The impact of derivatives on Malaysian stock market

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Abstract. The essential of derivatives has been discovered by researchers over recent decade. However, the conclusions made regarding the impact of derivatives on stock market volatility remains debatable. The main objective of this study is to examine the impact of derivatives on Malaysian stock market volatility by exploring FTSE Bursa Malaysia Kuala Lumpur Composite Index Futures (BMD FKLI) using FBM KLCI as the underlying asset. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (1, 1) model was employed to realize the objective. The results have shown that the introduction of futures trading has decreased the volatility of Malaysian stock market. The volatility increased vigorously during the Asian financial crisis compared to the Global financial crisis. However, the role of futures as a risk transfer is agreed as it could improve the market by decreasing the volatility in the spot market.

1. Introduction

Derivatives are financial instruments that derive their values from the underlying assets (stock, commodity, currency, index, bond and equity). Futures and options are the two common derivatives [1]. Stock market very related to volatility; it is the measure of uncertainty regarding the returns specified by the stock. In a clearer definition, volatility is the variation of an asset’s return from the asset’s mean. The higher the volatility, the higher the returns of stock but this also stipulates increasing risk. Volatility tends to average near 15%; the average used in many models for stock market volatility [2]. Higher volatility means the price of the stock can change drastically over a short term. Hence, it is vital to avoid a highly volatile market with negative returns as it will affect the stock market.

The financial crises may also be the causes of the fluctuations of stock market volatility. Beginning in July 1994, Asian Financial Crisis had caused market disturbances in many countries especially the East Asia. However, the worst crisis was the Global Financial Crisis (July 2007). The liquidity crisis started when there was a loss of confidence by United States investors regarding the value of sub-prime mortgages, and it became even worse by September 2008 where the volatility of stock markets all over the world experienced in serious inclination.

Stock market futures are one of the most vital instruments for the efficiency of hedging systemic risk in equity markets. Since stock market futures play major role in hedging and price discovery as well as asset allocation, they eventually contribute to the excellence of the market. However, the impact of futures trading on stock market volatility remains debatable. The question “does the establishment of futures actually increase or decrease the volatility of the underlying assets” is still pending since the empirical findings regarding this matter resulted in a mixed outcome. Therefore, this study extends the literature by testing the hypotheses on Malaysian perspective.

There are many studies on the impact of the introduction of futures trading towards the volatility of the stock markets, and the findings can be clustered into three groups of conclusions; declining of stock
market volatility [3, 4, 5], increasing of stock market volatility [6, 7, 8], and no difference in stock market volatility [9, 10, 11, 12]. This study explores the FTSE Bursa Malaysia Kuala Lumpur Composite Index Futures (BMD FKLI) using the FBM KLCI as the underlying asset. Financial crises are also taken into consideration. The main objective is to examine the impact of the introduction of futures trading on Malaysian stock market volatility.

2. Methodology

2.1. Data description
The FBM KLCI data are employed in this study together with the futures, BMD FKLI. A dummy variable is applied to indicate the Asian Financial Crisis (July 1997 to December 1998) and the Global Financial Crisis (August 2007 to January 2009). All spot price data were extracted from January 1991 to January 2015 while futures prices of BMD FKLI were extracted from December 1995 to January 2015 (since it was only introduced in December 1995).

2.2. Data analysis
Empirical methods are applied on Malaysian FBM KLCI and BMD FKLI data to examine the impact of futures trading on the volatility of Malaysian stock market using GARCH (1, 1) model. EViews 7 software is used to compute the empirical results.

2.2.1. Data cleaning and calculation of returns. Firstly, the data are cleaned and each missing value is filled with the day before closing price. This is essential to ensure a continuous data which is necessary for a GARCH model. Next, the returns are calculated using the following formula:

\[ R_t = \ln \left( \frac{P_t}{P_{t-1}} \right) \times 100 \]  

where \( P_t \) is the value of price index at the end of period \( t \).

2.2.2. Generalized autoregressive conditional heteroskedasticity (GARCH) (1, 1) model. The GARCH model is a variant of ARCH that allows for infinite lags, yet can be estimated with a small number of parameters. The GARCH (1, 1) model is as follows:

\[ \sigma_n^2 = (1 - \alpha - \beta) V_n + \alpha \mu_{n-1}^2 + \beta \sigma_{n-1}^2 \]  

where \( \mu_{n-1} \) is continuously compounded expected return; \( V_n \) is the long-run average variance; \((1 - \alpha - \beta)\), \( \alpha \) and \( \beta \) are the weightages for \( V_n \), \( \mu_{n-1}^2 \) and \( \sigma_{n-1}^2 \), respectively; and let \( \omega = (1 - \alpha - \beta) V_L \).

This process requires \( \alpha + \beta < 1 \) to gain a stable GARCH (1, 1). Using EViews 7, the volatility of FBM KLCI returns is estimated by GARCH (1, 1) model; i.e., one ARCH term and one GARCH term. However, higher order of GARCH such as GARCH (2, 3) and so on can also be applied, but many researchers prefer GARCH (1, 1) model as it produces better results [10]. A GARCH model is composed of mean equation and variance equation as in equations 3 and 4, respectively.

\[ KLCI(1991-2015) = C_1 + \varepsilon \]  

where \( C_1 \) is a constant and \( \varepsilon \) is the residual. \( KLCI(1991-2015) \) is later changed into five periods of five years: KLCI(1991-1995); KLCI(1996-2000); KLCI(2001-2005); KLCI (2006-2010); KLCI (2011-2015). The residuals derived from the mean equation are then plotted and analyzed.

\[ H_t = C_2 + C_3 \varepsilon_{t-1}^2 + C_4 H_{t-1} + C_5 FKLI + C_6 CRISIS \]
The residuals derived from mean equation are used in variance equation, where \( H_t \) is the variance of the residuals (volatility of price index); \( C_2 \) is a constant; \( \varepsilon_{t-1}^2 \) is the previous period’s squared residual (ARCH term); \( H_{t-1} \) is the previous period’s variance (GARCH term); \( FKLI \) is the Malaysian futures index; and \( CRISIS \) is a dummy variable for financial crisis. The conditional variance can be calculated using the following formula [19]:

\[
\sigma^2_t = \frac{\alpha_0}{1 - \alpha - \beta}; \quad \alpha \text{ is the ARCH term and } \beta \text{ is the GARCH term.}
\]

2.2.3 Model selection. Three types of distributions are considered; Normal Gaussian Distribution, Student’s t with fixed \( df \), and Generalized Error Distribution Assumption. To choose the best model, the following assumptions must be fulfilled by each distribution:

1. Correlogram square residual (\( Q \) test can be performed):
   - \( H_0 \): There is no serial correlation in the residuals.
   - \( H_1 \): There is serial correlation in the residuals.

2. Normality (Jarque-Bera Statistic will be used):
   - \( H_0 \): Residuals are normally distributed.
   - \( H_1 \): Residuals are not normally distributed.

3. ARCH Effects (ARCH Test will be used):
   - \( H_0 \): There is no ARCH effect. \( H_1 \): There is ARCH effect.

The best model is the model that satisfies all null hypotheses; i.e., no serial correlation, residual are normally distributed and no ARCH effect. From the best model, the conditional variances (volatilities) can be obtained.

To test for serial correlation in the residuals, \( Q \)-statistic [13] is applied:

\[
Q = n \sum_{k=1}^{m} \hat{\rho}_k^2,
\]

where \( n \) is the sample size, \( m \) is the lag length, and \( \hat{\rho}_k \) is the sample autocorrelation at lag \( k \). \( Q \)-statistic is usually used to detect whether the series has white noises. In a large sample, \( Q \)-statistic is approximately distributed as a chi-square distribution with \( m \) degrees of freedom. If the calculated value is larger than the critical value, the null hypothesis is rejected.

To test for normality of the residuals, Jarque-Bera test is used [14]. It is the most reliable test to identify the relative skewness and kurtosis, as follows:

\[
JB = \frac{1}{6}(S^2 + \frac{1}{4}(K - 3)^2)
\]

where \( n \) indicates the number of observations (degrees of freedom), \( S \) represents the series skewness, and \( K \) explains the series kurtosis. \( S \) and \( K \) are defined as follows:

\[
S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^3}{\left(\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2\right)^{3/2}}, \quad K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^4}{\left(\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2\right)^2};
\]

where \( \hat{\mu}_3 \) and \( \hat{\mu}_4 \) are the estimates of third and fourth central moments, \( \bar{x} \) is the sample mean and \( \hat{\sigma}^2 \) is the estimate of the variance. If the Jarque-Bera statistic asymptotically has a chi-squared distribution with 2 degrees of freedom, then the series comes from a normal distribution. If the statistic is less than the critical value, then \( H_0 \) is accepted (i.e., the variables are not significantly different from normal); if the value is greater than the critical value, \( H_0 \) is rejected (i.e., the variables are significantly different from normal).

ARCH-Lagragian Multiplier (ARCH-LM) was introduced by Engle [15] to detect Autoregressive ARCH effects. A time series that shows conditional heteroscedasticity may have such effect.
\[ \hat{u}_t = \alpha_1 + \alpha_2 X_t + \alpha_3 X_t^2 + \alpha_4 X_t^3 + v_t \]  

(8)

where \( v_t \) is an error term. A sample size \((n)\) times \( R^2 \) (estimated from equation 8) follows a chi-square distribution. If the chi-square value is more than the critical value, \( H_0 \) is rejected and conclude that there is ARCH effect.

3. Data analysis and results

3.1. Residuals of FBM KLCI returns

Figure 1 shows the residual plot of FBM KLCI returns. There is a prolonged period of high volatility from 1991 to 1998 and a prolonged period of low volatility from 1999 to 2006. There is a high fluctuation from 2007 to 2009 and a prolonged period of low volatility from 2010 to 2015. Hence, this suggests that the residual term is conditionally heteroscedastic and it can be represented by ARCH and GARCH models. Next, the returns are subdivided into five periods and the residuals are analyzed.

![Figure 1. Residual plot of FBM KLCI returns.](image)

3.2. Summary statistics

All results are obtained using EViews 7. In order to determine a suitable model for the data, several tests need to be conducted and their underlying assumptions must be verified empirically. Table 1 summarizes the statistics for FBM KLCI and BMD FKLI for the whole period 1991-2015.

|                        | FBM KLCI (1991-2015) | BMD FKLI      |
|------------------------|----------------------|---------------|
| Mean                   | 0.013225             | 0.005699      |
| Median                 | 0.000000             | 0.000000      |
| Skewness               | 0.528182             | -1.452609     |
| Kurtosis               | 80.58897             | 161.8381      |
| Jarque-Bera            | 2290802              | 9602004       |
| Probability            | 0.000000             | 0.000000      |
| Observations           | 9131                 | 9131          |

The mean values of FBM KLCI and BMD FKLI for the period 1991-2015 are 0.013225 and 0.005699, respectively. The statistics conclude that the variables are not perfectly normally distributed, but close to a normal distribution as the medians are close to the means. FBM KLCI skewness is 0.528182, kurtosis is 80.58897 and Jarque-Bera is 2290802; BMD FKLI skewness is -1.452609, kurtosis is 161.8381 and Jarque-Bera is 9602004. Hence, FBM KLCI (1991-2015) is skewed in a positive direction, while BMD FKLI is skewed in a negative direction.
The return series of FBM KLCI is then divided into five periods of five years for comparison and analysis. FBM KLCI (1991-2015) is divided into pre- and post-futures periods. The pre-futures period is 1991-1995 while the post-futures period is 1996-2015. The post-futures period is further divided into four periods of five years. The summary statistics for the five periods are shown in table 2.

### Table 2. Summary statistics for FBM KLCI returns in five periods of five years.

| Statistics | (1991-1995) | (1996-2000) | (2001-2005) | (2006-2010) | (2011-2015) |
|------------|-------------|-------------|-------------|-------------|-------------|
| Mean       | 0.037050    | -0.020873   | 0.015367    | 0.028383    | 0.005927    |
| Median     | 0.000000    | 0.000000    | 0.000000    | 0.000000    | 0.000000    |
| Skewness   | 0.193965    | 0.664151    | -0.688533   | -1.574591   | -0.316581   |
| Kurtosis   | 14.75267    | 42.48862    | 15.51856    | 24.33445    | 8.448390    |
| Jarque-Bera| 10520.48    | 118839.9    | 12067.62    | 35384.53    | 2289.032    |
| Probability| 0.000000    | 0.000000    | 0.000000    | 0.000000    | 0.000000    |
| Observations | 1826    | 1827        | 1826        | 1826        | 1826        |

The means of FBM KLCI for the five periods are 0.037050, -0.020873, 0.015367, 0.028383 and 0.005927, respectively. Hence, the variables are not perfectly normally distributed, but close to a normal distribution as the medians are close to the means (i.e., the data are not normally distributed). The values show how likely the random variables of the underlying dataset to be normally distributed. The skewness, kurtosis, Jarque-Bera and probability values conclude that KLCI (1991-1995) and KLCI (1996-2000) variables are skewed in a positive direction. Meanwhile, KLCI (2001-2005), KLCI (2006-2010) and KLCI (2011-2015) are skewed in a negative direction.

### Table 3. Model selection.

| Model               | Distribution | Serial Correlation | ARCH effect | Normality |
|---------------------|--------------|--------------------|-------------|-----------|
| KLCI (1991-2015)    | Normal       | More than 0.05*    | 0.3912*     | 0.0000    |
|                     | Student t    | More than 0.05*    | 0.0439      | 0.0000    |
|                     | GED          | More than 0.05*    | 0.0399      | 0.0000    |
| KLCI (1991-1995)    | Normal       | More than 0.05*    | 0.4057*     | 0.0000    |
|                     | Student t    | 0.0000             | 0.0000      | 0.0000    |
|                     | GED          | 0.0000             | 0.0000      | 0.0000    |
| KLCI (1996-2000)    | Normal       | More than 0.05*    | 0.9760*     | 0.0000    |
|                     | Student t    | More than 0.05*    | 0.0489      | 0.0000    |
|                     | GED          | More than 0.05*    | 0.0329      | 0.0000    |
| KLCI (2001-2005)    | Normal       | More than 0.05*    | 0.9438*     | 0.0000    |
|                     | Student t    | 0.0000             | 0.0149      | 0.0000    |
|                     | GED          | More than 0.05*    | 0.0000      | 0.0000    |
| KLCI (2006-2010)    | Normal       | More than 0.05*    | 0.5243*     | 0.0000    |
|                     | Student t    | More than 0.05*    | 0.0308      | 0.0000    |
|                     | GED          | More than 0.05*    | 0.0176      | 0.0000    |
| KLCI (2011-2015)    | Normal       | More than 0.05*    | 0.074*      | 0.0000    |
|                     | Student t    | More than 0.05*    | 0.0285      | 0.0000    |
|                     | GED          | More than 0.05*    | 0.0184      | 0.0000    |

* Note: * indicate that according to p-value, the null hypothesis is accepted.
For each model, there is no serial correlation in normal distribution since the p-value is higher than 5%. In heteroskedasticity test (ARCH effect) for each model, only normal distribution has a p-value higher than 5%; hence, there is no ARCH effect. Finally, in normality test for each model, all residuals are not normally distributed since the p-value is less than 5%. Hence, the best distribution for all six models is normal distribution. Even though the residuals of the three distributions are not normally distributed, many researchers suggested that this is not a serious problem as the estimators are still consistent. Therefore, the Normal Distribution is used for GARCH (1, 1) model.

3.4. GARCH analysis
The impact of BMD FKLI towards FBM KLCI (1991-2015) was analyzed using GARCH (1, 1) with Normal Distribution. Table 4 shows the results.

| Table 4. GARCH Analysis for FBM KLCI (1991-2015). |
|-------------------------------------------------|
| Constant (ω) | ARCH (α) | GARCH (β) | Conditional Variance |
| Pre-futures period | 0.065919 | 0.971535 | 0.289706 | 0.252330 |
| Post-futures period: | | | | |
| Without crisis | 0.000060 | 0.416795 | 0.795806 | 0.000282 |
| With crisis | 0.010053 | 0.252970 | 0.820643 | 0.136566 |

The ARCH term in the pre-futures period is 0.971535 and decreased in the post-futures period to 0.416795. Hence, there is no impact of the recent news on the volatility of FBM KLCI after the introduction of BMD FKLI. However, the GARCH term increased in the post-futures period to 0.795806 from 0.289706. This indicates that the old news on the market has an impact on this model. It caused the uninformed traders to move from futures market to the spot market. From the calculated conditional variances, we can conclude that the volatility of FBM KLCI (1991-2015) decreased after the introduction of BMD FKLI. However, the volatility increased when there was a financial crisis. Next, the post-futures period is subdivided into four periods, and the existence of financial crises are taken into consideration. The results are summarized in table 5.

| Table 5. GARCH analysis for five periods of FBM KLCI. |
|-------------------------------------------------|
| Constant (ω) | ARCH (α) | GARCH (β) | Conditional Variance |
| Pre-futures period (1991-1995) | 0.065919 | 0.971535 | 0.289706 | 0.252330 |
| Post-futures period (1996-2000) | 0.011725 | 0.491438 | 0.754762 | 0.047624 |
| With Asian Financial Crisis | 0.448706 | 0.244526 | 0.532625 | 2.013498 |
| Post-futures period (2001-2005) | -0.003015 | 0.650800 | 0.578897 | 0.013126 |
| Post-futures period (2006-2010) | 0.031068 | 0.200408 | 0.548855 | 0.123907 |
| With Global Financial Crisis | 0.306054 | 0.207643 | 0.545322 | 1.238909 |
| Post-futures period (2011-2015) | 0.000609 | 0.270576 | 0.709368 | 0.030365 |

Since the pre-futures period (1991-1995) was not affected by any crisis, the variable is not included. The conditional variance (volatility) is 0.252330. The ARCH and GARCH terms claimed that FBM KLCI (1991-1995) did not react to the recent news but has an impact on the old news. For the first post-futures period (1996-2000), the volatility decreased to 0.047624. Since there was Asian Financial Crisis in this period, the variable Crisis is included. The volatility increased to 2.013498 due to this crisis. For the second post-futures period (2001-2005), the volatility continued to decrease from 0.047624 to 0.013126. Based on the ARCH and GARCH terms, FBM KLCI (2001-2005) reacts vigorously to the old news compared to the recent news. For the third post-futures period (2006-2010), the volatility showed a slight increase from 0.013126 to 0.123907. However, the impact of the Global Financial Crisis in 2008 has increased the volatility to 1.238909. This has greatly influenced the Malaysian market performance. Similar to previous period, we could conclude that FBM KLCI (2006-2010) reacts strongly
to the old news. Finally, for the fourth post-futures period (2011-2015), the volatility decreased from 0.123907 to 0.030365. As for the ARCH and GARCH terms, FBM KLCI (2011-2015) also reacts to the old news compared to the recent news.

4. Conclusion
The objective of this study has been accomplished by conducting all the methods described in the methodology. From the results, every model is influenced by its own ARCH and GARCH terms. If the ARCH term is significant to the model, the information of FBM KLCI on previous days could influence today’s FBM KLCI volatility. Meanwhile, if the GARCH term is significant to the model, then the volatility of FBM KLCI on the previous day could influence today’s volatility.

It can be concluded that the introduction of BMD FKLI caused the declination of the volatility in FBM KLCI. The volatility of FBM KLCI in the pre-futures period decreased more than 50% in the post-futures period. From the findings, it is agreed that the introduction of futures market acts as a risk transfer and increases the market efficiency. However, the volatility increased when there was a financial crisis. This indicates that a financial crisis would impact the volatility of FBM KLCI, however, the impact was not as significant as the introduction of the futures market. The volatility of FBM KLCI continued to decrease in 1996 to 2000. However, the presence of the Asian Financial Crisis caused the volatility to rise in a high magnitude. The Global Financial Crisis also caused the volatility of FBM KLCI to increase. However, the increase was not as much as the impact of the Asian Financial Crisis.

This study concluded that the introduction of the futures market caused the stock market volatility to decline. One of the reasons is the reaction towards the old news compared to the recent news was higher. The reduction of persistence of the recent news caused the uninformed traders to move from the spot market to the futures market. Thus, this would eventually stabilize the Malaysian market. Finally, it can be concluded that the introduction of BMD FKLI in 1995 has improved the market performance and hence stabilized the volatility of FBM KLCI.

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