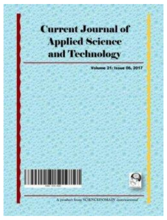

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Forecasting Currency in Circulation in Malaysia Using ARCH and GARCH Models

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Authors' contributions

This work was carried out in collaboration between all authors. Author NAAR performed the statistical analysis. Authors AK and MAAA designed the study and managed the analyses of the study and literature searches. Author SFS managed the language editing. All authors read and approved the final manuscript.

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ABSTRACT

The monthly economic time series commonly contains the volatility periods and it is suitable to apply the Heteroscedastic model to it where the conditional variance is not constant throughout the time trend. The aim of this study is to model and forecast the currency in circulation (CIC) in Malaysia over the time period, from January 1998 to January 2016. Two methods are considered, which are Autoregressive Conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Using the Root Mean Square Error (RMSE) as the forecasting performance measure, this study concludes that GARCH is a more appropriate model compared to ARCH.

Keywords: Forecasting; time series analysis; ARCH; GARCH; currency in circulation.

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1. INTRODUCTION

Currency in circulation (CIC) is the total value of the currency that has ever been issued minus the amount that has been removed from the economy by the central bank. It is a bit of the general cash supply, with a greater part of the general supply being secured in checking and investment accounts. Cash supply is generally found in two senses; cash supply in the customary sense incorporates notes and coins accessible which are repayable (on request) for the use of those stores with banks [1]. Standard money is the basic currency circulating within a monetary system. It has a legal recognition for prices and settlement [2]. According to [3], circulation is a process which is established by capital and formed from wealth.

Autoregressive Conditionally Heteroscedastic (ARCH) model was introduced by [4] as a non-linear model and known as volatility clustering where the variance is not uniform but heteroskedastic. ARCH models are commonly employed in modeling the financial time series, for example, the CIC that exhibits time-varying volatility and volatility clustering. Volatility clustering depicts the inclination for significant changes such as the beneficial thing expenses to take after little changes and little changes to take after the considerable changes [5]. Meanwhile, [6] expressed that General Autoregressive Conditional Heteroscedastic (GARCH) model which was introduced by [7] as a speculation of ARCH model. GARCH is a more adaptable model that records for nonstationarity issues when contrast with ARCH model. The advantage of the GARCH model compared to the ARCH model is that it can capture the serial correlation in residual using a smaller number of parameters.

Forecasting as expressed by [8] is the noteworthy information used to make sense of the pattern of future bearings. For instance, an association apply forecasting to pick up the data through the most proficient method in order to separate and convey their financial plans for a forthcoming time span. Additionally, forecasting accuracy is the way of ascertaining the precision estimation value with respect to actual value as expressed by [9]. Distinctive strategies for forecasting can prompt a diverse estimating exactness. In this way, it is critical to quantify the forecast accuracy by picking among a few anticipating models to measures the lead request and determined which model ought to be a top pick.

Thus, this study aims to propose and investigate the performance of the ARCH and GARCH models as an alternative tool in forecasting the currency in circulation in Malaysia.

2. MATERIALS AND METHODS

This study used two types of model which are most popular when dealing with the volatility situation in the data set; namely Autoregressive Conditional Heteroscedastic (ARCH) and General Autoregressive Conditional Heteroscedastic (GARCH) model.

2.1 ARCH Model

An ARCH model is a time series model for the variance. The ARCH model is used to describe the changes in the volatile variance. Although the ARCH model could possibly be used to describe a gradually increasing variance over time, however, it is frequently used in such situations where there are short periods of increased in the variation [10].

Suppose that we are modeling the variance of a series y_t. Then, the ARCH (q) model for variance y_t is conditionally on y_{t-i}, where the variance at time t is

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

where α_0 and α_i are non-negative constant, q is the lagged conditional volatility and ε_{t-i} is the white noise representing the residuals of time series.

Essentially, there are three stages required in fitting the ARCH model that is, model identification, parameter estimation and model diagnostic. For model identification, the least AIC value is chosen to figure out which ARCH (q) model is sufficient enough to portray the conditional variance of the data. At that point, the parameter is estimated using the likelihood estimator under the assumption that the errors are conditionally normally distributed and communicated as:

$$L = -\frac{n}{2}\log(2\pi) - \frac{n}{2}\log(\sigma^2) - \frac{1}{2\sigma^2}\sum_{j=1}^{n}(x_j - \mu)^2 \tag{2}$$

where n is the number of terms, μ is a mean and σ^2 is a variance. In diagnostic checking, the residuals must be checked for the presence of autocorrelation, where the residuals must carry out such as the white noise. This can be seen by showing the correlogram of the squared standardized residuals, to test the variance condition for the remaining ARCH. All Q-statistics ought not to be significant if the variance equation is accurately determined and there is no ARCH left in the squared residuals. The Q-stat is communicated as:

$$Q = n(n+2)\sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \tag{3}$$

where n is the sample size, $\hat{\rho}_k$ indicates the sample autocorrelation at lag k and h is the lag order that needs to be specified. Under the null hypothesis of no serial correlation up to lag k, both statistics are approximately distributed.

Then, the estimated model that meets the validity condition in diagnostic checking is used to forecast a k- step ahead. The forecast equation is,

$$\sigma_{t+i}^2 = \alpha_0 + \alpha_i \sigma_{ft}^2 + \varepsilon_{t-i} \tag{4}$$

where $i=0,1,2,...$, α_0 and α_i is the coefficient, σ_{ft}^2 is the value forecasted during period t and ε_{t-i} is the residuals of time series.

2.2 GARCH Model

The GARCH model has an extensive variety of the capital markets applications. The model depends on the presumption that the forecasts of variance changes in time as the lagged variance of capital resources [11]. A general GARCH (p,q) model is given by the accompanying condition:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{5}$$

where $i=0,1,2,...$ p and q is lagged conditional volatility, α_0, α_i *and* β_i are non-negative constant with $\alpha_i + \beta_i < 1$, ε_{t-i} is the residuals of time series.

The identification, estimation and diagnostics of the GARCH model are based on the same principles as the ARCH method [12]. The p and q orders of the standard GARCH (p,q) model were chosen by assessing the AIC value, where the most minimum value of AIC portrayed the conditional heteroscedasticity of the data.

The same equation as mentioned in the ARCH parameter estimation is used in this model in order to estimate the parameter of the chosen GARCH model. Then, the error terms of the identified model were analyzed in the diagnostic checking in order to check the fitted model carefully, refer equation (3). Once the model is valid, it then can be used for forecasting. The forecast equation *for k*-steps ahead is:

$$\sigma_{t+i}^2 = \alpha_0 + (\alpha_i + b_i)\sigma_{ft}^2 + \xi_{t+i} \tag{6}$$

where $i=0,1,2,...$ σ_{t+i}^2 is the actual value of volatility and σ_{ft}^2 is the value forecasted during period t.

2.3 Forecast Accuracy Performance

There are numerous approaches to estimate the accuracy of a model; however, generally there is not a single acknowledged measurement to compare the models. Thus, the forecast accuracy method employed in this study is the Root Mean Square Error (RMSE). It provides a measurement of the true distance from the forecast value, see [13]. The forecast sample is $j = T+1, T+2, ..., T+h$ and y_t denote the actual and forecast value in period t as $\hat{y}_t$, respectively. The forecast evaluation measures are defined as:

$$RMSE = \sqrt{\sum_{t=T+1}^{T+1} (y_t - \hat{y}_t)^2 / h} \tag{7}$$

3. RESULTS AND DISCUSSION

The data used in this study is a monthly basis economic indicator of currency in circulation (CIC), from January 1998 to January 2016. The CIC historic data were provided by the Malaysian Ministry of Finance. The statistical analysis was done by using the software E-views 9.

3.1 ARCH Model

The preliminary identification of the ARCH model is done by selecting the lowest AIC values in order to select the q order for the ARCH (q) model (as shown in Table 1). The value of q (in Table 1) is restricted to 1 until 5 because the values of AIC increases as the number of q increase. In Table 1, it shows that the ARCH (1) obtained the lowest AIC value.

Parameters are then estimated based on the result obtained from the ARCH (1) model as shown in Table 2. From the estimated parameter in Table 2, it can be seen that all the p-values of each coefficient are significantly different from zero for a confidence level of 95%.

To test the adequacy of the model, the Q-statistic in correlogram of standardized squared residuals is applied and is shown in Table 3.

Table 3 shows that both of the statistics tests (Q-stat and prob.) are statistically insignificant. It implies that there is no ARCH effect left in the models and the variance equation is effectively determined. Then, the ARCH (1) model is used to forecast the future values for 46 months steps ahead.

Table 1. Lag order for ARCH model

q	AIC
1	-3.5204
2	-3.4961
3	-3.4508
4	-3.2586
5	-3.2075

Table 2. ARCH(1) estimation Output

Variable	Coefficient	t-Stat	Probability
C	0.0071	25.94	0.00
AR(1)	0.7060	13.80	0.00
MA(1)	-0.9879	-79.74	0.00
C	0.0013	10.00	0.00
RESID(1)	0.1714	2.1746	0.02

Table 3. ARCH(1) correlogram residual

Lag	Q-stat	Prob.
1	0.1304	0.718
2	0.1458	0.930
3	0.2633	0.967
4	0.4350	0.980
5	0.9066	0.970

3.2 GARCH Model

Preliminary identification of the GARCH model is done by analyzing the lowest AIC measurement in order to select the *p* and *q* order for the GARCH (p,q) model (as shown in Table 4). The lag on the ARCH is unrelated to what the lag on the GARCH model should be. Therefore, the estimation of *p* and *q* in Table 4 are restricted to 1 until 4 because of the estimation of AIC increase as the quantity of *p* and *q* increases.

In Table 4, it shows that the GARCH (1,1) model suits the CIC as it obtained the lowest AIC values. The estimation results of each GARCH (1,1) model is shown in Table 5.

Table 5 indicates that all the coefficients are statistically significant at the confidence level of 90% which included in the GARCH forecasting model. Meanwhile, Table 6 shows the Q-statistic of the correlogram residuals for the GARCH model.

Table 4. Lag order for GARCH Model

q \ p	1	2	3	4
1	-3.5046	-3.4959	-3.5033	-3.3976
2	-3.4896	-3.5040	-3.4363	-3.3586
3	-3.4994	-3.4813	-3.4894	-3.3576
4	-3.4535	-3.4399	-3.4180	-3.3630

Table 5. GARCH estimation output

Variable	Coefficient	t-Stat	Probability
C	0.0009	6.21	0.00
RESID(1)	0.3115	3.25	0.00
GARCH(1)	0.1582	1.79	0.07

Table 6. GARCH correlogram residual

Lag	Q-stat	Prob.
1	0.0077	0.979
2	0.1304	0.937
3	0.4100	0.938
4	0.5984	0.963
5	1.0409	0.959

The results in Table 6 showed that the test statistics are statistically insignificant at the confident level of 1%. It means that there are no ARCH effects left in the model, as all the p-values are bigger than the alpha (0.01). Thus, GARCH (1,1) model is used to describe the CIC since there is no autocorrelation effect in the models.

The accuracy of the model is measured by using RMSE. An analysis was done where ARCH and GARCH models produced 2582.74 and 1879.58, respectively. The model with the lowest RMSE value is chosen as the best model for forecasting. It can be concluded that the GARCH model is slightly better than the ARCH model for forecasting the CIC because the error value is smaller.

4. CONCLUSION

The estimation of RMSE for the GARCH model is smaller than the ARCH model, for forecasting CIC, provided that GARCH (1,1) model is better than ARCH(1) model. In conclusion, this study uncovers that the GARCH model slightly outperformed the ARCH model in term of highest forecasting accuracy measurement, for predicting the CIC values. Therefore, the ARCH model has a statistically significant parameter.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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