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Investigation of Leverage Effect in Indonesian Stock Market

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ABSTRACT

Financial market is a very dynamic market, and then it will be an advantage for the industry to know the market behavior as an advisement for making decision. This study aims to find the behavior of Indonesian Stock Market by empirically investigating its volatility pattern using daily return series. In order to find more evidences, this study examines the stock market in certain condition that gave big shocks to the market by examining the condition during the global financial crisis of 2008/2009. We use both symmetric and asymmetric Generalized Autoregressive Conditional Heteroscedasticity (GARCH) to model the conditional mean and the conditional variance in order to examine asymmetric and leverage effect in Indonesian Stock Market. Using Jakarta Composite Index (JCI) divided into two periods, the first period is from 2001 to 2007, before global financial crisis happened, and the second one includes the financial crisis, from 2001 to 2012. EGARCH (1,1) is found as the best fitting and also the best forecasting performance model in modeling volatility of returns. The market also shows the existence of leverage effect in both periods and this leverage effect increases in period with crisis.

Keywords: volatility, leverage effect, GARCH, Indonesian Stock Market

INTRODUCTION

One of big moment in financial market history was the global financial crisis in 2008/2009. It caused and is still causing a huge impact on financial markets and institutions around the world (Angabini and Wasiuzzaman, 2011). It was a time when securities suffered huge loss during the late 2008 and early 2009, and Indonesian market experienced the impact of this

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condition (International Monetary Fund 2009). In the end 2007, JCI closed at 2745.83 and it dropped to 1355.41 in the end 2008 and it was also the biggest decline after the Asian Financial Crisis of 1997.

As we know that financial market is a dynamic market and its volatility is an important indicator on the fluctuations in stock prices movement (Raja and Selvam 2011). Furthermore, it will be an advantage for the industry to know the market behavior as an advisement for making decision. Thus, this study aims to find the behavior of Indonesian Stock Market by empirically investigating its volatility pattern using daily return series. In order to find more evidences, this study examines the stock market in certain condition that gave shocks to the market, by examining the condition during the global financial crisis of 2008/2009.

In analysing the market with financial time series, there are several main characteristics or facts; 1) Leptokurtosis, which financial data tends to have fat tails resulting in a higher peak than the curvature found in a normal distribution, 2) Volatility Clustering, which describes that large swings are followed by large changes and small changes are followed by small changes, and 3) Leverage Effect, which the negative news has a greater impact on volatility than a positive news and also volatility seems to rise when stock prices go down and decreases when stock price go up. Several studies have implicated the widely use of Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) class of models in volatility and forecasting the financial time series. ARCH and GARCH models have become effective tools in the analysis of time series data, especially in financial area. These models are very useful when the goal of the study is to analyze and forecast volatility (Engle, 1982). ARCH and GARCH have symmetric distribution and they can capture leptokurtosis and volatility clustering but fail to model the leverage effect, which is asymmetric. One of the primary restrictions of the GARCH Models is that they enforce a symmetric response of volatility to positive and negative shocks, 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 model the asymmetric shock of conditional variance, the Exponential GARCH (EGARCH) model was proposed by Nelson (1991). This study uses both symmetric and asymmetric Generalized Autoregressive Conditional Heteroscedasticity (GARCH) to model the conditional mean and the conditional variance in order to find the most appropriate model.

This paper is organized as follows : Section 2 reviews the literature; Section 3 lays out the methodology; Section 4 contains a discussion of the empirical findings; and Section 5 provides conclusions.

LITERATURE REVIEW

Several studies were conducted in modeling the stock market volatility by investigating the performance of GARCH model in explaining stock volatility of some stock markets (Chou, 1988, Baillie and DeGennaro, 1990; Bekaert and Wu, 2000; Chand *et al.*, 2012; Kenneth, 2013; Banumathy and Azhagaiah; 2015). The findings of those studies vary in capturing the leverage effect. Some studies found existence of leverage effect either with positive sign or negative sign, but also there is some findings that no leverage effect detected in the market, as Albaity and Ahmad (2011) reports that Kuala Lumpur Syariah Index (KLSI) of the Bursa Malaysia has no leverage effect.

Some of the studies were conducted on modeling the volatility of developed stock market, only few studies has been done on developing stock market such as Indonesian Stock Market. Some studies in Indonesian Stock market has done only by few researchers. Lestano and Sucito (2010) constructed a volatility spillover model using EGARCH using data from 2001-2005. They reveals that the degree of volatility persistence slightly increases and also that strong evidence of volatility spillover effect from Singapore to Indonesia stock market. Guidi and Gupta (2012) forecasted the volatility of stock markets belonging to the five founder member of ASEAN, include Indonesia Stock Market, using data from 2002-2012 and reported the Asymmetric-PARCH (APARCH) models with t-distribution usually performs better and found that Indonesian stock market has high volatility asymmetry. This study will examine Indonesian Stock Market with more specific condition and longer period of time, that is how the volatility of Indonesian Stock Market during the crisis compared with the non-crisis condition.

Indonesia Stock Exchange

Indonesia Stock Exchange (IDX) is a stock exchange located in Indonesia capital city, Jakarta. As end of 2011, IDX has 440 listed companies with 3,537,294 billion IDR market capitalizations. Table 1 shows the statistical highlights of IDX period 2007-2011.

Table 1 IDX Statistical Highlights

	2007	2008	2009	2010	2011
Listed Companies	383	396	398	420	440
Listed Shares (Million Shares)	1,128,174	1,374,412	1,465,655	1,894,828	2,198,133
New Issues					
Company(s)	22	19	13	23	25
Shared Offered (Million Shares)	25,699	25,698	9,379	47,053	32,114
Amount Raised (IDR Billion)	16,868	24,388	3,854	29,678	19,593
Delisted Company(s)	8	6	12	1	5
Market Capitalization (IDR Billion)	1,988,329	1,076,491	2,019,375	3,247,097	3,537,294

IDX successfully achieved positive 3.2% growth of JCI in 2011 and it was as the second-best growth in Southeast Asia. Furthermore, the stock market capitalization also obtained the positive growth by 8.94% from 2010 (IDX Fact Book, 2012). The stock trading in IDX shows the increasing trend, in 2011 the stock trading value increased by 4.01% to 1,223.44 trillion IDR. Daily average stock transaction during 2011 peaked 3.17% over 2010 to 4,953 billion IDR per day. The total stock trading volume in 2011 increased by 8.12% to 1.2 trillion shares with daily average volume of trading is 4.9 billion shares. The total stock trading frequency was 28 million transactions in 2011, with daily average frequency of 113 thousand transactions (IDX Fact Book, 2012).

IDX's stock primary market indices are known as Jakarta Composite Index (JCI). The JCI was introduced the first time on 1 April 1983 as the indicator of the prices movement of all stocks listed in the Jakarta Stock Exchange (former IDX), for both the regular and preferred stocks. The base date for the JCI's calculation is 10 August 1982, with a base index value of 100. At that date, the number of listed stocks was 13 stocks. Besides JCI, The LQ45 Index is the well-known index in IDX. The LQ45 Index was established to provide the market with an index that represents 45 of the most liquid stocks. To date, the LQ45 Index covers at least 70% of the stock market capitalization and transaction values in the Regular Market. The based date for the calculation of LQ45 Index is July 13, 1994, with a base IDX successfully achieved positive 3.2% growth of JCI in 2011 and it was as the second-best growth in Southeast Asia. Furthermore, the stock market capitalization also obtained the positive growth by 8.94% from 2010 (IDX Fact Book, 2012).

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Below are some of the factors for a stock to be included in the Q45 Index:

1. The stocks should have been listed at the IDX for at least 3 months.
2. The performance of the stock in the regular market, which include its trading value, volume and frequency of transactions.
3. The number of trading days in the regular market.
4. The stock's market capitalization at a certain time period.
5. Besides the liquidity and market capitalization factors, the stocks selection for LQ45 Index is also based on the financial condition and the prospect of growth of the companies.

Indonesia Stock Exchange regularly monitors the performance of the component stocks included in the calculation LQ45 Index. Replacement stock will be conducted every 6 months, i.e. at the beginning of February and August. Indonesian market allows foreign investor to invest in IDX with some regulations. It regulates the portion of ownership of foreign investors, as follows: Until August 1997, foreign investors might own a maximum of 49% of total listed shares. Later, in order to anticipate the market, on 11 September 1997, the Minister of Finance of the Republic of Indonesia published the Decision Letter No.467/KMK.010/1997 and the BAPEPAM's letter No. S-2138/PM/1997 stating that there is no more buying limitation on the listed stocks in the Jakarta Stock Exchange (JSX) for foreign investors, except for the banks' stocks that allow the maximum of 49% of the paid-in capital. In May 1999, the Indonesian government released Regulation No. 29/1999 on the Buying of the Shares of Commercial Banks. It regulates the portion of ownership of foreign investors as follows:

1. The ownership of shares of banks by foreign investors and/or foreign institutions through direct placement or through the Stock Exchange is allowed for a maximum of 99% of the total shares.
2. The purchase of shares by foreign investors or foreign institutions through the Stock Exchange can reach 100% of the total shares listed on the Stock Exchange.
3. Banks can list their shares on the Stock Exchange to a maximum of 99% of the total shares.
4. At least 1% of the banks' shares, which are not listed on the Stock Exchange, must be owned by an Indonesian citizen or by an Indonesian company.

Table 2 Trading Activity's Statistical Highlights

	2007	2008	2009	2010	2011
Trading Days	246	240	241	245	247
Total Trading Volume of Shares (Million Shares)					
Total	1,039,542	787,846	1,467,659	1,330,865	1,203,550
Daily Average	4,226	3,283	6,090	5,432	4,873
Total Trading Values of Shares (Billion IDR)					
Total	1,050,154	1,064,528	975,135	1,176,237	1,223,441
Daily Average	4,269	4,436	4,046	4,801	4,953
Total Trading Frequency of Shares					
Total (Thousand)	11,861	13,417	20,977	25,919	28,023
Daily Average	48,216	55,905	87,040	105,790	113,000
Foreign Transaction of Shares					
BUY					
Volume (Million Shares)	145,431	164,531	143,934	187,944	242,522
Value (Billion IDR)	243,803	294,660	253,014	383,643	441,240
Frequency (Thousand)	874	1,298	1,851	3,032	4,781
SELL					
Volume (Million Shares)	107,261	135,438	129,067	162,303	198,165
Value (Billion IDR)	211,196	276,007	239,724	363,662	416,950
Frequency (Thousand)	783	1,541	1,849	2,861	4,892

Table 2 (Cont.)

Domestic Transaction of Shares					
BUY					
Volume (Million Shares)	894,112	623,315	1,323,725	1,142,921	961,028
Value (Billion IDR)	806,351	769,868	722,120	792,594	782,200
Frequency (Thousand)	10,988	12,119	19,125	22,887	23,242
SELL					
Volume (Million Shares)	932,281	652,408	1,338,592	1,168,562	1,005,385
Value (Billion IDR)	838,958	788,521	735,411	813,576	806,491
Frequency (Thousand)	11,078	11,876	19,127	23,058	23,131

For the composition of foreign investors' asset in Indonesia stocks, it is always higher than domestic investors' asset. In 2011, foreign investors own 55.35% and domestic investors own slightly lower amount, it is about 44.64%. This foreign composition actually is declining recently. Compare to in 1990s, foreign investors own almost 80% of Indonesia stocks. This shows that Indonesian people is getting known about the stock market and have tried to invest in capital market. The ideal composition actually is about 70% domestic investors and 30% foreign investors. Furthermore, this condition is good for Indonesian growth. But the problem now is about the way of domestic investor playing their money in stock market, it is indicated that domestic investors still do investment by following foreign investors' action and this makes domestic investors could not get the better return to foreign investors. Table 2 also shows the statistical highlights of trading activity in IDX divided also into two types, foreign and domestic transaction.

Leverage Effect

Leverage Effect appears firstly in Black (1976), who noted that:

> *``A drop in the value of the firm will cause a negative return on its stock, and will usually increase the leverage of the stock. [...] That rise in the debt-equity ratio will surely mean a rise in the volatility of the stock".*

The term "leverage" refers to one possible economic interpretation of this phenomenon, developed in Black (1976) and Christie (1982): as asset prices decline, companies become mechanically more leveraged since the relative value of their debt rises relative to that of their equity. As a result, it is natural to expect that their stock becomes riskier, hence more volatile. While this is only a hypothesis, this explanation is sufficiently prevalent in the literature that the term "leverage effect" has been adopted to describe the statistical regularity in question. It has also been documented that the effect is generally asymmetric (Sahalia *et al*., 2013).

A general overview for the leverage effect is negative returns imply a larger proportion of debt through a reduced market value of the firm leads to a higher volatility. The volatility reacts first to larger changes of the market value, but some empirical studies showed that there is a high volatility after smaller changes. On other side, Black said nothing about the effect of positive returns on the volatility. Although the positive returns cause smaller increasing effects, they do cause an increase in the volatility (Cizek *et al*., 2005). Sahalia *et al*. (2013) also stated that the leverage effect refers to the observed tendency of an asset's volatility to be negatively correlated with the asset's returns. Typically, rising asset prices are accompanied by declining volatility, and vice versa.

Several studies has been tried to estimate the leverage effect empirically, but there are some aspect need to be concerned to get the better estimation. Sahalia *et al*. (2013) showed that there are different sources of error when estimating the leverage effect using high frequency data, a discretization error due to not observing the full instantaneous stochastic processes, a smoothing error due to using integrated volatility in place of spot volatilities, an estimation error due to the need to estimate the integrated volatility using the price process, and a noise correction error introduced by the need to correct the integrated volatility estimates for the presence of market microstructure noise. These errors tend to be large even when the window size is not long enough and lead to have an error on the assessment of the leverage effect.

The financial crisis of 2007/2009 was blamed in part on excessive leverage, some remarks are as following:

- Consumers in the United States and many other developed countries had high levels of debt relative to their wages, and relative to the value of collateral assets.
- Financial institutions were highly levered
- Banks' notional leverage was more than twice as high, due to off-balance sheet transactions.

ARCH AND GARCH MODELS

One of the most great tools of applied econometrics is the least squares model that common to be used for determining how much one variable will change in response to a change in some other variable. However, there was a question how to forecast and analyze the size of the errors of the model. In this case the questions are about volatility and this is what ARCH/GARCH models work for. The econometric challenge is to specify how the information is used to forecast the mean and variance of the return, conditional on the past information. While many specifications have been considered for the mean return and have been used in efforts to forecast future returns, virtually no methods were available before the introduction of ARCH models. The model allowed the data to determine the best weights to use in forecasting the variance. A useful generalization of this model is the GARCH parameterization introduced by Bollerslev (1986). This model is also a weighted average of past squared residuals but it has declining weights that never go completely to zero. It gives parsimonious models that are easy to estimate and even in its simplest form, has proven surprisingly successful in predicting conditional variances. The most widely used GARCH specification, asserts that the best predictor of the variance in the next period is a weighted average of the long run average variance, the variance predicted for this period and the new information this period which is the most recent squared residual. Such an updating rule is a simple description of adaptive or learning behavior and can be thought of as Bayesian updating (Engle, 1982).

The basic concept of the least squares model assumes that the squared-expected-value-of-all-errors is the same at any given point. This assumption is called homoskedasticity and it is the focus assumption of ARCH/GARCH models. ARCH and GARCH models have been applied to a wide range of time series analyses but implementation in finance have been particularly successful (Engle, 1982). Bera and Higgins (1993) mention the some reasons for the ARCH :

- ARCH models are simple and easy to handle
- ARCH models take care of clustered errors
- ARCH models take care of nonlinearities
- ARCH models take care of changes in the econometrician's ability to forecast

Perrelli (2001) made some resume of the history of ARCH literature, interesting interpretations of process can be found as following:

- Lamoureux and Lastrapes (1990). They mention that the conditional heteroskedasticity may be caused by time dependence in the rate of information arrival to the market. They use the daily trading volume of stock markets as a proxy for such information arrival, and confirm its significance.
- Mizrach (1990). He associates ARCH models with the errors of the economic agents' learning processes. In this case, contemporaneous errors in expectations are linked with past errors in the same expectations, which is somewhat related with the old-fashioned adaptable-expectations-hypothesis in macroeconomics.
- Stock (1998). His interpretation may be summarized by the argument that "any economic variable, in general, evolves an on 'operational' time scale, while in practice it is measured on a 'calendar' time scale. And this inappropriate use of a calendar time scale may lead to volatility clustering since relative to the calendar time, the variable may evolve more quickly or slowly" (Bera and Higgins, 1993; Diebold, 1986).

The general form of ARCH process is as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon^2_{t-i} \ \ldots\ldots\ldots \ (1)$$

Standard deviation and variance cannot be negative, hence the value of ω and α should be greater than zero and also to be stationary, the value of β should be less than one.

The GARCH processes are generalized ARCH processes in the sense that the squared volatility σ_t^2 is allowed to depend on previous squared volatilities, as well as previous values of the process (Duffie and Schaefer, 2005). GARCH models include lagged values of the conditional variance and permit a wider range of behaviour, in particular, a more persistent volatility. The general form of the GARCH model is (Bollerslev, 1986):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_i \, \sigma^2_{t-1} \ \ldots\ldots\ldots \ (2)$$

where, $\alpha_i \varepsilon^2_{t-i}$ is an ARCH component and $\beta_i \, \sigma^2_{t-1}$ is GARCH component.

This GARCH model is symmetric and does not capture the asymmetric characteristic, such as leverage effect. Nelson (1991) proposed asymmetric GARCH type models, called Exponential GARCH (EGARCH) which is taking into account the different effects of positive or negative shocks on the conditional variance. Actually, there are a large number of alternative GARCH models suggested in the econometrics literature to represent the dynamic evolution of volatilities with leverage effect. Rodriguez and Esther (2009) compare the properties of five popular asymmetric GARCH models that restricted to guarantee positivity of conditional standard deviations, stationary and existence of fourth order moments. They considered the QGARCH, TGARCH, GJR, EGARCH and APARCH models. They showed that the leverage effect that the QGARCH, TGARCH and GJR models can represent is heavily restricted when these models guarantee positive conditional standard deviations and finite fourth order moments. Summarizing, among the models, the EGARCH model seems to be more flexible to represent leverage effect and simultaneously satisfy the restrictions for positivity and existence of the kurtosis. The general form of EGARCH is defined as:

$$log\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}} + \sum_{k=1}^{z} \beta_k \log\sigma_{t-k}^2 \quad \ldots.. (3)$$

where γ is the asymmetric response parameter or leverage parameter. The effect of a positive shock is given by the sum of parameter $\alpha_i + \gamma_i$ and the effect of negative shock is given by a subtraction respectively. Since logarithms of conditional variance could be negative, no further restrictions are necessary.

After examining the GARCH models, it also needs to check the forecast performance of each model. One of measurements to compare the forecast performance is Root Mean Squared Error (RMSE). It is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled or measures the differences between values predicted by a hypothetical model and the observed values. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. In other words, it measures the quality of the fit between the actual data and the predicted model. The RMSE indicates a forecast error, and

$$RMSE = \sqrt{\frac{1}{D}\sum_{d=1}^{D}\left(x_f^d - x_a^d\right)^2} \;\ldots\ldots\ldots (4)$$

the RMSE score of zero (0.0) demonstrates a perfect skill. The RMSE is defined as:

where x_f^d and x_a^d indicate the forecast and analysis values at the grid-point *d*, respectively. *D* is the number of grid points in the spatio–temporal for seasonal score or temporal domains for daily score.

DATA AND METHODOLGY

We use Jakarta Composite Index (JCI) daily returns from 2001-2012 as data in this study. The data is divided into two period, the first period is from 2001 to 2007 (1687 daily returns), before global financial crisis happened, and the second one is include the financial crisis, from 2001 to 2012 (2909 daily returns), then it is called as in-sample data. We also use out-sample data as input in examining forecast performance of the models, this out-sample data is taken from six-month data (+/- 120 daily returns) after in-sample data. This study uses EViews as a computational tool to examine the process.

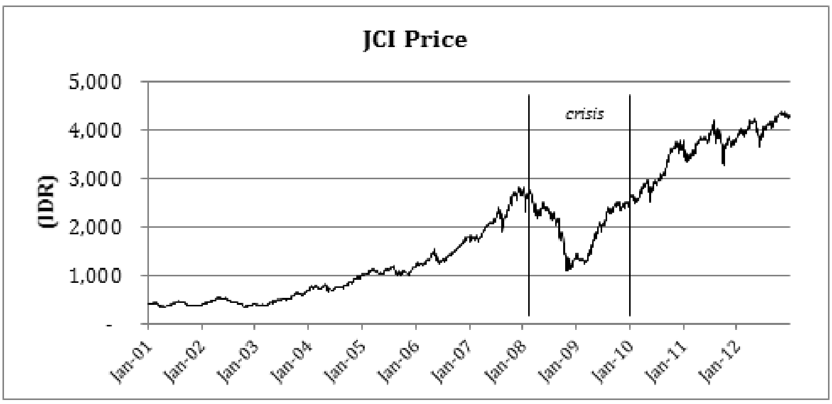

Figure 1 JCI Price Period 2001-2012

Figure 1 shows the monthly price movement of JCI, the price started to go down in early 2008 and continued to go down until 2009. It started to recover and go up in mid-2009. Since the JCI price is non-stationary, its daily price is transformed to daily returns as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad \text{........ (5)}$$

where R_t is daily returns day t and P_t is daily price day t.

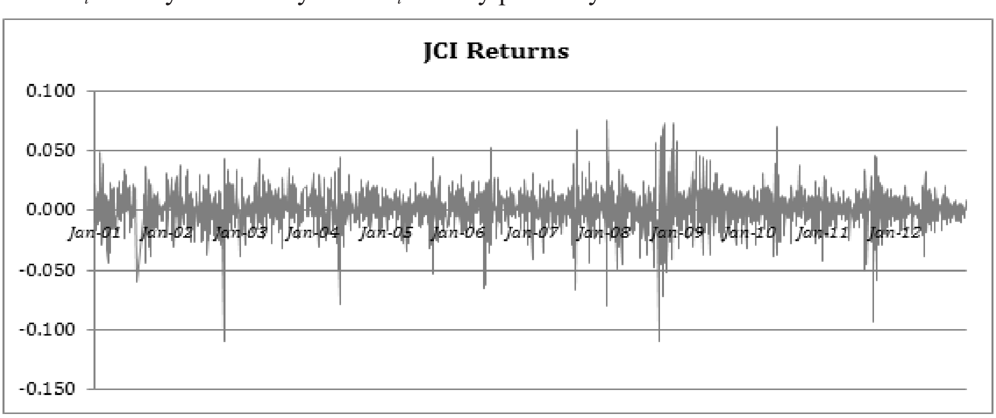

Figure 2 JCI Log Returns

Figure 2 shows the volatility-clustering phenomenon is clearly observed from the plot, it tends to cluster with periods of low volatility and periods of high volatility. It also shows that the volatility increase in period of 2008-2009, when global financial happened. It indicates that GARCH models may be appropriate models for explaining these data. Furthermore, we will model this volatility using both symmetric GARCH and asymmetric EGARCH models due to the crisis.

RESULT AND DISCUSSION

In Table 3 below, the statistic for JCI returns series are shown. There is high difference between the maximum and minimum value, the standard deviation is also high for the number of observation it indicates high level of fluctuation of JCI daily returns. The mean is closed to zero and also positive as expected for a time series of return. The skewness is negative, it indicates an asymmetric tail and JCI has non-symmetric returns. Table 3 shows the kurtosis statistic is high and indicates the JCI returns are leptokurtic. For both series of periods the return data are non-normal according the Jarque and Bera test of normality based on skewness and kurtosis, which rejects normality at the 1% level.

Table 3 Descriptive Statistic of JCI Returns

Statistical analysis	Periods	
	2001-2007	2001-2012
Mean	1.52e-18	4.03e-07
SD	0.013588	0.014701
Max	0.072627	0.083555
Min	-0.108176	-0.109573
Skewness	-0.605334	-0.586244
Kurtosis	8.014917	9.394219
Jarque-Bera	1868.602	5120.596
Probability	0.000000	0.000000

First, the log return data is analysed in order to see the fits data for ARMA's family models. The analysis includes the unit root test to check the stationarity. To check the stationarity we use Augmented Dickey-Fuller (ADF) test statistic criteria. The returns are stationer when absolute ADF test statistic higher than absolute test critical values at any significant level.

Table 4 below show the result of unit root test, ADF test statistic is applied both series of periods. 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 the time.

Table 4 Unit Root Test

Time periods	**t-statistic**	**p-value**
2001 – 2007 (without crisis)	-22.27584	0.0000
2001 – 2012 (with crisis)	-48.17402	0.0000

Thus, we estimate the fittest ARMA model for the returns of the series from autocorrelation function, the different ARMA model are examined at different legs as shown in figure 3. The ARMA model can be selected with observe the diagram, first we can pick the bar which over the bartlett line (the line). Thus, we choose lag 1 and 11 then check the Akaike's information criterion (AIC) and the probability should less than 5%. But in this case we rejected lag 11 because the p-value is more than 5%, and accept the lag 1.

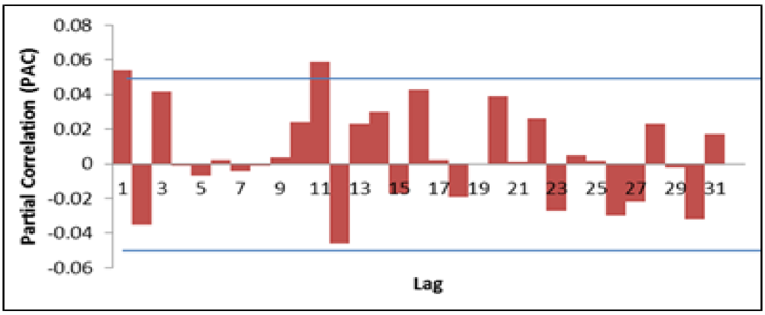

Figure 3. Correlogram Exclusion Crisis Period

We do the same things to get the fittest ARMA model for the second period which include crisis, from the figure 4 below we observe all lag and then we find that only lag 1 which has p-value less than 5%.

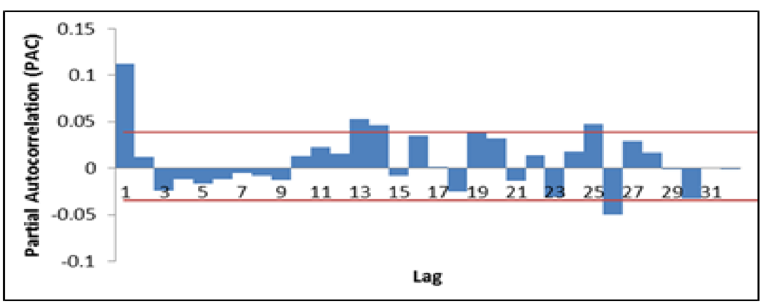

Figure 4 Correlogram Inclusion Crisis Period

Furthermore for both periods we select lag 1 as the best ARMA for p-value criteria, next we choose the fittest ARMA's model based on the smallest AIC values. Among the models, some are rejected due to the stationary condition since the sum of absolute coefficients is greater than unity and then some are rejected due to the magnitude of the p-value is greater than 5%. After we test the different model and lag, then we choose AR (1) for exclude crisis period time and MA (1) for model for period with crisis as the best model for our study.

We first estimate the fittest ARMA model for the returns of the series, the different ARMA model are examined at different lags as shown in Table 5 we can choose the best ARMA's model based on the smallest AIC values. After we test the different model and lag, then we choose AR (1) for exclude crisis period time and MA (1) for model for period with crisis as the best model for this study.

Table 5 AIC Values

Exclusion of crisis 2001-2007		Inclusion of crisis 2001-2012	
	AIC		AIC
Lag	1		1
AR	5.757474	AR	5.601193
MA	5.758577	MA	5.600832
ARMA	5.758577	ARMA	5.602293

From the table 3, we choose AR (1) as the best model for exclude crisis period and MA (1) model used for the crisis period, because both models have smallest AIC value. Therefore, by using the ARCH LM test we would like to observe the ARCH effect in the residual and Table 6 is shown the result of ARCH LM test.

Table 6 ARCH LM Test

	Exclusion crisis 2001-2007	Inclusion crisis 2001-2012
	AR (1)	MA (1)
F statistic	43.84685	89.93556
	(0.000000)	(0.000000)
Obs* R-squared	42.78369	87.29492
	(0.000000)	(0.000000)

*p-value is in parenthesis. Obs*R-squared is the number of observations times the R-squared value

The zero p-value at all lags strongly indicates the presence of ARCH effect in both periods. Both periods shows a significant presence of ARCH effect with low p-value of 0.000000, therefore we reject the null hypothesis of no ARCH effect and detect a strong presence of ARCH effect as expected for most financial time series.

We examine symmetric GARCH and asymmetric EGARCH in this study, with GARCH (1,1) and EGARCH (1,1) as the most successful models according to AIC value. The results are presented in Table 7, with the entire coefficient for both periods are significant at all levels, it means the strong validity of the models.

Table 7 GARCH Model

	Exclusion crisis (2001-2007)		**Inclusion crisis (2001-2012)**	
Coefficient	**GARCH(1,1)**	**EGARCH(1,1)**	**GARCH(1,1)**	**EGARCH(1,1)**
ω	2.38E-05	-1.735115	8.69E-06	-0.716283
	(0.0000)	(0.0002)	(0.0000)	(0.0000)
α	0.181763	0.286350	0.139562	0.250651
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.694549	0.826306	0.824905	0.939185
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	-	-0.129238	-	-0.092245
		(0.0000)		(0.0000)

According to the statistical test both model GARCH and EGARCH are significant and capture ARCH effect and volatility clustering successfully, the comparison of the model for both periods is present in Table 8. The difference for the coefficients of each model are obtained and expressed in percentage terms. The differences are acquired by subtracting the first periods values from the second periods values and the percentage is achieved by dividing the difference with the first period values.

Table 8 Model Result Difference

Models	Exclusion crisis (2001-2007)	Inclusion crisis (2001-2012)	Difference	Percentage
α				
GARCH	0.181763	0.139562	-0.0422	-23.22%
EGARCH	0.286350	0.250651	-0.0357	-12.40%
β				
GARCH	0.694549	0.824905	0.1303	18.77%
EGARCH	0.826306	0.939185	0.1128	13.66%
γ				
GARCH	-	-	-	-
EGARCH	-0.129238	-0.092245	0.0369	28.62%

Table 8 shows that the value of α, β, and γ of each model in both period. It shows the difference result between two periods. Regarding the crisis, the value of α decrease in both models and it means that the volatility has decreased while the persistency in volatility has increased shown by the increasing β values. It also shows an increase in leverage effect during the crisis shown by the increasing γ values and indicates the asymmetric condition in market. The asymmetric effect captured by the parameter (γ) in EGARCH model is negative, which means that negative news or shocks have more effect in the variance when compared to the positive ones.

To compare the model, which has best performance, it has to have the lowest AIC value. In both periods, the EGARCH (1,1) has outperformed the GARCH (1,1). It indicates that EGARCH (1,1) model is the fittest model for modeling the volatility in both periods. Besides that, the models also have to perform best forecasting of the future returns. Some studies show that the best-fitting model (lowest AIC values) does not always provide the best forecasting performance. In order to check the forecasting performance, this study use out-sample data as evaluation of forecasting performance measured by Root Mean Squared Error (RMSE), the lower RMSE score the better model in forecasting data. Six-month data after in-sample data used in estimation is used in evaluating the forecasting performance. Table 9 shows the results of the forecast and figure 5 and 6 show the comparison log returns value between observed values and forecasted valued from EGARCH (1,1) model.

Table 9. AIC & RMSE

	Exclusion crisis (2001-2007)		Inclusion crisis (2001-2012)	
	GARCH(1,1)	**EGARCH(1,1)**	**GARCH(1,1)**	**EGARCH(1,1)**
AIC	-5.87922	-5.89387	-5.82750	-5.84035
RMSE	0.019638	0.019586	0.011985	0.011979

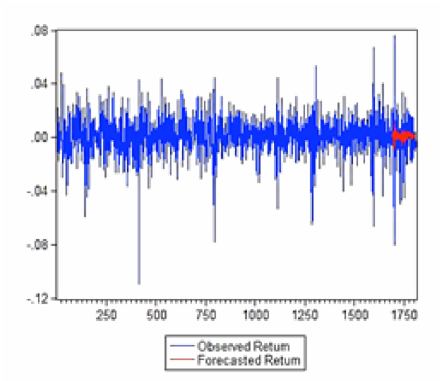

Figure 5 EGACRH (1,1)
Forecasting Result (exclusion crisis)

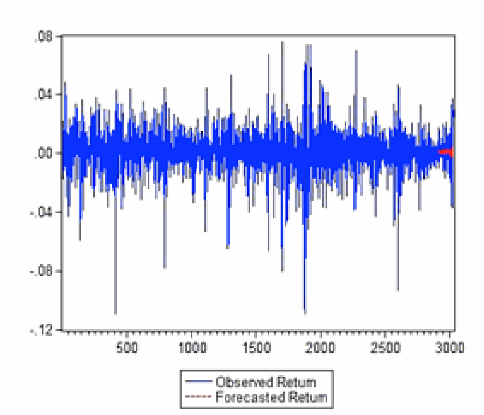

Fig. 6. EGACRH (1,1)
Forecasting Result (inclusion crisis)

The EGARCH (1,1) still shows as the best model in forecasting since has the lower values of RMSE. These empirical results prove that Indonesian Market experiences asymmetry and leverage effect which bad news tend to increase volatility more than good news.

CONCLUSION

This study aims to investigate the change in volatility using daily return series in Indonesian Stock Market. We also examined the effect of bad condition towards the change of volatility using global financial crisis in period of time.

In both periods, the EGARCH (1,1) has outperformed the GARCH (1,1). It indicates that EGARCH (1,1) model is the best fitting and also best forecasting performance model in both periods. It also indicates that Indonesian market experiences asymmetry and leverage effect which bad news tend to increase volatility more than good news. The result also shows the increasing leverage effect when the crisis happened, it indicates that crisis which has many bad news will have bigger effect on the volatility of a series in Indonesian stock market. These finding insights can be used as an advisement for making decision in stock market and also contributes to the literature in analyzing the volatility of developing stock market specifically in Indonesian Stock Market.

As remark for further studies, the study can be extended using high frequency data, i.e intraday stock data, to get more accurate result. Furthermore, it also can be extended by comparing Indonesian stock market with other stock market, i,e ASEAN countries' stock market. It will give more insight in understanding the stock market behavior.

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