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**Article**

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# Modeling and Forecasting Closing Prices of some Coal Mining Companies in Indonesia by Using the VAR(3)-BEKK GARCH(1,1) Model

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**ABSTRACT**

Today, coal is the main source of energy in both developed and developing countries. The use of coal fuel for power generation and industry continues to increase. This research will discuss the closing price relationship model for the share prices of two coal companies in Indonesia, namely ABM and IND_E, from January 2018 to July 2023. The modeling used is a multivariate time series approach. From the results of data analysis, the best model that fits the data is the VAR(3)-BEKK GARCH(1,1). Based on this best model, further analysis of Granger causality, impulse response function (IRF), and forecasting for the next 30 periods as well as the proportion of prediction error covariance are discussed.

**Keywords:** Vector Autoregressive, BEKK GARCH Model, Forecasting, Granger causality, Proportion Prediction Error Covariance
**JEL Classifications:** C01, C53, Q47, L72

## 1. INTRODUCTION

Coal is a physically and chemically heterogeneous and combustible sedimentary rock composed of both inorganic and organic matter. Inorganically, coal consists of various ash-forming compounds dispersed throughout the coal, and organically, coal consists mainly of carbon, hydrogen, and oxygen, with lesser amounts of sulfur and nitrogen (Miller, 2005). The main fuels for electricity generation in the world are oil, gas and coal. According to Danning (2000) states that the prediction of the availability of long-term resources from fossil fuels, oil will last 40 years based on current consumption levels, gas will last around 65 years, and coal will last around 219 years. Danning (2000) also stated that coal will still be the main source of energy, especially for electricity generation. Today, coal is again being considered as an alternative fuel source for oil, especially for electricity generation (Speight, 2015). Petroleum, natural gas and coal are the cheap fossil fuels that have been used in America for more than a century and account for nearly 90% of America's primary energy use. The US has enormous domestic coal reserves, more than 94% of US fossil energy reserves (DOE, 1993a). The United States is importing large amounts of oil and gas, while coal is a net export commodity for the US economy. In the 1980s coal prices fell markedly, mainly due to higher mining productivity, excess capacity and competition from natural gas (Speight, 2015). Coal's cheapness and abundance make it an attractive energy material, but environmental controls and the inconvenience of using solid fuels have made oil and natural gas the main fuels in developed countries for many domestic, industrial and commercial applications (Speight, 2015). Power generation is the largest use of coal in the United States. Of the total US domestic energy production in 1992, 27% was natural gas, 23% crude oil, 32% (21.6 quadrillion Btu) was coal, and the remaining 18% was from nuclear power and renewables (EIA, 1993a; 1993b). In 1992, coal-fired steam power plants accounted for 56% of the electricity produced in the United States (EIA, 1993b). During the last 20 years the use of coal for electricity consumption and industry has doubled.

Since 2000, coal has contributed to 40% of global primary energy growth (Hecking, 2016). The main international market for coal utilization is power generation. The two main components of the market are the rehabilitation of existing crops and the building of the new power generation capacity (DOE, 1993b). China is the biggest market for coal, with capacity additions projected to be roughly three times that of South Asia, the second biggest market. China's need for new capacity by 2010 is more than four times that of all industrialized countries combined (Speight, 2015). Hecking (2016) explains that the reason why coal is the main fuel for energy purposes is due to the fact that it is abundant, cheap, and available as a domestic resource.

The development of the use of oil, natural gas and coal serving as the three main sources of energy for electricity generation in America continues to grow (Mohammadi, 2011); in India and China, the development is very fast and continues to increase in the use of coal fuel, especially for industrial purposes. In all of these developed countries (USA, China and India), the main generator technology is trying to burn pulverized coal (PC). The use of PC combustion technology continues to undergo improvements to increase the efficiency and reduce emissions. The 21st century is the coal century, no energy source has developed bigger than coal since 2000, both oil, natural gas, and renewable energy (Hecking, 2016).

Energy is one of the central issues of the 21st century, and oil and coal are the two most important primary sources for energy. Oil and Coal illustrate the complex relationship between humans and these fuels as a source of energy and the consequences. The nature of these energies, the manner in which they are used, and the technical, environmental, social, and policy consequences of large-scale consumption of oil and coal. Billions of dollars' worth of infrastructure has been created to find, produce, transport, process and burn oil and coal. In most parts of the world, coal-fired power plants generate at least half of all the electricity needed, and in almost all countries, transportation is synonymous with oil consumption (Tabak, 2009). Coal is the main source of electrical energy for China's consumption and industry today. The large dependence on electrical energy from coal and fluctuating coal prices, this affects various industries and has an impact on the prices of merchandise in China (Zhihua et al., 2011). Many studies studying the relationship of energy prices, especially oil and coal, have been carried out. Studies that discuss the existence of a long-term positive correlation between oil prices and merchandise prices (Cunado and Perez de Gracia, 2005; Cologni, 2008; Chang and Jiang, 2003). Chen (2008) in his study concluded that the proportion of changes in commodity prices is due to changes in oil prices. Coal is the main form of energy used in both industry and household consumption in China. Therefore, variations in coal prices are expected to affect goods prices in China. By using monthly data from January 2002 to October 2010 (Zhihua et al., 2011) in his study he built a state-of-the-parameter model and error correction model to estimate the effect of coal prices on goods prices in China. The long-run equilibrium relationship between coal prices and PPI, and CPI, can be observed. From the results of his research, Zhihua et al. (2011) concluded that there is a positive correlation between coal prices and CPI and PPI in China in the long term. This research will discuss modeling the closing prices of shares of two coal industry companies in Indonesia, namely coal companies ABM and IND_E (Indika Energy) from January 2018 to July 2023. Data modeling uses a multivariate time series analysis approach.

## 2. STATISTICAL MODEL

In a modeling data multivariate time series, we need to check the assumptions of stationarity, cointegration, autoregressive conditional heteroscedasticity (ACR) effect, and cross correlation among the variables. Checking these assumptions is very important in modeling multivariate time series analysis (Hamilton, 1994; Wei, 2006; 2019; Tsay, 2010; 2014; Virginia et al., 2018; Warsono et al., 2019a; 2019b; 2020; Russell et al., 2022; 2023). The stationarity of the time series data can be checked by checking the pattern of the plot of the data and by testing the stationarity using the Augmented Dickey-Fuller test (ADF test) (Pankratz, 1991; Wei, 2006; 2019; Tsay, 2010; 2014). To check that there is a cointegration between the variables, it can be tested using the Johansen test (Johansen, 1988), to check the ARCH effect, the Lagrange Multiplier test (LM test) can be used, and the cross correlation between the variables can be checked using Portmanteau test (Wei, 2006; 2019; Tsay, 2010; 2014).

### 2.1. Stationary Data

To test whether the data meet the stationary assumptions using the Augmented Dickey-Fuller (ADF-test) is conducted by the following model:

$$\Delta z_t = c + \phi_t + \delta z_{t-1} + \sum_{i=1}^{m} \beta_i \Delta z_{t-1} + e_t \tag{1}$$

The null and alternative hypotheses are as follows:

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

In the statistical test to test the null hypothesis, we use the test-A or Dickey-Fuller test as follows:

$$\tau = \frac{\delta}{S_\delta} \tag{2}$$

The null hypothesis is rejected if the P-value ≤ α, for α=0.05, (Virginia et al., 2018, Warsono et al., 2019a; 2019b).

If the stationary assumptions are not met, the common method to eliminate nonstationary assumptions is differencing (Pankratz, 1991; Montgomery et al., 2008). We define differencing with the operator ∇:

$$\nabla Z_t = Z_t - Z_{t-1} = (1 - B) Z_t \tag{3}$$

where

$$BZ_t = Z_{t-1} \tag{4}$$

The power functions for operators B and $\nabla$ are defined as follows:

$$B^n Z_t = Z_{t-n},$$

$$\nabla^n(Z_t) = \nabla(\nabla^{n-1} Z_t), \tag{5}$$

and

$$\nabla^0(Z_t) = Z_t.$$

One approach to eliminating trends in time series data is differencing. Differentiation has two relative advantages in fitting the trend model to the data. First, it does not need to estimate parameters, so it is a simple approach and usually we just have to look at the data plot after differencing whether the data meets the stationary assumption or not; Second, the fitting model assumes that the trend remains the same throughout the time series and will continue to exist. Differentiation can allow the trend component to change from time to time (Montgomery et al, 2008). In practice, usually one or two differencing is enough to eliminate trends in the data (Warsono, 2019a; 2019b).

## 2.2. Cointegration

Engle and Granger (1987) introduced the concept of cointegration, and Johansen (1988) developed the concept of estimation and inferentiality. The time series $Z_t$ is said to be integrated with order one process, I(1), if $(1-B)Z_t$ is stationary (Tsay, 2014). In general, the univariate time series $Z_t$ is an I(d) process, if $(1-B)^d Z_t$ is stationary (Hamilton, 1994; Wei, 2006; 2019; Tsay, 2014). Rachev et al. (2007) stated that cointegration is a feedback mechanism that forces processes to stay close together or large data sets are driven by the dynamics of a small number of variables, this is one of the important concepts of the theory of econometrics. This cointegration implies a long-term stable relationship between variables in forecasting (Tsay, 2014). If in the vector autoregressive (VAR) model, there exists cointegration between variables, then the model needs to be modified into VECM (Hamilton, 1994; Tsay, 2010; 2014; Wei, 2006; 2019). To check if there is a cointegration between vector time series, then one needs to test the cointegration rank. One of the methods that can be used to test the rank of cointegration is the trace test. The test is as follows:

$$Tr(r) = -T \sum_{i=r+1}^{k} \ln(1-\widehat{\lambda}_i). \tag{6}$$

## 2.3. Test for ARCH effect (Lagrange Multiplier Test (LM- Test))

Weiss (1984) showed the importance of detecting the ARCH effect in time series data. Engle (1982) stated that the data time series has a problem with autocorrelation and also with heteroscedasticity. The test that can be used to detect the heteroscedasticity or ARCH effect is ARCH-LM (Engle, 1982; Tsay, 2010).

To check whether there is an ARCH effect, we can build a model and test it as follows, consider the AR(p) model

$$Z_{it} = \alpha_0 + \alpha_1 Z_{1t-1} + \dots + \alpha_p Z_{1t-p} + \varepsilon_{1t} \tag{7}$$

from model (7), we can build a model

$$\varepsilon_{1t}^2 = \gamma_0 + \gamma_1 \varepsilon_{it-1}^2 + \dots + \gamma_q \varepsilon_{1t-q}^2 + u_{1t} \tag{8}$$

To check whether there is an ARCH effect, we test whether the null hypothesis is Ho: $\gamma_i = 0 \ \forall i,\ i = 1, 2 \dots, q$ or Ho: no ARCH effect. The test statistic is using the Lagrange Multiplier test (LM-test),

$$LM = T R^2,$$

where T is the sample size and $R^2$ is calculated from the model (8). Reject the null hypothesis if P-value <0.05. LM approximately has a Chi-square distribution with degrees of freedom equal to q.

## 2.4. Cross Correlation

One of the requirements in multivariate time series modeling is the existence of a lag-correlation between series components, which in the end the cross-correlation matrix is used as a measure of the strength of the linear relationship between time series data (Wei, 2014). The lag-k cross-correlation matrix of $Z_t$ is defined as follows:

$$\rho_k = [\rho_{ij}(k)] = D^{-1} \Gamma_k D^{-1}. \tag{9}$$

Where

$$\rho_{ij}(k) = \frac{\Gamma_{ij}(k)}{\sqrt{\Gamma_{ii}(0)\ \Gamma_{jj}(0)}} = \frac{Cov(Z_{it}, Z_{jt-k})}{Sd(Z_{it}).Sd(Z_{jt})}, \tag{10}$$

$\rho_{ij}(k)$ is correlation coefficient between $Z_{it}$ and $Z_{j,t-k}$, k>0. Given the data $\{Z_t \mid t = 1, 2, \dots, T\}$, the cross-covariance matrix $\Gamma_k$ can be estimated by

$$\hat{\Gamma}_k = \frac{1}{T} \sum_{t=k+1}^{T} (Z_t - \bar{Z})(Z_{t-k} - \bar{Z})', \qquad k > 0.$$

where $\bar{Z} = \frac{1}{T}\sum_{t=1}^{T} Z_t$ is the vector sample mean. The cross-correlation $\rho_k$ is estimated by

$$\hat{\rho}_k = [\hat{\rho}_{ij}(k)] = \hat{D}^{-1} \hat{\Gamma}_k \hat{D}^{-1}, \tag{11}$$

where $k \geq 0$ and $\hat{D}$ are $m \times m$ matrix diagonal from the sample standard deviation from the component of the series. To test whether there is a cross correlation between variables, the following null hypothesis is tested:

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

The statistical test is

$$Q_m(k) = T^2 \sum_{s=1}^{k} \frac{1}{T-s} tr\left[ \hat{\Gamma}'_s \hat{\Gamma}_0^{-1} \hat{\Gamma}_s \hat{\Gamma}_0^{-1} \right], \quad (12)$$

where T is the sample size, m dimension of $Z_t$, tr(A) is a trace matrix A, namely the sum of diagonal elements of matrix A. The test is called the Portmanteau test, if the P-value <0.05, then the null hypothesis is rejected.

### 2.5. VAR(p)-BEKK GARCH(s,t) model

Model VAR(P) can be written as follows:

$$Z_t = \theta_o + \sum_{i=1}^{p} \theta_i Z_{t-i} + \varepsilon_t$$

where $Z_t$ is m×1 vector observation at time t, $\theta_o$ is m×1 vector parameter constant, $\theta_i$ is m×m parameter matrix, $\varepsilon_t$ is m×1 vector residual. Studies on volatility modeling, especially in the fields of finance, business, and capital markets, are very important. To study the volatility of time series or multivariate time series data, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is widely used because it is a good approach to conditional variance modeling analysis. Engle and Kroner (1995) developed a general multivariate GARCH model called BEKK representation. Let F(t-1) be the past values of $\varepsilon_t$ and suppose that $H_t$ is the conditional covariance matrix of the m-dimensional random vector $\varepsilon_t$. Suppose $H_t$ is conditional variance with respect to F(t-1), then the multivariate GARCH(s,t) model can be written as follows:

$$\varepsilon_t | F(t-1) \sim N(\mathbf{0}, H_t),$$

$$H_t = \delta_o + \sum_{i=1}^{s} A_i' \varepsilon_{t-1} \varepsilon_{t-1}' A_i + \sum_{i=1}^{t} G_i' H_{t-1} G_i.$$

where $\delta_o$, $A_i$, and $G_i$ are m×m parameter matrices.

### 2.6. Normality Test of Residuals

Some methods are available to check the normality of the 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:

$$JB = \frac{T}{6}\left[ S^2 + \frac{(K-3)^2}{4} \right], \quad (13)$$

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

### 2.7. Stability Test

Hamilton (1994), Lutkepohl (2005), and Wei (2019) stated that to check that the VAR(p) model is stationary covariance, it can be checked from the inverse roots of the AR polynomial characteristics. A VAR(p) model is said to be stable (stationary, in both the mean and variance) if all its roots have a modulus smaller than one and all of them lie within the unit circle. For example, the VAR(p) model can be written

$$Z_t = c + \Phi_1 Z_{t-1} + \ldots + \Phi_p Z + \varepsilon_t \quad (14)$$

The characteristic polynomial on the matrix is called the characteristic polynomial of the VAR(p) model is said to be stable if the root of

$$|\lambda^p I - \lambda^{p-1}\Phi_1 - \lambda^{p-2}\Phi_2 - \ldots - \Phi_p| = 0 \quad (15)$$

Are all inside the unit circle or have moduli smaller than one. Therefore, the VAR(p) model is covariance stationary as long as $|\lambda| < 1$ for all values of $\lambda$ satisfying (15) (Hamilton, 1994; Wei, 2019). Lutkepohl (2005) states that $|\lambda| < 1$ is the stability condition.

### 2.8. Granger Causality Test

One of the most popular causality tests used in various multivariate time series data studies is the Granger causality Test. According to (Hamilton, 1994; Lutkepohl, 2005; Warsono et al., 2020; Russel et al., 2022; 2023), the Granger causality test is used to determine the short-term relationship in the form of reciprocity between variables under study. Suppose that we analyze the Granger causality between variables X and Y and the model for Granger causality Test is:

$$\begin{aligned} x_t &= c_1 + \alpha_t x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_p x_{t-p} + \beta_1 y_{t-1} \\ &+ \beta_2 y_{t-2} + \ldots + \beta_p y_{t-p} + u_t \end{aligned} \quad (16)$$

Based on the assumption of ordinary least squares (OLS), the null hypothesis to be tested is as follows:

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_p = 0$$

(Y is not Granger Causal X) against

$$H_1 : \text{at least one of } \beta_p \neq 0$$

(Y Granger Causal X). The statistic test is as follows:

$$\text{F Test} = \frac{(\text{RSS}_0 - \text{RSS}_1)/\text{p}}{\text{RSS}_1/(\text{T} - 2\text{p} - 1)} \quad (17)$$

Reject the null hypothesis if F-Test > $F_{(\alpha, p, T-2p-1)}$ or if P-value <0.05 (Hamilton, 1994).

Where to calculate the residual sum of squares 1 or $RSS_1$ using the shocks of model (16) is calculated as follows:

$$\text{RSS}_1 = \sum_{t=1}^{T} \hat{u}_t^2 \quad (18)$$

Under the null hypothesis the model (16) is written as follows:

$$x_t = c_0 + \gamma_t x_{t-1} + \gamma_2 x_{t-2} + \ldots + \gamma_p x_{t-p} + e_t \quad (19)$$

To calculate the residual sum of squares 0 or $RSS_0$ using the shocks of model (19) is calculated as follows:

$$RSS_0 = \sum_{t=1}^{T} \hat{e}_t^2 .$$

## 2.9. Impulse Response Function (IRF)

Hamilton (1994) and Tsay (2014) stated that IRF is an analytical technique used to analyze the response of a variable due to shock in another variable. Wei (2006) stated that the VAR model can be written in vector MA (∞) as follows:

$$Z_t = \mu + \mu_t + \Psi_1 \mu_{t-1} + \Psi_2 \mu_{t-2} . \quad (20)$$

Thus, the matrix is interpreted as follows:

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

The element of the i-th row and j-th column indicates the consequence of the increase of one unit in innovation of variable $j$ at time $t$ ($\mu_{jt}$) for the $i$ variable at time $t + s$ ($Z_{i,\,t+s}$) and fixed all other innovation. If the element of $\mu_t$ changed by δ1, at the same time, the second element will change by $\delta_2$,…, and the $n$th element will change by $\delta_n$, then the common effect from all of these changes on the vector $Z_{t+s}$ will become

$$\Delta Z_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}} \delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}} \delta_2 + \ldots + \frac{\partial X_{t+s}}{\partial u_{nt}} \delta_n = \Psi_s \delta . \quad (21)$$

The plot of the i-th row and jth column of $\Psi_s$ as a function of $s$ is called IRF.

## 2.10. Forecasting *m*-steps ahead and Proportion of Prediction Error Covariance

In analyzing the ABM and IND_E data, forecasting will also be carried out using the best model that fits the $\{Z_t\}$ data. By using the best model that fits the data, forecasting is performed directly for the next 30 periods (days). 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 (Hamilton, 1994; Lutkepohl, 2005; Florens, 2007; Tsay, 2014).

# 3. RESULTS AND DISCUSSION

Figure 1 shows that in 2018 the daily closing price for ABM shares was relatively stable but with quite high price fluctuations, in 2019 it had a downward trend with relatively stable fluctuations, in 2020 the daily closing price for ABM shares was in the lowest and stable position, namely with low fluctuations, from 2021 to June 2022 the price trend continues to rise with relatively large price fluctuations, which means even though the daily closing price rises but the volatility is high, from June 2022 to December 2022 the trend decreases and fluctuates, and in 2023 ABM's daily closing share price tends to rise and fluctuate. Figure 1 shows the pattern of changes in the closing price from IND_E from January 2018 to June 2019, it can be seen that the closing price trend is decreasing and fluctuating, from July 2019 to March 2020 the closing price trend is increasing and fluctuating, and from April 2020 to December 2020 the price is relatively stable with a flat trend and relatively small price fluctuations. From 2021 to June 2021 to June 2022 the trend is up and fluctuates relatively high. From July 2022 to July 2023, the closing price trend is decreasing and fluctuating. Figure 1 indicates that the closing prices of ABM and IND_E are not stationary and have a high diversity, which indicates an autoregressive conditional heteroscedasticity (ACRH) effect.

Table 1 shows that the variables ABM and IND_E are not stationary, and this is consistent with Figure 2, where the autocorrelation decreases very slowly, this shows that the data is not stationary (Pankratz, 1991). Table 2 shows the cointegration test with the null hypothesis that there is no cointegration relationship between the variables ABM and IND_E. From the results of the cointegration test with the trace test, Ho was not rejected (Table 2), where the test on Ho with rank (r) = 0 and 1 both tests had P-values of 0.2296 and 0.1158, respectively. In the absence of cointegration between variables, there is no long-term relationship between ABM and IND_E variables (Hamilton, 1994; Wei, 2006; 2019; Tsay, 2010; 2014).

From the results of the cross correlation analysis (Table 3) and the results of the cross correlation test presented in the form of a schematic representation of cross correlation (Table 4) with the null hypothesis there is no cross correlation and the test results up to the 11th lag obtained a plus sign (+) which shows that the test is significant with alpha = 0.05, which means that there is a cross

**Figure 1.** Plot of daily closing price data ABM and IND_E from January 2018 to July 2023

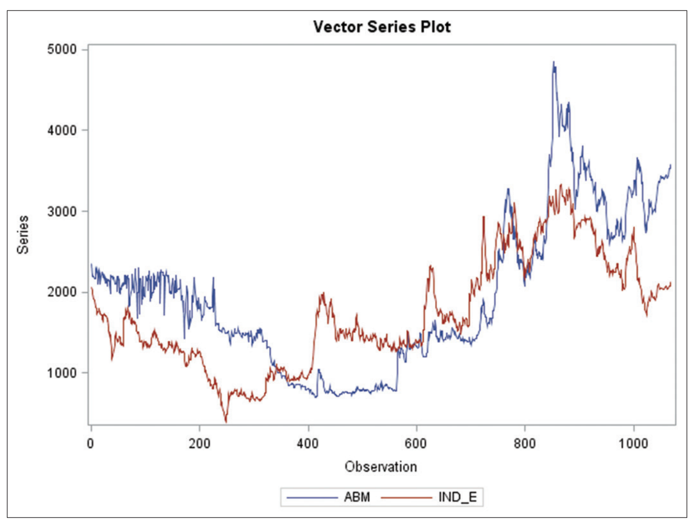



**Table 1: Dickey-Fuller unit root tests**

| Variable | Type | Rho | P | Tau | P |
|---|---|---|---|---|---|
| ABM | Zero mean | 0.09 | 0.7028 | 0.07 | 0.7051 |
| | Single mean | –2.60 | 0.7059 | –0.91 | 0.7864 |
| | Trend | –6.09 | 0.7370 | –1.82 | 0.6966 |
| IND_E | Zero mean | –0.57 | 0.5547 | –0.51 | 0.4961 |
| | Single mean | –4.64 | 0.4707 | –1.51 | 0.5294 |
| | Trend | –12.31 | 0.2979 | –2.77 | 0.2084 |

IND_E: Indika energy

**Figure 2:** Autocorrelation function for (a) ABM and (b) IND_E

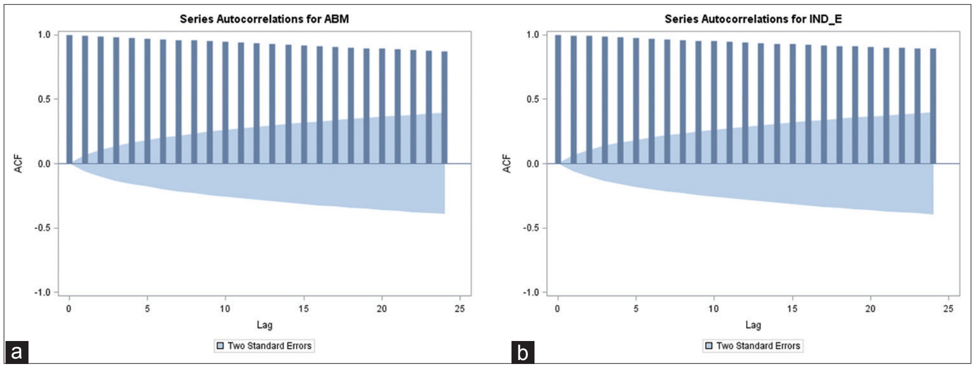



**Table 2: Cointegration rank test using trace**

| H0: Rank=r | H1: Rank>r | Eigen value | Trace | P | Drift in ECM | Drift in process |
|---|---|---|---|---|---|---|
| 0 | 0 | 0.0077 | 10.7122 | 0.2296 | Constant | Linear |
| 1 | 1 | 0.0023 | 2.4715 | 0.1158 | | |

correlation up to lag 11 between ABM and IND_E data. From the results obtained in Tables 3 and 4, it is suggested that modeling the relationship between the ABM and IND_E variables should involve autoregressive modeling. From the autoregressive conditional heteroscedasticity (ARCH) test (Table 5) with null there is no ARCH effect tested with the Lagrange Multiplier test (LM test), the null hypothesis is rejected. So there is an ARCH effect on the ABM and IND_E data. Therefore, based on Tables 3-5, it is suggested that modeling the relationship between ABM and IND_E variables does not only need to involve autoregressive modeling but also needs to involve ARCH or GARCH modeling. From Table 6, the minimum AICC is in AR2 and AR3, which are relatively very close to the AICC values. Based on the results of the analysis, the model to be used was the VAR(3)-BEKK GARCH(1,1) model.

## 3.1. Model VAR(3)-BEKK GARCH(1,1)

The mean model VAR(3):

$$\begin{bmatrix} ABM_t \\ IND\_E_t \end{bmatrix} = \begin{pmatrix} -12.5608 \\ 6.6257 \end{pmatrix} + \begin{bmatrix} 0.9592 & -0.0099 \\ -0.0045 & 1.0059 \end{bmatrix} \begin{pmatrix} ABM_{t-1} \\ IND\_E_{t-1} \end{pmatrix} + \begin{bmatrix} -0.0018 & 0.0816 \\ 0.0187 & 0.0427 \end{bmatrix} \begin{pmatrix} ABM_{t-2} \\ IND\_E_{t-2} \end{pmatrix} + \begin{bmatrix} 0.0382 & -0.0601 \\ -0.0176 & -0.0485 \end{bmatrix} \begin{pmatrix} ABM_{t-3} \\ IND\_E_{t-3} \end{pmatrix} + \varepsilon_t \tag{22}$$

And the BEKK GARCH(1,1) model:

$$H_t = \begin{bmatrix} 16.5097 & -13.9464 \\ -13.9464 & 98.9567 \end{bmatrix} + \begin{bmatrix} 0.4452 & -0.0019 \\ -0.1113 & 0.2506 \end{bmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1} \end{pmatrix} \begin{bmatrix} 0.4452 & -0.0019 \\ -0.1113 & 0.2506 \end{bmatrix} + \begin{bmatrix} 0.9157 & 0.0027 \\ 0.0299 & 0.9540 \end{bmatrix}' H_{t-1} \begin{bmatrix} 0.9157 & 0.0027 \\ 0.0299 & 0.9540 \end{bmatrix}. \tag{23}$$

From Table 7, the relationship models and parameters significantly affect $ABM_t$ and $IND\_E_t$ (Figure 3). Figure 3 explains that $ABM_t$ is significantly influenced by $ABM_{t-1}$, $IND\_E_{t-2}$, and $IND\_E_{t-3}$ with the magnitude of the estimated parameter (Influence) being 27.50, 2.94 and -2.82 with P-values respectively 0.0001, 0.0149, and 0.0048. Figure 3 also explains that $IND\_E_t$ is significantly influenced by $IND\_E_{t-1}$ with the estimated parameter (influence) being 31.36 with a P-value of 0.0001. This means that if the value of $IND\_E_{t-1}$ increases by 1 unit, then $IND\_E_t$ increase by 31.36. Table 8 shows that the BEKK GARCH(1,1) model (Model 23) most of the parameters are significant with the P-values <0.05.

## 3.2. Diagnostic Model

$$ABM_t = -12.5608 + 0.9592 ABM_{t-1} - 0.0099 IND\_E_{t-1} - 0.0018 ABM_{t-2} + 0.0816 IND\_E_{t-2} + 0.0382 ABM_{t-3} - 0.0601 IND\_E_{t-3} + \varepsilon_{1t} \tag{24}$$

$$IND\_E_t = 6.6257 - 0.0045 ABM_{t-1} + 1.0059 IND\_E_{t-1} + 0.0187 ABM_{t-2} + 0.0427 IND\_E_{t-2} - 0.0176 ABM_{t-3} - 0.0485 IND\_E_{t-3} + \varepsilon_{2t} \tag{25}$$

From Table 9, the univariate model ANOVA diagnostics show that the model (24) and model (25) are significant with P-values <0.0001 and <0.0001 and R-square values of 0.9899 and 0.9923, respectively. This means that model (24) and model (25) are able to explain the diversity of ABMt and IND_E respectively by 98.99% and 99.23%. From Table 10, it can be seen that the normality test with the null hypothesis that the residuals are normally distributed is rejected with P-values <0.0001 and <0.0001 respectively, but from Figure 4, the prediction error distribution for ABMt and IND_Et does not appear to deviate much from the normal distribution. Table 10 also provides the results of the ARCH effect test, with the null hypothesis that there is no ARCH effect, and the results show that the null hypothesis is rejected, which means there is an ARCH effect. This indicates that modeling involving the GARCH model is very relevant for ABM and IND_E data. Table 11 shows that the modulus of the Roots of AR and GARCH characteristic polynomials is smaller than 1. This shows that the VAR(3)-BEKK GARCH (1,1) (Table 8) model is a stable model (Hamilton, 1995; Lutkepohl, 2005; Wei, 2019). Thus, the VAR(3)-BEKK GARCH (1,1) model is a reliable model and can be used for further analysis.

**Table 3: Cross correlations of dependent series up to lag 11**

| Lag | Variable | ABM | IND_E | Lag | Variable | ABM | IND_E |
|---|---|---|---|---|---|---|---|
| 0 | ABM | 1.00000 | 0.72392 | 6 | ABM | 0.96718 | 0.69221 |
| | IND_E | 0.72392 | 1.00000 | | IND_E | 0.73497 | 0.97059 |
| 1 | ABM | 0.99335 | 0.71875 | 7 | ABM | 0.96182 | 0.68652 |
| | IND_E | 0.72585 | 0.99583 | | IND_E | 0.73627 | 0.96522 |
| 2 | ABM | 0.98836 | 0.71362 | 8 | ABM | 0.95687 | 0.68080 |
| | IND_E | 0.72777 | 0.99125 | | IND_E | 0.73769 | 0.96031 |
| 3 | ABM | 0.98289 | 0.70814 | 9 | ABM | 0.95107 | 0.67564 |
| | IND_E | 0.72948 | 0.98610 | | IND_E | 0.73901 | 0.95577 |
| 4 | ABM | 0.97770 | 0.70309 | 10 | ABM | 0.94583 | 0.67035 |
| | IND_E | 0.73117 | 0.98110 | | IND_E | 0.74009 | 0.95141 |
| 5 | ABM | 0.97199 | 0.69768 | 11 | ABM | 0.93976 | 0.66503 |
| | IND_E | 0.73311 | 0.97590 | | IND_E | 0.74089 | 0.94683 |

IND_E: Indika energy

**Table 4: Schematic representation of cross correlations**

| Variable/Lag | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ABM | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ |
| IND_E | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ | ++ |

+ is >2*SE, - is <−2*SE, is between. SE: Standard error, IND_E: Indika energy

**Table 5: Tests for ARCH disturbances based on OLS residuals ABM and Indika energy**

| Variable | Order | Q | P | LM | P | Variable | Order | Q | P | LM | P |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ABM | 1 | 998.1640 | <0.0001 | 992.0887 | <0.0001 | IND_E | 1 | 974.8729 | <0.0001 | 961.4543 | <0.0001 |
| | 2 | 1932.6626 | <0.0001 | 992.1519 | <0.0001 | | 2 | 1853.7624 | <0.0001 | 961.7116 | <0.0001 |
| | 3 | 2803.8389 | <0.0001 | 992.2094 | <0.0001 | | 3 | 2643.8686 | <0.0001 | 961.7249 | <0.0001 |
| | 4 | 3613.2042 | <0.0001 | 992.2504 | <0.0001 | | 4 | 3360.0286 | <0.0001 | 961.8562 | <0.0001 |
| | 5 | 4357.4338 | <0.0001 | 992.5427 | <0.0001 | | 5 | 4016.5953 | <0.0001 | 962.0016 | <0.0001 |
| | 6 | 5043.8709 | <0.0001 | 992.5600 | <0.0001 | | 6 | 4621.1409 | <0.0001 | 962.0126 | <0.0001 |

IND_E: Indika energy, LM: Lagrange multiplier, OLS: Ordinary least squares, ARCH: Autoregressive conditional heteroscedasticity

**Table 6: Minimum information criterion based on AICC**

| Lag | AR0 | AR1 | AR2 | AR3 | AR4 | AR5 |
|---|---|---|---|---|---|---|
| IACC | 25.994 | 17.246 | 17.225 | 17.227 | 17.234 | 17.238 |

## 3.3. Granger Causality Test and Impulse Response Function

From the results of the Granger causality test presented in Table 12 for Test 1 with the null hypothesis that ABM is influenced by itself and is not influenced by past and current information from IND_E, test with Chi-square=9.75 with P-value=0.0208 < 0.05. So the null hypothesis is rejected and we conclude that in the multivariate time series model, ABM is not only influenced by past information from itself, but is also influenced by past and current information from IND_E. Test 2 with the null hypothesis is that IND_E is influenced by itself and is not influenced by past and current information from ABM, Chi-square test = 0.98 with P-value = 0.8057 > 0.05. So the null hypothesis is not rejected, and this means that IND_E is only affected by IND_E's own past information and is not affected by ABM.

Figure 5a and b show that if a shock of one standard deviation (Impulse) occurs in ABM, then ABM and IND_E will respond (ABM → ABM, and ABM → IND_E). It can be seen that the long-run response of ABM to the impulse ABM (ABM → ABM) (Figure 5a), the responses decrease and are significant, for the next 10 lags the response values are: 0.9592, 0.9183, 0.9169, 0.9156, 0.9116, 0.9077, 0.9039, 0.9001, 0.8962, and 0.8923. The long-run IND_E responses to the impulse ABM (ABM → IND_E) (Figure 5b), the responses decrease and are not significant because zero values are in the interval, for the next 10 lags the response values are: −0.0049, 0.0097, 0.0057, 0.0026, −0.0007, −0.0041, −0.0074, −0.0108, −0.0141, and −0.0175. Figure 5b indicates that a change in the ABM score does not affect a change in IND_E, and this result is in accordance with the results of the Granger causality test (Test 2, in Table 12).

Figure 6a and b show that if a shock of one standard deviation (Impulse) occurs in IND_E, then ABM and IND_E will respond (IND_E → ABM, and IND_E → IND_E). It can be seen that ABM's long-run response to impulse IND_E (IND_E → ABM) (Figure 6a) responses with an upward and significant trend, for the next 10 lags the response values are: −0.0099, 0.0621, 0.0711, 0.0829, 0.0940, 0.1052, 0.1162, 0.1272, 0.1381, and 0.1489. The long-run IND_E responses to the IND_E impulse (IND_E → IND_E) (Figure 6b), the responses decrease and are not significant because zero values are in the interval, for the next 10 lags the response values are: 1.0059, 1.0546, 1.0548, 1.0583, 1.0583, 1.0584, 1.0583, 1.0582, 1.0580, and 1.0578. Figure 6b indicates that the presence of an impulse value on IND_E affects changes in ABM and IND_E, and this result is in accordance with the results of the Granger causality test (Test 1, in Table 12).

**Table 7: Model parameter estimate and test of vector autoregressive (3)**

| Equation | Parameter | Estimate | SE | t | P | Variable |
|---|---|---|---|---|---|---|
| ABM | CONST1 | −12.56088 | 4.37772 | −2.87 | 0.0042 | 1 |
| | AR1_1_1 | 0.95926 | 0.03488 | 27.50 | 0.0001 | ABM (t-1) |
| | AR1_1_2 | −0.00992 | 0.02434 | −0.41 | 0.6838 | IND_E (t-1) |
| | AR2_1_1 | −0.00187 | 0.04615 | −0.04 | 0.9677 | ABM (t-2) |
| | AR2_1_2 | 0.08162 | 0.03348 | 2.44 | 0.0149 | IND_E (t-2) |
| | AR3_1_1 | 0.03827 | 0.03371 | 1.14 | 0.2565 | ABM (t-3) |
| | AR3_1_2 | −0.06010 | 0.02129 | −2.82 | 0.0048 | IND_E (t-3) |
| IND_E | CONST2 | 6.62576 | 4.13303 | 1.60 | 0.1092 | 1 |
| | AR1_2_1 | −0.00459 | 0.01726 | −0.27 | 0.7905 | ABM (t-1) |
| | AR1_2_2 | 1.00594 | 0.03208 | 31.36 | 0.0001 | IND_E (t-1) |
| | AR2_2_1 | 0.01877 | 0.02063 | 0.91 | 0.3632 | ABM (t-2) |
| | AR2_2_2 | 0.04271 | 0.04547 | 0.94 | 0.3477 | IND_E (t-2) |
| | AR3_2_1 | −0.01762 | 0.01675 | −1.05 | 0.2931 | ABM (t-3) |
| | AR3_2_2 | −0.04857 | 0.03177 | −1.53 | 0.1266 | IND_E (t-3) |

SE: Standard error, IND_E: Indika energy

**Table 8: GARCH model parameter estimates and test**

| Parameter | Estimate | SE | t | Pr > \|t\| |
|---|---|---|---|---|
| GCH C1_1 | 16.50975 | 14.37014 | 1.15 | 0.2509 |
| GCHC1_2 | −13.94647 | 16.96394 | −0.82 | 0.4112 |
| GCHC2_2 | 98.95676 | 26.67641 | 3.71 | 0.0002 |
| ACH1_1_1 | 0.44521 | 0.02955 | 15.07 | 0.0001 |
| ACH1_2_1 | −0.11137 | 0.02558 | −4.35 | 0.0001 |
| ACH1_1_2 | −0.00193 | 0.01181 | −0.16 | 0.8705 |
| ACH1_2_2 | 0.25065 | 0.02551 | 9.83 | 0.0001 |
| GCH1_1_1 | 0.91573 | 0.00808 | 113.34 | 0.0001 |
| GCH1_2_1 | 0.02990 | 0.00893 | 3.35 | 0.0008 |
| GCH1_1_2 | 0.00271 | 0.00327 | 0.83 | 0.4076 |
| GCH1_2_2 | 0.95409 | 0.00832 | 114.70 | 0.0001 |

SE: Standard error

**Table 9: Univariate model ANOVA diagnostics**

| Variable | R-square | SD | F | P |
|---|---|---|---|---|
| ABM | 0.9899 | 94.12578 | 17233.2 | <0.0001 |
| IND_E | 0.9923 | 60.21690 | 22599.1 | <0.0001 |

SD: Standard deviation, IND_E: Indika energy

**Table 10: Univariate model white noise diagnostics**

| Variable | Durbin Watson | Normality | | ARCH | |
|---|---|---|---|---|---|
| | | $\chi^2$ | P | F | P |
| ABM | 2.22578 | 4305.62 | <0.0001 | 77.19 | <0.0001 |
| IND_E | 1.89579 | 1334.85 | <0.0001 | 8.55 | 0.0035 |

IND_E: Indika energy

## 3.4. Forecasting and Proportion Prediction Error Covariance

Figure 7a shows that the VAR(3)-BEKK GARCH(1,1) model is a reliable model, while Figure 7a shows that the predicted values and real data are very close. This indicates that the built model sounds good and can be used for forecasting for next several periods. Figure 7b is the result of forecasting for the next 30 periods. Table 13 shows that the forecasting value for the next 30 periods has a slightly downward trend and the further the confidence interval, the forecasting period tends to widen. This indicates that forecasting with distant periods tends not to be stable. Figure 8a provides information on the proportion of prediction error covariance of ABM and IND_E in ABM forecasting data for

**Figure 3:** Parameters that have a significant effect on $ABM_t$ and $IND\_E_t$

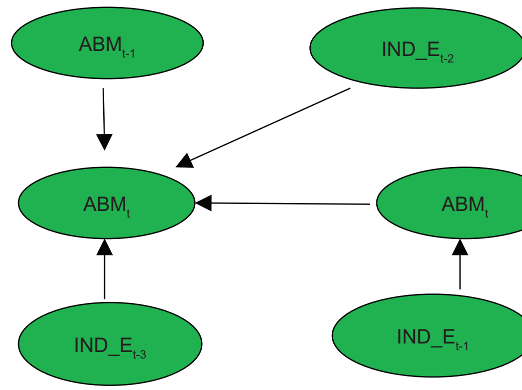



**Figure 4:** Prediction error normality for (a) ABM and (b) IND_E

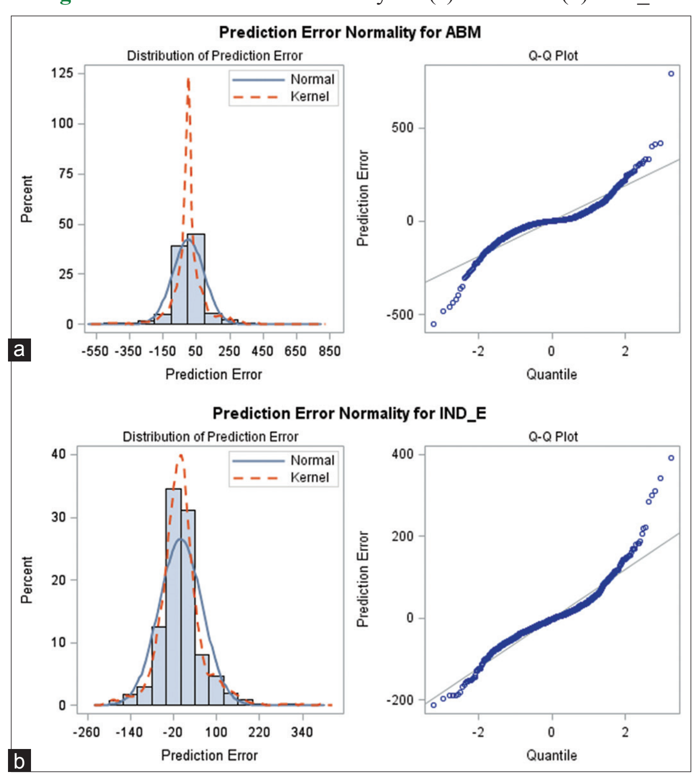


**Table 11: Roots of AR and GARCH characteristic polynomial**

| Characteristic polynomial | Index | Real | Imaginary | Modulus | Radian | Degree |
|---|---|---|---|---|---|---|
| VAR | 1 | 0.9980 | 0.0059 | 0.9981 | 0.0059 | 0.3402 |
| | 2 | 0.9980 | −0.0059 | 0.9981 | −0.0059 | −0.3402 |
| | 3 | 0.2428 | 0.0000 | 0.2428 | 0.0000 | 0.0000 |
| | 4 | −0.0141 | 0.2212 | 0.2217 | 1.6347 | 93.6632 |
| | 5 | −0.0141 | −0.2212 | 0.2217 | −1.6347 | −93.6632 |
| | 6 | −0.2454 | 0.0000 | 0.2454 | 3.1416 | 180.0000 |
| GARCH | 1 | 1.0353 | 0.0000 | 1.0353 | 0.0000 | 0.0000 |
| | 2 | 0.9870 | 0.0000 | 0.9871 | 0.0000 | 0.0000 |
| | 3 | 0.9849 | 0.0000 | 0.9850 | 0.0000 | 0.0000 |
| | 4 | 0.9730 | 0.0000 | 0.9730 | 0.0000 | 0.0000 |

VAR: Vector autoregressive, GARCH: Generalized autoregressive conditional heteroscedasticity

**Table 12: Granger-causality Wald test**

| Test | Group variable | Null hypothesis | Test | DF | $\chi^2$ | P |
|---|---|---|---|---|---|---|
| Test 1 | Group 1 variable: ABM<br>Group 2 variable: IND_E | ABM is influenced by itself and is not affected by past and current information of IND_E | 1 | 3 | 9.75 | 0.0208 |
| Test 2 | Group 1 variable: IND_E<br>Group 2 variable: ABM | IND_E is influenced by itself and not affected by past and current information of ABM | 2 | 3 | 0.98 | 0.8057 |

IND_E: Indika energy

**Figure 5:** Response to Impulse in ABM with two standard errors (a) Response ABM, (b) Response IND_E

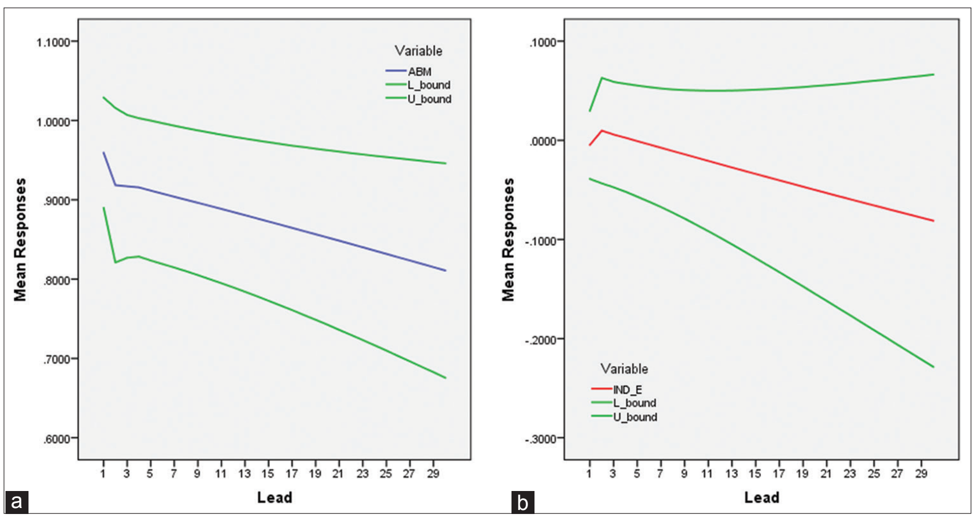



**Figure 6:** Response to Impulse in IND_E with two standard errors (a) Response ABM,(b) Response IND_E

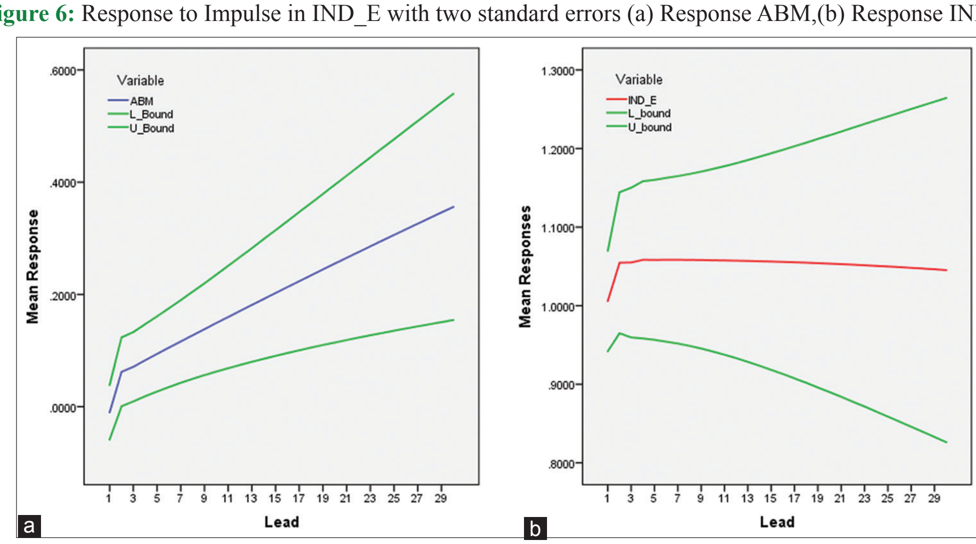


**Figure 7:** (a) Model and forecast, (b) forecast, and (c) prediction error for ABM

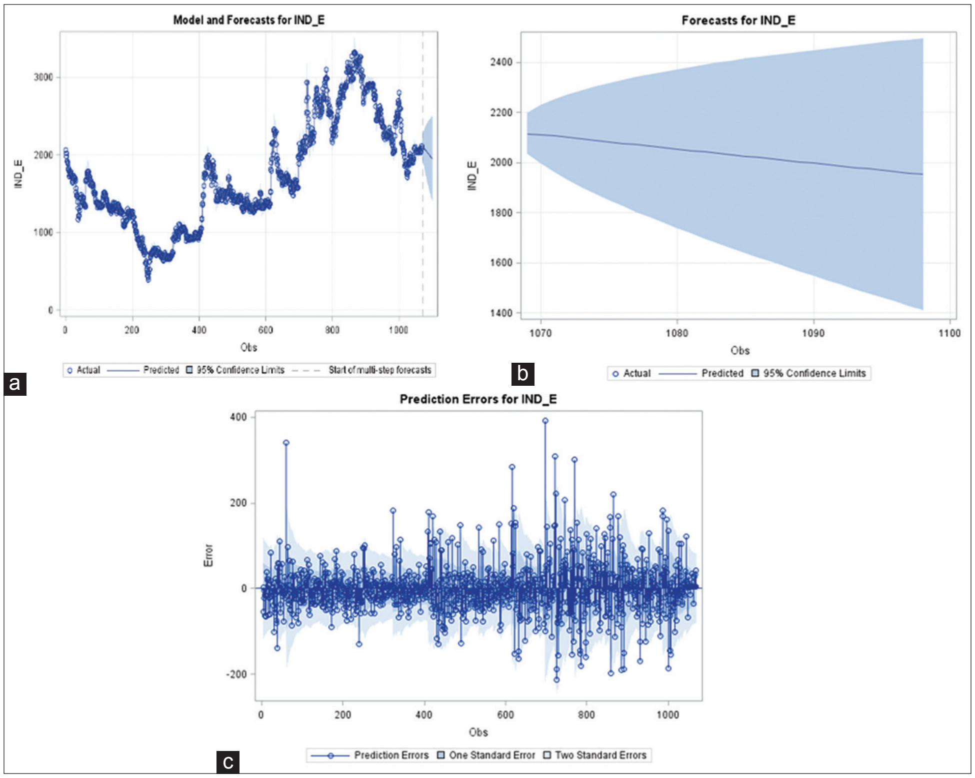



**Table 13: Forecasting ABM and IND_E for the next 30 periods**

| Variable | Obs | Forecast | SE | 95% confidence limits | Variable | Obs | Forecast | SE | 95% confidence limits |
|---|---|---|---|---|---|---|---|---|---|
| ABM | 1069 | 3573.865 | 46.859 | 3482.023–3665.707 | IND_E | 1069 | 2114.674 | 41.373 | 2033.583–2195.766 |
| | 1070 | 3571.205 | 65.350 | 3443.120–3699.289 | | 1070 | 2111.992 | 59.091 | 1996.175–2227.809 |
| | 1071 | 3567.766 | 79.965 | 3411.035–3724.496 | | 1071 | 2106.140 | 74.372 | 1960.372–2251.909 |
| | 1072 | 3564.396 | 92.739 | 3382.631–3746.162 | | 1072 | 2100.471 | 87.308 | 1929.350–2271.593 |
| | 1073 | 3560.809 | 104.396 | 3356.194–3765.423 | | 1073 | 2094.647 | 98.884 | 1900.837–2288.457 |
| | 1074 | 3557.188 | 115.240 | 3331.321–3783.056 | | 1074 | 2088.844 | 109.468 | 1874.289–2303.399 |
| | 1075 | 3553.516 | 125.499 | 3307.541–3799.492 | | 1075 | 2083.042 | 119.322 | 1849.174–2316.909 |
| | 1076 | 3549.797 | 135.321 | 3284.572–3815.022 | | 1076 | 2077.252 | 128.604 | 1825.192–2329.312 |
| | 1077 | 3546.030 | 144.806 | 3262.214–3829.846 | | 1077 | 2071.474 | 137.425 | 1802.125–2340.823 |
| | 1078 | 3542.217 | 154.031 | 3240.320–3844.113 | | 1078 | 2065.708 | 145.864 | 1779.820–2351.597 |
| | 1079 | 3538.357 | 163.052 | 3218.780–3857.934 | | 1079 | 2059.955 | 153.979 | 1758.162–2361.749 |
| | 1080 | 3534.451 | 171.913 | 3197.506–3871.395 | | 1080 | 2054.215 | 161.814 | 1737.064–2371.366 |
| | 1081 | 3530.499 | 180.650 | 3176.431–3884.567 | | 1081 | 2048.487 | 169.405 | 1716.458–2380.516 |
| | 1082 | 3526.501 | 189.292 | 3155.496–3897.507 | | 1082 | 2042.772 | 176.780 | 1696.289–2389.255 |
| | 1083 | 3522.459 | 197.862 | 3134.655–3910.263 | | 1083 | 2037.071 | 183.960 | 1676.514–2397.627 |
| | 1084 | 3518.372 | 206.383 | 3113.868–3922.875 | | 1084 | 2031.383 | 190.966 | 1657.096–2405.670 |
| | 1085 | 3514.240 | 214.870 | 3093.102–3935.378 | | 1085 | 2025.708 | 197.811 | 1638.005–2413.412 |
| | 1086 | 3510.064 | 223.339 | 3072.328–3947.801 | | 1086 | 2020.048 | 204.510 | 1619.214–2420.882 |
| | 1087 | 3505.845 | 231.803 | 3051.518–3960.171 | | 1087 | 2014.401 | 211.075 | 1600.701–2428.100 |
| | 1088 | 3501.582 | 240.274 | 3030.652–3972.512 | | 1088 | 2008.768 | 217.513 | 1582.449–2435.087 |
| | 1089 | 3497.275 | 248.763 | 3009.708–3984.843 | | 1089 | 2003.150 | 223.835 | 1564.440–2441.859 |
| | 1090 | 3492.927 | 257.279 | 2988.668–3997.185 | | 1090 | 1997.545 | 230.047 | 1546.660–2448.430 |
| | 1091 | 3488.535 | 265.830 | 2967.517–4009.554 | | 1091 | 1991.956 | 236.156 | 1529.097–2454.814 |
| | 1092 | 3484.101 | 274.425 | 2946.238–4021.965 | | 1092 | 1986.381 | 242.168 | 1511.739–2461.023 |
| | 1093 | 3479.626 | 283.070 | 2924.818–4034.434 | | 1093 | 1980.821 | 248.088 | 1494.577–2467.065 |
| | 1094 | 3475.109 | 291.773 | 2903.244–4046.974 | | 1094 | 1975.276 | 253.920 | 1477.601–2472.951 |
| | 1095 | 3470.551 | 300.539 | 2881.505–4059.598 | | 1095 | 1969.746 | 259.669 | 1460.803–2478.689 |
| | 1096 | 3465.953 | 309.374 | 2859.589–4072.316 | | 1096 | 1964.232 | 265.338 | 1444.177–2484.286 |
| | 1097 | 3461.313 | 318.285 | 2837.486–4085.141 | | 1097 | 1958.733 | 270.932 | 1427.715–2489.750 |
| | 1098 | 3456.634 | 327.275 | 2815.185–4098.083 | | 1098 | 1953.249 | 276.452 | 1411.413–2495.086 |

SE: Standard error, IND_E: Indika energy

the next 30 periods. Figure 8a explains that for ABM forecasting up to a lag of 20 in the future, the effect of IND_E is <1%. For long-run forecasting (lag 30), IND_E contributes 2% of the variance to ABM. Figure 7c shows the prediction error for ABM,

**Figure 8:** Proportion prediction error covariance for data (a) ABM and (b) IND_E

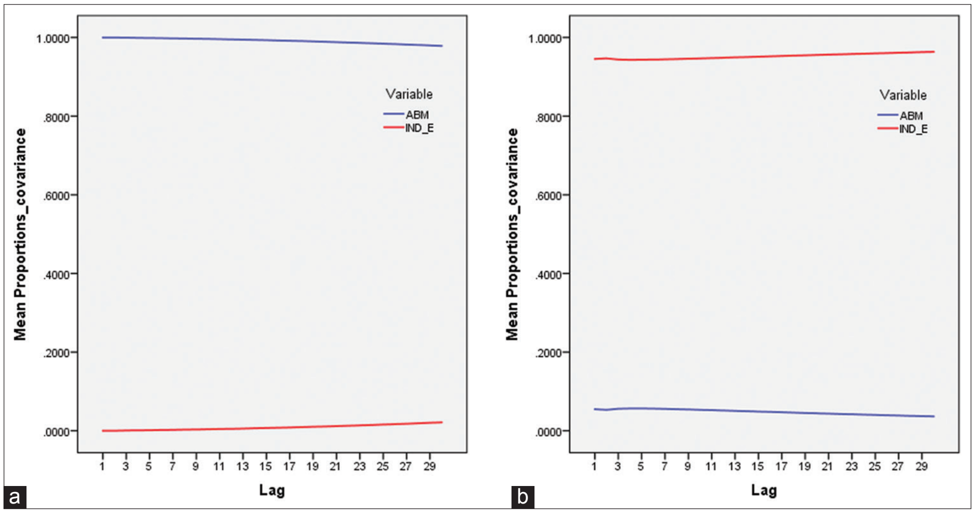



**Figure 9:** Conditional variance from model VAR(3)-BEKK GARCH(1,1) for (a) ABM and (b) IND_E

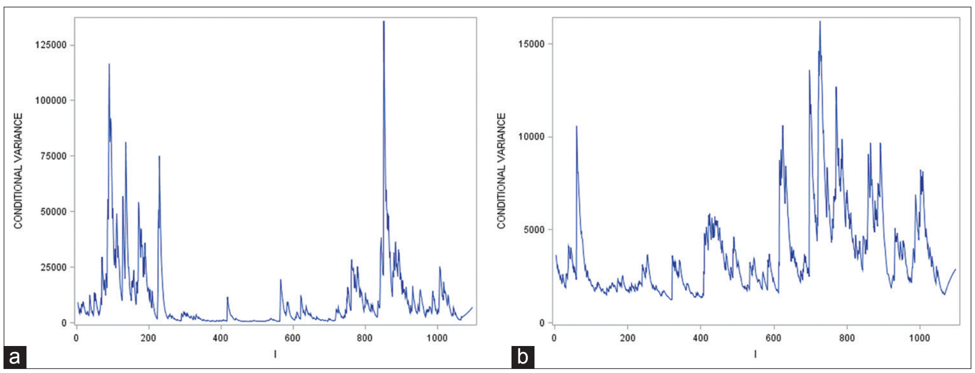
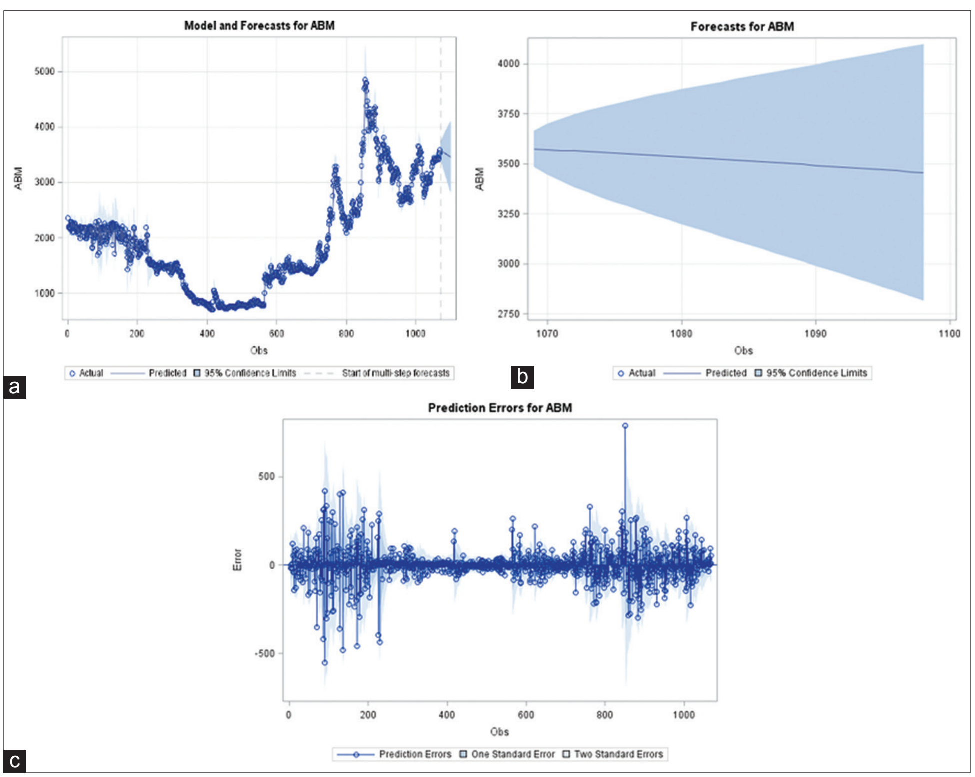



**Figure 10:** (a) Model and forecast, (b) forecast, and (c) prediction error for IND_E



it appears that the residual is very high in 2018 and in 2021, 2022, and 2023 until July. This indicates that the use of the BEKK GARCH model to explain the pattern of data diversity seen from conditional variance is very appropriate. Figure 9a shows the conditional variance of the VAR(3)-BEKK GARCH(1,1) model for ABM data. It appears that the conditional variance during 2018 and from January 2021 to July 2023 fluctuated and was high, this shows that price changes during this period are unstable. From January 2019 to December 2020, the conditional variance (volatility) was relatively low, this indicated that the price changes that occurred were not drastic.

Figure 10a shows that the VAR(3)-BEKK GARCH(1,1) model is a reliable model to explain the behavior of IND_E data, where Figure 10a shows that the predicted value and real IND_E data are very close together. This indicates that the built model sounds good and can be used for forecasting for next several periods of IND_E data. Figure 10b and Table 13 are the results of forecasting for the next 30 periods, Table 13 shows that the forecasting value for the next 30 periods has a downward trend and the further the confidence interval the forecasting period tends to widen, this indicates that forecasting with a long period tends to be unstable. Figure 8b provides information on the proportion of prediction error covariance of ABM and IND_E data to explain IND_E forecasting data for the next 30 periods. Figure 8b explains that for forecasting IND_E up to lag 13 in the future, the effect of ABM is around 5% and the influence of IND_E itself is around 95%. For long-run forecasting (lag 30), ABM contributed 3.6% of the variance to IND_E and IND_E itself contributed around 96.4% of the variance. Figure 10c shows the prediction error for IND_E, showing relatively high residuals from January 2018 to July 2023. This indicates the use of the BEKK GARCH model to explain the pattern of data diversity seen from conditional variance, which is very suitable for IND_E data. Figure 9b shows the conditional variance of the VAR(3)-BEKK GARCH(1,1) model for the IND_E data. It appears that the conditional variance from January to June 2018 was relatively high, and from June 2018 to December 2020 the conditional variance was relatively low and from January 2021 to July 2023 the conditional variance was relatively high. This shows that in the period January 2021 to July 2023 the price changes have occurred drastically.

## 4. CONCLUSION

The study of energy is an interesting topic, both oil energy and coal energy. These two energy sources are still the largest contributor to the need for electrical energy in the world today, especially for electrical energy both for households and for industry. This research discusses the closing price of the share prices of coal companies in Indonesia, namely ABM and IND_E, from January 2018 to July 2023. The best model that describes the pattern of data relationships between ABM and IND_E is VAR(3)- BEKK GARCH(1,1).

Based on this best model, further analysis was carried out with the following results: From the Granger causality analysis it can be concluded that IND_E has a significant effect on changes in ABM prices in the short term; From the Impulse Response Function (IRF) analysis, if there is a shock of one standard deviation on IND_E, ABM responds significantly and this result is in accordance with the results of the Granger causality analysis where in the short term IND_E has an effect on ABM, whereas if there is a shock of one standard deviation on ABM, IND_E responds but changes are not significant; For forecasting the next 30 periods (days) the ABM data tends to trend slightly downward, while the IND_E data tends to trend downward. In forecasting ABM data for the next 30 days IND_E provides information of less than 2%, whereas in forecasting data of IND_E for the next 30 days ABM provides information of less than 5%.

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