Application of ARCH-GARCH Model to Predict USD/IDR Currency Amounts

Muhammad Wahyu Bagus Prasojo[1] , Hevi Mona Uti[2] , Fajri Maulana[3] , Absalom Zakharia Ady Ena[4] , Syahdan Rasyid Syaukani[5] , Resa Septiani Pontoh[6]

[1, 2,3,4,5,6] Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Indonesia
(E-mail: muhammad21264@mail.unpad.ac.id, hevi21001@mail.unpad.ac.id, fajri21002@mail.unpad.ac.id, absalom21001@mail.unpad.ac.id, syahdan21002@mail.unpad.ac.id, resa.septiani@unpad.ac.id.)

ABSTRACT

This research focuses on analysing the US Dollar to Rupiah exchange rate price data by applying the ARCH/GARCH model. The main objective of this research is to understand and model the volatility of the US Dollar to Rupiah exchange rate price and identify the best model that can provide an accurate forecast of the exchange rate price changes. The analysis used ARCH/GARCH models with various parameter configurations to identify the most appropriate model for the exchange rate data. The results of the study show that the ARIMA (0,1,1) GARCH (2,2) model is the most appropriate model to predict the price of the US Dollar to Rupiah exchange rate. From the calculation results and based on the smallest AIC value obtained of 40.31 and obtained a MAPE value of 1.574589 which means it is good enough so that it can be used to predict the price of the US Dollar to Rupiah exchange rate for the next 12 months. The implication of this research is that governments, companies as well as investors and financial market analysts can use this model as a tool in making better decisions related to investment, hedging, and financial planning.

Keywords: *ARCH, GARCH, Volatility, Exchange Rate, Forecasting*

1. Introduction

Indonesia has experienced several changes in the exchange rate system along with the change of leadership period of the Republic of Indonesia. Changes in the exchange rate system in Indonesia are caused by the government that sets the policy of enforcing the exchange rate system adjusted to the conditions of Indonesia's macroeconomic conditions.

The volatility of the IDR/USD exchange rate can affect the exchange rate. Previous exchange rates will be used to form expectations about changes in exchange rates. Volatility does not only measure changes but also shows the risk factors of the currency (Adiningsih et al, 2008:44). The more volatile a currency is, the greater the risk of that currency. Volatility is calculated using the standard deviation of the nominal exchange rate. Increased volatility has several significant impacts. One of the impacts relates to the rupiah currency. The increase resulted in the rupiah exchange rate becoming very weak. The increase in volatility itself resulted from the continuous withdrawal of global funds, especially in developing countries. In addition, the improvement of the US economy and the prospect of interest rate hikes in the country triggered the weakening of the exchange rate.

Based on the background that has been explained, the problem that will be discussed in this study is forecasting the Rupiah to US Dollar exchange rate using the ARCH-GARCH method which allows to identify and model non-constant volatility in currency exchange rate data. The data used in this study is secondary data obtained through the *investing.com* website for the exchange rate of the Rupiah to the US Dollar for the period October 2018 - September 2023 which amounts to 60 data.

This research aims to develop a forecasting model for the Rupiah to US Dollar exchange rate using the ARCH-GARCH approach. This method will be used to measure volatility and model it more precisely, thus allowing us to perform more accurate forecasting of how the Rupiah exchange rate will change in the future. As such, this research will make an important contribution in helping governments, companies, and investors make better decisions regarding investment, hedging, and financial planning.

2. Research Methods

2.1 Stationarity Check

Data is said to be stationary if the mean and variance of the time series do not change significantly over time. In the context of time series analysis, stationarity is an important concept as many statistical methods and models, such as ARIMA (AutoRegressive Integrated Moving Average) models, require stationary data. It is important to understand that in many cases, to achieve stationarity in mean or variance, it is necessary to transform the data such as differencing or logarithmic transformation.

2.2 Model Identification

Identification of autoregressive (AR) and moving average (MA) models in ARIMA models using ACF (Autocorrelation Function) plots and PACF (Partial Autocorrelation Function) plots involving the main components: autoregressive (p) and moving average (q).

2.3 Parameter Estimation and Best Model Selection

Once several potential models are identified, the next step is to estimate the model parameters. The main objective is to obtain significant coefficient values from the model. One of the criteria used to select the best model is using AIC (*Akaike Information Criteria*).

2.4 Model Diagnostic Test

After obtaining the ARIMA estimator, the next step is to choose a model that can explain the data well. The data is seen whether the residuals are random so that they are relatively small residuals. If not, then you have to go back to the first step to choose another model. Predicting, after obtaining the appropriate model, then predict using the model according to the desired forecasting time period.

2.5 ARCH-LM Test

In order to prove that the ARIMA model used contains heteroscedasticity problems is to conduct heteroscedasticity testing. The test used is the ARCH-Lagrange Multiplier (ARCH-LM test) (Teguh Santoso: 2011). The ARCH-LM test is useful to see if there is an ARCH/GARCH effect in the Box-Jenkins test estimation.

2.6 ARCH-GARCH Method

The ARCH model is a basic model used to address the problem of conditional heteroskedasticity in time series data. Conditional heteroscedasticity refers to volatility fluctuations that change over time.

The GARCH model is a development of the ARCH model that is more flexible and robust. It combines an ARCH component with an autoregression component, which makes it possible to model more complex volatility in time series data. The GARCH (p, q) Model formula is as follows:

$$\sigma_t^2 = \alpha_0 + \Sigma_{i=1}^{p}\alpha_i . y_{t-1}^2 + \Sigma_{j=1}^{q}\beta_j\sigma_{t-j}^2 \quad (1)$$

2.7 Model Verification

Verification of the ARCH-GARCH (Autoregressive Conditional Heteroskedasticity - Generalized Autoregressive Conditional Heteroskedasticity) model involves a number of steps that need to be taken to ensure that the model is appropriate and can be used to analyze time series data.

2.8 ARCH-GARCH Prediction

After selecting the best model, the last step is to perform prediction to predict future stock price changes.

3. Analysis

3.1 Data Stationarity Test

Stationary test in variance is done by looking at the lambda value using the *Box-Cox transformation* method with the *Box-Cox* test results lambda value is 1.99924. With a lambda value of 1.99924, it can be concluded that the value is close to 1 and the data is stationary in variance. While the stationary test in the average is carried out using the*Augmented Dickey Fuller* (ADF) *test* method*,* with

H_0 : Data does not meet stationarity assumptions

H_1 : Data meets the assumption of stationarity

Reject H_0 if $p - value < \alpha$. Accept in all other cases.

Based on the calculation using R, it can be seen that the p-value [0.2355] > α [0.05], then H0 is accepted so that the data used does not meet the assumption of stationary or time series data for circulation of banknotes is not stationary, then differencing is needed. After differencing once, the p-value of [0.01] < α [0.05], then H0 is rejected, which means that the Rupiah to US Dollar exchange rate data for the 2018-2023 period is stationary.

3.2 Model Identification

After obtaining data that meets the assumption of good stationarity, the next step is to identify the AR(p) and MA(q) models. In determining the order will be seen based on the ACF plot and PACF plot. The results of the ACF and PACF plots using R software are as follows.

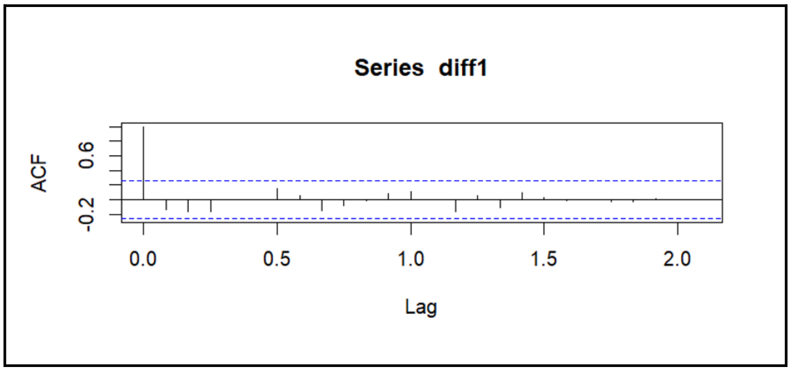

Figure 1. ACF plot of Rupiah to US Dollar exchange rate

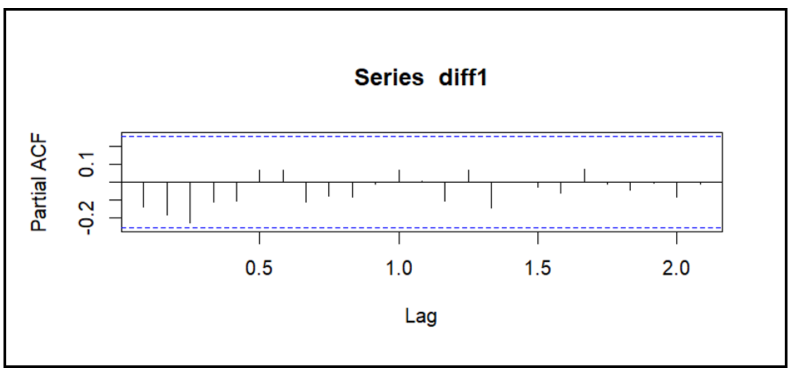

Figure 2. PACF plot of Rupiah to US Dollar exchange rate

The stationary data can be seen in the ACF and PACF plots above. Based on the results of the ACF plot, it is obtained that there is a *cuts off* at lag 1, while from the PACF plot it is identified that there is a *dies down cuts off* at lag 0.

3.3 Parameter Estimation and Best Model Selection

Based on the results of the ACF plot, it is obtained that there is a *cuts off* at the 1st lag so that the possibility for the value of q = 1 is obtained, while from the PACF plot it is identified that there is a *dies down*. To determine the best model, selection is made based on the AIC value of each model. The selection uses AIC criteria or the like where the best significant model criteria are seen from the smallest AIC value. Based on the results of calculations with RStudio software, the smallest AIC value is obtained in the ARIMA (0,1,1) model, which is 871.77.

Parameters	Estimation	Standard Error	T-Count	*p-value*	Description
MA1(0,1,1)	-0,29491	0,12546	-2,3506	0,01874	Significant
Intercept	- 1,00000	0,04792	-20,868	< 2e-16	Significant

3.4 Model Diagnostics

H_0: Data does not meet assumptions

H_1: Data meets assumptions

Reject H_0 if $p - value < \alpha$. Accept in all other cases.

Normality Assumption Test

Kolmogorov-Smirnov Test		*p-value*
D	0,22034	0,1141

By using R software, the result of the p-value [0.1141] > α $[0,05]$, then H0 is accepted. Thus, it can be concluded that the residuals of the ARIMA (0,1,1) model are normally distributed.

White Noise Autocorrelation Test

Box-Ljung Test		*p-value*
Chi-squared	0,86236	0,3531

Based on the results of this analysis, the p-value [0.3531] > [0.05] is obtained, so H0 is accepted. Thus, it can be concluded that the residuals of the ARIMA (0, 1, 1) model are not autocorrelated. So that the assumption of non-autocorrelation is fulfilled.

White Noise Heteroscedasticity Test

Box-Ljung Test		*p-value*
Chi-squared	15.325	9.051e-05

Based on the results of this analysis, the p-value [9.051e-05] < [0.05] is obtained. Thus, it can be concluded that the residuals of the ARIMA (0, 1, 1) model do not have a homogeneous variance. Since the ARIMA (0, 1, 1) model does not meet the assumption of homogeneity, it is necessary to identify the ARCH effect in the model.

3.5 ARCH-GARCH Model

In determining the ARCH-GARCH model, it can be seen in the ACF and PACF correlograms of the squared residuals as follows.

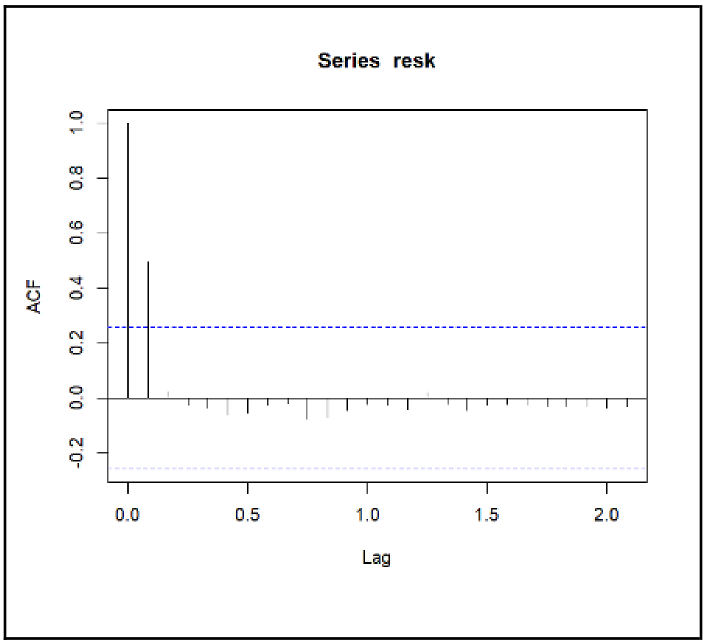

Figure 3. ACF Plot of Squared Residuals of ARIMA (0,1,1)

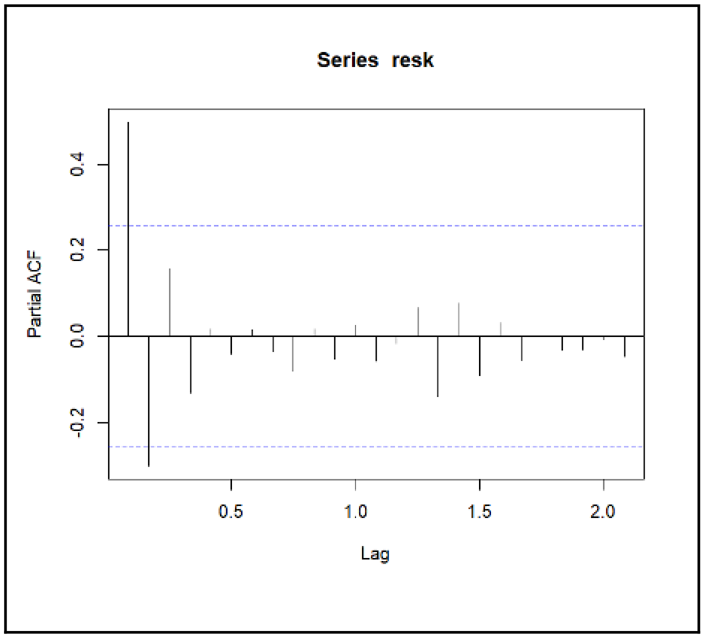

Figure 4. PACF Plot of Squared Residuals of ARIMA (0,1,1)

It can be seen that the ACF *correlogram* shows a cutoff at the 2nd lag while the PACF *correlogram* dies down so that the GARCH model estimate is GARCH (2,2). Then the GARCH (2,2) model estimation is carried out to see whether the parameters used are significant or not. The results of the parameter estimation and significance test are as follows.

3.6 ARCH-LM Test

H_0 : there is no ARCH effect on the data

H_1 : there is an ARCH effect on the data

Reject H_0 if $p - value < \alpha$, accept in other cases.

ARCH-LM Test		*p-value*
Jarque Bera Test	4817,7	2,2e-16
Box-Ljung Test	0,10542	0,7454

Based on the results of the analysis using Software R, it states that there are no longer elements of Heteroscedasticity and autocorrelation in the model, which means that the GARCH (2,2) model is suitable for forecasting.

3.7 Model Significance

H_0 : parameter is not significant

H_1 : significant parameter

If *p-value* < α, then reject H0. Accept in all other cases

Model	Parameters	Estimation	*p-value*
GARCH(2,2)	a0	2.028e-01	0.795
	a1	1.907e-01	0,283
	a2	5.638e+01	0,0147
	b1	2.355e-02	0,995
	b2	1.657e+02	0,0434

Based on the results of the analysis, there is only one significant parameter so that the model used is ARIMA (0,1,1) GARCH (2,2).

3.8 Forecasting

The following are the results of forecasting using ARIMA (0,1,1) GARCH (2,2).

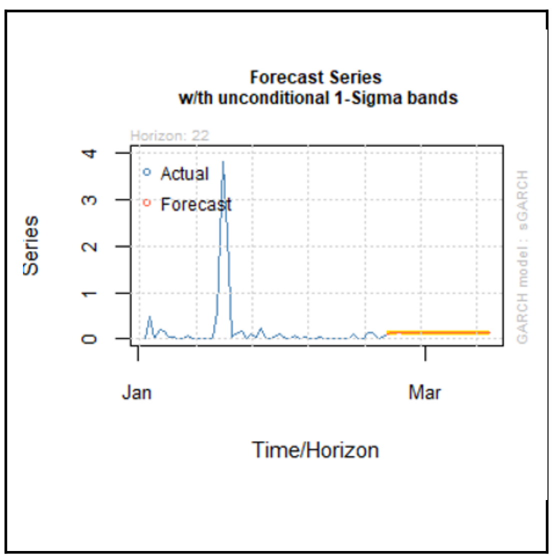

Figure 5. Time Series Prediction

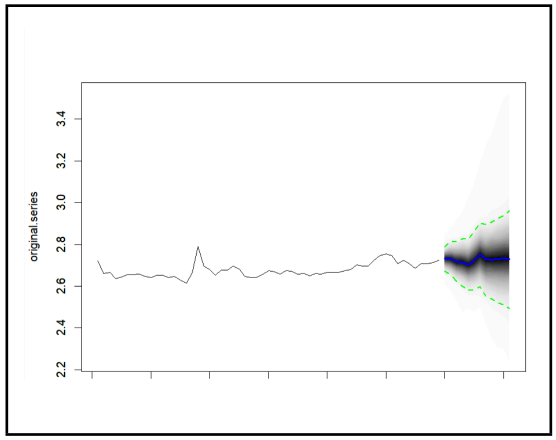

Figure 6. Sigma Prediction

After getting the best model, forecasting can be done on the Rupiah to US Dollar exchange rate data for the next 12 months in a row.

Period	**Volatility**
Jan-24	14.032
Feb-24	14.100
Mar-24	13.880
Apr-24	13.650
May-24	14.340
Jun-24	16.300
Jul-24	14.825
Aug-24	14.575
Sep-24	14.180
Oct-24	14.520
Nov-24	14.560
Dec-24	14.840

In this study, the MAPE value is used to measure the accuracy of the original data and the predicted results. In the training data, the MAPE value is 1.574589 and in the testing data, the MAPE value is 0.9924408, which means that it is highly accurate and can be used to predict data.

4. Conclusion

Based on the results of the analysis that has been done, the best model used to predict the price of the US Dollar to Rupiah exchange rate with 60 data starting from October 2018 to September 2023 is ARIMA (0,1,1) GARCH (2,2). From the calculation results and based on the smallest AIC value obtained of 40.31 and the MAPE value obtained on the training data of 1.574589 and on the Testing Data obtained a MAPE value of 0.9924408 which means that it is high accurate and good enough so that it can be used to predict the price of the US Dollar exchange rate to Rupiah.

References

[1] Real-time Data USD/IDR - US Dollar Indonesian Rupiah *https://www.investing.com/currencies/usd-idr*

[2] Desvina, A. P., & Rahmah, N. (2016). Application of ARCH/GARCH Method in Forecasting Sectoral Stock Price Index. Science of Mathematics and Statistics.

[3] Yolanda, N. B., Nainggolan, N., & Komalig, H. A. (2017). Application of ARIMA/GARCH to Predict BRI Bank Stock Price. MIPA Sam Ratulangi University, 92-96.

[4] Khairunisa & Desvina, A. P. (2018). Application of the Arch/Garch Method in Forecasting Exchange Rate Transactions (Kurs) Selling Indonesian Currency (IDR) Against European Currency (GBP)

[5] Faydian P, Hasana, E.H., Irfan, M., & Taqiyuddin, TA (2021). Deployment Model ARCH/GARCH To Predict Tokai Carbon Company Share Prices