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 \( Y_t, Y_{t+1}, \ldots, Y_n \). Thus, \( Y_t \) represents the time at \( t \), where \( Y \) is a random variable. The stochastic process is a part of the time index of random variables \( Y(o, t) \), 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) \( \text{Cov}(X_t) = \Sigma, k \times k \) 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:

\[
\Delta X_t = \alpha + \phi X_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta X_{t-i} + \epsilon_t
\]

where \( \Delta X_t = X_t - X_{t-1} \), and \( \epsilon_t \) is white noise. The null hypothesis is \( H_0: \phi = 0 \), and the data are nonstationary. The statistic test is \( \tau(\tau) \) 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:

\[
\text{ADF} = \frac{\phi}{\text{Se}(\phi)}
\]

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:

\[
\text{Tr}(r) = -T \sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i)
\]

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

\[
\hat{\lambda}_{max}(r, r+1) = -T \ln\left(1-\hat{\lambda}_i\right)
\]
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:

\[ Y_t = \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t \]  
(5)

where \( Y_t \) is the \( n \times 1 \) vector observation at the time \( t \), \( \Phi_i \) is the \( n \times n \) matrix coefficient of vector \( Y_{t-i} \) for \( i = 1, 2, \ldots, p \), and \( p \) is the lag length, and \( \varepsilon_t \) 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):

\[ \Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \]  
(6)

The VECM model can consider deterministic values. The deterministic term (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:

\[ \Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \sum_{i=0}^{s} \Phi_{it} X_{t-i} + \sum_{i=0}^{s} \Phi_{xti} X_{t-i} + \varepsilon_t \]  
(7)

where \( \Delta \) is the operator of differences, \( \Delta Y = Y_{t+i} - Y_{t+i-1} \), \( Y_{t+i-1} \) is the vector of an endogenous variable at lag \(-1\), \( \varepsilon_t \) is the \( k \times 1 \) vector white noise, \( \Pi \) is the matrix coefficient of cointegration, and \( \Pi = \alpha \beta \), \( \alpha \) is matrix adjustment, \((k \times r)\) and \( \beta \) is matrix cointegration \((k \times k)\) for the \( i \) variable endogenous, and \( \Phi_i \) is 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:

\[ JB = \frac{N}{6} b_1^2 + \frac{N}{24} (b_2 - 3)^2 \]  
(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 \( \chi^2 \) distribution with 2 degrees of freedom (Jarque and Bera, 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:

\[ y_t = \psi_1 y_{t-1} + \cdots + \psi_p y_{t-p} + \varepsilon_t \]  
(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

\[ \det (L_p - \Phi) = \det (I - \Phi z - \cdots - \Phi_{p-1} z^{p-1}) \]  
(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:

\[ y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{m,t} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mp} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{m,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ \vdots \\ e_{m,t} \end{bmatrix} \]  
(11)

where \( y_t \) consists of vectors \( y_{1,t}, y_{2,t}, \ldots, y_{m,t} \) and is said not to be a Granger causality for \( y_{j,t} \) if the coefficient matrix of parameter \( B_{ij} \) for \( i = 1, \ldots, p \) (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 \( X_i \) is said to be Granger because of variable \( Y_j \) if the past and present values of \( X_i \) can predict the current value of \( Y_j \). If a variable of \( X_i \) is the Granger causality of variable \( Y_j \) and not vice versa, then it is called direct Granger causality. If Granger causality exists in both, from \( X_i \) to \( Y_j \) and from \( Y_j \) to \( X_i \), 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 (\( \infty \)) as follows:

\[ X_t = \mu + \mu_1 \Psi_1 X_{t-1} + \cdots + \mu_n \Psi_n X_{t-n} + \varepsilon_t \]  
(12)

Thus, the matrix is interpreted as follows:

\[ \frac{\partial X_{t+1}}{\partial \mu_i} = \Psi_{s+1} \]  

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 \( t \) for the \( i \) variable at time \( t+s \) (\( X_{t+i} \)) and all other innovation. If the element of \( \mu_i \) changed by \( \delta_1 \), at the same time, the second element will change by \( \delta_2 \), and the \( n \)th element will change by...
\[ \Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial h_t} \delta_1 + \frac{\partial X_{t+s}}{\partial h_{t+1}} \delta_2 + \cdots + \frac{\partial X_{t+s}}{\partial h_{n}} \delta_n = \Psi_s \delta \]  

The plot of the \(i\)-th row and \(j\)-th column of \(\Psi_s\) 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 (Export_OG) data also decays very slowly, showing that the export oil and gas data also is not stationary.

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 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 (\(\tau\)) 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 (\(d = 1\)).

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.
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.

| 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  |

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.
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 \( H_0 : \text{rank} > r \) (\( r = 0 \)). The test for \( H_0 : \text{rank} = 1 \) 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.
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 \( \Delta Y_t = \begin{bmatrix} M_{2t} \\ \text{Gasoline}_{P_t} \end{bmatrix}, X_t = \begin{bmatrix} \text{Import}_\text{CONSP} \\ \text{Export}_\text{OG} \end{bmatrix}, \) and \( \Gamma_1, \Gamma_2, \Phi_0 \) and \( \Phi_1 \) are 2 × 2 matrix parameters and \( \varepsilon_t = \begin{bmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \end{bmatrix}. \)

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

\[ \begin{bmatrix} M_{2t} \\ \text{Gasoline}_{P_t} \end{bmatrix} = \begin{bmatrix} 0.0057 & 8.8018 \\ -0.0008 & -12.198 \end{bmatrix} \begin{bmatrix} M_{2t-1} \\ \text{Gasoline}_{P_{t-1}} \end{bmatrix} + \begin{bmatrix} -1.0111 & -7.3126 \\ 0.0002 & 0.3609 \end{bmatrix} \begin{bmatrix} M_{2t-1} \\ \text{Gasoline}_{P_{t-1}} \end{bmatrix} + \begin{bmatrix} -0.4956 & -100952 \\ 0.0001 & 0.2037 \end{bmatrix} \begin{bmatrix} M_{2t-2} \\ \text{Gasoline}_{P_{t-2}} \end{bmatrix} + \begin{bmatrix} 47.9851 & 49.4068 \\ 0.0987 & 0.2575 \end{bmatrix} \begin{bmatrix} \text{Import}_\text{CONSP} \\ \text{Export}_\text{OG} \end{bmatrix} + \begin{bmatrix} 6.4711 & 31.9977 \\ -0.0834 & 0.4013 \end{bmatrix} \begin{bmatrix} \text{Import}_\text{CONSP}_{t-1} \\ \text{Export}_\text{OG}_{t-1} \end{bmatrix} \]

with the Covariance of Innovations

\[ \text{Var} \begin{bmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \end{bmatrix} = \begin{bmatrix} 4822729872.3 & 134363.1558 \\ 134363.1558 & 141361.7650 \end{bmatrix} \]

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). 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) 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_2_1   | 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_2_1   | 31.99778 | 30.88119       | 1.04    | 0.3028  | Export_OG (t-1) |
|          | AR1_1_1   | 0.00572  | 0.01794        | -0.49346| 0.6628  | Import_CONSP (t-2) |
|          | AR1_1_2   | 8.80184  | 27.61405       | -1.0926 | 0.25757 | Export_OG (t-1) |
|          | AR2_1_1   | -1.01107 | 0.08755        | -11.55  | 0.0001  | Import_CONSP (t-2) |
|          | AR2_1_2   | -7.31258 | 21.36010       | -0.34   | 0.7329  | Export_OG (t-1) |
|          | AR3_1_1   | -0.49562 | 0.08510        | -5.82   | 0.0001  | Import_CONSP (t-3) |
|          | AR3_1_2   | -10.09524| 17.14879       | -0.59   | 0.5575  | Export_OG (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   | 0.6996  | 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        | -0.36   | 0.7196  | Export_OG (t-1) |
|          | AR1_2_2   | -1.21978 | 0.14950        | -0.0047 | 0.9883  | Export_OG (t-1) |
|          | AR2_2_1   | -0.36093 | 0.11564        | 3.12    | 0.0024  | Export_OG (t-1) |
|          | AR3_2_1   | 0.00012  | 0.00046        | 0.25    | 0.8014  | Export_OG (t-1) |
|          | AR3_2_2   | 0.20376  | 0.09284        | 2.19    | 0.0306  | Export_OG (t-1) |

Table 8: Univariate model ANOVA diagnostic

| Variable  | R-square | Standard deviation | F value | P-value |
|-----------|----------|--------------------|---------|---------|
| M2        | 0.6151   | 69.445.87729       | 16.69   | <0.0001 |
| Gasoline_P| 0.5139   | 37.98107           | 11.04   | <0.0001 |

Table 9: Univariate model white noise diagnostics

| Variable  | Durbin–Watson | Normality | ARCH |
|-----------|---------------|-----------|------|
| Durbin–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 | 1.00000 | 0.00000 | 0.00000 |
| 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

Money Supply (M2) → Import_CONSP → Gasoline Price → Export_OG

Figure 5a 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). In month t = 0, M2 responded by 49.4068, in the following month, M2 (M2<sub>t</sub>) responded at 32.168, in the 2<sup>nd</sup> month, M2 (M2<sub>t+1</sub>) responded at 25.1589 due to a shock in oil and gas exports of one unit, in the 3<sup>rd</sup> month, M2 (M2<sub>t+2</sub>) responded at 42.4186 due to a shock in the export of oil and gas of one unit, in the 4<sup>th</sup> month, M2 (M2<sub>t+3</sub>) responded at 34.2014 due to a shock in the export of oil and gas of one unit, in the 5<sup>th</sup> month, M2 (M2<sub>t+4</sub>) responded at 0.3815 due to a one-unit M2 shock.

Figure 6a 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). In month t = 0, M2 responded by 49.4068, in the following month, M2 (M2<sub>t</sub>) responded at 32.168, in the 2<sup>nd</sup> month, M2 (M2<sub>t+1</sub>) responded at 25.1589 due to a shock in oil and gas exports of one unit, in the 3<sup>rd</sup> month, M2 (M2<sub>t+2</sub>) responded at 42.4186 due to a shock in the export of oil and gas of one unit, in the 4<sup>th</sup> month, M2 (M2<sub>t+3</sub>) responded at 34.2014 due to a shock in the export of oil and gas of one unit, in the 5<sup>th</sup> month, M2 (M2<sub>t+4</sub>) responded at 0.3815 due to a one-unit M2 shock.
M2 (M2\_t) responded at 0.4385 due to a one-unit M2\_t shock, in the 9\textsuperscript{th} month, M2 (M2\_t) responded at 0.3722 due to an M2\_t shock of one unit, in the 10\textsuperscript{th} month, M2 (M2\_t) responded at 0.4114 due to an M2\_t shock of one unit, in the 11\textsuperscript{th} month, M2 (M2\_t) responded at 0.4048 due to an M2\_t shock of one unit, and in the 12\textsuperscript{th} month, M2 (M2\_t) 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.

Table 11: Granger causality wald test

| Test | Group variables | DF | Chi-square | P-value | Conclusion |
|------|-----------------|----|------------|---------|------------|
| 1 | Group 1 Variables: M2 | 2 | 0.76 | 0.6825 | Do not reject Ho |
| 2 | Group 2 Variables: Import_CONSP | 2 | 0.30 | 0.8608 | Do not reject Ho |
| 3 | Group 1 Variables: M2 | 2 | 8.87 | 0.0119 | Reject Ho |
| 4 | Group 2 Variables: Export_OG | 4 | 1.07 | 0.8989 | Do not reject Ho |
| 5 | Group 1 Variables: M2 | 4 | 9.24 | 0.0054 | Reject Ho |
| 6 | Group 2 Variables: Import_CONSP, Export_OG | 4 | 11.02 | 0.0026 | Reject Ho |
| 7 | Group 1 Variables: Gasoline_P | 2 | 0.39 | 0.8215 | Do not reject Ho |
| 8 | Group 2 Variables: Import_CONSP | 2 | 0.39 | 0.8215 | Do not reject Ho |
| 9 | Group 1 Variables: Gasoline_P | 2 | 0.39 | 0.8215 | Do not reject Ho |
| 10 | Group 2 Variables: Import_CONSP, M2 | 4 | 3.67 | 0.4527 | Do not reject Ho |
| 11 | Group 1 Variables: Gasoline_P | 4 | 7.30 | 0.1207 | Do not reject Ho |
| 12 | 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 | Gasoline_P |
|---------------------------|-----|--------------|-----------|------------|
| M2                        | 0   | 47.98511     | 49.40681  | 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     | 32.62133  | 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 | Gasoline_P |
|---------------------------|-----|----|------------|------------|
| M2                        | 1   | −0.0093 | 1.4892     | 1.4892     |
|                           | 2   | 0.5140  | −2.5804    | −2.5804    |
|                           | 3   | 0.4930  | 10.2773    | 10.2773    |
|                           | 4   | 0.2488  | 0.8026     | 0.8026     |
|                           | 5   | 0.5100  | 3.2118     | 3.2118     |
|                           | 6   | 0.3658  | 3.2774     | 3.2774     |
|                           | 7   | 0.3819  | 1.4320     | 1.4320     |
|                           | 8   | 0.4385  | 3.7324     | 3.7324     |
|                           | 9   | 0.3722  | 2.9174     | 2.9174     |
|                           | 10  | 0.4114  | 2.7235     | 2.7235     |
|                           | 11  | 0.4048  | 3.1689     | 3.1689     |
|                           | 12  | 0.3918  | 2.6410     | 2.6410     |

M2 (M2\_t) responded at 0.4385 due to a one-unit M2\_t shock, in the 9\textsuperscript{th} month, M2 (M2\_t) responded at 0.3722 due to an M2\_t shock of one unit, in the 10\textsuperscript{th} month, M2 (M2\_t) responded at 0.4114 due to an M2\_t shock of one unit, in the 11\textsuperscript{th} month, M2 (M2\_t) responded at 0.4048 due to an M2\_t shock of one unit, and in the 7\textsuperscript{th} month, M2 (M2\_t) 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.
price (Gasoline\_P). In month $t = 1$, M2 responded at 1.4892, in the 2\textsuperscript{nd} month, M2 (M2\_t-2) responded at −2.5804, in the 3\textsuperscript{rd} month, M2 (M2\_t-3) responded due to a shock (Gasoline\_P) at 10.2773, in the 4\textsuperscript{th} month, M2 (M2\_t-4) responded due to a shock (M2) at 0.8026, in the 5\textsuperscript{th} month, M2 (M2\_t-5) responded due to a Gasoline\_P shock of one unit, in the 6\textsuperscript{th} month, M2 (M2\_t-6) responded at 3.2774 due to a Gasoline\_P shock of one unit, in the 7\textsuperscript{th} month, M2 (M2\_t-7) responded at 1.4320 due to a Gasoline\_P shock of one unit, in the 8\textsuperscript{th} month, M2 (M2\_t-8) responded at 3.7324 due to a Gasoline\_P shock of one unit, in the 9\textsuperscript{th} month, M2 (M2\_t-9) responded at 2.9174 due to a Gasoline\_P shock of one unit, in the 10\textsuperscript{th} month, M2 (M2\_t-10) responded at 2.7235 due to a Gasoline\_P shock of one unit, in the 11\textsuperscript{th} month, M2 (M2\_t-11) responded at 3.1689 due to a Gasoline\_P shock of one unit, and in the 12\textsuperscript{th} month, M2 (M2\_t-12) responded at 2.6410 due to a Gasoline\_P 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); 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). In month $t = 1$, gasoline price responded at 0.1411, in the 2\textsuperscript{nd} month, gasoline price (Gasoline\_P\_t+2) responded at −0.1386, in the 3\textsuperscript{rd} month, gasoline price (Gasoline\_P\_t+3) responded due to a shock (Gasoline\_P) at −0.2426, and its influence in the following months weakened toward balance.
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, and Gasoline_P, 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 exogenous 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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