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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:

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

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:

$$\tau = \frac{\delta}{S_\delta} \quad (2)$$

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 ∇:

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

where

$$BZ_t = Z_{t-1} \quad (4)$$

The power functions for operators B and ∇ are defined as follows:

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

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

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:

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

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

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

from model (7), we can build a model

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

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:

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

Where

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

$\rho_{ij}(k)$ 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 Γ_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 ρ_k is estimated by

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

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, θ_o is m×1 vector parameter constant, θ_i is m×m parameter matrix, ε_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 ε_t and suppose that H_t is the conditional covariance matrix of the m-dimensional random vector ε_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 δ_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 λ 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:

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

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* (μ_{jt}) for the *i* variable at time *t* + *s* ($Z_{i, t+s}$) and fixed all other innovation. If the element of μ_t changed by δ1, 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 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 Ψ_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

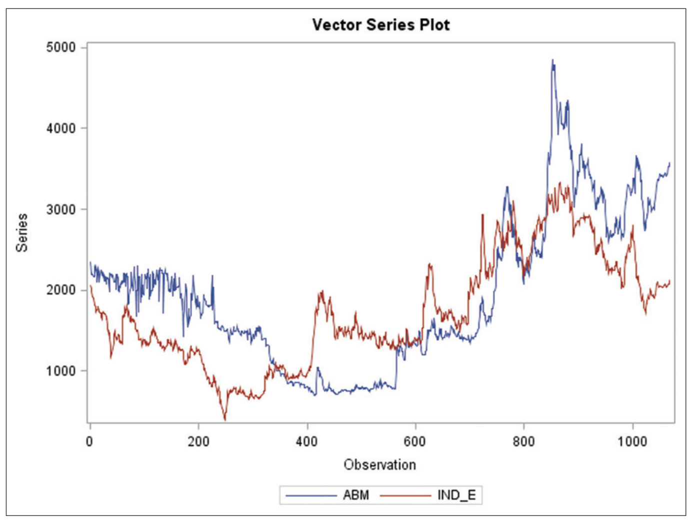


Table 1: Dickey-Fuller unit root tests

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

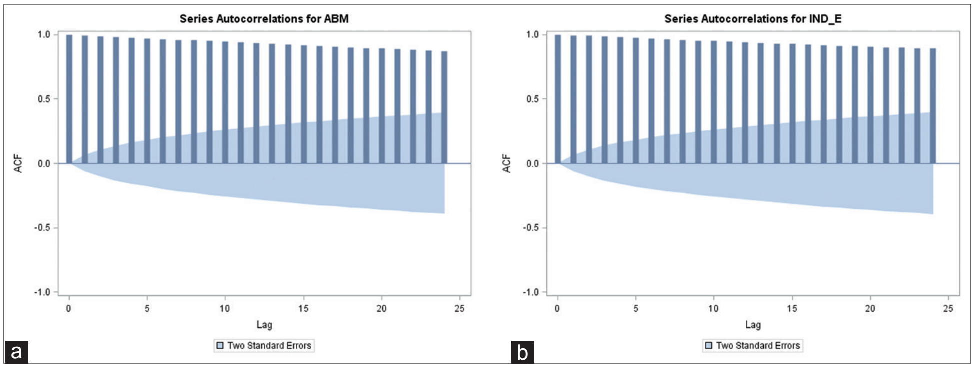


Table 2: Cointegration rank test using trace

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	
		χ^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

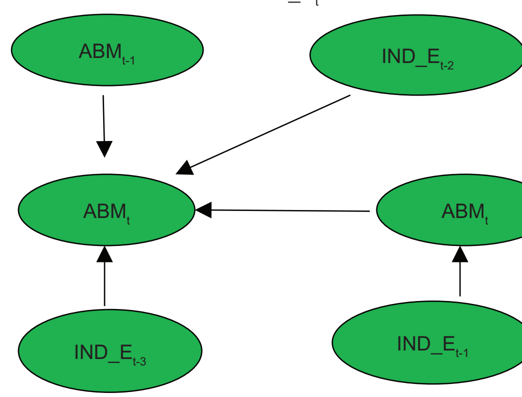


Figure 4: Prediction error normality for (a) ABM and (b) IND_E

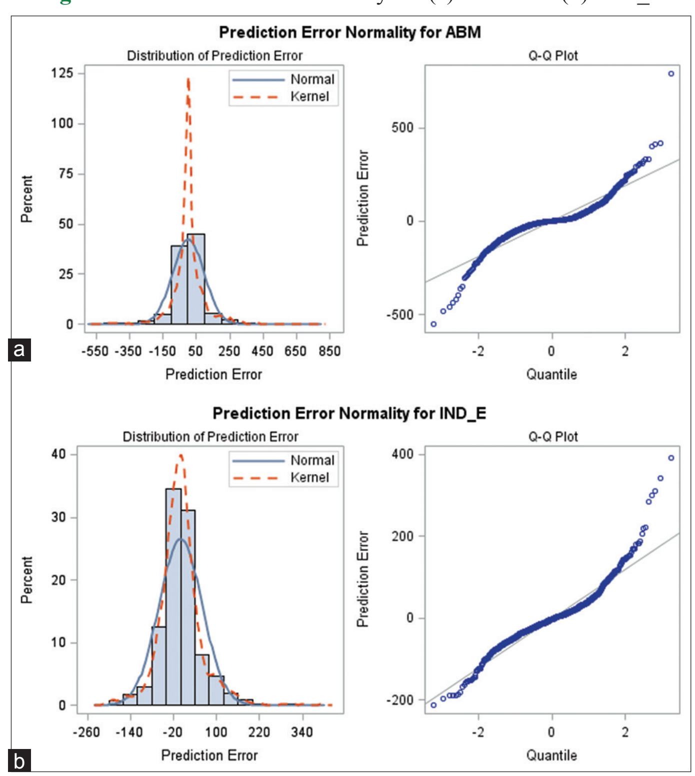


Table 11: Roots of AR and GARCH characteristic polynomial

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	χ^2	P
Test 1	Group 1 variable: ABM 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 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

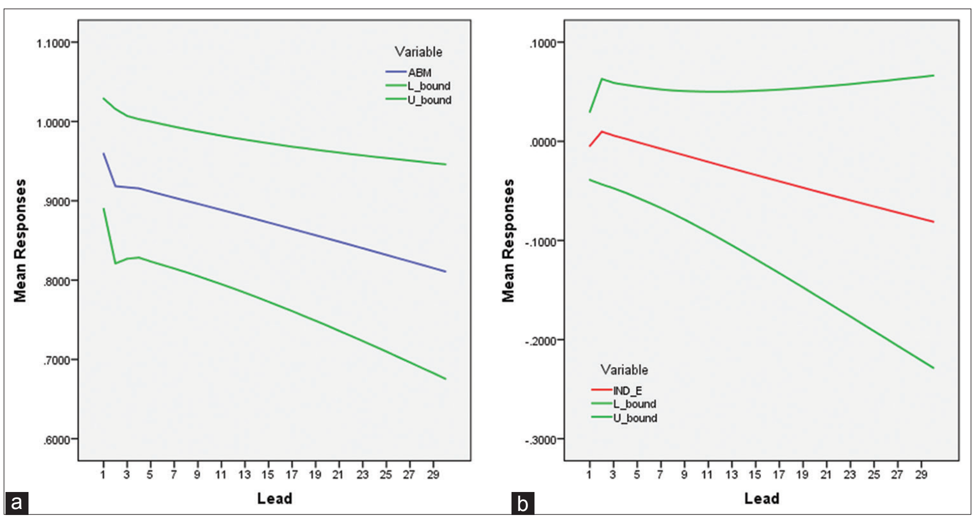


Figure 6: Response to Impulse in IND_E with two standard errors (a) Response ABM,(b) Response IND_E

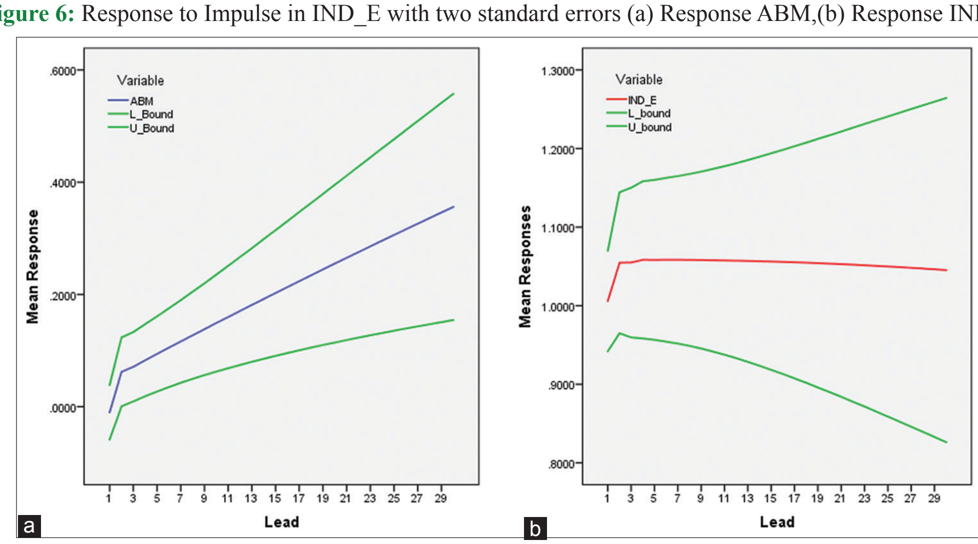


Figure 7: (a) Model and forecast, (b) forecast, and (c) prediction error for ABM

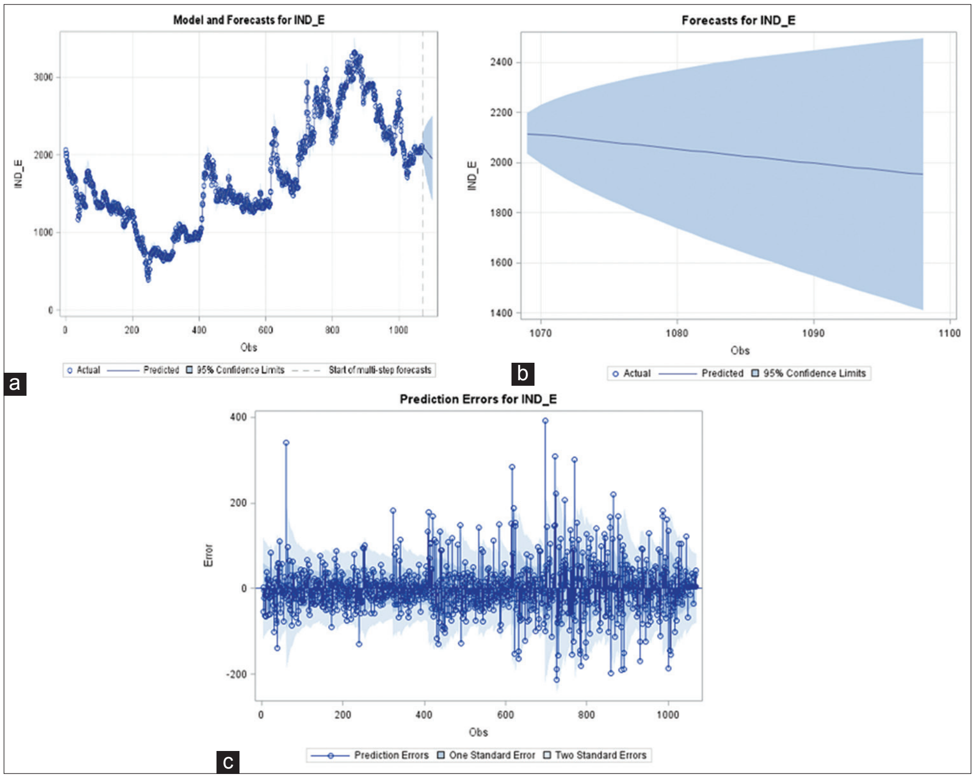


Table 13: Forecasting ABM and IND_E for the next 30 periods

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

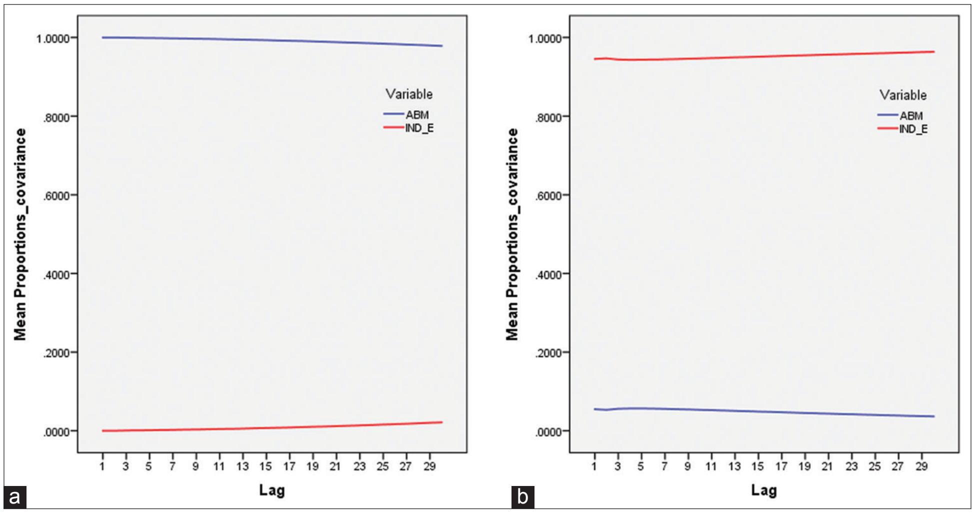


Figure 9: Conditional variance from model VAR(3)-BEKK GARCH(1,1) for (a) ABM and (b) IND_E

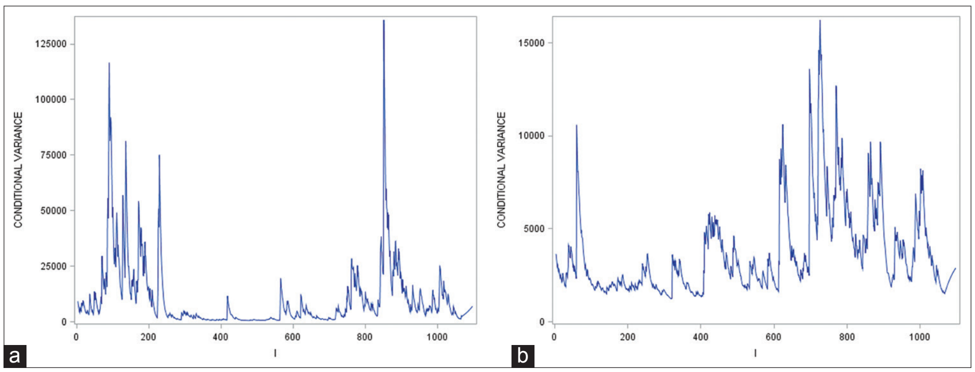
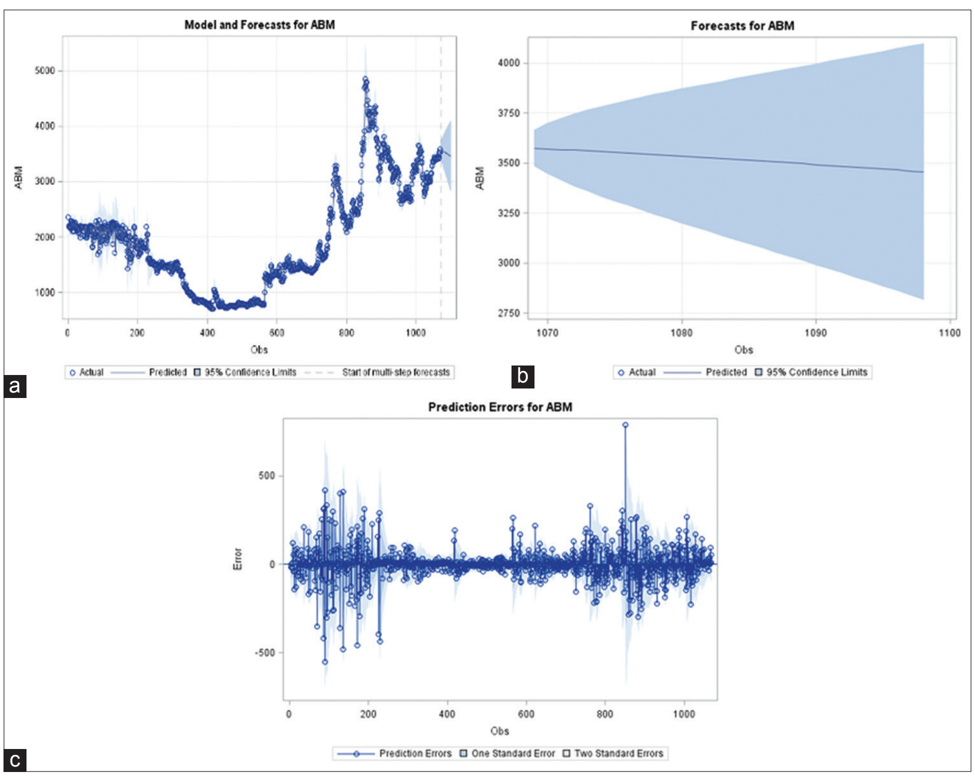


Figure 10: (a) Model and forecast, (b) forecast, and (c) prediction error for IND_E



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%.

5. ACKNOWLEDGEMENTS

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