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Dynamic Modeling and Analysis of Some Energy Companies of Indonesia Over the Year 2018 to 2022 By Using VAR(p)-CCC GARCH(r,s) Model

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ABSTRACT

The stock price plays an important role in a financial market. In this research, the natural relationship of the daily stock prices of two energy companies, namely the daily stock price of ADRO and PTBA, from January 2018 to December 2022 will be discussed. The purpose of this research is to obtain the best model that fits the data of the daily share price of the two companies, ADRO and PTBA. The analysis used to model the data is the multivariate time series method. From the results of the analysis, it was found that the best model is VAR(3)-CCC-GARCH)(1,1). Based on this VAR(3)-CCC-GARCH(1,1) model, further analysis: impulse response function (IRF), granger causality, the proportion of prediction error covariances, and forecasting for the next 30 days are discussed. The granger causality test found that the ADRO and PTBA have mutual granger causality (bidirectional). The results of the IRF analysis explain: If there is a shock of one standard deviation in ADRO, ADRO and PTBA have a response. ADRO's response is positive for the next 24 days with a downward trend, while PTBA's response is positive with an upward trend; If there is a shock of one standard deviation in PTBA, PTBA itself and ADRO respond. ADRO's response is negative and weak and has a downward trend in the next 24 days, while PTBA's response is quite large and positive with a downward trend. From the forecasting results for the next 30 days (period), ADRO's closing price has decreased, and PTBA data has a downward trend for the next 30 days.

Keywords: VAR(p) model, CCC GARC(r,s) Model, Impulse Response Function, Granger-Causality, Variance Decomposition, Forecasting
JEL Clasifications: C53, Q4, Q47

1. INTRODUCTION

Autoregressive Conditional Heteroscedasticity (ARCH) modeling was first developed by Engle (1982), and the ARCH modeling concept continues to develop both in theory and in its application, especially research in the field of financial econometrics (Bauwens et al., 2012). With ARCH modeling, volatility modeling in the financial sector is developing rapidly (Bauwens et al., 2012). The generalization of the ARCH model was later developed by Bollerslev (1986), better known as the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. In GARCH modeling, it is explained that the current variance is a function of the residual and past variance. Since 1986 the GARCH model was introduced by Bollerslev (1986); the model has become extremely popular among academicians and practitioners. The GARCH models have led to fundamental changes in finance studies (Franco and Zakoian, 2016). With the development of the univariate GARCH model and its application to time series data, the expansion of this model's application to multivariate time series cases is also growing rapidly. Multivariate time series data modeling the cross-correlation between variables based on the concept of time lag are discussed (Hamilton, 1994; Wei, 2006; 2014; Lutkepohl, 2005; 2020; Tsay, 2010; 2014; Bauwens et al., 2012; Basu et al., 2019; Hamzah et al., 2020). The application of statistical modeling for multivariate time series data has encouraged research in the fields of finance, business, economics, and sciences (Lutkepohl, 2005; 2020; Tsay, 2014; Chamalwa and Bakari, 2016; Zhang et al., 2016; Keng et al., 2017; Bulteel, 2018; Dumitrescu et al., 2019). Kraft and Engle (1982) and Engle et al. (1984) were the first researchers to discuss the application of GARCH to multivariate time series data. They applied it to inflation models in the USA so that conditional covariance adapts over time. Bollerslev et al. (1988) applied multivariate data in the financial field, which expanded the concepts of ARCH and GARCH in the field of multivariate time series. The problem in ARCH and GARCH modeling applications in multivariate time series is the number of parameters involved. The next problem is estimating the parameters for multivariate time series with large dimensions.

Several researchers then developed several methods to overcome this. Engle and Kroner (1995) developed the BEKK-GARCH method. Engle et al. (1990) developed the factor model, Bollerslev (1990) developed the CCC-GARCH method, and Tse and Tsui (2002) developed the DCC-GARCH Dynamic Correlation model. Many studies have been conducted in the last four decades using the GARCH model. Lin et al. (2020) discussed forecasting crude oil price volatility using the Hidden Markov Exponential GARCH (HM-GARCH) model. In their research, Lin et al. (2020) compared the uni-regime GARCH model, the GARCH model with the Hidden Markov (HM) Switching regime in its ability to forecast in the West Texas Intermediate (WTI) crude oil market and the HM-GARCH model perform better than uni-regime GARCH model. Herera et al. (2018) discussed forecasting crude oil price volatility with the GARCH(1,1) model. Abounoori et al. (2015) used the GARCH model and discussed its ability to forecast the volatility of the Tehran Stock Exchange. Cheong (2009) in his study discussed the volatility of two major crude oil markets, namely the WTI and Europe Brent. In his analysis, Cheong (2009) uses the ARCH model to explain forms of volatility such as clustering, asymmetric impact, and long memory volatility. Crifter (2013) discusses electricity price behavior in the Nordic Electric power market using the HM-GARCH model. Crifter's research results (2013) explain that with the HM-GARCH model, the price of electric volatility is high and very dependent on the regime. Usman et al. (2022) discussed the energy companies variables for the cases of several energy companies in Qatar, namely the weekly stock price of Qatar Fuel Company (QFLS), Qatar Electricity and Water Company, and Qatar Gas Transport Company using the VAR(3)-GARCH(1,1) model. Using this model, IRF analysis, granger causality, and forecasting were carried out for the three energy companies. Nairobi et al. (2020) discuss a dynamic model for export oil and gas and non-oil and gas data for cases in Indonesia using ARMA(2,1)-GARCH(1,1) modeling, and this model is used for forecasting the next 12 months. Warsono et al. (2019) discussed export coal and oil data for cases in Indonesia using vector autoregressive moving average modeling.

In this study, daily stock price data of ADRO and PTBA from January 2018 to December 2022 will be analyzed using a multivariate time series analysis approach to get the best model that fits the data. Based on this objective, the VAR(p)-CCC-GARCH(r,s) model was developed to explain the relationship between ADRO's and PTBA's daily share price data. Methods for finding the best model, parameter estimation and testing, model checking, and vector time series forecasting are also discussed. Based on the best model, IRF analysis, granger causality, proportion prediction error covariance, and forecasting are discussed.

2. STATISTICAL MODELING

Untransformed data time series of economic or finance are often characterized by a trend (Burke and Hunter, 2017). One of the basic assumptions in time series analysis is the property of stationarity. Stationarity is central in time series analysis because it replaces naturally independent hypotheses and identically distributed observations in standard statistical analysis. A process $\{X_t\}$ is called second-order stationarity if (i) $EX_t^2 < \infty, \forall t \in Z$; (ii) $EX = m, \forall t \in Z$; and (iii) $Cov(X_t, X_{t+h}) = \gamma_X(h), \ \forall t, h \in Z$. (Franco and Zakoian, 2010; Wei, 2019). The study modeling the relationship simultaneously among variables share prices two big energy companies, ADRO and PTBA of Indonesia, are the interested variables to be analyzed. The vector time series for the said variables can be written as follows:

$$X_t = \begin{pmatrix} ADRO_t \\ PTBA_t \end{pmatrix} \tag{1}$$

Where $ADRO_t$ is the daily share price of ADRO at time t, and $PTBA_t$ is the daily share price of PTBA at time t. In this study, to check or to test the stationarity of the data time series will be checked by the plot of the data and by the Augmented Dickey-Fuller test (ADF test) or unit root test (Wei, 2006; Tsay, 2010). To check the stationarity of the data time series by using the ADF test of a parameter can be conducted by the following model:

$$\Delta X_t = \mu + \beta_t + \delta X_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta X_{t-1} + e_t \tag{2}$$

The null and the alternative hypotheses are as follows:

H_0: $\delta = 0$ and H_1: $\delta < 0$

and the statistical test, to test the null hypothesis, we use test-τ (Tau-test) or Dickey-Fuller test as follows:

$$\tau = \frac{\delta}{S_\delta} \tag{3}$$

null hypothesis is rejected if the $P \le \alpha$, for $\alpha = 0.05$ (Brockwell and Davis, 1991; 2002; Warsono, et al., 2019a, 2019b, 2020).

2.1. The Test for Autocorrelation and Cross-Correlation Matrix

The Box-Pierce Q statistic to test the autocorrelation in the univariate case is defined as follows:

$$Q = N\sum_{j=1}^{p} r_j^2 \tag{4}$$

Q is based on the squares of the first *p* autocorrelations coefficient of the Ordinary Least Squares (OLS) residuals and

$$r_j = \frac{\sum_{t=j+1}^{N} e_t\, e_{t-j}}{\sum_{t=1}^{N} e_t^2} \tag{5}$$

Under the null hypothesis of zero autocorrelation for the residuals Q will have asymptotically χ^2 distribution with the degree of freedom equal to p minus the number of parameters estimated in the AR model. The test for cross-correlation for the case of multivariate time series has been developed by Hosking (1980, 1981) and Li and McLeod (1981) as an extension of the univariate autocorrelation case. The null hypothesis for multivariate time series is as follows:

$$Ho: \rho_1 = \rho_2 = \ldots = \rho_k = 0,$$

with the alternative

$$Ha: \rho_i \neq 0 \quad \text{for some} \quad i \in \{1, 2, \ldots, k\}.$$

The test statistic is as follows:

$$Q_m(k) = N^2 \sum_{s=1}^{k} \frac{1}{N-s}\, tr\left[\hat{\Gamma}_s'\, \hat{\Gamma}_0^{-1}\, \hat{\Gamma}_s\, \hat{\Gamma}_0^{-1}\right], \tag{6}$$

where *N* is the sample size, *m* is the dimension of X_t, and $tr(A)$ is a trace of a matrix *A*, and the cross-covariance matrix Γ_k can be estimated by

$$\hat{\Gamma}_k = \frac{1}{N}\sum_{t=k+1}^{N} (X_t - \overline{X})(X_{t-k} - \overline{X})', \qquad k > 0. \tag{7}$$

where $\overline{X} = \frac{1}{N}\sum_{t=1}^{N} X_t$ is the vector sample mean. The cross-correlation ρ_k is estimated by:

$$\hat{\rho}_k = [\hat{\rho}_{ij}(k)] = \hat{D}^{-1}\hat{\Gamma}_k\, \hat{D}^{-1}, \tag{8}$$

where $k \geq 0$ and $\hat{D}$ is m×m the matrix diagonal from the sample standard deviation from the series component.

Under the null hypothesis, $Q_m(k)$ asymptotically has a Chi-square distribution with degrees of freedom m^2k. Reject the null hypothesis if the $P < 0.05$, which means that the test confirms the interdependence of the time series at a significance level of 5% (Lutkepohl, 2005; Tsay, 2010, Wei, 2019). If the null hypothesis is rejected, the class of vector autoregressive model should be involved in building a multivariate time series data study.

2.2. Vector Autoregressive (VAR) Model

If the time series modeling involves more than one variable, for example, if m time series variables are to be analyzed simultaneously, then the time series data can be presented as a vector time series. Suppose X_t is m-dimensional vector time series, then the vector autoregressive model with order p, VAR(p), and can be written as follows:

$$X_t = \varphi_0 + \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + \varepsilon_t \tag{9}$$

or

$$\Phi_p(B)\, X_t = \varphi_0 + \varepsilon_t \tag{10}$$

where ε_t is vector white noise with mean vector zero and covariance matrix $E(\varepsilon_t\, \varepsilon_t') = \Sigma$, $\Phi_p(B) = I - \Phi_1 B - \ldots - \Phi_p B^p$ with $B^i X_t = X_{t-i}$ (Wei, 2019). The model (9) will be stationary if the characteristic values of $\left|\alpha^p I - \alpha^{p-1}\Phi_1 - \ldots - \Phi_p\right| = 0$ are all lie within the unit circle (Hamilton, 1994; Tsay, 2014; Wei, 2019). The VAR(p) model treats all the variables symmetrically; in the left side, one vector contains more than one variable, and on the right side, there is a lag value (lagged value) of the dependent variable as a representation of the autoregressive property in the model.

2.3. CCC-GARCH(r,s)

The multivariate GARCH model can be defined by specifying their first two conditional moments. An R^m-valued GARCH process (ϵ_t), with $\varepsilon_t = (\varepsilon_{1t}, \ \ldots, \ \varepsilon_{kt})'$ have to satisfy, ∀t∈*Z*,

$$E(\varepsilon_t \,|\, \varepsilon_u,\ u < t) = 0, \text{ and}$$

$$Var(\varepsilon_t \,|\, \varepsilon_u,\ u < t) = E(\varepsilon_t \varepsilon_t' \,|\, \varepsilon_u,\ u < t) = H_t$$

The multivariate GARCH process is based on the following equation:

$$\varepsilon_t = H_t^{1/2}\, \eta_t \tag{11}$$

where (η_t) is a sequence of iid R^m-valued variables with zero mean and identity covariance matrix. The matrix $H_t^{1/2}$ can be symmetric and positive definite, but it can also be triangular, with positive diagonal elements (Harville, 1997, theorem 14.5.11). If $H_t^{1/2}$ is chosen to be lower triangular, the first component of ε_t only depends on the first component of η_t. When m = 2, we can set

$$\begin{cases} \varepsilon_{1t} = h_{11,t}^{1/2}\, \eta_{1t} \\ \varepsilon_{2t} = \dfrac{h_{12,t}}{h_{11,t}^{1/2}}\, \eta_{1t} + \left(\dfrac{h_{11,t}\, h_{22,t} - h_{12,t}^2}{h_{11,t}}\right)^{1/2} \eta_{2t} \end{cases} \tag{12}$$

where η_{1t} and $h_{ij,t}$ denote the generic elements of η_t and H_t (Franco and Zakoian, 2010). Consider a multivariate GARCH process of the form (11), all the past information on ε_{kt}, involving all the variables $\varepsilon_{l,t-1}$, is summarized in the variable $h_{kk,t}$, with $E\,h_{kk,t} = E\,\varepsilon_{kt}^2$. Let $\bar{\eta}_{kt} = h_{kk,t}^{-1/2}\,\varepsilon_{kt}$ and the variable $\bar{\eta}_{kt}$ are generally correlated, so let the correlation matrix $R = Var(\bar{\eta}_{kt}) = \rho_{kl}$, where $\bar{\eta}_t = (\bar{\eta}_{1t}, \bar{\eta}_{2t}, \dots, \bar{\eta}_{mt})'$. The conditional variance of

$$\varepsilon_t = diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, \dots, h_{mm,t}^{1/2})\,\bar{\eta}_t .$$

is written as

$$H_t = diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, \dots, h_{mm,t}^{1/2})\,R\,diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, \dots, h_{mm,t}^{1/2}) \tag{13}$$

In multivariate cases, we can define as follows:

$$\underline{h}_t = \begin{pmatrix} h_{11,t} \\ \vdots \\ \vdots \\ h_{mm,t} \end{pmatrix},\; D_t = diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, \dots, h_{mm,t}^{1/2})\,\bar{\eta}_t \text{ , and } \underline{\varepsilon}_t = \begin{pmatrix} \varepsilon_{1t}^2 \\ \vdots \\ \vdots \\ \varepsilon_{mt}^2 \end{pmatrix}$$

A process (ε_t) is called Constant Conditional Correlation (CCC)-GARCH(r,s) if it satisfies

$$\begin{cases} \varepsilon_t = H_t^{1/2}\eta_t \\ H_t = D_t\,R\,D_t \\ \underline{h}_t = \underline{\alpha} + \sum_{i=1}^{s} A_i\,\underline{\varepsilon}_{t-i} + \sum_{j=1}^{r} B_j\,\underline{h}_{t-j} . \end{cases} \tag{14}$$

where R is correlation matrix, $\underline{\alpha}$ is a m×1 vector with positive coefficients, and A_i and B_j are m×m matrices with nonnegative coefficients (Franco and Zakoian, 2010).

2.4. Normality Test of Residuals

Some methods are available to check the normality of the errors (residuals). Some methods are commonly used to check whether the errors (residuals) are normally distributed: (1) check the histogram of the residuals; (2) check the Q-Q plot of the data or error (residuals); and (3) use the statistical test, the Jarque-Bera (JB) test, with the null hypothesis that the data are normally distributed (Brockwell and Davis, 2002; Wei, 2006; Tsay, 2010). The JB test is calculated as follows:

$$JB = \frac{N}{6}\left[S^2 + \frac{(K-3)^2}{4} \right], \tag{15}$$

where N is the sample size, S is the expected skewness, and K is the expected excess kurtosis.

2.5. Granger Causality

In multivariate time series analysis, the interesting one is that we can ask whether there is a causal effect between the variables involved in the VAR(p) model. From equation (10), suppose we partition the vector X_t into two components $X_t = [X_{1t}', X_{2t}']'$ so that model (10) can be written as follows:

$$\begin{bmatrix} \Phi_{11}B & \Phi_{12}B \\ \Phi_{21}B & \Phi_{22}B \end{bmatrix} \begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} \varphi_1 \\ \varphi_2 \end{bmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{16}$$

If Φ_{12}=B=0 equation (16) can be written as follows:

$$\begin{cases} \Phi_{11}B(X_{1t}) = \varphi_1 + \varepsilon_{1t} \\ \Phi_{22}B(X_{2t}) = \varphi_2 + \Phi_{21}B(X_{1t}) + \varepsilon_{2t} \end{cases} \tag{17}$$

Equation (17) can be interpreted as follows: the future values of X_{1t} are affected by its past values, and the future values of X_{2t} are affected not only by its past values but also by the past values of X_{1t}. This concept is known as the Granger causality (Wei, 2019).

2.6. Impulse Response Function (IRF)

One of the interesting analyses in dynamic modeling is to discuss the IRF; namely, we are interested in a process with white noise with orthogonal components, as this allows us to analyse how a shock on a variable in the model propagates over time. Wei (2006) and Hamilton (1994) stated that the IRF is an analytical technique used to analyse a response of a variable due to shock in another variable. Wei (2006) stated that the VAR model could be written in vector MA (∞) as follows:

$$X_t = \mu + \mu_t + \Psi_1\mu_{t-1} + \Psi_2\mu_{t-2} \tag{18}$$

Thus, the matrix is interpreted as follows:

$$\frac{\partial X_{t+s}}{\partial \mu_t} = \Psi_s$$

The element of the i^{th} row and j^{th} column indicates the consequence of the increase of one unit in the innovation of variable j at time t (μ_{jt}) for i variable at time $t + s$ ($X_{i,\,t+s}$) and fixed all other innovations. If the element of μ_t changed by δ_1, at the same time, the second element will change by δ_2,…, and the n^{th} element will change by δ_n, then the common effect from all of these changes on the vector X_{t+s} will become

$$\Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}}\delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}}\delta_2 + \dots + \frac{\partial X_{t+s}}{\partial u_{nt}}\delta_n = \Psi_s\,\delta \tag{19}$$

The plot of the i^{th} row and j^{th} column of Ψ_s as a function of s is called IRF.

2.7. Forecasting *l*-Steps Ahead

Forecasting is one of the important analyses in multivariate time series (Tsay, 2010). After the diagnostic model is done and the model is adequate, then we can use the model for forecasting future values. Let we are interested in predicting the l-step ahead X_{h+1} based on the information available at time $t = h$. Such prediction is called the l-step ahead forecast of the series at the time index h. Let F_h is the information available at time h. For the VAR(p) model, the one-step ahead forecast is:

$$X_h(1) = E(X_{h+1}\,|\,F_h) = \varphi_0 + \sum_{i=1}^{p}\Phi_i X_{h+1-i} .$$

The two-step ahead forecast is:

$$X_h(2) = E(X_{h+2}\,|\,F_h) = \varphi_0 + \Phi_1 E(X_{h+1}\,|\,F_h) + \sum_{i=2}^{p}\Phi_i X_{h+1-i}$$

In general, for l-step ahead forecast is:

$$X_h(l) = E(X_{h+l} | F_h) = \varphi_0 + \sum_{i=1}^{p} \Phi_i X_h(l-i), \quad (20)$$

Where $X_h(l) = X_{h+1}$ (Tsay, 2014; Wei, 2019).

2.8. Proportion of Prediction Error Covariance

The proportion of predicted error covariance will be used to explain the contribution of other variables to a variable in forecasting for the next several periods ahead, and the contribution of other variables to the long-term forecasting results of a variable will also be evaluated (Lutkepohl, 2005; Wei, 2006; 2019; Florens, 2007; Tsay, 2014).

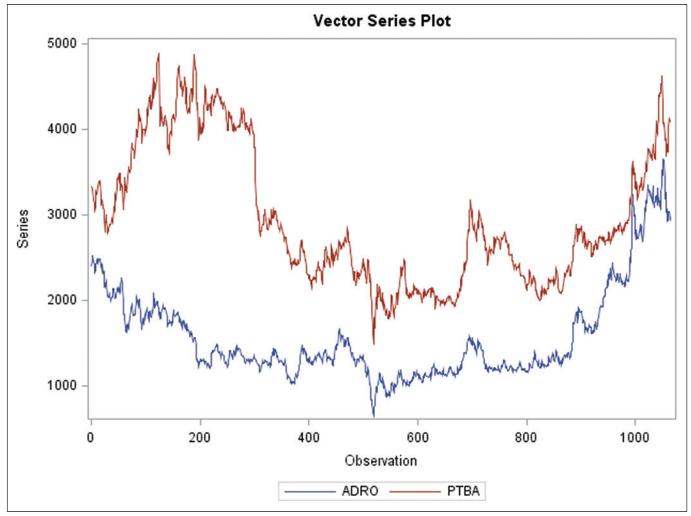
3. RESULTS AND DISCUSSION

The data used in this study are daily stock price data for some energy companies in Indonesia, namely ADRO and PTBA data from January 2018 to December 2022. Adaro Energy Indonesia Tbk (ADRO) was established under PT Padang Karunia on 28 July 2004, and began operating as a commercial in July 2005. PT. Adaro Energy Indonesia Tbk (ADRO) is an integrated coal mining company based in Indonesia. ADRO and its subsidiaries are engaged in coal mining, mining contractor services, coal trading, coal logistics and power generation activities, and infrastructure (PT. Adaro Energy Indonesia Tbk, 2023). PT. Bukit Asam Tbk (PTBA) was established on March 2, 1981. The controlling shareholder of Bukit Asam Tbk is the Government of the Republic of Indonesia, owning five Preferred Shares (Dwiwarna Series A Shares) and indirect control through PT Indonesia Asahan Aluminum (Persero). In 1993, Bukit Asam Tbk was appointed by the Government of Indonesia to develop a Briquette Production Unit. Based on the Company's Articles of Association, the scope of activities of PTBA and its subsidiaries (Group) is to engage in the coal mining industry and related activities, including exploration, exploitation, processing, refining, transportation and trading, management of special coal jetty facilities both for own and other parties' needs, operation of steam power plants both for their own needs and for other parties' needs and providing consulting and engineering services in fields related to the coal mining industry and its processed products, plantation development sector, and health service sector (PT. Bukit Asam Tbk, 2022).

Figure 1 shows ADRO and PTBA plot data. The plot shows that the daily share price data of ADRO and PTBA stock prices fluctuate and are not stationary; This is also shown in Figure 2a and b, where the data graphs are not stationary and fluctuate. Figure 2a and b show the Autocorrelation Function (ACF) graphs where both ADRO and PTBA data show ACF decaying very slowly; this strengthens the notion that ADRO and PTBA data are nonstationary. The ADF test also shows that the data is not stationary. A differencing process will be carried out to meet the assumptions of stationary data. Data Table 1 knows that the data after differentiation meets the stationary assumption.

After differencing, using the ADF test with the null hypothesis that the data are nonstationary, the results show the null hypotheses are rejected, so the ADRO and PTBA data fulfill the stationary

Figure 1: Plot data ADRO and PTBA from January 2018 to December 2022



assumption (Table 1). Checking the autocorrelation (Table 2) and the results of the Box-Pierce test show that the ADRO and PTBA data have autocorrelation at the residuals up to lag 24; this shows that ADRO and PTBA data modeling requires modeling that involves autoregressive. Based on the cross-correlation analysis and the schematic representation cross-correlation results, it shows a significant cross-correlation (Tables 3 and 4). Thus, multivariate time series modeling will involve autoregressive vector modeling (VAR).

Further examination will examine the effect of Autoregressive Conditional Heteroscedasticity (ARCH). Using the Lagrange Multiplier (LM) test, Table 5 shows that ADRO and PTBA variables have an ARCH effect. Where the results of the LM test up to lag-6 are significant with $P < 0.0001$. Thus, based on the results of the LM test and indicating the existence of the ARCH effect, the ADRO and PTBA data modeling that will be built will involve autoregressive modeling (VAR) and involve GARCH modeling for the residuals.

Based on Table 6, the minimum AICC value is at lag-3, which is 16.4050. However, the difference in AICC values at lag-2, lag-3, and lag-4 is not too big. To determine the best model, this research will compare three models, namely: VAR(2)-CCC-GARCH(1,1), VAR(3)-CCC-GARCH(1,1), and VAR(4)- CCC-GARCH(1,1). From the results of a comparison of the three models from Table 7, the smallest AICC value is in the VAR(3)-CCC-GARCH(1.1) model, which is 16.4287. So, the best model chosen is VAR(3)- CCC-GARCH(1,1) for further study.

3.1. VAR(3)- CCC GARCH(1,1) Model

From the results of analysis, the estimate model of VAR(3)-CCC-GARCH(1,1) is:

$$\begin{bmatrix} ADRO_t \\ PTBA_t \end{bmatrix} = \begin{bmatrix} 19.9918 \\ 19.8265 \end{bmatrix} + \begin{bmatrix} 0.9511 & 0.0472 \\ 0.0191 & 0.9969 \end{bmatrix}$$

$$\begin{bmatrix} ADRO_{t-1} \\ PTBA_{t-1} \end{bmatrix} + \begin{bmatrix} 0.0812 & -0.0939 \\ 0.0625 & -0.0990 \end{bmatrix} \begin{bmatrix} ADRO_{t-2} \\ PTBA_{t-2} \end{bmatrix}$$

Figure 2: Trend and Correlation analysis for (a) ADRO, (b) PTBA

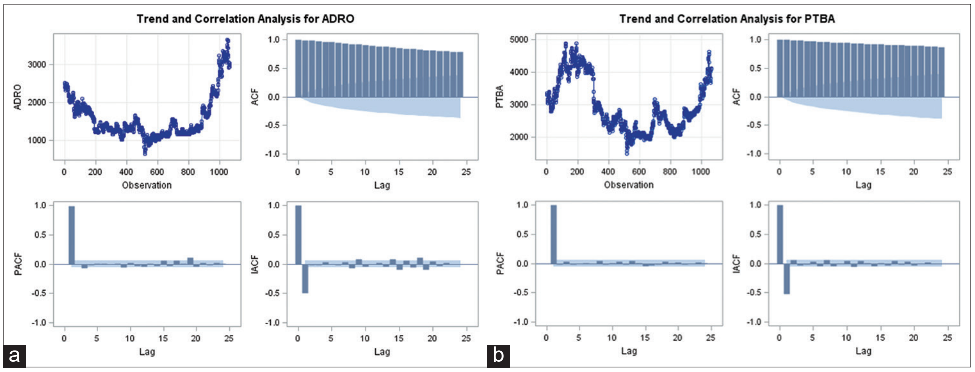


Table 1: Dickey-Fuller unit roots test before and after differencing (d=1)

Variable	Type	Before differencing				After differencing (d=1)			
		Rho	P-value	Tau	P-value	Rho	P-value	Tau	P-value
ADRO	Zero Mean	−0.00	0.6825	−0.00	0.6824	−931.77	0.0001	−21.59	<0.0001
	Single Mean	−2.67	0.6972	−0.88	0.7957	−932.00	0.0001	−21.58	<0.0001
	Trend	−4.33	0.8661	−1.40	0.8593	−947.09	0.0001	−21.75	<0.0001
PTBA	Zero Mean	−0.08	0.6656	−0.09	0.6545	−1151.7	0.0001	−23.98	<0.0001
	Single Mean	−4.69	0.4655	−1.40	0.5843	−1152.0	0.0001	−23.97	<0.0001
	Trend	−4.07	0.8821	−1.09	0.9297	−1155.3	0.0001	−23.99	<0.0001

Table 2: Autocorrelation for white noise

Variable	To lag	Chi-square	DF	P-value	Autocorrelations					
ADRO	6	6020.17	6	<0.0001	0.992	0.983	0.973	0.964	0.954	0.945
	12	9999.99	12	<0.0001	0.936	0.927	0.917	0.907	0.897	0.887
	18	9999.99	18	<0.0001	0.877	0.866	0.856	0.845	0.836	0.828
	24	9999.99	24	<0.0001	0.821	0.813	0.806	0.799	0.792	0.785
PTBA	6	6148.81	6	<0.0001	0.994	0.988	0.982	0.976	0.970	0.964
	12	9999.99	12	<0.0001	0.958	0.952	0.947	0.941	0.936	0.931
	18	9999.99	18	<0.0001	0.927	0.922	0.917	0.912	0.907	0.902
	24	9999.99	24	<0.0001	0.897	0.892	0.887	0.882	0.878	0.873

Table 3: Cross correlations of dependent series up to lag-13.

Lag	Variable	ADRO	PTBA	Lag	Variable	ADRO	PTBA
0	ADRO	1.0000	0.4874	7	ADRO	0.9356	0.4844
	PTBA	0.4874	1.0000		PTBA	0.4291	0.9578
1	ADRO	0.9915	0.4871	8	ADRO	0.9266	0.4841
	PTBA	0.4792	0.9939		PTBA	0.4210	0.9523
2	ADRO	0.9830	0.4870	9	ADRO	0.9168	0.4829
	PTBA	0.4705	0.9876		PTBA	0.4124	0.9467
3	ADRO	0.9734	0.4862	10	ADRO	0.9074	0.4823
	PTBA	0.4620	0.9818		PTBA	0.4038	0.9412
4	ADRO	0.9637	0.4855	11	ADRO	0.8974	0.4815
	PTBA	0.4534	0.9758		PTBA	0.3952	0.9363
5	ADRO	0.9541	0.4850	12	ADRO	0.8869	0.4802
	PTBA	0.4454	0.9698		PTBA	0.3867	0.9313
6	ADRO	0.9449	0.4848	13	ADRO	0.8765	0.4790
	PTBA	0.4373	0.9638		PTBA	0.3786	0.9267

$$+\begin{bmatrix} -0.0410 & 0.0434 \\ -0.0741 & 0.0894 \end{bmatrix}\begin{bmatrix} ADRO_{t-3} \\ PTBA_{t-3} \end{bmatrix},$$

and the estimate of CCC-GARCH(1,1) (Table 9) is:

$$\sigma_{1t}^2 = 9.0214 + 0.0.0490\ \varepsilon_{1t-1}^2 + 0.9513\ \sigma_{1t-1}^2$$

$$\sigma_{2t}^2 = 37.5419 + 0.0927\ \varepsilon_{2t-1}^2 + 0.9122\ \sigma_{2t-1}^2$$

$$\sigma_{2t}^2 = 37.5419 + 0.0927\ \varepsilon_{2t-1}^2 + 0.9122\ \sigma_{2t-1}^2, \quad (19)$$

From the results of the analysis of Table 8 and Figure 3, it shows that $ADRO_{t\text{-}1}$ is significantly influenced by information on $ADRO_{t\text{-}1}$, namely information on the previous day, and $PTBA_{t\text{-}1}$, $PTBA_{t\text{-}2}$, and $PTBA_{t\text{-}3}$, which are influenced by PTBA information on 1 day, 2 days, and 3 days before with a significance level of P-values 0.0165, 0.0006, and 0.0273, respectively. $PTBA_t$ was significantly influenced by $PTBA_{t-1}$, $PTBA_{t-2}$, and $PTBA_{t-3}$ information, which was influenced by PTBA information 1 day, 2 days, and 3 days before, with a significance level of P-values 0.0001, 0.0826, and 0.0311, respectively.

3.2. Diagnostic Model

The results of the univariate model test for ADRO and PTBA data (Table 10) show significant results with $P < 0.0001$ and < 0.0001, respectively. Table 10 also shows the R-square values for the univariate ADRO and PTBA models, respectively 0.9913 and 0.9899; this means that the univariate model for ADRO with R-square = 0.9913 means the model can explain the variation of ADRO values by 99.13%; and the univariate model for PTBA with R-square = 0.9899 means that the model can explain the variation of PTBA values by 98.99%. From the normality results

Table 4: Schematic representation cross-correlation

Variable/Lag	0	1	2	3	4	5	6	7	8	9	10	11	12	13
ADRO	++	++	++	++	++	++	++	++	++	++	++	++	++	++
PTBA	++	++	++	++	++	++	++	++	++	++	++	++	++	++

\+ is >2 *std error

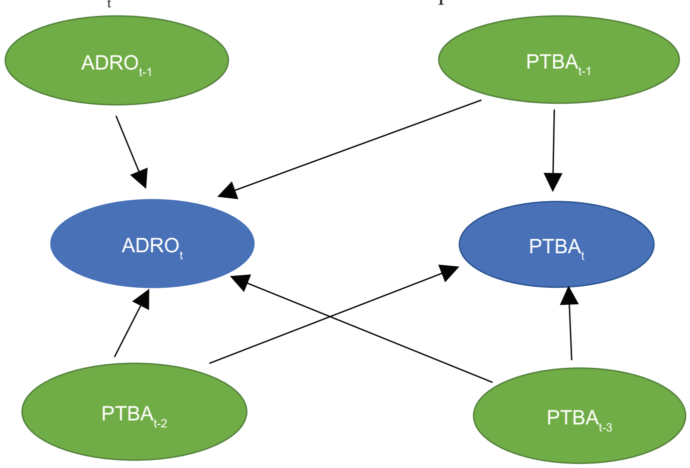
Table 5: Test for ARCH effect

Variable	Order	Q	P-value	LM	P-value
ADRO	1	1022.5272	<0.0001	1022.9432	<0.0001
	2	2006.2309	<0.0001	1022.9706	<0.0001
	3	2937.1623	<0.0001	1024.2396	<0.0001
	4	3819.9773	<0.0001	1024.2658	<0.0001
	5	4656.2125	<0.0001	1024.2671	<0.0001
	6	5451.6160	<0.0001	1024.3239	<0.0001
PTBA	1	991.4214	<0.0001	1004.9871	<0.0001
	2	1906.6543	<0.0001	1005.1520	<0.0001
	3	2754.2083	<0.0001	1005.3062	<0.0001
	4	3535.1813	<0.0001	1005.5910	<0.0001
	5	4261.8075	<0.0001	1005.5956	<0.0001
	6	4939.2588	<0.0001	1005.6089	<0.0001

Table 6: Minimum information criterion based on AICC

Lag	AR0	AR1	AR2	AR3	AR4	AR5
AICC	25.7334	16.4073	16.4097	**16.4050**	16.4079	16.4119

Figure 3: The variables that have significant effect on $ADRO_t$, and $PTBA_t$ based on the results of test of the parameters in Table 8



using the Jarque–Bera (JB) test with the null hypothesis that the residuals are normally distributed, rejected for the ADRO and PTBA data with P-values <0.0001 and <0.0001 respectively, which means the residuals are not normally distributed. However, Figure 4 shows that the residual distribution is close to the normal distribution for ADRO residuals (Figure 4a) and close to the normal distribution for PTBA residuals (Figure 4b). Table 11 also shows the ARCH effect for the ADRO and PTBA variables with $P < 0.0001$ and 0.0204, respectively. So involving the GARCH model for residuals is appropriate (Hamilton, 1994; Tsay, 2010; Wei, 2019). Table 12 shows the modulus values for the root characteristic polynomials VAR, indicating that the VAR(3)-CCC-GARCH(1,1) model is stable (Lutkepohl, 2005; Tsay, 2014).

3.3. Granger Causality Wald Test

From the results of Wald's granger causality test (Table 13), test 1 and test 2 are significant, with P-values 0.0088 and 0.0275, respectively. Granger causality test results are presented in Figure 5. The results from Table 13 and Figure 5 are interpreted as follows: Test 1 is significant, which means that ADRO is not only influenced by itself but also influenced by past information from PTBA; Test 2 is significant, which means that PTBA is not only influenced by itself but also influenced by past information from ADRO.

3.4. Impulse Response Function

The IRF explains how the response of a variable if there is a change in a variable (shock) in standard deviation units. Figure 6a and Table 14 show what happens if a one standard deviation shock occurs in ADRO. Figure 6a illustrates the response changes in ADRO itself. ADRO's response if a shock occurs to ADRO, the response is positive, above 0.80 standard deviations with a downward trend until day 24. The response and standard deviation for the first 10 days can be seen in Table 14. Figure 6a illustrates changes in response to PTBA if there is a one standard deviation shock in ADRO. PTBA's response if a shock occurs to ADRO, the response is positive and significant and ranges above 0.1000 up to an upward trend up to day 24. The response and standard deviation for the first 10 days can be seen in Table 14. Figure 6b and Table 15 show how it affects if there is a shock of one standard deviation at PTBA. Figure 6b illustrates changes in response to ADRO and PTBA. The ADRO response if a shock occurs at PTBA, the response is negative below zero in standard deviation units with a downward trend up to day 24. The response and standard deviation for the first 10 days can be seen in Table 15. Figure 6b illustrates changes in response to PTBA if there is a one standard deviation shock on PTBA. PTBA's response if a shock occurs to PTBA, the response is positive and significant and ranges above 0.8000 with a downward trend up to day 24. The response and its standard deviation for the first 10 days can be seen in Table 15.

3.5. Forecasting and Proportions of Prediction Error Covariances

The VAR(3)-CCC-GARCH(1,1) model for ADRO and PTBA data is the best. The univariate model (Table 10) shows that for the dependent variable ADRO, the model is very significant with $P < 0.0001$ and R-square = 0.9913. This shows that the model with the dependent variable ADRO can explain 99.13% of the diversity of ADRO values explained by the model. Table 10 shows that the model is very significant for the dependent variable PTBA, with $P < 0.0001$ and R-square = 0.9899. This shows that the model with the dependent variable PTBA can

Figure 4: Prediction error normality untuk data (a) ADRO, (b) PTBA.

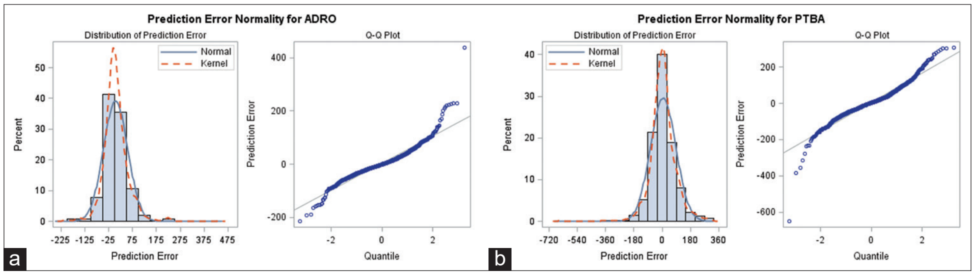


Table 7: Comparison of AICC from models VAR(3)-CCC GARCH(1,1), VAR(3)-CCC GARCH(1,1), dan VAR(4)-CCC GARCH(1,1)

Information criterion	Model		
	VAR(2)-CCC GARCH(1,1)	VAR(3)-CCC GARCH(1,1)	VAR(4)-CCC GARCH(1,1)
AICC	16.4298	**16.4287**	16.4340

Table 8: Model parameter estimates and test VAR(3)

Equation	Parameter	Estimate	Standard error	t-value	P-value	Variable
ADRO	CONST1	19.9918	5.8613	3.41	0.0007	1
	AR1_1_1	0.9511	0.0368	25.84	0.0001	ADRO(t−1)
	AR1_1_2	0.0472	0.0196	2.40	0.0165	PTBA(t−1)
	AR2_1_1	0.0812	0.0504	1.61	0.1073	ADRO(t−2)
	AR2_1_2	−0.0939	0.0273	−3.44	0.0006	PTBA(t−2)
	AR3_1_1	−0.0410	0.0363	−1.13	0.2588	ADRO(t−3)
	AR3_1_2	0.0434	0.0196	2.21	0.0273	PTBA(t−3)
PTBA	CONST2	19.8265	9.5004	2.09	0.0371	1
	AR1_2_1	0.0191	0.0559	0.34	0.7318	ADRO(t−1)
	AR1_2_2	0.9969	0.0407	24.49	0.0001	PTBA(t−1)
	AR2_2_1	0.0625	0.0780	0.80	0.4224	ADRO(t−2)
	AR2_2_2	−0.0990	0.0569	−1.74	0.0826	PTBA(t−2)
	AR3_2_1	−0.0741	0.0557	−1.33	0.1838	ADRO(t−3)
	AR3_2_2	0.0894	0.0414	2.16	0.0311	PTBA(t−3)

Table 9: CCC-GARCH(1,1) model parameter estimates

Parameter	Estimate	Standard error	t-value	P-value
GCHC1_1	9.0215	9.7578	0.92	0.3554
GCHC2_2	37.5419	24.1304	1.56	0.1201
ACH1_1_1	0.0490	0.0150	3.27	0.0011
ACH1_2_2	0.0927	0.0163	5.68	0.0001
GCH1_1_1	0.9513	0.0174	54.46	0.0001
GCH1_2_2	0.9122	0.0153	59.45	0.0001

Table 10: Univariate model ANOVA diagnostic

Variable	R-square	Standard deviation	F-value	P-value
ADRO	0.9913	51.1004	20068.3	<0.0001
PTBA	0.9899	81.2181	17256.9	<0.0001

Table 11: Univariate model white noise diagnostic

Variable	Durbin	Normality		ARCH	
	Watson	Chi-Square	P-value	F-value	P-value
ADRO	1.9525	3085.86	<0.0001	37.59	<0.0001
PTBA	1.9482	1523.71	<0.0001	5.39	0.0204

explain 98.99% of the diversity in PTBA values explained by the model. Figure 7a the univariate model for the ADRO dependent variable is very fit with the data; this is shown by the predictions and real data, which are very close. Figure 7b shows ADRO forecasting for the next 30 days; the predicted value is decreasing

Table 12: Roots dari AR characteristic polynomial

Roots of AR Characteristic Polynomial					
Index	Real	Imaginary	Modulus	Radian	Degree
1	0.9897	0.0043	0.9897	0.0044	0.2493
2	0.9897	−0.0043	0.9897	−0.0044	−0.2493
3	0.0837	0.0000	0.0837	0.0000	0.0000
4	−0.0077	0.2357	0.2358	1.6038	91.8909
5	−0.0077	−0.2357	0.2358	−1.6038	−91.8909
6	−0.0995	0.0000	0.0995	3.1416	180.0000

Table 13: Granger causality wald test

Test	Variable	Null hypothesis Granger causality	DF	Chi-square	P-value
Test 1	Group 1 variables: ADRO Group 2 variables: PTBA	ADRO is influenced only by itself, and not by PTBA.	3	11.62	0.0088
Test 2	Group 1 variables: PTBA Group 2 variables: ADRO	PTBA is influenced only by itself, and not by ADRO.	3	9.14	0.0275

for the next 30 days. The magnitude of the prediction value for the next 30 days is presented in Table 16. From Table 17 and

Figure 8a and b, the proportion of prediction error covariance for forecasting ADRO data for the next 30 days, it can be seen that the forecasting value for the next 30 days is only influenced by itself (ADRO) above 99%, and PTBA did not make a significant contribution.

Figure 9a the univariate model for the PTBA dependent variable is very fit with the data; this is shown by the predictions and real data, which are very close. Figure 9b shows PTBA's forecasting for the next 30 days; the predicted value is decreasing for the next 30 days. The magnitude of the prediction value for the next 30 days is presented in Table 16. From Table 17 and Figure 8a and b, the proportion of prediction error covariance for forecasting PTBA data for the next 30 days, it can be seen that the forecasting value for the next 30 days is influenced not only by itself (PTBA) but also influenced by ADRO, and PTBA and ADRO for forecasting the next 5 days: for the 1st day PTBA and ADRO respectively give an effect of 77.12% and 22.88%; for the 2nd day PTBA and ADRO had an effect of 76.69% and 23.31% respectively; for the 3rd day PTBA and ADRO had an effect of 75.25% and 24.75% respectively; for the 4th day PTBA and ADRO had an effect of 74.46% and 25.54% respectively; for the 5th day PTBA and ADRO had an effect of 73.95% and 26.05% respectively; And for future long-term forecasting PTBA and ADRO have an influence of 70% and 30% respectively (Table 17).

Figure 5: Granger causality Wald test variable ADRO and PTBA based on the results of Table 13

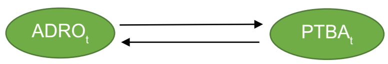


Figure 6: (a) Response to Impulse in ADRO (b) Response to Impulse in PTBA

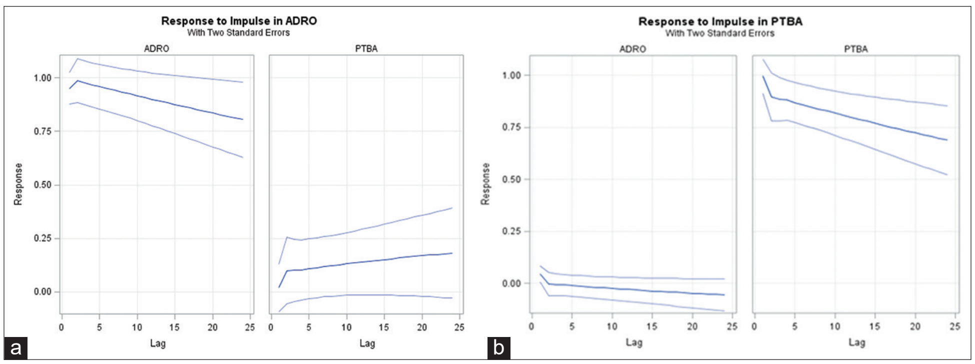


Figure 7: (a) Model for ADRO, and (b) Forecasting for ADRO for the next 30 days

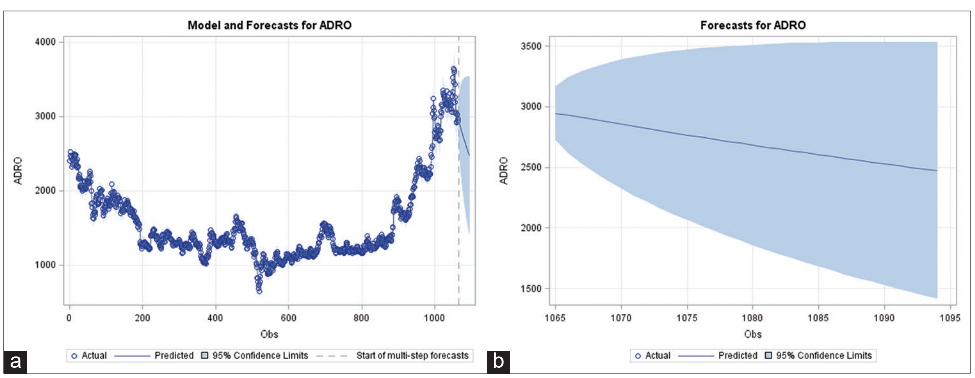


Table 14: Impulse on ADRO (in Standard deviation) and its impact up to the next 10 days

Variable	Impulse on ADRO										
Response	Lead	1	2	3	4	5	6	7	8	9	10
ADRO	Response	0.9511	0.9868	0.9778	0.9674	0.9588	0.9502	0.9417	0.9332	0.9247	0.9163
	Std	0.0368	0.0514	0.0508	0.0515	0.0518	0.0525	0.0535	0.0547	0.0561	0.0578
PTBA	Response	0.0191	0.0999	0.1020	0.1034	0.1085	0.1134	0.1181	0.1226	0.1270	0.1313
	Std	0.0559	0.0773	0.0725	0.0699	0.0698	0.0698	0.0702	0.0708	0.0719	0.0731

Table 15: Impulse on PTBA (in standard deviation) and its impact up to the next 10 days

Variable	Impulse on PTBA										
Response	Lead	1	2	3	4	5	6	7	8	9	10
ADRO	Response	0.0472	−0.0018	−0.0058	−0.0066	−0.0095	−0.0125	−0.0153	−0.0180	−0.0207	−0.0233
	Std	0.0196	0.0276	0.0263	0.0253	0.0254	0.0256	0.0258	0.0262	0.0266	0.0272
PTBA	Response	0.9969	0.8958	0.8867	0.8807	0.8700	0.8593	0.8489	0.8387	0.8286	0.8185
	Std	0.0407	0.0573	0.0522	0.0482	0.0486	0.0491	0.0497	0.0506	0.0518	0.0532

Table 16: Forecast for the next 30 days of ADRO and PTBA

Variable	Obs	Forecast	Standard error	95% Confidence limit	
ADRO	1065	2947.2595	113.2405	2725.3121	3169.2068
	1066	2929.8515	159.0174	2618.1831	3241.5199
	1067	2911.0760	194.3527	2530.1517	3292.0004
	1068	2892.3971	223.5533	2454.2407	3330.5536
	1069	2873.9622	248.8403	2386.2441	3361.6802
	1070	2855.7270	271.3264	2323.9370	3387.5170
	1071	2837.6800	291.6679	2266.0213	3409.3387
	1072	2819.8223	310.2946	2211.6560	3427.9887
	1073	2802.1529	327.5069	2160.2512	3444.0547
	1074	2784.6699	343.5244	2111.3744	3457.9655
	1075	2767.3717	358.5141	2064.6969	3470.0464
	1076	2750.2565	372.6062	2019.9617	3480.5513
	1077	2733.3229	385.9051	1976.9628	3489.6830
	1078	2716.5691	398.4958	1935.5317	3497.6066
	1079	2699.9937	410.4488	1895.5287	3504.4587
	1080	2683.5950	421.8235	1856.8360	3510.3541
	1081	2667.3714	432.6705	1819.3528	3515.3901
	1082	2651.3215	443.0331	1782.9925	3519.6504
	1083	2635.4435	452.9490	1747.6796	3523.2074
	1084	2619.7361	462.4515	1713.3478	3526.1243
	1085	2604.1976	471.5694	1679.9384	3528.4567
	1086	2588.8265	480.3289	1647.3991	3530.2539
	1087	2573.6213	488.7529	1615.6832	3531.5595
	1088	2558.5806	496.8623	1584.7484	3532.4128
	1089	2543.7028	504.6757	1554.5565	3532.8491
	1090	2528.9864	512.2102	1525.0727	3532.9001
	1091	2514.4300	519.4813	1496.2652	3532.5948
	1092	2500.0321	526.5031	1468.1048	3531.9594
	1093	2485.7913	533.2886	1440.5648	3531.0178
	1094	2471.7061	539.8496	1413.6201	3529.7920
PTBA	1065	4077.0638	139.2207	3804.1962	4349.9313
	1066	4069.6018	197.8092	3681.9028	4457.3009
	1067	4059.4611	238.0832	3592.8266	4526.0956
	1068	4049.1705	272.1455	3515.7751	4582.5659
	1069	4039.0060	302.2730	3446.5618	4631.4502
	1070	4028.8547	329.3899	3383.2623	4674.4470
	1071	4018.7025	354.1874	3324.5078	4712.8972
	1072	4008.5574	377.1354	3269.3856	4747.7292
	1073	3998.4213	398.5572	3217.2635	4779.5791
	1074	3988.2949	418.6904	3167.6767	4808.9131
	1075	3978.1792	437.7163	3120.2710	4836.0874
	1076	3968.0752	455.7766	3074.7693	4861.3811
	1077	3957.9840	472.9852	3030.9499	4885.0180
	1078	3947.9065	489.4346	2988.6322	4907.1809
	1079	3937.8438	505.2019	2947.6662	4928.0214
	1080	3927.7968	520.3516	2907.9264	4947.6672
	1081	3917.7663	534.9387	2869.3057	4966.2269
	1082	3907.7534	549.0104	2831.7126	4983.7942
	1083	3897.7589	562.6079	2795.0676	5000.4501
	1084	3887.7836	575.7668	2759.3013	5016.2659
	1085	3877.8285	588.5188	2724.3527	5031.3043
	1086	3867.8943	600.8919	2690.1677	5045.6208
	1087	3857.9818	612.9110	2656.6983	5059.2653
	1088	3848.0918	624.5984	2623.9013	5072.2824
	1089	3838.2252	635.9744	2591.7381	5084.7123
	1090	3828.3826	647.0572	2560.1737	5096.5915
	1091	3818.5648	657.8634	2529.1762	5107.9534
	1092	3808.7724	668.4080	2498.7167	5118.8282
	1093	3799.0063	678.7050	2468.7688	5129.2438
	1094	3789.2670	688.7671	2439.3082	5139.2259

Table 17: Proportions of prediction error covariances by variable

Variable	Lead	ADRO	PTBA	Variable	Lead	ADRO	PTBA
ADRO	1	1.0000	0.0000	PTBA	1	0.2287	0.7712
	2	0.9978	0.0022		2	0.2332	0.7667
	3	0.9985	0.0014		3	0.2474	0.7525
	4	0.9988	0.0011		4	0.2553	0.7446
	5	0.9990	0.0009		5	0.2604	0.7395
	6	0.9991	0.0008		6	0.2644	0.7355
	7	0.9992	0.0007		7	0.2678	0.7322
	8	0.9992	0.0007		8	0.2706	0.7293
	9	0.9992	0.0007		9	0.2732	0.7267
	10	0.9992	0.0007		10	0.2756	0.7243
	11	0.9992	0.0008		11	0.2778	0.7221
	12	0.9991	0.0008		12	0.2799	0.7200
	13	0.9990	0.0009		13	0.2819	0.7180
	14	0.9989	0.0010		14	0.2838	0.7161
	15	0.9988	0.0011		15	0.2857	0.7143
	16	0.9987	0.0012		16	0.2874	0.7125
	17	0.9986	0.0014		17	0.2892	0.7107
	18	0.9984	0.0015		18	0.2909	0.7090
	19	0.9983	0.0017		19	0.2926	0.7073
	20	0.9981	0.0018		20	0.2942	0.7057
	21	0.9979	0.0020		21	0.2958	0.7041
	22	0.9977	0.0022		22	0.2974	0.7025
	23	0.9975	0.0024		23	0.2990	0.7009
	24	0.9973	0.0026		24	0.3005	0.6994

Figure 8: Proportions of prediction error covariances (a) for forecasting ADRO, (b) for forecasting PTBA

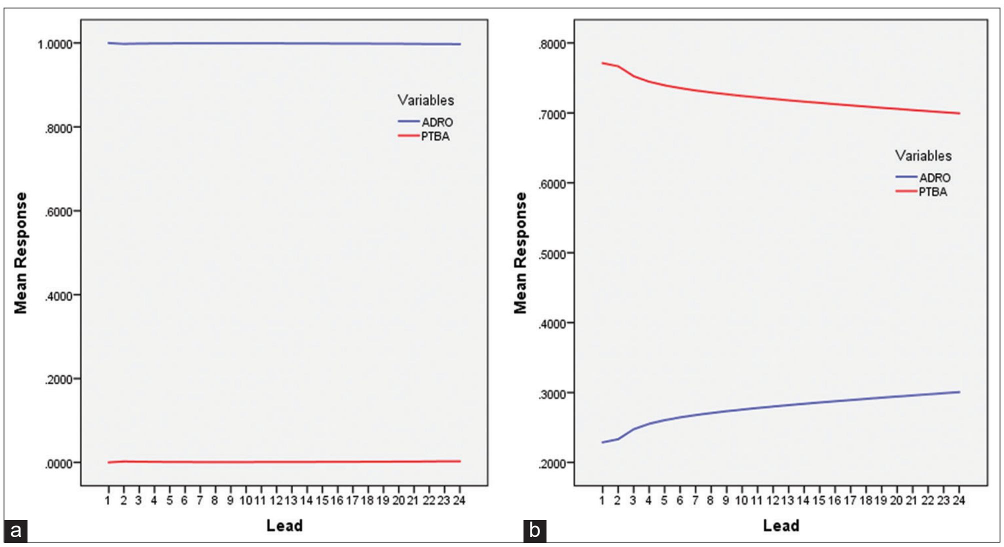
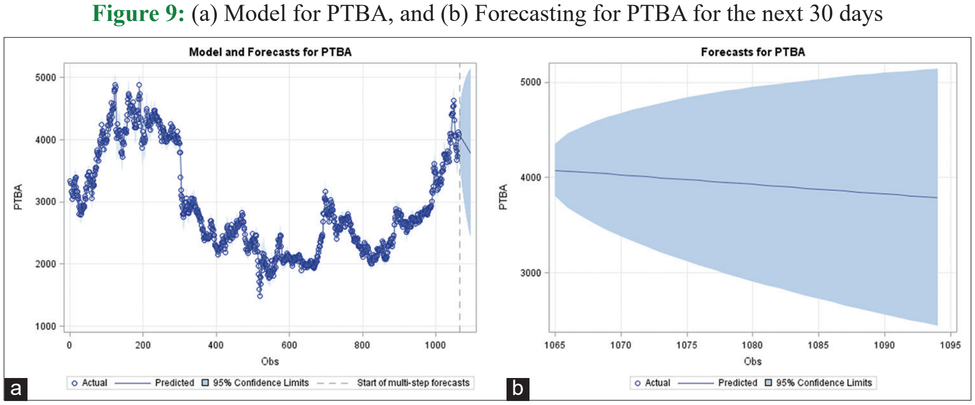


Figure 9: (a) Model for PTBA, and (b) Forecasting for PTBA for the next 30 days



4. CONCLUSION

In this study, the daily stock prices of ADRO and PTBA from two energy companies in Indonesia and the data are taken from January 2018 to December 2022. The data are analyzed using a multivariate time series analysis approach. From the preliminary study, the data shows nonstationary cross-correlation and has an ARCH effect. After the differentiation process, the data is stationary. Based on the study of the assumptions, the VAR(p)-CCC-GARCH(r,s) model is applied to the data. For the CCC-GARCH(r,s) model, the parameter estimation used is the Constant Conditional Correlation (CCC-GARCH(r,s)) applied to the data. The best and most suitable model for the data is the VAR(3)-CCC-GARCH(1,1) model. The granger causality analysis shows that ADRO and PTBA are mutually granger causality (bidirectional granger causality), meaning that future predictions from ADRO will be influenced by themselves and past information from PTBA and future predictions.

PTBA's future will be influenced not only by himself but also by past information from ADRO. The IRF analysis results explain: If a shock of one standard deviation occurs in ADRO, ADRO and PTBA respond. ADRO's response is positive for the next 24 days with a downward trend, while PTBA's response is positive with an upward trend; If a shock of one standard deviation occurs in PTBA, PTBA itself and ADRO respond. ADRO's response is negative and weak and has a downward trend in the next 24 days, while PTBA's response is quite large and positive with a downward trend. From the results of forecasting for the next 30 days (period), ADRO's closing price is decreasing, as well as PTBA's closing price which has a downward trend for the next 30 days.

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