International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2020, 10(6), 175-184.

Dynamic Modeling Data Export Oil and Gas and Non-Oil and Gas by ARMA(2,1)-GARCH(1,1) Model: Study of Indonesian's Export over the Years 2008-2019

Nairobi[1]*, Edwin Russel[1,2], Ambya[1], Arif Darmawan[1], Mustofa Usman[3], Wamiliana[3]

[1]Department of Economic Development, Faculty of Economic and Business, Universitas Lampung, Indonesia, [2]Department of Mathematics, Faculty of Mathematics and Sciences, Universitas Lampung, Indonesia, [3]Department of Mathematics, Faculty of Mathematics and Sciences, Universitas Lampung, Indonesia. *Email: nairobi.saibi@gmail.com

Received: 03 May 2020 **Accepted:** 25 August 2020 **DOI:** https://doi.org/10.32479/ijeep.9892

ABSTRACT

It is well known that a country's economy is very dependent on the export of goods and services produced by that country. This depends on exporting either mining products such as oil and gas or non-oil and gas. This paper will study the data export of oil and gas and data export of non-oil and gas of Indonesian over the years 2008-2019. The aim of this study is to obtain the best model that can describe the pattern of the data export of oil and gas and data export of non-oil and gas. From the results of the analysis, researchers found that the best models that can describe the pattern of data export of oil and gas and data export of non-oil and gas are the same, namely: ARMA (2.1) -GARCH (1.1) models. These models for both data are very significant with $P < 0.0001$ and < 0.0001, respectively, R-squares are 0.8797 and 0.7604, respectively and mean average percentage errors are 12.41 and 6.92, respectively. These models are very reliable, and they can be used to predict (forecast) for the next 12 periods (months).

Keywords: Akaike's Information Criterion, Autoregressive Moving Average, Generalized Autoregressive Conditional Heteroscedasticity, Mean Average Percentage Error
JEL Classifications: C32, Q4, Q47

1. INTRODUCTION

Nowadays, modeling time series data has become an interesting area of research for many scientists. Modeling time series data have been widely used in the fields of economic, business, financial, stock market, social sciences, and many others. Many studies of modeling data time series exist, especially the modeling for forecasting and prediction of future values. Three types of forecasting classification exist based on the periods of times, namely the short term forecast, medium term forecast, and long-term forecast (Montgomery et al., 2008). Short term forecast is used for forecasting for a short period of time: daily, weekly, or monthly. Many studies exist that are related to forecasting: Warsono et al. (2019a; 2019b), Virginia et al. (2018), who discussed the application of GARCH model to forecast data and volatility share price of energy, Neslihanoglu et al. (2017), who studied modeling for forecasting market model, and application of GARCH model for forecasting volatility model by (Chia et al., 2016).

Many economists are interested on modeling volatility (variance) of asset return. Volatility (or variance of return) is considered as a measure of risk. This kind of measure is very important for investors to measure the risky asset. Banks and many financial institutions apply the concept of volatility and the so-called value-at-risk model to measure the risk. Therefore, modeling and forecasting volatility (variance of return) by using the autoregressive conditional heteroscedasticity (ARCH) or GARCH model is very important (Terasvirta, 2009). The ARCH model is the

first model of conditional heteroscedasticity (Engle, 1982). Engle (1982), in his study, applied his ARCH model in a wage-price for the United Kingdom. Even though in his first application, Engle (1982) was not in finance, but many economists and scientists soon realized the potential application of the ARCH model in financial, business, economic and social sciences. The ARCH model and its generalization (Bollerslev, 1986) are thus applied to modeling in the field of financial, exchange rate, and stock market. The GARCH model has been widely used by many practitioners. Application in daily and monthly temperature measurement can be found in a study conducted by Tol (1996), Campbell and Diebold (2005), and Romilly (2006). The McAleer and Chan (2006) study showed the modeling trends and volatility in atmospheric carbon dioxide concentrations. Application in the stock market can be found in the study conducted among others by Schwert (1989), Sabbatini and Linton (1998), Pagan and Schwert (1990), Barusman, et al. (2018), and King et al. (1994). Application in asset return can be found in study conducted, among others, by Nelson (1991). Application in option pricing modeling can be found in study conducted, among others, by Hsieh and Ritchken (2005), Huang, et al. (2008), and Hull and White (1987).

In this study, the data that are going to be used are the data export of oil and gas and the data export of non-oil and gas of Indonesia over the year 2008-2019 from Central Bureau of Statistics Indonesia (BPS, 2019a; 2019b). The aim of this study is going to be to find the best model for both data export of oil and gas and data export of non-oil and gas, but first, all the assumptions of the model will be checked, so that the best model we build will be meet the underlying assumptions.

2. TIME SERIES MODELING

In this study the data used are the data export of oil and gas and data export of non-oil and gas of Indonesia over the year 2008-2019 (BPS, 2019a; 2019b). First, before we analyze the data, we need to check the behavior of the data and whether they satisfied the assumption of the model that we are going to use. The assumptions that are commonly used are stationarity, autocorrelation, and equal variance. To examine the assumption of stationarity, we can use a graph (or plot) of the data or through the statistical analysis. Through the plot of the data time series, we can examine the behavior of the data and examine if it shows the following: a constant mean, a trend, and equal variances. By using statistical analysis, the augmented dickey-fuller (ADF) test with the null hypotheses is that the data are nonstationary (Tsay, 2005; Virginia, 2018). By the autocorrelation function (ACF) plot, we can inspect the white noise of the data. If the data are nonstationary, then we can transform the data, by using the process of differencing (Brockwell and Davis, 2002; Montgomery et al., 2008) to make the data more stationary.

To estimate the order of ARMA model, an Akaike's Information Criterion (AICC) criterion is used. The Portmanteau Q test and Lagrange Multiplier (LM) test are used to know whether the data export of oil and gas and data export non-Oil and Gas exhibit an ARCH effect. If the data exhibit ARCH effect, the data then will be modeled by using the ARCH or GARCH model.

2.1. Graph of the Data

Through the graph of the time series data export of oil and gas and data export of non-oil and gas, the behaviors of the data can be explore, the behavior pattern can be described whether the assumption of stationarity satisfied, or if the pattern of the error demonstrates a difference variances (heteroscedasticity). Based on graphs or plots of the data, we can judge whether the assumption of time series modeling is satisfied.

2.2. ADF Test

To check the stationary data export of oil and gas and the data export non-oil and gas, besides the plot of the time series data, statistical analysis can be used, the ADF test can be used. This nonstationary time series test is called the unit root nonstationary test (Tsay, 2005; Wei, 2006; Warsono et al., 2019a). Said and Dickey (1984) augment the basic Autoregressive unit root test for general Autoregressive Moving Average (ARMA) models, and their test is called the ADF test. In the ADF tests, the null hypothesis is that the data are nonstationary with the alternative hypothesis being that the data are stationary (Brockwell and Davis, 2002; Virginia et al., 2018; Warsono et al., 2020). The ADF test is built based on the following regression model (Zivot and Wang, 2006; Tsay, 2005), with lag = p:

$$X_t = \mu_t + \alpha X_{t-1} + \sum_{i=1}^{p-1} \varphi_i \Delta X_{t-i} + \mu_t \quad (1)$$

Where μ_t is constant function at time t, $\Delta X_n = X_n - X_{n-1}$ is the difference series of X_t, and ε_t is the error. The test statistic is as follows:

$$\text{ADF test} = \frac{\hat{\alpha} - 1}{\text{std}(\hat{\alpha})} \quad (2)$$

Reject null hypothesis if the $P < 0.05$. The ADF test also sometimes called the τ-test (Tau-test) (Wei, 2006; Brockwell and Davis, 2002).

2.3. Corrected Akaike's Information Criterion (AICC)

Let's consider a linear regression model with p as the coefficient and the likelihood estimator for variance is as follows:

$$\hat{\sigma}_p^2 = \frac{RSS_p}{n} \quad (3)$$

Where $RSS_p = \sum_{t=1}^{p} (X_t - \bar{X})^2$ denotes the regression sum of squares under the model with p regression coefficients. The Corrected AICC, which was proposed by Sugiura (1978), is defined as follows:

$$AICC = \ln \hat{\sigma}_p^2 + \frac{n+p}{n-p-2} \quad (4)$$

Where $\hat{\sigma}_p^2$ is given in (3), p is number of parameters in the regression model, and n is sample size (Shumway and Stoffer, 2006).

2.4. Testing for White Noise

If time series data exhibit uncorrelated observation and a constant variance (homoscedasticity), then the error is said to be as white noise (Wei, 2006; Tsay, 2005). If the errors are white noise and

exhibit a normal distribution, the time series is called Gaussian White Noise (Virginia et al., 2018). Statistics that are commonly used to test the present of white noise are Q Statistics (or Box-Pierce Test) or Ljung-Box test (Ljung and Box, 1978). The null hypothesis regarding the testing of the white noise is that the errors (residuals) are white noise. Under the null hypothesis, all the autocorrelations r_j for j >0 are zero (Zivot and Wang, 2006). To test this null hypothesis, Box and Pierce (1970) propose the Q-Statistic as follows:

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

Where r_j is autocorrelation at lag j and T is the sample size. Under the null hypothesis, the Q_{BP} statistic asymptotically demonstrates a Chi-squares distribution with k degrees of freedom, $\chi^2(k)$.

2.5. Test for Normality Distribution

To check for normality distribution of the data or the error (residual), some methods exist that can be used. First, we can check by visual inspection, by looking at the pattern of histogram of the data or error (residuals). Second, we can check by inspection of the Q-Q plot of the data or error (residuals). Third, we can use the statistical analysis method, the Jarque-Bera (JB) test. The JB test with the null hypothesis is that the data are normally distributed and defined as follows (Brockwell and Davis, 2002):

$$JB = n\left[\frac{m_3^2}{6m_2^3} + \frac{\left(\frac{m_4}{m_2^3} - 3\right)^2}{24}\right] \quad (6)$$

where n is the sample size, and $m_r = \sum_{i=1}^{n} (X_i - \bar{X})^r / n$. Under the null hypothesis, the JB test approximately exhibits chi-square distribution with two degrees of freedom, $\chi^2(2)$.

2.6. Testing for ARCH Effect

In a classical regression model, the basic idea of the ordinary least square (OLS) method assumes that the expected value of all the square error is the same at any given point (Virginia et al., 2018). This assumption is called equal variances or homoscedasticity (Brockwell and Davis, 2002; Montgomery et al., 2008). The ARCH or Generalized ARCH (GARCH) model is built based on the assumption that the variances are not constant (Heteroscedasticity). Engle (1982) introduced an ARCH model, and Bollerslev (1986) proposed the GARCH model. Before estimating the ARCH or GARCH model for the data export of oil and gas and export of non-oil and gas, first, we need to check the presence of ARCH effects in the error (residuals). If no ARCH effect in the errors (residuals) are present, then the ARCH or GARCH model are unnecessary. To test the ARCH effects, first, the ARCH model is written as the Autoregressive (AR) Model in terms of squares error (residuals), as follows (Zivot and Wang, 2006):

$$\varepsilon_t^2 = \gamma_o + \gamma_1 \varepsilon_{t-1} + \ldots + \gamma_p \varepsilon_{t-p} + u_t \quad (7)$$

To test the ARCH effect, the statistics LM test is used with the null hypothesis being that no ARCH effect is present. The LM test is defined as follows:

$$LM = T.\ R^2$$

Where T is sample size, and R^2 is R-Squares computed from the regression model (7) using estimated error (residuals). Under the null hypothesis, LM approximately exhibits a Chi-squares distribution with p degrees of freedom, $\chi^2(p)$.

2.7. Generalized ARCH Model

In the traditional ARMA model, we assume that the error ε_t to be i.i.d. But in practice, this assumption sometimes is inadequate. For example, the presence of conditional variances of the error (residuals) may contain much useful information if we consider the modeling data time series. Engle (1982) shows that the serial correlation in squared return, or conditional heteroscedasticity, can be modeled using the ARCH model. Bollerslev (1986) proposed a GARCH, where he proposed that the present conditional variance is a function of the previous squared error and previous variances. Let the data or the observations $X_1, X_2, \ldots, X_n$ be generated by the ARMA model with the error being generated by the GARCH process,

$$X_t = \sum_{i=1}^{m} \varphi_i X_{t-i} + \sum_{i=1}^{n} \psi_i \varepsilon_{t-i} + \varepsilon_t \quad (8)$$

and

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p} \theta_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \mu_i \sigma_{t-i}^2 \quad (9)$$

Model (8) and (9) are called the ARMA(m,n)-GARCH(p,q) model. If p = q = 0, the model is just an ARMA(m,n) model; If q = 0, then the model reduces to the ARMA(m,n)-ARCH(p)model; If n = 0, then the model reduces to the AR(m)-GARCH(p,q) model; If n = q = 0, then the model reduces to the AR(m)-ARCH(p) model. Under the GARCH(p,q) model, the conditional variance depends on the squares error (residual) in the previous p periods and the conditional variance in the previous q periods. Usually a GARCH (1,1) model is adequate to obtain a good model fit for financial time series (Zivot and Wang, 2006).

3. RESULTS AND DISCUSSION

In this study, the data to be analyzed are the data export of oil and gas and export non-oil and gas of Indonesia from January 2008 to November 2019. The data are from the Bureau of Statistics Indonesia (BPS, 2019a; 2019b). Before further analysis of the data, first we have to check the assumption of stationarity, some approaches to check this assumption exist: (1) by looking at the behavior of the plot of the data, from where we can analyze and conclude whether the data are stationary or not, and (2) by using analytical approach or statistical test, the ADF test, and other relevant tools (Virginia et al., 2018; Warsono et al., 2019b; 2020).

From the plot of the data export of oil and gas, as presented in Figure 1a, the results show that the data are nonstationary. Additionally, the plot shows that six trends in six difference periods exist. In the first 6 months of 2008, the trend increased and fluctuated; for second period in the last 6 month of 2008, the trend decreased and fluctuated; for the third period from 2009 to mid-2011, the trend increased and fluctuated; in the

fourth period from mid-2011 to 2016, the trend decreased and fluctuated; in the fifth period from 2016 to December 2018, the trend increased; and in 2019, the trend decreased and fluctuated. From the plot of the data export of non-oil and gas, as presented in Figure 1b, the results show that the data are nonstationary, and the plot shows that six trends exist in six different periods. For the first six months of 2008, the trend increased and fluctuated; for second period, in the last 6 months of 2008 the trend decreased; for third period from 2009 to mid-2011, the trend increased and fluctuated; in the fourth period from mid-2011 to mid-2016, the trend decreased and fluctuated; in the fifth period from mid-2016 to mid-2018, the trend increased; and in the mid-2018 to November 2019, the trend increased and fluctuated. Based on the behavior of the data export of oil and gas and non-oil and gas (Figure 1a and b), we conclude that the data are nonstationary.

By using statistical analysis and the ADF test to test the nonstationary data, the null hypotheses was that the data are nonstationary. The ADF test is presented in Table 1, and it shows that the P-values for export oil and gas and export non-oil and gas are 0.8340 and 0.0893, respectively. The ADF test of the export oil and gas and export non-oil and gas are nonsignificant, which temporary concluded that the data are nonstationary.

Table 1: ADF unit root test for data export oil and gas and non-oil and gas

Type	Data	Lags	Tau	P-value
Mean	Export oil and gas	3	−0.7300	0.8340
	Export non-oil and gas	3	−2.6300	0.0893

ADF: Augmented dickey-fuller

From Figure 2a, for data of export oil and gas, the ACF indicates that the series is nonstationary, since the ACF decays very slowly. Based on Figure 2b, for the data of export non-oil and gas, the ACF indicates that the series is nonstationary, since the ACF decay is very slow.

Since the data export of oil and gas and export non-oil and gas are nonstationary, the next step is to transform those data into a stationary series by differencing. By using differencing with lag = 1 (d = 1), the data of data export oil and gas and export non-oil and gas attained as stationary. The stationary data can be seen from the behavior of the residual data after differencing, which are distributed around zero (Figure 3a and 3b), for residual data of data export of oil and gas and export of non-oil and gas, respectively. Furthermore, the ACF in Figure 3a and b decays very fast, and this indicates that the data are stationary. Table 2 shows the ADF test, and we reject the null hypothesis that the data are nonstationary. The next step in the Box-Jenkins methodology is to examine the patterns in the autocorrelation lag, to choose candidates of ARMA models for these series. The partial ACF plots are also useful aids in identifying appropriate ARMA

Figure 1: (a) Plot of the data of export oil and gas, (b) Plot of the data of export non-oil and gas

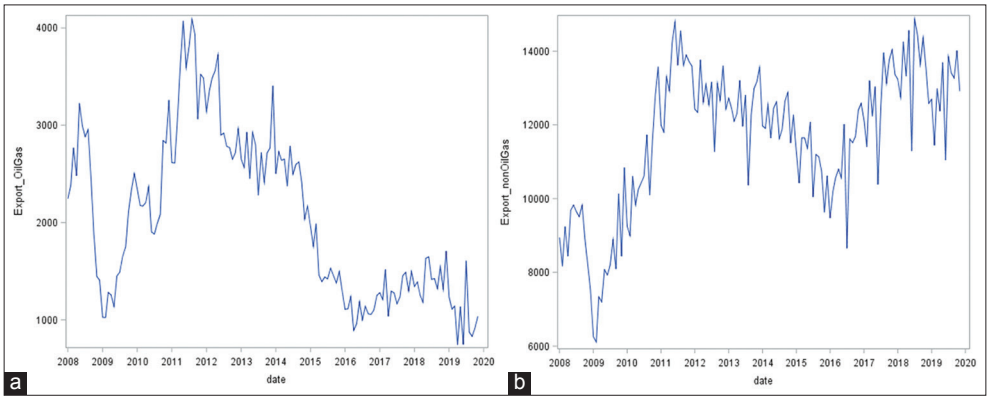
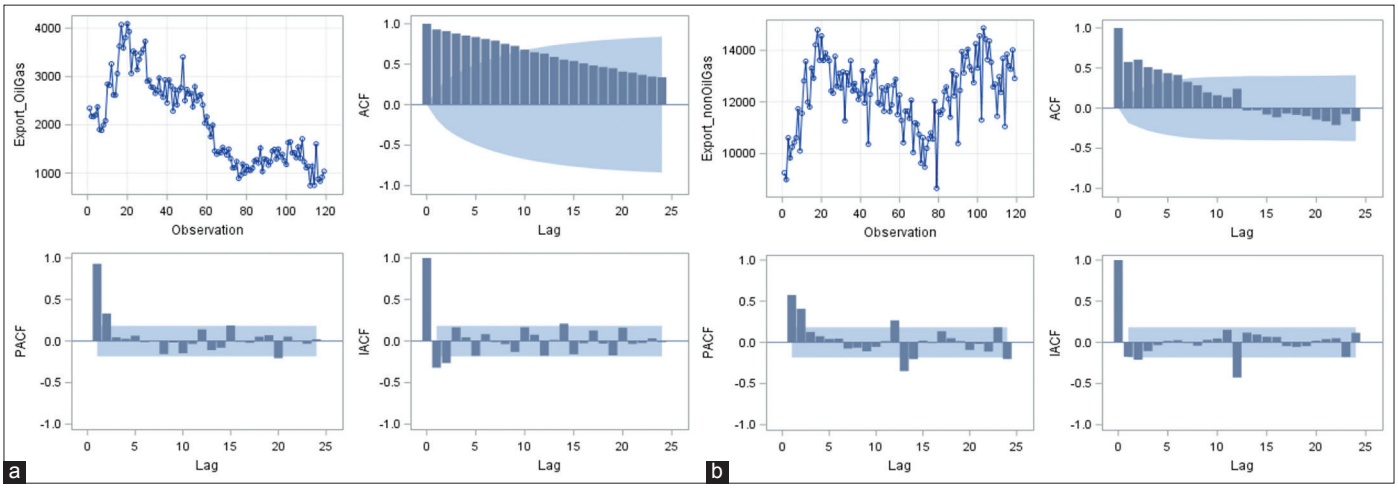


Figure 2: (a) Correlation analysis for data export oil and gas, (b) Data export non-oil and gas



models for these series (Box and Jenkins, 1976). To check for white noise, shown in Table 3 (before differencing) and Table 4 (after the data are differentiated with lag = 1(d = 1)), the results show that the data export of oil and gas and export of non-oil and gas are highly autocorrelated. Thus, autocorrelation models, AR (2) models, for data of data export of oil and gas and export of non-oil and gas are used. It might be a suitable candidate model to fit for these processes.

3.1. Check for Heteroscedasticity and Model Building

Tables 5 presents the results of the Portmanteau Q and LM Test for ARCH effects. The null hypotheses is that the data exhibit no ARCH effect. The Q statistics are calculated from the squared residuals and are used to test for nonlinear effects (for example, GARCH effects) of the residuals. One of the key assumptions on the OLS regression is that the error exhibits the same variance (homoscedasticity). If the error variance is not constant throughout the sample, the data are called to be heteroscedastic. Since OLS assumes constant variance, the present of heteroscedasticity causes the application of OLS for estimation to be inefficient. Models are taken into account because of the presence of heteroscedasticity, which should be applied to make more efficient use of data. In regression analysis, general linear model 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 presence of heteroscedasticity needs to be checked. LM test can be used to check the presence of heteroscedasticity.

From Table 5, the test statistics of Portmanteau Q and LM Tests, the null hypothesis of no ARCH effects, were rejected, since the

Table 2: ADF unit root test for data export oil and gas, and non-oil and gas after differencing with lag = 1(d = 1)

Type	Data	Lags	Tau	P-value
Mean	Export oil and gas	3	−6.2500	<0.0001
	Export non-oil and gas	3	−7.6600	<0.0001

ADF: Augmented dickey-fuller

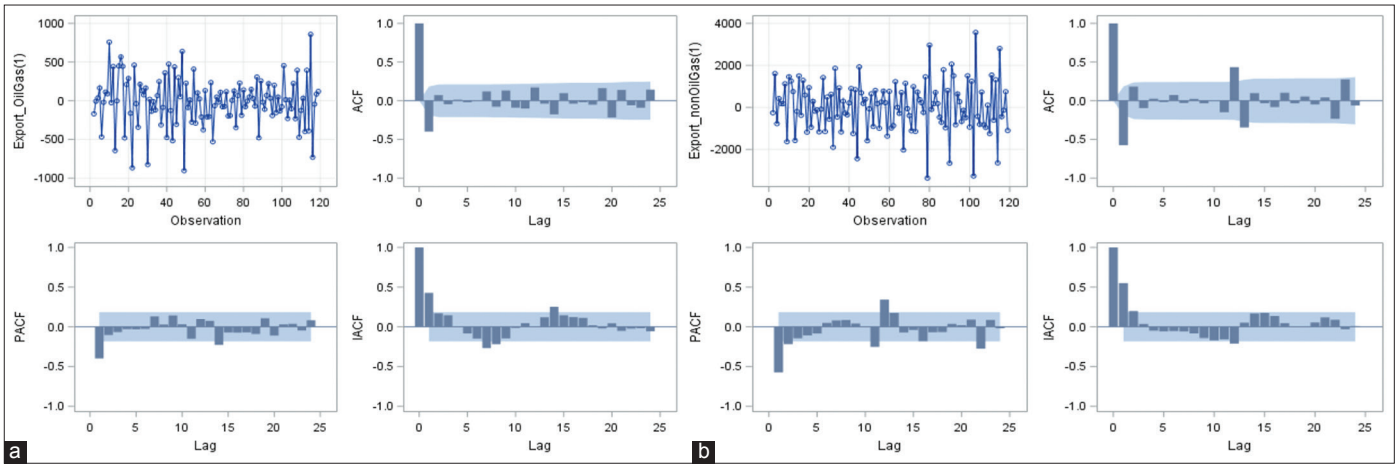
Table 3: Checking for white noise data export of oil and gas and data export of non-oil and gas

Data	To Lag	Chi-square	DF	P-value	Autocorrelations					
Export oil and gas	6	567.59	6	<0.0001	0.930	0.910	0.880	0.855	0.837	0.812
	12	961.59	12	<0.0001	0.793	0.753	0.727	0.681	0.648	0.631
	18	1192.20	18	<0.0001	0.590	0.556	0.540	0.511	0.485	0.465
	24	1324.55	24	<0.0001	0.451	0.409	0.396	0.369	0.347	0.339
Export non oil and gas	6	193.29	6	<0.0001	0.576	0.605	0.512	0.483	0.437	0.415
	12	236.34	12	<0.0001	0.328	0.285	0.197	0.160	0.135	0.241
	18	240.82	18	<0.0001	−0.028	−0.026	−0.079	−0.114	−0.067	−0.083
	24	260.55	24	<0.0001	−0.099	−0.143	−0.164	−0.211	−0.074	−0.162

Table 4: Checking for the white noise data export of oil and gas and data export of non-oil and gas after differencing with lag = 1 (d = 1)

Data	To lag	Chi-square	DF	P-value	Autocorrelations					
Export oil and gas	6	20.20	6	0.0025	−0.399	0.072	−0.046	0.013	−0.020	−0.002
	12	31.44	12	0.0017	0.120	−0.077	0.132	−0.089	−0.101	0.172
	18	37.72	18	0.0042	−0.038	−0.175	0.098	−0.038	−0.019	−0.050
	24	55.89	24	0.0002	0.163	−0.215	0.139	−0.058	−0.090	0.144
Export non oil and gas	6	45.96	6	<0.0001	−0.574	0.183	−0.095	0.026	−0.017	0.074
	12	74.42	12	<0.0001	−0.029	0.023	−0.033	0.003	−0.148	0.435
	18	94.52	18	<0.0001	−0.345	0.098	−0.032	−0.081	0.103	−0.033
	24	115.44	24	<0.0001	0.055	−0.048	0.042	−0.233	0.276	−0.061

Figure 3: (a) Correlation analysis for data export oil and gas, (b) Data export of non-oil and gas after differencing with lag = 1 (d = 1)



P-values for data export of oil and gas up to lag 12 are <0.0001, while data export of non-oil and gas are significant up to lag 8. Therefore, based on these results, we can conclude that the data export of oil and gas and data export of non-oil and gas exhibit heteroscedasticity. Thus, a model of which ARCH effect is needed which can solve the problems of unequal variances (heteroscedastic). In this study a GARCH model is used to explain the behavior of the heteroscedasticity variance of the data export of oil and gas and export of non-oil and gas.

From Table 6, based on minimum AICC criteria, the candidate models for data export Oil and Gas are ARMA(1,1)-GARCH(1,1), ARMA(2,1)-GARCH(1,1), ARMA(1,2)-GARCH(1,1), and for data non-Oil and Gas are ARMA(2,1)-GARCH(1,1), ARMA(2,0)-GARCH(1,1), ARMA(3,0)-GARCH(1,1). From the analysis of the data, researchers found that all the models are very significance with P < 0.0001. This indicates that all model can be used for further analysis. From Table 7, R-squares for data export of oil and gas are very close to each other. Also, for the data export of non-oil and gas, the R-squares are much close to each other. The AICC for data export of oil and gas model ARMA(2,1)-GARCH(1,1) is the smallest, and for data export of non-oil and gas the smallest is model ARMA(3,0)-GARCH(1,1). The p-values for ARCH test for data export of oil and gas model ARMA(2,1)-GARCH(1,1) and ARMA(1,2)-GARCH(1,1) are very closed to each other. For data export of non-oil and gas, the smallest p-value is model ARMA(2,1)-GARCH(1,1). Based on the analysis above and the results of Tables 5-7. In this study, the model ARMA(2,1)-GARCH(1,1) is used for both data export of oil and gas and data export of non-oil and gas.

From Table 8, we present that the R-squares for model ARMA(2,1)-GARCH(1,1) data export of oil and gas and data export of non-oil and gas are 0.8797 and 0.7604, respectively. These means that 87.97% of the variation of data export of oil and gas can be explained by the model; and 76.04% of the variation of data export of non-oil and gas can be explained by the model. These arevery high R-Square values that indicate that the model ARMA(2,1)-GARCH(1,1) are very fit to the data export of oil and gas and the data export of non-oil and gas.

Table 9 shows the results analysis of data export of oil and gas by using model ARMA(2,1)-GARCH(1,1). The estimation of the

Table 5: ARCH lagrange multiplier test data export oil and gas and data export non-oil and gas

Test for disturbances based on OLS residuals								
Order	Data export oil and gas				Data export non-oil and gas			
	Q	P-value	LM	P-value	Q	P-value	LM	P-value
1	675.1760	<0.0001	647.0891	<0.0001	7.7347	0.0054	6.3448	0.0118
2	1309.1374	<0.0001	652.3676	<0.0001	21.3987	<0.0001	13.1210	0.0014
3	1911.2133	<0.0001	653.3791	<0.0001	28.7649	<0.0001	14.0800	0.0028
4	2480.1076	<0.0001	653.4138	<0.0001	31.6284	<0.0001	14.2009	0.0067
5	3026.1355	<0.0001	653.7225	<0.0001	33.1298	<0.0001	14.4400	0.0130
6	3546.9266	<0.0001	653.7370	<0.0001	34.2724	<0.0001	14.4575	0.0249
7	4048.9336	<0.0001	653.9161	<0.0001	34.3749	<0.0001	16.0574	0.0246
8	4542.9154	<0.0001	654.6921	<0.0001	34.6791	<0.0001	16.0827	0.0412
9	5014.6210	<0.0001	654.8297	<0.0001	34.8557	<0.0001	16.5314	0.0566
10	5458.0136	<0.0001	655.3669	<0.0001	36.7799	<0.0001	18.9050	0.0415
11	5889.4879	<0.0001	655.7642	<0.0001	36.8225	0.0001	19.2728	0.0564
12	6296.5266	<0.0001	655.9675	<0.0001	36.9048	0.0002	19.2892	0.0818

Table 6: Selection for candidate model based on minimum AICC for data export oil and gas and data export non-oil and gas

Minimum information criterion based on AICC data export oil and gas							Minimum information criterion based on AICC Data export non-oil and gas					
Lag	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	13.49	13.46	13.39	13.31	13.25	13.19	15.12	15.06	14.99	14.95	14.91	14.85
AR 1	11.49	11.39*	11.39*	11.41	11.41	11.38	14.06	13.80	13.77	13.77	13.78	13.79
AR 2	11.42	11.39*	11.41	11.42	11.42	11.39	13.75*	13.75*	13.77	13.79	13.80	13.81
AR 3	11.42	11.41	11.42	11.44	11.43	11.40	13.75*	13.77	13.78	13.80	13.82	13.82
AR 4	11.44	11.41	11.42	11.43	11.44	11.41	13.77	13.78	13.80	13.82	13.83	13.83

*The selected candidate models of ARMA(m,n)- GARCH(p,q)

Table 7: Comparison some models ARMA-GARCH for data export oil and gas and data export non-oil and gas

Data	Model	R2	AICC	ARCH test P-value	Test model P-value
Export oil and gas	ARMA(1,1)-ARCH(1,1)	0.8779	1767.40	0.0236	<0.0001
	ARMA(2,1)-ARCH(1,1)	0.8795	1742.38	0.0127	<0.0001
	ARMA(1,2)-ARCH(1,1)	0.8800	1766.73	0.0113	<0.0001
Export non-oil and gas	ARMA(2,1)-ARCH(1,1)	0.7604	2083.09	0.0139	<0.0001
	ARMA(2,0)-ARCH(1,1)	0.7555	2085.91	0.1068	<0.0001
	ARMA(3,0)-ARCH(1,1)	0.7603	2070.08	0.0296	<0.0001

mean model ARMA(2,1) and variance model GARCH(1,1) are as follows

The mean model ARMA(2,1):

$$X_t = -17.7508 - 0.9858X_{t-1} - 0.2616\,X_{t-2} - 0.6359\varepsilon_{t-1} + \varepsilon_t \quad (10)$$

and the variance model GARCH(1,1):

$$\sigma_t^2 = 90276.9722 + 0.1738\,\varepsilon_{t-1}^2 - 0.2076\,\sigma_{t-1}^2 \quad (11)$$

Table 8: The statistics of GARCH estimate data export oil and gas and data export non-oil and gas

Statistics	GARCH Estimate Data Export Oil and Gas (Model ARMA(2,1)-GARCH(1,1))	GARCH Estimate Data Export non-Oil and Gas (Model ARMA(2,1)-ARCH(1,1))
Observations	143.00	143.00
Root MSE	294.51	963.65
MAPE	12.41	6.92
R-square	0.8797	0.7604
Normality test	1.95	3.26
P-value	0.3772	0.1956

MAPE: Mean average percentage error

Table 9: The parameter estimates model ARMA(2,1))-GARCH(1,1) data export oil and gas

Variable	DF	Estimate	Standard error	t-value	P-value
Intercept	1	−17.7508	39.7074	−0.45	0.6555
AR1	1	−0.9858	0.1870	−5.27	0.0001
AR2	1	−0.2616	0.1027	−2.55	0.0120
MA1	1	−0.6359	0.1766	−3.60	0.0004
ARCH0	1	90276.9722	0.0123	999.00	0.0001
ARCH1	1	0.1738	0.1054	1.65	0.1013
GARCH1	1	−0.2076	0.1267	−1.64	0.1035

Table 10: The parameter estimates model ARMA(2,1)-GARCH(1,1) data export non-oil and gas

Variable	DF	Estimate	Standard error	t-value	P-value
Intercept	1	813.30	343.517	2.37	0.0193
AR1	1	0.7030	0.1475	4.77	0.0001
AR2	1	0.2303	0.1372	1.68	0.0957
MA1	1	0.4094	0.1409	2.91	0.0043
ARCH0	1	907141.58	0.0927	999.00	0.0001
ARCH1	1	0.1710	0.1153	1.48	0.1403
GARCH1	1	−0.1561	0.1159	−1.35	0.1802

where X_t is the data for export non-Oil and Gas, ε_t is residual, and σ_t^2 variance at time t.

Table 10 shows the results analysis of the data export of non-oil and gas by using model ARMA(2,1)-GARCH(1,1). The estimation of the mean model ARMA(2,1) and variance model GARCH(1,1) are as follows:

The mean model ARMA(2,1):

$$X_t = 813.3000 + 0.7030X_{t-1} + 0.2303X_{t-2} + 0.4094\varepsilon_{t-1} + \varepsilon_t \quad (12)$$

and the variance model GARCH(1,1):

$$\sigma_t^2 = 907141.5800 + 0.1710\,\varepsilon_{t-1}^2 - 0.1561\,\sigma_{t-1}^2 \quad (13)$$

where X_t is the data for the export of non-oil and gas, ε_t is residual, and σ_t^2 variance at time t.

3.2. Check for the Behavior of Error (residuals)

Table 8 shows also the results of the normality test for the error (residuals) from the model ARMA(2,1)-GARCH(1,1) of the data export of oil and gas and data export of non-oil and gas. The normality test, with the null hypotheses that the error are normally distributed, and the results of the test for model ARMA(2,1)-GARCH(1,1) for the data export of oil and gas and data export of non-oil and gas P-values are 0.3772 and 0.1956, respectively. Therefore, we can conclude that the error (residuals) from both models are normally distributed. These results are also in line with the results in Figure 4a and b, the graphs or error from model ARMA(2,1)-GARCH(1,1) from the data export of oil and gas and data export of non-oil and gas. The graphs depicted the normally distributed of the error. The Q-Q plot also shows that the error from both models are normally distributed. The Table 7 shows the ARCH test for model ARMA(2,1)-GARCH(1,1) for both the data export of oil and gas and data export of non-oil and gas. The null hypotheses is no ARCH effect. The results of the test, the p-values, are 0.0127 and 0.0139 respectively. Therefore, we conclude that the null hypotheses are rejected. So, the error for both models from the data export of oil and gas and data export of non-oil and gas exhibit ARCH effects.

Figure 5 shows that the ARCH effect model ARMA(2,1)-GARCH(1,1) for the data export of oil and gas, which shows that the conditional variances fluctuates high and low on the

Figure 4: The distribution of prediction error of (a) data export oil and gas, (b) data export non-oil and gas

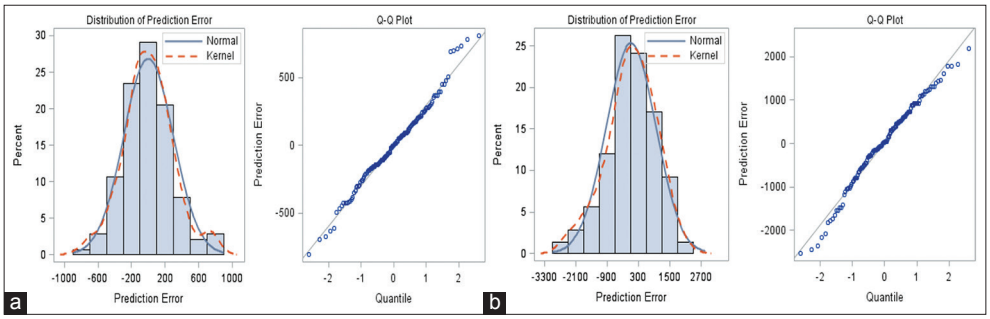


Figure 5: The conditional variance of ARMA(2,1)-GARCH(1,1) model data export of oil and gas

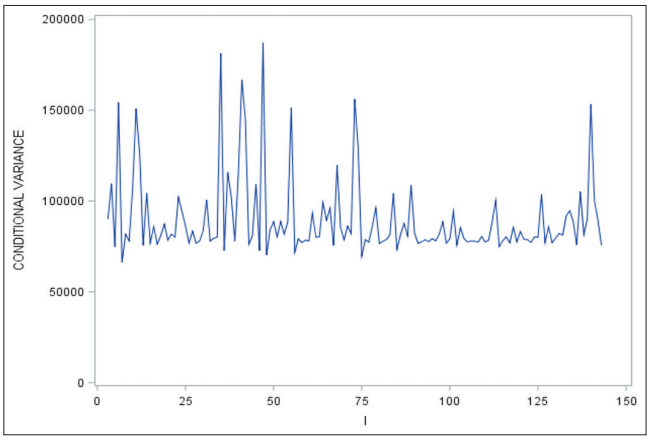
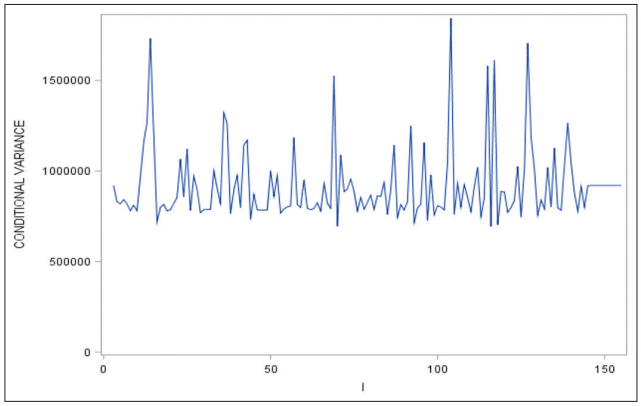


Figure 6: The conditional variance of ARMA(2,1)-GARCH(1,1) model data export non-oil and gas



horizon, January 2008–November 2019 (143 months). In the first 18 months, the conditional variances are very high and unstable. From the 18th to the 35th month, the conditional variances are small and fluctuate. For the 35th to the 75th month, the conditional variances are very high and unstable. From the 75th to the 130th month, the conditional variances are small and fluctuate. In the last part, from the 130th to the 143th month, the conditional variances are very high and unstable. Figure 6 shows that the ARCH effect model ARMA(2,1)-GARCH(1,1) for the data export of non-oil and gas. In the first 12 months (2008), the conditional variances are very high and unstable. For the 12th to the 62nd month, the conditional variances are small and fluctuate. For the 62nd to the 68th month, the conditional variances are very high and unstable. From the 68th to the 100th month, the conditional variances are small and fluctuate. From the 100th to the 130th month, the conditional variances are very high and unstable. From the 130th to the 143th month, the conditional variances are small.

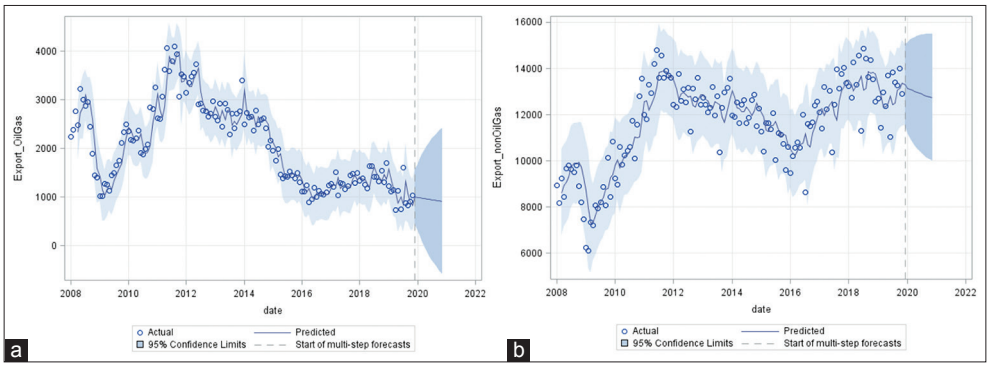
3.3. Forecasting

From Table 8, the results show that the root Mean Squares Error (MSEs) for model ARMA(2,1)-GARCH(1,1) of the data export of oil and gas and data export of non-oil and gas are 294.51 and 963.65, respectively. They are relatively small compared to the values of the data. The R-squares are 0.8797 and 0.7604, respectively. They are also considered very high and indicate that the models are sound. The mean average percentage error (MAPE) are 12.41 and 6.92, respectively, and they are considered very small values. Furthermore, the model ARMA(2,1)-GARCG(1,1) for both the data export of oil and gas and data export of non-oil and gas are very significant,

Table 11: Forecast data for the next 12 months of data export oil and gas and data export non-oil and gas

			Forecasts			
Variable	**Obs**	**Time**	**Forecast**	**Standard error**	**95% Confidence limits**	
Export_oil and gas	144	DEC2019	1004.01869	286.19226	443.09216	1564.94522
	145	JAN2020	986.88110	349.46337	301.94549	1671.81672
	146	FEB2020	994.55084	410.32131	190.33585	1798.76583
	147	MAR2020	973.72196	465.29349	61.76349	1885.68044
	148	APR2020	974.49876	510.86753	−26.78320	1975.78071
	149	MAY2020	961.43083	555.48705	−127.30379	2050.16545
	150	JUN2020	956.35971	595.00892	−209.83634	2122.55576
	151	JUL2020	947.02669	633.05864	−293.74546	2187.79883
	152	AUG2020	939.80332	668.42797	−370.29142	2249.89806
	153	SEP2020	931.61505	702.26919	−444.80728	2308.03737
	154	OCT2020	923.82614	734.43901	−515.64787	2363.30016
	155	NOV2020	915.89594	765.30497	−584.07424	2415.86611
Export_non-oil and gas	144	DEC2019	13303.96877	894.24390	11551.28294	15056.65460
	145	JAN2020	13139.56255	993.98915	11191.37962	15087.74547
	146	FEB2020	13114.48006	1073.58242	11010.29719	15218.66293
	147	MAR2020	13058.98435	1134.78867	10834.83942	15283.12927
	148	APR2020	13014.19362	1187.74977	10686.24684	15342.14040
	149	MAY2020	12969.92456	1233.04966	10553.19164	15386.65748
	150	JUN2020	12928.48757	1272.29619	10434.83287	15422.14228
	151	JUL2020	12889.16171	1306.43521	10328.59575	15449.72767
	152	AUG2020	12851.97222	1336.27239	10232.92646	15471.01798
	153	SEP2020	12816.77082	1362.43967	10146.43813	15487.10351
	154	OCT2020	12783.45908	1385.45588	10068.01544	15498.90271
	155	NOV2020	12751.93364	1405.74945	9996.71534	15507.15193

Figure 7: (a) The plot of data and its prediction and the forecasts for the next 12 periods (month) data export oil and gas, (b) The plot of data and its prediction and the forecasts for the next 12 periods (month) data export non-oil and gas



with P < 0.0001 and < 0.0001, respectively (Table 7). Those properties of the models ARMA(2,1)-GARCH(1,1) for both the data export of oil and gas and data export of non-oil and gas indicate that the models are very reliable, demonstrate high accuracy, and are sound for prediction or forecasting for the next values.

Figure 7a and b shows that the actual data (circle) and its predicted (line) are very close to each other, and this indicates that the models are very sound. Some data in Figure 7b look as an outlier or are far from the predicted values. Table 11 shows the forecasts for the next 12 periods (months). It shows that the values demonstrate a trend that is decreasing and with a small fluctuation for both models ARMA(2,1)-GARCH(1,1) of the data export of oil and gas and data export of non-oil and gas. Table 11 also shows that the standard error of forecasts is increasing, and this indicates that for long periods of forecasts, the predicted values are unstable (high standard error). Figure 7a and b shows that the graph of the forecast (predicted) values (line) exhibit a trend that is decreasing and its confidence interval. The graph also shows that the farther the forecast period, the greater the confidence interval values.

4. CONCLUSION

In this study, the data time series of the data export of oil and gas and data export of non-oil and gas of Indonesia over the year 2008 to 2019, the data are from Central Bureau of Statistics Indonesia and are studied by using statistical analysis of time series modeling. From the analysis, researchers found that the data export of oil and gas and data export of non-oil and gasare nonstationary and exhibit ARCH effects. Based on the assumption above, the model ARMA(m,n)-GARCH(p,q) are used to model the data export of oil and gas and data export of non-oil and gas. Based on the AICC criteria, researchers found that the best model for both the data export of oil and gas and data export of non-oil and gas is the ARMA(2,1)-GARCH(1,1) model. These error of the models for both the data export of oil and gas and data export of non-oil and gas are normally distributed, and the models are very significant and exhibit high R-squares. Besides, they demonstrate small MAPE for forecasting data. The model is used to forecasts for the next 12 periods (months).

5. ACKNOWLEDGMENTS

The authors would like to thank Central Bureau of Statistic Indonesia (BPS) for providing the data in this study. The authors would also like to thank Universitas Lampung for financially supporting this study through the Scheme Research Professorship. The authors would like to thank Enago (www.enago. com) for the English language review.

REFERENCES

Barusman, M.Y.S., Usman, M., Ambarwati, R., Virginia, E. (2018), Application of generalized autoregressive conditional heteroscedasticity (GARCH) model for forecasting. Journal of Engineering and Applied Sciences, 13, 3418-3422.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 31, 307-327.

Box, G.E.P., Jenkins, G.M. (1976), Time Series Analysis: Forecasting and Control. San Fransisco: Holden-Day.

Box, G.E.P., Pierce, D.A. (1970), Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. Journal of the American Statistical Association, 65, 1509-1526.

BPS. (2019a), Data Export Oil and Gas. Available from: https://www.statistik.kemendag.go.id/export-import. [Last accessed on 2020 Feb 10].

BPS. (2019b), Data Export Non-oil and Gas. Available from: https://www.statistik.kemendag.go.id/export-import. [Last accessed on 2020 Feb 10].

Brockwell, P.J., Davis, R.A. (2002), Introduction to Time Series and Forecasting. New York: Springer-Verlag.

Campbell, S.D., Diebold, F.X. (2005), Weather forecasting for weather derivatives. Journal of the American Statistical Association, 100, 6-16.

Chia, C.L., Skindilias, K., Karathanasopoulos, A. (2016), Forecasting latent volatility through a Markov chain approximation filter. Journal of Forecasting, 35, 54-69.

Engle, R. (1982), Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50, 987-1007.

Hsieh, K.C., Ritchken, P. (2005), An empirical comparison of GARCH option pricing models. Review of Derivatives Research, 8, 129-150.

Huang, H.H., Shiu, Y.M., Liu, P.S. (2008), HDD and CDD option pricing with market price of weather risk for Taiwan. Journal of Futures Markets, 28, 790-814.

Hull, J., White, A. (1987), The pricing of options on assets with stochastic volatilities. Journal of Finance, 42, 281-300.

King, M., Sentana, E., Wadhwani, S. (1994), Volatility and links between

national stock markets. Econometrica, 62, 901-933.
Ljung, G.M., Box, G.E.P. (1978), On a measure of lack of fit in time series models. Biometrika, 65, 297-303.
McAleer, M., Chan, F. (2006), Modelling trends and volatility in atmospheric carbon dioxide concentrations. Environmental Modelling and Software, 21, 1273-1279.
Montgomery, D., Jennings, C., Kulachi, M. (2008), Introduction Time Series Analysis and Forecasting. Hoboken, New Jersey: John Wiley & Sons Inc.
Nelson, D.B. (1991), Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347-370.
Neslihanoglu, S., Sogiakas, V., McColl, J.H., Lee, D. (2017), Nonlinearities in the CAPM: Evidence from developed and emerging markets. Journal of Forecast, 36, 867-897.
Pagan, A.R., Schwert, G.W. (1990), Alternative models for conditional stock volatility. Journal of Econometrics, 45, 267-290.
Romilly, P. (2006), Time series modelling of global mean temperature for managerial decision making. Journal of Environmental Management, 76, 61-70.
Sabbatini, M., Linton, O. (1998), A GARCH model of the implied volatility of the Swiss market index from option prices. International Journal of Forecasting, 14, 199-213.
Said, S.E., Dikey, D.A. (1984), Testing for unit roots in autoregressive moving-average models with unknown order. Biometrika, 71, 599-607.
Schwert, G.W. (1989), Why does stock market volatility change over time? Journal of Finance, 14, 1115-1153.
Shumway, R.H., Stoffer, D.S. (2006), Time Series Analysis and its Applications with R Examples. 2nd ed. New York: Springer-Verlag.
Sugiura, N. (1978), Further analysis of the data by Akaike's information criterion and the finite corrections. Communications in Statistics, Theory Methods, 7, 13-26.
Terasvirta, T. (2009), An introduction to univariate GARCH MODEL. In: Anderson, T.G., Davis, R.A., Kreiss, J.P., Mikosch, T., editors. Handbook of Financial Time Series. New York: Springer.
Tol, R.S.J. (1996), Autoregressive conditional heteroscedasticity in daily temperature measurements. Environmetrics, 7, 67-75.
Tsay, R.S. (2005), Analysis of Financial Time Series. Hoboken, New Jersey: John Wiley & Sons, Inc.
Virginia, E., Ginting, J., Elfaki, F.A.M. (2018), Application of GARCH model to forecast data and volatility of share price of energy (study on Adaro energy Tbk, LQ45). International Journal of Energy Economics and Policy, 8(3), 131-140.
Warsono, R.E., Putri, A.R., Wamiliana, W., Widiarti, U.M. (2020), Dynamic modeling using vector error-correction model: Studying the relationship among data share price of energy PGAS Malaysia, AKRA, Indonesia, and PTT PCL-Thailand. International Journal of Energy Economics and Policy, 10(2), 360-373.
Warsono, Russel, E., Wamiliana, W., Widiarti, Usman, M. (2019a), Vector autoregressive with exogenous variable model and its application in modeling and forecasting energy data: Case study of PTBA and HRUM energy. International Journal of Energy Economics and Policy, 9(2), 390-398.
Warsono, Russel, E., Wamiliana, W., Widiarti, Usman, M. (2019b), Modeling and forecasting by the vector autoregressive moving average model for export of coal and oil data (case study from Indonesia over the years 2002-2017). International Journal of Energy Economics and Policy, 9(4), 240-247.
Wei, W.W. (2006), Time Series Analysis: Univariate and Multivariate Methods. New York: Pearson.
Zivot, E., Wang, J. (2006), Modeling Financial Time Series with S-plus. New York: Springer-Verlag.