

## Forecasting The Share Price of PT Merdeka Copper Gold Tbk By Using Arch-Garch Model

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### ABSTRACT

*This study aims to obtain a forecasting model and compare PT Merdeka Copper Gold Tbk share price using the time series method, ARCH-GARCH model. The data used is historical data for the period December 2021 – December 2022. The initial steps are the stationarity test, identifying the ARIMA model, and checking the heteroscedasticity effect of the best ARIMA model. Then from this model, identify the ARCH-GARCH model. After the model has been formed, compare those models that have been assumed by using the smallest AIC and SBC values and checking the model's heteroscedasticity effect. The last step is forecasting for January 2023 using GARCH (1,0). The equation is  $\sigma_t^2 = 11658.24 + 0.171429\varepsilon_{t-1}^2 + 0.326916\sigma_{t-1}^2$ .*

*Keywords: ARCH, ARIMA, GARCH, Share Price, Time Series*

### Introduction

Forecasting the stock price index is quite difficult because it is included in the time series. Many factors affect changes in stock prices, making them non-linear and non-stationary. Forecasting the stock price index involves many steps, this is because there is a lot of noise and conditions that are always changing. Stock price data, which includes time series data. Financial industry data, namely stock price indicators, are often random, very volatile, and heteroscedasticity or have high volatility [1]. Time series data with conditional heteroscedasticity, namely time series data with non-uniform variance, are known as time series data with volatility as a measure of uncertainty [2]. The ARCH and GARCH models use heteroscedasticity as the variance to be modeled, so that we know the expected output of the error variance and forecasting itself is an interesting thing, especially in financial applications [3].

Residuals that have a constant variance (homoscedasticity) are one of the fundamental presumptions in estimating the regression coefficients with OLS so that the estimation results have a low standard error [4]. Unfortunately, this criterion is often not met, especially when examining cross-sectional data. Residuals that have non-constant variance for each observation (heteroscedasticity) can use the ARCH and GARCH methods to model stock price volatility [5].

The purpose of this research is to obtain a stock price forecasting model and to obtain a comparison of the stock price forecasting results of PT Merdeka Copper Gold Tbk. using the ARCH-GARCH model [6].

### Research Methods

Source of data used in this study is using secondary data. Researcher uses secondary data that has been collected from primary sources to conduct research, where secondary data is research data collected by researchers indirectly through intermediary media. In this study, historical data on the daily stock price of PT Merdeka Copper Gold Tbk will be used. period December 2021 – December 2022 through Finance Yahoo (<https://finance.yahoo.com/>). The steps for forecasting the share price of PT Merdeka Copper Gold Tbk. by applying the ARCH-GARCH model is [7]–[11]:

1. Data collection
2. Plot the data visually using graphs
3. Test the stationarity of the data using the Augmented Dickey-Fuller Unit Root Test type
4. Correlogram test to determine the order of AR and MA
5. Formation of the ARIMA model

6. Selection of the best ARIMA model
7. Verify the model using the residual independence test and normality test
8. Heteroscedasticity test using the Lagrange Multiplier test
9. Provisional model estimation for ARCH-GARCH modeling
10. Selection of the best ARCH-GARCH models
11. Examination of the model to see whether the model still contains elements of heteroscedasticity by using the ARCH-LM test
12. Forecast stock prices using the best model
13. Draw conclusions from the analysis results that have been obtained, as well as provide suggestions in order to obtain perfection in the next research

### Time Series Analysis

A time series is a collection of variables where all are observed at the same point in time, usually spaced at uniform intervals—daily, weekly, quarterly, monthly or yearly. Time series analysis is an important tool for forecasting future periods based on past periods [12]. The time series numbers show stationarity in the variance, so it can be said that the variance of the data is stationary if the time series plot does not clearly describe the change in variance during the series [13].

### ACF and PACF Function

The autocovariance function is defined as follows:

$$\gamma(k) = E[(z_{t+k} - \mu)(z_t - \mu)] \quad (1)$$

Note that the variance of the time series is  $\gamma(0)$ . It can be defined the autocorrelation function (ACF) for a stationary time series as:

$$\rho(k) = \frac{\gamma(k)}{\sqrt{\gamma(0)}\sqrt{\gamma(0)}} = \frac{\gamma(k)}{\gamma(0)} \quad (2)$$

Partial autocorrelation lag  $k$  can be considered as the final regression coefficient  $\phi_{kk}$  if the regression equation fits  $k = 1, 2, \dots$

$$\tilde{z}_t = \phi_{k1}\tilde{z}_{t-1} + \dots + \phi_{kk}\tilde{z}_{t-k} + \alpha_t \quad (3)$$

This model can be written directly in  $z_t$ . Using substitution  $\tilde{z}_t = z_t - \mu$  we get:

$$\begin{aligned} z_t - \mu &= \phi_1(z_{t-1} - \mu) + \phi_2(z_{t-2} - \mu) + \alpha_t \\ z_t &= \mu - \phi_1\mu - \phi_2\mu + \phi_1z_{t-1} + \phi_2z_{t-2} + \alpha_t \\ z_t &= \text{konstan} + \phi_1z_{t-1} + \phi_2z_{t-2} + \alpha_t \\ \text{where constant} &= \mu - \phi_1\mu - \phi_2\mu \text{ atau } \mu = \text{constant}/(1 - \phi_1 - \phi_2) \end{aligned}$$

### Parameter Estimation

The next step is to estimate the possible parameters of the ARIMA model, the method that can be applied is maximum likelihood. The parameters in the equation can be estimated by maximizing the model possibilities given the data. The probability of a data set is denoted by  $L$  and is an estimate proportional to the probability of obtaining the data given the model. The maximum likelihood method finds the parameter values that maximize the likelihood of  $L$ . This estimate must be found iteratively [14].

### Residual Independence Test

$H_0$  : there is no residual correlation between lags

$H_1$  : there is no residual correlation between lags

The significance level used is  $\alpha = 0.05$ , with statistic test (Adi et al, 2016):

$$Q = n(n+2) \sum_{k=1}^m (n-k)^{-1} p_k^2 \quad (5)$$

### Normality Test

$H_0$  : error is normally distributed

$H_1$  : error is not normally distributed

The significance level used is  $\alpha = 0.05$ , with statistic test (Adi et al, 2016):

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

### ARCH and GARCH Models

In the ARCH process (q), the conditional variance at time t is affected by the square of the residue at time (t - 1), (t - 2), ..., (t - q) and:

$$\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2} + \dots + \alpha_q \varepsilon^2_{t-q} \quad (7)$$

The GARCH model considers the conditional variance to depend on the previous lag as well as the squared residual requirement of the ARCH model. The general form of the GARCH model (p,q):

$$\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2} + \dots + \alpha_q \varepsilon^2_{t-q} + \beta_1 \sigma^2_{t-1} + \beta_2 \sigma^2_{t-2} + \dots + \beta_p \sigma^2_{t-p} \quad (8)$$

### Heteroscedasticity Test

$H_0$  : there is no ARCH-GARCH element in the error

$H_1$  : there is ARCH-GARCH element in the error

The significance level used is  $\alpha = 0.05$ , with statistic test (Tsay, 2010):

$$F = \frac{(SSR_0 - SSR_1)/m}{SSR_1/(T - 2m - 1)} \quad (9)$$

### Selection of The Best Model

The model that has the smallest AIC and SBC values is the best model. In general, AIC is formulated as follows:

$$AIC = 2k - 2ln \quad (10)$$

General form of SBC:

$$BC(M) = nln\hat{\sigma}_a^2 + Mlnn \quad (11)$$

### Share

Shares are a symbol of investor or trader ownership in a corporation, both institutional investors and traders [15]. Share price is the value of rupiah shares created from buying and selling shares of other exchange members in the capital market [16]. Based on these definitions, it can be concluded that shares are ownership of money invested in a company by individual or institutional investors in the form of securities, which are part of the company's assets.

### Volatility

Volatility, which is basically the rate of growth or decline in prices, is defined statistically as the standard deviation of the market's annual return or investment over a certain period [8].

$$S_d = \sqrt{\frac{1}{n-1} \sum_{t=1}^n (r_t - \bar{r})^2} \quad (12)$$

## Results and Discussion



Figure 1 Plot Data of PT Merdeka Copper Gold Tbk Share Price Fluctuations.

Figure 1 shows that the share price of PT Merdeka Copper Gold Tbk. the period from December 2021 to December 2022 will experience fluctuations every day.

### Stationarity Test

Table 1. Stationarity test (first difference)

	t-Statistic	Prob
Augmented Dickey-Fuller test statistic	-18.30137	0.0000
5% level	-2.872203	

Stationary data at first difference with an absolute ADF value of 18.30137 which is greater than the absolute value of  $\alpha = 0.05$ , which is 2.8722 with an ADF probability of 0.000. Therefore it can be concluded that  $H_0$  is rejected and the data is stationary.

### ARIMA Model Identification

Table 2. ARIMA parameter estimation

No.	ARIMA Model	Parameter Diagnostic		Heteroscedasticity
		Parameter	Inference	
1.	ARIMA (1,2,0)	$\phi_1$	✓	×
2.	ARIMA (0,2,1)	$\omega_1$	✓	×
3.	ARIMA (6,2,0)	$\phi_6$	✓	✓
4.	ARIMA (0,2,6)	$\omega_6$	✓	×
5.	ARIMA (7,2,0)	$\phi_7$	✓	✓
6.	ARIMA (0,2,7)	$\omega_7$	✓	✓
7.	ARIMA (1,2,1)	$\phi_1$	×	×
		$\omega_1$	×	
8.	ARIMA (1,2,6)	$\phi_1$	×	×
		$\omega_6$	✓	
9.	ARIMA (6,2,1)	$\phi_6$	×	×
		$\omega_1$	×	
10.	ARIMA (6,2,6)	$\phi_6$	×	×
		$\omega_6$	×	
11.	ARIMA (1,2,7)	$\phi_1$	✓	×
		$\omega_7$	✓	
12.	ARIMA (7,2,1)	$\phi_7$	✓	×
		$\omega_1$	×	
13.	ARIMA (7,2,7)	$\phi_7$	✓	✓
		$\omega_7$	✓	
14.	ARIMA (6,2,7)	$\phi_6$	✓	×
		$\omega_7$	✓	
15.	ARIMA (7,2,6)	$\phi_7$	✓	×
		$\omega_6$	✓	

Tabel 3. Comparison of ARIMA Models

No	ARIMA Model	AIC	SBC
1	ARIMA (6,2,0)	12.63929	12.67959
2	ARIMA (7,2,0)	12.63637	12.67668
3	ARIMA (0,2,7)	12.63576	12.67606
4	ARIMA (7,2,7)	12.63034	12.68408

Based on table 3, it can be seen that the smallest AIC and SBC values are found in the ARIMA model (0,2,7), so it can be determined that this model is the best model, the equation is  $Y_t = 1.548950 + 0.142643e_{t-1}$ .

### Diagnostic Model

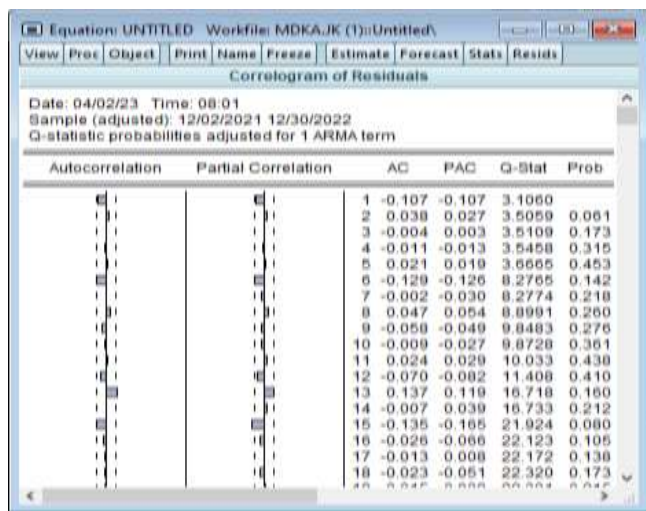


Figure 2. ARIMA (0,2,7) Residual Independence Test

Figure 2 shows that the probability value for each lag in the ARIMA model (0,2,7) is not significant because each lag has a probability value of  $> 5\%$ , so  $H_0$  is rejected and it can be concluded that there is a residual relationship between lags in the ARIMA model (0, 2,7).

Table 4. Normality test of ARIMA (0,2,7)

Model	p-value
ARIMA (0,2,7)	0.0000

Table 4 shows that the probability value is  $0.00000 \leq \alpha$  therefore  $H_0$  is rejected and it can be concluded that the data is not normally distributed

### Heteroscedasticity Test

Table 5. Heteroscedasticity test of ARIMA (0,2,7)

Model	Prob. Chi-Square
ARIMA (0,2,7)	0.034

It can be seen that the probability value is 0.0334, then based on the Lagrange Multiplier test  $H_0$  is rejected because the p value  $<$  significance value (0.05). Then it can be determined that the model contains ARCH elements so that it can be continued with ARCH/GARCH modeling.

### ARCH-GARCH Model

Table 6. Heteroscedasticity test of GARCH Models

Model	Prob. Chi-Square
GARCH (1,0)	0.1095
GARCH (0,1)	0.0333
GARCH (1,1)	0.1215

GARCH (1.0) and GARCH (1.1) are free from heteroscedasticity because the p value  $> \alpha$  (0.05) so that  $H_0$  is accepted, while the GARCH model (0,1) still contains elements of heteroscedasticity.

### Selection of The Best Model

Table 7. Heteroscedasticity test of GARCH Models

Model	AIC	SBC
GARCH (1,0)	12.64528	12.69903
GARCH (1,1)	12.64015	12.70732

GARCH (1,1) has the smallest AIC and SBC values, namely 12.64015 and 12.70732. So it can be said that this model is the best model for forecasting the stock price of PT Merdeka Copper Gold Tbk. The variance equation is  $\sigma_t^2 = 11658.24 + 0.15\varepsilon_{t-1}^2 + 0.326916\sigma_{t-1}^2$

### Forecasting

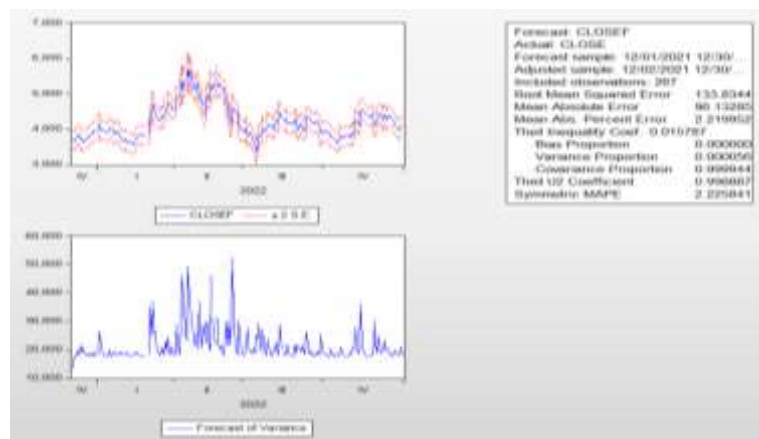


Figure 3. Graph of PT MDKA Forecasting Result

The results of stock price forecasting for the same period as the original data do not have much difference from the result of forecasting. The ARCH-GARCH modeling has deficiencies in distinguishing between low volatility and high volatility, therefore the ARCH-GARCH model can be modified by applying the IGARCH model.

### Conclusion

Based on the results of the analysis and discussion, it can be concluded that the ARCH-GARCH time series forecasting model has fairly good forecasting results. The best model in forecasting the stock price of PT Merdeka Copper Gold Tbk. the period December 2021 – December 2022 is ARIMA (0,2,7). Because this model contains elements of heteroscedasticity, it is continued by using the ARCH-GARCH model. The best model obtained is GARCH (1,1) with the equation  $\sigma_t^2 = 11658.24 + 0.15\varepsilon_{t-1}^2 + 0.326916\sigma_{t-1}^2$ . The next step is forecasting for the period December 2021 – December 2022, and continuing forecasting for the next month, namely January 2023.

In this study, it is hoped that future researchers will use historical data and different program assistance, as well as compare other time series methods in detecting heteroscedasticity problems, especially the Integrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH) model.

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