Forecasting Malaysian Gold Using GARCH Model

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Abstract

The purpose of the current study is to forecast the prices of Kijang Emas, the official Malaysian gold bullion. Two methods are considered, which are Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Using Akaike's information criterion (AIC) as the goodness of fit measure and mean absolute percentage error (MAPE) as the forecasting performance measure, the study concludes that GARCH is a more appropriate model. Analysis are carried out by using the E-views software.

Keywords: Box-Jenkins Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), volatility

1 Introduction

One goal of time series analysis is to forecast the future values of the time series data. In the case of Kijang Emas, the official Malaysian gold bullion coin, the forecasting of its prices is useful for investment purposes in Malaysia.

Nor Hamizah Miswan et al. [1] developed Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model to forecast Kijang Emas prices. Kijang emas prices however are volatile with huge price swings. Volatility is a condition where the conditional variance changes between extremely high and low values. In the literature, when dealing with such series, the emphasis has been given on forecasting the volatility or the time-varying conditional variance of the...
The ARCH class of models, pioneered by Engle in 1982 and generalized by Bollerslev in 1986 are popular class of econometric models for describing a series with time-varying conditional variance [2]. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models were developed to capture volatility clustering or the periods of fluctuations, and predict volatilities in the future [3].

Setting Box-Jenkins ARIMA as the benchmark model, the current study forecast *Kijang Emas* prices using GARCH model. By using the E-views software, the GARCH model is used to provide a volatility clustering measure of the gold series. The goodness of fit and the forecasting performances of these models are measured by Akaike's information criterion (AIC) and mean absolute percentage error (MAPE) respectively.

2 Methodology

The methods that are used in the current study are Box-Jenkins ARIMA and GARCH where the former is used as a benchmark model. The data used are Malaysian gold prices that are non-stationary in nature.

**Box-Jenkins ARIMA**

To apply the Box-Jenkins ARIMA procedures to such time series, the series need to be reduced to stationarity by taking a proper degree of differencing. This results in a model denoted by ARIMA \((p,d,q)\) where \(p\) is the autoregressive order, \(q\) is the moving average order and \(d\) is the order of differences.

The ARIMA\((p,d,q)\) can be written as

\[
\phi_p(B)(1-B)^d y_t = \delta + \theta_q(B)a_t,
\]

where \(\phi_p(B) = 1 - \phi_1B - ... - \phi_pB^p\) is the autoregressive operator of order \(p\); \(\theta_q(B) = 1 - \theta_1B - ... - \theta_qB^q\) is the moving average operator of order; \((1-B)^d\) is the \(d^{th}\) difference; \(B\) is backward shift operator; and \(a_t\) is the error term at time \(t\).

**GARCH**

The GARCH model on the other hand, has the ability to model time-varying conditional variances. The model uses past variances and past variance forecasts to forecast future variances. The GARCH \((p, q)\) model is
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\[ y_t = \mu + \varepsilon_t, \]

where \[ u_t = \varepsilon_t \sigma_t^2 = \varepsilon_t \sqrt{h_t}, \quad \varepsilon_t \sim N(0, 1) \]

\[ h_t = \delta + (\alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots) + (\beta_1 h_{t-1} + \beta_2 h_{t-2} + \cdots) \]

\[ = \delta + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \]

where \[ \delta = \alpha_0(1 - \beta_1), \quad h_t = \sigma_t^2, \quad \alpha_1 + \beta_1 < 1 \] for stationarity; \[ \alpha_i, \beta_i > 0 \]

\[ p \] is the order of the GARCH terms \[ \sigma_t^2 \], which is the last period forecast variance.
\[ q \] is the order of the ARCH terms \[ \varepsilon_t^2 \], which is the information about volatility from the previous period measured as the lag of squared residual from the mean equation.

Akaike Information Criterion (AIC)

AIC is a technique for selecting a model from a set of models to measure the goodness of fit of an estimated statistical model. It is based on information theory and is a criterion that seeks a model which has a good fit to the truth but few parameters. The model is chosen by minimizing the Kullback-Leibler distance between the model and the truth. AIC is computed as follows: \[ \text{AIC} = -2 \ln \ell + 2k \] where \[ \ell \] is the maximized value of the likelihood function for the estimated model; \[ k \] is the number of free and independent parameters in the model. From several models of a given data set, the best model is the one which has the lowest AIC value.

Forecast Accuracy Measure

There are several measures for evaluating forecasts. For the current study, the mean absolute percentage error (MAPE) will be calculated. MAPE measures the accuracy of forecast in terms of percentage. The formula is as follows:

\[ \text{MAPE} = \left( \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100\% \]

where \[ y_t \] is the actual value; \[ \hat{y}_t \] is the forecast value; \[ n \] is the number of periods.

In comparing the performances between two models, the smaller the value of MAPE, the better the model is.

3 Data Analysis and Results

Figure 1 plots the daily Kijang Emas prices recorded from 18 July 2001 until 25 September 2012 that are used in the study.
Figure 1: Daily *Kijang Emas* Prices from 18 July 2001 until 25 September 2012

Trend is apparent from the plot, indicating the necessity for transformation and differencing to make the series stationary. Box-Cox transformation was first applied, followed by taking the first difference of the data. Figure 2 illustrates the first difference of the transformed series.

Figure 2: First Difference of Transformed *Kijang Emas*

To identify the model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the transformed data are plotted in Figure 3.
As identified by Nor Hamizah Miswan et al. [1], the most appropriate ARIMA model for this series is ARIMA(1,1,1) with an AIC value of 10.08545 and forecasting error of 0.812356.

For the GARCH analysis, the testing of stationarity was followed by the testing of volatility. The trend that affected the non-stationarity of the series was first removed by taking the first difference of the series resulting in a series as plotted in Figure 4, with the volatility clusterings circled.

Figure 3: ACF and PACF for Transformed Kijang Emas

Figure 4: Volatility Clustering for the Differenced Kijang Emas
Model identification of the GARCH model is based on the ACF and PACF plots. GARCH (1, 1) was developed where the parameters of the model were estimated by using maximum likelihood estimation (MLE). Engle, the developer of ARCH and Bollerslev, the developer of GARCH have proven that MLE was the best estimation method for these models. The estimates for GARCH (1, 1) model are $\mu = 0.000656$, $\alpha_0 = 2.95E-06$, $\alpha_1 = 0.060305$ and $\beta_1 = 0.917482$. The values of mean equations are small and positive indicating significant parameters. These satisfy the positivity constraint of GARCH model. The value of $\alpha_0 + \alpha_1 + \beta_1$ is less than but close to unity and $\beta_1 > \alpha_0 + \alpha_1$. This indicates that volatility shocks are quite persistent. The coefficient of the lagged squared returns is positive and statistically significant indicating that strong GARCH effects are apparent for the gold market. Also, the coefficient of lagged conditional variance is significantly positive and less than one indicating that the impact of old news on volatility is significant. Higher value of $\beta_1$ indicates a long memory in the variance. The AIC value for this model is -6.241475 with a forecasting error of 0.809767.

Conclusion

The kijang emas prices data considered in the current study can be characterized by GARCH (1, 1) model. Based on a lower SIC value, GARCH (1, 1) is more appropriate than ARIMA (1, 1, 1) in forecasting its future values. The lower value of MAPE for GARCH (1, 1) when compared to that of ARIMA (1, 1, 1) showed that GARCH (1, 1) is the more appropriate model.

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References


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