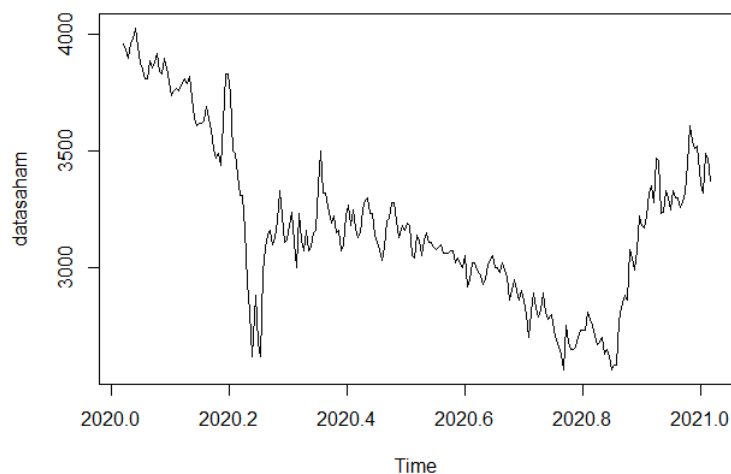

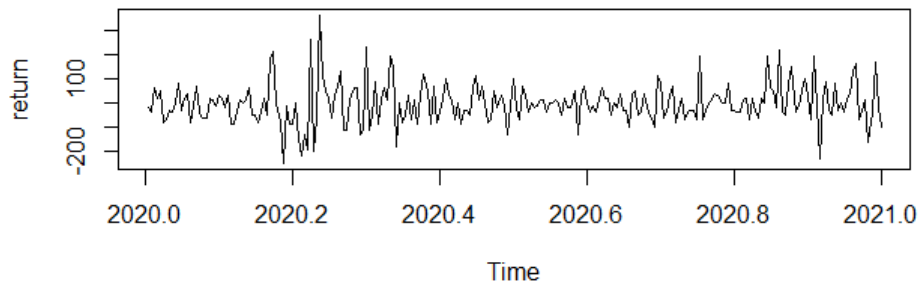**Figure 1.** Stock Price Closing Data

Figure 2. Data differencing 1 Stock Closing Data

Based on the stock data plot, it can be seen that there are differences in Figure 1, namely the actual stock data before the first difference, and Figure 2, which is the stock data after the first difference. In Figure 1 it can be explained that the plot of stock price data experienced unstable movements so that the data can be said to be not stationary on average. Figure 2 shows that the stock price data pattern is around a constant average value, which means the data is stationary. To strengthen the assumptions, it can be continued to the next stage.

Hypothesis:

$H_0 : \quad = \quad$ There is a unit root so the data is not stationary

$H_1 : \quad = \quad$ There is no unit root so the data is stationary

Significance level $\alpha = 0.05$

Table 1. Augmented Dickey-Fuller Before Differencing

	Lag	ADF	P-Vale
[1,]	0	-0.725	0.420
[2,]	1	-0.700	0.428
[3,]	2	-0.715	0.423
[4,]	3	-0.715	0.423
[5,]	4	-0.756	0.408

Based on Table 1 above, shows that the data is not stationary because all p-values are greater than $\alpha = 0.05$. So the data is said to be not stationary. To be stationary, order 1 differencing can be done.

Table 2. Augmented Dickey-Fuller After Differencing

	Lag	ADF	P-Vale
[1,]	0	-15.05	0.01
[2,]	1	-12.92	0.01
[3,]	2	-8.65	0.01
[4,]	3	-8.12	0.01
[5,]	4	-7.12	0.01

From Table 2. above, a p-value of 0.01 is obtained, which means it is smaller than α so H_1 is accepted, which means that the data is stationary and can be continued to the next stage, namely the identification of the ARIMA model.

2. Identify the ARIMA Model

To perform the identification stage of AR and MA models from a time series data, it can be done by looking at the Auto-correlation Function (ACF) and Partial Autocorrelation Function (PACF) plots at various lags. The ACF diagram can be seen in Figure 3 and Figure 4 below.
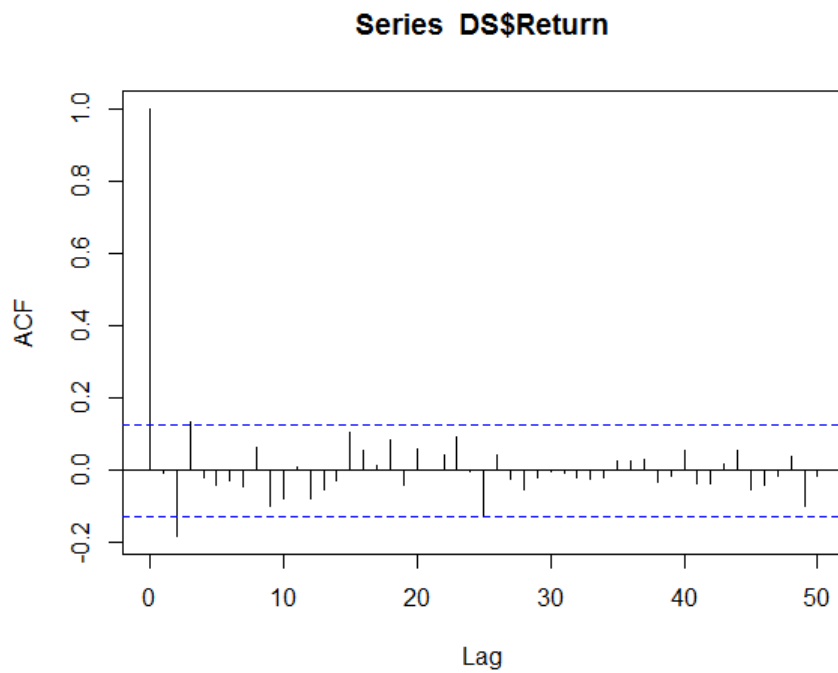
Series DS$Return
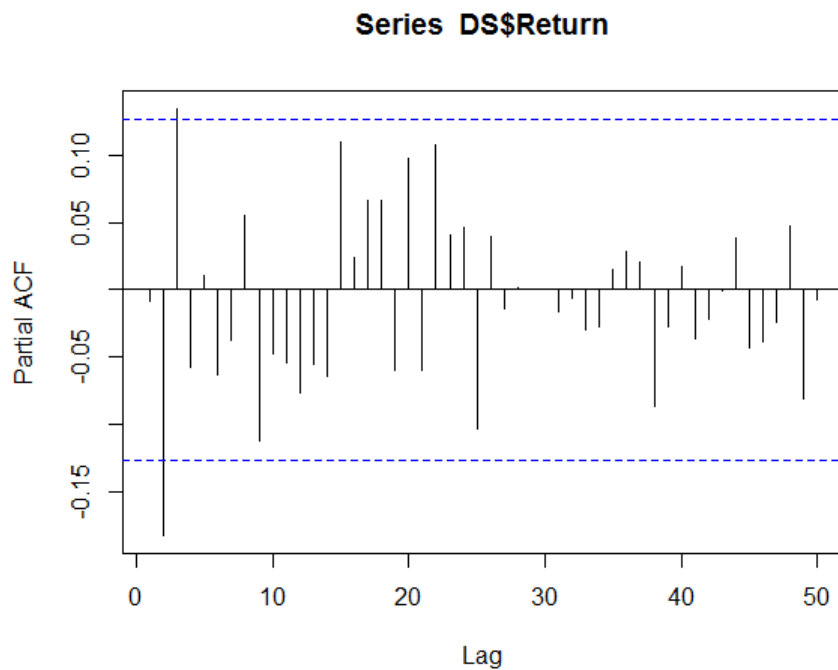

Figure 3. ACF

Series DS$Return

Figure 4. PACF

Based on Figures 3 and 4 above, it can be seen that lag 2 is slowly decreasing towards 0 so that the model that can be generated is AR(2), then the results on the ACF and PACF plots show that the ACF and PACF values are on the interval line (5%), lags that exceed the boundary line are identified as AR (based on ACF plots) and MA (based on ACF plots) levels.

3.   Estimation and Selection of ARIMA Model (p, d, q)

After the identification stage on the ARIMA model (p, d, q) is carried out, the ARIMA model parameter estimation process (p, d, q) is carried out. ARIMA model estimation can be seen in Table 3 below:

Table 3. Estimated ARIMA Model

Model	AIC
ARIMA (0,1,1)	2792.85
ARIMA (1,1,1)	2799.72
ARIMA (1,1,2)	2795
ARIMA (1,1,3)	2793.64
ARIMA (1,1,4)	2793.17
ARIMA (2,1,1)	2793.51
ARIMA (2,1,2)	2790.63
ARIMA (2,1,3)	2787.84
ARIMA (2,1,4)	2788.45
ARIMA (3,1,1)	2791.56
ARIMA (3,1,2)	2792.23
ARIMA (3,1,3)	2794.59
ARIMA (3,1,4)	2789.24

More than one model is formed, so in R, the best ARIMA model is obtained. Judging from the smallest AIC value, the best model is ARIMA (2,1,3) where AIC = 2787.84, so that the model can be used to the next stage.

4.   ARIMA Model Verification

An examination of the adequacy of the model is carried out to prove that the model obtained is adequate, as can be seen in Table 4 below.

Table 4. ARIMA Modeling $(2, 1, 3)$

Parameter	Estimation	S.E	Z-Value	$Pr(> |z|)$
AR (1)	-1.489264	0.095727	-15.5574	$< 2.2e^{-16}$
AR (2)	-0.812673	0.065233	-12.4581	$< 2.2e^{-16}$
MA (1)	0.634092	0.100978	6.2795	$3.397e^{-10}$
MA (2)	-0.742370	0.063144	-11.7568	$< 2.2e^{-16}$
MA (3)	-0.100344	0.081988	-10.7466	$< 2.2e^{-16}$

Based on Table 4 above, the $p - values$ for all parameters AR(1), AR(2), MA(1), MA(2), MA(3) are less than 0.05 which indicates that they represent statistically significant estimates.

5.   Heteroskedasticity Test

The heteroscedasticity test is a test conducted to see whether there is a heteroscedasticity effect on the best ARIMA (p, d, q) model. Previously, the best ARIMA model was obtained, namely, the ARIMA model $(2, 1, 3)$ using the ARCH-LM. Test. With the following hypothesis:

$H_0 :$ =   No ARCH-GARCH effect on residue
$H_1 :$ =   There is an ARCH-GARCH effect on the residual
The level of significance used is = 0.05, while the results of the ARCH-LM test are in the Table 5 as follows:

Table 5. ARCH LM test results

Model	Order	LM	P-Value
[1,]	4	105.55	$0.00e^{+00}$
[2,]	8	45.37	$1.16e^{-07}$
[3,]	12	25.37	$8.05e^{-03}$
[4,]	16	16.37	$3.58e^{-01}$
[5,]	20	11.21	$9.17e^{-01}$
[6,]	24	8.07	$9.98e^{-01}$

Based on Table 5 above, it can be seen that the $p-value$ on the Lagrange-Multiplier test which is smaller than 0.05 means H_1 accepted which indicates that there is an ARCH effect on the estimated model.

6. Estimation and Selection of the Best Model

Based on the parameter estimation results of the ARCH-GARCH model. Selection of the best model based on the smallest significance (5%) of the AIC and BIC models. The estimation results of the ARCH-GARCH model can be seen in Table 6 below:

Table 6. Best ARCH-GARCH Model

company stock	Best Model (p,q)	AIC	BIC
PT. Telekomunikasi Indonesia	ARCH(1,0)	11.558	11.689
	ARCH-GARCH(1,1)	11.441	11.586

Based on Table 6 above, the shares of PT. The best Indonesian telecommunications model is the ARCH-GARCH(1,1) model with the smallest AIC value of 11.558 and the smallest BIC value of 11.689. After the best model is found, a residual diagnostic test or model verification will be carried out to determine whether the model found does not contain the ARCH (Heteroscedasticity) effect, which can be seen in Table 7 below.

Table 7. ARCH-LM test

Company Stock	Best Model (p,q)	Lag ke	Statistic	P-Value
PT. Telekomunikasi Indonesia	ARCH(1) GARCH(1)	1	0.2697	0.6036
		2	5.2946	1.0000
		4	9.5231	0.8762

Based on Table 7, it can be seen that all models do not contain heteroscedasticity, where the p-value is greater than $= 0.05$, so the model is declared valid for use in forecasting. After obtaining a valid model used in forecasting.

The results of forecasting the share price of PT. Telekomunikasi Indonesia from 06 January 2020 to 6 January 2021, which is in Table 8 below.

Table 8. Forecasting Results for the Next 10 Days

Date	Forecasting (Idr)
07/01/2021	3374.884
08/01/2021	3379.617
11/01/2021	3378.305
12/01/2021	3376.610
13/01/2021	3380.050
14/01/2021	3376.372
15/01/2021	3379.071
18/01/2021	3377.964
19/01/2021	3377.515
20/01/2021	3379.002

Based on Table 8 above, the forecasting results for the next 10 days are 07/01/2021, 08/01/2021, 11/01/2021, 12/01/2021, 13/01/2021, 14/01/2021, 15/01/2021, 18/01/2021, 19/01/2021, 20/01/2021 is 3374.884, 3379.617, 3378.305, 3376.610,

3380.050, 3376.372, 3379.071, 3377.964, 3377.515, 3379.002. These results are close to factual data so they are worth considering in investing.

E.   CONCLUSION AND SUGGESTION

The ARIMA model applied to the stock data of PT.Telekomunikasi Indonesia is the ARIMA model (2,1,3) with an AIC value of 2787.84. In this study, the best ARCH-GARCH model was selected on the stock data of PT. Telekomunikasi Indonesia is the ARCH-GARCH (1.1) model with an AIC value of 11.441 and a BIC of 11.586. and the model is declared valid, the residual diagnostic test or model verification is found to no longer contain the ARCHGARCH (Heteroskedatisits) effect. Forecasting results for the next 10 days are IDR 3374.884, IDR 3379.617, IDR 3378.305, IDR 3376.610, IDR 3380.500, IDR 3376.372, IDR 3379.071, IDR 3377.964, IDR 3377.515, IDR 3379.002.

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