

Forecasting Currency in Circulation in Malaysia Using ARCH and GARCH Models

ABSTRACT

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The monthly economic time series commonly contains volatility periods and it is suitable to apply heteroscedastic model where 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 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 compare to ARCH.

Keywords: forecasting, time series analysis, ARCH, GARCH, currency in circulation

1. INTRODUCTION

Currency in circulation (CIC) is the total value of 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, for example, cash supply in the customary sense incorporates notes and coins accessible for use in addition to those stores with banks which are repayable on request [1]. Standard money is the basic currency circulating within a monetary system. It has 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 introduced by [4] is a non-linear model and known as volatility clustering because the variance is not uniform, but heteroskedastic. ARCH models are commonly employed in modeling financial time series, for example, the CIC that exhibits time-varying volatility and volatility clustering. Volatility clustering depicts the inclination for significant changes in beneficial thing expenses to take after little changes and little changes to take after considerable changes [5]. Meanwhile, [6] expressed that General Autoregressive Conditional Heteroscedastic (GARCH) model introduced by [7] is 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 over 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 a data on the most proficient method to separate and convey their financial plans for a forthcoming time span. Additionally, forecasting accuracy is the way toward ascertaining the precision of estimates value with respect to actual value as expressed by [9]. Distinctive strategies for forecasting can prompt diverse estimating exactness yield. In this way, it is critical to quantify the forecast accuracy to pick among a few anticipating models that serve to measure the lead request which model ought to be 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. MATERIAL AND METHODS

are the most popular

This study used two types of model which is most popular when dealing with 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 model for the variance of a time series. ARCH models are used to describe a changing, possibly volatile variance. Although an ARCH model could possibly be used to describe a gradually increasing variance over time, most often it is used in situations in which there may be short periods of increased variation [10].

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

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

where α_0 and α_i are non negative constant, q is lagged conditional volatility and ε_{t-i} is white noise representing 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 for portraying the conditional variance of the data. At that point, the parameter is estimated using likelihood estimator under the assumption that the errors are conditionally normally distributed, communicated as:

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

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

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

Where n is the sample size, $\hat{\rho}_k$ indicates the sample auto-correlation 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.

meets

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

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

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

2.2 GARCH Model

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

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

Where $i=0,1,2,\dots$ 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 residuals of time series.

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

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

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

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

2.3 Forecast Accuracy Performance

There are numerous approaches to assess the estimating accuracy of a model and there is no generally acknowledged single measure to compare models. Thus, the forecast accuracy employed in this study is Root Mean Square Error (RMSE). It provides a measure of the distance of the true from the forecast value, see [13]. The forecast sample is $j = T+1, T+2, \dots, T+h$ and y_t denote the actual and forecast value in period t as $\hat{y}_t$, respectively. The forecast evaluation measures are defined as:

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

3. RESULTS AND DISCUSSION

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

3.1 ARCH Model

Preliminary identification of the ARCH model is done by selecting the lowest AIC values to select the q order for the ARCH (q) model as shown in Table 1. The values of q in Table 1 is restricted to 1 until 5 due to the value of AIC increments as the number of q increments as well. From the Table 1, it can be seen that ARCH (1) obtained the lowest AIC value.

Table 1. Lag order for ARCH model

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

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%.

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

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. 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

Table 3 showed that both test statistics (Q-stat and prob.) are statistically insignificant. It implies 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.

3.1 GARCH Model

Preliminary identification of the GARCH model is done by analyzing the lowest AIC measurement to select the p and q order for the GARCH (p,q) model as shown in Table 4. The lag on the ARCH is kind of unrelated to what the lag on the GARCH model should be. 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 increase as well.

Table 4. Lag order for GARCH Model

$q \backslash p$	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

From the Table 4, it shows that GARCH (1,1) suits the CIC model as it obtained the lowest AIC values. The GARCH (1,1) model for each model is estimated and the result is shown in Table 5.

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

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

Result in Table 6 showed that test statistics are statistically insignificant at level of 1%. It means 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 auto correlation effect in the models.

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

4. CONCLUSION

The estimation of RMSE for the GARCH model is smaller than that of the ARCH model for forecasting CIC, stated 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 though the ARCH model has a statistically significant parameter.

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