Modelling Malaysian Gold Using Symmetric and Asymmetric GARCH Models

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Abstract

The purpose of the current study is to model Malaysian gold prices, known as *Kijang Emas*, using a popular class of generalized econometric models called Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and three of its variants. The variant models selected are GARCH in the mean (GARCH-M), Threshold GARCH (TGARCH) and Exponential GARCH (EGARCH). While the standard GARCH and GARCH-M are symmetric models, TGARCH and EGARCH are asymmetric. Using Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) as model selection criteria, the best fit model for modelling Malaysian gold is TGARCH.

Keywords: Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M, TGARCH, EGARCH

1 Introduction

Malaysia’s own gold bullion coins called *Kijang Emas* provide an alternative form of investment. Minted by the Royal Mint of Malaysia in three different sizes of 1 oz, ½ oz and ¼ oz, the prices are quoted daily, while pegged to the international gold price. In the current market, *Kijang Emas* prices remain volatile, a condition where the conditional variance changes between extremely high and low values [1].
The purpose of the current study is to model *Kijang Emas* prices using symmetric and asymmetric models from the Garch family. Bollersvlev generalized the popular class of econometric models called Autoregressive Conditional Heteroskedasticity (ARCH) pioneered by Engle and developed Generalized Autoregressive Conditional Heteroskedasticity (GARCH). GARCH can capture volatility clustering or the periods of fluctuations and is used to predict volatilities in the future [2]. Since the introduction of this model, many extensions or variants of the GARCH model have been introduced.

In the current study, the symmetric models considered are Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and GARCH in the mean (GARCH-M), while the asymmetric models are Threshold GARCH (TGARCH) and Exponential GARCH (EGARCH). The method of maximum likelihood is used in estimating the parameters [3]. Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are used to select the best model. All analyses are carried out using a software called E-views.

The paper is organized as follows: Section 2 presents the methodology of the current study, while Section 3 presents the data analysis. Section 4 concludes the study.

### 2 Methodology

**Considered Symmetric and Asymmetric GARCH Models**

The standard GARCH models is symmetric in response to the past volatility and variance. A GARCH model makes volatility or variance depends on the volatility or variance of the past and keeps the expected return constant. The GARCH model is $y_t = \mu + \varepsilon_t$, where $y_t$ is returns and the mean value, $\mu$ is expected to be positive and small. $u_t = \varepsilon_t$, $\sigma_t^2 = \sigma_t^2$, $h_t = \sigma_t^2$, $\varepsilon_t \sim N(0,1)$

The conditional variance equation is

\[
\begin{align*}
\sigma_t^2 &= \delta + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2_{t-i} \\
&= \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{p} \beta_i \sigma^2_{t-i}
\end{align*}
\]

where $\delta = \alpha_0 (1 - \beta_1)$, $h_t = \sigma_t^2$, $\alpha_1 + \beta_1 < 1$ for stationarity; $p$ is the order of the GARCH terms $\sigma^2$, which is the last period forecast variance; $q$ is the order of the ARCH terms $\varepsilon^2$, which is the information about volatility from the previous; and $\varepsilon$ is the error and assumed to be normally distributed with zero mean and conditional variance, $\sigma^2_t$. All parameters in the variance equation must be
positive.

The value of \( \alpha + \beta \) is expected to be less than but close to unity and \( \beta > \alpha \).

GARCH-M is an extension of the GARCH model proposed by Engle, Lilien and Robins [4] that allows the conditional mean to be a function of conditional variance. GARCH-M is a symmetric model where its expected return is a function instead of a constant. The conditional variance or standard deviation is introduced into the mean equation that allows for so-called time varying risk premiums. The model is:

\[
y_t = \mu + \delta h_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2)
\]

\[
h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}
\]

where \( \alpha_i, \beta_j > 0, i > 0 \) to ensure that the conditional variance is positive. When \( \alpha_1 + \beta_1 \) approaches to one, the persistence of volatility is greater. The parameter \( \delta \) is called the risk premium parameter. When it is greater than zero and significant, the return of the model is positively related to its volatility.

Black [5] stated that good news and bad news have different effects on volatility. Bad news is said to affect future volatility of returns much more when compared with good news. In such a case, symmetric GARCH models are unable to capture the asymmetry of volatility response. Leverage effect is a characteristic of asymmetric volatility. Leverage effect is asymmetry in volatility induced by big ‘positive’ and ‘negative’ asset returns. Asymmetric GARCH models are able to explain the leverage effects by enabling conditional variance to respond asymmetrically to rises and falls in volatility returns. A model that treats positive and negative news symmetrically as proposed by Glosten, Jagannathan and Runkle [6] is Threshold GARCH (TGARCH). With positive or good news, \( \varepsilon_{t-1} < 0 \) and with negative or bad news, \( \varepsilon_{t-1} > 0 \). TGARCH can capture the phenomenon of positive news hitting on the financial market with the market being in a calm period; and the negative news hitting on the financial market with the market entering into a fluctuating period and high volatility. The model is as follows:

\[
h_t = \delta + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1} d_{t-1} + \sum_{j=1}^{p} \beta_j h_{t-j}
\]

where \( h_t = \sigma_t^2 \), \( \gamma \) is the leverage term and \( \alpha_i, \beta_j \) and \( \gamma \) are constant parameters. \( d_t \) is an indicator imitation variable where
Another model that can be used to handle leverage effects is Exponential GARCH (EGARCH). The model explicitly allows for asymmetries in the relationship between return and volatility, which assumes the asymmetric between positive and negative shocks on conditional volatility. In this model, the conditional probability density function decays exponentially with the return as proposed by Nelson [7]. The parameters on EGARCH are not restricted to ensure that the conditional variance is always positive while the log form of conditional variance can be negative. The conditional variance of EGARCH in logarithmic form is:

\[ \log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \]

where \( \alpha_i, \beta_j \) and \( \gamma_k \) are constant parameters.

### Selecting the Best Fit Model

Akaike Information Criterion (AIC) is used to determine the best fit model. The formula is as follows:

\[ AIC = -2 \ln \ell + 2k \]

where \( \ell \) is the maximized value of the likelihood function for the estimated model and \( k \) is the number of free and independent parameters in the model. The model with the lowest AIC value is the best fit model.

Another criterion used in the current study is Schwarz Information Criterion (SIC). SIC is a criterion for selecting among class of parametric models with different number of parameters. The formula is as follows:

\[ SIC = -2 \ln L + k \ln n \]

where \( L \) is the maximized value of the likelihood function for the estimated model, \( n \) is the sample size and \( k \) is the number of free parameters to be estimated. The model with the lowest SIC value is the best fit model.

### 3 Data Analysis and Results

The data is made of log returns of daily prices of the 1 oz Kijang Emas recorded from 18 July 2001 until 25 September 2012. Daily returns are computed as logarithmic price relatives. The data consists of 2875 daily observations. The results for in-sample estimations for GARCH and variant GARCH models (GARCH-M (1, 1), TGARCH (1, 1) and EGARCH (1, 1)) are shown in Table 1.
The table also reports the goodness of fit for each model.

Table 1: Variance Specifications and In-Sample Results

<table>
<thead>
<tr>
<th>Model Type</th>
<th>GARCH (1, 1)</th>
<th>GARCH-M (1, 1)</th>
<th>TGARCH (1, 1)</th>
<th>EGARCH (1, 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>0.000656</td>
<td>0.001253</td>
<td>0.000611</td>
<td>0.000788</td>
</tr>
<tr>
<td>(0.000179)</td>
<td>(0.000344)</td>
<td>(0.000182)</td>
<td>(0.000183)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_0 )</td>
<td>2.95E-06</td>
<td>2.96E-06</td>
<td>2.06E-06</td>
<td>-2.27254</td>
</tr>
<tr>
<td>(3.61E-07)</td>
<td>(3.67E-07)</td>
<td>(2.67E-07)</td>
<td>(0.021940)</td>
<td></td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.060305</td>
<td>0.061151</td>
<td>0.083172</td>
<td>0.115890</td>
</tr>
<tr>
<td>(0.004930)</td>
<td>(0.004972)</td>
<td>(0.007004)</td>
<td>(0.007368)</td>
<td></td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.917482</td>
<td>0.916510</td>
<td>0.934060</td>
<td>0.984174</td>
</tr>
<tr>
<td>(0.007057)</td>
<td>(0.007104)</td>
<td>(0.008813)</td>
<td>(0.006251)</td>
<td></td>
</tr>
<tr>
<td>( \delta )</td>
<td>-5.978634</td>
<td>-9.34060</td>
<td>-0.061029</td>
<td>0.044680</td>
</tr>
<tr>
<td>(2.931640)</td>
<td>(0.005274)</td>
<td>(0.00813)</td>
<td>(0.006251)</td>
<td></td>
</tr>
<tr>
<td>AIC = -6.241475</td>
<td>AIC = -6.242051</td>
<td>AIC = -6.249520</td>
<td>AIC = -6.242289</td>
<td></td>
</tr>
<tr>
<td>SIC = -6.233175</td>
<td>SIC = -6.231676</td>
<td>SIC = -6.239145</td>
<td>SIC = -6.231915</td>
<td></td>
</tr>
</tbody>
</table>

The values in parentheses are standard errors.

From the estimates of GARCH (1, 1) model, 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 indicating that strong GARCH effects are apparent for the gold market. At the same time, the coefficient of lagged conditional variance is 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. From GARCH-M model, since \( \delta \neq 0 \) and \( \gamma = 0 \) indicating that there is asymmetry in the model. Since \( \alpha > \gamma \), this indicates the presence of the leverage effect. Since \( \gamma < 0 \), this implies that conditional volatility was increased more by the positive shocks than negative shocks at an equal size. From the EGARCH estimates, since \( \gamma > 0 \), this means that negative shocks provide less volatility than the positive shocks.

**Conclusion**

The current study analyzes a set of Malaysian gold prices with the purpose of modelling using symmetric and asymmetric Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. GARCH models were generalized by Bollersvlev from Autoregressive Conditional Heteroskedasticity (ARCH) models pioneered by Engle. These models have the capability of capturing volatility clustering or the periods of fluctuations, and predict future volatilities. From the SIC and AIC values, TGARCH exhibits the lowest value which indicates that it is the best fit model.
Acknowledgement

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References

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