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Application of GARCH Model to Forecast Data and Volatility of Share Price of Energy (Study on Adaro Energy Tbk, LQ45)

Erica Virginia[1], Josep Ginting[2], Faiz A. M. Elfaki[3]*

[1]Department of Accounting, President University, Cikarang-Bekasi, Indonesia, [2]Department of Accounting, President University, Cikarang-Bekasi, Indonesia, [3]Department of Mathematics, Statistics and Physics, College of Arts and Sciences, Qatar University, Qatar. *Email: felfaki@qu.edu.qa

ABSTRACT

Most of the times, Economic and Financial data not only become highly volatile but also show heterogeneous variances (heteroscedasticity). The common method of the Box Jenkins cannot be used for data modeling as the method has an effect of heteroscedasticity (autoregressive conditional heteroscedastic ARCH effects). One of the usable methods to overcome the effect of heteroscedasticity is GARCH model. The aim of this study is to find the best model to estimate the parameters, to predict the share price, and to forecast the volatility of data share price of Adaro energy Tbk, Indonesia, from January 2014 to December 2016. The study also discuss the Window Dressing. The best model which fits the data is identified as AR(1)-GARCH (1,1). The application of this best model for forecasting the share price of Adaro energy Tbk, Indonesia, for the next 30 days showed very promising results and the mean absolute percentage error was determined as 2.16%.

Keywords: Volatility, Heteroscedasticity, Autoregressive Conditional Heteroscedastic Effect, GARCH Model, Window Dressing
JEL Classifications: C5, Q4, Q47

1. INTRODUCTION

Forecasting is a method to predict the future by evaluating the information and data in the prior period. Financial analysts, as the mediators of information, play an extensive role to examine the useful information through profit and share forecast (Jahangir, 2013; Chunhui et al., 2013). Financial analysts are the intercessor of information as they conduct retrospective analysis towards firm private and financial information to generate future information. Forecast conducted by financial analyst and management of the association could help the firm to evaluate and valuat the firm to improve the quality of their financial reporting as forecasting links to the expected amount of earnings that raised on the current year (Beaver et al., 1980). There are three types of classification methods based on the time period, which are short-term forecasting, medium-term forecasting, and long-term forecasting (Montgomery et al., 2008). Short-term forecasting is used to forecast daily, weekly, and monthly basis forecasting. The concrete short-term forecasting helps the management to take decision regarding the human resource planning, inventory control, and cash-flow management (Fildes and Goodwin, 2007). There are many studies have been conducted, such as forecasting of the market model (Neslihanoglu et al., 2017), Forecasting to study a recession of a country, recession forecasting as a key activity which was performed by many economic institutions (Fornaro, 2016; Morana, 2017), forecasting volatility by using GARCH (1,1) model (Chia et al., 2016; Tsung-Han and Yu-Pin, 2013), and so on.

Public presume volatility as the same as the risk in the market. The lowest volatility in share price would raise the lowest share price movements in the market. In the low volatility share price, to received capital gain, investors have to hold the share as a long-term investment. The highest the volatility in the market, the highest the uncertainty or return. This situation of volatility and highest return is commonly known as “Risk and Return Tradeoff.” When the daily volatility of a share price is high, there could arise high increase or decrease of share prices which provides a space for trading in order to receive gain by the differences of the opening and closing share prices, which can be called as “High Risk High Return” (Hull, 2015). Investors who usually plan a strategic trading would like to choose the high volatility (risk taker), while investors who tend to invest for long-term investment would prefer to choose a low volatility as the share price would increase in the future (risk adverse) (Chan and Wai-Ming, 2000). Nowadays, many economic and statistical studies are used to forecast the market condition (Dzikevičius and Šaranda, 2011).

Many studies have been conducted to discuss the effect of energy on economic growth and the forecasting of energy price. Tehranchian and Seyyedkolaee (2017) investigated the relationship between volatility of oil prices and economic growth in Iran as an oil-exporting country. They also discussed the impact of oil price volatility on the economic growth in the country. Vijayalakshmi et al. (2014) discussed the forecasting of electricity prices in deregulated wholesale spot electricity market. Weron (2006) and Weron and Misiorek (2006; 2008) studied on modeling the forecasting of electricity loads and prices. Volatility in capital market means the gap between increase or decrease of a stock price which is highly fickle and there would be a moment where the volatility will go up and down. High volatility means that the stock price increases and decrease significantly within a second. The volatility (price changes) in capital market is significantly affecting the return of an investment. The situation could also follow the theory of risk and return trade-off as known as "high risk, high return". Volatility is also considered as the fundamental to asset pricing and important information for investment (Kongsilp and Mateus, 2017).

2. DATA AND STATISTICAL MODELING

In this study the used data are the share prices of Adaro energy Tbk. which is an Indonesia-based company engaged in integrated coal mining through its subsidiaries. Its business activities include mining, barging, ship loading, dredging, port services, marketing, and power generation (PT Adaro energy, Tbk, 2017).

The data were taken from index LQ45, Jakarta. To analyze the data, some steps were conducted. Firstly, to plot the time series data to see the behavior of the data. Secondly, to examine the stationary data where the stationary mean is checked through the plot of the data, statistical test using Augmented Dickey Fuller (ADF) test, autocorrelation function (ACF) plot of the data, and inspecting the white noise data. The stationary data sets were determined through the plot of the data. If the data are non-stationary, differencing and transformation of the data were used. When the data are stationary, ACF and partial ACF (PACF) were applied to estimate the order of ARMA. Thirdly, to estimate and test the parameters, to diagnose and test the residuals, and to select the best model based on the criteria of the smallest values of Akaike information criterion (AIC) or SC. The residuals obtained from the best ARMA model were checked by using lagrange multiplier (LM) test to know whether or not they have autoregressive conditional heteroscedastic (ARCH) effect. If there is ARCH effect, the data are modeled by using ARCH or GARCH model. The order of ARCH or GARCH model was identified through the plot of the squared residuals of PACF. Fourthly, to estimate and test the parameters of the model and to forecast the daily closing price of LQ45.

2.1. Plotting the Data

To see the behavior of the data closing price of LQ45, the time series data were plotted. From the plotted graph of the data, the behavior pattern can be described, especially about the stationary data, stationary in mean and variance, which are the basic assumption in time series analysis.

2.2. Testing for Stationary Data

To analyze the stationary data, besides the plot of time series graph, statistical test was conducted by using Augmented Dicky Fuller test (ADF test). Some time series data tend to be non-stationary, for example, a price series data, due to the fact that there is no fixed level for price. This non-stationary series is called unit-root non-stationary time series (Tsay, 2005). A unit-root is a feature of some stochastic processes that can cause problems in time series modeling. The process of ADF test is presented as follows (Brockwell and Davis, 2002; Tsay, 2005).

Let $x_1, x_2, \ldots, x_n$ are time series data and $\{x_t\}$ follows the AR(p) model with mean μ. The mathematical expression of the model can be presented in Equation (1).

$$x_t = \mu + \varphi_1 x_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta x_{t-1} + \varepsilon_t \quad (1)$$

Where is the difference sequence of x_t, ε_t is white noise with mean 0 and variance σ^2 ($\varepsilon_t \sim WN(0, \sigma^2)$). ADF test as the unit-root test was conducted through the calculation of the value of τ statistic as follows:

Ho: $\varphi_1 = 1$ (data non-stationary).

Ho: $\varphi_1 < 1$ (data stationary).

The test statistics is (ADF test)

$$\tau = \frac{\varphi_i}{\hat{S}e_{\varphi_1}} \quad (2)$$

For the level of significance ($\alpha = 0.05$), reject Ho if $\tau < -2.57$ or if $P < 0.05$ (Brockwell and Davis, 2002. p. 195).

2.3. Checking for White Noise

If a time series consists of uncorrelated observation (data) and has a constant variance, it can be said as white noise (Montgomery et al., 2008). If the observations of this time series are normally distributed, the time series is called Gaussian white noise. If a time series is white noise, the distribution of the sample autocorrelation coefficient at lag k in a large sample is approximately normal distribution with mean 0 and variance 1/T, where T is number of observations (Montgomery et al., 2008; Brockwell and Davis, 2002; Pankratz, 1991). is the expression is presented in Equation (3).

$$r_k \sim N(0, \frac{1}{T}) \quad (3)$$

Based on the Equation (3), it is possible to test the hypothesis of autocorrelation of lag k Ho: $\rho_k = 0$ against Ha: $\rho_k \neq 0$ by using the test statistic, presented in Equation (4).

$$Z=\frac{r_k}{\sqrt{1/T}}=r_k\sqrt{T} \quad (4)$$

Reject Ho if $|Z| > Z_{\alpha/2}$ where $Z_{\alpha/2}$ is the upper $\alpha/2$ percentage point of the standard normal distribution or by using p-value, reject Ho if $P < 0.05$. The test statistic given by Equation (4) can be used to test for ACF and PACF (Wei, 2006). If the ACF is in very slow decay, the time series is indicated as non-stationary.

The procedure presented above is a one-at-a-time test; namely, the significance level applies to the autocorrelation and considered individually. This study aims to evaluate a set of autocorrelations jointly if the time series is indicated as white noise. To deal with this problem, the statistic expression can be used, given by Box-Pierce statistic (Box-Pierce, 1970), as shown in Equation (5).

$$Q_{BP}=T\sum_{k=1}^{K} r_k^2 \quad (5)$$

It is distributed approximately as chi-squares with K degrees of freedom and under null hypothesis that the time series is white noise (Montgomery et al., 2008). Ho would be rejected if $Q_{BP}>\chi^2_{\alpha,K}$ and concluded that the time series is not white noise. It is also possible to use p-value to reject Ho if $P < 0.05$.

If the data are non-stationary, the process of differencing and transformation of the data are used. When the data become stationary in mean, ACF and PACF needs to apply to estimate the order of ARMA. When the differencing is done, the process of innovation data is checked by the same method as above: Checking the plot of the data, testing the autocorrelation by using Box-Pierce test, and examining the behavior of ACF.

2.4. Testing for the ARCH Effects

This step is to estimate and test the parameters, to diagnose and test the residuals, and to select the best model based on the criteria of the smallest values of AIC or SC. The residuals obtained from the best ARMA model are checked by using LM test to know the ARCH effect. If there is ARCH effect, the data are modeled by using ARCH or GARCH method. The order of ARCH or GARCH model is found through the plot of the squared residuals of PACF.

2.5. Autoregressive Model of Order p, AR (p), Moving Average (MA (q)) Model, and ARMA Model

General form of AR(p) model is presented in Equation (6).

$$x_t=\delta+\phi_1 x_{t-1}+\phi_2 x_{t-2}+..+\phi_p x_{t-p}+\varepsilon_t \quad (6)$$

Where, white noise.

MA model with order q is defined by MA(q) and can be written as shown in Equation (7).

$$x_t=\mu+\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\theta_3\varepsilon_{t-3}-\ldots-\theta_q\varepsilon_{t-q};\ \varepsilon_t\sim N(0,\sigma^2) \quad (7)$$

where, x_t is a variable at time t; ε_t is an error at time t; θ_i is regression coefficient, i is the series of positive real numbers (i=1,2,3,…,q); and q is the order of MA.

In general form, autoregressive MA of order p, q, ARMA (p,q), is defined as shown in Equation (8).

$$x_t=\delta+\phi_1 x_{t-1}+\phi_2 x_{t-2}+\cdots+\phi_p x_{t-p}+\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\cdots-\theta_q\varepsilon_{t-q}$$
$$=\delta+\sum_{i=1}^{p}\phi_i x_{t-i}+\varepsilon_t-\sum_{i=1}^{q}\theta_i\varepsilon_{t-i} \quad (8)$$

Where is variable at lag t; ϕ_i is the coefficient of regression, I = 1, 2, 3..., p; p is the order of AR; θ_j is the parameter MA model, j = 1, 2, 3...,, q; and ε_t is the error at time t.

2.6. Model ARCH

The basic idea of the least squares model assumes that the expected value of all the square error is the same at any given point. This assumption is called homoscedasticity (Engle, 2001). The ARCH/GARCH models are build based on the assumption that the variances are not constant. This assumption is called Heteroscedasticity. The ARCH and GARCH models treat heteroscedasticity as a variance which needs to be modeled (Engle, 2001; Bollerslev, 1986). Engle (1982) introduced a model time-varying conditional variance with autoregressive conditional heteroscedasticity (ARCH) model by using lagged disturbances. ARCH is a function of autoregression which assumes that the variance is not constant over time and also affected by past data. The idea behind this model is to see the relationship between the current and the previous random variable. The ARCH model is built as: Let $x_1, x_2,, x_T$ be the sequence of random data, and be the set of random data up to time t, then ARCH model with degree q with respect to x_t is: $x_t\,|\,F_{t-1}\sim N(0,\sigma_t^2)$, where F_{t-1} is the information available at time t-1.

Conditional variance of the residual ε_t which is σ_t^2, can be written as,

$$\sigma_t^2=\omega+\lambda_{t-1}^2+\lambda_2\varepsilon_{t-2}^2+\cdots+\lambda_q\varepsilon_{t-q}^2$$

Where the variance residual depends on the-q squares of residual, and is called ARCH. The ARCH model can be written as shown in Equation (9).

$$x_t=\delta+\sum_{i=1}^{p}\phi_i x_{t-i}-\sum_{i=1}^{q}\theta_i\varepsilon_{t-i}+\varepsilon_t \quad (9)$$

εt~N(0, σ2)

$$\sigma_t^2=\omega+\lambda_1\varepsilon_{t-1}^2+\lambda_2\varepsilon_{t-2}^2+\cdots+\lambda_q\varepsilon_{t-q}^2$$

x_t is the equation of conditional mean (Brooks, 2014).

2.7. LM Test

Engle (1982) stated that the time series data has a problem with autocorrelation also has a problem with heteroscedasticity. Weiss (1984) showed the importance of detecting the presence of ARCH effect in time series data. He ignored the presence of heteroscedasticity not only for the estimation of parameters to be inefficient, but also could result in an overparameterized ARMA model. The test that can be used to detect the heteroscedasticity or ARCH effect is ARCH-LM (Engle, 1982; Tsay, 2005).

The steps are as follows:

1. Define the linear regression,
   $x_t=\mu+\lambda_1 x_{t-1}+\lambda_2 x_{t-2}+\ldots+\lambda_p x_{t-p}+\varepsilon_t$
2. Squares the residual and regress on the variance t to test the order of q ARCH,
   $\sigma_t^2=\lambda_0+\lambda_1\varepsilon_{t-1}^2+\lambda_2\varepsilon_{t-2}^2+\cdots+\lambda_q\varepsilon_{t-q}^2$

Where ε_t is residual. Now from this residual, the needs to be found.

3. The test statistic is:

$$LM=TR^2 \quad (10)$$

Where,

$$R^2=\frac{\sum_{i=1}^{n}\left(\hat{x}_i-\bar{x}\right)^2}{\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}$$

T is total number of observation, R^2 is R-square with χ^2 (q) distribution.

4. The null and alternative hypothesis that given by Brooks (2014) are,

$H_0=\lambda_1=\lambda_2=\ldots=\lambda_q=0$, against,

$H_1\ldots\ \lambda_1\neq 0$ or $\lambda_2\neq 0$ or … or $\lambda_q\neq 0$.

Although the LM is helpful in detecting ARCH effect, it is still difficult in practice to determine the order of the process. One method to determine the order of the model is to fit several competing models and then compare the AIC values for these competing models.

2.8. Generalized ARCH (GARCH) Model

GARCH model (Generalized Autoregressive Conditional Heteroscedastic) model is a generalized form of ARCH. This model is built to avoid the order of ARCH model which is too high. GARCH model not only observes the relationship among some residuals, but also depends on some past residuals. GARCH was introduced by Bollerslev (1986). GARCH model with degree p and q is defined as follows.

$$x_t|F_{t-1}\sim N(0,\sigma_t^2)$$

GARCH model allows the conditional variance based on the conditional variance of the previous lag. So, the equation of conditional variance becomes as presented by Equation (11).

$$\sigma_t^2=\omega+\sum_{i=1}^{q}\lambda_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \quad (11)$$

Where the present values of the conditional variance are parameterized based on the q lag from the squares residual and the p lag of the conditional variance and is written as GARCH (p,q). So, time-varying conditional variance of GARCH model is heteroscedastic with both autoregression and MA (Wang, 2009). GARCH model can be written as shown in Equation (12).

$$x_t=\delta+\sum_{i=1}^{p}\phi_i x_{t-i}-\sum_{i=1}^{q}\theta_i\varepsilon_{t-i}+\varepsilon_t \quad (12)$$

$\varepsilon_t\sim N(0,\sigma^2)$

$$\sigma_t^2=\omega+\sum_{i=1}^{q}\lambda_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\beta_j\sigma_{t-j}^2$$

x_t is the equation of conditional mean (Bollerslev, 1986).

2.9. Criteria of Selecting Model

In selecting a best model, the AIC criterion is used. The aim of AIC is to find the best prediction. The criterion is defined as follows:

$$AIC=-2\left(\frac{1}{T}\right)+2\left(\frac{k}{T}\right),$$

Where,

$$l=-\frac{Td}{2}(1+\ln 2\pi)-\frac{T}{2}\ln\left|\hat{\Omega}\right|,\left|\hat{\Omega}\right|=\det\left(\frac{\sum_t\hat{\varepsilon}_t\hat{\varepsilon}_t'}{T}\right)$$

Here l is log-likelihood function, k is number of parameters to be estimated, and T is total number of observation.

2.10. Checking the Window Dressing

Conceptually, window dressing is a short-term deviation of a financial variable from its long-term level (Owens and Wu, 2011). Based on this concept, the long-term level is presenting respective years and the short term level is indicating months in a year. Therefore, first, the average of the year and the average of months in the year were calculated and the deviation of the month with respect to the average of the year was found. Then the deviation was divided by the average of the year and multiplied by 100 to find the % deviation. Based on this concept the behavior of the share price can be compared, whether it is above or below the average of the share price of the year.

3. RESULTS AND DISCUSSION

The data used in this study are Data of closing Share Price of Adaro energy Tbk. Before analyzing the data, a set of stationary data were checked. There are many ways to check the stationary data, (1) by looking at the plot of the data subjectivity and it is possible to judge whether the data are stationary or not, (2) by testing the stationary data by using ADF test. Figure 1 is presenting the plotted data of Adaro energy Tbk.

The Graph of Figure 1 shows that the data are non-stationary, the first two hundred data show the increasing trend, then the trend decreased up to around the fifth hundred data, and again the trend is in increasing up to the last data. This behavior confirms that the data are not constant around a certain number, thus the data of Adaro energy Tbk. are non-stationary.

From Table 1 presents the ADF unit-root test statistic for non-stationary data where the tests (P-values) show that the data for Adaro energy Tbk is 0.9652. From these tests, it can be confirmed that the data of Adaro Energy are non-stationary. Table 2 shows that the tests statistics for the intercepts (Ho: Intercept =0) is very significant with the P-values as < 0.0001. These mean that the intercepts are different from zero. From the analysis of correlation for the data, Figure 2 can be presented.

By examining these plots, it can be judged that whether the data series of Adaro energy Tbk are stationary or non-stationary. From Figure 2 for data of Adaro energy Tbk, the ACF indicates that the series is non-stationary, as the ACF decays are very slow. Table 3 is used to examine the stationary data by checking the White Noise.

To check the stationarity of data, it is possible to use the behavior of White Noise. This test is an approximate statistical test of the hypothesis that none of the autocorrelations of the series up to a given lag are significantly different from zero. If this is true for all lags, there is no information about the series. The autocorrelation are checked in groups of six (Table 3) where the white noise hypothesis is rejected very strongly ($P < 0.0001$), which are expected as the data series of Adaro energy Tbk (Figure 3) are non-stationary.

In the next step, data differencing is performed to make the series as stationary in mean. The following are the results of differencing data and the correlation analysis, as presented in Figure 3.

3.1. Identification of the Differenced Series for the Data of Adaro Energy Tbk

Since the data series are non-stationary, next step is to transform the data to a stationary series by differencing. By using differencing with lag = 2 (d = 2), the data Adaro energy Tbk attain the stationary. The stationarity can be seen from the behavior of the residual data after differencing which are distributed around zero (Figure 3), for residual data of Adaro energy Tbk. This also can be seen from the behavior of the plot of ACF that decrease rapidly (Figure 3).

The next step in the Box-Jenkins methodology is to examine the patterns of the autocorrelation lot to choose the candidate ARMA models of the series. The PACF plots are also useful aids in identifying appropriate ARMA models for the series. The white noise, shown in Table 4, indicate that the change in data of Adaro energy Tbk is highly autocorrelated. Thus, autocorrelation models, for example, AR(2) models for data Adaro energy Tbk might be a good candidate model to fit with these process.

Table 1: Augmented Dickey-Fuller unit root test

Type	Data	Lags	Tau	P-value
Mean	Adaro energy Tbk	3	0.0936	0.9652

Table 2: The parameters estimate for intercepts

Variable	Data	DF	Estimate	Standard Error	t-value	P-value
Intercept	Adaro energy Tbk	1	959.08	10.8384	88.49	0.0001

Table 3: Checking for white noise of the data of adaro energy Tbk

To lag	Chi-square	DF	P-value	Autocorrelation					
6	4447.04	6	<0.0001	0.992	0.984	0.977	0.969	0.962	0.995
12	8541.13	12	<0.0001	0.948	0.941	0.933	0.926	0.920	0.913
18	9999.99	18	<0.0001	0.905	0.898	0.892	0.885	0.878	0.870
24	9999.99	24	<0.0001	0.861	0.853	0.846	0.838	0.832	0.824

Table 4: Checking for white noise data Adaro energy Tbk after differencing (d=2)

To lag	Chi-square	DF	P-value	Autocorrelation					
6	168.56	6	<0.0001	0.459	−0.069	−0.007	0.023	−0.021	−0.013
12	171.37	12	<0.0001	0.009	−0.027	−0.046	−0.016	0.013	−0.013
18	208.20	18	<0.0001	−0.076	−0.057	0.063	0.146	0.113	0.011
24	218.99	24	<0.0001	−0.030	−0.019	0.059	0.052	0.051	0.051

Figure 1: Plot of the data Adaro energy Tbk

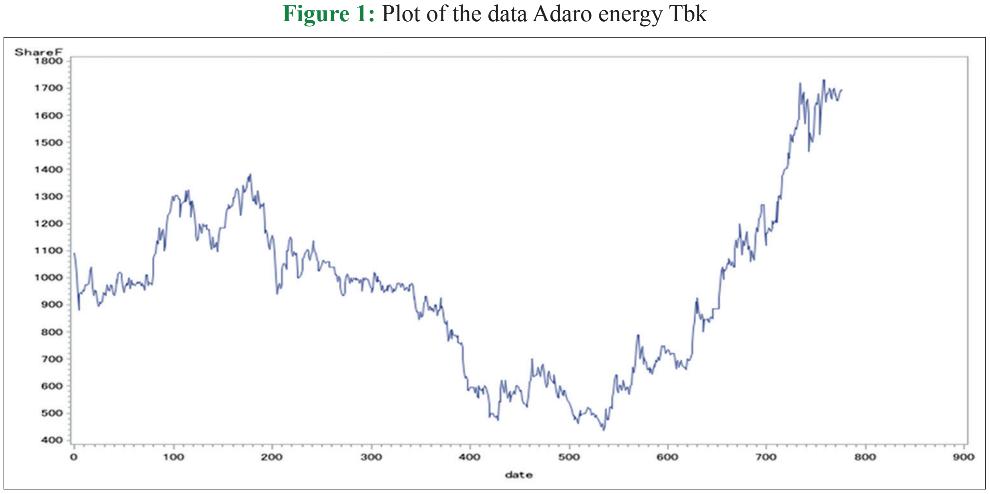


Figure 2: Correlation analysis for the data of Adaro energy Tbk

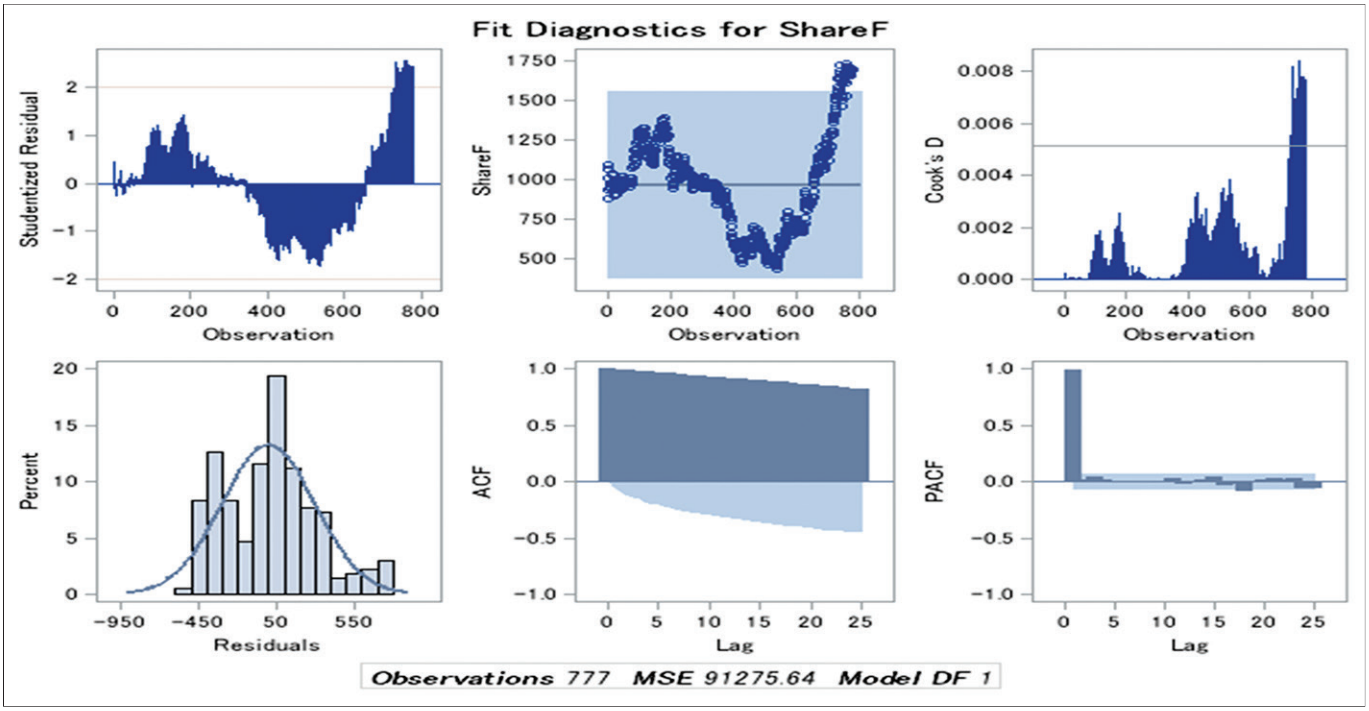
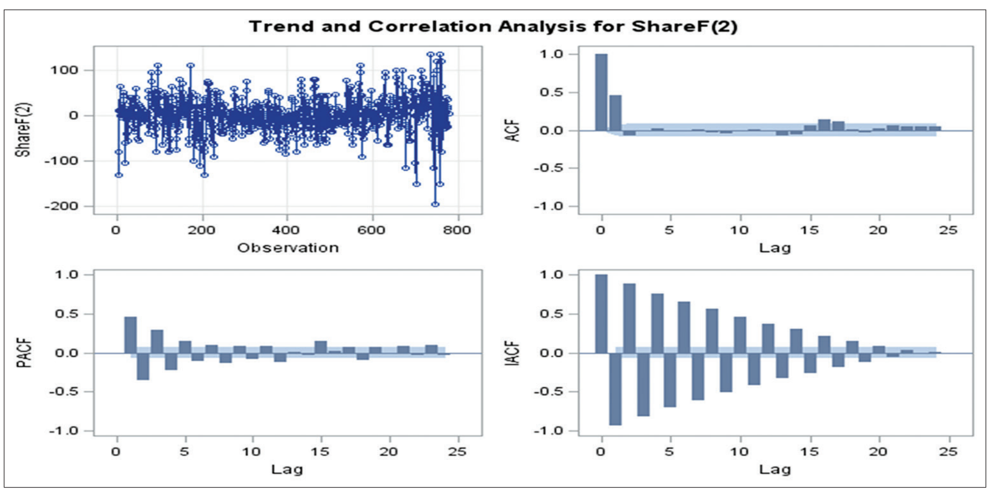


Figure 3: Plot of residuals, autocorrelation function (ACF), partial ACF, and inverse ACF after differencing with d = 2 (differencing with lag = 2) for data Adaro energy Tbk



3.2. Testing for ARCH Effect

One of the key assumptions on the ordinary least squares (OLS) regression is that the error has the same variance (homoscedasticity). If the error variance is not constant throughout the sample, the data are said to be heteroscedastic. As OLS assumes constant variance, the present of heteroscedasticity causes the application of OLS is inefficient for estimation. Models that take into account the presence of heteroscedasticity should be applied to make more efficient use of the data. In regression analysis, general linear model (GLM) can be used to cope with this heteroscedasticity problem. In time series analysis, some methods, such as GARCH models, can be used. Therefore, before using the GARCH model, the present of heteroscedasticity needs to be checked. ARCH LM test can also be used to check the presence of heteroscedasticity

Table 5: ARCH LM test data for adaro energy Tbk

Test for ARCH disturbances based on OLS residuals				
Order	Q	P-value	LM	P-value
1	774.0236	<0.0001	757.1325	<0.0001
2	1515.617	<0.0001	757.1558	<0.0001
4	2925.964	<0.0001	757.79	<0.0001
5	3595.516	<0.0001	757.8749	<0.0001
6	4245.03	<0.0001	758.1264	<0.0001
3	232.1119	<0.0001	757.7645	<0.0001
7	4873.598	<0.0001	758.1282	<0.0001
8	5478.215	<0.0001	758.2621	<0.0001
9	6055.321	<0.0001	758.2832	<0.0001
10	6600.781	<0.0001	758.367	<0.0001
11	7145.042	<0.0001	758.3681	<0.0001
12	7657.635	<0.0001	758.4107	<0.0001

OLS: Ordinary least squares, LM: Lagrange multiplier or ARCH effect. Table 5 presents portmanteau Q and LM test for ARCH effects.

From Table 5, the Q statistics are calculated from the squared residuals and are used to test for nonlinear effects (for example, GARCH effects) presented in the residuals. The null hypotheses (Ho) is tested against Ha in Table 5 as follows:

Ho: The OLS residuals data of Adaro energy Tbk are white noise (or no ARCH effects).

Against Ha: The OLS residual data of Adaro energy Tbk are not white noise (or there is ARCH effects).

From the test statistics of Portmanteau Q and LM tests, Ho is rejected as the p-value in Table 5 is < 0.0001 (P < 0.0001). Therefore, we can conclude that the data of Adaro energy Tbk has ARCH effects. This conclusion is also supported by the behavior of conditional variance for the data of Adaro energy Tbk (Figure 4). Thus, a model is needed which can cope with the problems of heteroscedastic variance. In this cases, ARCH/GARCH model is used to explain the behavior of the data.

3.3. Autoregressive (AR) - GARCH (AR-GARCH) Modeling

From the results of the analysis of data by using AR(1)-GARCH(1,1) model, the estimation of the mean model (AR1) and variance model GARCH(1,1) are presented in Table 7. Based on the results of the analysis, given in Table 7, the estimation model AR(1)-GARCH(1,1) can be presented as follows:

The mean model

$$x_t = 1090 - 0.9992\, x_{t-1} + \varepsilon_t$$

and the variance model

$$\sigma_t^2 = 27.8789 + 0.0934\varepsilon_{t-1}^2 + 0.8714\sigma_{t-1}^2$$

Where, x_t is the share price data of Adaro energy Tbk at time t.

From Tabel 6 we have that the AR(1)-GARCH(1,1) has R-squares=0.99, this means that 99% of the variability can be explained by the model; MSE=771.57 (Table 6). So we can calculate the Root Means Square Error (RMSE) is 27.78 which is very small relative to the prediction share price (P_SP) (Table 8). Since RMSE is very small this mean that the model has a better forecasting ability. This also supported by the graph of forecasting and the real values are very close to each other (Figure 6). Means Absolute Error (MAE) which is 19.79 (Table 6) also relatively very small compared to the prediction share price (P_SP) (Table8). The MAPE is 2.16 (Table 6) which is very small, this indicate the accuracy of the prediction are very good.

Table 6: The statistics of GARCH estimate data of Adaro energy Tbk

Statistics	GARCH estimate data Adaro energy Tbk (model AR (1)-GARCH (1,1))
Observations	777.00
SSE	599507.51
MSE	771.57
Log likelihood	−3638.42
SBC	7310.11
AIC	7286.84
AICC	7286.92
HQC	7295.79
MAE	19.79
MAPE	2.16
Uncond var	791.47
R^2	0.99
Normality test	40.99
P-value	<0.0001

Table 7: The parameter estimates model AR (1)-GARCH (1,1) data of Adaro energy Tbk

Variable	DF	Estimate	Standard error	t-value	P-value
Intercept	1	1090.0000	1049.0000	1.04	0.2991
AR1	1	−0.9992	0.0029	−337.28	<0.0001
ARCH0	1	27.8789	8.1608	3.42	0.0006
ARCH1	1	0.0934	0.0192	4.87	<0.0001
GARCH1	1	0.8714	0.0226	38.58	<0.0001

Figure 4: Conditional variance (volatility) data of Adaro energy Tbk

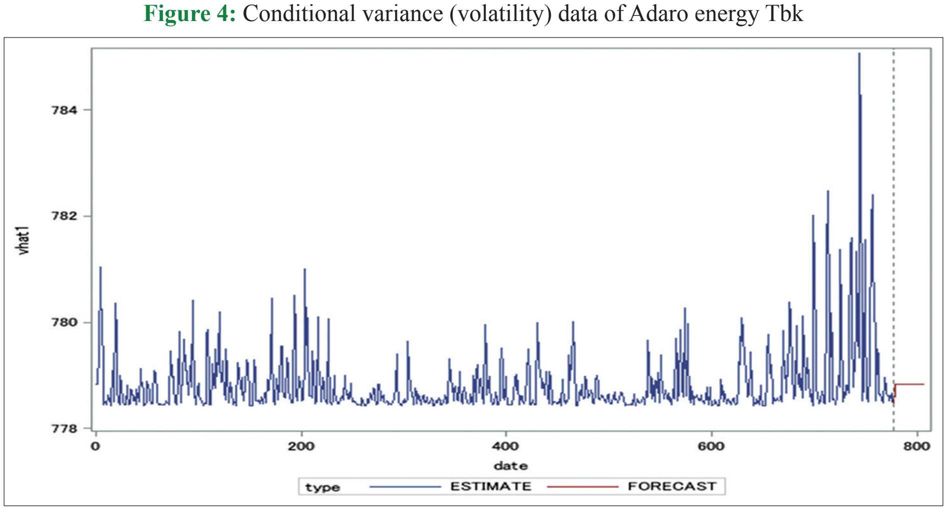


Figure 5: The conditional variance (volatility) AR(1)-GARCH(1,1) model data of Adaro energy Tbk

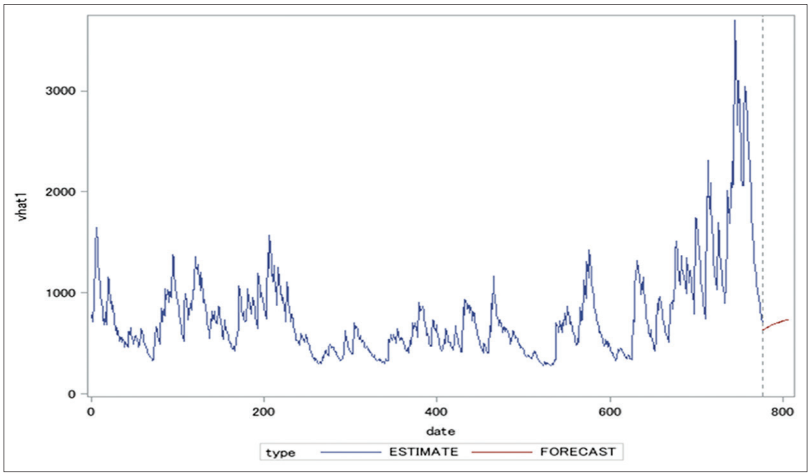


Table 8: Forecasting data of Adaro energy Tbk for the next 30 days (date)

Day (date)	Data Adaro energy Tbk		
	LL	P_SP	UL
778	1645.10	1694.49	1743.88
779	−656.54	1693.97	4044.49
780	1607.58	1693.46	1779.34
781	−656.63	1692.95	4042.53
782	1581.16	1692.44	1803.72
783	−656.74	1691.93	4040.59
784	1559.29	1691.42	1823.54
785	−656.86	1690.90	4038.67
786	1540.09	1690.39	1840.69
787	−657.00	1689.89	4036.77
788	1522.71	1689.38	1856.05
789	−657.15	1688.87	4034.88
790	1506.65	1688.36	1870.07
791	−657.31	1687.85	4033.01
792	1491.63	1687.34	1883.05
793	−657.48	1686.84	4031.15
794	1477.45	1686.33	1895.21
795	−657.66	1685.82	4029.31
796	1463.97	1685.32	1906.67
797	−657.84	1684.81	4027.47
798	1451.08	1684.31	1917.54
799	−658.04	1683.80	4025.65
800	1438.70	1683.30	1927.90
801	−658.25	1682.80	4023.84
802	1426.78	1682.29	1937.81
803	−658.46	1681.79	4022.04
804	1415.26	1681.29	1947.32
805	−658.68	1680.79	4020.25
806	1404.09	1680.29	1956.48
807	−658.90	1679.79	4018.47

The graph of the conditional variance for the data of Adaro energy Tbk is given in Figure 5 along with the forecast conditional variances. The graph shows that the conditional variance is varying over time (date).

3.4. Window Dressing Analysis

From the average share price of Adaro Energy Tbk, in 3 years from 2014 to 2016, it seems from the Table 9 that the average share price was 1109 in 2014, 752 in 2015, and 1031 in 2016. As the relative share price growth toward the average share price of 2014, it indicates that January to April and October to December, the share price is below the average share price of 2014, perhaps from May to September the share price is above the average share price of 2014. The average share price in September boosted to 16.8% as above the average share price of the year 2014, while the minimum share price is on February with the average share price of −15.4% as below the average share price of 2014. In December, the average share price is −3.8% that is below the average share price of the year 2014, which indicate that there is a small probability of Window Dressing at the year end of 2014. From the relative share price growth toward the average share price of 2015, from January to June it shows that the average share price is between 9.6% and 31.7% as above the average share price of the year 2015. But in July to December, the share price is below the average share price of 2015, which is in between −16.4% and −32.8%. the highest average share price in 2015 is on January which is 31.9%, beyond the average share price of 2015, while the lowest average share price happens in December, which is −32.8% as below the average share price of the year 2015. The December average share price shows a decrease of −32.8% comparing to the average share price of the year 2015 and this could indicate that the probability of Window Dressing is small. From the relative share price growth towards the average share price in the year 2016, from January to July seems that the share price is below the average share price of 2016 which is −2.5% to −52.2%. Perhaps from August to December, the share price is above the average share price of 2016, which is from 10.4% to 65.9%. The highest average share price on this year is in December with the average of 65.9% as above of the average share price, while the lowest average share price is in January which is −52.2% as below the average share price of the year 2016. December shows that the average share price is beyond the average share price of the year 2016, which is interesting and by the percentage, it shows that there is a small probability of window dressing as the share price movement is consistent and increasing from January to December.

Figure 7 shows that the share price data of Adaro Energy Tbk are the deviation of the average price of months with respect to the mean of the share price of the year 2014, 2015, and 2016. The deviation of the year 2016 is very high comparing with the other 2 years, 2014 and 2015. This indicated that the volatility of the

Table 9: (%) gain of monthly share price with respect to the average of the share price of the year to check the possibility of window dressing

Company	Year	Average of the share price of the year	(%) gain with respect to the average of the share price of the year											
			Jan	Feb	Mar	April	May	June	July	Aug	Sep	Oct	Nov	Dec
Adaro energy Tbk	2014	1109	−12.0	−15.4	−11.2	−9.0	10.7	12.1	4.4	14.7	16.8	−4.0	−3.2	−3.8
	2015	752	31.9	30.9	29.1	22.4	17.9	9.7	−16.4	−28.4	−23.1	−17.1	−20.6	−32.8
	2016	1013	−52.2	−41.3	−31.1	−29.8	−31.7	−16.7	−2.6	10.4	18.8	42.9	58.7	65.8

Figure 6: The plot of lower confidence limit (LL), predicted (P_SP) and upper confidence limit (UL) data of Adaro energy Tbk

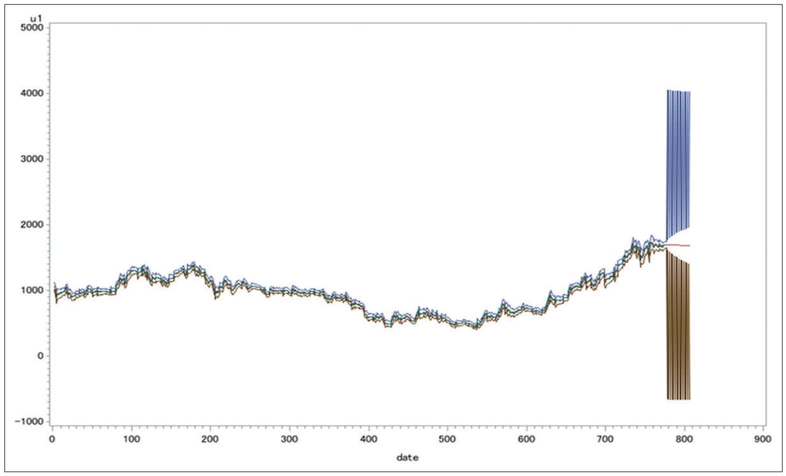
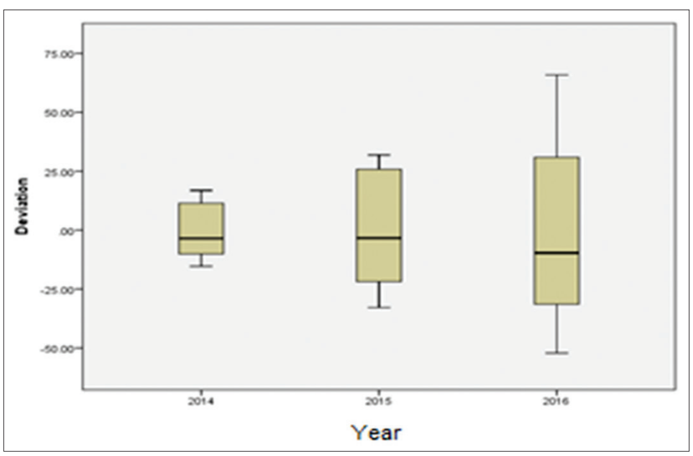


Figure 7: (%) deviation of the mean share price of months with respect to the mean of the year for the data of Adaro energy Tbk



price of Adaro energy Tbk in 2016 is very high compared to the volatility of the other 2 years, 2014 and 2015.

4. CONCLUSION

In this study, the data of Adaro Energy Tbk from Indonesia LQ45 are studied by using analysis time series AR(p)-GARCH(p,q) modeling. From the analysis it is found that the data of Adaro Energy Tbk are non-stationary. To make the data stationary, the differencing process with lag = 2 (d = 2) is used and the time series data then become stationary. From the test of ARCH effects by using Q test and LM, it concludes that the data of Adaro Energy Tbk have ARCH effects. Based on this situation, the AR(p)-GARCH(p,q) model are used to model the data.

The best model for all data of Adaro Energy Tbk is AR(1)-GARCH(1,1) model. The models is significant and the R-squares is identified as 0.99 for the model data of Adaro Energy Tbk, the application of these model for prediction are quite good based on the criteria of MAPE (the Mean Absolute Percentage Error) for the forecasting of data for Adaro Energy Tbk as 2.16%. The model is also used for forecasting for the next 30 days (date).

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