Application of GARCH Model in Forecasting IDR/USD Exchange Rate

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Abstract: Modeling and Forecasting the IDR to USD exchange rate is crucial in business as it provides information on the model of exchange rate fluctuation and taking the right financial decisions. Therefore, financial managers in a multinational company are required to be able to understand exchange rate forecasting in order to make financial decisions to optimize the value of the company. The purpose of this research is to do the modeling and forecasting of IDR exchange rate against USD using GARCH model. The GARCH model is a suitable model used for financial analysis because assuming the existence of heteroscedasticity not a problem but can be used to predict future price volatility. GARCH models pay attention to the variance and errors in doing the forecasting. The results showed that the GARCH model (1,1) was the best model in representing exchange rate movements during the study period. The result of forecasting of IDR to USD exchange rate for 5 days after the research period are 14065, 04072, 14078, 14084 and 14090.

1 INTRODUCTION

Globalization has brought about openness in many ways, including in terms of trade and economics. Foreign exchange activities or shortened as forex is often done by all business actors in the world, such as import export activities, market needs and bank institutions. Information on exchange rates helps business people in making investment decisions and trading their money in order to earn a profit.

Exchange rate forecasting, especially between IDR to USD is one of the most important aspects in Indonesia. The exchange rate of IDR/USD is one of the foundations in the current national economic activity. The exchange rate is the ratio between the currency of a country and the currency of another country. The exchange rate is also one of the most important macroeconomic variables, because strong currency exchange rates can maintain economic stability in an area or country. The economic crisis that struck Indonesia was preceded by the emergence of the IDR exchange rate crisis which was a consequence of an increasingly globally integrated financial system. This can trigger issues in financial and banking transaction activities. Forecasting can minimize the risks that may occur due to demand uncertainty and others (Natsir and Mimi, 2017). However, the IDR against USD exchange rate modeling has not been studied thoroughly. Through this modeling will provide a strong signal in the determination of policy and planning everything related to financial transactions involving the exchange rate of IDR against USD.

The exchange rate movement of IDR/USD always fluctuates over time. The high volatility of the exchange rate makes it difficult to model with classic OLS, because according to Gauss Markov theorem, one of the requirements in OLS model is the variance and error must be constant (homoscedasticity). This is as such so that the estimator obtained is BLUE (Hueter and No, 2016).

In this era of globalization, especially in a floating exchange rate policy, exchange rate movements will be highly volatile or have high volatility due to the large number of local or global factors that affect it. High volatility has the potential to cause heteroscedastic variance and error. Therefore, the GARCH model would be more appropriately used to analyze the exchange rate because this model does not regard heteroscedasticity as a constraint, but instead uses that condition to build the model.

Several studies on exchange rate modeling using ARCH and GARCH models have attracted the attention of previous researchers. The study of

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ARCH /GARCH Model Implementation for Farmer Exchange Rate Forecasting has been conducted by Pani et al., (2018). Additionally, a study on Neuro-Garch modeling on the exchange rate of Rupiah against the US dollar has been conducted (Adi et al., 2016). In the capital market research conducted on the stock price movement of SSE Composite Index shows that EGARCH (1,1) is the best model (Lin, 2017). The implementation of the GARCH model on short-term daily interest rate volatility has been carried out in the euro-yen market with daily data of 980 observations. The results show that the ARMA-RGARCH model is the model that best matches the data analysed (Tian and Hamori, 2015). Kristjanpoller and Minutolo (2016) developed ANN-GARCH mixed model to analyze and predict oil price volatility.

The purpose of this study is to determine if the GARCH model in accordance to the movement of the IDR/USD exchange rate and then forecast the exchange rate of IDR/USD 5 periods ahead.

2 THEORETICAL BACKGROUND

2.1 Arima Model

One of the famous time series data models is the Autoregressive Integrated Moving Average (ARIMA), commonly called the Box-Jenkins method (Widarjono, 2002). ARIMA does not use other variables in its model, but data movement is explained by past data.

ARIMA method is divided into three groups of linear time series model, namely:

a. Autoregressive Model (AR). The general form of AR model with the order p or AR(p) or ARIMA model (p, d, 0) in general is:

$$Z_t = b_0 + b_1 Z_{t-1} + b_2 Z_{t-2} + ... + b_p Z_{t-p} + e_t \qquad (1)$$

b. Moving Average Model (MA). The equation of MA model with the order q or MA(q) or ARIMA model (0, d, q) in general is:

$$Z_t = b_0 + e_t - c_1 e_{t-1} - c_2 e_{t-2} - .... - c_q e_{t-q} \qquad (2)$$

c. Autoregressive Integrated Moving Average (ARIMA. The general form of this model is:

$$Z_t = b_0 + b_1 Z_{t-1} + b_2 Z_{t-2} + \ldots + b_p Z_{t-p} + e_t - c_1 e_{t-1} - c_2 e_{t-2} - \ldots - c_q e_{t-q} \qquad (3)$$

The ARIMA process is generally denoted by ARIMA (p, d, q), where:

- p shows autoregressive order (AR)
- d is the process of differentiating
- q denotes moving average order (MA).

The main requirement of ARIMA use is the presence of stationary data. Stationary means the data fluctuations are around a constant mean value, independent of the time and variance of the fluctuations. If the data is not stationary, then the stationary data process is done using the process of differentiation.

Stages for model estimation with ARIMA consist of model identification process, parameter estimation, and model evaluation.

2.2 ARCH/GARCH Model

Time series data, especially financial data such as stock price index, interest rate, exchange rate and so on, often have high volatility. This implies the variance of error is not constant (heteroscedastic). The existence of heteroscedasticity will require a wide confidence interval in estimation with the OLS, so the conclusion of the model may be misleading. To handle the volatility of data, a certain approach to measure residual volatility. One approach used is to include independent variables that can predict the residual volatility.

According to Engle (1982, 987), residual variance is fickle because residual variance is not only a function of the independent variable but also the function of residuals in the past. Engle develops models where the mean and variance of a time series data can be modeled simultaneously. The model is called Autoregressive Conditional Heteroscedasticity (ARCH).

If the variance of the residual depends on the quadratic residual fluctuations of some previous period (lag p), then the ARCH(p) model can be expressed in terms of the following equation:

$$Y_t = \beta_0 + \beta_1 X_t + e_t \qquad (4)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + ... + +\alpha_p e_{t-p}^2 \qquad (5)$$

while the GARCH model is as follows:

$$Y_t = \beta_0 + \beta_1 X_t + e_t \qquad (6)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \lambda_1 \sigma_{t-1}^2 \qquad (7)$$

The GARCH(p,q) model where q denotes the number of previous lags can be expressed as follows;

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + ... + \alpha_p e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + ... + \lambda_q \sigma_{t-q}^2 \qquad (8)$$

2.3 Variation Model of ARCH / GARCH

Some ARCH/ GARCH models are shown as follows:

a. ARCH-M. This model was first introduced by Robert F. Engle et al (1987). If the residual variance is included in the regression equation, the model is called ARCH in mean (ARCH-M), can be written as:

$$y_t = x_t\gamma + \sigma_t^2 + \varepsilon_t \qquad (9)$$

b. TARCH/EGARCH model assumes a symmetrical shock to volatility. But the reality of money market and capital market data is often found to be volatile contain errors that occur when the negative shock is greater than when the positive shock (asymmetric shock). The TARCH model was introduced by Zakoian (1990) and Glosten et al., (1993)

The TARCH model equation is:

$$Y_t = \beta_0 + \beta_1 X_t + e_t \qquad (10)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \emptyset e_{t-1} d_{t-1} + \sum_{i=1}^{q} \lambda_q \sigma_{t-i}^2 \qquad (11)$$

The EGARCH model was introduced by Nelson. Daniel B (1991). This model has the following equation:

$$Y_t = \beta_0 + \beta_1 X_t + e_t \qquad (12)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \left|\frac{e_{t-1}}{\sigma_{t-1}}\right| + \phi \left|\frac{e_{t-1}}{\sigma_{t-1}}\right| + \ldots + \alpha_p \left|\frac{e_{t-p}}{\sigma_{t-p}}\right| + \phi_p \frac{e_{t-q}}{\sigma_{t-q}} + \lambda_1 h\sigma_{t-1}^2 + \ldots + \lambda_j h\sigma_{t-q}^2 \qquad (13)$$

The steps in applying ARCH and GARCH models consist of Arch effect identification, model estimation, model evaluation and forecasting.

3 RESEARCH METHOD

This study uses daily from data of IDR exchange rate against USD in the period January 2, 2018 to 24 May 2018. In the early stages the model is estimated using some mean model of ARIMA, and the best model is chosen. Then we tested whether there is an ARCH effect on the selected model. If there was an ARCH effect then some estimation of ARCH / GARCH model is conducted. From the estimation model obtained the best model was selected and several periods ahead were forecasted.

4 RESULT AND DISCUSSION

4.1 Data Description

The movement of the IDR to USD exchange rate from 2 January 2018 to 24 May 2018 is shown in the following figure.

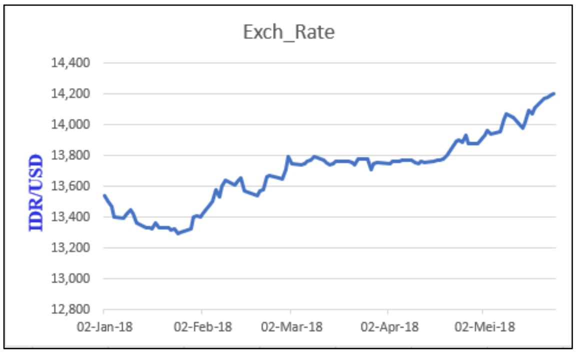

Figure 1: Movement of the IDR / USD exchange rate perod Jan 2-May 24, 2018.

The strongest IDR rate occurred on January 25, 2018 with the exchange rate of 13.290, But unfortunately the next day IDR weakened.

4.2 Testing of Data Stationarity

In the early stages, exchange rate data (KURST) is transformed into natural logarithmic form with the aim that the stationary data to the variance. To avoid spurious regression, the data analyzed must be stationary (Sumaryanto, 2009). The stationarity test was done using Augmented Dickey Fuller (ADF) method to Log KURST (LKURST) and the result showed in Table 1.

Table 1: Results of the ADF stationarity test at Level.

	Stationary test results at Level		
	t-Statistic	Prob	Description
	0.567448	0.9882	
1% level	-3.498439		Non-stationary
5% level	-2.891234		Non-stationary
10% level	-2.582678		Non-stationary

The stationary test results indicate that the data (LKURST) is not stationary at the level. This can be seen on the value of t-statistic test which was not significant, either at alpha 1%, 5%, or 10%. Therefore it was then tested on the first difference (DLKURST).

Table 2: ADF test results on First Difference.

	Stationary test results at 1st-difference		
	t-Statistic	Prob.*	Description
	-8.517092	0.0000	
1% level	-3.499910		Stationary
5% level	-2.891871		Stationary
10% level	-2.583017		Stationary

The result of the stationary test at the first difference indicates that the data is stationary. This can be seen in the significant t-statistical test values at alpha 1%, 5%, or 10%, where the probability is 0.000

4.3 Model Identification

The suitable ARIMA model used can be identified through ACF and PACF plots of DLKURST as shown in Figure 2.

Date: 07/19/18 Time: 13:05
Sample: 1/02/2018 5/24/2018
Included observations: 98

Lag	AC	PAC	Q-Stat	Prob
1	0.075	0.075	0.5731	0.449
2	-0.232	-0.239	6.0693	0.048
3	0.072	0.120	6.6101	0.085
4	0.066	-0.011	7.0644	0.133
5	0.074	0.122	7.6391	0.177
6	0.087	0.076	8.4443	0.207
7	0.027	0.053	8.5229	0.289
8	-0.049	-0.039	8.7844	0.361
9	-0.022	-0.019	8.8373	0.452
10	0.049	0.011	9.0999	0.523
11	0.066	0.044	9.5904	0.568
12	-0.054	-0.063	9.9250	0.623
13	-0.049	-0.014	10.200	0.678
14	-0.045	-0.079	10.433	0.730
15	0.016	0.025	10.462	0.790
16	0.120	0.093	12.195	0.730
17	0.014	0.016	12.218	0.787
18	-0.114	-0.058	13.813	0.741
19	-0.075	-0.059	14.513	0.753
20	0.024	-0.010	14.585	0.800
21	-0.038	-0.085	14.766	0.834
22	-0.018	-0.006	14.807	0.870
23	-0.077	-0.102	15.587	0.872
24	-0.055	0.003	15.983	0.889
25	-0.032	-0.049	16.122	0.911
26	-0.001	0.015	16.122	0.933
27	-0.038	-0.062	16.324	0.946
28	-0.185	-0.152	21.109	0.821
29	-0.002	0.049	21.109	0.855
30	0.068	0.014	21.771	0.862
31	0.040	0.087	22.000	0.883
32	-0.075	-0.085	22.837	0.883
33	-0.114	-0.074	24.790	0.847
34	-0.047	-0.045	25.122	0.865
35	-0.015	-0.040	25.156	0.890
36	0.046	0.029	25.486	0.904

Figure 2: First Difference Correlogram.

The ACF and PACF patterns show that the spike is significant in lag 2, whereas the others are not significant. Therefore, the tentative ARIMA models are:

$$DLKURST = C + AR(2) \quad (14)$$

$$DLKURST = C + MA(2) \quad (15)$$

$$DLKURST = C + AR(2) + MA(2) \quad (16)$$

A comparison of the estimation of the three models is shown in Table 3 below:

Table 3: Comparison of models estimation parameters.

Model	Parameter Estimation Significance (α=5%)		R-squared	AIC	SIC
	AR(2)	MA(2)			
AR(2)	0.0268*	x	0.055393	-9.009309*	-8.930177*
MA(2)	x	0.0439	0.050387	-9.004228	-8.925096
AR(2)+MA(2)	0.5417	0.9908	0.055394	-8.988903	-8.883394

From the comparison of the three models, the AR(2) model is most statistically significant. In addition the AR(2) model also has the smallest AIC and SIC values compared to the other two models. Based on these considerations, the AR(2) model is the best model.

4.4 Model Evaluation

The ACF and PACF residual corelogram of the selected model is shown in the following figure:

Date: 07/19/18 Time: 13:20
Sample: 1/02/2018 5/24/2018
Included observations: 98
Q-statistic probabilities adjusted for 1 ARMA term

Lag	AC	PAC	Q-Stat	Prob
1	0.119	0.119	1.4362	
2	0.003	-0.011	1.4373	0.231
3	0.117	0.120	2.8575	0.240
4	0.037	0.009	3.0021	0.391
5	0.106	0.106	4.1844	0.382
6	0.100	0.065	5.2558	0.385
7	0.041	0.023	5.4410	0.489
8	-0.023	-0.052	5.4973	0.600
9	-0.001	-0.014	5.4975	0.703
10	0.030	0.010	5.5951	0.780
11	0.056	0.044	5.9487	0.820
12	-0.061	-0.085	6.3761	0.847
13	-0.035	-0.019	6.5197	0.888
14	-0.034	-0.039	6.6535	0.919
15	0.008	0.033	6.6619	0.947
16	0.094	0.087	7.7166	0.935
17	0.000	-0.005	7.7166	0.957
18	-0.090	-0.079	8.7147	0.949
19	-0.089	-0.077	9.6906	0.942
20	-0.006	0.006	9.6954	0.960
21	-0.080	-0.091	10.505	0.958
22	-0.028	-0.008	10.605	0.970
23	-0.103	-0.092	12.003	0.957
24	-0.065	0.008	12.569	0.961
25	-0.064	-0.043	13.124	0.964
26	-0.060	-0.022	13.607	0.968
27	-0.051	-0.041	13.967	0.973
28	-0.190	-0.144	19.012	0.870
29	-0.001	0.079	19.013	0.898
30	0.011	0.026	19.029	0.921
31	0.015	0.051	19.061	0.939
32	-0.079	-0.102	19.980	0.936
33	-0.121	-0.096	22.180	0.903
34	-0.059	-0.016	22.709	0.911
35	-0.039	-0.019	22.950	0.925
36	0.009	0.011	22.962	0.941

Figure 3: Residual corelogram of DLKURST = C + AR (2).

From ACF and PACF plots of residual values there is no significant lag up to 36. This showed that the estimated residual value is random, so the selected model is already the best model.

4.5 ARCH/GARCH Model

The estimation results in AR(2) above is an ARIMA model estimation without including ARCH/GARCH element. So, it must be detected whether the model contains heteroscedasticity or not. If the model contains heteroscedasticity problems, the ARIMA model should be estimated by the ARCH/GARCH approach.

The test results using Heteroscedasticity Test White are as follows:

Table 4: Results of Heteroscedasticity Test White.

Heteroskedasticity Test: White			
F-statistic	1.49E+24	Prob. F(9,88)	0.0000
Obs*R-squared	98.00000	Prob. Chi-Square(9)	0.0000

The result shows the value of Obs * R-squared is 98.0000 while the probability value is 0.0000 (<0.05). This means that Heteroskedasticity Test White indicates that the data contains heteroscedasticity problems or there is an ARCH effect on the estimated model.

4.6 ARCH Model Estimation

Since the estimated model contains ARCH elements, the next step is to estimate and simulate several models of variance equations by incorporating the ARCH element and selecting the best model of the simulation performed.

4.7 ARCH(1)

The result of ARCH(1) estimation is obtained as shown in Table 5.

Table 5: Output of ARCH(1) model.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-2.755971	0.059602	-46.23968	0.0000
C	0.008015	0.000159	50.35400	0.0000
AR(2)	0.154284	6.54E-05	2359.571	0.0000
Variance Equation				
C	4.45E-06	1.20E-07	37.00636	0.0000
RESID(-1)^2	0.147819	0.000404	365.7453	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.541021	0.002507	-215.8099	0.0000
GARCH(-1)	0.592952	0.003746	158.2886	0.0000

In the variance equation it is shown that the coefficients of ARCH(1) (at output stated as RESID (-1)^2) are not statistically significant, which means there is no volatility in the exchange rate data in the study period. This means that the exchange rate residual is not affected by the residuals of the previous period.

4.8 GARCH(1,1)

The estimation result of GARCH(1,1) model is shown in the following table:

Table 6: Output of GARCH(1,1).

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000472	0.000210	2.252501	0.0243
AR(2)	-0.286827	0.099455	-2.884000	0.0039
Variance Equation				
C	2.03E-07	8.86E-08	2.296303	0.0217
RESID(-1)^2	-0.104423	0.010121	-10.31752	0.0000
GARCH(-1)	1.061335	0.000287	3694.371	0.0000

The variance equation shows that the ARCH(1) coefficient is statistically significant, which means there is volatility in the exchange rate data within the study period and the exchange rate residual is affected by the residual of the preceding period of ARCH(1). The GARCH coefficient is also statistically significant. This means residual volatility affects the exchange rate.

4.9 ARCH-M

The ARCH-M model was developed using GARCH elements with additional standard deviation representations. The regression results are shown in Table 7.

Table 7: Output of ARCH-M model.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	-2.683436	0.236003	-11.37036	0.0000
C	0.007839	0.000381	20.58527	0.0000
AR(2)	-0.249713	0.074348	-3.358704	0.0008
Variance Equation				
C	-7.47E-07	7.86E-08	-9.503588	0.0000
RESID(-1)^2	0.102965	0.011191	9.200471	0.0000
GARCH(-1)	0.988377	1.17E-05	84275.01	0.0000

The variance equation shows that the ARCH(1) coefficient is statistically significant, which means there is volatility in the exchange rate data. This also means that the exchange rate residual is influenced by the residuals of the previous period. The GARCH coefficient is also statistically significant. This means residual volatility affects the exchange rate.

4.10 TARCH

In this model, GARCH (1,1) is used with the addition of threshold. The regression results are shown in the following Table:

Table 8: TARCH Model Estimation.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000493	0.000206	2.400764	0.0164
AR(2)	-0.260230	0.105901	-2.457291	0.0140
Variance Equation				
C	7.12E-06	1.16E-06	6.120771	0.0000
RESID(-1)^2	-0.055597	0.114733	-0.484583	0.6280

The existence of symmetric effects in the model is shown in the variance equation, ie the RESID (-1) ^ 2 * (RESID (-1) <0) variable. This variable is statistically significant at alpha 5%, so it can be concluded that the exchange rate behavior of the model shows a symmetrical effect.

4.11 Selection of the Best Model

The selection of the best model is based on the significance of the estimation parameter, the largest Likelihood Log and the smallest AIC and SIC criteria. Summaries for these indicators based on the models of variance simulation are shown in table 9.

Table 9: Summary of indicators for best model selection.

Model	Parameter Estimation Significance (α=5%)		Log likelihood	AIC	SIC
	AR(2)	RESID(-1)^2			
ARCH(1)	√	x	444.6087	-8.992014	-8.886505
GARCH(1,1)	√	√	453.0292*	-9.148890*	-9.017004*
ARCH-M	√	√	430.4356	-8.661952	-8.503688
TARCH	√	√	293.9520	-5.856162	-5.671522

Based on the comparison of the indicators, the GARCH (1,1) model was chosen as the best model.

Furthermore, the best models are then evaluated with the Residual Normality Test, Residual Random Test and ARCH Effect Test.

4.12 Testing of Residual Normality

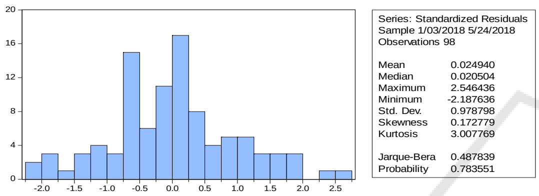

Figure 4: Residual Normality Test of GARCH (1,1).

The test results show that the Jarque-Bera Probability value is 0.783551 (> 0.05), means that the residual is normal and stationary to the variance.

4.13 Testing Residual Randomness

The residual randomness test is performed using ACF and PACF plots as shown in the following figure.

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob*</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.046</td><td>0.046</td><td>0.2134</td><td></td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.019</td><td>0.017</td><td>0.2520</td><td>0.616</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>3</td><td>0.144</td><td>0.143</td><td>2.3969</td><td>0.302</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.004</td><td>-0.009</td><td>2.3987</td><td>0.494</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>5</td><td>0.110</td><td>0.108</td><td>3.6657</td><td>0.453</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>6</td><td>0.095</td><td>0.067</td><td>4.6175</td><td>0.464</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.020</td><td>0.013</td><td>4.6597</td><td>0.588</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.000</td><td>-0.034</td><td>4.6598</td><td>0.701</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.008</td><td>-0.013</td><td>4.6664</td><td>0.793</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>0.052</td><td>0.039</td><td>4.9674</td><td>0.837</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>11</td><td>0.092</td><td>0.079</td><td>5.9190</td><td>0.822</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>12</td><td>-0.054</td><td>-0.073</td><td>6.2554</td><td>0.856</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.029</td><td>-0.038</td><td>6.3555</td><td>0.897</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>-0.029</td><td>-0.048</td><td>6.4569</td><td>0.928</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>-0.018</td><td>-0.004</td><td>6.4940</td><td>0.952</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>16</td><td>0.109</td><td>0.099</td><td>7.9054</td><td>0.928</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>17</td><td>0.084</td><td>0.091</td><td>8.7672</td><td>0.923</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>18</td><td>-0.108</td><td>-0.104</td><td>10.202</td><td>0.895</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.043</td><td>-0.052</td><td>10.429</td><td>0.917</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>0.030</td><td>0.019</td><td>10.540</td><td>0.938</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>21</td><td>-0.094</td><td>-0.095</td><td>11.669</td><td>0.927</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.010</td><td>-0.006</td><td>11.683</td><td>0.948</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>23</td><td>-0.110</td><td>-0.107</td><td>13.261</td><td>0.926</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>24</td><td>-0.061</td><td>0.002</td><td>13.753</td><td>0.934</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>25</td><td>-0.077</td><td>-0.070</td><td>14.548</td><td>0.933</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>26</td><td>-0.067</td><td>-0.036</td><td>15.150</td><td>0.938</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>27</td><td>-0.038</td><td>-0.052</td><td>15.353</td><td>0.951</td></tr>
<tr><td>**|. |</td><td>**|. |</td><td>28</td><td>-0.235</td><td>-0.205</td><td>23.067</td><td>0.681</td></tr>
<tr><td>.|. |</td><td>.|* |</td><td>29</td><td>-0.008</td><td>0.080</td><td>23.076</td><td>0.729</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>30</td><td>-0.053</td><td>-0.017</td><td>23.480</td><td>0.754</td></tr>
<tr><td>.|. |</td><td>.|* |</td><td>31</td><td>0.017</td><td>0.109</td><td>23.523</td><td>0.793</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>32</td><td>-0.071</td><td>-0.094</td><td>24.266</td><td>0.800</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>33</td><td>-0.125</td><td>-0.111</td><td>26.603</td><td>0.736</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>34</td><td>-0.049</td><td>-0.010</td><td>26.965</td><td>0.761</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>35</td><td>-0.031</td><td>0.018</td><td>27.117</td><td>0.793</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>36</td><td>-0.038</td><td>-0.021</td><td>27.350</td><td>0.818</td></tr>
</table>

Figure 5: The results of residual randomness testing using ACF and PACF.

ACF and PACF results from residual values were not significant until lag 36, so it can be concluded that the residual value of the estimated GARCH (1,1) model is random.

4.14 ARCH Effect Testing

The ARCH effect test on GARCH (1,1) was performed by ARCH-LM. Test results are obtained as follows:

Table 10: Output of Arch Effect Testing.

Heteroskedasticity Test: ARCH			
F-statistic	0.327748	Prob. F(1,95)	0.5683
Obs*R-squared	0.333498	Prob. Chi-Square(1)	0.5636

Based on the calculation, Obs * R-squared value is 0.5636 with a probability value of 0.5636 (> 0.05). The ARCH-LM test indicates that the estimated GARCH (1,1) model is free from the ARCH effect.

4.15 Forecasting

Based on all evaluations that have been done, the best model with optimal result is GARCH (1,1). This model can be used to forecast the exchange rate 5-days ahead, that is from 25 May 2018 until 31 May 2018. The forecasting results are obtained as follows:

Table 11: Forecasting result of IDR against USD.

Date	Forecast
25-May-2018	14,065
28-May-2018	14,072
29-May-2018	14,078
30-May-2018	14,084
31-May-2018	14,090

Based on Forecasting using GARCH (1,1), we obtained MAPE value of 0.201594. This means the average error is 0.20%. According to Zainun (2010, 16) a model has a very good performance if the MAPE value is below 10%, and has a good performance if the MAPE value is between 10% and 20%. With the acquisition of MAPE of 0.20% it can be said that the GARCH (1.1) model is able to provide excellent forecasting performance on IDR/USD exchange rate.

5 CONCLUSION

A study of the volatility of the IDR/USD exchange rate has been conducted. The results showed that there was heteroscedasticity in observation data. Therefore, based on volatility analysis during the observation period, the most suitable GARCH model is GARCH (1,1).

Using the above volatility model, we forecasted the IDR/USD exchange rate for 5 days from 25 May 2018 to 31 May 2018 and the results are are as follows 14065, 04072, 14078, 14084 and 14090.

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