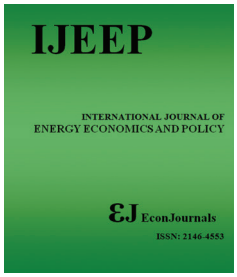

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Dynamic Modeling Using Vector Error-correction Model: Studying the Relationship among Data Share Price of Energy PGAS Malaysia, AKRA, Indonesia, and PTT PCL-Thailand

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ABSTRACT

Vector error-correction model (VECM) is a method of statistical analysis frequently used in many studies in time series data of economy, business and finance, and data energy. It is applied across researches due to its simplicity and limited restrictions. VECM can explain not only the dynamic behavior of the relationship among variables of endogenous and exogenous, but also among the endogenous variables. Moreover, it also explains the impact of a variable or a set of variables on others by means of impulse response function (IRF) and granger causality analysis. It can also be used for forecasting multivariate time series data. In this research, the relationship of three share price of energy (from three Asean countries: PGAS Malaysia, AKRA Indonesia, and PTT Thailand) will be studied. The data in this study were collected from October 2005 to August 2019. Based on the comparison of some VECM models, it was found that the best model is VECM (2) with cointegration rank = 3. The dynamic behavior of the data is studied through IRF, Granger Causality analysis and forecasting for the next five periods (weeks).

Keywords: Cointegration, Vector Autoregressive Model, VECM Model, Granger Causality, Impulse Response Function, Forecasting
JEL Classifications: C32, Q4, Q47

1. INTRODUCTION

The study of energy economics as a research area is being conducted by many researchers, especially due to the existing problems regarding energy, including lack of energy and renewable energy (Iazzolino et al., 2019; Forero et al., 2019; Warsono et al., 2019a; 2019b). Pala (2013) investigated the relationship between food price index and crude oil price using VECM modeling. Yu et al. (2006) studied the relationship between higher crude oil price and vegetable oil price by using cointegration and causality approach. Warsono et al. (2019a) discussed the relationship and forecasting between the price indexes of two coal companies in Indonesia using the vector autoregressive (VAR) model. Campiche et al. (2007) discussed the relationship between crude oil prices and agricultural commodities prices by using cointegration and vector error-correction model (VECM). Yu et al. (2008) used error-correction model, cointegration analysis, and IRF to discuss the connection between Economic Growth and China Energy. VAR is one of the models commonly used in the fields of economy, finance, and business, and plays an important role in techniques of analysis, especially in finance and economy (Hamilton, 1994; Kirchgassner and Wolters, 2007). The VAR model was introduced by Sims (1980) as a method to analyze macroeconomic data. He developed the VAR model as an alternative to the traditional system of simultaneous equation methods (Kirchgassner and Wolters, 2007). However, if the set of data time series has cointegration, then the VAR model has to be modified into VECM.

According to Granger (1981) and Engle and Granger (1987), variables which have a common stochastic trend are labeled as

cointegrated. If cointegrating relations are present in a system of variables, then the VAR form is not convenient to be used and it is useful to consider specific parameterizations which support the analysis of the cointegration structure. Those models are known as VECMs or vector equilibrium correction models. If data time series have to be differenced m time before it become stationary, then the series is said to be integrated of order m, I(m), so that a series X_t is I(m) if X_t is nonstationary, but $\Delta^m X_t$ is stationary, where $\Delta X_t = X_t - X_{t-1}$ (Cuthbertson et al., 1992). The basic ideas of cointegration analysis are that, although many data time series tend to trend up and down over time in nonstationary form, group of variables may drift together (Cuthbertson et al., 1992). The modal strategy in applied work for modeling a vector of I(1) variables is to use a model selection criterion to choose the lag length of the VAR, then test for cointegration conditional on the lag order, and finally, estimate the VECM (Athanasopoulos et al., 2010). There is a closed relationship between cointegration and VECM (Cuthbertson et al., 1992; Lutkepohl, 2005; Hunter et al., 2017).

Many studies have been conducted in the literature on the effect of cointegration on forecasting (Lutkepohl, 2005; Campiche et al., 2007; Wang et al., 2008; Hunter et al., 2017). Engle and Yoo (1987) have compared the forecasts generated from an estimated VECM based on the assumption that the lag order and the cointegrating rank are known. They found that the VECM produces forecasts with smaller mean squared forecast errors. Recently, the application of VECM in the study of multivariate nonstationary data time series has increased. The main reason is that VECM allows one to describe the long- and short-run relationships of nonstationary variables (Johansen, 1995 or Lütkepohl, 2005). In the literature, useful tools have been developed to analyze the long-run relationships, in particular, the identification of the cointegrating rank (Raissi, 2010). Testing for causality is a central issue in econometrics and macroeconometrics (Cuthbertson et al., 1992; Hamilton, 1994). The Wald Test has been widely used for testing zero restrictions implying Granger-noncausality since Granger (1969) introduced an operational concept of causality. Because all variables are assumed to be endogenous, in VAR, it is important to find causal structures.

The aims of this study are to discuss modeling data stock price of energy from three big companies: PGAS Malaysia, AKRA Indonesia, and PCL PTT Thailand. The stock prices of the companies are converted into US dollars, so that we have the same standard prices in the analysis. To find the relationship model among the three companies, the VECM is used. Furthermore, the analysis of IRF, Granger Causality, and forecasting will be discussed.

2. DYNAMIC MODELING

Data multivariate time series is considered to be simultaneous multiple time series. It is a branch of multivariate statistical methods, but deals with dependent data. It is more complicated than the univariate time series analysis, especially when the number of data series is large. In multivariate time series, the multiple inter-related variables are oftenly involved under study. Therefore, in decision making, one needs to understand the relationships among those variables in order to provide an accurate prediction (Brockwell and Davis, 1991; Lutkepohl, 2005; Tsay, 2014). The main objectives of the analysis of multivariate time series are: (1) to study the dynamic relationships between or among variables and (2) to improve the accuracy of prediction (Tsay, 2005, 2014; Wei, 2006; Montgomery et al., 2008). In multivariate time series, we deal with a k-dimensional time series or vector time series. $X_t = (X_{t1}, X_{t2}, ..., X_{tk})'$ is a random vector consisting of k random variables (Hamilton, 1994; Tsay, 2014). In time series analysis, we assume that the data time series is stationary. In statistical terms, stationarity requires that the probability distribution of an arbitrary collection of X_t is time invariant (Tsay, 2014). In a k-dimensional time series, X_t is stationary if the first two moments exist, namely, if (a) $E(X_t) = \mu$, a k-dimensional constant vector, and (b) $Cov(X_t) = \Sigma_t$ a constant kxk positive definite matrix (Hamilton, 1994; Tsay, 2014). Stationarity of the multivariate time series data can be checked by investigating the graph of the data and whether they are fluctuating around a certain number or not; if not, we suppose that the data are nonstationary. Statistically, we can check the stationary data by using the augmented dickey fuller test (ADF Test) or unit roots test. Besides, we can also check the autocorrelation function (ACF) graph; if the ACF decays very slowly, we suppose that the data are nonstationary. In unit-Root Tests with lag-p, the model with a constant is defined as follows:

$$\Delta X_t = \alpha + \phi X_{t-1} + \sum_{i=1}^{p-1} \phi_i^* \Delta X_{t-i} + u_t \quad (1)$$

Where $\Delta X_t = X_t - X_{t-1}$ and u_t is white noise. The null hypothesis is H_o: $\phi=0$ against the alternative hypothesis, which is H_a: $\phi<0$. The test statistic is the τ (tau) with the limiting distribution being t-ratio (Tsay, 2014). For the level of significance ($\alpha = 0.05$), Ho is rejected if $\tau < -2.57$ or if the $P < 0.05$ (Brockwell and Davis, 2002; Tsay, 2005). The test statistic is as follows:

$$\text{ADF } \tau = \frac{\phi}{Se(\phi)} \quad (2)$$

2.1. Cointegration

The concept of cointegration is introduced by Engle and Granger (1987) and the development of practical estimation and inferential methods is given by Johansen (1988). In many literatures, a time series X_t is said to be integrated with order 1, I(1) process, if (1-B) X_t is stationary and invertible. If time series data are stationary and invertible, then it is said I(0) process. In general, a univariate time series X_t is an I(d) process, if $(1-B)^d X_t$ is stationary and invertible (Lutkepohl, 2005; Tsay, 2005, 2014). The cointegration term was first introduced by Granger (1983). The fact that a linear combination of several unit root nonstationary time series can become stationary series was observed in the literature. Rachev et al. (2007) state that the idea of cointegration states there are feedback mechanisms that force processes to stay close together or the idea that the behavior of large sets of data is driven by the dynamics of a smaller number of variables, and it is one of the key concepts of modern econometrics. It is noted that, for multivariate time series given a vector time series X_t. it could happen that for each component vector time series, X_{it} is nonstationary, but its linear combination $Z_t = \beta' X_t$ is stationary for

some β'. In this case, one should use its error-correction representation. Yoo (1986) used Granger representation theorem and the Smith–McMillan form to transform Vector Moving Average into an error-correction model so that cointegration is able to be described in terms of VECM. Burke and Hunter (2005) proposed a procedure to determine the existence of the VAR along with the Johansen approach to estimation and inference, while an application was developed based on the models of the UK effective exchange rate estimated by Hunter (1992), Johansen and Juselius (1992), and Hunter and Simpson (1995). If there is a cointegration between the vector time series, then one should test the rank of the cointegration. Some methods of testing the rank of the cointegration are as follows: Trace test and Test of maximum eigen values. The tests are as follows:

In the Trace Test, the hypothesis is as follows:
H_0: There are at most r eigen value positive, against the alternative
H_1: There are more than r eigen value positive.

The test statistic is:

$$Tr(r) = -T\sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i) \quad (3)$$

Test for maximum eigen value, the hypothesis is as follows:
H_0: There are r eigen value positive, against the alternative
H_1: There are r+1 eigen value positive.

The test statistics is:

$$\lambda_{max}(r, r+1) = -T \ln\left(1-\hat{\lambda}_i\right) \quad (4)$$

Where $\hat{\lambda}_i$ = estimate of eigen value, T = total number of observation, and k = total number of endogenous variables.

2.2. Vector Autoregressive (VAR)

The VAR model is used to analyze data multivariate time series. This model is extensively used in econometric research (Tsay, 2014). The reason is, first, the model is relatively easy to estimate–one is able to use the maximum likelihood method, the least squares method, or the Bayesian method (Hamilton, 1994; Lutkepohl, 2005; Tsay, 2005; 2014). Second, the VAR model has been studied extensively in the literature (Lutkepohl, 2005; Wei, 2006; 2019). Third, the VAR model is similar to multivariate linear regression in multivariate analysis. Several literatures exist that discuss the developments in VAR modeling in dynamic econometric analysis (e.g., Hamilton, 1994; Hendry, 1995; Johansen, 1995; Hatanaka, 1996; Lutkepohl, 2005). Surveys of Vector Autoregressive modeling include Wei (2019) and Lutkepohl (2011). The k-dimensional vector autoregressive (VAR) process with order p, VAR(p), is written as the following:

$$X_t = \mu_0 + \Phi_1 X_{t-1} + ... + \Phi_p X_p + u_t \quad (5)$$

or

$$\Phi_p(B)X_t = \mu_0 + u_t, \quad (6)$$

Where u_t is a sequence of k-dimensional vector white noise process with mean vector 0_{kx1} and variance covariance matrix Σ which is positive definite matrix, VWN(0, Σ), and

$$\Phi_p(B) = I - \Phi_1 B - ... - \Phi_p B^p \quad (7)$$

The VAR model is invertible. It will be stationary if the characteristics values of $|I - \Phi_1 B - ... - \Phi_p B^p| = 0$ lie outside of the unit circle, or equivalently, the roots of $|\gamma^p I - \gamma^{p-1}\Phi_1 - ... - \Phi_p| = 0$ all lie inside the unit circle. According to Granger (1981) and Engle and Granger (1987), variables are called cointegrated if they have a common stochastic trend. If cointegrating relations are present in a system of variables, the VAR form is not the most convenient model setup. In that case, it is useful to consider specific parameterizations that support the analysis of the cointegration structure. The resulting models are known as VECMs (Lutkepohl and Kratzig, 2004). If there is cointegration between the variables, error-correction representation of the VAR model is modified, so that the model becomes the VECM model (Asteriou and Hall, 2007; Wei, 2019).

2.3. Vector Error-Correction Model (VECM)

VECM is a VAR model designed for nonstationary time series data, but has cointegration among the variables. VECM model is very useful since it can estimate the short-run effect and long-run effect of the variables. Granger showed that a multivariate time series in integrated process is cointegrated only if they can be represented in ECM (Rachev et al., 2007). The general form of VECM(p) where p is lag of endogenous variable with the rank of cointegration $r \leq k$ is as follows:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + u_t \quad (8)$$

where:
Δ: operator differencing, with $\Delta X_t = X_t - X_{t-1}$, X_{t-1}: vector variable endogenous with the-1 lag, u_t: vector residual with order (k × 1), Π: matrix coefficient cointegration ($\Pi = \alpha\beta^t$; α = vector adjustment, matrix with order (k × r) and β: vector cointegration (long-run parameter) matrix [k × r]), Γ_i: the-i matrix coefficient variable endogenous with order (k × k) (Lutkepohl, 2005). There are some advantages to the application of VECM(p) model which are: (1) The multicollinearity which commonly exists in time series data is reduced in the error-correction form, (2) Long-run effects information is summarized in the level matrix (denoted by Π) (3) The interpretation of estimates is easier mo, and (4) The VECM model easier to interpret (Juselius, 2006). To find the best VECM(p) model, the information criteria: Akaike Information Criterion(AIC), Schwarz Bayesian criterion (SBC), Hanna-Quinn criterion (HQC) and corrected Akaike Information Criterion (AICC) will be used.

2.4. Test for Normality

To test for normality of residual of multivariate model, we will use Jarque-Bera (JB) Test of Normality. We will also look at the behavior of the graph of the residuals. The test is given as follows:

$$JB = \frac{n-k}{6}\left[S^2 + \frac{(K-3)^2}{4}\right] \quad (9)$$

where:
n = number of samples

$$S = \text{Expected skewness} = \frac{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2\right)^{3/2}}$$

$$K = \text{Expected excess kurtosis} = \frac{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2\right)^2}$$

k = Number of independent variables.

JB test of normality has Chi-square χ^2 distribution with 2 degrees of freedom (Jarque and Berra, 1987).

2.5. Test for Stability of the Model

The eigen value of matrix F satisfies

$$|I_n\lambda - \Phi_1\lambda^{p-1} - \Phi_2\lambda^{p-2} - \ldots - \Phi_p| = 0 \quad (10)$$

is covariance stationary as long as $|\lambda|<1$ for all values of λ. Or equivalently, the VAR is covariance stationary if all values of z are satisfying

$$|I_n - \Phi_1 z - \Phi_2 z^2 - \ldots - \Phi_p z^p| = 0 \quad (11)$$

It lies outside the unit circle (Hamilton, 1994; Kirchgassner and Wolters, 2007; Warsono, 2019a; 2019b).

2.6. Test for Granger Causality

Many scientists have long been arguing about the meaning and nature of causality and causality has an important role in economics (Sampson, 2001). Granger Causality is an attempt to make the notion of causality amenable to time series analysis (Hamilton, 1994; Hunter et al., 2017). The basic idea of the causality is that it is the past which causes the present and not vise-versa. If we say that X_{1t} cause X_{2t}, then we would expect past values of X_{1t} to be useful in predicting present X_{1t} (Sampson, 2001). Econometric tests of whether a particular observed series, for example, Y Granger-Causes X, can be based on the following model (Hamilton, 1994):

$$X_t = c_1 + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + u_t \quad (12)$$

By OLS, the null hypothesis is H_0: $\beta_1=\beta_2=\ldots\beta_p=0$, then Sum squared residual from model (12) is calculated as follows:

$$RSS_1 = \sum_{i=1}^{T}\hat{u}_t^2$$

Under null hypothesis, the model is

$$X_t = c_o + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \ldots + \gamma_p X_{t-p} + u_t^* \quad (13)$$

To calculate Sum squared residual from model (13),

$$RSS_0 = \sum_{i=1}^{T}\hat{u}_t^2$$

The statistics test

$$F = \frac{(RSS_o - RSS_1)/p}{RSS_1/(T-2p-1)} \quad (14)$$

Ho is rejected if $F > F_{0.05;\,(p,\,T-2p-1)}$.

2.7. Impulse Response Function

VAR model can be written in vector MA(∞) as

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

Thus, the matrix Ψ_s has the following interpretation

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

The row i, column j element of Ψ_s identifies the consequences of a one unit increase in the jth variable's innovations at date t (μ_{jt}) for the value of the ith variable at time t + s ($X_{i,t+s}$), holding all other innovations at all constant dates. If the first element of u_t is changed by δ_1, at the same time, the second element changes by δ_2,…, and the n element by δ_n, then the combined effect of these changes on the value of the vector X_{t+s} would be

$$\Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}}\delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}}\delta_2 + \ldots + \frac{\partial X_{t+s}}{\partial u_{nt}}\delta_n = \Psi_s\delta \quad (15)$$

A plot of the row i, column j element of Ψ_s

$$\frac{\partial X_{i,t+s}}{\partial u_{jt}}$$

a function of s is called IRF.

2.8. Forecasting

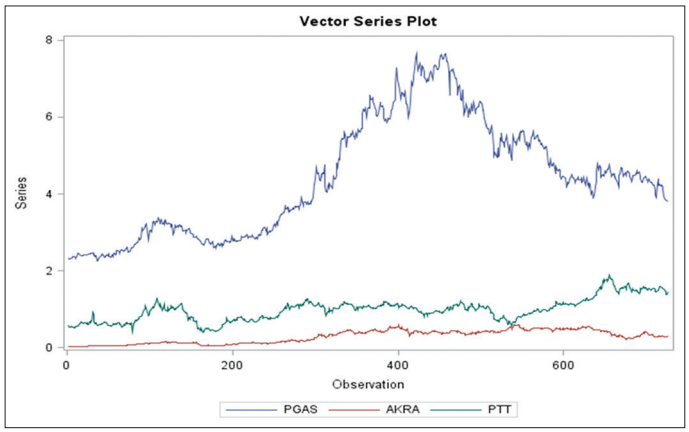
Forecasting is one of the main objectives in the analysis of multivariate time series data. Forecasting in a VECM(p) with cointegration rank = r is similar to forecasting in a univariate model. The basic idea in the process of forecasting is that, first of all, it needs to find the best VECM(p) model by using certain criteria of choosing the best model. Once the model is found, it can be used for forecasting. Therefore, the forecasting will be attained from the best VECM(p) model selected.

3. RESULTS AND DISCUSSION

The first step before the data time series are analyzed is that it needs to be checked for the assumption of stationarity. There are some methods to check the stationarity of the data: (1) Through the graph of the data, where we can evaluate the behavior of the data and whether they are constant around a certain number, increasing or decreasing; (2) through the ACF plot; and (3) through the testing hypotheses by using ADF test. The data in this study are closing share price data petronas-gas bhd (PGAS), Malaysia, Akr Corporindo Tbk (AKRA), Indonesia, and PTT PCL (PTT), Thailand from October 2005 to August 2019. In this study, the short-term and long-term relationship among the three energy companies from Malaysia, Indonesia, and Thailand are discussed. From the analysis to check the stationarity either through the behavior of data and ACF plot or testing the hypotheses, the results are as follows:

In Figure 1, the plot of the observation data series closing price of share of PGAS, Malaysia, shows that in the first 100 data the graph looks flat, from the 100 to the-200 data, the trend increases slowly, from the 200 data to 450 data, the trend increases and fluctuates, from 450 to 600 data the trend decreases and fluctuates, and from 600 to the last data, the trend is flat and fluctuates. Futhermore, from Figure 2, the plot of ACF, the autocorrelations decrease very slowly. This confirmd that the data time series PGAS are nonstationary and this condition is supported by the result of the ADF test. From Table 1, ADF test for PGAS, Malaysia, the Tau-test for single mean is −1.42 with P = 0.5763, which can be concluded that the null hypothesis is not rejected. This means that we do not have enough evidence to reject that the data are nonstationary.

Figure 1: Plot of the data series PGAS Malaysia, AKRA Indonesia, and PTT Thailand



From Figure 1, the plot of the observation data closing price of share of AKRA, Indonesia, it can be seen that in the first 150 observations, the data increases, from 150 to 180, the trend decreases, from 180 to 400, the trend increases and fluctuates, from 400 to 500, the trend is flat and fluctuates, from 500 to 550, the trend increases, from 550 to 630, the trend is flat, from 630 to 670, the trend decreases, from 670 to 700, the trend increases, and from 700 to the last observation, the trend decreases. Furthermore, from Figure 3, the plot of ACF the autocorrelations, decrease very slowly. This confirms that the data time series closing price of share of AKRA are nonstationary and this condition is supported by the result of the ADF test. From Table 1, ADF test for AKRA, Indonesia, the Tau-test for single mean is −1.68 with P = 0.4391, which implies that the null hypothesis is not rejected. This means that we do not have enough evidence to reject that the data are nonstationary. From Figure 1, the plot of the observation data closing price of share of PTT PCL, Thailand, it can be seen that in the first 30 observations, the data increases, from 30 to 80, the trend is flat, from 80 to 120, the trend increases, from 120 to 180, the trend decreases, from 180 to 300, the trend increases and fluctuates, from 300 to 400, the trend is flat, from 400 to 430, the trend decreases, from 430 to 480, the trend increases, from 480 to 530, the trend decreases, from 530 to 650, the trend increases, and from 650 to the last observation, the trend is flat but fluctuates greatly.

Furthermore, as evident from Figure 3, the plot of ACF of data PTT-PCL, the autocorrelations decrease very slowly. This confirms that the data time series closing price of share of PTT-PCL are nonstationary and this condition is supported by the results of the ADF test. From

Figure 2: Trend and correlation analysis of PGAS

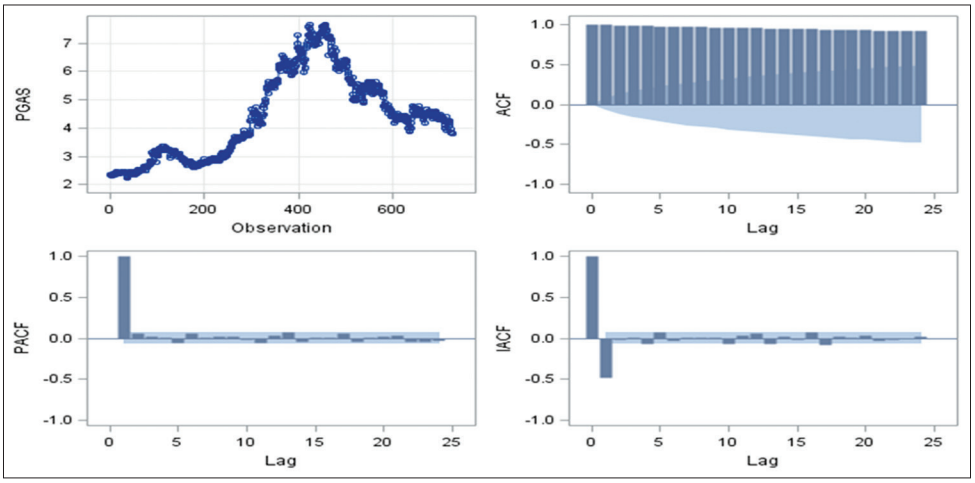


Table 1: Augmented dickey fuller unit roots test of PGAS-Malaysia, AKRA Indonesia, and PTT PCL-Thailand

Energy company	Type	Lags	Rho	Pr<Rho	Tau	Pr<Tau
PGAS, Malaysia	Zero mean	3	0.0332	0.6906	0.06	0.7007
	Single mean	3	−2.6612	0.6981	−1.42	0.5763
	Trend	3	−1.1772	0.9860	−0.50	0.9835
AKRA, Indonesia	Zero mean	3	−0.3636	0.6002	−0.29	0.5807
	Single mean	3	−4.1210	0.5255	−1.68	0.4391
	Trend	3	−6.1490	0.7319	−1.46	0.8417
PTT PCL, Thailand	Zero mean	3	0.3088	0.7579	0.30	0.7723
	Single mean	3	−6.5338	0.3064	−1.79	0.3859
	Trend	3	−13.8491	0.2261	−2.59	0.2829

Table 1, ADF test for PTT-PCL, Thailand, the Tau-test for single mean is −1.79 with P = 0.3859, and thus, it can be concluded that the null hypothesis is not rejected. This means that we do not have enough evidence to reject that the data are nonstationary. From the analysis above, all the time series data of PGAS, Malaysia, AKRA, Indonesia, and PTT PCL, Thailand are nonstationary. To make the data stationary, the method of differencing is used and the results of first differencing (d=1) are as follows (Table 2 and Figure 4):

From Figures 5-7, it can be seen that, after differencing, the data fluctuate around certain numbers. This indicates that after differencing (d=1), the data are stationary. This is also confirmed by the plot of ACF for data PGAS, Malaysia, AKRA, Indonesia, and PTT PCL, Thailand, where the autocorrelations decay very quickly toward zero. From the unit root tests using ADF test, the ADF test for data PGAS, Malaysia, AKRA, Indonesia, and PTT PCL, Thailand are Tau-test = −13.00 with P < 0.0001, Tau-test = −13.04 with P < 0.0001, and Tau-test = −13.59 with P < 0.0001, respectively for data PGAS, Malaysia, AKRA, Indonesia and PTT PCL, Thailand. Therefore, we can conclude that the data are stationary after the first differencing.

3.1. Test for Lag Optimum

To find the lag optimum for VAR model from endogenous variables that are PGAS, AKRA, and PTT PCL using the criteria of the smallest values of information criteria AIC, SBC, HQC, and AICC, where the lag optimum signed by the star sign (*) and the results are as follows:

From Table 3, we can see the three smallest information criteria of AIC, HQC, and AICC are at lag 2, and therefore, the cointegration test is conducted at lag 2.

Figure 3: Trend and correlation analysis of AKRA, Indonesia

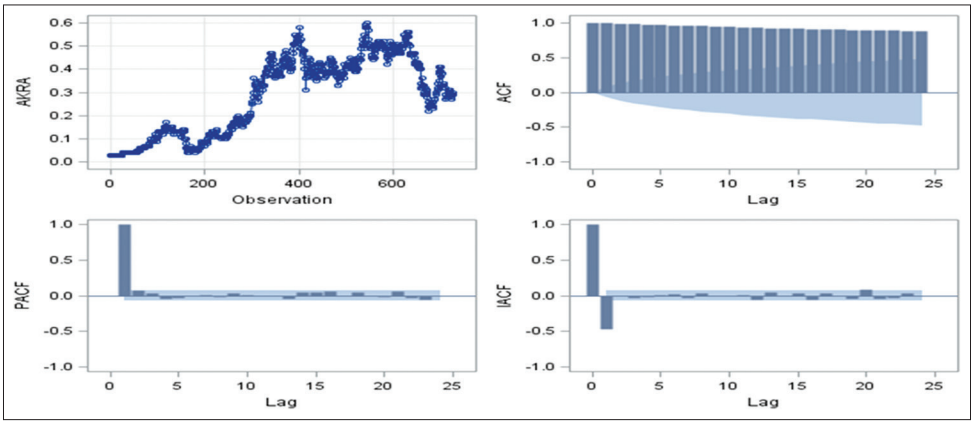


Figure 4: Trend and correlation analysis of PTT PCL, Thailand

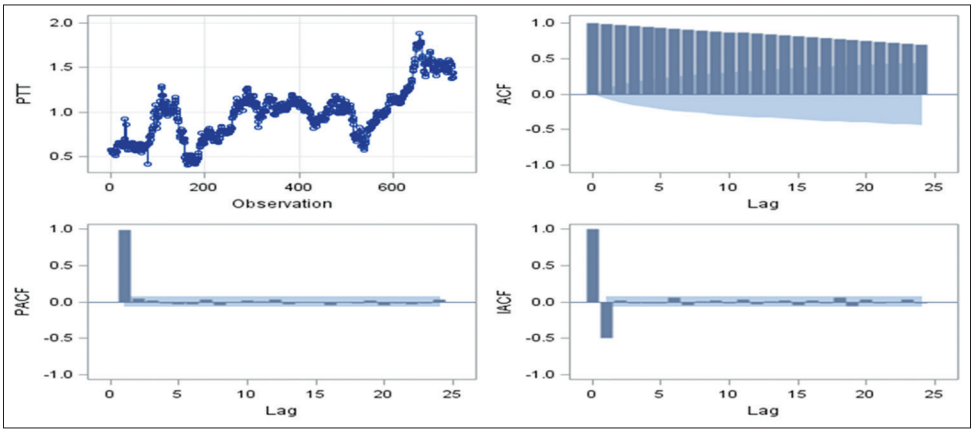


Table 2: Augmented dickey fuller unit roots test of PGAS-Malaysia, AKRA-Indonesia, and PTT PCL-Thailand (after differencing d=1)

Energy company	Type	Lags	Rho	Pr<Rho	Tau	Pr<Tau
PGAS, Malaysia	Zero mean	3	−641.944	0.0001	−29.36	<0.0001
	Single mean	3	−644.119	0.0001	−13.00	<0.0001
	Trend	3	−665.244	0.0001	−13.10	<0.0001
AKRA, Indonesia	Zero mean	3	−650.951	0.0001	−13.03	<0.0001
	Single mean	3	−654.326	0.0001	−13.04	<0.0001
	Trend	3	−663.791	0.0001	−13.08	<0.0001
PTT PCL, Thailand	Zero mean	3	−764.066	0.0001	−13.57	<0.0001
	Single mean	3	−771.214	0.0001	−13.59	<0.0001
	Trend	3	−771.236	0.0001	−13.58	<0.0001

Figure 5: Trend and correlation analysis of PGAS, Malaysia (After differencing, d=1)

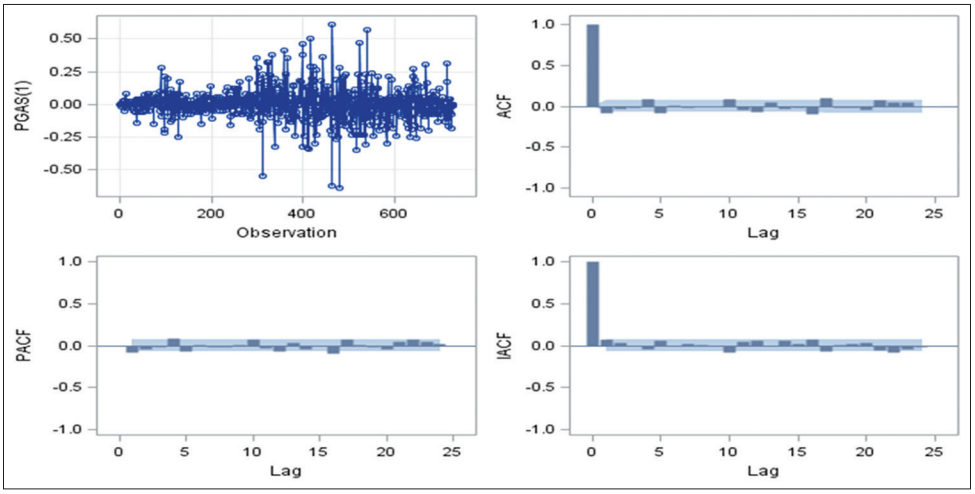


Figure 6: Trend and correlation analysis of AKRA, Indonesia (After differencing, d=1)

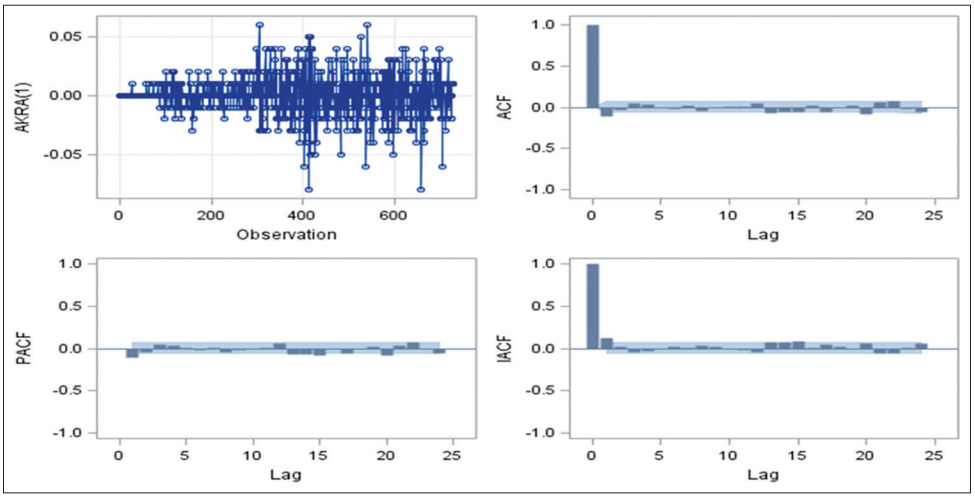
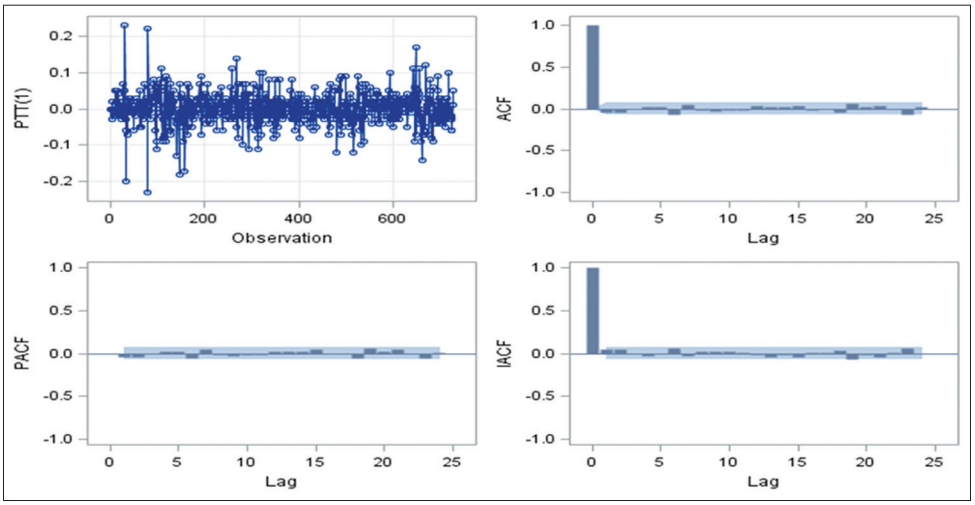


Figure 7: Trend and correlation analysis of PTT PCL, Thailand (After differencing, d=1)



3.2. Test for Cointegration

The method used to test cointegration is Johansen test at lag optimum from VAR model. If the value of trace statistic is greater than critical value, then we conclude that there are at least two cointegration relation among the variables.

Hypotheses: H_0: Rank = r (there is no cointegration) against H_1: Rank > r (there is cointegration), for r = 0,1,2. Table 4 shows that the P-values at rank >2 is <0.000 and we conclude that we reject H_0: Rank = 2 and there is cointegration at rank = 3. Since the data time series has cointegration relationship, then the

VAR(p) model used is the VECM(p) model with cointegration rank r = 3.

3.3. The Estimation of Parameters VECM(2) Model with Cointegration Rank r = 3

From the above analysis, we gage the best model is VECM(2) with the cointegration rank = 3. The next step is to estimate the parameters of VECM(2) model (Tables 5-9). The results are as follows:

From the results of the estimation of parameters, we have the estimate of VECM(2) model as follows:

$$\Delta X_t = \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + u_t \quad (16)$$

$$\Delta \begin{bmatrix} X_{t1} \\ X_{t2} \\ X_{t3} \end{bmatrix} = \begin{bmatrix} -1.1536 & 0.1730 & 0.0955 \\ 0.0238 & -1.2023 & 0.0155 \\ -0.0013 & 0.0131 & -1.0958 \end{bmatrix} X_{t-1} + \begin{bmatrix} 0.0425 & 0.3609 & 0.0215 \\ -0.0073 & 0.0604 & 0.0161 \\ 0.0209 & 0.0675 & 0.0327 \end{bmatrix} \Delta X_{t-1} + \begin{bmatrix} u_{t1} \\ u_{t2} \\ u_{t3} \end{bmatrix} \quad (17)$$

where $X_{t1} = PGAS_t$, $X_{t2} = AKRA_t$ and $X_{t3} = PTT_t$, respectively.

3.4. Normality of Residual

Checking for white noise residuals in terms of univariate equation are shown in Tables 10 and 11. The Table 11 shows the test statistics for normality distribution using JB normality test. In Table 11, the test shows that the P-value for PGAS, AKRA, and PTT are all <0.0001, and therefore, we reject the null hypothesis that the residual has normality. From Figures 8-10, we show that the residual is not too far from the normal distribution. Table 10 shows the F-test for testing AR(1), AR(1,2), AR(1,2,3), and AR(1,2,3,4) model of residual to test the null hypothesis that the residual are uncorrelated. The tests show that all P-values are greater than 0.05, therefore, we do not reject the null hypothesis. We conclude that the residuals are uncorrelated.

Table 3: Criteria to select of lag VAR model for all endogenous variables

VAR lag order selection criteria				
Lag	AIC	SBC	HQC	AICC
AR 0	−6.60521	−6.58626	−6.59790	−6.60520
AR 1	−18.7591	−18.6832*	−18.7298	−18.7589
AR 2	−18.7935*	−18.6605	−18.7421*	−18.7929*
AR 3	−18.7805	−18.5903	−18.7071	−18.7793
AR 4	−18.7720	−18.5245	−18.6765	−18.7700
AR 5	−18.7669	−18.4619	−18.6492	−18.7639

Table 4: Cointegration rank test using trace statistics

H_0: Rank=r	H_1: Rank>r	Eigen value	Trace	Pr>Trace
0	0	0.4034	1027.016	<0.0001
1	1	0.3695	653.540	<0.0001
2	2	0.3577	320.075	<0.0001

Table 5: The long-run parameter beta estimate (β) when rank=3

Variable	1	2	3
PGAS	1.0000	1.0000	1.0000
AKRA	−7.9659	9.6008	4.6863
PTT	0.2394	6.2766	−3.2258

Table 6: Adjustment coefficient alpha estimates when RANK=3 (α)

Variable	1	2	3
PGAS	−5.5160	−0.1934	−0.4441
AKRA	0.0943	−0.0246	−0.0458
PTT	−0.0407	−0.1009	0.1403

3.5. Test for Stability Model

Test for stability is conducted to see whether the model used is stable or not.

Table 12 shows that the modulus of the characteristic roots at all lags are < 1. Thus, the VECM (2) model can be used and has high stability.

Figure 8: Prediction error normality for PGAS Malaysia

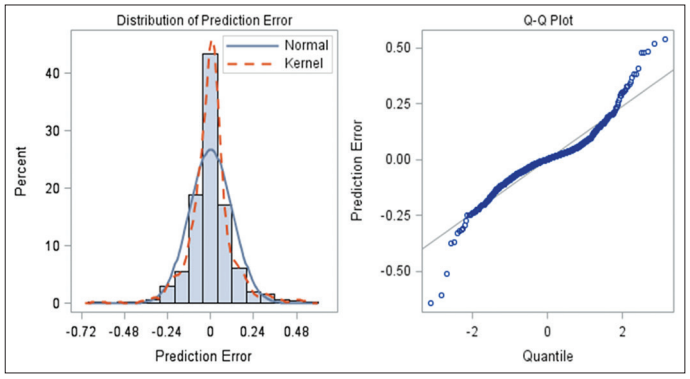


Figure 9: Prediction error normality for AKRA Indonesia

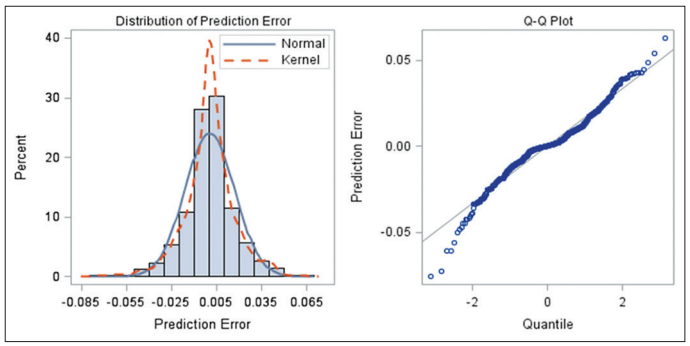
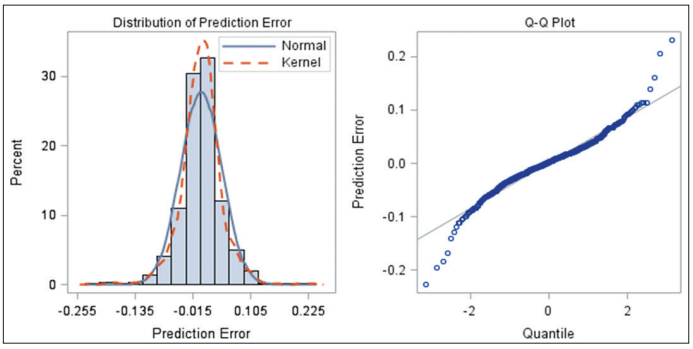


Figure 10: Prediction error normality for PTT-Thailand



3.6. Test for the Fitness of Model

The test for fitness of model can be seen from the ANOVA table of univariate model to assure that the model is significant. Based on the equation of VECM, equation (1), the model can be written as a univariate model as follows:

$$\Delta X_{t1} = -1.1536X_{t1-1} + 0.1730X_{t2-1} + 0.0955X_{t3-1} + 0.0425\Delta X_{t1-1} + 0.3609\Delta X_{t2-1} + 0.0215\Delta X_{t3-1} + u_{t1} \quad (18)$$

$$\Delta X_{t2} = 0.0238X_{t1-1} - 1.2024X_{t2-1} + 0.0155X_{t3-1} - 0.0073\Delta X_{t1-1} + 0.0604\Delta X_{t2-1} + 0.0161\Delta X_{t3-1} + u_{t2} \quad (19)$$

$$\Delta X_{t3} = -0.0013X_{t1-1} + 0.0131X_{t2-1} - 1.0958X_{t3-1} + 0.0209\Delta X_{t1-1} + 0.0675\Delta X_{t2-1} + 0.0327\Delta X_{t3-1} + u_{t3} \quad (20)$$

Tests for significant of the Model (18), (19), and (20) given in Table 13. All the univariate models (18), (19), and (20) are significant with P-values <0.0001 and its R-squares are 0.5499, 0.5649, and 0.5288 respectively.

3.7. Analysis Granger Causality

Analysis of Granger Causality is commonly used to analyze causal relationship among economic variables (Tsay, 2005; 2014; Wei, 2006; Warsono et al., 2019a). To study the relationship and forecasting among economic variables, a key question that can be addressed with vector autoregression (VAR) model or VECM model is how useful some variables are for forecasting others (Hamilton, 1994). The test of Granger Causality is based on the Wald Test, which has chi-squares distribution or F-test as an alternative. The null hypothesis of the Granger Causality test is that Group 1 is induced only by itself and not by Group 2 (SAS/ETS 13.2, 2014).

Figure 11: Model granger causality among variables: PGAS Malaysia, AKRA Indonesia and PTT Thailand

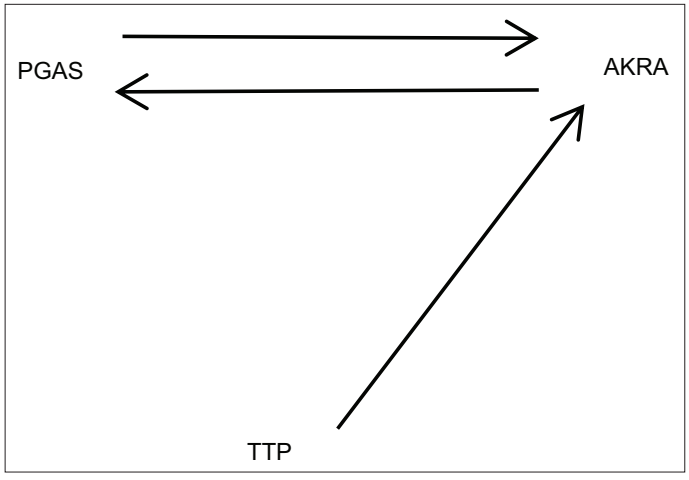


Table 7: The estimate parameter Π

Parameter Alpha * Beta' estimates			
Variable	**PGAS**	**AKRA**	**PTT**
PGAS	−1.1538	0.1731	0.0955
AKRA	0.0238	−1.2023	0.0155
PTT	−0.0013	0.0131	−1.0958

Table 14 represents the PGAS, Malaysia as Group 1 and AKRA as Group 2 (test 1), the result of the test with Chi-square test is 6.95 with P-value is 0.0310 > 0.05, and we conclude that the null hypothesis is rejected, therefore, PGAS is induced by itself and by AKRA Indonesia. In other words, there is Granger causal of AKRA to PGAS. Test 2 represents PGAS, Malaysia as Group 1 and PTT as Group 2. The result of the test with Chi-square test is 1.69 with P-value 0.4282 > 0.05, and we conclude that the null hypothesis fails to reject. Therefore, PGAS is induced by itself and not by PTT Thailand. In other words, there is no Granger causal of PTT to PGAS. Test 3 represents AKRA Indonesia as Group 1 and PGAS Malaysia as Group 2 (test 3), the result of the test with Chi-square test is 13.67 with P-value is 0.0011 < 0.05, and we conclude that the null hypothesis is rejected, therefore, AKRA is induced by itself and by PGAS Malaysia. In other words, there is Granger causal of PGAS to AKRA. Test 4 represents AKRA Indonesia as Group 1 and PTT Thailand as Group 2 (test 4). The result of the test with Chi-square test is 9.62 with P-value is 0.0082 < 0.05, and we conclude that the null hypothesis is rejected. Therefore, AKRA is induced by itself and PTT Thailand. In other words, there is Granger causal of PTT to AKRA. Test 5 represents PTT Thailand as Group 1 and PGAS as Group 2, the result of the test with Chi-square test is 5.20 with P-value is 0.0744 > 0.05, and we conclude that the null hypothesis fails reject. Therefore, PTT is induced by itself and not by PGAS Malaysia. In other words, there is no Granger causal of PGAS to PTT Thailand. Test 6 represents PTT Thailand as Group 1 and AKRA as Group2, the result of the test with Chi-square test is 1.68 with P-value is 0.4316 > 0.05, and we conclude that the null hypothesis fails to reject. Therefore, PTT is induced by itself and not by AKRA Indonesia. In other words, there is no Granger causal of AKRA to PTT Thailand. The results of Granger Causality analysis can be depicted as given in Figure 11. PGAS and AKRA has directional Granger causal; this mean that PGAS has Granger causal to AKRA and AKRA has Granger causal to PTT, and PTT has Granger causal to AKRA Indonesia.

3.8. Impulse Response Function (IRF)

Figure 12 is the graph of IRF if there is a shock 1 standard deviation in PGAS and its impact to the variables PGAS itself, AKRA, and PTT. If the graph of IRF moves close to equilibrium point or back to the original equilibrium (zero) line, this means that the response

Table 8: Schematic representation of cross correlation of residuals

Variable/Lag	0	1	2	3	4	5	6	7	8	9	10	11	12
PGAS	+++	…	…	+	+	-	…	…	…	…	…	…	-
AKRA	+++	…	…	…	…	…	…	…	…	…	…	…	…
PTT	+++	…	…	…	…	…	…	…	…	…	…	…	…

+ is > 2*std error, - is < -2*std error, is between

of a variable to shock other variables disappears, such that the shock does not have a permanent effect on the variable. Shock of one standard deviation in PGAS causes the PGAS to respond negatively from the 1st week up to 6 weeks. The response of PGAS itself from the 1st week to the 6 weeks are: −0.11106, −0.01906, −0.00023, −0.00177, −0.00187, and −0.00029, respectively. After 7 weeks, the response keeps getting smaller and smaller due to the equilibrium point (zero point). The shock of one standard deviation in PGAS causes the AKRA to give a fluctuating response from the 1st week up to the 2nd week, when the response is positive. In the 3rd week, the response is negative, and in the 4th week, the response is positive. The response of AKRA from the 1st week to the 4th week are: 0.01650, 0.00376, −0.00370, and 0.00059, respectively. After the 5th week, the response keeps getting smaller and smaller to the equilibrium point (zero point). The shock of one standard deviation in PGAS causes PTT Thailand to give a fluctuating response: in the 1st week, the response is positive, in the 2nd week, the response is negative, and in the 3rd week to the 5th week, the responses are positive. The response of AKRA from the 1st week to the 5th week are: 0.01968, −0.02304, 0.00195, 0.00047, and 0.00017, respectively. After the 5th week, the response keeps getting smaller and smaller and tends to the equilibrium point (zero point).

Table 9: Portmanteau test for cross correlations of residuals

Up to lag	DF	Chi-square	Pr>Chi-square
3	9	16.07	0.0654
4	18	29.14	0.0467
5	27	36.21	0.1108
6	36	41.77	0.2345
7	45	46.49	0.4109
8	54	51.70	0.5635
9	63	59.78	0.5920
10	72	66.43	0.6630
11	81	74.47	0.6825
12	90	82.48	0.7007

Figure 13 is the graph of IRF if there is a shock 1 standard deviation in AKRA and its impact on the variables PGAS, AKRA itself, and PTT. Shock of one standard deviation in AKRA causes the PGAS to respond in fluctuation. In the 1st week, the response is positive, in the 2nd week, the response is negative, in the 3rd week

Table 10: Univariate model AR diagnostics

Variable	AR1		AR2		AR3		AR4	
	F value	Pr>F	F value	Pr>F	F value	Pr>F	F value	Pr>F
PGAS	0.01	0.9292	0.03	0.9737	0.06	0.9814	1.08	0.3666
AKRA	0.00	0.9983	0.00	0.9994	1.06	0.3639	1.06	0.3771
PTT	0.01	0.9042	0.01	0.9881	0.01	0.9986	0.09	0.9846

Table 11: Univariate model white noise diagnostics

Variable	Durbin watson	Normality		ARCH	
		Chi-square	Pr>Chi-square	F value	Pr>F
PGAS	2.00591	713.44	<0.0001	36.99	<0.0001
AKRA	1.99823	149.48	<0.0001	35.22	<0.0001
PTT	1.98741	505.84	<0.0001	14.73	0.0001

Figure 12: Impulse response function for shock in variable PGAS

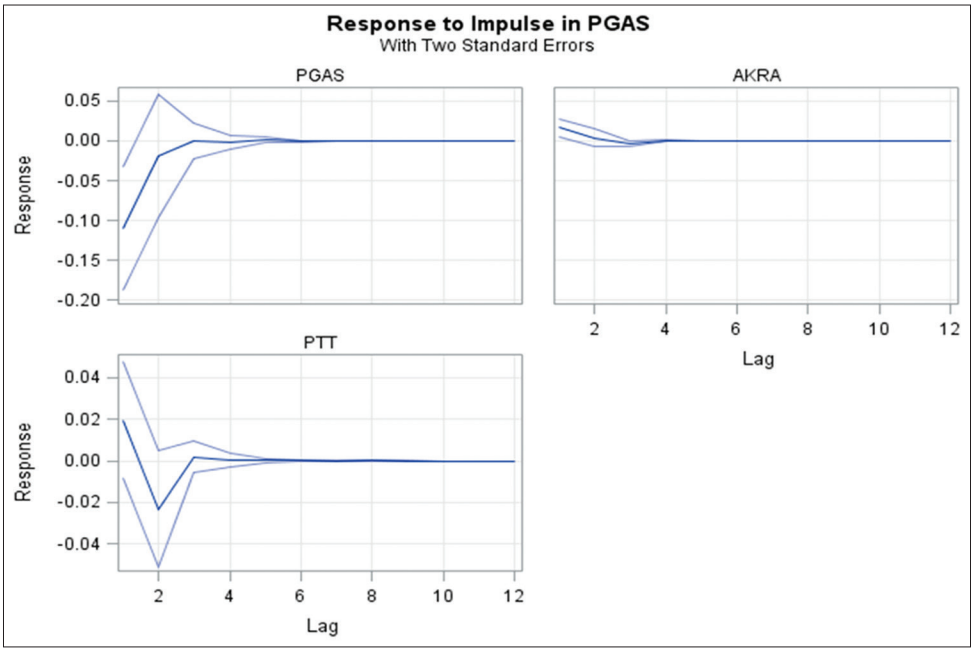


Figure 13: Impulse response function for shock in variable AKRA

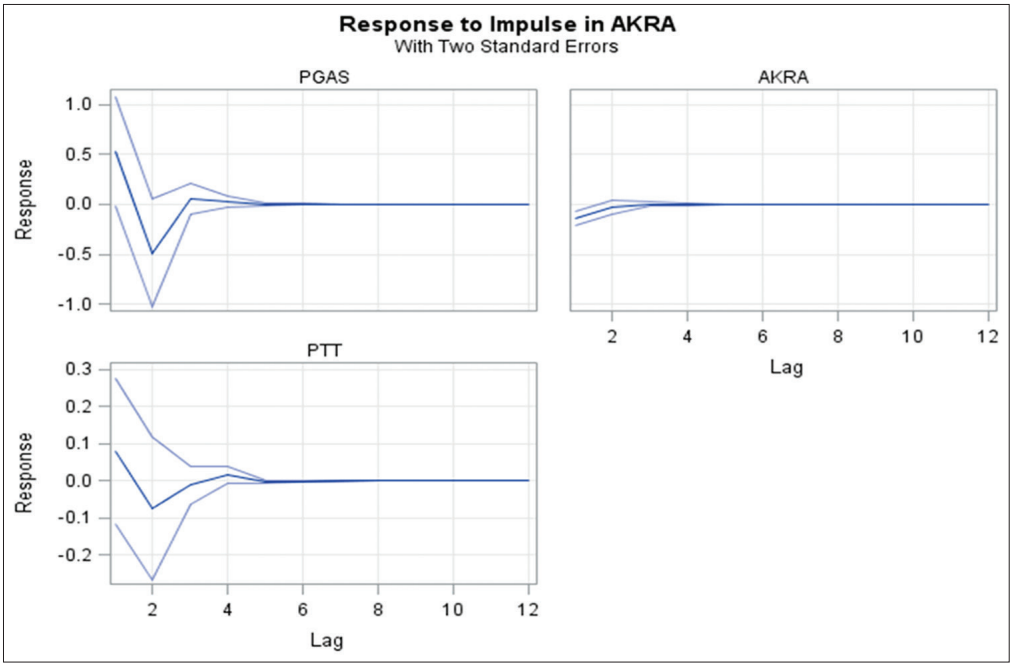
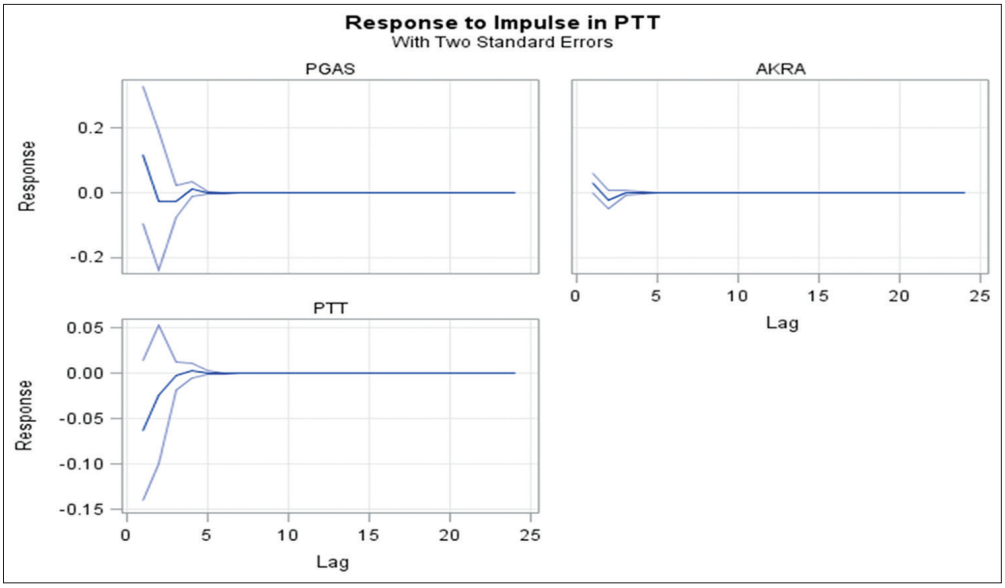
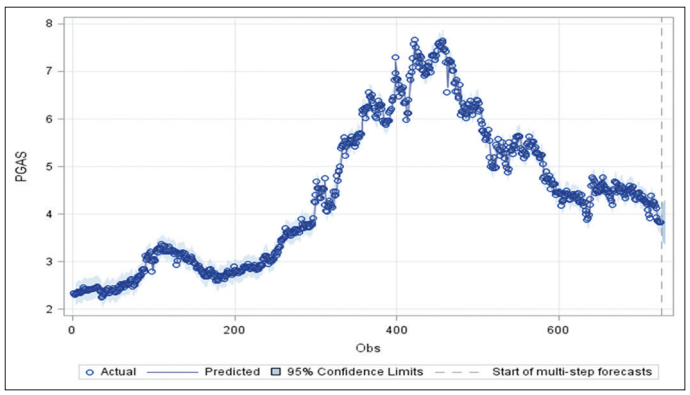


Figure 14: Impulse response function for shock in variable PTT



to the 4th week, the response is positive, and in the 5th week to the 7th week, the response is negative. The response of PGAS from the 1st week to the 7th week are: 0.53392, −0.48684, 0.05683, 0.02765, −0.00546, −0.00011, and −0.00053, respectively. After the 7th week, the response keeps getting smaller and smaller, tending to the equilibrium point (zero point). Shock of one standard deviation in AKRA cause AKRA itself to respond in fluctuation. In the 1st week to the 2nd week, the responses are negative, in the 3rd week, the response is positive, in the 4th week, the response is negative, in the 5th week, the response is positive, and in the 6th week, the response is negative. The response of AKRA from the 1st week to the 6th week are: −0.14198, −0.02886, 0.00492, −0.00076, 0.00140, and −0.00037, respectively. After the 6th week,

Figure 15: Model and forecasts for PGAS Malaysia



the response keeps getting smaller and smaller, tending to the equilibrium point (zero point). Shock of one standard deviation in AKRA cause PTT to give a fluctuating response. In the 1st week, the response is positive, in the 2nd week to the 3rd week, the responses are negative, in the 4th week, the response is positive, and in the 5th week to the 6th week, the responses are negative. The response of PTT from the 1st week to the 6th week are: 0.08055, −0.07348, −0.01150, 0.01678, −0.00172, −0.00096, respectively. After the 6th week, the response keeps getting smaller and smaller tending to the equilibrium point (zero point).

Figure 16: Model and forecasts for AKRA Indonesia

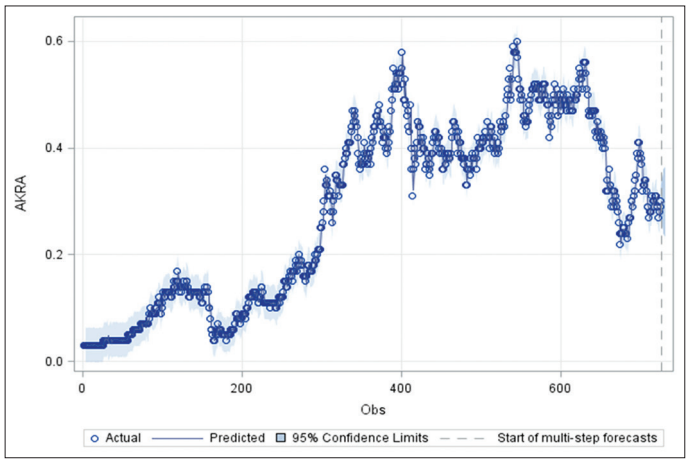


Table 12: Test for stability model

Roots of AR characteristic polynomial					
Index	**Real**	**Imaginary**	**Modulus**	**Radian**	**Degree**
1	0.03121	0.16230	0.1653	1.3808	79.1149
2	0.03121	−0.16230	0.1653	−1.3808	−79.1149
3	0.02825	0.29816	0.2995	1.4763	84.5876
4	0.02825	−0.29816	0.2995	−1.4763	−84.5876
5	−0.21752	0.19377	0.2913	2.4139	138.3045
6	−0.21752	−0.19377	0.2913	−2.4139	−138.3045

Table 13: Test for significant of the model

Univariate model ANOVA diagnostics					
Model	**Variable**	**R-square**	**Standard deviation**	**F value**	**Pr>F**
(18)	PGAS	0.5499	0.11922	175.22	<0.0001
(19)	AKRA	0.5649	0.01660	186.17	<0.0001
(20)	PTT	0.5288	0.04311	160.92	<0.0001

Figure 14 is the graph of IRF if there is a shock 1 standard deviation in PTT and it impacts the variables PGAS, AKRA, and PTT itself. Shock of one standard deviation in PTT causes the PGAS give a fluctuating response. In the 1st week, the response is positive, in the 2nd week to the 3rd week, the responses are negative, in the 4th week, the responses are positive, and in the 5th week to the 6th week, the response is negative. The response of PGAS from the 1st week to the 6th week are: 0.11700, −0.02503, −0.02607, 0.01248, −0.00018, and −0.00076, respectively. After the 7th week, the response keeps getting smaller and smaller to tend to the equilibrium point (zero point). Shock of one standard deviation in PTT causes AKRA to give a fluctuating response. In the 1st week, the responses are positive, in the 2nd week, the response is negative, and in the 3rd week to the 4th week, the responses are positive. The response of AKRA from the 1st week to the 4th week are: 0.03163, −0.02066, 0.00173, and 0.00076, respectively. After the 4th week, the response keeps getting smaller and smaller to tend to the equilibrium point (zero point). Shock of one standard deviation in PTT causes PTT itself to give a fluctuating response. In the 1st week to the 3rd week, the responses are negative, in the 4th week to the 5th week, the responses are positive, and in the 6th week, the response is negative. The response of PTT from the 1st week to the 6th week are: −0.06309, −0.02389, −0.00317, 0.00253, 0.00067, and −0.00044, respectively. After the 6th week, the response getting smaller and smaller to tend to the equilibrium point (zero point).

3.9. Forecasting

In forecasting data for PGAS Malaysia, AKRA Indonesia, and PTT Thailand, we used the model given in equation (18, 19, and 20), which is very significant with P-values all <0.0001, respectively and R-squares 0.5499, 0.5649, and 0.5288 respectively. These models indicate that they can be used for forecasting future values. This is also supported by Figures 15-17, which show that the predicted values and its observation are very close to each other. This indicates that the model used is good. The forecasts for the next five periods or 5 weeks are not very varied, but the forecast error or confidence interval of forecasting is getting larger as the forecast period grows (Table 15).

Table 14: Test for granger causality

Granger-Causality wald test					
Test	**Group variable**	**Nul hypotheses (H_0)**	**Chi-square**	**P value**	**Conclusion**
1	Group 1 variables: PGAS Group 2 variables: AKRA	H_{01}: PGAS is induce by itself and not by AKRA	6.95	0.0310	Reject Ho
2	Group 1 variables: PGAS Group 2 variables: PTT	H_{02}: PGAS is induce by itself and not by PTT	1.69	0.4289	Do not reject Ho
3	Group 1 variables: AKRA Group 2 variables: PGAS	H_{05}: AKRA is induce by itself and not by PGAS	13.67	0.0011	Reject Ho
4	Group 1 variables: AKRA Group 2 variables: PTT	H_{06}: AKRA is induce by itself and not by PTT	9.62	0.0082	Reject Ho
5	Group 1 variables: PTT Group 2 variables: PGAS	H_{07}: PTT is induce by itself and not by PGAS	5.20	0.0744	Do not reject Ho
6	Group 1 variables: PTT Group 2 variables: AKRA	H_{08}: PTT is induce by itself and not by AKRA	1.68	0.4316	Do not reject Ho

Figure 17: Model and forecasts for PTT Thailand

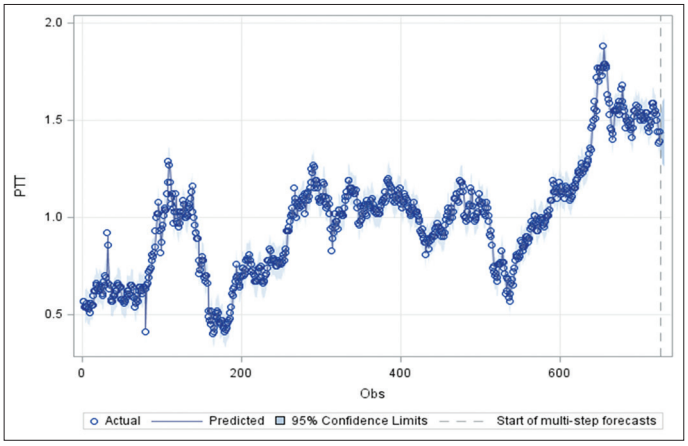


Table 15: Forecasting for the next five periods of PGAS Malaysia, AKRA Indonesia, and PTT Thailand

Forecasts					
Variable	Obs	Forecast	Standard error	95% Confidence limits	
PGAS	727	3.82779	0.11922	3.59412	4.06146
	728	3.82151	0.16178	3.50443	4.13859
	729	3.82127	0.19282	3.44336	4.19918
	730	3.82214	0.21943	3.39206	4.25223
	731	3.82205	0.24317	3.34545	4.29866
AKRA	727	0.29932	0.01660	0.26679	0.33185
	728	0.29804	0.02238	0.25418	0.34190
	729	0.29820	0.02666	0.24594	0.35046
	730	0.29824	0.03032	0.23881	0.35767
	731	0.29825	0.03359	0.23241	0.36408
PTT	727	1.43686	0.04311	1.35237	1.52135
	728	1.43485	0.05966	1.31792	1.55177
	729	1.43473	0.07143	1.29474	1.57473
	730	1.43503	0.08146	1.27537	1.59469
	731	1.43503	0.09046	1.25773	1.61233

4. CONCLUSIONS

Based on time series data of energy of PGAS Malaysia, AKRA Indonesia, and PCL PTT Thailand from October 2005 to August 2019, this study has explored and examined the relationship among the three companies. Based on the analysis results, there is a cointegration relationship among the three companies' data with rank = 3. Based on the existence of the cointegration, the VECM is established and the best model which fits the data is VECM (2) with cointegration rank = 3. Based on the best VECM (2) model with cointegration rank = 3, the results of Granger Causality, IRF, and forecasting are analyzed. From the Granger Causality, it was found that there are be direction of Granger causal effect between PGAS Malaysia and AKRA Indonesia, and there is a direct Granger causal effect of PTT Thailand to AKRA Indonesia.

According to the results of IRF, if there is shock in PGAS for one standard deviation, this causes PGAS to respond negatively from the 1st week up to the 6th week; AKRA have a fluctuating response: from the 1st week up to the 2nd week, the response is positive, in the 3rd week, the response is negative, and in the 4th week, the response is positive; PTT Thailand gave a fluctuate response: in the 1st week, the response is positive, in the 2nd week, the response is negative, and from the 3rd week to the 5th week, the responses are positive. Shock of one standard deviation in AKRA causes PGAS to give a fluctuating response: in the 1st week, the response is positive, in the 2nd week, the response is negative, in the 3rd week to the 4th week, the response is positive, and in the 5th week to the 7th week, the response is negative. AKRA itself gave a fluctuating response. In the 1st week to the 2nd week, the responses are negative, in the 3rd week, the response is positive, in the 4th week, the response is negative, in the 5th week, the response is positive, and in the 6th week the response is negative. PTT also gave a fluctuating response. In the 1st week, the response is positive, in the 2nd week to the 3rd week, the responses are negative, in the 4th week, the response is positive, and in the 5th week to the 6th week, the responses are negative. Shock of one standard deviation in PTT causes PGAS to give a fluctuating response. In the 1st week, the response is positive, in the 2nd week to the 3rd week, the responses are negative, in the 4th week, the responses are positive, and in the 5th week to the 6th week, the response is negative. AKRA gave a fluctuating response. In the 1st week, the responses are positive, in the 2nd week, the response is negative, and in the 3rd week to the 4th week, the responses are positive. PTT itself gave a fluctuating response. In the 1st week to the 3rd week, the responses are negative, in the 4th week to the 5th week, the responses are positive, and in the 6th week, the responses are negative.

The model univariate for forecasting is very significant and the predicted values are very close to the observations. This indicates that the model is very reliable to be used for forecasting, the results of forecasting for the next five periods (weeks) do not fluctuate too much, but the confidence intervals are getting larger as the forecast period grows.

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