

Volatility Modeling Using ARCH/GARCH Method: Application on Asia Pacific Index

Irni Yunita

School of Economic & Business, Telkom University
40267 Bandung, Indonesia
irniyunita@telkomuniversity.ac.id; irniyunita81@yahoo.com

Abstract - The purpose of this study is to estimate the volatility model of Asia Pacific Index such as LQ45 (Indonesia), HSI (Hongkong), KLSE (Malaysia), and STI (Singapore). The best ARIMA model for Asia Pacific Indexes are: LQ45 (ARIMA (1,1,26)), HSI (ARIMA (14,1,14)), KLSE (ARIMA (17,1,1)), and STI (ARIMA (17,1,11)). The heteroscedasticity test against the best ARIMA models detect that the data still contains heteroscedasticity. Then the determination of volatility is obtained using Autoregressive Conditional Heteroscedasticity approach/ Generalized Autoregressive Conditional Heteroscedastic (ARCH/GARCH). The result indicates that the best GARCH model to determine the volatility of LQ45, STI, and HSI is GARCH (1.1) whereas for KLSE is GARCH (3.0).

Keywords: Volatility, Index, ARIMA, ARCH/GARCH

I. INTRODUCTION

Volatility is a variance statistical measurement of the data. The volatility, or standard deviation is an important measure of market risk. It is often used to price derivative (e.g. options) instruments. The data which has a high volatility reflects higher risks compared to the data with low volatility. The volatility calculation, such as forecasting volatility is further needed for risk management, for asset allocation, and for taking bets on future volatility. A large part of risk management measures the potential future losses of a portfolio of assets. Therefore, in order to measure these potential losses, estimations must be made for future volatilities and correlations [1].

In 2008, the index movement in some stock exchanges in Asia Pacific had a quite high movement fluctuation caused by the global crisis which hit United States. The stock prices index in the global stock exchanges followed the deterioration of the stock prices index in United States (US). In Asia, including Indonesia, the stock prices index fell sharply exceeding the decline of the stock prices index in US. The movement of index return LQ 45 in Indonesia can be seen in figure 1.

Figure 1 indicates that the data return is not constant. Once it is high, the other time it turns to low, far from the average return as seen on the figure. In other words, the time series data of LQ 45 index is non-stationary and indicates a varying volatility and so is the other indexes in Asia Pacific. The time series are periods in which their prices show wide swings for an extended period of time followed by periods in which there is relative calm. Modeling the time varying volatility phenomenon is well known and is generated by Engle (1982), Bollerslev (1986). They introduce the (generalized) autoregressive conditionally heteroskedastic ((G)ARCHi) process and the stochastic volatility model, respectively. Therefore, this research uses the Autoregressive Conditional Heteroscedasticity/ Generalized Autoregressive Conditional Heteroscedastic (ARCH/GARCH) in the determination of Asia Pacific Index volatility forecasting model.

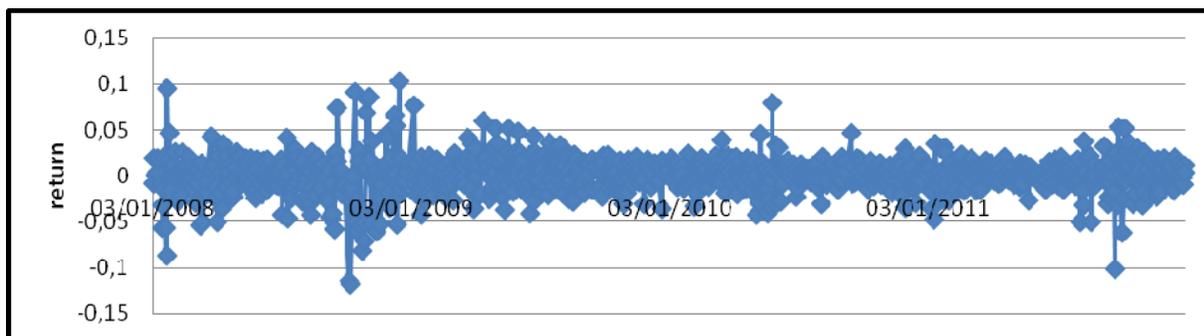


Figure 1. Return of LQ45 Index (Source : Data Processed)

II. LITERATURE REVIEW

The Concept of GARCH and The Economics of Time Series

A. Return Measurement

Return is a result obtained from an investment. Actual return is a return which has occurred, calculated based on the historical data [2]. To calculate the actual return of the stock from each sample by using daily stock, the formulation will be as follow: [3]

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \quad (1)$$

Description:

R_{it} : the i^{th} actual return of securities on the day t^{th}

P_{it} : the i^{th} price of securities on the day t^{th}

P_{it-1} : the i^{th} price of securities on the day $t-1^{\text{th}}$

B. Stationarity

The requirements in the time series analysis should be systematic in the mean and the variance. One of ways to test the stationarity is conducted by analyzing whether it has the unit root or not, using the graphic test. The test is conducted using an observation against the correlogram; which is the auto-correlation function graphic and its partial auto-correlation. If the results of correlogram in its auto-correlation function present a slow decline when there are more lags participate and its auto-correlation function directly leads to zero point in the second lag, so it can be said that the data have been stationary (it has no unit root) and the data process continues to the next stage.

The data which are not stationary in the modeling will draw a misleading conclusion. For instance, the regression model which produces a high determination coefficient (R^2) gives the impression as if there was a strong connection between the dependent variables and the independent variables.

C. Volatility

Volatility is a statistical measurement of the price of an instrument [3]. Volatility of return is indicated by the variance or the standard deviation of return. There are different methods in measuring the volatility, each of them has particular characteristics [4]. Volatility is commonly assumed to be constant from time to time, although the fact that it is not. According to [5], the constant volatility is called homoscedastic, whereas the non-constant volatility is called heteroscedastic. There are some methods which are commonly used in measuring the constant and non-constant volatility: (1) Constant volatility (standard Deviation, simple Moving Average and percentile Method/ Historical Simulation methods), (2) Non-Constant Volatility (exponential Weighted Moving Average (EWMA) and Generalized Autoregressive Conditional Heteroskedastic (GARCH)

An autocorrelation is considered as ARCH (Auto Regressive Conditional Heteroskedasticity) when the

error variance is connected with the square error term in the previous periods [6]. Thus, ARCH/GARCH is used to analyze the estimate of Ordinary Least Square which has a heteroskedasticity issue (non-constant error variance).

D. Auto-regressive Integrated Moving Average (ARIMA)

GARCH method is implemented through two processes: mean process and variance process. The mean process was firstly proposed by [7] by analyzing the time series combined with auto-aggressive (AR) and moving average (MA). This method is then integrated to be ARIMA in obtaining the stationary time series. ARIMA model is only used for forecasting dependent variables in a short term.

ARIMA model has inaction time. The inaction time of one period at the auto-regressive process is called the first order of auto-regressive. The symbol to state the amount of inaction time at the auto-regressive process is p . The inaction time of one period at the moving average is called the first order of moving average. The symbol to state the amount of inaction time at the moving average process is q . The common form of auto-regressive p or AR(p) is:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \dots + \alpha_p Y_{t-p} + \epsilon_t \quad (2)$$

Y_t : the observed variable

α_0 : auto-regressive constants

$\alpha_1 \dots \alpha_p$: parameter $Y_{t-1} \dots Y_{t-p}$

The common form of moving average q or MA(q) is

$$Y_t = \beta_0 + \beta_1 \epsilon_t + \beta_2 \epsilon_{t-1} + \dots + \beta_q \epsilon_{t-q}$$

Y_t : the observed variable

β_0 = moving average constants

$\beta_1 \dots \beta_q$: parameter $\epsilon_t \dots \epsilon_{t-q}$

The common form of ARIMA model with the auto-regressive p and moving average q is:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \dots + \alpha_p Y_{t-p} + \epsilon_t + Y_t = \beta_0 + \beta_1 \epsilon_t + \beta_2 \epsilon_{t-1} + \dots + \beta_q \epsilon_{t-q} \quad (3)$$

The four steps of Box-Jenkins methodology [8] are: identification, estimation, diagnostic examination, and forecasting. The first step in ARIMA process is identification. That is to discover the appropriate values of p , d , and q . We will show shortly how the correlogram and partial correlogram aid in this task. This step is the stationary test. The stationarity test is conducted by using Dickey-Fuller unit root test.

The second step is Estimation. Having identified the appropriate p and q values, the next stage is to estimate the parameters of the auto-regressive and moving average terms included in the model. Sometimes this calculation can be done by simple least squares but sometimes we will have to resort to nonlinear (in

parameter) estimation methods. Since this task is now routinely handled by several statistical packages, we do not have to worry about the actual mathematics of the estimation; the enterprising student may consult the references on that.

The third step is Diagnostic checking. Having chosen a particular ARIMA model, and having estimated its parameters, we next see whether the chosen model fits the data reasonably well, for it is possible that another ARIMA model might do the job as well. This is why Box–Jenkins ARIMA modeling is more an art than a science; considerable skill is required to choose the right ARIMA model. One simple test of the chosen model is to see if the residuals estimated from this model are white noise; if they are, we can accept the particular fit; if not, we must start over. Thus, the Box-Jenkins methodology is an iterative process.

The fourth step is Forecasting. One of the reasons for the popularity of the ARIMA modeling is its success in forecasting. In many cases, the forecasts obtained by this method are more reliable than those obtained from the traditional econometric modeling, particularly for short-term forecasts. Of course, each case must be checked.

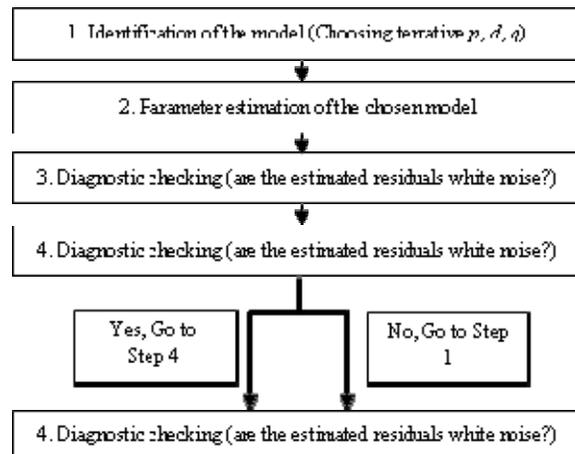


Figure 2 The Box-Jenkins Methodology

E. Generalized Auto-regressive Conditional Heteroscedastic (GARCH)

Bollerslev (1986) refined by Engle's (1982) working results of ARCH model by inserting the AR process in the heteroscedasticity from the variance into Generalized Auto Regressive Conditional Heteroscedasticity. The simplest GARCH model is the GARCH(1, 1) model, which can be written as:

$$\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 \sigma^2_{t-1} \quad (4)$$

It says that the conditional variance of u at time t depends not only on the squared error term in the previous time period [as in ARCH(1)] but also on its conditional variance in the previous time period. This model can be generalized to a GARCH (p, q) model in

which there are p lagged terms of the squared error term and q terms of the lagged conditional variances. GARCH is the development of ARCH models [8].

III. METHODS

A. Type of Research

The type of research is descriptive quantitative. Descriptive research is conducted to discover and to be capable of explaining the characteristics of observed variables in a situation. [9]. According to [10], "The quantitative research with descriptive format aims to explain, summarize some conditions, situations, or variables which emerge in society. The emergence makes the research objects to be based on what happened at that time." This research aims at estimating the index option prices in Asia Pacific with ARCH/GARCH volatility approach using daily index data, period of January 2008 until December 2011.

B. Population and Sample

According to [11], population is the generalization area which consists of object or subject possessing certain quality and characteristics determined by the researcher to be learned and then to be concluded. The population in this research is all indexes which are in Asia Pacific. The sampling method is conducted by using non-probability sampling with purposive sampling method. Purposive sampling is a technique of sampling determination with certain considerations [11]. The sample in this research is: LQ45 index (Indonesia), Hongkong Index (HSI), KLSE Index (Malaysia), and STI Index (Singapore).

C. Data Analysis

1) Return Index Data

The calculation of return is conducted by using formula (1).

2) Volatility Estimation Model

In the calculation of index volatility estimation, GARCH model will be used. However, ARIMA modeling is previously conducted. The usage of the ARIMA formula is conducted after the stationarity test, the normality test and homoscedacity test are conducted. If the characteristic of the data from return is heteroscedastic, non-stationary, and abnormal, then the estimation with ARIMA method is conducted. [8] elaborated the ARIMA methodology into four steps: identification, estimate, diagnostic examination, and forecasting.

The first step in ARIMA process is identification. This step is conducted to reveal whether the observed data are stationary or not. If the data are stationary, the difference process is conducted until the data are stationary. Furthermore, the stationarity test is conducted by using Dickey-Fuller unit root test [8]. The second step is the estimation of auto-regressive parameter and moving average parameter based on the order (p and q) obtained at the identification phase.

The third step is selecting the suitable ARIMA model. A good model is a model which has randomly-distributed residual (white noise). The examination is conducted by comparing the amount of auto-regressive coefficient (ACF) and the partial auto-regressive coefficient (PACF) obtained from residual correlogram. A model is considered to have the white noise characteristic if the ACF and PACF are not significant (coefficient value < critical value).

The fourth step is by forecasting. The best forecasting model is retested with the heteroscedasticity test to discover whether the data still have the heteroscedasticity or not. If the results show that the data are still heteroscedastic, so the modeling will be conducted by using ARCH/GARCH model.

ARCH/GARCH modeling is conducted by estimating the equation of mean process with ARCH method. The selected ARCH and GARCH can be selected from various orders of ARCH and GARCH and from various types of ARCH/GARCH.

To measure the volatility of ARCH/GARCH, there are some steps to select the best model. The first step which should be conducted is examining the significance of ARCH coefficient or residual coefficient (α) and GARCH coefficient or variance coefficient (β). A coefficient is considered to be significant if the probability of z-statistic value is less than the probability of critical value.

The first step to determine the best GARCH is by using ARCH until it shows the insignificant probability. Furthermore, the modeling of GARCH is conducted until the order of GARCH is achieved, which shows the insignificant probability. Those models are then selected based on the lowest of AIC and SIC and the highest number of Log Likelihood. A model is considered to be persistent if the addition of constants α and β is same or closer to 1.

D. Hypothesis Test Instrument

Stages of the hypothesis test are:

1) Stationarity test

A set of data is stated to be stationary if the average value and variance are constant. The stationarity test is conducted to ensure that the return data have been stationary. The stationarity test of return data is conducted by using ADF (Augmented Dickey-Fuller) Test. ADF test aims to find out whether the return data still contain the unit root or not. If the return data do not contain the unit root, it means that the data have been stationary. Then it can be used in the further calculation process. However, if the ADF test results show that the return data still contain the unit root (not stationary) so the difference process of the data should be conducted until its condition becomes stationary. The ADF test is conducted with the hypothesis procedures as follow:

Ho : $\gamma = 1$, there are unit roots and non-stationary data

H1 : stationary data

If the ADF test value is smaller than the critical value or possessing the probability which is smaller than 5% , it means that the data do not contain the unit roots anymore, which is stationary. If the data are not stationary yet, then it is necessary to conduct the difference process of the data until the ADF test value is smaller than its critical value.

2) Heteroscedasticity Test

The heteroscedasticity test aims to discover whether the variance from the return data is constant or time varying. The first step is to estimate the equation of moving average with the least square method. The second step is to conduct the heteroscedasticity test with White Heteroscedasticity Test or ARCH-LM Test. The hypothesis of heteroscedasticity test is:

Ho: volatility homoscedastic

H1: volatility heteroscedastic

If the probability value is smaller than 5% so it rejects Ho at α . This can conclude that the return data are heteroscedasticity. Meanwhile, if the probability number is still greater than 5% so it does not reject Ho which can conclude that the data are homoscedastic. If the probability is $nR^2 < 5\%$, Ho is rejected because it tends to be heteroscedastic, but if the probability is $nR^2 > 5\%$, Ho is accepted because σ tends to be homoscedastic. If σ is homoscedastic, so the volatility value is calculated by using the formula of standard deviation. If it is heteroscedastic, the volatility value is calculated by using ARCH/GARCH method.

IV. RESULTS AND DISCUSSION

In this chapter, several steps are taken in estimating volatility model of indexes in Asia Pacific stock exchanges: LQ45 (Indonesia) , HSI (Hongkong), KLSE (Malaysia), STI (Singapore). The analysis is initiated with the descriptive analysis about the index return data. Then, it is continued with a set of statistical test of return data to determine the most suitable model in forecasting the volatility value.

A. The Determination of Observation Data

The data of this research are the data of daily stock price list of 4 indexes in Asia Pacific within the period of 2008 until 2011, which are obtained from www.financeyahoo.com. For this index, the data of daily stock price list are the index price at the closing price, which began from January 2008 until 30 December 2011.

B. Index Return

Actual return describes the level of the real index advantage in certain period. The formula (2.1) is used to calculate the amount of actual return during the period of observation. The data of actual return calculation

from one of indexes in Asia Pacific is LQ45 index (Indonesia) as seen in table 1.

TABLE I RETURN OF LQ45 INDEX

Date	No.	Closing Price	Return
3/01/2008	1	591.35	-0.008716
4/01/2000	2	602.35	0.018601
7/01/2000	3	602.53	0.000298
...
30/12/2011	970	673.51	0.00357616

Source : Data Processed

By using the same formula, the actual return for HSI, KLSE, and STI index are obtained. Based on the calculation of actual return of index during the period of observation, it can be concluded that:

- The positive value indicates that there is an increase of the stock price at the t-day from the stock price at the t-1 day.
- The zero value indicates that the stock price at the t-day is same as the price stock at the t-1 day. In other words, the stock price does not change from the previous days.
- The negative value indicates that there is a decline of stock price at the t-day from the stock price at the t-1 day.

Based on the table 1 and figure 3, it can be seen that there is a high movement change of the return data of LQ45. Once it sharply increases and also sharply falls. Likewise, it does for the other indexes (STI, HSI and KLSE index). It indicates that there is a high volatility at the index data in Asia Pacific, which will be proved further through the statistical test data results.

C. Descriptive Statistical Analysis of Data

The descriptive statistical analysis results at the return data of LQ45 index can be seen in Figure 4.

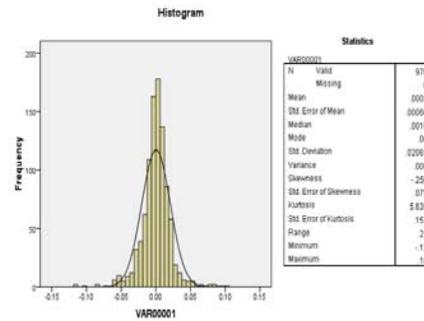


Figure 4. Descriptive Statistic Data of Return of LQ45 Index (Source : data Processed)

It can be seen from the figure 4 that the amount of the standard deviation is 0.02061. It shows that the deviation average of daily return against the entire return average is 0.02061. The mean value of LQ45 index is 0.0003. It shows that the average value of return is closer to zero, which means that the spread from return data is closer to the normal distribution. Besides, the descriptive analysis for Asia Pacific index of HSI, KLSE, and STI is also conducted.

D. Characteristic Test of Data

In this part, two tests of data characteristics which cover the stationary test and the heteroscedasticity test will be analyzed.

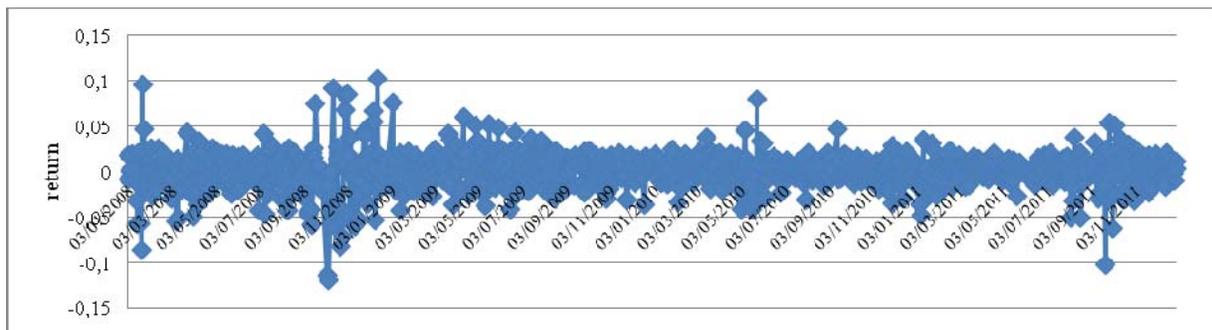


Figure 3. Return of LQ45 Index (Source : Data Processed)

1) Stationary Test

After discovering the movement from the index return data, the next step is detecting the stationarity of data. To avoid the spurious regression, the data which are analyzed should be stationary (Diebold and Killian in [12]. The data are considered to be stationary if they do not contain the unit root. The unit root test is conducting the Augmented Dickey Fuller (ADF) test. The data are considered to be stationary if the absolute value of ADF statistic > the critical value of MacKinnon at $\alpha=1\%$, $\alpha=5\%$ and $\alpha=10\%$. The data process results for the stationary test of LQ45 index can be seen in figure 5.

Null Hypothesis: RETURN_LQ45 has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on SIC, maxlag=21)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-27.90664	0.0000
Test critical values:		
1% level	-3.436878	
5% level	-2.864311	
10% level	-2.568298	

*MacKinnon (1996) one-sided p-values.

Figure 5. ADF test Statistic Result of Return LQ45 Index

Based on the unit root test at table 5, it is known that LQ45 index has been stationary at level of return data. It is proven by the ADF statistical value ADF (27.90664) > the MacKinnon critical value 1%, 5%, and 10% whereas the probability is less than α 1%, α 5%, and α 10%. Therefore, the prediction of the most suitable ARIMA model can be conducted.

By using the unit root of ADF test, the statistical values are obtained ADF for HSI, KLSE, STI indexes, as can be seen in table 2

TABLE II AUGMENTED DICKEY- FULLER TEST RESULT

Index	t-Statistic	Prob.*
HSI	-33.48875	0.0000
KLSE	-28.94669	0.0000
STI	-27.69429	0.0000

Source : data Processed

Table 2 illustrates that the data of HSI, KLSE, and STI indexes have been stationary. It is indicated from the statistical t value (28.94669) > critical value, and the probability is less than 1%, α 5%, and α 10%, so that the prediction of the most suitable ARIMA model can be conducted.

2) ARIMA Model Estimation

The Dickey Fuller test results show that the entire indexes are stationary, therefore the identification can be conducted to determine the most suitable and the best ARIMA model in predicting the movement of that

index return. Furthermore, the data processing is conducted with the correlogram for LQ45 index.

Based on the correlogram results, the maximum order of AR (p) is obtained when the value of PAC passes the dotted line at the lag 1 and 3; meanwhile the maximum order of MA (p) is obtained when the value of AC passes the dotted line at the lag 1, 14, 25, and 26.

After the order of AR and MA are determined, the further step is to determine the estimation of parameter value in the ARIMA model for LQ45 return which is in the table 3.

TABLE III ARIMA ESTIMATION MODEL OF RETURN LQ45 INDEX

No.	Return LQ45	AIC	SIC	Prob
1	AR(1)	-4.926548	-4.916483	0.0006
2	AR(3)	-4.916279	-4.906198	0.0798
3	MA(1)	-4.926221	-4.916165	0.0020
4	MA(14)	-4.922088	-4.912031	0.0058
5	MA(25)	-4.921680	-4.911624	0.0110
6	MA(26)	-4.921966	-4.911909	0.0095
7	AR(1) AR(3)	-4.927266	-4.912144	0.0004 0.0512
8	AR(1) MA(1)	-4.927179	-4.917114	0.3310 0.5812
9	AR(1) MA(25)	-4.930973	-4.920909	0.0012 0.0195
10	AR(1) MA(14)	-4.931048	-4.915952	0.0008 0.0068
11	AR(1) MA(26)	-4.931379	-4.921314	0.0014 0.0247
12	AR(3) MA(1)	-4.925639	-4.910517	0.0667 0.0016
13	AR(3) MA(14)	-4.921550	-4.906428	0.0780 0.0046
14	AR(3) MA(25)	-4.920225	-4.905103	0.1031 0.0147
15	AR(3) MA(26)	-4.920804	-4.905682	0.0758 0.0099
16	MA(1) MA(14)	-4.930959	-4.915874	0.0021 0.0067
17	MA(1) MA(25)	-4.928842	-4.913758	0.0063 0.0214
18	MA(1) MA(26)	-4.928446	-4.913362	0.0070 0.0141
19	MA(14) MA(25)	-4.926136	-4.911052	0.0133 0.0085
20	MA(14) MA(26)	-4.924292	-4.909208	0.0254 0.0187
21	MA(25) MA(26)	-4.925355	-4.910271	0.0186 0.0197

Source : data Processed

Table 3 shows that the estimation parameter of AR (1) MA (26) is statistically significant at $\alpha=5\%$. The value of AIC and SIC is quite low compared to the estimation results of other ARIMA models. F test also shows a significant result at $\alpha=1\%$. Thus, the ARIMA model (1, 1, 26) is the most suitable ARIMA model for LQ45 index. By using the same step, the most suitable ARIMA model is obtained from HSI, KLSE, and STI indexes which can be seen in table 4.

TABLE IV. THE BEST ARIMA MODEL FOR HSI, KLSE, STI AND PSEI INDEXES

Index	Model ARIMA	AIC/SIC	Probability
HSI	ARIMA (14, 1, 14)	-4.923397/ -4.908591	0.0071
KLSE	ARIMA (17, 1, 1)	-5.6243/ -5.60924	0.000
STI	ARIMA (17, 1, 11)	-5.572229/ -5.5574	0.0006

Source : Data Processed

From table 4.4 above, the best ARIMA model from each index is found out, except for PSEI. It does not use the ARIMA modeling since the model has already been stationary.

3) Heteroscedasticity Test

The heteroscedasticity test aims at revealing whether the error variance (residual variance) is constant (homoscedastic) or non-constant/fluctuating (heteroscedastic). To examine whether the return data are homoscedastic or heteroscedastic, White Heteroscedasticity test is conducted in this research. If the data are heteroscedastic, thus, the volatility calculation of return data model is with the ARCH/GARCH approach. The data are considered to be heteroscedastic if the probability of F-statistics < the probability of critical value. The heteroscedastic test results at the ARIMA model of LQ45 index can be seen in figure 5.

Heteroskedasticity Test: White

F-statistic	13.32441	Prob. F(9,959)	0.0000
Obs*R-squared	107.7023	Prob. Chi-Square(9)	0.0000
Scaled explained SS	420.8827	Prob. Chi-Square(9)	0.0000

Figure 6. White Heteroscedasticity Test

Based on the figure 6 above, it is seen that the probability of F-statistic (LQ45) is 0.000000, where the probability value is smaller than 5% ($0.000000 < 5\%$) that can conclude that the data are heteroscedastic and they contain the ARCH effect at the estimated model, so it can be continued to discover the ARCH/GARCH model.

By conducting the same test against HSI, KLSE, and STI index, the heteroscedasticity test results are as shown in table 5.

TABLE V. WHITE HETEROSKEDASTICITY TEST RESULT

Index	Prob. F-Statistic
HSI	0.0000
KLSE	0.0000
STI	0.0000

Source : Data Processed

Based on the table 4.5 above, it can be seen that the probability of F-statistic for the entire indexes is 0.000000, where the probability value is smaller than 5% ($0.000000 < 5\%$). It can be concluded that the data are heteroscedastic and they contain the ARCH effect at the estimated model, so it can be continued to discover the ARCH/GARCH model.

4) The Volatility Measurement using GARCH

The Estimation of ARCH/GARCH Model

At the previous sub-chapter, it is given that the data are not normal, stationary, and heteroscedastic (they contain the ARCH effect). Consequently, the volatility modeling should use the ARCH/GARCH model.

From the output results, the significance from error coefficient (α) /ARCH coefficient and the variance coefficient (β) / GARCH coefficient are observed. The hypothesis (H_0) which is about to be rejected in this significance test is the non-significant coefficient. The model is considered to be significant if the probability of Z-statistic value is smaller than the probability of the critical value ($\alpha= 5\%$). Furthermore, the highest adjusted R-Square value and the smallest AIC and SIC value are observed. The estimation results of ARCH/GARCH for the LQ45 return can be seen in table 6.

TABLE VI ARCH/GARCH ESTIMATION FOR LQ45 INDEX

MODE L (p,q)	p=1	p=2	p=3	q=1	q=2	q=3	AIC	SIC
GARCH (1.0)	0.4922						-5.020924	-4.995762
GARCH (2.0)	0.30251 7	0.21 3684					-5.103087	-5.072893
GARCH (3.0)	0.19541 1	0.16 9263	0.22 5645				-5.142595	-5.107369
GARCH (1.1)	0.13439 7			0.84628 3			-5.250390	-5.220197
GARCH (1.2)	0.10837 5			1.12387 2	-0.246308		-5.248902	-5.213676
GARCH (1.3)	0.12547 9			0.81546 8	0.220920	0.17921 2	-5.246982	-5.206724
GARCH (2.1)	0.11418 0	0.02 9490		0.83718 5			-5.248682	-5.213457
GARCH (2.2)	0.10845 1	0.00 0299		1.12535 4	-0.247538		-5.246838	-5.206580
GARCH (3.1)	0.10554 6	0.01 4155	0.05 0574	0.80833 8			-5.247691	-5.207433
GARCH (3.2)	0.10367 2	0.04 9208	0.07 0007	0.45690 2	0.291724		-5.246067	-5.228828

Source : data Processed

From the table 6 above, the best GARCH model against the return data of LQ45 index is obtained with the GARCH model (1.1). The model is considered to be persistent and stable due to the value of $p + q < 1$. The equation result of GARCH (1.1) used to measure the volatility from LQ45 index is as follow:

$$\sigma_t^2 = 0.00000966 + 0.134397 * e_{t-1} + 0.846283 * \sigma_{t-1}^2 \tag{5}$$

The model above provides information that the risk level of LQ45 index is influenced by the amount of the

residual return value a day before. In addition, the amount of the return standard deviation is average for a day before.

By conducting the same step, the estimation of the best ARCH/GARCH model is obtained for HSI, KLSE, and STI index. This result can be seen in table 7.

TABLE VII THE BEST ARCH/GARCH ESTIMATION OF HSI, KLSE AND STI INDEXES

Index	Model (p,q)	p=1	p=2	p=3	q=1	q=2	q=3	AIC	SIC
HSI	GARCH(1.1)	0.088013			0.901961			5.323568	5.293956
KLSE	GARCH(3.0)	0.140763	0.017379	0.015407				5.854471	5.819331
STI	GARCH(1.1)	0.093694			0.898717			5.984891	5.955232

Source : Data Processed

From the result above, the value of $p+q < 1$ is obtained. This result shows that the GARCH model has been persistent and stable for the entire models.

ARCH-LM Test of ARCH/GARCH Model

After the best model from each index is obtained, the next step is by conducting ARCH-LM test to evaluate the estimation results whether the model still contains the heteroscedastic element or not. The testing is conducted by using the LM test procedure. If the value of $\text{Obs} \times R\text{-Squared} < \text{the value of } X^2 \text{ table}$, or the probability value $> 5\%$, thus, it can be said that the model does not contain the heteroscedasticity issue. The ARCH-LM test results of LQ45 can be seen in table 8.

TABLE VIII ARCH-LM TEST OF LQ45 INDEX

Heteroskedasticity Test: ARCH

F-statistic	9.47E-06	Prob. F(1,966)	0.9975
Obs*R-squared	9.49E-06	Prob. Chi-Square(1)	0.9975

Source : Data Processed

Based on the ARCH-LM test which is in the table 4.8, it shows that the estimation results of GARCH model is free from heteroscedasticity which is proven by the significance value of $> 5\%$ as well as the HSI, KLSE, and STI index. These results can be seen in table 9.

TABLE IX ARCH-LM TEST RESULT OF HSI, KLSE, AND STI INDEXES

Indexes	Prob. F	
HSI	Prob. F (1,990)	0.0916
KLSE	Prob. F (1,969)	0.2223
STI	Prob. F (1,988)	0.4580

Source : Data Processed

V. CONCLUSION

Based on the best ARCH/GARCH model, the volatility model for each index can be seen in table 10.

TABLE X. INDEXES VOLATILITY MODEL

Indexes	Model	Volatility Model
LQ45	GARCH (1.1)	$\sigma^2 = 0.00000966 + 0.134397 \cdot \epsilon_{t-1}^2 + 0.846283 \cdot \sigma_{t-1}^2$
HSI	GARCH (1.1)	$\sigma^2 = 0.00000323 + 0.088013 \cdot \epsilon_{t-1}^2 + 0.901961 \cdot \sigma_{t-1}^2$
KLSE	GARCH (3.0)	$\sigma^2 = 0.00016 + 0.140763 \cdot \epsilon_{t-1}^2 - 0.017379 \cdot \epsilon_{t-2}^2 + 0.015407 \cdot \epsilon_{t-3}^2$
STI	GARCH (1.1)	$\sigma^2 = 0.00000163 + 0.093694 \cdot \epsilon_{t-1}^2 + 0.898717 \cdot \sigma_{t-1}^2$

Source : Data Processed

The table above shows that the volatility of LQ45, HSI and STI indexes is influenced by previous residual (lag - 1) and previous volatility (lag - 1). While the KLSE index volatility is influenced by previous residual (lag - 1, lag - 2 and lag - 3). Most of the results show that the best volatility estimation model is by using the GARCH (1.1)

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