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GARCH Models and the Financial Crisis-A Study of the Malaysian Stock Market

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ABSTRACT

Financial market volatility is an important aspect when setting up strategies related to portfolio management, options pricing and market regulation. Occurrence of the global financial crisis of 2007/2008 affected all financial markets around the world and a major concern was about the volatility changes in stock markets. This study has investigated the change in volatility of the Malaysian stock market, with respect to the global financial crisis of 2007/2008, using both symmetric and asymmetric Generalized Autoregressive conditional heteroscedasticity (GARCH) models. Using the Kuala Lumpur Composite Index (KLCI), two periods are selected. The first period is from June 2000, after the recovery of the East Asian crisis, to the end of 2007 and excludes the global financial crisis 2007/2008 and the second period includes the crisis, i.e., from June 2000 to March 2010. AR (4) is found to be the best in modelling the conditional mean and GARCH (1, 1), EGARCH (1, 1), GJR-GARCH (1, 1) for conditional variance. As expected from financial time series, for both periods, the KLCI exhibits stylized characteristics such as leptokurtosis, clustering effect and asymmetric and leverage effect. It is also found that there was a significant increase in volatility and leverage effect but just a small drop in persistency due to the financial crisis.

Key words: Volatility, leverage effect, global financial crisis, GARCH models, financial markets

INTRODUCTION

Financial market volatility is an important indicator of the dynamic fluctuations in stock prices (Raja and Selvam, 2011). An understanding of volatility in stock markets is important for determining the cost of capital and for assessing investment and leverage decisions as volatility is synonymous with risk. Substantial changes in volatility of financial markets are capable of having significant negative effects on risk-averse investors (Premaratne and Balasubramanyan, 2003).

The global financial crisis which happened at the end of 2007 caused and is still causing, a huge impact on financial markets and institutions around the world. Questions regarding bank solvency, declines in credit availability and damaged investor confidence had an impact on global stock markets, where securities suffered huge losses during the late 2008 and early 2009 and Malaysia was no exception (International Monetary Fund, 2009). The Kuala Lumpur Composite Index (KLCI) which is the main index and market indicator in Malaysia, dropped around 558.93 points in 2008 and this comes to around a 40% drop in its value. Ever since the Asian Financial Crisis of 1997, this was the biggest decline (Chin, 2009). So, how huge an impact did the global financial crisis have on the Malaysian stock market volatility? The main objective of this study is thus to investigate the volatility of the KLCI with regards to the recent financial crisis of 2007/2008, after the Asian financial crisis 1997.

Studies on investment and financial market volatility have widely made use of ARCH models and the existence of ARCH effects is well documented by Hsieh (1984), Akgiray (1989), Engle (1990) and Engle and Mustafa (1992) and they used these models for various types of markets. It has been shown that ARCH effects are highly significant with daily and weekly data due to the amount or quality of information reaching the markets or the time between information arrival and processing by the participants in the market (Diebold, 1988; Drost and Nijman, 1993) but the effects actually weaken when frequency of the data decreases (Diebold and Nerlove, 1989).

With so many different types of models, the forecasting ability of the models is important and several studies have documented this. Brailsford and Faff (1996) showed that in volatility forecasting, ARCH and simple regression models provide superior forecasting ability but are sensitive to the error statistic used to assess the accuracy of the forecasts. However, Barucci and Reno (2002) found that when Fourier analysis is used calculate the diffusion process volatility, GARCH models have better forecasting properties. Erdington and Guan (2004) found that the GARCH(1,1) model 'generally yields better forecasts than the historical standard deviation and exponentially weighted moving average models..' although it is still lacking in forecasting accuracy. Awartani and Corradi (2005) also found that the GARCH (1,1) model is superior when not allowing for asymmetries but when taking asymmetries into consideration, this model is inferior to the asymmetric GARCH models.

Similar results were found for Asian markets. The ARCH/GARCH type models have been shown to provide the best fit in volatility forecasting for studies done on the Indian stock markets. For instance, Rijo (2004) found that the GARCH (1,1) model gives the best fit according to all model selection criteria for the National Stock Exchange (NSE) of India, while Radha and Thenmozhi (2006) showed that GARCH based models are more appropriate to forecast short term interest rates than the other models. Padhi (2006) analysis revealed that the GARCH (1, 1) model is persistent for all the five aggregate market indices of India and for the individual company.

For the Malaysian case, using asymmetric GARCH, Shamiri and Abu Hassan (2007) showed that that the AR (1)-GJR model provides the best out-of- sample forecast for the Malaysian stock market while AR (1)-EGARCH provides a better estimation for the Singaporean stock market which implies that Malaysian stock market has asymmetric effects. However, Haniff and Pok (2010) comparison of the four non-period GARCH models revealed that the EGARCH produced consistently superior results compared to the other GARCH models. Assis *et al.* (2010) compared various univariate time-series methods in the forecasting of coffee bean prices and found that the ARIMA/GARCH models outperformed the others.

Guidi (2010) found that while some indices were better forecasted using asymmetric GARCH models, the simple symmetric GARCH models with the normal distribution actually performed better in volatility forecasting of 5 Asian stock markets and were good enough to be used for forecasting purposes. Fahimifard *et al.* (2009) found that while non-linear models outperformed liner ones, when comparing the linear models, the GARCH model outperformed the ARIMA model. Most recently, in their analysis, Mukherjee *et al.* (2011) found that the EGARCH model was a better model compared to the TARCH model for the SENSEX because there was an indication that there was considerable amount of asymmetry in the series. Yaziz *et al.* (2011) found that while the ARIMA (1,2,1) model was able to produce good forecasts of crude oil prices based on historical patterns, the GARCH (1,1) was actually much better as it was able to capture the volatility effect.

MATERIALS AND METHODS

Univariate models of conditional volatility: Financial time series usually exhibit a set of characteristics. Stock market returns display "volatility clustering" where large changes in these returns tend to be followed by large changes and small changes by small changes (Mandelbrot, 1963), leading to contiguous periods of volatility and stability.

The Autoregressive Conditional Heteroskedasticity models (ARCH) (Engle, 1982) have been used extensively to model volatility. The general form of ARCH (q) process is as follows:

$$\sigma_t^2 = \alpha + \sum_{i=1}^{q} \beta_i \, \varepsilon_{t-i}^2$$

The value of α and β should be greater than zero since standard deviation and variance cannot be negative and value of betas should be less than one in order for the process to be stationary. A deficiency of ARCH (q) models is that the conditional standard deviation process has high frequency oscillation with high volatility coming in short bursts. Bollerslev (1986) generalized the ARCH model by including lagged values of the conditional variance. The GARCH models permit a wider range of behaviour, in particular, a more persistent volatility. The general form of the GARCH (p, q) model is:

$$\sigma_t = \sqrt{\alpha_0} + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \, \sigma_{t-1}^2$$

where, $\alpha_i \, \varepsilon^2_{t-1}$ is an ARCH component and $\beta_i \, \sigma^2_{t-1}$ is a GARCH component. However, the GARCH (p, q) is symmetric and does not capture the asymmetry that characterizes most financial time series and it is known as" leverage effect". It refers to the characteristic of time series on asset prices that "bad news" tends to increase volatility more than good news. One of the primary restrictions of the GARCH models is that they enforce a symmetric response of volatility to positive and negative shocks (Brooks, 2002). In these models, therefore, a big positive shock will have exactly the same effect on the volatility of a series as a negative shock of the same magnitude (Asteriou and Hall, 2007).

In order to capture the asymmetric shock to the conditional variance, Nelson (1991) proposed the Exponential GARCH (EGARCH) model. In the EGARCH model the natural logarithm of the conditional variance is allowed to vary over time as a function of the lagged error terms rather than lagged squared errors. The EGARCH (p, q) model can be written as follows:

$$\text{Log}\,(\sigma_t^2) = \alpha + \sum_{i=1}^{p} \alpha_i \, \text{Log}\left(\sigma_{t-1}^2 \right) + \sum_{j=1}^{q} \beta_i \frac{\varepsilon_{t-j}}{\sigma_{t-j}} + \sum_{k=1}^{r} \gamma_i \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$$

The exponential nature of the EGARCH ensures that conditional variance is always positive even if the parameter values are negative, thus there is no need for parameter restrictions to impose non-negativity. The impact is asymmetric if γ_i is not equal to zero whereas the presence of the leverage effect can be tested by hypothesis that γ_i is less than zero.

The Threshold GARCH (TGARCH) modifies the original GARCH specification using dummy variables. The main target of this model is to capture asymmetries in terms of negative and positive shocks by adding into a variance equation a multiplicative dummy variable to check whether there is statistically a significant difference when shocks are negative. The specification of conditional variance for TGARCH is as follows:

$$\sigma_t = \alpha + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j} 1(\varepsilon_{t-j} < 0) + \sum_{k=1}^{z} \beta_k \sigma_{t-k}$$

For ε^2_{t-1}, 1 (.) = 1, or 1 (.) = 0 for $\varepsilon^2_{t-j} > 0$. If γ_i coefficients have positive values, this indicates a presence of leverage effect. The GJR-GARCH model is a similar model to TGARCH. The difference lies in the fact that we are dealing with conditional standard deviation in the TGARCH model or conditional variance in GJR-GARCH model.

Data and analysis: The Asian financial crisis of 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 out-break of the global financial crisis. Malaysia had a good recovery by the middle of 1999. There is no specific date of full economic recovery from the Asian financial crisis, but by the middle of 2000, it was almost recovered. Guidi (2010) showed a downward pattern in Asian stock prices at the end of 2007 with signals of recovery from late 2008, indicating the presence of the global financial crisis.

Thus, in order to capture the impact of the crisis on volatility and asymmetry of returns, 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 half years after the financial crisis of 1997 in East Asia and before the crisis of 2008.

The sample of data used in this study is the daily closing prices of Kuala Lumpur Composite Index (KLCI) from 1 June 2000 till the end of 2007 and also cover a period of 10 years from 1 June 2000 until the middle of March 2010 which includes the crisis. 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. Daily closing price of the Kuala Lumpur Composite Index (KLCI) to analyze the volatility is transformed to daily returns 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

The statistics for the KLCI returns series are shown in Table 1. Generally, there is a large difference between the maximum and minimum return of the index. The standard deviation is also high with regards to the number of observations, indicating a high level of fluctuation of the KLCI daily returns. The mean is close to zero and positive as is expected for a time series of returns.

There is also evidence of negative skewness, indicating an asymmetric tail which exceeds more towards negative values rather than positive ones and an indication that KLCI has non-symmetric returns. KLCI returns are leptokurtic, given its large kurtosis statistics in Table 1. The kurtosis

Table 1: Descriptive statistics of returns of KLCI

	Series period	
Statistical analysis	2000-2007	2000-2010
Mean	0.000237	0.000142
SD	0.008616	0.009129
Max	0.04502	0.045027
Min	-0.063422	-0.099785
Skewness	-0.646365	-0.950694
Kurtosis	9.402523	12.97233
Jarque-Bera	3514.402	10963.28
Probability	0.00000	0.000000

Table 2: Unit root tests

Time 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 test critical value at 1, 5 and 10% is -3.43 , -2.86 and -2.56, respectively. For both series, the number exceeds the critical values at all levels, corresponding to zero p-value

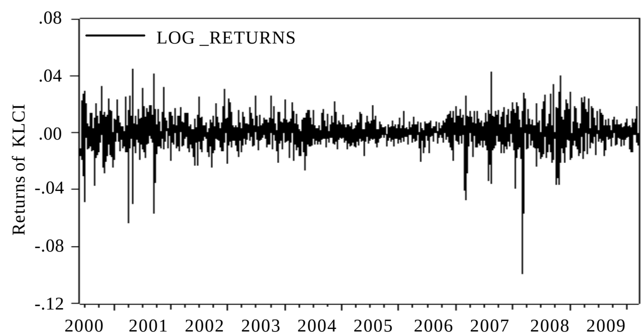

Fig. 1: KLCI Returns from June 2000 to March 2010. Note: The x-axis represents the year, i.e. year 2000 to 2010 while the y-axis represents the returns of the KLCI

exceeds the normal value of three indicating that the return distribution is fat-tailed. Jarque and Bera (1980) test for normality confirms the results based on skewness and kurtosis and both series are non-normal according to Jarque-Bera which rejects normality at the 1% level.

Table 2 below shows the result of unit root tests. The Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) is applied to both series. Based on the test results, we reject the null hypothesis that returns have unit roots. It shows that both series are stationary as the mean is constant across time.

In Fig. 1, we present the KLCI returns from June 2000 to March 2010. Virtual inspection shows that volatility changes over time and it tends to cluster with periods of low volatility and periods of high volatility. The volatility is relatively consistent from 2001 to the year 2007 and seems to increase in the middle of 2007 till 2009. Next, we model this volatility in order to capture the effect of the crisis on the index returns.

Table 3: ARMA models

Coefficients	ϖ	γ_{t-1}	γ_{t-2}	γ_{t-3}	γ_{t-4}	AIC	Q-statistic p-value
2000-2007	0.000267	0.187965	-0.03362	0.051904	0.038073	-6.70704	0.490
		(0.0000)	(0.1417)	(0.0233)	(0.0905)		
2000-2010	0.000165	0.000165	0.153826	-0.01973	0.047459	-6.579161	0.075
		(0.0000)	(0.3244)	(0.0178)	(0.6107)		

γ_{t-k} represents the lag values at lag k = 1,2,3,4 with their corresponding coefficients, ϖ is the intercept. Values in parenthesis are the p-values of the parameters

Table 4: ARCH LM test

	2000 to 2007 crisis			2000 to 2010 crisis		
No. of lags	1	5	10	1	5	10
F statistic	70.911	54.277	29.163	67.2531	33.544	17.260
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs* R-squared	68.517	239.139	255.153	65.57384	157.699	162.272
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

The test is conducted at different numbers of lags. Values in parenthesis indicate the p-values. The zero p-value at all lags strongly indicates the presence of ARCH effect in both series. Obs*R-squared is the number of observations times the R-squared value

We first estimate simple ARMA models as our conditional mean and select the best ARMA model that fits the return of the series. Different ARMA models are examined at different lags based on the p-values, residual of Q-statistic p-values, AIC values and adjusted R-squared. Among the models, some are rejected due to the stationarity condition since the sum of the absolute coefficients is greater than unity and then some rejected due to the magnitude of their p-values. For both series, ARMA (4, 0) or AR (4) has been chosen as the best process for modelling the conditional mean since the relevant AIC were at minimum and the model meets all the criteria including white noise residuals (Table 3).

Next, we perform the ARCH LM test to see if there is any ARCH effect in the residuals. Table 4 presents the results of this test.

The LM test for both periods shows a significant presence of ARCH effect with low p-value of 0.0000. So, we reject the null hypothesis of no ARCH effect and detect a strong presence of ARCH effect as expected for most financial time series.

As the return exhibits an ARCH effect, we use GARCH-type models. In most empirical implementations, the values ($p <= 2$, $q <= 2$) are sufficient to model the volatility which provides a sufficient trade-off between flexibility and parsimony (Knight and Satchell, 1998). Franses and Van Dijk (1996) and Gokcan (2000) have also shown that models with a small lag like GARCH (1, 1) are sufficient to cope with the changing variance. According to Brooks (2002), the lag order (1, 1) model is sufficient to capture all of the volatility clustering that is present from the data.

We examine symmetric GARCH and nonlinear asymmetric EGARCH, GJR-GARCH models at different ($p <= 2$, $q <= 2$) lags. We also find that the GARCH (1, 1), EGARCH(1,1), GJR-GARCH (1,1) are the most successful models according to AIC as they have the smallest value while satisfying restrictions such as non-negativity for symmetric GARCH. The models are estimated for both series using Quasi-Maximum likelihood assuming the Gaussian normal distribution. The results are presented in Table 5. The coefficients of all models for both periods are significant at all levels implying the strong validity of the models.

Table 5: GARCH models

	Exclusion of crisis			Inclusion of crisis		
Coefficients	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ϖ	1.06E-06	-0.386782	1.14E-06	1.31E-06	0.375809	1.46E-06
α	0.090685	0.174485	0.051474	0.112945	0.181139	0.069183
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.896916	0.973789	0.900913	0.877529	0.975113	0.878792
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	-	-0.060726	0.066091	-	-0.067746	0.078221
		(0.0000)	(0.0000)		(0.0000)	(0.0000)

Values in parenthesis are the p-values. All coefficients are significant at 1, 5 and 10% levels

Table 6: GARCH models residual diagnostics

	Exclusion of crisis		Inclusion of crisis	
Type of models	LM test p-values	Standardised residuals (squared) p-values	LM test p-values	Standardised residuals (squared) p-values
GARCH (1,1)	0.097639	0.933	0.688418	0.835
		(0.834)		(0.734)
EGARCH (1,1)	0.104778	0.936	0.322484	0.872
		(0.662)		(0.450)
GJR-GARCH (1,1)	0.146674	0.923	0.878096	0.833
		(0.919)		(0.808)

All correlogram Q-statistics and correlogram squared residuals p-values are greater than 1, 5 and 10% level at lag 500, suggesting that residuals are white noise. All p-values for ARCH LM test are greater than 1 and 5% level at lag one, suggesting no presence of ARCH effect

In order to test whether present models have adequately 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 p-values of LM test, standardized residuals and standardized residuals squared are shown in Table 6.

The results of the diagnostic tests show that the GARCH models are correctly specified. The Q-statistics for the standardized residuals and standardized squared residuals are insignificant with high p-values for all models, suggesting the GARCH models are successful at modelling the serial correlation structure in conditional means and conditional variances.

We have found the AR (4)/GARCH (1, 1), AR (4)/EGARCH (1, 1) and AR (4)/GJR-GARCH (1, 1) to be good models to describe the process for the first series which excludes the crisis and also for the second period which includes the crisis. According to the statistical tests and diagnostics, all models are significant and capture the ARCH effect and volatility clustering successfully. Table 7 presents the comparison of the models for both periods. The difference for the coefficients of each model are obtained and also expressed in percentage terms.

The difference is obtained by subtracting the first period values from the second period values and the percentage is obtained by dividing the difference with the first period values.

Forecasting performance: The models are also evaluated based on their forecasting ability of the future returns. The out of sample period of 6 months for each period is used to evaluate this. The sample for forecasting is from 1 January 2008 to 1 July 2008, to include the crisis and from

Table 7: Model differences

Models	June 2000 to end of 2007	June 2000 to mid 2010	Difference	Percentage
α				
GARCH	0.090685	0.112945	0.02226	24.5% (0.245)
EGARCH	0.174485	0.181139	0.0381	21.8% (0.218)
GJR-GARCH	0.051474	0.069183	0.0177	34.4% (0.344)
β				
GARCH	0.896916	0.877529	-0.0198	-2.16% (-0.0216)
EGARCH	0.973789	0.975113	0.001324	0.1% (0.0013)
GJR-GARCH	0.900913	0.878792	-0.02212	-7.45% (-0.0745)
γ				
GARCH	-	-	-	
EGARCH	-0.06073	-0.06775	0.00702	11.56% (0.1156)
GJR-GARCH	0.066091	0.078221	0.01213	18.35% (0.1835)

The difference is obtained by subtracting the first period values from the second period values and the percentage is obtained by dividing the difference with the first period values

Table 8: Forecasting performance

	1 January 2008 to 1 July 2008			16 March 2010 to 16 September 2010		
Measurse	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
RMSE	0.014151	0.014127	0.014130	0.005721	0.005669	0.005678
MAE	0.008904	0.008891	0.00889	0.004303	0.004246	0.004250
MAPE	118.4306	110.5714	110.9470	177.2291	145.0511	146.8261
TIC	0.970571	0.979293	0.978818	0.933415	0.950361	0.951295

The best model for forecasting is determined by the highest values for RMSE, MAE, MAPE and lowest value for TIC

16 March 2010 to 16 September 2010. The common measures of forecast evaluation, i.e., Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean absolute Percentage Error (MAPE) and Theil Inequality Coefficient (TIC) are used. Results are presented in Table 8.

DISCUSSION

In Table 7, with regards to the symmetric GARCH model, the value of the beta which indicates the correlation between σ^2_t and σ^2_{t-1}, shows that the conditional variance has decreased by 2.16%, implying 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%. This is consistent with EGARCH and GJR-GARCH results of an increase of 21.8 and 34.4% in the rate of change of conditional variance respectively. However, since these two models are extensions of the simple GARCH model to be used to capture asymmetries effects mostly and some complications are added to them for this purpose, we will use them for this purpose solely. Thus, with respect to the GARCH model which has explicit and simple coefficients of lagged squared error and conditional variance, the volatility has increased by 24.5% while the persistency in volatility has just decreased by 2.16% during the crisis period.

The asymmetric (leverage effect) is examined by the nonlinear asymmetric models EGARCH and GJR-GARCH. The coefficient γ in the case of GJR-GARCH is significantly different from zero implying that both series are not symmetric. This was also shown in the descriptive analysis earlier, where the series exhibited negative skewness. The positive value of the parameter indicates the presence of leverage effect. In the case of EGARCH, the presence of the leverage effect can be detected by the hypothesis $\gamma<0$ whereas the impact is asymmetric if γ is not equal to zero. For both series, the parameter is significantly different from zero, indicating the presence of asymmetry and is also less than zero suggesting leverage effects.

For both series under consideration the asymmetry exists. Both nonlinear asymmetric EGARCH and GJR-GARCH produce the same results in terms of asymmetry and also leverage effects. These results are consistent with the findings of Shamiri and Abu Hassan (2007) and Haniff and Pok (2010) for the Malaysian market. The comparison between the two series' asymmetric parameters, show an increase in leverage effect in the market by 11.5 and 18.5% by EGARCH and GJR-GARCH respectively. Since the leverage effect refers to the characteristics of time series on asset prices that "bad news" tend to increase volatility more than "good news", it is expected that the crisis will increase the impact of the different kinds of news as the percentages in Table 5 suggest.

In Table 8, according to these measures and their criteria, the symmetric AR (4)-GARCH (1, 1) has outperformed both the EGARCH and GJR-GARCH models, indicating that the GARCH(1, 1) model is the most appropriate model for modelling the volatility of both series, despite the presence of asymmetry and leverage effect. However, Present findings are different from those of Shamiri and Abu Hassan (2007) who found that the GJR model best suits the Malaysian market and of Haniff and Pok (2010) who found that the EGARCH model produced consistently superior results compared to the other GARCH models.

CONCLUSION

This study examined different GARCH models to investigate and quantify the changes in volatility of the Malaysian stock market with respect to the global financial crisis 2007/2008. The KLCI was used as the main market indicator and the prices were transformed to log returns. Descriptive statistics showed that KLCI returns the presence of skewness in the series for both periods.

The unit root test was applied to check for stationarity and both series were found to be stationary. Conditional mean was then modelled using ARMA models and the AR (4) model was selected as the best model, which satisfied all criteria, had the lowest AIC as well as white noise residuals for both periods. Using the ARCH-LM test at different lags, we detected a high presence of ARCH effect in the residuals and evidence of a clustering effect. The GARCH models were estimated for both series using Quasi-Maximum likelihood assuming the Gaussian normal distribution. Different lags were examined for each model and the GARCH (1, 1), EGARCH (1, 1), GJR-GARCH (1, 1) were found to be the most successful models, in line with previous literature. Rechecking using the ARCH-LM test then showed no presence of ARCH effect. Standardized residuals and Standardized residuals squared were found to be white noise.

AR (4)/GARCH (1, 1), AR (4)/EGARCH (1, 1) and AR (4)/GJR-GARCH (1, 1) were the final models to describe the process. Both asymmetric models produced the same results for both series which were found to be asymmetric and also suggested leverage effect. A comparison of the models for both series revealed significant increases in volatility and the presence of leverage effect with just a small drop in persistency due to the global financial crisis.

With respect to the simple GARCH (1,1) model which has explicit and simple coefficients of lagged squared error and conditional variance, the volatility has increased by 24.5% and at the persistency in volatility has just decreased by 2.16% during the crisis period. Asymmetric GARCH models, which are extensions of the simple GARCH model to capture asymmetries, are used for interpretation of the asymmetric effect. A comparison of the two series' asymmetric parameters, show an increase in leverage effect in the market by 11.5% and 18.5% using EGARCH and GJR-GARCH, respectively. Since the leverage effect refers to the characteristics of time series on asset prices that "bad news" tend to increase volatility more than "good new", it is expected that the occurrence of the crisis will increase this impact significantly.

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