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IMPACT OF THE GLOBAL FINANCIAL CRISIS ON THE VOLATILITY OF THE MALAYSIAN STOCK MARKET

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***Abstract*— Stock market volatility is important in determining the cost of capital and to assess investment and leverage decisions since volatility is synonymous with risk. Risk-averse investors could be affected negatively due to substantial changes in volatility of the financial markets. We focus on the global crisis of 2007/2008 and its impact on the Malaysian financial market. We use GARCH models to model the volatility in order to determine the effect of the crisis on the KLCI. In order to be able to model the volatility, we first test the efficiency of the market using ARIMA models. We found that because of the financial crisis there was an increase in the impact of news about volatility from the previous periods but only a slight drop in the persistency of the conditional variance.**

Keywords- Financial market, volatility forecasting, global financial crisis

I. INTRODUCTION

The financial crisis which happened at the end of 2007 and beginning of 2008 caused a huge impact on all financial markets around the world. The crisis was triggered by a liquidity shortfall in the United States banking system. Questions regarding bank solvency, declines in credit availability, and damaged investor confidence had an impact on global stock markets, where securities suffered large losses during the late 2008 and early 2009. Malaysia was not an exception. The KLCI, which is the main index and market indicator in Malaysia, dropped around 670 points within the period of 14^{th} of January 2008 to 12^{th} of September 2008 and this comes to around a 45% drop in its value. That was the biggest decline in the KLCI value after the East Asian financial crisis of 1997.

The question does arise then as to the size of the impact of the 2008 global financial crisis on the stock market volatility. The main objective of this study is thus to investigate the volatility of the Bursa Malaysia with regards to the recent financial crisis of 2007/2008, after the Asian financial crisis 1997.

II. LITERATURE REVIEW

When it comes to volatility, GARCH models come to mind. Various studies have been done on the modeling of volatility of the various financial markets around the world. We discuss some of these studies and those on market efficiency.

A. Tests of weak form market efficiency

One of the main indicators of weak-form market efficiency is the random walk. The degree of mean reversion in stock prices is frequently used as a measure to test market efficiency. If changes are highly predictable, this could show that investors are not always rational. So, if an autocorrelated structure exists, then returns are perfectly predictable and the market may not be efficient.

From various studies, various tests consistently suggest that KLSE prices do not follow a random walk process. It should however be noted that rejecting the random walk hypothesis does not necessary contradict market efficiency. As Summers [1] argues, contradicting the random walk hypothesis in a given market may only mean that the obtained results are consistent with the particular martingale process of random walk.

Several studies have been conducted to support market efficiency. Among them are studies on developed markets by Kendall [2], Larson [3], Fama [4], Roberts [5], Cowles and Jones [6] and Schwartz and Whitcomb [7]. According to one group of findings, weak-form efficiency holds in both developing and less developed countries too. They are Branes [8], who studied the Kuala Lumpur Stock Exchange, Chan et al. [9] on major Asian markets, Dickinson and Muragu [10] on the Nairobi stock exchange (NSE) and Ojah and Karemera [11] on the four Latin American countries market. Studies done on the KLSE by Arief [12], Lim [13] and Laurence [14] found some evidence of the weak- form efficiency.

On the other hand, Larson [3], Cootner [15], Osborne [16], Neiderhoffer and Osborne [17], Poterba and Summers [18] and Fama and French [19] and Lo and MacKinlay [20] produced strong evidence that stock returns are correlated. More studies show that stock returns are predictable to some extent using macroeconomic instrument variables. Merton's [21] observation also rejects the random walk hypothesis for weekly US stock returns. Another group of studies confirmed this for developing and less developed markets are not efficient in the weak-sense. They are Cheung et al. [22] who studied the stock market of Korea and Taiwan, Roux and Gilberson [23] on the Johannesburg stock exchange, Poshakwale [24] on the Indian market and Mobarek and Keasey [25] on the Dhaka stock market of Bangladesh. All of them produced the same conclusion that violates the weak-form of EMH and find evidence of non-random stock price behaviour.

B. Modeling of returns and volatility using ARCH/GARCH models

ARCH effects are documented in the finance literature by Hsieh [26] for five different US dollar rates, Akgiray [27] for index returns, Schwert [28] for future markets, and Engle and Mustafa [29] for individual stock returns. Diebold [30], Baillie and Bollerslev [31] and Drost and Nijman [32] found that ARCH effects, which are highly significant with daily and weekly data, weaken as the frequency of the data decreases. Diebold and Nerlove [33] try to explain the existence of ARCH effects in the high frequency data due to the amount of information or the quality of the information reaching the markets in clusters or the time between information arrival and the processing of information by market participants.

Brailsford and Faff [34] argue that volatility forecasting is very difficult and though in their study ARCH models and simple regression provided superior forecasting ability, the models were 'sensitive to the error statistic used to assess the accuracy of the forecasts'. Brooks et al. [35] support the applicability of the ARCH-GARCH models to South-African stock data. However, Barucci and Reno [36] find that GARCH models have better forecasting properties when Fourier analysis is used to calculate the diffusion process volatility, instead of the cumulative squared intraday returns.

Rijo [37] also found that the GARCH(1,1) model gives the best fit for the National Stock Exchange (NSE) of India. Radha and Thenmozhi [38] forecasted short term interest rate using ARMA, ARMA-GARCH and ARMA-EGARCH on the Indian market. Their results show that GARCH based models are more appropriate for forecasting than the other models. Padhi [39] used the ARCH, GARCH and ARCH-in-mean models to explain the stock market volatility of the Indian market at the individual script level and at the aggregate indices level. The analysis reveals the same trend of volatility in the case of aggregate indices and five different sectors and the GARCH (1, 1) model is persistent for all the five aggregate indices and individual companies. The study on the effect of the global financial crisis on stock return volatility in India by Mishra [40] on the S&P CNX Nifty using GARCH models concludes the persistence of stock return volatility and its asymmetric effect.

Ederington and Guan [41] compare the forecasting ability of various volatility forecasting models and find that the GARCH(1,1) model 'generally yields better forecasts than the historical standard deviation and exponentially weighted moving average models..' but some reservations are still there in terms of the forecasting accuracy. Awartani and Corradi [42] find that when allowing for asymmetries, the GARCH(1,1) model is beaten by the asymmetric GARCH models, but when not allowing for asymmetries it was the best model compared to other GARCH models.

Magnus and Fosu [43] rejected the random walk hypothesis for the Ghana Stock Exchange and support the superiority of the GARCH(1,1) model compared to other models 'under the assumption that the innovations follow a normal distribution.' Shamiri and Abu Hassan [44] modeled and forecasted the volatility of the Malaysian and the Singaporean stock indices using Asymmetric GARCH. They estimate the three GARCH (1, 1) models (GARCH, EGARCH and GJR-GARCH) using daily price data. They found that the AR(1)-GJR model provides the best out-of-sample forecast for the Malaysian stock market, while AR(1)-EGARCH provide a better estimation for the Singaporean stock market which implies that Malaysian stock market has asymmetric effects. Haniff and Pok [45] compared the four non-period GARCH models and found that the EGARCH produced consistently superior results compared to the other GARCH models.

III. METHODOLOGY AND DATA ANALYSIS

The Asian financial crisis in 1997 caused a huge collapse of the stock markets in the South East Asian region. However, from January 2000 onwards, stock prices had resumed their increasing trend until the eve of the outbreak of the global financial crisis. Malaysia had a good recovery by the middle of 1999. There is no specific date of full economic recovery, but by the middle of 2000, it had almost recovered.

Thus, in order to capture the impact of the crisis, two different periods are used to see the effect and both periods are selected after the recovery of Asian financial, which was in the middle of year 2000, to make sure there is no effect of the 1997 Asian financial crisis in our analysis. This study uses secondary data collected from DataStream, covering a period of six and a half years after the East Asian financial crisis of 1997 and before the global crisis of 2008. We analyze data from 1st June 2000 until the end of 2007 and then a period of 10 years from 1st of June 2000 until the 16th of March 2010 which includes the crisis which happened at the end of year 2007 and beginning of year 2008. In the first analysis the crisis is excluded but it is included in the second analysis, so if there is any impact of the crisis, a significant change in the models can be detected. We use the daily closing price of the Kuala Lumpur Composite Index (KLCI) to analyze the volatility

The prices are used to get the daily returns of the KLCI as below:

$$R_t = \log (P_t / P_{t-1})$$

Where R_t represents the daily returns of the KLCI
P_t represents the daily prices of the KLCI

We run the unit root test to detect stationarity of this series for both periods and the results are presented in Table 1 below:

TABLE 1 UNIT ROOT TEST

Period	t-Statistic	P-value
June 2000 to end of 2007	-36.92449	0.0000*
June 2000 to March 2010	-43.30531	0.0000*

The null hypothesis that both the series are non-stationary is rejected with a low p value of 0.000 and we conclude that both the series are stationary.

Next, we estimate and select the best ARMA model that fits the return of the series. We select our model based on the p-values, residual of Q-statistic p values and AIC values. Among the models, some are rejected due to the stationary condition since the sum of the absolute coefficients is greater than 1 and some are rejected due to magnitude of their p-values. Then, the ARMA models with residuals that are statistically different from zero can be rejected as it means that the residuals are not just white noise. All our models have residuals which are white noise.

The good models which satisfy all of the conditions are as in Table 2 below:

TABLE 2. GOOD ARMA MODELS

Model	AIC	
	2000 to 2007	***2000 to 2010***
ARMA (1, 0)	-6.704296	-6.578003
ARMA (0, 1)	-6.704299	-6.577677
ARMA (1, 1)	-6.704005	-6.577360
ARMA (2, 0)	-6.703790	-6.577339
ARMA (0, 2)	-6.703325	-6.576896
ARMA (3, 0)	-6.705046	-6.578815
ARMA (0, 3)	-6.705113	-6.578370
ARMA (4, 0)	-6.707036	-6.579161
ARMA (0, 4)	-6.704510	-6.577587

According to Akaike's information criterion, ARMA (4, 0) is chosen to be the best model among all for both periods of study as it has the lowest AIC.

It is worth mentioning here that the random walk is a non-stationary stochastic process and implies that the best prediction of the price of a stock tomorrow is equal to its price today plus a purely random (stochastic) shock (error term). If this were in fact the case, forecasting assets prices would be an unsuccessful exercise [46]. So if the time series does not follow a random walk, it means they are somehow correlated and a model for forecasting can be employed and at the same time reject the weak form market efficiency since we can find a pattern in time series for prediction.

The random walk can be described by a particular ARIMA model which is ARIMA (0, 1, 0). Here, the first zero refers to the Autoregressive process and second zero to the moving average process which indicates some extent of dependency and correlation in the series, which is in conflict with random walk properties. One refers to the degree of differencing. If we model the series and do not find the ARIMA model mentioned above, we can assume that model is not a random walk and as a result reject the weak-from market efficiency.

We find that the model does not follow the ARIMA (0, 1, 0) as it was detected earlier that the data is stationary and no differencing is required. The market did not follow the random walk and so was not weak-efficient form for both periods.

Next, we perform the ARCH LM test to see if there is any ARCH effect in the residuals. Table 3 below presents the results of this test.

TABLE 3. ARCH LM TEST

	2000 to 2007	**2000 to 2010**
F-statistic	70.91180 (0.0000)	67.25315 (0.0000)
Obs*R-squared	68.51745 (0.0000)	65.57384 (0.0000)

The LM test for both periods shows a significant presence of ARCH effect with a value of 68.5174 (for the period of 2000 to 2007) and 65.57384 (for the period of 2000 to 2010) and low P value of 0.0000 for both periods. So, we reject the null hypothesis of no ARCH effect and detect a strong presence of ARCH effect.

Since there is an ARCH effect in the residuals, we need to model this too using the ARCH/GARCH models. To test the adequacy of the GARCH models, it is necessary to examine the standardized residuals, ε_t/σ_t , such that σ_t is the conditional standard deviation as calculated by the GARCH model and ε_t are the residuals of the conditional mean equation. If the GARCH model is well specified, the standardized residuals will be independent and identically distributed, for which the Q-statistics should be more than 0.05. Table 4(a) and 4(b) below present the estimation for the different GARCH(p,q) models for both periods. We assume that the innovation term follows a normal distribution as was done by Magnus and Fosu [43]. Here Alpha refers to the value of previous square error term and Beta refers to the value of previous variances.

TABLE 4. A. DIFFERENT GARCH MODELS FOR THE PERIOD 2000 TO 2007

GARCH model	**Coefficient**	**P values**	**Standardized residuals Q-statistics p-values**	**Standardized residuals squared Q-statistics p-values**	**AIC**
(1,0)	Alpha1: 0.3034	0.0000	0.673	0.000	-6.7980
(1,1)	Alpha1: 0.0906 Beta1: 0.8969	Alpha1: 0 Beta1: 0	0.933	0.834	-6.9419
(2,1)	Alpha1: 0.1441 Alpha2: -0.08449 Beta1: 0.931876	Alpha1: 0 Alpha2: 0 Beta1: 0	0.956	0.866	-6.9445
(2,2)	Alpha1: 0.0796 Alpha2: 0.0942 Beta1: -0.0501 Beta2: 0.8527	Alpha1: 0 Alpha2: 0 Beta1:0.02 Beta2:0	0.923	0.859	-6.9414

TABLE 4. B. DIFFERENT GARCH MODELS FOR THE PERIOD 2000 TO 2010

GARCH model	Coefficient	P values	Standardized residuals Q-statistics p-values (lag 500)	Standardized residuals squared Q-statistics p-values	AIC
(1,0)	Alpha1: 0.350438	Alpha1:0.0	0.005	0.000	-6.6507
(1,1)	Alpha1: 0.112945 Beta1: 0.877529	Alpha:0.0 Beta1: 0.0	0.835	0.784	-6.8380
(2,1)	Alpha1: 0.103713 Alpha2: 0.017279 Beta1: 0.868238	Alpha1:0.0 Alpha2: 0.28 Beta1: 0.0	0.826	0.755	-6.8374

Among all these models, the GARCH (1, 1) is the best model for both periods under study as it satisfies all conditions. The GARCH (2, 1) has higher AIC value but a negative coefficient which is not allowed in ARCH/GARCH models. As seen in previous studies, the GARCH (1, 1) is the successful model and we observe this here as well.

Finally, we again compute the LM statistic test after the incorporation of the GARCH into the model to check whether there is any GARCH effect left in the model. Table 5 below shows the LM statistic.

TABLE 5. ARCH LM TEST AFTER GARCH ESTIMATION

	2000 to 2007	2000 to 2010
F-statistic	2.746304 (0.097639)	0.160840 (0.688418)
Obs*R-squared	2.745265 (0.097543)	0.160956 (0.688278)

The results of the LM test does not show any significant presence of ARCH effects, with an F-statistic value of 2.7452 and high p-value of 0.0975, for the period of 2000 to 2007 and an F-statistic value of 0.160956 and a high p-value of 0.688278 for the period of 2000 to 2010. So, we accept the null hypothesis of no ARCH effect and do not detect presence of ARCH effect anymore.

Finally, we find that the AR (4)/GARCH (1, 1) to be the best model to capture the volatility of the market. The table 6 below presents the coefficients and statistical significance of the final model.

TABLE 6. FINAL MODEL FOR THE PERIODS OF 2000 TO 2007 AND 2000 TO 2010

ARMA	2000 to 2007	2000 to 2010
AR(1)	0.178277 (0.0000)	0.168785 (0.0000)
AR(2)	-0.004701 (0.8407)	0.002496 (0.9002)
AR(3)	0.051108 (0.0390)	0.043695 (0.0285)
AR(4)	-0.034397 (0.1307)	-0.023214 (0.2642)

GARCH	2000 to 2007	2000 to 2010
Alpha(1)	0.090685 (0.0000)	0.112945 (0.0000)
Beta(1)	0.896916 (0.0000)	0.877529 (0.0000)

For the period of 2000 to 2007, the conditional variance has the rate of change of 0.090 and the large value of 0.89 of beta causes σ_t^2 to be highly correlated with σ_{t-1}^2 and gives the conditional variance process a relatively long-term persistence. For the period of 2000 to 2010, the conditional variance has the rate of change of 0.1106 and the large value of 0.87 of beta causes σ_t^2 to be highly correlated with σ_{t-1}^2 and again gives the conditional variance process a relatively long-term persistence.

The following Table 7 shows the conditional variance for each period, the difference and percentage change in value of the coefficients between the two time periods.

TABLE 7. DIFFERENCE BETWEEN THE GARCH MODELS

Period	2000 to 2007	2000 to 2010	Difference	%
α_1	0.090685 (0.0000)	0.112945 (0.0000)	0.02226	24.5465%
β_1	0.896916 (0.0000)	0.877529 (0.0000)	0.019387	- 2.1615%

The value of the beta, which indicates the correlation between σ_t^2 and σ_{t-1}^2, shows that the conditional variance has decreased by 2.16%, which implies that the persistency in conditional variance has decreased by 2.16%. On the other hand, the rate of change of conditional variance has increased by 24.5%. Thus, we can say that the volatility has increased by 24.5% and at the same time the persistency in volatility has just decreased by 2.16% during the crisis period.

IV. CONCLUSION

In this study, two statistical models are identified and used to observe the volatility clustering effect and impact of the 2007/2008 crisis on the volatility of the market. The KLCI is used as the main market indicator and its returns are log transformed for each period. The unit root test indicates stationarity of the data for both periods considered. Various ARMA models using different lags are examined and the ARMA (4, 0) or AR (4) model is selected as the best model according to the AIC criteria. Using the ARCH LM test we detect the presence of high ARCH effect in the residuals. Then the different GARCH models are examined and the GARCH (1, 1) model is found to be the best model among all according to the AIC criteria. This is in accordance with our expectations. Rechecking using the ARCH LM test shows no significant presence of GARCH effect. Standardized residuals and Standardized residuals squared are also examined and found to be white noise. As a result, the AR(4)/GARCH(1,1) is found to be the best model for our analysis during both the periods studied.

Also, for both periods, the prices were not found to follow the random walk. According to the model which we found to describe the process, the ARIMA (4, 0, 0) is chosen to be the best. Since the data is already stationary and mean reverting it requires no differencing. Thus, there is dependency in the data structure and we conclude that for the period of 1 June 2000 until the end of 2007 and 1 June 2000 until 16 March 2010, the KLCI has not been in an efficient form.

There exists a volatility clustering effect for the periods under consideration as expected for stock markets. For both periods, the GARCH (1, 1) is found to be the best model which is in line with previous research results. The two models indicate a high persistence of high or low volatility where the coefficient of σ_{t-1}^2 is high for both. It shows that the conditional standard deviation process has a relatively long term persistency.

The effect of the crisis can be observed by comparing the two models. The value of beta, which indicates the correlation between σ_t^2 and σ_{t-1}^2, gives the conditional variance a relatively long-term persistence, which has decreased by 0.0216 and this implies that the persistency in conditional variance has decreased by 2.16%. On the other hand, the rate of change of conditional variance has increased by 24.5%. Thus, we can say that the volatility has increased by 24.5% and at the same time the persistency in volatility has just decreased by 2.16% during the crisis period.

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