MODELLING VOLATILITY OF MALAYSIAN STOCK MARKET USING GARCH MODELS

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Abstract— **Stock market volatility was changed over time. The factor such as financial crisis can easily influence the movement of the volatility. This unpredictable change means uncertain risks and not well preferred by the most of the stock market players. It is because higher risk can lead to a higher returns or losses. For these reason, this study has modelled volatility to investigate the behavior of stock return volatility of FTSE Bursa Malaysia KLCI with regard to the global financial crisis occurred in 2008 until 2009. The sample consists of 2473 observations of daily index return of FBM KLCI from January 2002 to December 2011. In order to model volatility of Malaysian stock market, three of the family of GARCH models was used. The results of GARCH (1, 1), indicate the presence of volatility clustering and persistence effects on the stock market volatility. Besides, the asymmetric models which are TGARCH and EGARCH detect the presence of leverage effects in the data series. Finally, the last evaluation shows that EGARCH model has outperformed the other class of GARCH model and has the best ability in forecasting the volatility. In conclusion, the results from this study show the ability of GARCH model in modelling volatility and indicate the existence of volatility clustering, leverage effects, and fat tailed in the Malaysian stock returns data.**

Keywords-stock market; volatility; financial crisis; GARCH models;

I. INTRODUCTION

A stock market or equity market is a public entity for the trading of company stocks (shares) and derivatives at an agreed price. These include the securities listed on a stock exchange as well as those traded privately. Malaysian stock market has a background of 50 years history and one of the biggest stock markets in Southeast Asia. In 1988, there are only 295 companies listed in Bursa Malaysia Berhad, but the figure increased to 977 companies in 2008. It consists of 634 from the main board, 221 from the second board and 122 from the MESDAQ market. However, the statistics in 2011 shows that the number of the listed companies has dropped to 941, where the main market consists of 822 companies and the other 119 is from the ACE market. One of the reason that have changes the figure is the occurrence of the US subprime crisis that started to affect the Malaysia‘s economy in the second half of 2008 and first quarter of 2009. Financial crisis is a situation in which some financial institutions or assets suddenly lose a large part of their value. Most of the financial crises were associated with banking panics and the recessions coincided with these panics. There are numerous studies that have been conducted to investigate the effects of the financial crisis on the Malaysian economy. The studies included various sectors and focus on the certain elements such as the contagion of the stock market, the trend, and the co-movement [[3], [17]]. During the global financial crisis in 2008, the Malaysian average GDP growth was 5.9% in the first nine months of 2008. The real GDP fell by 6.2% year-on-year (yoy) in the first quarter of 2009 [12]. The global financial crisis is transmitted to Malaysia mainly through the financial and trade channels. In addition, the Kuala Lumpur Composite Index (KLCI) has dropped around 558.93 points in 2008 and was the biggest decline since the Asian Financial Crisis in 1997.

According to International Monetary Fund (2009), Malaysia was no exception from the impact on global stock market that causes huge losses in the securities. The subprime crisis has scared the investors and reduced their confidence on the Malaysian stock market. It is stated that the foreign investors care about the volatility of the stock market they invested. It is because the size of the swings in an investment's price shows the level of their worried. Besides that, higher volatility also means a greater chance of a shortfall. This statement was proven by [15] that analysed the effect of Asian and Russian crises on European stock markets was no positive relationship between volatility and expected return in pre- crisis period, this relationship became positive in crisis period. Therefore, they confirmed that investors had high degree of risk aversion in crisis period. Other than that, it is found that the global financial crisis became sharply out of control following the Lehman Brothers collapse on 15 September 2008. [18] find that the bad news produces stronger effect than good news for the Chinese stock market during the crisis. Therefore, the researches on modelling volatility of a stock market have recently become more important.

One of the most well-known tools for capturing the changing variance was the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH (GARCH) models developed [[7],[8],[14]]. The GARCH model has been developed into a class of models. Those models have been applied to stock markets, foreign exchange markets and future markets and they are proven to

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be easily used and relatively accurate. Using the ARCH, GARCH, GJR-GARCH and EGARCH models, [5] has indicated that the standard GARCH model produces the best overall performance for forecasting monthly US dollar-Deutsche mark exchange rate volatility, whereas the GJR-GARCH model seems a poor alternative. Contrast to the above statements, other researchers has come to the conclusion that the EGARCH model achieves superior performance in predicting stock market volatility. The current studies in modelling the volatility of Chinese [15] stated that EGARCH model fits the sample data better than GARCH model stock returns. While [2] found that EGARCH models had been demonstrated to be superior compare to other competing asymmetric conditional variance in many studies. The previous studies have investigated the performance of GARCH models on explaining volatility of mature stock markets [9]. Moreover, a few have tested GARCH models using daily data from Middle East stock markets.

Differ to the others, this paper focused on emerging country which is Malaysian stock market and use the daily data from the FTSE Bursa Malaysia KLCI (FBM KLCI). It is because Kuala Lumpur Composite Index (KLCI) has served as an accurate performance indicator of the Malaysian stock market and represents the 30 largest companies in the market. The purposes of this study are to model the volatility of Malaysian stock market and to see the changes of stock market volatility during financial crisis and lastly, to evaluate the performance of GARCH family models.

II. RESEARCH METHODOLOGY

This paper involved the daily stock price of Kuala Lumpur Composite Index (KLCI) from 2002 to 2011. According to the [16], daily data are more volatile than the other series (weekly and monthly), confirming the results of [5]. Therefore, the daily data that is high in frequency is more volatile and provide us more information regarding the stock market.

A. Implementation Steps

This investigation was performed using the five-step procedures that have been highlighted as follow.

Step 1: Data Collection
The data was downloaded from Yahoo! Finance.
Step 2: Calculate the continuous compounded daily return, Rt.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), t = 1,2,3..., N$$

Where
P_t = FBM KLCI index at time t
P_{t-1} = FBM KLCI index at time t − 1

Step 3: Descriptive data analysis on the continuously compounded daily return, Rt for the index returns.

Step 4: Model identification and parameter estimation. The estimation parameter for each model was done. The models included in this study are:

i. Generalized Autoregressive Conditional Heteroscedasticity (GARCH)
ii. Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH)
iii. Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)

Step 5: Model Evaluation
The models from the index returns were evaluated with six performance measurements which are:

i. Akaike Information Criterion (AIC)
ii. Schwarz Criterion (SC)
iii. Mean Absolute Error (MAE)
iv. Root Mean Square Error (RMSE)
v. Mean Absolute Percentage Error (MAPE)
vi. Theil Inequality Coefficient (Theil-U)

B. Methods of Study

The considered models in this research were chosen based on the concise studies of past researches. They were proven fit and suitable for the volatility analysis in order to gain more reliable results.

1) Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

A general observation about the unexpected component of asset returns is that large shocks tend to be followed by larger shocks, and small shocks, tend to be followed by more small changes, in either direction. In other words, the volatility of asset returns appears to be serially correlated. The econometric term has describing this feature as the autoregressive conditional heteroscedasticity (ARCH), which states that the variance of time series is conditional on their past realizations. The standard ARCH model was introduced by [7] and generalized (GARCH) by [8]. In his model, Engle defines the conditional variance as a deterministic function of lagged squared residuals. In the ARCH (p) model the conditional variance is given by:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2$$

Where ω and α non-negative constants (in order for σ_t^2 to be non-negative). The ARCH model given by equation above and is formulated to depict volatility as the clustering of large shocks to the dependent variable. Engle's specification was extended by Bollerslev and introducing lagged conditional variances in the conditional variance equation. This representation allows the number of parameters in the model to be considerably reduced. The innovation here is that GARCH allows past conditional variances to enter the previous ARCH (p) model. The intention of GARCH is that it can parsimoniously represent a higher order ARCH process. The GARCH model is commonly used in its most simple form where the simplest GARCH (1,1) specification is:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where
ω is a constant
ε_{t-1}^2 is the ARCH term
σ_{t-1}^2 is the GARCH term

Higher order GARCH models, denoted GARCH (q,p), can be estimated by choosing either q or p greater than 1 where q is the order of the autoregressive GARCH terms and p is the order of the moving average ARCH terms. The representation of the GARCH (q,p) variance is:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \in_{t-1}^2$$

2) Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH)

TARCH or Threshold ARCH and Threshold GARCH were introduced independently [19]. The generalized specification for the conditional variance is given by:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \in_{t-1}^2 + \sum_{k=1}^{r} \gamma_k \in_{t-k}^2 I_{t-k}$$

where $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise

In this model, good news, ε _(t-i)>0, and bad news. ε _(t- i)<0, have differential effects on the conditional variance; good news has an impact of α_(i), while bad news has an impact of α_(i)+γ_(i).If γ_(i)>0, bad news increases volatility, and we say that there is a leverage effect for the i-th order. If γ _(i)≠0, the news impact is asymmetric.

3) Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)

EGARCH represents a more successful attempt to model excess conditional kurtosis in stock return indices based on a generalized exponential distribution [14]. Nelson was the first investigator to model leverage effects by defining the down movements are more influential for predicting volatility than the upward movements. The specification for the conditional variance of EGARCH model is:

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

The left-hand side is the *log* of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$.

III. RESULTS AND DISCUSSIONS

A. Descriptive Analysis

The daily prices and returns for the FBM KLCI for the period under review are presented in Fig.1 and Fig. 2.

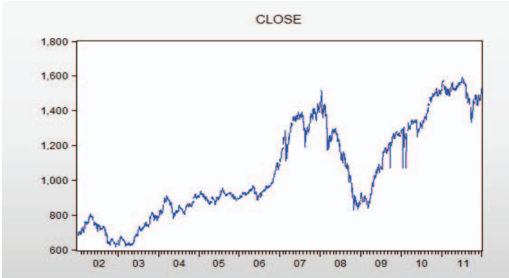

Figure 1 Daily Closing Price of FTSE Bursa Malaysia KLCI

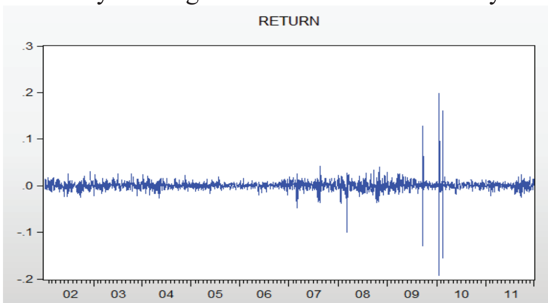

Figure 2 Return of FTSE Bursa Malaysia KLCI

From Fig.1, the graph shows that there was a substantial increment in the daily closing price from 2003 to 2007. However, the closing price has dropped sharply in 2008 till the first quarter of 2009. This analysis has proven the statement of International Monetary Fund (2009) that stated Malaysia was no exception from the impact of global financial crisis during the late 2008 and early 2009. Besides that, virtual inspection on the return of FBM KLCI shows that the volatility changes over time and tends to cluster with periods of low volatility and periods of high volatility. This turbulence and tranquility suggests the existence of volatility clustering in the graph of return. The volatility is relatively consistent from 2002 to 2006, but increase from 2007 to 2009 especially in the middle of 2008 till early 2009.

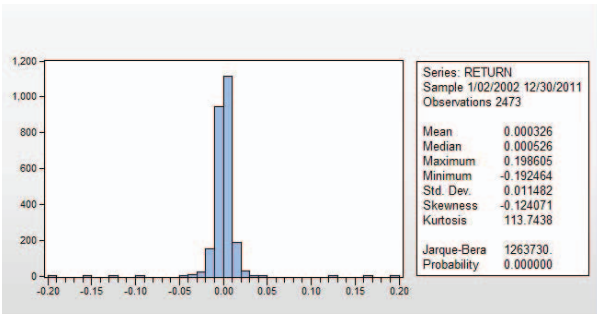

Figure 3 Histogram and Statistic for Return of FTSE Bursa Malaysia KLCI

Fig. 3 shows the statistics for the FBM KLCI return series. The figure shows that there is a large difference between the maximum (0.198605) and minimum (-0.192464) return of the index which are 0.391069. This difference shows an estimate of the spread of the data. This statement has been strengthening when the standard deviation is also high, 0.011482 with regards to the number of observations which is 2473. The value was considered high since it is far from the mean, 0.000326 and considering the statistics and probability theory, the value also indicates a high level of fluctuation of the FBM KLCI daily returns. In addition, the mean is close to zero and positive as commonly expected for a time series of returns. Then, the negative skewness indicates an asymmetric tail that exceeds more towards negative values rather than positive one. It shows that FBM KLCI has non-symmetric returns. The large kurtosis statistics illustrate the leptokurtic when the value exceeds the normal value of three and indicate that the return distribution is fat-tailed. Other than that, the Jarque and Bera (1980) test for normality confirms the results that the series is abnormal according to Jarque Bera that rejects the normality at the 5% confidence level.

The unit root test or Augmented Dickey-Fuller test was performed. The hypotheses for this test are as follows.

H_0 : There is a unit root, which means that the series is nonstationary.
H_1 : There is NO unit root, which means that the series is stationary.

The result shows that the p-value for the series was 0.0001 and the null hypothesis was rejected. It can be conclude that at 5% significance level, there is no unit root and the series was stationary.

Next, the existence of the ARCH effect in the data has been tested using the most widely used method which is Lagrange Multiplier (LM) test. The hypotheses for this test are as follows.

H_0 : There is no ARCH effect.
H_1 : There is ARCH effect.

Based on the TABLE 1, the LM test shows a significant presence of ARCH effect with low p-value of 0.000. The null hypothesis of no ARCH effect was rejected and a strong presence of ARCH effect has been detected. Therefore, it proven that the volatility of asset return was serially correlated. The test is conducted at different number of lags. Values in parenthesis indicate the p-values. The zero p-value at all lags strongly indicates the presence of ARCH effect in the series. Obs* R-squared is the number of observations times the R-squared value.

TABLE 1. ARCH-LM TEST RESULTS

No. of lags	1	5	10	15	20
F statistic	757.033	287.941	152.670	101.915	106.462
p-value	0.000	0.000	0.000	0.000	0.000
Obs* R-squared	579.909	910.677	945.098	946.325	1145.091
p-value	0.000	0.000	0.000	0.000	0.000

B. Model Identification

The test on Autocorrelation (AC) and Partial Autocorrelation (PAC) has been done to measure the degree of independence among the observations in the series and take the value between -1 and +1. From Fig. 4, the series is proven stationary when the serial lags are in the confidence interval. It is also shown clearly which lag has a spike. The ACF and PACF correlogram illustrate that there is a few significant spike. So, the best ARMA model has been determined based on the Akaike info criterion (AIC) and Schwarz criterion (SC).

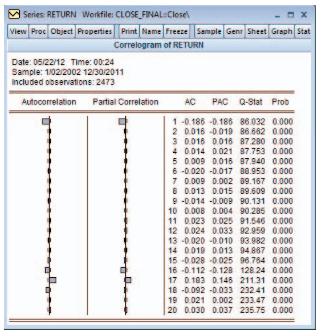

Figure 4 ACF and PACF Correlogram for FTSE Bursa Malaysia KLCI

The result shown that the ARMA (3,3) has the lowest AIC which is -6.138559 and ARMA (1,1) has the lowest SC which is -6.122257. However, the difference of SC value between ARMA (1,1) and ARMA (3,3) is small. Therefore, ARMA (3,3) has chosen as the best model. However, this research has make used of GARCH (1,1) model in order to have a more sufficient analysis.. Thus, this investigation has been proceed using GARCH (1,1), TGARCH (1,1), and EGARCH (1,1) models. The results of the analysis shown in the Table 2.

TABLE 2. SUMMARY OF PARAMETER ESTIMATIONS OF THE MODELS

		ω	α	β	
FTSE Bursa Malaysia KLCI	GARCH (1,1)	1.11E-05	0.068158	0.830333	
	TGARCH (1,1)	1.03E-05	-0.027387	0.857995	0.129468
	EGARCH (1,1)	-0.627535	0.164847	0.946806	-0.034902

For the GARCH (1,1) model, the ARCH and GARCH coefficients (0.068 and 0.830) are statistically significant and exhibit the expected sign. The significance of α and β indicates that, lagged conditional variance and lagged squared disturbance have an impact on the conditional variance. In other words, it means that news about volatility from the previous periods have an explanatory power on current volatility. Moreover, the sum of the two estimated ARCH and GARCH coefficients in the GARCH (1,1) is very close to one (0.898) which indicates that volatility shocks have a persistent effect on the conditional variance.

Furthermore, the asymmetric models TGARCH (1,1) and EGARCH (1,1) are used to investigate the existence of leverage effect in the returns of the FBM KLCI. The main difference between these two models is that in the EGARCH model, there is no need of nonnegative restrictions of the parameters but, in the TGARCH model parameters must follow the positive condition. From estimation results of the TGARCH (1,1) model in Table 3.2, the coefficient of the leverage effect is positive and statistically significant. The significance of this coefficient indicates that negative shocks (bad news) have a larger effect on the conditional variance (volatility) than positive shocks (good news) of the same magnitude. In addition, the asymmetrical EGARCH (1,1) model estimated for the returns of the FBM KLCI indicates that all the estimated coefficients are statistically significant at the 5% confidence level. The asymmetric (leverage) effect captured by the parameter estimate γ is also statistically significant with negative sign, indicating that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, which indicates the existence of leverage effects in the returns of the Malaysian stock market during the study period.

In order to test whether present models have captured the persistence in volatility and there is no ARCH effect left in the residual of models, the ARCH-LM test is conducted again. The results are shown in Table 3. It shows that all p-values for ARCH-LM test are greater than 1% and 5% confidence level at lag one, suggesting no presence of ARCH effect.

TABLE 3. ARCH-LM TEST

Type of Models	F-statistic	p-value	Obs*R-squared	p-value
GARCH (1,1)	2.364592	0.1242	2.364243	0.1241
TGARCH (1,1)	1.143180	0.2851	1.143576	0.2849
EGARCH (1,1)	0.004096	0.9490	0.004100	0.9489

C. Model Evaluation

In order to determine which model is preferred, this research will consider the value of Akaike info criterion (AIC) and Schwarz criterion (SC) for all the three used models. The principle here is the lower the value of AIC and SC, the higher the performance of the model. As a result, Table 4 indicates that the EGARCH model is the preferred models with the lowest value of AIC and SC which are -6.936254 and -6.92215, followed by TGARCH and GARCH.

TABLE 4. SUMMARY OF AIC AND SC VALUES

		AIC	SC
FTSE Bursa Malaysia KLCI	GARCH (1,1)	-6.4427	-6.433297
	TGARCH (1,1)	-6.466735	-6.454982
	EGARCH (1,1)	-6.936254	-6.92215

In addition, the model evaluation has been strengthened using the results of the errors statistics from out-of-sample estimation that comprised of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (Theil-U). Table 5 has outlined the result of the errors measurement for all three GARCH models which are GARCH, TGARCH, and EGARCH. By looking at Table 5, EGARCH has shown the lowest value for the MAE and Theil-U which are 0.003741 and 0.901213. In contrast, the value of MAPE has shown a reverse ranking when GARCH has the lowest value which is 96.36417, followed by TGARCH with 97.95757 and finally the highest value is EGARCH with 101.8550. For the value of RMSE, the errors are very close for each of the model. Even though GARCH has the smallest value which is 0.004798, the difference with EGARCH is very low which is only 0.0001. Overall, considering all those four models, it can be concluded that EGARCH is the best model in this research.

TABLE 5. SUMMARY OF ERROR MEASUREMENTS OF MODELS

	Models	**RMSE**	**MAE**	**MAPE**	**Theil-*U***
FTSE Bursa Malaysia KLCI	GARCH (1,1)	0.004798	0.003780	96.36417	0.970370
	TGARCH (1,1)	0.004801	0.003792	97.95757	0.983046
	EGARCH (1,1)	0.004799	0.003741	101.8550	0.901213

IV. CONCLUSIONS AND RECOMMENDATIONS

Modelling volatility is a very important study for an investor since the volatility of stock market always changes even by a small event and affect their investment. In this research, the GARCH model has been used to model the FBM KLCI return with regard to the global financial crisis. This choice has been done based on the study by Assis et al (2010) that found the ARIMA/GARCH models outperformed the other univariate time-series methods in the forecasting of coffee bean prices. The selected models used are GARCH (1,1), TGARCH and EGARCH. Then, the models were evaluated using six evaluation measures which are AIC and SC for the within-sample evaluation and RMSE, MAE, MAPE, and Theil-U for out-of-sample evaluation.

From the graph of the sample data used, it shows that the global financial crisis occurred in the middle of 2008 has affected the stock market and only started to recover by the end of 2009. While the return of FBM KLCI has proven volatility clustering exist during the sample data of 2002 to 2011. Besides that, the descriptive statistics also indicate high level of fluctuation with a high standard deviation and large difference between maximum and minimum value. In other words, it also means a higher level of risk. Then, the negative skewness indicates an asymmetric tail and large kurtosis means that the return distribution is fat-tailed, where there will be additional risk for investors. The Augmented Dicker Fuller (ADF) test was conducted and the series was found stationary. In addition, a strong presence of ARCH effects (volatility of asset return was serially correlated) has led to the implementation of GARCH models.

The results found strong evidence that daily returns could be characterized by the above mentioned models. FBM KLCI data showed a significant departure from normality and existence of conditional heteroscedasticity in the residuals series. GARCH (1,1) model shows that the sum of α and β is close to one which indicate the persistent effect on the conditional variance. Other than that, the existence of leverage effects has been detected by the asymmetric models which are TGARCH and EGARCH. It shows that bad news have greater impact to volatility compared to good news. Finally, the models' performance evaluation found that EGARCH has the best volatility forecasting ability compared to the other GARCH family. This statement consistent to the previous researches that agreed that EGARCH can produced a superior results compared to the other GARCH models (Haniff and Pok (2010); Mukherjee et al. (2011)).

For the future purpose, there are several improvements that other researchers can do regarding the volatility of stock market. Firstly, they can use a larger sample of data that might include a few crises faced by Malaysia. The sample data can be as large as 30 years that can include a few important crisis such as dot-com bubble, Asian Financial Crisis, and subprime crisis. By doing this, the changes in the volatility of the stock market can be seen clearly. Besides that, they can also use the other GARCH models that rarely used by the other researchers such as GARCH-in-mean, autoregressive stochastic volatility (SV) model, Integrated GARCH (IGARCH) and others. Finally, it is preferable if the researchers can make comparison between the movements of Malaysian stock market with the stock market of the other countries.

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