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Modelling and Forecasting US Dollar/ Malaysian Ringgit Exchange Rate

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Abstract

Exchange rate forecasts are important because these forecasts help in hedging decisions, capital budgeting decisions and earnings assessments. While numerous methods are available for forecasting exchange rates, the current study employs time series models to forecast daily data of US Dollar exchange rate against Malaysian Ringgit (USD/MYR). Using hybrid ARIMA-GARCH and hybrid ARIMA-EGARCH models, the modelling and forecasting performances are compared using Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE) respectively. Such findings are important since exchange rate forecasts can help to evaluate the foreign denominated cash flows involved in international transactions.

Keywords: exchange rate forecasts, symmetric GARCH, asymmetric GARCH, ARIMA-GARCH, ARIMA-EGARCH

1 Introduction

Currency exchange rates are monitored by investors so as to evaluate the benefits and risks attached to the international business environment. For Malaysian investors, knowing the value of Malaysian currency in relation to different foreign currencies helps them to analyze investments priced in those foreign currencies. In other words, such forecasts can help them to minimize risks and maximize returns.

Generating quality forecasts is not an easy task. However, various forecasting models can be developed for that purpose. Examples of such models are econometric and time series models. To build econometric models, factors that are believed to significantly affect and influence the movement of a certain currency need to be gathered and then, a model that relates these factors to the exchange rate can be developed. Time series models such as Autoregressive Integrated Moving Average (ARIMA) on the other hand, use its own past values as explanatory variables [1].

The current study focuses on developing time series models to forecast exchange rate. In this study, ARIMA model is developed since it can provide an evolution equation with a simple interpretation [1]. However, since the exchange rate series present a high volatility, ARIMA model is hybridized with GARCH family models [2]. GARCH models can be categorized as symmetric and asymmetric models [3]. The current study aims to compare modelling and forecasting performances of hybrid ARIMA and symmetric GARCH, specifically ARIMA-GARCH with hybrid ARIMA and asymmetric GARCH, specifically ARIMA-EGARCH in modeling and forecasting United States Dollar to Malaysian Ringgit rate. In the next section, the methodology used in the current study will be described.

2 Methodology

2.1 ARMA/ARIMA Models

In time series analysis, a popular model to predict future points in the series is autoregressive moving average (ARMA) model. However, in cases where data show evidence of non-stationarity, a generalization of ARMA, called autoregressive integrated moving average (ARIMA) model should be applied [2]. To use such models, non-stationarity which can exist in mean and/or in variance must be removed. The general equation of ARMA model is:

$$y_t = \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

where the general form for AR (*p*) model and MA (*q*) model are respectively:

$$y_t = \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t$$

$$y_t = \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} - \varepsilon_t$$

with $B^p y_t = y_{t-p}$ the backshift operator for autoregressive part, and

$B^q \varepsilon_t = \varepsilon_{t-q}$ the backshift operator for moving average part

2.2 Handling Non-stationarity in Time Series

Non-stationary time series in mean can achieve stationarity by using differencing. Differencing can help to stabilize the mean of a time series by removing changes in the level of a time series, and so eliminating trend and seasonality. By doing this transformation, it will produce ARIMA model, where "I" is refered to as Integrated. This model is denoted by ARIMA (*p*,*d*,*q*) where *p* is the autoregressive order, *d* is the number of differencing and *q* is the moving average order. The general form of ARIMA (*p*,*d*,*q*) is:

$$\emptyset_p(B)(1-B)^d y_t = \delta + \theta_q(B)\varepsilon_t$$

Thus, the general equation of ARIMA (*p*,*d*,*q*) can be written as:

$$(1-\emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p)(1-B)^d y_t =$$

$$\delta + (1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)\varepsilon_t$$

For non-homogeneous time series data, a proper variance stabilizing transformation is necessary. Whenever normalizing data or equalizing variance is desired, the most common method for a variance stabilizing transformation is by using Box-Cox Transformation [4].

2.3 Testing for Stationarity

For stationarity testing of time series, the current study tests the presence of unit root by using Augmented Dickey-Fuller (ADF) test that was developed by David Dickey and Wayne Fuller in 1979. To carry out the ADF test, the testing procedure is applied to the model

$$\Delta y_t = \alpha_0 + \beta_t + \theta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-1} + \varepsilon_t$$

where y_t represents the tested time series; *t* symbolizes the time trend variable; Δ indicates the first differences; *k* is the lag order of the autoregressive process.

2.4 Volatility Testing

In the modelling of heteroscedasticity data, volatility is an important aspect. If volatility clustering is present in the data, ARCH or GARCH family models can be used. Volatility clustering can be defined as large changes that tend to be followed by large changes, of either signs, and small changes that tend to be followed by small changes, also of either signs.

2.5 GARCH Family Models

GARCH-type model can be divided into two categories which are symmetric and asymmetric. In the symmetric models, the conditional variance only depends on the magnitude, and not the sign of the underlying asset, while in the asymmetric models, the shocks of the same magnitude, positive or negative have different effect on future volatility [5].

2.5.1 Symmetric GARCH Models

There are two symmetric models which are GARCH and GARCH-in-Mean (GARCH-M) models. However, in the current study, we will only focus on GARCH model. Engle (1982) first developed Autoregressive Conditional Heteroscedasticity (ARCH) model. Later, the generalization of this model known as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was introduced by Bollerslev in 1986.

ARCH process can be defined as follows: Assume

$$\varepsilon_t = z_t \sigma_t$$

where z_t is the sequence of independent identically distributed random variables

with zero mean and unit variance which implies

$$\varepsilon_t \sim D(0, \sigma_t^2)$$

Therefore, ARCH (*q*) model can be defined as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where σ_t^2 = the estimated conditional variance

ε_{t-i}^2 = the past squared return

In order to acquire a positive value, the sufficient condition for conditional variance, σ_t^2 is $\alpha_0 > 0$ and $\alpha_i \geq 0$, $i > 0$. However, through empirical studies,

ARCH model requires a high ARCH order in order to capture significantly the dynamic behaviour of volatility [6]. Bollerslev later introduced GARCH model to overcome this weakness. GARCH (*p*,*q*) model consisted of both autoregressive and moving average components in the heteroskedastic variance. This model drastically reduced the number of estimated parameters. The general form of GARCH model can be written as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where

σ_t^2 = the estimated conditional variance

ε_{t-i}^2 = the past squared return

σ_{t-j}^2 = the past of conditional variance

In order to acquire the positive value, the sufficient conditions for the conditional variance are $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0$, i = 1,…, p and $j = 1, \ldots, q$.

When
p = 0, the GARCH (p,q) model reduces to the ARCH (q) model.

2.5.2 Asymmetric Model

Symmetric models perform well in capturing volatility clustering and leptokurtosis of financial returns. But as their distribution is symmetric, they fail in modelling leverage effect [6]. This limitation of symmetric model has led to the development of various asymmetric models including Exponential GARCH (EGARCH), Threshold GARCH (TGARCH) and Power ARCH (PGARCH). In this study, the asymmetric model of focus is EGARCH model.

Exponetial GARCH (EGARCH) Model

Exponential GARCH (EGARCH) model was developed to resolve the limitations of symmetric GARCH model [7]. EGARCH model can capture leverage effect which exhibits the negative association between lagged stock returns and contemporaneous volatility [8]. Leverage effects occur when volatility tends to react asymmetrically to stock price increase and decrease. The variance equation of EGARCH model is given as follows:

$$In(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{q} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j In(\sigma_{t-j}^2)$$

where

α_0 = mean of the volatility

α_i = size effect

β_j = the degree of volatility persistence

γ_i = sign effect

There are some advantages in using EGARCH model compared to GARCH model which are as follows:

a) EGARCH model allows positive and negative shocks to have a different impact on volatility.
b) EGARCH model allows large shocks to have a greater impact on volatility than the standard GARCH model.
c) EGARCH model also ensures that the variance is always positive even if the parameters are negative

The presence of leverage effects can be tested by the hypothesis that $\delta < 0$. If $\delta \neq 0$, the news impact is asymmetric. The effect on volatility is $(1+\delta_i)\,|\varepsilon_{t-i}|$ when there is good news $(\varepsilon_{t-i} > 0)$ while the effect on volatility is $(1-\delta_i)\,|\varepsilon_{t-i}|$ when there is bad news $(\varepsilon_{t-i} < 0)$. Thus, this allows the conditional variance to respond asymmetrically to the rises and falls of the process.

2.6 Diagnostic Checking

Adequacy of identified models can be investigated by using Jarque-Bera test, Breusch-Godfrey Serial Correlation LM Test, ARCH-LM test and correlogram squared residuals on the residuals of the model.

2.6.1 Jarque-Bera Test

Jarque-Bera test is used to check on the normality of the residuals of the model under investigated. The hypotheses to be tested are as follows:

H_o : Residuals follow normal distribution

H_1 : Residuals do not follow normal distribution

2.6.2 Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test is used to check for serial correlation. The hypotheses of the Breusch-Godfrey test are:

H_o : There is no serial correlation up to a certain lag

H_1 : There is serial correlation up to a certain lag

2.6.3 ARCH-LM Test

The residuals of the model are tested for ARCH effects using ARCH-LM test. This test will determine whether the standardized residuals exhibit ARCH behavior or not. The hypotheses of the heteroscedasticity test are:

H_o : No ARCH effects

H_1 : Exist ARCH effects

2.6.4 Correlogram Squared Residuals

In a hybrid model, the existence of serial correlation can be determined using correlogram squared residuals. The hypotheses to be tested are as follows:

H_o : There is no serial correlation

H_1 : There is serial correlation

2.7 Criteria for Choosing the Best Model

2.7.1 Akaike Information Criterion (AIC)

Akaike Information Criterion (AIC) is used for selecting the best model from a set of tentative models. The best model is chosen based on the minimum value of AIC. The formula for AIC is

$$\text{AIC} = 2k - 2 \ln (L)$$

where

k = number of free and independent parameters in the model
L = maximized value of the likelihood function for the estimated model

2.7.2 Accuracy Measures

Root Mean Square Error (RMSE) is used to measure the difference between the values forecasted by a model and the values actually observed. The formula is given as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}((y_t - \hat{y}_t)^2}{n}}$$

Mean absolute percentage error (MAPE) on the other hand, measures the forecast accuracy in percentage terms. It is calculated as the average of the unsigned percentage errors as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|(y_t-\hat{y}_t)|}{(y_t)} \times 100$$

where

y_t = original value in the time period *t*

$\hat{y}_t$ = prediction value in the time period t

n = number of observations

The model that gives the smallest values of AIC, RMSE and MAPE is the better model.

3 Data and Statistical Tests

In this study, daily data of US Dollar/Malaysian Ringgit (USD/MYR) exchange rate was used from the period of 1st November 2010 until 30th August 2016. The data were obtained from the Central Bank of Malaysia (Bank Negara Malaysia). The data are plotted in Figure 1.

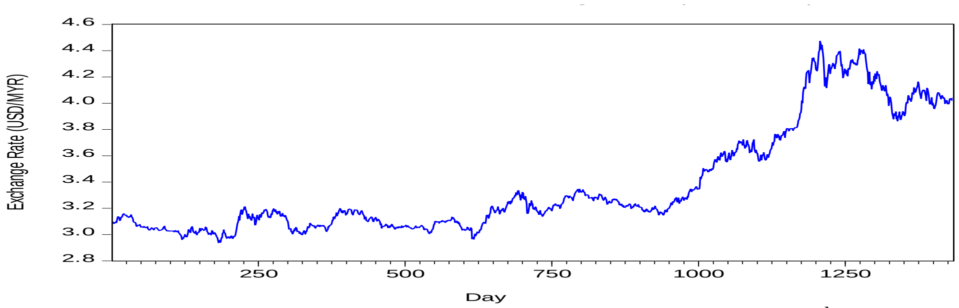

Figure 1: Daily exchange rate series from 1st November 2010 to 30th August 2016

In this study, non-stationary in variance was removed by variance stabilizing transformation which is natural logarithm. Returns were used since an upward trend existed in the data. The return on the t^{th} day is defined as $r_t = \ln(y_t) - \ln(y_{t-1})$. The returns are plotted in Figure 2.

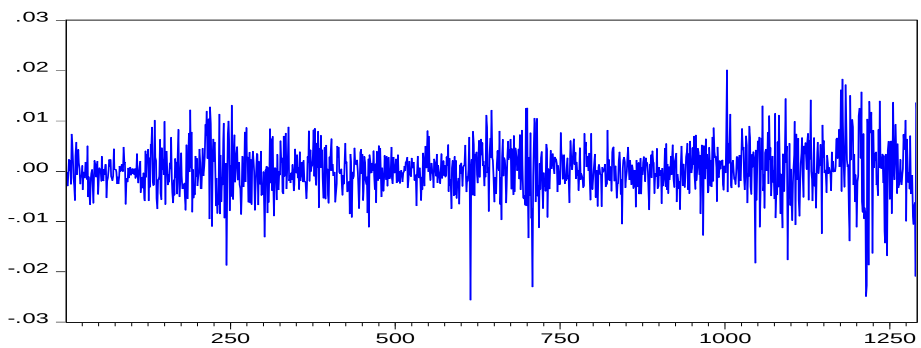

Figure 2: Plot of first difference of the transformed exchange rate series

Augmented Dickey-Fuller (ADF) test was applied to examine the stationarity properties of the series. The results are summarized in Table 1.

Table 1: Unit Root Test (ADF)

Null Hypothesis: RETURNS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-34.30373	0.0000
Test critical values:	1% level	-3.435211	
	5% level	-2.863574	
	10% level	-2.567903	

*MacKinnon (1996) one-sided p-values.

From Table 1, it can be concluded that the series is now stationary. Ninety percent of the observations, that is from 1st November 2010 until 3rd February 2016, were used for modelling to obtain an ARIMA model and for generating in-sample forecasts. Using ordinary least squares method to estimate the parameters, the most appropriate ARIMA model for this series is ARIMA(2, 1, 2) with an AIC value of -7.781418.

Descriptive statistics and the plot of residuals of ARIMA (2,1,2) are presented in Figure 3 and Figure 4 respectively.

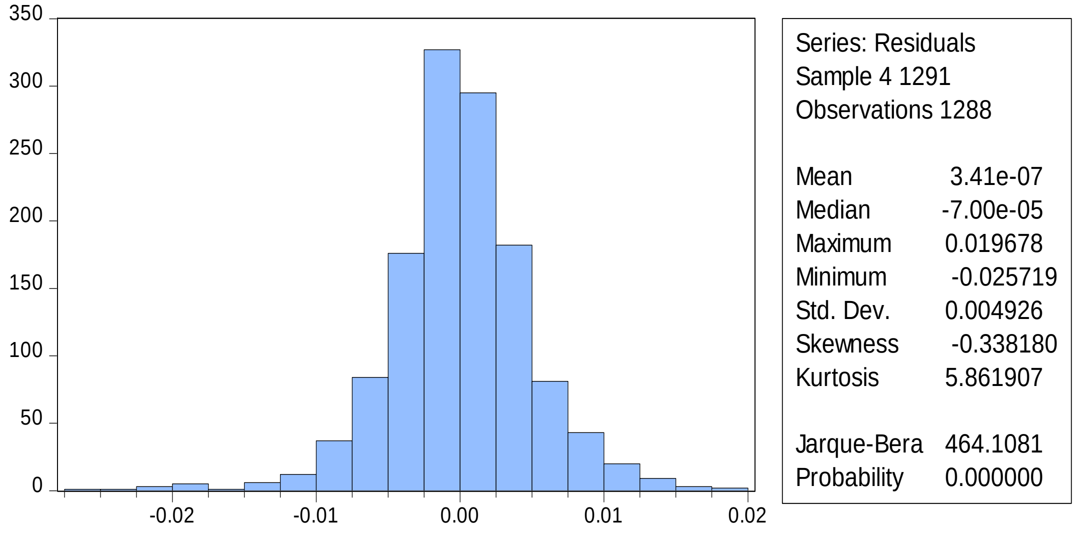

Figure 3: Descriptive statistics of the Residuals for ARIMA (2,1,2)

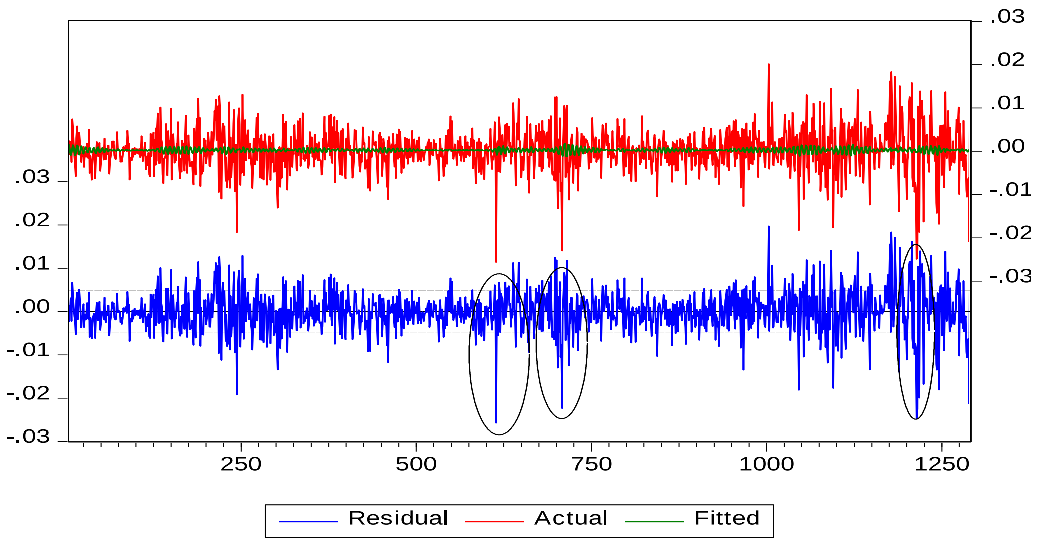

Figure 4: Volatility clusterings in the Residuals for ARIMA (2,1,2)

As presented in Figure 3, the mean of the exchange rate returns is -0.000000341 which is close to zero. The skewness value is -0.338180 which implies that the distribution is skewed to the left. There is also evidence of excess kurtosis since the value of kurtosis of 5.861907 exceeds the value for normal kurtosis of 3. It indicates that the distribution is leptokurtic or fat tailed because of its large kurtosis value. Thus, null hypothesis is rejected since the Jarque-Bera test is not satisfied with the assumption of normality of the standardized residuals for the model. This implies that the residuals do not follow normal distribution. As plotted in Figure 4, there also exist clear volatility clustering in the residuals. The model is then checked for serial correlation using Breusch-Godfrey Serial Correlation LM Test. The hypotheses of the Breusch-Godfrey test are:

H_o : There is no serial correlation up to lag 2

H_1 : There is serial correlation up to lag 2

The results are shown in Table 2.

Table 2: Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.473556	Prob. F(2,1281)	0.6229
Obs*R-squared	0.951584	Prob. Chi-Square(2)	0.6214

From Table 2, it indicates that the null hypothesis cannot be rejected because the *p*-value of 0.6229 is greater than the significance level of 5%. Failing to reject null hypothesis implies that there is no serial correlation up to lag 2. Hence, there is no need to search for another ARIMA model.

The residuals of ARIMA (2,1,2) are tested for ARCH effects using ARCH-LM test. The outputs are displayed in Table 3.

Table 3: Heteroscedasticity Test

Heteroskedasticity Test: ARCH

F-statistic	52.91419	Prob. F(1,1285)	0.0000
Obs*R-squared	50.90055	Prob. Chi-Square(1)	0.0000

From Table 3, the null hypothesis of ARCH effects do not exist is rejected because the *p*-value of 0.0000 is less than significance level of 5%. Therefore, it indicates that there are ARCH effects in the exchange rate series.

4 Hybrid ARIMA-GARCH Model

The presence of volatility clustering in the residuals and the results of the normality and heteroscedasticity tests show that ARIMA (2,1,2) model is not a good fit although the hypothesis of no serial correlation up to lag 2 in the model is not rejected. Hybrid ARIMA-GARCH model is proposed to handle heteroscedasticity. Since GARCH models can be categorized into symmetric and asymmetric models, the current study aims to compare which model, between ARIMA-GARCH and ARIMA-EGARCH is more superior for modelling and forecasting exchange rate series.

In developing hybrid ARIMA-GARCH, seven hybrid models were considered. Hybrid ARIMA (2,1,2)-GARCH (1,3) is the most appropriate model because it has the smallest value of AIC of -7.978035. The residuals of ARIMA(2,1,2)-GARCH(1,3) are tested for ARCH effects using ARCH-LM test. The results are presented in Table 4.

Table 4: Heteroscedasticity Test

Heteroskedasticity Test: ARCH

F-statistic	0.183893	Prob. F(1,1285)	0.6681
Obs*R-squared	0.184153	Prob. Chi-Square(1)	0.6678

From Table 4, the null hypothesis of ARCH effects do not exist cannot be rejected because the *p*-value of 0.6681 is greater than significance level of 5%. This indicates that the conditional heteroscedasticity is no longer present in the data series. When the hybrid model is tested for serial correlation using correlogram squared residuals, the null hypothesis of no serial correlation cannot be rejected using significance level of 5% which implies that there is no serial correlation in the series.

5 Hybrid ARIMA-EGARCH Model

Financial time series data are known to exhibit certain stylized patterns such as fat tails, volatility clusterings, leverage effect and long memory. Symmetric models such as GARCH model performs well in capturing volatility clusterings of financial time series data but as their distribution is symmetric, they fail in modelling leverage effect. Since EGARCH model can handle leverage effect in the data, a hybrid ARIMA-EGARCH model is considered as an appropriate model for the exchange rate series. Therefore, the potential of hybrid ARIMA-EGARCH model is investigated in this study.

Several hybrid ARIMA-EGARCH models were developed. Based on the smallest AIC value, ARIMA (2,1,2)-EGARCH (3,1) is the most appropriate model. It has the smallest AIC value of -7.987444. Using both hybrid ARIMA (2,1,2)-GARCH (1,3) and ARIMA (2,1,2)-EGARCH (3,1) models, forecasts are produced. Table 5 presents the results.

Table 5: Comparison of Forecasting Performances

Type of sample	**Evaluation Criteria**	**ARIMA (2,1,2) -GARCH (1,3)**	**ARIMA (2,1,2) -EGARCH (3,1)**
In-sample	RMSE	0.017593	0.017586
	MAPE	0.359562	0.359297
Out-sample	RMSE	0.028380	0.028354
	MAPE	0.552891	0.552875

The results in Table 5 show that the values of RMSE and MAPE for in-sample and out-sample forecasting of hybrid ARIMA (2,1,2)-EGARCH (3,1) are smaller than hybrid ARIMA (2,1,2)-GARCH (1,3). Therefore, it can be concluded that hybrid ARIMA (2,1,2)-EGARCH (3,1) is a better model for forecasting exchange rate data series.

6 Concluding Remarks

In this study, the performances of hybrid ARIMA-GARCH and hybrid ARIMA-EGARCH in modelling and forecasting US Dollar exchange rate against Malaysian Ringgit (USD/MYR) are compared. ARIMA-EGARCH fits the data better due to its AIC value being smaller than the AIC value for ARIMA-GARCH. In terms of forecasting, ARIMA-EGARCH also performs better since it can capture volatility clustering and leverage effect in the series.

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