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Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia

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Abstract

We conduct empirical analyses to model the volatility of stock market in Malaysia. The GARCH type models (symmetric and asymmetric GARCH) are used to model the volatility of stock market in Malaysia. Their performances are compared based on three statistical error measures tools, i.e. mean squared error, root means squared error and mean absolute percentage error for in sample and out sample analyses. Apart from that, we also determine the factors contribute to the stock market movements. The data is ranging from January 1990 to December 2010. The data is divided into three time frames, i.e. pre-crisis 1997, during crisis and post-crisis 1997. Our results reveal that symmetric and asymmetric GARCH models have different performances in different time frames. In general, for the normal period (pre and post-crisis), symmetric GARCH model perform better than the asymmetric GARCH but for fluctuation period (crisis period), asymmetric GARCH model is preferred. Our results also show that exchange rate and crude oil price have significant impacts on the Malaysia stock market volatility in the pre-crisis and post-crisis periods and but the impact is not significant in the crisis period.

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***Keywords*: stock market volatility; GARCH modeling; financial crisis**

1. Introduction

The study on the volatility of stock market is closely linked to the risk of assets. Indeed, volatility is the measurement of risk. Higher volatility leads to large variations of return, hence higher risk. As volatility of

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stock market provide useful information in measuring risk, many models/ theory are applied in forecasting stock market movement and evaluating the performance of the stock market. Many studies show that random walk model is superior in explaining the stock market movement. However, more recent studies reveal results that stock market deviates from the random walk behaviour. We further the investigation on stock market movement by looking at different aspects (i.e. different models and different time frames).

Among the models that have been applied to capture the stock market volatility include ARCH which was proposed by Engle (1982) and generalized ARCH proposed by Bollerslev (1986) and Taylor (1986). After the introduction of ARCH and GARCH models, many researchers have proposed the extensions and alternative specifications on the models such as GARCH-M, IGARCH, EGARCH (Nelson (1991)), Threshold GARCH (Glosten *et al.* (1993)), Asymmetric GARCH model AGARCH (Engle (1990)) and Fractionally Integrated FIGARCH (Baillie *et al.* (1996)). These alternative models seek to improve the GARCH model in capturing the characteristics of return series. However, previous studies show no consensus on the best model in capturing volatility. Some studies show preferable results using simple GARCH (p,q) models but some show extensions of GARCH models perform better. The performance of these models varies across markets and time period. The performance of these forecast models is affected by error measures.

In this study, we seek to identify the superior model in capturing the characteristics of Malaysia's stock market. The models to be compared are symmetric GARCH and asymmetric GARCH (EGARCH and TGARCH). In particular, we evaluate the performance of these models using the error measurement approaches such as MSE, RMSE and MAPE. Apart from this, we also seek to investigate if exchange rate can influence the stock market movement in Malaysia. The results are compared for three different time frames i.e. pre-crisis, crisis period and post-crisis periods. Our results show that the performance of GARCH-type models is dependent on the time/ periods, i.e. during pre-crisis, crisis and post-crisis and also the error measures. In general, the total rank show that GARCH/ TGARCH model perform the best in the pre-crisis period while GARCH model works well during the crisis and TGARCH model work well in the post-crisis period in capturing the stock market volatility in Malaysia.

The remaining paper is organized as follows: section two provides some concepts and literature reviews. Section three is about the data and methodology. Section four is about model evaluations while section five summarizes the findings. Section six concludes.

2. Literature review

The study on stock market volatility is broad. Empirical studies apply GARCH and ARCH models in capturing the stock market volatility. These studies cover different regions/ countries. The studies that focus on stock market in developed countries (United States, United Kingdom, Germany, and Japan) include Claessen & Mittnik (2008), Ou & Wang (2011), Choo & Lee (2011), and Mootamri (2011). These studies applied different frequency data. Among the studies that focused on the stock market in developing countries (Malaysia, Singapore, India, Saudi, China, Egypt and Vietnam) are Mishra (2010), Alshogeathri (2011), Abdalla (2012), Wong & Kok (2005) and Liu *et al*. (2009), Hien (2008).

In evaluating the performance of models, previous studies apply different evaluation measures. The most widely applied measures include Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percent Error (MAPE). In practice, when comparing the different models, it is rarely the case that one model dominate the other with respect to all evaluation measures. The common way to solve the problem is to carry out the average figures of some statistical measures and then compare the forecast models based on the parameter obtained.

Some studies report that GARCH/ GARCH type models is the best model for forecasting stock market volatility. Examples of these studies are Liu *et al.* (2009), Alberga *et al.* (2008), and Hien (2008). For instance, Liu *et al.* (2009) investigated the forecast of stock market volatility in China using GARCH model. They found that volatility forecasts by the GARCH-SGED model are more accurate than those generated using the GARCH-N model, indicating the significance of both skewness and tail-thickness in the conditional distribution of returns, especially for the emerging financial markets. GARCH-SGED models yield lower MSEs and MAEs than the GARCH-N models for the Shanghai and Shenzhen composite indices across all forecast horizons. Incorporating SGED returns innovation into the GARCH (1,1) model generates superior volatility forecasts for stock markets in China.

Alberga *et al.* (2008) investigated the predictable stock market volatility in Israel using GARCH model. The result show that asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. The results also show that asymmetric GARCH models improve the forecasting performance. Among the forecasts tested, the EGARCH skewed Student-t model outperformed GARGH, GJR and APARCH models.

Besides, there are studies reveal that ARCH and random walk is the superior model to capture the stock market's volatility (Wong & Kok (2005)). For instance, Wong & Kok (2005) compared the forecasting models for ASEAN stock markets (Malaysia, Singapore, Thailand, Indonesia and Philippines). The results indicated that the ARCH-M model has the best forecast performance for three markets (Malaysia, Singapore, Thailand), while the remaining two markets are best modeled by the random walk model (Indonesia and Philippines). In the post-crisis period, the TGARCH and EGARCH models are found to be the most suitable models. The asymmetry of the market returns is not significant in all the markets modeled by the TGARCH and EGARCH models.

2.1. Stock market volatility

The volatility of a stock can be used as indicator of the uncertainty of stock returns. In financial market, volatility is measured in terms of standard deviation σ or variance σ^2 and it is computed as follows:

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(R_i - \mu) \tag{1}$$

where μ and *R* are the mean return and return respectively. Larger σ^2 implies higher volatility and higher risk. According to Hull (2000), the percentage changes in the stock price in short time period are assumed to be normally distributed, and this implies that

$$\ln(\frac{S_t}{S_0}) \sim \Phi[(\mu - \frac{\sigma^2}{2})T, \sigma\sqrt{T}] \tag{2}$$

where S_t represent daily stock prices. From the above equation, the volatility of a stock price can be formally defined as the standard deviation of the natural logarithm of the change in stock price in one year.

Return is defined to be the total gain or loss from an investment over a given period of time. It is measured in terms of cash distribution plus changes in value in a given period. The rate of return (*R*) earned on any asset over a period is calculated as

$$R_t = \frac{P_t - P_{t-1} + C_t}{P_t} \tag{3}$$

where P_t and C_t are the stock price at time *t* and cash received from the investment during period *t*-1 to *t* respectively (Stephen *et al*. (2006)). On the other hand, Wong & Kok (2005) computed the daily closing prices are as

$$R_t = \ln(\frac{P_t}{P_{t-1}}) \tag{4}$$

where R_t is the daily returns and P_t is the daily prices.

3. Data and methodology

The study is focused on the stock market of Malaysia, for the period of 2nd January 1990 to 30th December 2010. Besides, we also investigate if crude oil price and exchange rate (RM/1US$) are determinants to the volatility of stock market Malaysia. All data are obtained from Yahoo Finance (http://finance.yahoo.com) and crosschecked with the data downloaded from OANDA and FOREXPROS. We divide the data into three main periods to consider the impact of Asia financial crisis 1997: pre-crisis (2nd January 1990 to 30th June 1997), crisis period (1st July 1997 to 30th September 1998 and post-crisis period (1st October 1998 to 30th December 2010).

We apply the three GARCH type models to capture the stock market volatility, i.e. symmetric GARCH and asymmetric GARCH (EGARCH and TGARCH). We evaluate the forecasting performance of these models using the errors measures of mean squared error (MSE), root means squared error (RMSE) and mean absolute percentage error (MAPE) for both in sample and out sample analyses. Following Hien (2008), we assume that the conditional mean equation of stock return is constructed as the constant term plus residuals term.

$$r_t = \mu + \varepsilon_t$$

3.1 GARCH (1,1)

Under GARCH specification, the time-varying conditional volatility is a function of its own past lag one term plus the past innovations. The conditional variance equation in GARCH (1, 1) process can be modelled as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{5}$$

ε_t is a discrete-time stochastic defined to be $\varepsilon_t = z_t \sigma_t$ given $z_t \sim$ *iid* (0,1) and σ_t is the conditional standard deviation of return at time *t*. All parameters α_0, α_1 and β_1 are non negative. The stationary condition of $\alpha + \beta < 1$ should hold to ensure weakly stationarity of GARCH process. α_1 indicates the short-run persistency of shocks while β implies the long-run persistency. One of the weaknesses in GARCH model is the model is symmetric in modelling volatility. GARCH model is modified to include the asymmetric feature of stock market volatility. Among the asymmetric GARCH models are the threshold Autoregressive conditional heteroskedasticity (TGARCH) and the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) models (Oskooe & Shamsavari (2011)).

In this study, we include two determinant factors in the basic GARCH model (exchange rate (RM/1USD) and world crude oil price). The modified GARCH (1, 1) model is written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + a_1 (exchange\_rate) + a_2 (crude\_oil\_price) \quad (6)$$

3.2 TGARCH (1,1)

The threshold-GARCH process allows analysis on the effects of good and bad news (negative and positive return shocks) on the volatility. TGARCH (1, 1) model is the standard GARCH (1,1) model add up with the asymmetric threshold effect:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad (7)$$

γ is the asymmetric or leverage effect and I_{t-1} is the dummy variable used to differentiate the good and bad news, i.e. $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ indicating bad news, and $I_{t-1} = 0$ if $\varepsilon_{t-1} \geq 0$ indicating good news. The TGARCH model specification assumes that unexpected changes in the market returns or ε_t will have different effect on the volatility of stock return, σ_t^2. Good news will lead to higher return, hence it is associated with higher variance through γ. According to Ahmed & Suliman (2011), a non-zero value of γ indicate the asymmetric nature of the returns. On the other hand, when γ is zero, we get back to the standard symmetric GARCH model. When γ is positive, there is a leverage effect.

Our GARCH (1, 1) model has two additional exogenous variables which are exchange rate and world crude oil price. The modified TGARCH (1, 1) model can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + a_1 (exchange\_rate) + a_2 (crude\_oil\_price) \quad (8)$$

3.3 EGARCH (1,1)

The EGARCH model with the exponential nature of the conditional variance in the EGARCH model captures the effect of external unexpected shocks on the predicted volatility. The EGARCH (1, 1) model is formulated as:

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2 \quad (10)$$

As in the TGARCH model, the presence of γ indicates an asymmetric effect of shocks on volatility and the positive value of this parameter implies the presence of leverage effect (Ahmed & Suliman (2011)).

In order to investigate the impact of exchange rate and crude oil price on volatility of return, we write our EGARCH (1, 1) model as:

$$\ln \sigma_t^2 = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2 + a_1 (exchange\_rate) + a_2 (crude\_oil\_price) \quad (11)$$

4. Model evaluations

We apply three error measures to evaluate the forecasting performance of our models. These error measures are mean squared error (MSE), root means squared error (RMSE) and mean absolute percentage error (MAPE).

4.1 Means Squared Errors (MSE)

MSE is commonly used for comparing the model's forecasting performance. Characteristically, it has the tendency to penalize large forecast errors more severely than other common accuracy measures and therefore is considered as the most appropriate measure to determine which methods avoid large errors. The MSE is given as,

$$MSE = \sum_{t}^{n} \frac{e_t^2}{n} \tag{12}$$

for which $e_t = y_t - \hat{y}_t$, where y_t is the actual observed value in time t and $\hat{y}_t$ is the fitted value in time *t*.

4.2 Root Means Squared Error (RMSE)

RMSE is the most favored measure among the practitioners and has even stronger preference among the academics even though it is not unit free. It is given as,

$$RMSE = \sqrt{\sum_{t}^{n} \frac{e_t^2}{n}} \tag{13}$$

where $e_t = y_t - \hat{y}_t$, with y_t as actual observation value at the point and $\hat{y}_t$ is the fitted value in time *t*. Just as the MSE, the RMSE also gives equal weights to all the errors, irrespective of any time period.

4.3 Mean Absolute Percentage Error (MAPE)

MAPE is written as,

$$MAPE = \sum_{t=1}^{n} \frac{\left|(\frac{e_t}{y_t})\right| * 100}{n} \tag{14}$$

where *n* denotes effective data points and $\left|(\frac{e_t}{y_t})\right| * 100$ is defined as the absolute percentage error calculated on the fitted values for a particular forecasting method.

5. Results

The estimation of GARCH-type models show that both the ARCH term α_1 (short-run persistency of shocks) and GARCH term β_1 (long-run persistency of shocks) for GARCH (1, 1) are highly significant in all periods, indicating the impacts of shocks on stock market volatility (the results is not provide here due to space constraint). Comparing the results of asymmetric and asymmetric models, we observe that the coefficient of γ for TGARCH and EGARCH are insignificant at pre-crisis period. The result implies no significant asymmetric effect of shocks on stock market volatility. Therefore, linear model is sufficient to model the volatility of stock market in the pre-crisis period. On the other hand, there are significant asymmetric effects of shocks during the crisis and post-crisis periods in Malaysia. Therefore, asymmetric models are the better models used to represent the stock market volatility during the economic fluctuation periods (crisis period) and economic recovery period (post crisis). The effect of asymmetric shocks is larger during the crisis period, indicating larger leverage effect during crisis period relative to post-crisis period.

Next, comparing the effects of short run and long run persistency of shocks (α_1 and β_1), our results reveal that long-run shocks are more persistent compared to short-run shocks, indicating larger impacts of long-run shocks on stock market volatility. The result holds for all three periods and three models.

Investigating the impacts of exchange rate and crude oil price on stock market volatility, we observe that both variables only have small impacts or non-significance impacts on stock market volatility in Malaysia. The only exception is the result reported by EGARCH for the pre and post-crisis periods. Our results imply that both variables fail to explain the stock market volatility during the crisis period when the stock index is highly fluctuated. During the stable periods (pre and post-crisis), exchange rate and crude oil price have some powers on predicting stock market volatility.

The three GARCH-type models are evaluated using three measurements, i.e. mean square error (MSE), root mean squared error (RMSE) and mean absolute percent error (MAPE).

5.1. In sample analysis

For in sample analysis, the models are estimated using the full sample with one month shorter, i.e. up to end of November 2010. The performance of the models is ranked from the lowest error. The total rank is the summation values of rank from the three measurements.

Table 1. Overall Model Evaluation (In Sample)

Model	Errors Measures						
	MSE	Ranking	RMSE	Ranking	MAPE(%)	Ranking	Total Rank
Pre Crisis Period							
GARCH	0.000157775	1	0.012560851	1	109.4740	2	4
TGARCH	0.000157776	2	0.012560891	3	107.3696	1	6
EGARCH	0.000157778	3	0.012560871	2	106.5497	3	8
Crisis Period							
GARCH	0.001184216	1	0.034412439	1	147.6658	1	3
TGARCH	0.001208099	3	0.034757718	3	222.9189	3	9
EGARCH	0.001189480	2	0.034488838	2	178.0566	2	6
Post Crisis Period							
GARCH	0.000172664	2	0.013140167	2	107.7394	2	6
TGARCH	0.000172662	1	0.013140091	1	107.8859	3	5
EGARCH	0.000172887	3	0.013148650	3	101.2583	1	7

Comparing the performance of symmetric and asymmetric GARCH models, our results of total ranks show that symmetric GARCH model is the best model to capture the stock market volatility in Malaysia during the pre- and crisis periods. On the other hand, TGARCH model is superior in the post-crisis period. However, one has to be caution because the ranking for these three measurements are different under three time frames. The values of errors do not vary much for MSE and RMSE but when the error is measured in percentage, the values are much more different.

5.2. Out of sample analysis

In this part, the out-of-sample forecast is performed for one month ahead from the full sample generating 20 observations.

Table 2 describes the overall evaluation for three models by using three error measures. The MSE statistic indicates that the TGARCH model provides the most accurate forecast for the pre-crisis period. The next ranked models are EGARCH and GARCH in that order. Besides, the RMSE implies that the TGARCH model provides the most accurate forecast for the pre-crisis period. The next ranked models are EGARCH and TGARCH in that order. The MAPE statistic indicates that EGARCH provides the most accurate forecast for the pre-crisis period. The next ranked models are TGARCH and the worst performing model is GARCH. In order to choose the best performing models, we used the total rank which generated from the ranking of three statistics. From the ranking of the three statistics, the total rank of TGARCH is the lowest in the pre- and post-crisis periods. Therefore, we indicate that TGARCH model outperform the other models in the pre- and post-crisis periods. On the other hand, GARCH model performs the best in the crisis-period.

Table 2. Overall Model Evaluation (Out of Sample)

Model	Errors Measures						
	MSE	Ranking	RMSE	Ranking	MAPE(%)	Ranking	Total Rank
Pre Crisis Period							
GARCH	0.000157564	3	0.012552449	3	109.4903	3	9
TGARCH	0.000157560	1	0.012552303	1	107.3061	2	4
EGARCH	0.000157561	2	0.012552322	2	106.4940	1	5
Crisis Period							
GARCH	0.0011400015	1	0.033763909	1	144.0898	1	3
TGARCH	0.0011681337	3	.0341779715	3	217.4841	3	9
EGARCH	0.0011470467	2	0.033868078	2	173.6390	2	6
Post Crisis Period							
GARCH	0.0001716995	2	0.013103418	2	107.8626	2	6
TGARCH	0.0001716994	1	0.013103413	1	107.8752	3	5
EGARCH	0.0001719257	3	0.013112042	3	101.2477	1	7

From the result of both in sample forecast and out of sample forecast, we found that the performance of GARCH-type models is affected by the period of time, i.e. pre-crisis, crisis and post-crisis periods. Using different error measures also give different evaluations on the ranking of performance. MSE and RMSE show very small differences in the performance of these three models. However, when the measurement is made in percentage using MAPE, the differences on the performance of these models are larger and more apparent. In general, the total rank show that GARCH/ TGARCH model perform the best in the pre-crisis period while GARCH model works well during the crisis and TGARCH model work well in the post-crisis period in capturing the stock market volatility in Malaysia. The evaluation results are consistent to the estimation results that show no significant asymmetric effect during the pre-crisis period, i.e. asymmetric GARCH model is sufficient to capture volatility in the pre-crisis period; there are significant asymmetric effect in the crisis and post-crisis period, implying possibility that asymmetric GARCH models work better than symmetric GARCH model.

6. Conclusion

We conduct comparative analyses in evaluating the forecasting performance of symmetric and asymmetric GARCH-type models in capturing stock market volatility in Malaysia. These models include GARCH, TGARCH and EGARCH models. These models are evaluated using three error measures which are MSE, RMSE and MAPE. We divide the data into three sub-periods, i.e. pre-crisis, crisis and post-crisis of 1Asia financial periods. Our results show that the performances of these models vary across periods and error measurement methods. . In general, the total rank show that GARCH/ TGARCH model perform the best in the pre-crisis period while GARCH model works well during the crisis and TGARCH model work well in the post-crisis period in capturing the stock market volatility in Malaysia. The evaluation results are coincide with the results of estimation which imply symmetric GARCH works well in the pre-crisis period and asymmetric GARCH model(s) can be the better model in capturing volatility of stock market Malaysia in the crisis and post-crisis periods.

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