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ESTIMATION AND MODELLING OF VOLATILITY IN THE MALAYSIAN STOCK MARKET

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ABSTRACT

Last three decades, the issues on the volatility of the stock market have attracted many researchers, academics and also the players in the financial market. In the stock market investors and researchers able to use the stock market index to measure the volatility. Volatility considered as the measurement for the uncertainty of fluctuation of stock price and measurement of risk. This paper intends to shed light the volatility behaviour via the persistency and leverage effect in the Malaysian stock market. The data of this paper starting from 2000 until 2018 and employ symmetric and asymmetric volatility model with a different distribution. The symmetric model can capture via Generalized Autoregressive Conditional Heteroscedasticity (GARCH) while asymmetric shock using Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) and Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH). The GARCH model showed weekly data of FTSE BM KLCI, FTSE BM Top100, FTSE BM Mid70 and FTSE BM Small presence of volatility clustering and persistence effect on the stock market volatility. Besides, asymmetric models found that weekly data, only several indices found the leverage effect. The best fit model also provided in the results and discussion.

INTRODUCTION

The stock market is essential to all players involved in investment activities. It is always associated with the volatility exposure, which is sensitive towards the market players on every dollar invested. Therefore, the higher volatility means that price change dramatically over a short period in either direction. A market with high volatility characterizes by wide price fluctuations and heavy trading. It portrays that when the market was volatile, the risk on the particular market will be higher. Besides, investors can use the stock market index to measure the volatility in the stock market. Baillie (1997) has mentioned that "volatility is a measurement of the intensity of unpredictable changes in asset return, and it is commonly time-varying dependent".

A theoretical and empirical analysis of stock market volatility is a niche area of research in finance which has been continuously investigated over the last few decades since in the 1980s. Volatility research in the stock market concerned about the modelling of volatility behaviour in the stock market and the application of the volatility behaviour in portfolio risk management. Therefore, theoretical research is concerned about the development of volatility theory and model that explains the theoretical foundation of asset volatility in a marketplace. In empirical research, attention is devoted to verifying the validity of volatility theory and models in the stock market applications. In investment practice, volatility is as a determinants factor to estimate the real value or intrinsic value of the stock and inducing the variation of stock prices through changes in investors' expectations due to the flow of information in the financial markets (Emenike, 2010; Mamtha & Srinivasan, 2016; Ross, 1989). Also, volatility is considered as a critical variable for assessing the condition of the stock market (Panait & Slăvescu, 2012). Hence, it is essential to comprehend the behaviour of the Malaysian stock market returns volatility.

In regard to this paper, it tries to shed light the symmetry and asymmetry volatility behaviour in Malaysian stock market and use weekly data from different indices which are FTSE BM KLCI, FTSE BM Top100, FTSE BM Mid70 and FTSE Small. The purpose of this study is to examine the persistency and leverage effect in Malaysian stock return and best fit model for all the series return. The paper employs GARCH, EGARCH and TGARCH with normal and non-normal distribution which are student-t and generalized error distribution (GED).

LITERATURE REVIEW

In finance research, growing global empirical evidence on symmetries and asymmetries modelling have been documented in finance literature since the volatility modelling seminal article by Engle's (1982) which provide the theoretical foundation and model for volatility measurements. Volatility research started from Engle (1982) introduced autoregressive conditional Heteroscedasticity (ARCH), model. (1986) had extended the model into generalized autoregressive conditional Heteroscedasticity (GARCH) model by modelling the conditional variance to depend on its lagged value as well as squared lagged values of disturbance. From this point, various GARCH family models such as Exponential GARCH, Threshold GARCH models performed to capture the volatility behaviour in the stock market and deals with the asymmetric information. Furthermore, it is closely associated with the financial times series data and the number of salient features of volatility behaviour that exhibit the phenomenon of volatility persistency, mean reversion, volatility clustering, and leverage effect. The volatility model validation tested in various factors such as different data frequencies, indices, countries and markets in order to capture both symmetric and asymmetric volatility (Abdalla & Winker, 2012; Dana, 2016; Caiado, 2004; Floros, 2008; Frimpong & Oteng-Abayie, 2006; Mamoon, 2007; Panait &

Slăvescu, 2012; Parvaresh & Bavaghar, 2014; Rafique & Kashif-Ur-Rehman, 2011; Selçuk, 2005). Extension of volatility modelling with non-normal distribution has been discussed in a research paper by Emenike (2010). The paper highlight several studies about the non-normal distribution using student-t and GED. The finding suggested that GARCH model fails to capture economic phenomenon due to the presence of leptokurtic and fat-tail distribution. Bollerslev (1987) proposed to use a student-t distribution assumption for the ARCH or GARCH model with a conditional normal error. However, capturing the leptokurtosis and combination of student-t fully for financial asset returns tend to have fatter tails than the Gaussian distribution.

In Malaysian review, several studies had been conducted that associate with the symmetric and asymmetric volatility, which Har, Sundaram, and Ong (2008). The researchers aim to estimate the leverage effect of the Malaysian Stock Market using EGARCH and to investigate the efficiency in the Malaysian Stock Market using Augmented Dickey-Fuller (ADF). They used weekly closing prices for Malaysian Stock Market indices starting from 9 January 2004 until 8 June 2007. The outcome shows that the EGARCH model did not confirm the existence of the leverage effect. In the same vein, Omar and Halim (2015) investigated the behaviour of stock return volatility of FTSE Bursa Malaysia KLCI and the data starting from January 2002 until December 2011. The researcher employed three of the family of GARCH and GARCH (1,1) showed that the presence of volatility clustering and persistence effects. Moreover, TGARCH and EGARCH found the leverage effects in data series.

From the brief review of literature above, volatility modelling seminal article by Engle (1982) gives more impact in volatility area until there are a vast number of articles validate that GARCH model able to capture symmetric volatility. However, most of the researchers criticize that GARCH model unable to capture asymmetric volatility. As a consequence, the asymmetric model such as EGARCH and TGARCH developed to capture the asymmetric behaviour and non-normal distribution. Also, capturing the fully leptokurtic and fat-tail distribution. This paper extends the existing literature review on modelling stock returns volatility in the Malaysian Stock Market by using recent data and compare volatility modelling with non-normal distribution to portray volatility behaviour.

RESEARCH METHODOLOGY

This paper involved the weekly data stock price of FTSE BM KLCI, FTSE BM Top100, FTSE BM Mid70 and FTSE BM Small starting from January 2000 until December 2018. In volatility research, long span of data is needed to capture both calm and deterioration of the market condition. Therefore, the range of data used in this study includes the event of the global financial crisis in 2007 until the first quarter of 2009 (Angabini & Wasiuzzaman, 2011). According to Abdalla and Winker (2012), the definition of volatility is the variance of stock returns. Hence, the data has been transformed into a stock return by using logarithmic transformation. The equation is shown below:

$$r_t = \log\left(\frac{p_t}{p_{t-1}}\right)$$

Implementation Steps

This examination was performed using the five-step procedure that has been highlighted as follow.

Step 1: Data collection and calculate the return as at the equation above. The data was collected from Thomson Reuters. Then calculate the return series for each index.
Step 2: Descriptive analysis of the return series.

Step 3: Unit root test by using the Augmented Dickey-Fuller test (ADF) and diagnostic test (Heteroscedasticity/ARCH Effect) the return series.

Step 4: Model-identification and parameter estimation. All the return series estimate by using symmetry and asymmetry volatility model with normal and non-normal distribution.

Step 5: Model Evaluation. The models from the index return were evaluated with two performance measurements to find out which best fit model for return series.

Method of the Study

General Autoregressive Conditional Heteroscedasticity (GARCH) Model

GARCH model was introduced by Bollerslev (1986), which is the GARCH model extended of the ARCH model created by Engle (1986). In general, the GARCH (1,1) model is presented in the following formula:

Mean equation $r_t = \mu + \varepsilon_t$

Variance equation $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

Where $\omega > 0, \alpha_1 \geq 0$ and $\beta_1 \geq 0$, and:

r_t = return of the asset at time t,

μ = average return,

ε_t = residual return, defined as: $\varepsilon_t = \sigma_t z_t$

Where,

σ_t= the conditional variance

z_t = standardized residual returns

Exponential General Autoregressive Conditional Heteroscedasticity (EGARCH) Model

EGARCH model was developed by Nelson (1991), which is the model has been used for leverage effect, and it also to allow asymmetric responses of the time-varying to shock. The indicator of leverage effect (asymmetric) is the value of gamma () and must be both negative and significant. The EGARCH model can be expressed as follow:

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

Threshold General Autoregressive Conditional Heteroscedasticity (TGARCH) model

According to Gokbulut and Pekkaya (2014), TGARCH is similar to GRJ in using dummy variables but using standard deviations instead of variance. Prior TGARCH model, TARCH model is developed to deal with conditional standard deviations. Therefore, (Zakoian, 1994) extend the model into a TGARCH model to identify the leverage effect. The model can be shown below:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \tau d_{t-1} \varepsilon_{t-1}^2$$

$$d_{t-1} = 1, \text{ if } \varepsilon_{t-1}^2 < 0 \text{ (bad news)}$$

$$= 0, \text{ if } \varepsilon_{t-1}^2 \geq 0 \text{ (good news)}$$

The Normal Distribution (Gaussian):

In the original paper of Engle (1982), the standard normal distribution is expressed below:

$$f(z_t) = \frac{1}{\sqrt{2\pi}} e^{\frac{z_t^2}{2}}$$

The Student-t Distribution:

The student-t distribution proposed by Bollerslev (1986):

$$f(z_t, t) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{\pi(v-2)}} \left(1 + \frac{z_t^2}{v-2}\right)^{-\frac{v+1}{2}}$$

Generalized Error Distribution (GED):

$$f(x) = \frac{\lambda . s}{2.\Gamma\left(\frac{1}{s}\right)} . \exp\left(-\lambda^s . |x - \mu|^s\right)$$

RESULT AND DISCUSSION

Descriptive Analysis

The weekly price and returns for FTSE BM KLCI, FTSE BM TOP100, FTSE BM Mid 70 and FTSE BM SMALL are presented in Figure 1. As shown in Figure 1, all the price indices influenced by external or internal factors such as political, economics, government, the performance of the company, and investors. Based on observation from the graph, it showed that the massive changes of return series move in tandem and vice versa for small changes. It implies that the variance change over time and confirming the existence of volatility clustering for all the series.

Based on Table 1, it shows the statistic for FTSE BM KLCI, FTSE BM TOP100, FTSE BM Mid 70 and FTSE BM SMALL return series. The figure shows that the mean return for all series is positive, which ranging from minimum 0.12390 (FTSE BM KLCI) to a maximum 6.939344 (FTSE BM Mid 70). Moreover, the standard deviation reflected the risk and return, which indicate that a significant positive relationship whereby high risk and high return, vice versa. The highest standard deviation is 305.4926 (FTSE BM SMALL) and the least volatile series with a standard deviation of FTSE BM KLCI 3.325303. Also, all the series shows negative skewness which indicates that an extended left tail distribution and the result for the kurtosis are higher than the standard normal distribution which implies the data has leptokurtic and sharply peaked distribution. Jarque-Bera statistic has rejected the null hypothesis of the normal distribution.

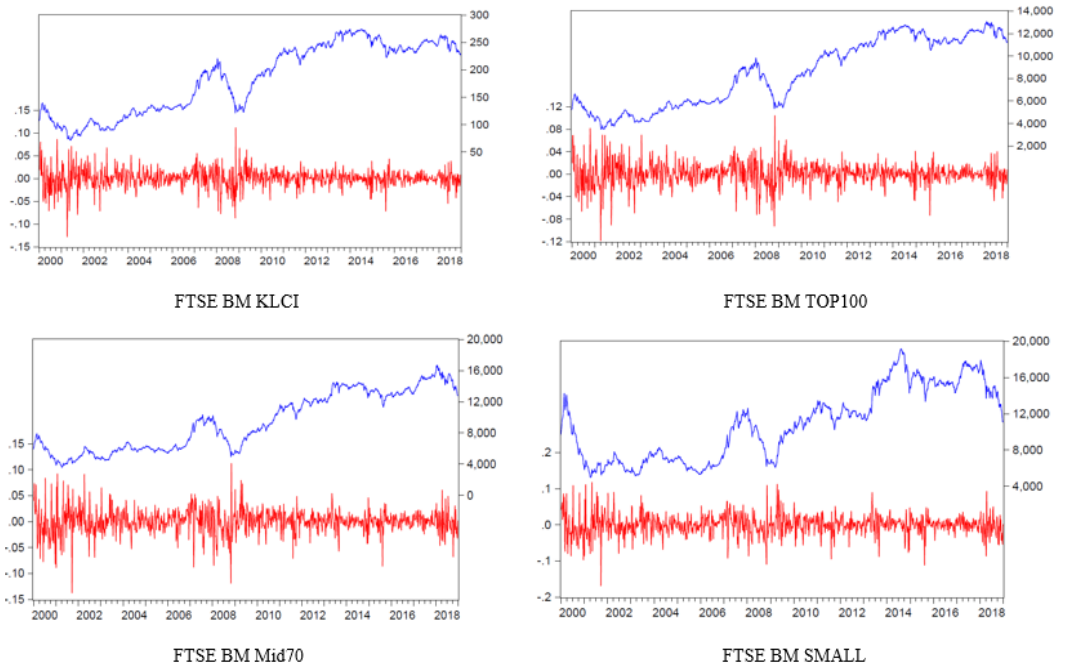

Figure 1 Weekly Price and Return of FTSE BM KLCI, FTSE BM TOP100, FTSE BM Mid70 and FTSE BM SMALL

Table 1 Descriptive statistics for the return series of FTSE BM KLCI, FTSE BM TOP100, FTSE BM Mid 70 and FTSE BM SMALL

Data series	FTSE BM KLCI	FTSE BM TOP100	FTSE BM Mid 70	FTSE BM SMALL
Mean	0.123290	6.109788	6.939344	1.405106
Median	0.250000	13.18000	16.80000	12.55000
Maximum	14.32000	584.0900	931.1100	1329.400
Minimum	−16.84000	−815.3400	−1049.820	−1676.750
Std. Dev.	3.325303	151.2555	201.3128	305.4926
Skewness	−0.497986	−0.525490	−0.490127	−0.402923
Kurtosis	5.724791	5.743930	6.109662	6.328848
Jarque-Bera	347.5290***	356.5002***	438.9675***	484.3767
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. of observation	991	991	991	991

Note: The values in parentheses are the actual probability values *, **, *** indicate rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% level respectively.

The unit root test has been performed by using Augmented Dickey-Fuller to test the stationary of data (Table 2). All the return series of FTSE BM KLCI, FTSE BM TOP100, FTSE BM Mid 70 and FTSE BM SMALL has rejected the null hypothesis at the 1% significance at the level. It implies that all the series shows no unit root and the series was stationary.

Table 2 Results of returns series using the Augmented Dickey-Fuller test

Data Series	Level
	Weekly
FTSE BM KLCI	−28.86813***
FTSE BM Top100	−28.61837***
FTSE BM Mid70	−28.44731***
FTSE BM small	−27.86974***
Critical values	−3.967345
	−3.414359
	−3.129305
No. of observation	990

Note: The values in parentheses are the actual probability values *, **, *** indicate rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% level respectively.

Based on Table 3, the result of autocorrelation test is based on correlogram *Q*-statistic (Ljung Box test) whereby, the test showed that strong evidence whereby most of the return series fail to reject the null hypothesis which indicates there is no serial correlation in the series. Furthermore, all the series have rejected the null hypothesis for ARCH effect or heteroscedasticity problem except for ARCH (10) on the FTSE BM Mid 70 and FTSE BM SMALL. However, the series still have the ARCH effect/ heteroscedasticity problem.

Table 3 Result of autocorrelation using Correlogram *Q*-statistic and ARCH effect/ heteroscedasticity

Data Series	FTSE BM KLCI	FTSE BM Top100	FTSE BM Mid70	FTSE BM Small
$\tilde{a}_t$, Q(10)	15.115	13.993	7.0792	8.6619
	(0.088)	(0.123)	(0.629)	(0.469)
$\tilde{a}_t^2, Q(10)$	162.54***	160.37***	103.19***	93.489***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH (1)	0.172703***	0.186458***	0.151412***	0.131983***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH (10)	0.104793***	0.101187***	0.021862	−0.006751
	(0.000)	(0.001)	(0.4908)	(0.8319)

Based on Table 4, α and β are the indicators for the GARCH model to capture the symmetric volatility. The results show that both α and β from all the return series were significant. Therefore, it means the lagged conditional variance and lagged squared disturbance influences the conditional variance. In other terms, the news on previous volatility has an impact on the current volatility (& Halim, 2015). Furthermore, the sum of the two estimated α and β coefficients is to measure the persistency of the volatility. Besides, the most persistence is very close to one, which indicates that volatility shocks have a persistent effect on the conditional variance.

Moreover, in order to capture asymmetric volatility, this paper employed the EGARCH and TGARCH model with normal and non-normal distribution. Based on estimation from EGARCH model, it shows the return for all indices presence of leverage effect except for FTSE BM Mid70 (student-t and GED distribution) while FTSE BM SMALL all EGARCH model normal and non-normal also does not exist leverage effect. Indicator for EGARCH model is from the coefficient whereby if the coefficient statistically significance this indicates that negative shock (bad news) more effect on the conditional variance (volatility) as compared to positive shock (good news) of the same magnitude. Moreover, the asymmetric (leverage) effect captured by the gamma (γ) and the coefficient statistically significance with negative sign must be correlated which indicate that previous negative shock more impact rather than previous positive shock towards the next period of conditional variance. While the TGARCH model is different as compared to the EGARCH model due to the coefficient whereby TGARCH model follows the positive condition, not the negative sign. The rules of thumb for this model based on positive coefficient and statistically significance. The result implies that only FTSE BM KLCI and FTSE BM Top100 shows the presence of leverage effect for TGARCH normal and non-normal distribution while for the rest does not show the existence of leverage effect.

Table 4 Result of GARCH, EGARCH and TGARCH

Data Weekly		GARCH				EGARCH			TGARCH		
		Normal	Student-t	GED		Normal	Student-t	GED	Normal	Student-t	GED
FTSE BM KLCI	α	0.085670***	0.097157***	0.088869***	γ	−0.059578***	−0.08427***	−0.057905***	0.060453***	0.059484*	0.059840**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.053)	(0.043)
	β	0.906336***	0.895799***	0.901298***							
		(0.000)	(0.000)	(0.000)							
	$\alpha+\beta$										
TSE BM TOP100	α	0.104129***	0.111743***	0.104501***	γ	−0.060761***	−0.066904***	−0.063180***	0.068019***	0.070071	0.068371**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.004)	(0.004)	(0.000)	(0.042)	(0.036)
	β	0.891012***	0.882354***	0.888543***							
		(0.000)	(0.000)	(0.000)							
	$\alpha+\beta$										
TSE BM Mid70	α	0.095647***	0.166119***	0.121511***	γ	−0.027470***	−0.045501	−0.030560	0.017911	0.062608	0.020697
		(0.000)	(0.000)	(0.000)		(0.018)	(0.099)	(0.1824)	(0.3347)	(0.2299)	(0.5737)
	β	0.895710***	0.823783***	0.865905***							
		(0.000)	(0.000)	(0.000)							
	$\alpha+\beta$										
TSE BM SMALL	α	0.103555***	0.249285***	0.175601***	γ	−0.017773	−0.006826	−0.006927	−0.005073	0.003367	−0.016174
		(0.000)	(0.000)	(0.000)		(0.1663)	(0.8453)	(0.8204)	(0.8217)	(0.9634)	(0.7762)
	β	0.869383***	0.727063***	0.783890***							
		(0.000)	(0.000)	(0.000)							
	$\alpha+\beta$										
FTSE BM KLCI	AIC	−5.196691	−5.263313	−5.263015		−5.202255	−5.261131	−5.262948	−5.202519	−5.265047	−5.265423
	SC	5.171975	−5.233653	−5.233356		−5.172516	−5.226529	−5.228345	−5.172860	−5.230445	−5.230821
TSE BM TOP100	AIC	−5.217577	−5.276560	−5.273821		−5.229963	−5.279830	−5.279116	−5.222907	−5.278572	−5.276350
	SC	−5.192861	−5.246901	−5.244161		−5.200303	−5.245228	−5.244514	−5.193248	−5.243969	−5.241747
TSE BM Mid70	AIC	−4.864688	−4.936894	−4.929804		−4.869746	−4.940672	−4.932588	−4.863317	−4.936218	−4.928125
	SC	−4.839972	−4.907235	−4.900144		−4.840087	−4.927515	−4.897986	−4.833658	−4.901616	−4.893522
TSE BM SMALL	AIC	−4.400517	−4.496397	−4.487760		−4.392752	−4.490719	−4.481572	−4.398540	−4.494381	−4.485848
	SC	−4.375801	−4.466738	−4.458100		−4.363093	−4.456117	−4.446969	−4.387263	−4.459779	−4.472691

Note: The values in parentheses are the actual probability values *, **, *** indicate rejection of the null hypothesis of associated statistical tests at the 10%, 5% and 1% level respectively.

Model Evaluation

Model evaluation discussion is to determine which model is preferred; there are two criteria value will consider in this research which is Akaike info criterion (AIC) and Schwarz criterion. The rules of thumb for both criteria to choose the lower values to form the appropriate modelling. Table 5 shows a suitable model for symmetry volatility model and asymmetry volatility model:

Table 5 Result of Best fit model for each return series

Data series	Symmetry	Asymmetry
FTSE BM KLCI	GARCH student-t	TGARCH GED
FTSE BM Top100	GARCH student-t	EGARCH student-t
FTSE BM Mid70	GARCH student-t	EGARCH student-t
FTSE BM Small	GARCH student-t	TGARCH student-t

CONCLUSION AND RECOMMENDATION

This paper to examine the symmetry and asymmetry volatility behaviour in Malaysian stock market by using weekly data frequency. The selected symmetry and asymmetry volatility model are GARCH, EGARCH and TGARCH with normal and non-normal distribution. Then, to determine which model is preferred for FTSE BM KLCI, FTSE BM Top100, FTSE BM Mid70 and FTSE BM Small based on AIC and SC.

Based on the result, most of the GARCH model with normal & non-normal shows the α+β almost close to the one for FTSE BM KLCI, FTSE BM Top100, FTSE BM Mid70 and FTSE BM SMALL. It indicates that volatility shock has a persistent effect on the conditional variance in Malaysian stock market whereby this can be justified from the graph in Figure 1 above portray the volatility clustering exists in the all return series. In term of asymmetric volatility, most of the EGARCH and TGARCH model shows the presence of leverage effect except for FTSE BM Mid70 and FTSE BM SMALL which also supported by Ezzat (2012) who found the presence of leverage effect in the Egyptian stock market. The negative shock in the Malaysian stock market expresses more effectively on the volatility as compared to positive news. In other words, investors or traders in the Malaysian stock market more react to bad news very quickly as compared to the positive news. Finally, the four series returns suggest that a GARCH family with non-normal distributions are an appropriate model to estimate the volatility of the Malaysian stock market due to exhibit a very strong indication of fat-tail and leptokurtosis as shown in the descriptive statistics.

The current study may improve the literature by incorporating several improvements for future research. Firstly, the researcher can expand the analysis by using daily data by including a few crises period experienced by Malaysia to capture more news through the high-frequency data. Thus, it can portray a clear view on the volatility behaviour. Finally, the researcher can use 14 Malaysian sectorial indices to identify which sector shows the presence of leverage effect.

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