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Analysis of Some Energy and Economics Variables by Using VECMX Model in Indonesia

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ABSTRACT

Time series modeling analysis is one of the methods to forecast based on past data and conditions. The analytical tool that is commonly used to forecast multivariate time series data is the Vector Autoregressive (VAR) model. However, when the variables have cointegration and stationary at the first difference value, then the VAR model is modified into the Vector Error Correction Model (VECM). In VECM, all variables can be used as endogenous variables. If exogenous variables are involved in the VECM model, then the model is called as Vector Error Correction Model with Exogenous variables (VECMX). In the present study, a time series modeling analysis was used to analyze the price of gasoline, the money supply in a broad sense (M2), oil and gas exports, and consumption imports over the years from 2012 to 2020. By using information on the criteria of Akaike Information Criterion Corrected, Hannan–Quinn Criterion, Akaike Information Criterion, and Schwarz Bayesian Criterion, the best VAR(p) model is obtained with order 3, or lag 3. Based on the VAR(3) model, the cointegration test is conducted, and the result shows that there is a long-term relationship among variables, namely, there is a cointegration relationship between variables with rank = 1. Based on the cointegration rank = 1 and the smallest value of the information criteria and comparison of some candidate best models, namely, VECMX(2,1), VECMX(2,2), VECMX(3,1), VECMX(3,2), and VECMX(4,1), we found that the best model is VECMX(3,1) with lag 3 for endogenous variables and lag 1 for exogenous variables. Based on this best model, further analysis of Granger causality, Impulse Response Function (IRF), and forecasting is discussed.

Keywords: VAR model, VECMX, time series, Granger causality, Impulse response function
JEL Classifications: C53, Q4, Q47

1. INTRODUCTION

Time series data is data that is observed from time to time. Time series analysis is one method with the aim of knowing events that will occur in the future based on past data and conditions. In time series analysis, there is often a causal and cointegrated relationship between variables, so it is possible in a time series analysis to also pay attention to previous data from other variables. This needs to be done to support good and appropriate decision making. Initially, Tinbergen in 1939 built the first econometric model for the United States and then started a program of empirical econometric scientific research (Kirchgassner and Wolters, 2007). Sims (1980) introduced the VAR model and used it as an alternative to analyze macroeconomic data. The VAR model is commonly used to explain variable simultaneously that has an influence on each other. The VAR model is used if the data are stationary. If the data are not stationary at the level but are stationary at the first difference value and the variable has no cointegration, then we use Vector Autoregressive in Difference. When a variable has cointegration and is stationary at the first difference value, it uses the vector error correction model (VECM). In VECM, all variables can be used as endogenous variables, and endogenous variables are also influenced by other exogenous variables. Exogenous variables are variables that are considered to have an influence on other variables but are not influenced by other variables in the model. In contrast, endogenous variables are variables that are considered to be influenced by other variables in the model. If exogenous variables are added to the VECM model, then the model used is the vector error correction model with exogenous variables (VECMX).

According to Mustofa et al. (2017) in his studied found the best VECM model is order 2, and based on the impulse response function (IRF) graph, it is found that the response of Farmer's Exchange Rate to price shocks received and paid by farmers is volatile and temporary from time to time. According to Warsono et al. (2018), the VAR model used to model bad loans is VAR (17). From the results obtained, the Granger causality relationship shows a direct causal relationship between two-way or one-way bad credit data and an indirect causal relationship with LIR, EXR, and INF variables. According to Warsono et al. (2019a), based on the results of the analysis of the relationship between endogenous (PTBA energy and HRUM) and exogenous variables (Exchange rate), the VARX (3.0) model is the best model for the relationship between these variables. According to Warsono et al. (2020), based on the results of the analysis, there is a cointegration relationship between the data of three companies with rank = 3. Based on the existence of cointegration, VECM is determined, and the best model that fits the data is VECM (2) with cointegration rank = 3.

Based on previous research, this research will add exogenous variables for the formation of dynamic modeling that will be used, namely, VECMX. Furthermore, the causal relationship between time series variables will be evident using the Granger Causality Test. Meanwhile, to determine the effect of the shock of a variable on other variables, the IRF will be used. The data that will be used in this study are monthly data from the variable money supply in a broad sense (M2), oil and gas exports, consumption imports, and gasoline prices in the period January 2012–December 2020. The purpose of the present study is to formulate a time series data model with the VECMX approach, examine the behavior of time series data cointegrated with Granger causality, and investigate the behavior of one variable against other variables in the event of shock.

2. STATISTICAL MODEL

A time series is a set of observations that are ordered in time, with equal time intervals. The sequence of observations is indicated by $Y_{t_1}, Y_{t_2}, \ldots, Y_{t_n}$. Thus, Y_{t_i} represents the time at t_i where Y is a random variable. The stochastic process is part of the time index of random variables $Y(\omega, t)$, where represents the sample space and t represents the set of time indices (Box and Jenkins, 1970).

2.1. Model Dynamic

The main objective of analysis of multivariate time series data is to explain the dynamic relationship among variables of interest and improve prediction accuracy (Granger, 1981; Wei, 2006; Montgomery et al., 2008; Tsay, 2005; 2014). In multivariate time series data, several variables being analyzed often autocorrelate. Therefore, one needs to understand the nature of relationship between variables to be analyzed to obtain a good and appropriate model and produce accurate predictions (Brockwell and Davis, 1991; Lutkepohl, 2005; Tsay, 2014).

In the analysis of time series data, it is assumed that the data are stationary, in the sense that the probability distribution of an arbitrary collection of X_t be time invariant (Tsay, 2014). In a k-dimensional vector time series, X_t is stationary if (a) $E(X_t) = \mu$, k-dimensional vector constant, and (b) $\text{Cov}(X_t) = \Sigma_t$ $k \times k$ matrix constant and positive definite (Brockwell and Davis, 1991; Hamilton, 1994; Tsay, 2014). The stationarity of multivariate time series data can be checked by examining the graph of the data and analyzed the behavior of the data to check whether it is stationary or not. Analytically, one can check for stationary data using the Augmented Dicky Fuller test (ADF test) or the unit root test (Warsono et al., 2019a; 2019b; 2020; Brockwell and Davis, 1991). In addition, we can examine the graph of the autocorrelation function (ACF). In the ADF test or Unit Root Test with p-lag, the model is defined as follows:

$$\Delta X_t = \alpha + \phi X_{t-1} + \sum_{i=1}^{p-1} \phi_1^* \Delta X_{t-1} + \varepsilon_t \tag{1}$$

where $\Delta X_t = X_t - X_{t-1}$ and ε_t is white noise. The null hypothesis is H_0: $\phi = 0$, and the data are nonstationary. The statistic test is τ(tau) test or ADF test where the distribution approximately has t-ratio (Brockwell and Davis, 1991; Tsay, 2014). For the level of significance ($\alpha = 0.05$), reject null hypothesis (H_0) if $\tau < -2.57$ or if $P<0.05$ (Brockwell and Davis, 2002; Tsay, 2005; Virginia et al., 2018). The statistic test is as follows:

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

2.2. Cointegration

Engle and Granger (1987) introduced the concept of cointegration, and the development of the concept of estimation and inferential is provided by Johansen (1988). The time series X_t is said to be integrated with order one process, I(1), if $(1-B)X_t$ is stationary. If the time series data is stationary, then the process is called to be I(0). In general, the univariate time series X_t is an I(d) process, if $(1-B)^d X_t$ is stationary (Hamilton, 1994; Tsay, 2005; 2014). The fact that some time series data with unit roots or nonstationary, but their linear combination can become stationary. 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. If in the Vector Autoregressive (VAR) model, there exists cointegration, and then the model needs to be modified into VECM (Tsay, 2005; Wei, 2006; Lutkepohl, 2005). If a cointegration relationship is present in a system of variables, the VAR model is not the most convenient model. If there is cointegration, then the model used is VECM (Lutkepohl and Kratzig, 2004; Asteriou and Hall, 2007; Wei, 2019). If there is cointegration between vector time series, then one needs to test the cointegration rank. Some methods of testing of the rank of cointegration are as follows: trace test and maximum eigenvalue test. The trace test is as follows:

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

With the null hypothesis, there is an r positive eigenvalue. In the maximum eigenvalue test, the statistic test is as follows:

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

2.3. Vector Autoregressive (VAR) Model

To quantitatively analyze time series data involving more than one variable (multivariate time series), the VAR method is used. The VAR method treats all variables symmetrically. One vector contains more than two variables, and on the right side, there is a lag value (lagged value) of the dependent variable as a representation of the autoregressive property in the model. The VAR(p) model can be written in the following equation:

$$Y_t = \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t \tag{5}$$

where Y_t is the $n \times 1$ vector observation at the time t, Φ_i is the $n \times n$ matrix coefficient of vector Y_{t-i}, for $i = 1,2,\dots p$, p is the lag length, and ε_t is the $n \times 1$ vector of shock.

2.4. Vector Error Correction Model

VECM is a restricted VAR model designed to be used on a nonstationary time series data, but has a cointegration. VECM can be used to estimate the short-term and long-term effects between the variables. The VECM(p) model with endogenous variable and has cointegration rank $r \leq k$ is as follows (Lutkepohl, 2005):

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \tag{6}$$

The VECM model can consider deterministic values. The deterministic value (Dt) can be a constant, a linear trend, and a seasonal dummy variable. Exogenous variables can also be included in the model, and according to Seo (1999), some stationary exogenous variables can be included as independent variables along with some of their lags in the following model:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-p} + \sum_{i=0}^{S} \Phi_1 x_{1,t-i} + \sum_{i=0}^{S} \Phi_2 x_{2,t-i} + \varepsilon_t \tag{7}$$

where Δ is the operator of differencing, $\Delta Y_t = Y_t - Y_{t-1}$, Y_{t-1} is the vector of an endogenous variable at lag−1, ε_t is the $k \times 1$ vector white noise, Π is the matrix coefficient of cointegration, and $\Pi = \alpha\beta^t$, α = matrix adjustment, $(k \times r)$ and β = matrix cointegration $(k \times r)$, Γ_i = matrix coefficient $(k \times k)$ for the i variable endogenous, and Φ_i = matrix coefficient $(r \times k)$ for the i variable exogenous.

2.5. Normality Test of Residuals

The normality test of residuals is used to evaluate the distribution of the residuals. Normality test was performed using Jarque–Bera (JB) test of normality, and the test uses a measure of skewness and kurtosis. JB test is as follows:

$$\mathrm{JB} = \left[\frac{\mathrm{N}}{6} \mathrm{b}_1^2 + \frac{\mathrm{N}}{24} (\mathrm{b}_2 - 3)^2 \right] \tag{8}$$

where N is the sample size, b_1 is the expected skewness, and b_2 is the expected excess kurtosis. The JB test of normality has χ^2 distribution with 2 degrees of freedom (Jarque and Berra, 1980).

2.6. Stability Test

The stability of the VAR system is evident from the inverse roots of the AR polynomial characteristics. A VAR system 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. The following is a description according to Lutkepohl (2005) that the VAR(p) model can be written as:

$$y_t = c + \Phi_1 y_{t-1} + \dots + \Phi_p y_{t-p} + \varepsilon_t \tag{9}$$

The given definition of the characteristic polynomial on the matrix is called the characteristic polynomial of the VAR(p) process, so that it is said to be stable if

$$\det(I_{Kp} - \Phi_z) = \det(I_K - \Phi_1 z - \dots - \Phi_p z^p) \tag{10}$$

have a modulus smaller than one and all of them lie within the unit circle.

2.7. Granger Causality

The existence of cointegration indicates a long-term relationship between variables. Even when the variables are not cointegrated in a long-term relationship, these variables are still likely to have a short-term relationship. To understand the interdependence between variables, the Granger Causality Test is used. Consider the following models:

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} B_{11,1} & B_{12,1} \\ B_{21,1} & B_{22,1} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \dots + \begin{bmatrix} B_{11,p} & B_{12,p} \\ B_{21,p} & B_{22,p} \end{bmatrix} \begin{bmatrix} y_{1t-p} \\ y_{2t-p} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{11}$$

y_t consists of vectors y_{1t} and y_{2t}. y_{2t} is said not to be a Granger causality for y_{1t} if the coefficient matrix of parameter $B_{21,i}=0$ for $i = 1,2,\dots, p$ (Lutkepohl, 2005). Granger Causality Test is used to evaluate and examine whether there is an effect of one variable or group of variables to other variables. A variable X_t is said to be Granger because of variable Y_t, if the past and present values of X_t can predict the current value of Y_t. If a variable of X_t is the Granger causality of variable Y_t and not vice versa, then it is called direct Granger causality. If Granger causality exists in both, from X_t to Y_t and from Y_t to X_t, then it is called bidirectional Granger causality (Brooks, 2014).

2.8. Impulse Response Function (IRF)

Wei (2006), Hamilton (1994) stated that the IRF is an analytical technique used to analyze a 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:

$$X_t = \mu + \mu_t + \Psi_1 \mu_{t-1} + \Psi_2 \mu_{t-2} \tag{12}$$

Thus, the matrix is interpreted as follows:

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

The element of the i^{th} row and j^{th} column indicates the consequence of the increase of one unit in innovation of variable j at time t (μ_{jt}) for the i variable at time $t+s$ ($X_{i,t+s}$) and fixed all other innovation. If the element of μ_t changed by $\delta 1$, at the same time, the second element will change by $\delta_2, \dots$, and the n^{th} element will change by

δ_n, then the common effect from all of these changes on the vector X_{t+s} will become

$$\Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}}\delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}}\delta_2 + \ldots + \frac{\partial X_{t+s}}{\partial u_{nt}}\delta_n = \Psi_s \delta \qquad (13)$$

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

3. DATA ANALYSIS

In the first step before the data are analyzed, one needs to check the stationarity of the data, and it can be done by evaluating the plot of the data and by using augmented Dickey–Fuller (ADF) or unit root test. Stationary data is needed to fulfill the assumption of the application of the VECMX model. Figure 1a shows the import consumption data (Import_CONSP) from 2012 to 2020 (108 months) (Ministry of Trade, 2020), where the image shows that in the first 42 months, the trend is declining and fluctuating, indicating that prices tend to fall and are unstable; from the 42nd to the 80th month, the price trend is up and fluctuating; from the 80th to the 95th month, the trend is flat and fluctuating; and from the 95th to the 108th month, the trend is downwards and very fluctuating. The ACF graph is also slowly decreasing, showing that the import consumption data from 2012 to 2020 is not stationary. Figure 1b shows the data on export oil and gas (Ministry of Trade, 2020) from the 1st to the 50th month with a downward and fluctuating trend; from the 50th to the 82nd month an upward and fluctuating trend; and from the 82nd to the 108th month, the trend is decreasing and fluctuating. The ACF plot for export oil and gas (Export_OG) data also decays very slowly, showing that the export oil and gas data is not stationary. Figure 1c shows that the money supply (M2) (Bank Indonesia, 2020) data from 2012 to 2020 has an uptrend and the ACF plot also decays very slowly, showing that the data is not stationary. Figure 1d shows that in the gasoline price data (Gasoline_P) (Tradingeconomic, 2020) from the 1st month to the 30th month, the trend is up; from the 30th to the 50th month, the trend is down; and from the 50th to the 108th month, the trend is horizontal. The ACF plot of gasoline price data also decays very slowly, showing that gasoline price data is not stationary.

Based on Figure 1, the time series plot shows that the four variables, imports of consumption, exports of oil and gas, money supply (M2), and gasoline prices, are not stationary because they still contain trend elements. The nonstationary data is also shown by the ACF graph decay very slowly, showing that the autocorrelation coefficient is significantly different from zero. Based on Table 1, all variables contain unit roots or are not stationary. This can be seen in the p-value of the Tau statistic (τ) for all tests for each variable that is greater than the significance level of 0.05, so there is not enough evidence to reject H_0, i.e., the data is not stationary (there is a unit root). Since all variables are not stationary, differencing will be performed.

Based on Figure 2, the time series plot shows that the four variables no longer contain trend elements. Furthermore, the movement of the ACF plot from lag 0 to the next lag decreases exponentially toward zero. Thus, it can be concluded that the four variables above are stationary. Based on Table 2, the P-value of the Tau statistic for all tests for each variable is smaller than the significance level = 0.05, so that we reject H_0. Therefore, we conclude that the data are stationary (no unit root) after first differencing (d = 1).

Table 3 provides an analysis of whether there is an autocorrelation in the data imports consumption, exports of oil and gas, money supply (M2), and gasoline prices. The Box–Pierce test (Wei, 2006; Brockwell and Davis, 2002) to test whether there is an autocorrelation in the data with the null hypothesis is that the error is white noise. This test has a chi-square distribution with degrees of freedom K (K indicates lag). Test up to lag 6 for data imports consumption, exports of oil and gas, money supply (M2), and gasoline prices hypothesis is rejected, where chi-square test = 29.44 with $P < 0.0001$ for import consumption data, chi-square test = 31.22 with $P < 0.0001$ for export oil and gas data, Chi-square test = 29.38 with $P < 0.0001$ for money supply data, and chi-square test = 18.03 with $P = 0.0062$ for gasoline price data. Based on the results of the Box–Pierce test, a model with autocorrelation is needed in the analysis of data on

Figure 1: Trend and correlation analysis data for (a) imports of consumption, (b) exports of oil and gas, (c) money supply (M2), and (d) gasoline prices

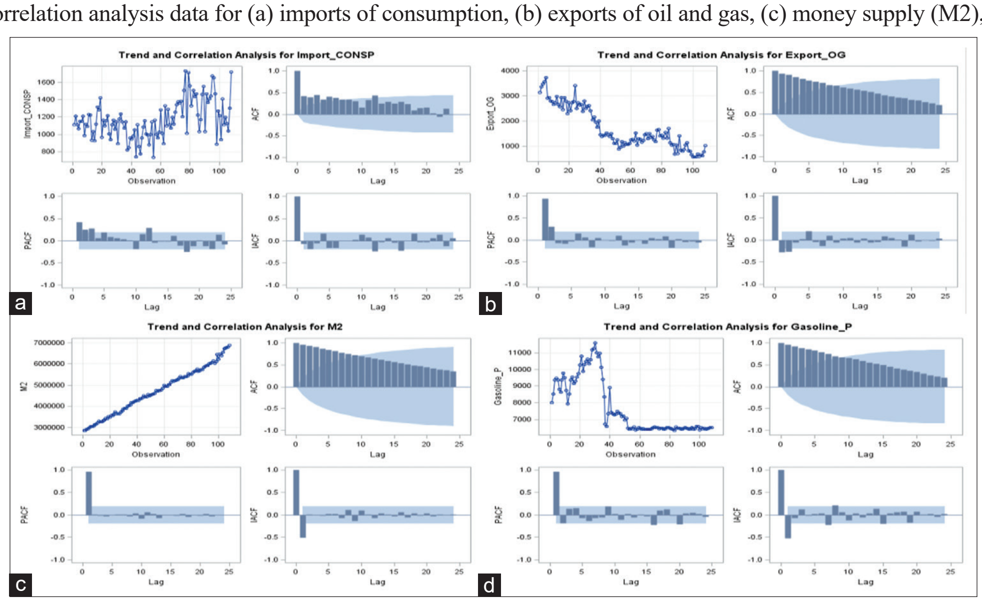


Table 1: Unit root test

Variable	Type	Lags	Rho	P-value	Tau	P-value
Import consumption	Zero Mean	3	0.0251	0.6867	0.03	0.6920
	Single Mean	3	–15.1201	0.0329	–2.39	0.1475
	Trend	3	–26.5172	0.0121	–3.15	0.1006
Export of oil and gas	Zero Mean	3	–1.9508	0.3350	–2.67	0.0079
	Single mean	3	–3.7744	0.5585	–2.19	0.2103
	Trend	3	–9.5452	0.4495	–2.17	0.5012
Money supply (M2)	Zero Mean	3	0.8096	0.8755	6.02	0.9999
	Single Mean	3	0.4157	0.9734	1.25	0.9983
	Trend	3	–5.2388	0.7968	–0.83	0.9592
Gasoline prices	Zero Mean	3	–0.4335	0.5829	–0.99	0.2856
	Single Mean	3	–2.5105	0.7129	–1.12	0.7055
	Trend	3	–6.5118	0.6932	–1.66	0.7628

Figure 2: Trend and correlation analysis for (a) imports consumption, (b) exports of oil and gas, (c) money supply (M2), and (d) gasoline prices after differencing (d = 1)

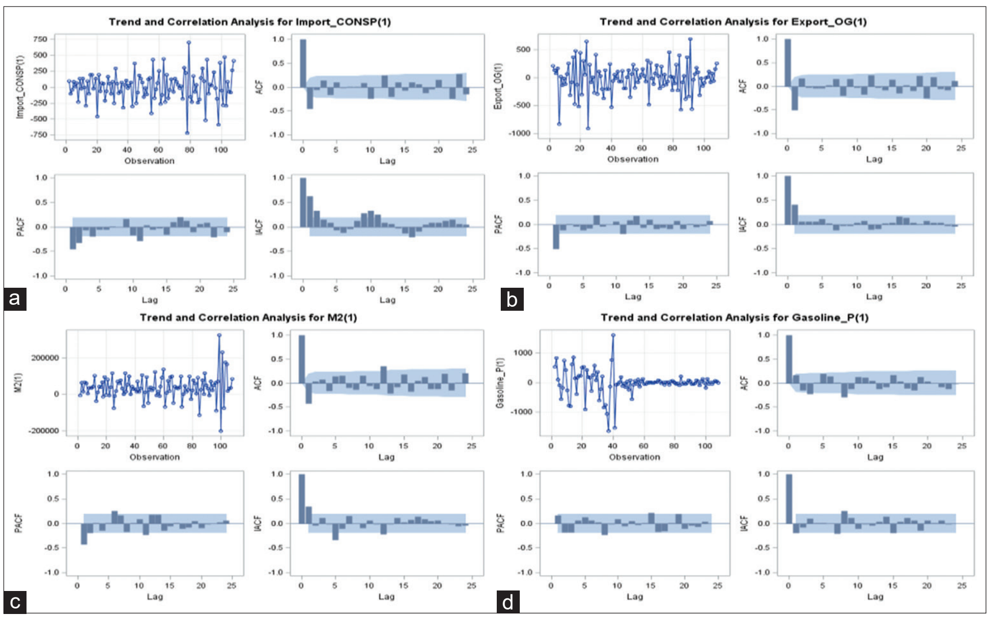
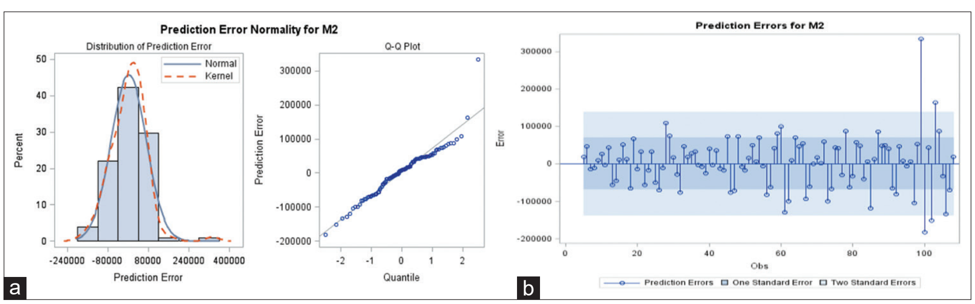


Figure 3: (a) Histogram and Q–Q plot of residuals for M2 and (b) prediction error for M2



imports consumption, exports of oil and gas, money supply (M2), and gasoline prices (SAS/ETS 13.2, 2014, p.193).

3.1. Test for Optimum Lag

To determination of the optimum lag for the VAR model from the endogenous variables, namely, the money supply (M2) and gasoline prices by looking the criteria information used, namely, Akaike Information Criterion Corrected (AICC), Schwarz Bayesian Criterion (SBC), Akaike Information Criterion (AIC), and Hannan–Quinn Criterion (HQC). Determination of the optimum lag is as shown in Table 4.

Based on Table 4, of the five information criteria used, four information criteria marked with an * (asterisk) are found in lag 3. The selection of lag 3 as the optimum lag is based on the smallest value of the information criteria. Thus, the cointegration test will be carried out on lag 3.

3.2. Cointegration Test

Based on the determination of the optimum lag of the VAR model, the determination of cointegration will be tested at the optimum lag, namely, lag 3. Cointegration testing is used to determine the long-term relationship between variables and is a requirement in VECMX

Table 2: Unit root test after differencing d = 1

Variabel	Type	Lags	Rho	P-value	Tau	P-value
Imports of Consumption	Zero Mean	3	326.0248	0.9999	–8.00	<0.0001
	Single Mean	3	326.0642	0.9999	–7.97	<0.0001
	Trend	3	327.0416	0.9999	–7.93	<0.0001
Exports of oil and gas	Zero Mean	3	–222.011	0.0001	–5.84	<0.0001
	Single Mean	3	–413.820	0.0001	–6.30	<0.0001
	Trend	3	–536.027	0.0001	–6.54	<0.0001
Money suply (M2)	Zero Mean	3	–17.3853	0.0029	–2.65	0.0083
	Single Mean	3	–929.942	0.0001	–6.63	<0.0001
	Trend	3	–3679.78	0.0001	–6.87	<0.0001
Gasoline prices	Zero Mean	3	–187.720	0.0001	–5.75	<0.0001
	Single Mean	3	–198.165	0.0001	–5.79	<0.0001
	Trend	3	–197.346	0.0001	–5.76	<0.0001

Table 3: Autocorrelation check for white noise

Variable	To Lag	Chi-square	DF	P-value	Autocorrelations					
Imports of Consumption	6	29.44	6	<0.0001	–0.452	–0.057	0.136	–0.169	0.104	–0.022
	12	45.35	12	<0.0001	0.006	0.013	0.086	–0.245	–0.006	0.251
	18	56.19	18	<0.0001	–0.206	0.095	–0.074	0.099	0.064	–0.122
	24	81.14	24	<0.0001	–0.042	0.160	–0.019	–0.238	0.274	–0.146
Exports of oil and gas	6	31.22	6	<0.0001	–0.502	0.161	–0.027	–0.040	–0.047	0.016
	12	51.71	12	<0.0001	0.149	–0.198	0.152	–0.033	–0.178	0.231
	18	59.20	18	<0.0001	–0.032	–0.084	0.142	–0.146	0.018	–0.095
	24	83.44	24	<0.0001	0.221	–0.260	0.194	–0.063	–0.085	0.120
Money supply (M2)	6	29.38	6	<0.0001	–0.434	0.029	0.080	–0.167	0.137	0.149
	12	53.38	12	<0.0001	–0.096	–0.135	0.156	–0.055	–0.130	0.355
	18	70.84	18	<0.0001	–0.217	–0.089	0.175	–0.181	0.042	0.132
	24	88.97	24	<0.0001	–0.128	–0.124	0.199	–0.145	0.009	0.200
Gasoline prices	6	18.03	6	0.0062	0.167	–0.155	–0.232	0.004	0.190	0.135
	12	33.43	12	0.0008	0.002	–0.290	–0.124	0.124	0.114	0.047
	18	44.25	18	0.0005	–0.120	–0.078	0.170	0.033	–0.114	–0.146
	24	49.95	24	0.0014	0.132	0.035	–0.005	–0.083	–0.127	–0.020

Figure 4: (a) Histogram and Q–Q plot of residuals for Gasoline_P and (b) prediction error for Gasoline_P

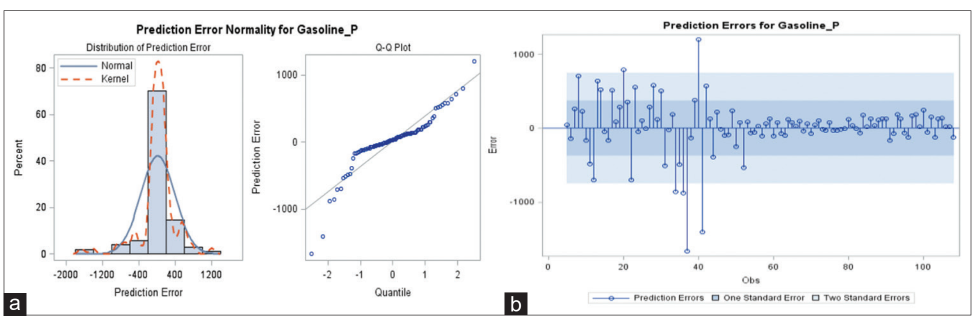


Table 4: Criteria for optimal lag of the VAR model

Information criteria	VAR (1)	VAR (2)	VAR (3)	VAR (4)	VAR (5)
AICC	34.5528	34.5036	34.4114*	34.4804	34.4936
HQC	34.5921	34.5795	34.5208*	34.6201	34.6594
AIC	34.5513	34.4975	34.3972*	34.4543	34.4510
SBC	34.6518*	34.6997	34.7024	34.8636	34.9657

estimation. The cointegration test used is the Johansen cointegration test. The results of the cointegration test are as shown in Table 5:

Based on Table 5, it can be seen that the P-value for rank = 0 < 0.05, so we reject the null hypothesis that the rank = 0, Therefore, we accept the hypothesis alternative that is H_1: rank > r (r = 0). The test for H_0: rank = 1 is not rejected. Thus, there is a cointegration relationship between variables with rank = 1, so the VAR model used is VECMX(p,s) with cointegration rank = 1. Then, the VAR(p) model is modified into a VECM(p) model with P = 3 (Wei, 2019; Tsay, 2014; Hamilton, 1994; Lutkepohl, 2005).

3.3. Selection of VECMX(p,s)

The selection of VECMX(p,s) is based on information criteria, namely, AICC, HQC, AIC, SBC, and FPEC, from the lag used. From the analysis, it was found that the results are as shown in Table 6.

Based on Table 6, it can be seen that of the four information criteria used, three information criteria marked with an * (asterisk) have the smallest value contained in VECMX(3,1), which is lag 3 for endogenous variables and lag 1 for exogenous variables. Thus, VECMX(3,1) is selected as the best model.

Table 5: Cointegration test

H0: Rank=r	H1: Rank>r	Eigenvalue	Trace	P-value	Drift in ECM	Drift in Process
0	0	0.3867	52.0310	<0.0001	NOINT	Constant
1	1	0.0066	0.6947	0.4637		

Table 6: Selection of the best VECMX (p, s)

Information criteria	AICC	HQC	AIC	SBC
VECMX (2,1)	34.7528	34.8771	34.7337	35.0876
VECMX (2,2)	34.7304	34.8826	34.6982	35.1532
VECMX (3,1)	34.5346*	34.6872*	34.5018*	34.9594*
VECMX (3,2)	34.5567	34.7333	34.5067	35.0661
VECMX (4,1)	34.5836	34.7605	34.5326	35.0953

3.4. Parameter Estimation of VECMX(3,1) with Cointegration Rank r = 1

Based on the above analysis, VECMX(3,1) with cointegration rank = 1 was selected as the best model. The model VECMX(3,1) is as follows:

$$\Delta Y_t=\Pi Y_{t-1}+\Gamma_1\Delta Y_{t-1}+\Gamma_2\Delta Y_{t-2}+\Phi_0 X_t+\Phi_1 X_{t-1}+\varepsilon_t,$$

where $\Delta Y_t = \Delta\begin{bmatrix} M2_t \\ Gasoline\_P_t \end{bmatrix}$, $X_t = \begin{bmatrix} Import\_CONSP_t \\ Export\_OG_t \end{bmatrix}$, and

Γ_1, Γ_2, Φ_0 and Φ_1 are 2 × 2 matrix parameters and $\varepsilon_t = \begin{pmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \end{pmatrix}$.

Then, the estimate model VECMX(3,1) is as follows:

$$\Delta\begin{bmatrix} M2_t \\ Gasoline\_P_t \end{bmatrix} = \begin{pmatrix} 0.0057 & 8.8018 \\ -0.0008 & -1.2198 \end{pmatrix}\begin{bmatrix} M2_{t-1} \\ Gasoline\_P_{t-1} \end{bmatrix}$$
$$+\begin{pmatrix} -1.0111 & -7.3126 \\ -0.0002 & 0.3609 \end{pmatrix}\Delta\begin{bmatrix} M2_{t-1} \\ Gasoline\_P_{t-1} \end{bmatrix}+$$
$$\begin{pmatrix} -0.4956 & -100952 \\ 0.0001 & 0.2037 \end{pmatrix}\Delta\begin{bmatrix} M2_{t-2} \\ Gasoline\_P_{t-2} \end{bmatrix}+$$
$$\begin{pmatrix} 47.9851 & 49.4068 \\ 0.0987 & 0.2575 \end{pmatrix}\begin{bmatrix} Import\_CONSP_t \\ Export\_OG_t \end{bmatrix}+$$
$$\begin{pmatrix} 6.4711 & 31.9977 \\ -0.0834 & 0.4013 \end{pmatrix}\begin{bmatrix} Import\_CONSP_{t-1} \\ Export\_OG_{t-1} \end{bmatrix}$$

with the Covariance of Innovations

$$Var\begin{pmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \end{pmatrix} = \begin{pmatrix} 4822729872.3 & 134363.1558 \\ 134363.1558 & 141361.7650 \end{pmatrix}$$

3.5. Check for the Residuals

Table 8 shows the univariate test results for money supply (M2) and gasoline price (Gasoline_P) from the F test obtained $P < 0.0001$ and <0.0001 for the M2 and gasoline univariate models, respectively. In addition to that, the R-squares are 0.6151 and 0.5139 for the univariate M2 and Gasoline_P models, respectively. From Table 9, the normality test for the two residuals from the model for M2 and gasoline price, the $P < 0.0001$ and < 0.0001, which can be concluded that the null hypothesis is rejected, meaning that the residual distribution is not normally distributed. From Figures 3a and 4a, it appears that the deviation from normality is not too far away.Figure 3b shows that there are four observations with residual greater than two standard errors and one observation can be considered outlier (Q-Q plot, Figure 3a). Figure 4b shows there are five observations with residual greater than two standard errors and two observations can be considered outlier (Q-Q plot, Figure 4a).

3.6. Test for Stability Model

The stability test of the model is used to determine the stability of the model VECM(3,1). Table 10 shows that the modulus is all within the unit circle. Therefore, we can conclude that the VECM(3,1) model with cointegration rank = 1 is a stable model to be used for further analysis.

3.7. Analysis of Granger Causality

The Granger Causality Test is intended to determine the causal relationship between one variable and another variable or between a variable and a set of variables. Granger causality test based on Wald test which has chi-square distribution or F distribution. The null hypothesis in the Granger causality test is that group 1 is influenced by itself not by Group 2.

Based on Table 11, from test 3, where the variable in group 1 is M2 and the variable in Group 2 is export oil and gas (Export_OG), the P-value is 0.0119 <0.05, which is smaller than the significance level. This means that H_0 is rejected, so it can be concluded that the variable money supply (M2) not only is influenced by past information itself but is also influenced by current and past information on the value of Export_OG. In test 6, where the variable in group 1 is gasoline price (Gasoline_P) and variables in Group 2 are import consumption (Import_CONSP) and export oil and gas (Export_OG), the P-value is 0.0263 <0.05, which is smaller than the significance level. This means that H_0 is rejected, so it can be concluded that the variable gasoline price (Gasoline_P) not only is influenced by past information itself but is also influenced by current and past information on the value of Import_CONSP and Export_OG. The results of Granger Causality Test are exhibited in Figure 5.

3.8. Impulse Response Function

IRF analysis is used to determine the movement of the effect or impact of a shock on one variable and its effect on the variable itself or on other variables in the current and future periods. To determine the behavior of a variable in response to the shock of another variable, the IRF graph is used as shown in Table 12.

Figure 6a and Table 12 show the response of M2 for the next several periods caused by a one-unit change (shock) of import consumption ($Import\_CONSP_t$). In month $t = 0$, M2 responded at 47.9851, in the following month, M2 ($M2_{t+1}$) responded at 6.3612, in the 2nd month, M2 ($M2_{t+2}$) responded due to a shock ($Import\_CONSP_t$) at 24.2527, in the 3rd month, M2 ($M2_{t+3}$) responded due

Table 7: Model parameter estimates

Equation	Parameter	Estimate	Standard error	t-value	P-value	Variable
D_M2	XL0_1_1	47.98511	35.63974	1.35	0.1814	Import_CONSP (t)
	XL0_1_2	49.40681	31.04327	1.59	0.1148	Export_OG (t)
	XL1_1_1	6.47111	35.99428	0.18	0.8577	Import_CONSP (t-1)
	XL1_1_2	31.99778	30.88119	1.04	0.3028	Export_OG (t-1)
	AR1_1_1	0.00572	0.01794			M2(t-1)
	AR1_1_2	8.80184	27.61405			Gasoline_P (t-1)
	AR2_1_1	-1.01107	0.08755	-11.55	0.0001	D_M2(t-1)
	AR2_1_2	-7.31258	21.36010	-0.34	0.7329	D_Gasoline_P (t-1)
	AR3_1_1	-0.49562	0.08510	-5.82	0.0001	D_M2(t-2)
	AR3_1_2	-10.09524	17.14879	-0.59	0.5575	D_Gasoline_P (t-2)
D_Gasoline_P	XL0_2_1	0.09873	0.19295	0.51	0.6101	Import_CONSP (t)
	XL0_2_2	0.25757	0.16807	1.53	0.1288	Export_OG (t)
	XL1_2_1	-0.08342	0.19487	-0.43	0.6696	Import_CONSP (t-1)
	XL1_2_2	0.40133	0.16719	2.40	0.0183	Export_OG (t-1)
	AR1_2_1	-0.00079	0.00010			M2(t-1)
	AR1_2_2	-1.21978	0.14950			Gasoline_P (t-1)
	AR2_2_1	-0.00017	0.00047	-0.36	0.7196	D_M2(t-1)
	AR2_2_2	0.36093	0.11564	3.12	0.0024	D_Gasoline_P (t-1)
	AR3_2_1	0.00012	0.00046	0.25	0.8014	D_M2(t-2)
	AR3_2_2	0.20376	0.09284	2.19	0.0306	D_Gasoline_P (t-2)

Table 8: Univariate model ANOVA diagnostic

Variable	R-square	Standard deviation	F value	P-value
M2	0.6151	69445.87729	16.69	<0.0001
Gasoline_P	0.5139	375.98107	11.04	<0.0001

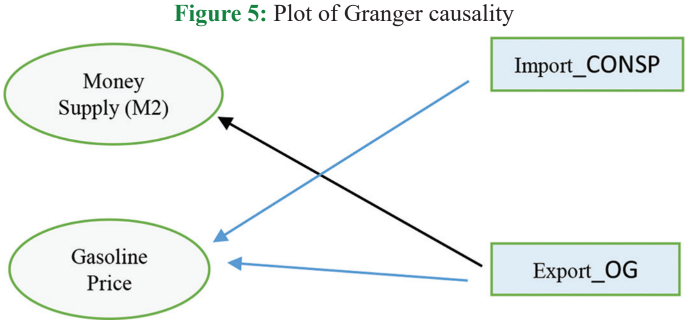
Table 9 : Univariate model white noise diagnostics

Variable	Durbin–	Normality		ARCH	
	Watson	Chi-square	P-value	F value	P-value
M2	2.19749	80.37	<0.0001	6.65	0.0114
Gasoline_P	1.93957	138.71	<0.0001	13.78	0.0003

Table 10: Roots of AR characteristic polynomial

Index	Real	Imaginary	Modulus	Radian	Degree
1	1.00000	0.00000	1.0000	0.0000	0.0000
2	0.30499	0.58843	0.6628	1.0926	62.6020
3	0.30499	–0.58843	0.6628	–1.0926	–62.6020
4	–0.44874	0.00000	0.4487	3.1416	180.0000
5	–0.51272	0.49346	0.7116	2.3753	136.0963
6	–0.51272	–0.49346	0.7116	–2.3753	–136.0963

Figure 5: Plot of Granger causality



to a shock (Import_CONSP$_t$) at 28,2142, in the 4th month, M2 (M2$_{t+4}$) responded at 14,3537 due to a shock of Import_CONSP$_t$ of one unit, in the 5th month, M2 (M2$_{t+5}$) responded at 26,3350 due to a shock of Import_CONSP$_t$ of one unit, from the 6th to the 12th month, M2 responded stably at approximately 21. Figure 6b and Table 12 show the response of M2 for the next several periods caused by a change (shock) of one unit of export oil and gas (Export_OG$_t$). In month t = 0, M2 responded by 49.4068, in the following month, M2 (M2$_{t+1}$) responded at 32.168, in the 2nd month, M2 (M2$_{t+2}$) responded at 25.1589 due to a shock in oil and gas exports of one unit, in the 3rd month, M2 (M2$_{t+3}$) responded at 42.4186 due to a shock in the export of oil and gas of one unit, in the 4th month, M2 (M2$_{t+4}$) responded at 32.4022 due to a shock of Export_OG$_t$ of one unit, from the 15th to 12 month, M2 responded stably at approximately 34. Figure 6a and Table 12 show the response of gasoline price for the next several periods caused by a one-unit change (shock) from import consumption (Import_CONSP$_t$). In month t = 0, gasoline price (Gasoline_P$_t$) responded at 0.0987, in the following month, gasoline price (Gasoline_P$_{t+1}$) responded negatively at −0.1157, in the second and next month, the impact of the shock (Import_CONSP$_t$) weakened and headed for balance. Figure 6b and Table 12 show the response of gasoline price for the next several periods caused by a change (shock) of one unit of export oil and gas (Export_OG$_t$). In month t = 0, gasoline price (Gasoline_P$_t$) responded at 0.2575, in the following month, gasoline price (Gasoline_P$_{t+1}$) responded at 0.3900, in the 3rd month, gasoline price (Gasoline_P$_{t+3}$) responded at −0.1348 due to export shock of oil and gas by one unit, and in the 4th month, gasoline price (Gasoline_P$_{t+4}$) responded at −0.1355 due to the Export_OG$_t$ shock of one unit in the clime month and the next effect from the shock (Export_OG$_t$) weakened toward balance.

Figure 7a and Table 13 show the response of M2 for the next several periods caused by a shock of one unit of money supply (M2$_t$). In the 1st month t = 1, M2$_{t+1}$ responded at −0.0053, in the 2nd month, M2 (M2$_{t+2}$) responded at 0.5140, in the 3rd month, M2 (M2$_{t+3}$) responded due to a shock (Import_CONSP$_t$) at 0.4930, in the 4th month, M2 (M2$_{t+4}$) responded due to a shock (M2$_t$) at 0.2488, in the 5th month, M2 (M2$_{t+5}$) responded at 0.5100 due to a shock of one unit M2$_t$, in the 6th month, M2 (M2$_{t+6}$) responded at 0.3658 due to a one-unit M2$_t$ shock, in the 7th month, M2 (M2$_{t+7}$) responded at 0.3815 due to a one-unit M2$_t$ shock, in the 8th month,

Table 11: Granger causality wald test

Test	Group variables	DF	Chi-square	P-value	Conclusion
1	Group 1 Variables: M2 Group 2 Variables: Import_CONSP	2	0.76	0.6825	Do not reject Ho
2	Group 1 Variables: M2 Group 2 Variables: Gasoline P	2	0.30	0.8608	Do not reject Ho
3	Group 1 Variables: M2 Group 2 Variables: Export_OG	2	8.87	0.0119	Reject Ho
4	Group 1 Variables: M2 Group 2 Variables: Import CONSP, Gasoline P	4	1.07	0.8989	Do not reject Ho
5	Group 1 Variables: M2 Group 2 Variables: Export OG, Gasoline_P	4	9.24	0.0554	Reject Ho
6	Group 1 Variables: Gasoline_P Group 2 Variables: Import CONSP, Export_OG	4	11.02	0.0263	Reject Ho
7	Group 1 Variables: Gasoline_P Group 2 Variables: Import_CONSP	2	0.39	0.8215	Do not reject Ho
8	Group 1 Variables: Gasoline_P Group 2 Variables: Export_OG	2	2.25	0.3250	Do not reject Ho
9	Group 1 Variables: Gasoline_P Group 2 Variables: M2	2	3.45	0.1778	Do not reject Ho
10	Group 1 Variables: Gasoline_P Group 2 Variables: Import_CONSP, M2	4	3.67	0.4527	Do not reject Ho
11	Group 1 Variables: Gasoline_P Group 2 Variables: Export_OG, M2	4	7.30	0.1207	Do not reject Ho
12	Group 1 Variables: Gasoline_P Group 2 Variables: Import_CONSP, Export_OG	4	3.45	0.4852	Do not reject Ho

Table 12: Impulse response function of transfer function by variable

Variable Response\Impulse	Lag	Import_CONSP	Export_OG	Variable Response\Impulse	Lag	Import_CONSP	Export_OG
M2	0	47.98511	49.40681	Gasoline_P	0	0.0987	0.2575
	1	6.36128	32.11689		1	–0.1157	0.3900
	2	24.25272	25.15892		2	–0.0242	–0.0021
	3	28.21428	42.41863		3	–0.0324	–0.1348
	4	14.35371	32.40225		4	0.0018	–0.1355
	5	26.33508	34.31191		5	0.0017	–0.0194
	6	20.91106	36.52846		6	–0.0179	0.0173
	7	20.56345	32.26133		7	–0.0174	0.0040
	8	23.76240	35.42289		8	–0.0168	–0.0227
	9	20.67835	34.67388		9	–0.0154	–0.0364
	10	22.17728	34.11217		10	–0.0114	–0.0293
	11	22.17266	35.07427		11	–0.0139	–0.0208

Table 13: Impulse response function of transfer function by variable

Variable Response/impulse	Lag	M2	Gasoline_P	Variable Response/impulse	Lag	M2	Gasoline_P
M2	1	−0.0053	1.4892	Gasoline_P	1	−0.00096	0.14115
	2	0.5140	−2.5804		2	0.00016	−0.13868
	3	0.4930	10.2773		3	−0.00044	−0.24261
	4	0.2488	0.8026		4	−0.00022	−0.05203
	5	0.5100	3.2118		5	−0.00015	0.06152
	6	0.3658	3.2774		6	−0.00037	0.06224
	7	0.3819	1.4320		7	−0.00022	0.00739
	8	0.4385	3.7324		8	−0.00026	−0.02209
	9	0.3722	2.9174		9	−0.00028	−0.02053
	10	0.4114	2.7235		10	−0.00023	−0.00284
	11	0.4048	3.1689		11	−0.00028	0.00511
	12	0.3918	2.6410		12	−0.00026	0.00274

M2 ($M2_{t+8}$) responded at 0.4385 due to a one-unit $M2_t$ shock, in the 9th month, M2 ($M2_{t+9}$) responded at 0.3722 due to an $M2_t$ shock of one unit, in the 10th month, M2 ($M2_{t+10}$) responded at 0.4114 due to an $M2_t$ shock of one unit, in the 11th month, M2 ($M2_{t+11}$) responded at 0.4048 due to an $M2_t$ shock of one unit, and in the 7th month, M2 ($M2_{t+12}$) responded at 0.3918 due to an $M2_t$ shock of one unit. Figure 7b and Table 13 show the response of M2 for the next several periods caused by a one-unit shock of gasoline

Figure 6: (a) Response to impulse in import consumption and (b) response to impulse in export oil and gas

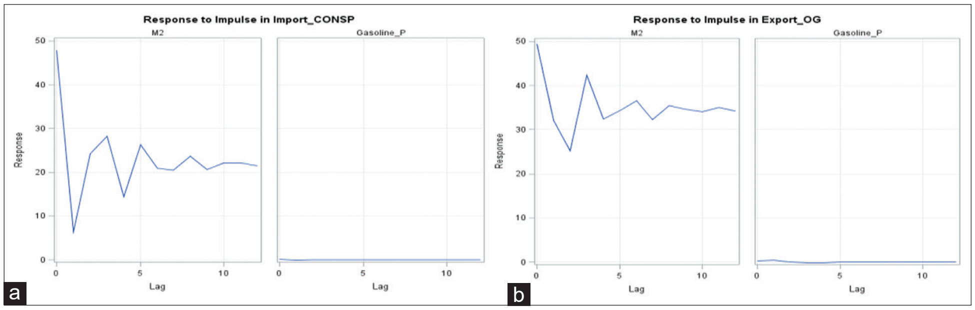


Figure 7: (a) Response to impulse in money supply (M2) and (b) response to impulse in gasoline price

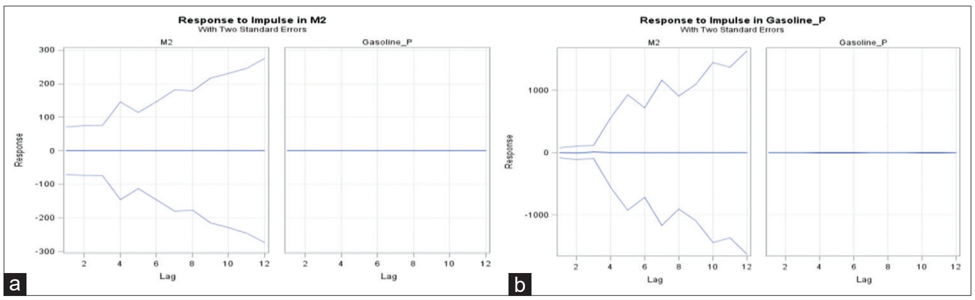


Figure 8: (a) Model and forecasting for M2 and (b) forecasting for M2

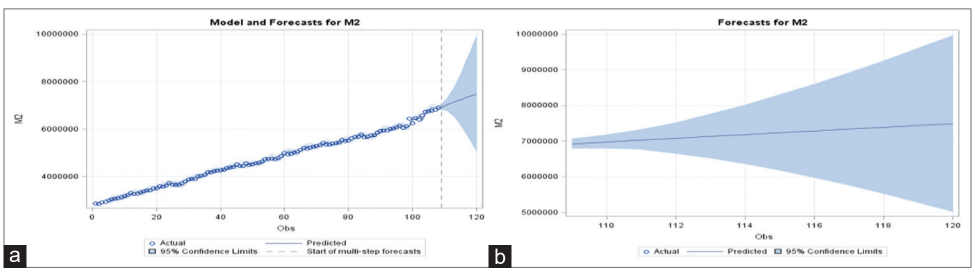
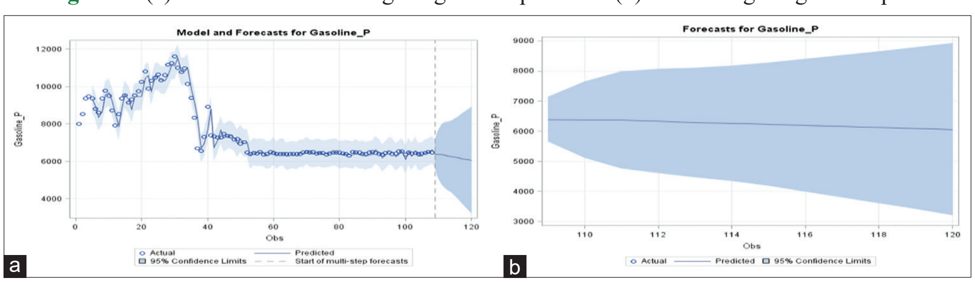


Figure 9: (a) Model and forecasting for gasoline price and (b) forecasting for gasoline price



price (Gasoline_P$_t$). In month $t = 1$, M2 responded at 1.4892, in the 2nd month, M2 (M2$_{t+2}$) responded at −2.5804, in the 3rd month, M2 (M2$_{t+3}$) responded due to a shock (Gasoline_P$_t$) at 10.2773, in the 4th month, M2 (M2$_{t+4}$) responded due to a shock (M2$_t$) at 0.8026, in the 5th month, M2 (M2$_{t+5}$) responded at 3.2118 due to a Gasoline_P$_t$ shock of one unit, in the 6th month, M2 (M2$_{t+6}$) responded at 3.2774 due to a Gasoline_P$_t$ shock of one unit, in the 7th month, M2 (M2$_{t+7}$) responded at 1.4320 due to a Gasoline_P$_t$ shock of one unit, in the 8th month, M2 (M2$_{t+8}$) responded at 3.7324 due to a Gasoline_P$_t$ shock of one unit, in the 9th month, M2 (M2$_{t+9}$) responded at 2.9174 due to a Gasoline_P$_t$ shock of one unit, in the 10th month, M2 (M2$_{t+10}$) responded at 2.7235 due to a Gasoline_P$_t$ shock of one unit, in the 11th month, M2 (M2$_{t+11}$) responded at 3.1689 due to a Gasoline_P$_t$ shock of one unit, and in the 12th month, M2 (M2$_{t+12}$) responded at 2,6410 due to a Gasoline_P$_t$ shock of one unit. Figure 7a and Table 13 show that there is no significant effect on gasoline price (Gasoline_P) for the next several periods caused by a one-unit shock of money supply (M2$_t$); this can be seen in the flat and flat IRF chart, very small values in Table 13. Figure 7b and Table 13 show the response of the gasoline price (Gasoline_P) for the next several periods caused by a shock of one unit of gasoline price (Gasoline_P$_t$). In month $t = 1$, gasoline price responded at 0.1411, in the 2nd month, gasoline price (Gasoline_P$_{t+2}$) responded at −0.1386, in the 3rd month, gasoline price (Gasoline_P$_{t+3}$) responded due to a shock (Gasoline_P$_t$) at −0.2426, and its influence in the following months weakened toward balance.

Table 14: Forecasting M2 and gasoline price for the next 12 months

Variable	Obs	Forecast	Standard error	95% Confidence limits	
M2	109	6920745.0529	71298.7977	6781001.9771	7060488.1286
	110	6980522.9206	99277.5555	6785942.4872	7175103.3540
	111	7040670.2889	144069.3370	6758299.5771	7323041.0008
	112	7076551.1534	226237.7535	6633133.3044	7519969.0023
	113	7135176.1026	319823.5311	6508333.5001	7762018.7050
	114	7184716.8870	424292.5392	6353118.7911	8016314.9829
	115	7232582.0079	543537.7752	6167267.5443	8297896.4716
	116	7285683.4903	669967.3157	5972571.6806	8598795.3000
	117	7334341.5502	806363.4861	5753898.1589	8914784.9414
	118	7385328.0278	951511.6585	5520399.4462	9250256.6093
	119	7436014.1721	1103878.640	5272451.7932	9599576.5510
	120	7485730.0022	1264305.752	5007736.2623	9963723.7421
Gasoline_P	109	6394.7824	381.7845	5646.4984	7143.0663
	110	6377.1202	648.7442	5105.6049	7648.6356
	111	6372.6568	820.7713	4763.9745	7981.3391
	112	6335.3253	888.8149	4593.2800	8077.3705
	113	6286.0547	930.1139	4463.0649	8109.0445
	114	6255.4893	978.7385	4337.1971	8173.7815
	115	6227.9807	1046.0754	4177.7104	8278.2510
	116	6195.6524	1125.3396	3990.0273	8401.2776
	117	6159.7520	1205.5393	3796.9384	8522.5657
	118	6129.8363	1286.8463	3607.6639	8652.0088
	119	6095.8961	1371.6207	3407.5688	8784.2233
	120	6062.2770	1461.8079	3197.1859	8927.3680

3.9. Forecasting

The VECMX(3,1) model with cointegration rank = 1 is the best model for money supply (M2) and gasoline price (Gasoline_P) data based on AICC criteria and from comparison with several other models, VECMX(2,1), VECMX(2, 2), VECMX(3,2), and VECMX(4,1). Table 10 shows that the VECMX(3,1) model is a stable model. From Table 8, which explains the shape of the univariate diagnostic ANOVA model with the dependent variables, respectively, $M2_t$ and $Gasoline\_P_t$, the model is very significant with p-values <0.0001 and <0.0001 for variables M2t and Gasoline_Pt, respectively. Graph of residuals in Figure 3a and Figure 4a show close to normality. From Figure 8a for the M2 data, it appears that the model is very good where the predicted and observed values are close to each other, as well as Figure 9a for the Gasoline_P data. Therefore, the VECMX(3,1) model with cointegration rank = 1 is very suitable to be used for forecasting for the next 12 months. From the forecasting results for M2 data, Table 14 and Figure 8b shows an increasing trend for the next 12 months and the confidence interval seems to enlarge as the forecast period is far away. Meanwhile, from forecasting for Gasoline_P data, Table 14 and Figure 9b, for the next 12 months, the trend is decreasing, although slightly where in the 1st month the forecast is 6394.7822 and in the 12th month the forecast is 6062.2770. Figure 9b shows that the confidence interval for forecasting is relatively homogeneous.

4. CONCLUSION

Based on the analysis of time series data on the gasoline price (Gasoline_P), the money supply in a broad sense (M2) as endogenous variables, and import consumption (Import_CONSP) and export oil and gas (Export_OG) as exogeneous variables of monthly data from 2012 to 2020, the best model is VECMX(3,1) with cointegration rank = 1. Based on this best model, VECMX(3,1), further analysis was carried out. From the results of the Granger causality analysis, it can be concluded that M2 is significantly influenced by its own past information and current and past information on the value of export oil and gas (Export_OG), whereas gasoline price is significantly influenced by its own past information and past information then and now of the Import_CONSP and Export_OG values. From the results of the IRF analysis for the shock of one unit of import consumption, it affects the M2 value for the next 12 months; if there is a shock of one Export_OG unit, it will affect the value of M2 for the next 12 months; if there is a shock of one unit on M2, then M2 will be affected for the next 12 months; and if there is a one unit shock in the gasoline price, then M2 will be affected for the next 12 months. From the results of the IRF analysis for the shock of one unit of import consumption, it will affect the value of gasoline price for the next 2 months; if there is a shock of one Export_OG unit, it will affect the value of gasoline prices for the next 4 months; if there is a shock of one unit on M2, the gasoline price will not respond; and if there is a one-unit shock on the gasoline price, the gasoline price will be affected for the next 3 months. From the results of forecasting for the next 12 months, the forecasting value for M2 has an upward trend, whereas forecasting for gasoline prices for the next 12 months has a downward trend.

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