Journal of Physics: Conference Series

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Application of Vector Error Correction Model (VECM) and Impulse Response Function for Daily Stock Prices

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Abstract. Vector Error Correction Model is a cointegrated VAR model. This idea of Vector Error Correction Model (VECM), which consists of a VAR model of the order p - 1 on the differences of the variables, and an error-correction term derived from the known (estimated) cointegrating relationship. Intuitively, and using the stock market example, a VECM model establishes a short-term relationship between the stock prices, while correcting with the deviation from the long-term comovement of prices. An Impulse Response Function traces the incremental effect of a 1 unit (or one standard deviation) shock in one of the variables on the future values of the other endogenous variables. Impulse Response Functions trace the incremental effect of the marketing action reflected in the shock. The data used in this analysis are 4 (four) daily plantation stocks prices in Indonesia with time period of January to July in three years which are 2018, 2019, and 2020. The objective of this study is to determine the relationship among 4 (four) stocks prices with VECM and to know the behaviour of each stocks prices with Impulse Response.

Keyword: Impulse Response Function, VAR, VECM, Granger Causality

1. Introduction

A time series data is a series of data listed in time order. The multivariate time series data is a time series data that has more than one time-dependent variable. In the stock market, there are various multivariate time series data. In this study, plantation stock prices analyzed with Vector Error Correction Model. According to Medvegyef (2015) Vector Error Correction Model is a cointegrated VAR model. The standard VAR (Vector Autoregression) models can only be estimated when the variables are stationary [6]. However not all data is stationary, with that reason VECM model is made. In this study the plantation stock prices which are going to be analyzed are daily stock prices of PT. Provident Agro Tbk, PT. PP London Sumatera Indonesia Tbk, PT. Sampoerna Agro Tbk, and PT. Sawit Sumbermas Sarana. Due to COVID-19 there is some shock in stock market, in this study the stock prices are going to be analyzed in three times periode,.with time period of January to July in three years which are 2018, 2019, and 2020 to see if the stock prices is affected by the shock. The data used in this paper cited from Yahoo Finance (2020) [9].

2. Statistical Model

2.1. Cointegration

According to Engle and Granger (1987), A cointegration test is used to establish if there is a correlation betweem several time series in the long term [3]. According to Lütkehpohl (2005), The Johansen test can be seen as a multivariate generalization of the augmented Dickey-Fuller test [5]. The generalization is the examination of linear combinations of variables for unit roots. If there are three variable seach with unit roots,there are at most two cointegrating vectors.

More generally, if there are n variables which all have unit roots,there are at most n−1 cointegrating vectors. The Johansen test provides estimates of all cointegrating vectors. The Johansen tests are based on eigenvalues of transformations of the data and represent linear combinations of the data that have maximum correlation (canonical correlations). To repeat, the eigenvalues used in Johansen's test are *not* eigenvalues of the matrix $\mathbf{\Pi}$ directly, although the eigenvalues in the test also can be used to determine the rank of $\mathbf{\Pi}$ and have tractable distributions.

Suppose that eigenvalues for the Johansen test have been computed. Order the n eigenvalues by size so $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n$ and recall that $\lambda_i \geq 0$ for all i. If $\lambda_1 = 0$, then the rank of $\mathbf{\Pi}$ is zero and there are no cointegrating vectors. If $\lambda_1 \, f= 0$, then the rank of $\mathbf{\Pi}$ is greater than or equal to one and there is at least one cointegrating vector. The Johansen tests are likelihood-ratio tests. There are two tests: 1. the maximum eigenvalue test, and 2. the trace test. For both test statistics, the initial Johansen test is a test of the null hypothesis of no cointegration against the alternative of cointegration. The tests differ in terms of the alternative hypothesis

2.1.1 *Maximum Eigenvalue Test*

The maximum eigenvalue test examines whether the largest eigenvalue is zero relative to the alternative that the next largest eigenvalue is zero. The first test is a test whether the rank of the matrix $\mathbf{\Pi}$ is zero. The null hypothesis is that rank ($\mathbf{\Pi}$) = 0 and the alternative hypothesis is that rank ($\mathbf{\Pi}$) = 1. For further tests, the null hypothesis is that rank ($\mathbf{\Pi}$) = 1,2... and the alternative hypothesis is that rank ($\mathbf{\Pi}$) = 2, 3,....

$$\lambda_{max}(r, r+1) = -T \ \ln(1 - \widehat{\lambda_\iota}) \tag{2.1}$$

2.1.2 *Trace Test*

The trace test is a test whether the rank of the matrix $\mathbf{\Pi}$ is r_0. The null hypothesis is that rank ($\mathbf{\Pi}$) = r_0. The alternative hypothesis is that r_0 < rank ($\mathbf{\Pi}$) $\leq n$, where n is the maximum number of possible cointegrating vectors. For the succeeding test if this null hypothesis is rejected, the next null hypothesis is that rank ($\mathbf{\Pi}$) = $r_0 + 1$ and the alternative hypothesis is that $r_0 + 1$ < rank ($\mathbf{\Pi}$) $\leq n$.

$$Tr(r) = -T \sum_{i=r+1}^{k} \ln(1 - \widehat{\lambda_\iota}) \tag{2.2}$$

$\widehat{\lambda_\iota}$: The estimation of Eigen values
T : Number of observations.
k : Number of endogenous variables.

2.2. Vector Autoregression (VAR)

Vector Autoregression (VAR) models were introduced by the macroeconometrician Christopher Sims (1980) to model the joint dynamics and causal relations among a set of macroeconomic variables. According to R S Tsay (2010) VAR(p) model is a multivariate version of Yule-Walker equation of a univariate AR(p) model [8]. The VAR(p) model can be written in the form

$$\mathrm{x_t} = \phi^*(\mathrm{x_{t-1}}) + \mathrm{b_t} \tag{2.3}$$

where:
$\mathrm{x_t}$: the element vector of at time
ϕ^*: Matrix order kp x kp which the elements are the coefficient of the vector $\mathrm{x_{t-1}}$
$\mathrm{b_t}$: Random vector of shock.

2.3. Vector Error Correction Model (VECM)

The standard VAR model discussed earlier can only be estimated when the variables are stationary. The conventional way to remove unit root model is to first differentiate the series. However, in the case of cointegraten series, this would lead to overdifferencing and losing information conveyed by the long-term comovement of variable levels. For that reason, the cointegrated VAR model is build.According to Medvegyev (2015) this idea of Vector Error Correction Model (VECM), which consists of a VAR model of the order p - 1 on the differences of the variables, and an error-correction term derived from the known (estimated) cointegrating relationship [6]. Intuitively, and using the stock market example, a VECM model establishes a short-term relationship between the stock prices, while correcting with the deviation from the long-term comovement of prices. An appropriate VECM model can be formulated as follows

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta y_{t-i} + \varepsilon_t \tag{2.4}$$

where:

Δ : Operator differencing, where $\Delta y_t = y_t - y_{t-1}$
y_{t-i} : Vector variable endogenous with the 1-st lag.
ε_t : Vector residual.
Γ_i : Matrix with order k × k of coefficient Endogenous of the i-th variable.
α : Vector adjustment, matrix with order (k × r)
β : Vector cointegration (long-run parameter) matrix (k × r)

2.4 The Length of The Optimal Lag

Minimum values of the criteria is used to determine the length of the lag to be chosen. Some commonly used criteria are as follows:

a. *Akaike Information Criterion* (AIC)

$$\text{AIC(p)} = \ln\left|\sum \hat{u}\,\hat{u}(p)\right| + (k + pk^2)\frac{2}{T} \tag{2.5}$$

b. *Final Prediction Error* (FPE)

$$\text{FPE(p)} = \left[\frac{T+kp+1}{T-kp-1}\right]^k \left|\sum \hat{u}\,\hat{u}(p)\right| \tag{2.6}$$

c. *Bayesian Criterion of* Gideon Schwartz (SBC)

$$\text{SC(p)} = \left|\sum \hat{u}\,\hat{u}(p)\right| + (k + pk^2)\frac{2\ln(\ln(\text{T}))}{T} \tag{2.7}$$

d. Hannan-Quinn *Criterion* (HQC)

$$\text{HQ} = \ln\left|\sum \hat{u}\,\hat{u}(p)\right| + (k + pk^2)\frac{\ln(\text{T})}{T} \tag{2.8}$$

Where $\hat{u}$ are denotes the residuals estimation from the model VAR(p), k number of dependent variables, T is number of observations and p is the length of model (Kirchgassner and Wolters, 2007).

2.5 Model Stability

According to Lütkehpohl (2005) a condition for stability for VAR(p) requires that all the eigenvalues of A (The AR Matrix of the comparison from Y_t) are smaller than one in modulus or all the roots larger than one [5]. Consider the VAR(p) model

$$Y_t = c + \emptyset_1 Y_{t-1} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t \tag{2.9}$$

Substituting t=1 we obtain

$$\begin{aligned}
Y_1 &= c + \emptyset_1 Y_0 + \varepsilon_1 \\
Y_2 &= c + \emptyset_1 Y_1 + \varepsilon_2 \\
&= c + \emptyset_1 (c + \emptyset_1 Y_0 + \varepsilon_1) + \varepsilon_2 \\
&= (I_k \emptyset_1)c + {\emptyset_1}^2 Y_0 + \emptyset_1 \varepsilon_1 + \varepsilon_2 \\
&\vdots
\end{aligned}$$

$$Y_t = \left(I_k + \emptyset_1 + \cdots + {\emptyset_1}^{t-1}\right)c + {\emptyset_1}^t Y_0 + \sum_{i=0}^{t-1} \phi_1^i \, \varepsilon_{t-i} \tag{2.10}$$

Therefore, if the eigenvalues are smaller than one in modulus then Y_t has the following representation

$$Y_t = (I - \emptyset)^{-1} + \sum_{i=0}^{j} \phi_1^i \, \varepsilon_{t-i} \tag{2.11}$$

Note that the eigenvalues of $\emptyset$ satisfy det $(I_{kp} + \emptyset_z) \neq 0$ for $|z|\leq 1$ therefore VAR(p) is called stable if

$$\det(I_{kp} + \emptyset_z) = \det(I_k - \emptyset_{1z} - \cdots - \emptyset_p z^p) \quad \text{for } |z|\leq 1 \tag{2.12}$$

2.6 Impulse Response Function

According to J A Petersen and V Kumar (2012), impulse response function traces the incremental effect of a 1 unit (or one standard deviation) shock in one of the variables on the future values of the other endogenous variables [7]. Consider the VAR(p) model

$$Y_t = A_0 + A_1 X_{t-1} + e_t \tag{2.13}$$

Where $A_0 = B^{-1}\Gamma_0$, $A_1 = B^{-1}\Gamma_1$ and $e_t = B^{-1}\varepsilon_t$

Vector error can be written as:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} = \frac{1}{\det(A_1)} \sum_{1=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}^i \times adj(A_1) \times \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \\ e_{3t-i} \end{bmatrix} \tag{2.14}$$

$\det(A_1)$ is a determinan value of A_1 and $\mathrm{adj}(A_1)$ is adjoint matrix of A_1, therefore:

$$\begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} + \frac{1}{\det(A_1)} \sum_{1=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}^i \times adj(A_1) \times \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \\ e_{3t-i} \end{bmatrix} \tag{2.15}$$

With ϕ matrix :

$$\begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix} + \sum_{1=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) & \phi_{13}(i) \\ \phi_{21}(i) & \phi_{22}(i) & \phi_{23}(i) \\ \phi_{31}(i) & \phi_{32}(i) & \phi_{33}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{xt-i} \\ \varepsilon_{yt-i} \\ \varepsilon_{zt-i} \end{bmatrix} \tag{2.16}$$

With elemen $\phi_{jk}(i)$:

$$\phi_i = \frac{1}{\det(A_1)} \sum_{1=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}^i \times adj(A_1) \tag{2.17}$$

That can also be written as:

$$Z_t = \mu + \sum_{1=0}^{\infty} \phi_i \, \varepsilon_{t-i} \tag{2.18}$$

The coefficient $\phi_{jk}(i)$ is called Impulse Response Function (IRF). $\phi_{jk}(i)$ plot is the best way to visualize the response toward the shocks [2].

2.7 Granger Causality

Granger causality is a method that attempts to determine whether one series is likely to influence a change in the other. This is done by taking different lags of one series and using this to models the change in the second series [1].

$H_0 = \alpha_{12,i} = 0$ for each $i = 1,2,\ldots,p$ (y_{2t} not "Granger-Cause" y_{1t})

$H_1 = \alpha_{12,i} \neq 0$ for at least one $i = 1,2,\ldots,p$ (y_{2t} "Granger-Cause" y_{1t})

$$F - Test = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T-2p-1)} \tag{2.19}$$

3. Data Analysis

3.1 *Stastionary*

Hypothesis:

H_0 = Data is nonstationary

H_1 = Data stationary

Table 1. ADF Test for 2018 Data

Augmented Dickey-Fuller Unit Root Tests								
Stock	**Type**	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
PALM	**Zero Mean**	3	-0.1603	0.6453	-0.94	0.3059		
	Single Mean	3	-10.5313	0.1126	-2.36	0.1553	3.15	0.2672
	Trend	3	-52.7932	0.0005	-4.38	0.0031	9.66	0.0010
LSIP	**Zero Mean**	3	-0.3119	0.6109	-1.05	0.2652		
	Single Mean	3	-2.2689	0.7440	-0.90	0.7875	0.85	0.8551
	Trend	3	-16.3044	0.1314	-2.80	0.1992	4.03	0.3730
SGRO	**Zero Mean**	3	-0.0834	0.6627	-1.60	0.1039		
	Single Mean	3	-1.6539	0.8171	-1.15	0.6963	1.87	0.5941
	Trend	3	-6.2856	0.7152	-1.43	0.8468	1.27	0.9232
SSMS	**Zero Mean**	3	-0.1735	0.6423	-0.88	0.3348		
	Single Mean	3	-2.8502	0.6720	-1.12	0.7065	0.94	0.8306
	Trend	3	-8.0612	0.5691	-1.94	0.6303	1.89	0.8003

Table 2. ADF Test for 2019 Data

Augmented Dickey-Fuller Unit Root Tests								
Stock	**Type**	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
PALM	**Zero Mean**	3	-0.1218	0.6540	-0.58	0.4660		
	Single Mean	3	-9.3751	0.1502	-1.77	0.3923	1.70	0.6379
	Trend	3	-19.9705	0.0608	-2.88	0.1736	4.50	0.2785
LSIP	**Zero Mean**	3	-0.2352	0.6283	-0.81	0.3659		
	Single Mean	3	-3.9810	0.5370	-1.31	0.6249	1.09	0.7931
	Trend	3	-12.3674	0.2811	-2.39	0.3844	2.87	0.6043
SGRO	**Zero Mean**	3	-0.0556	0.6690	-0.36	0.5516		
	Single Mean	3	-11.5680	0.0867	-2.21	0.2017	2.50	0.4345
	Trend	3	-18.5452	0.0825	-2.84	0.1857	4.07	0.3642
SSMS	**Zero Mean**	3	-0.2006	0.6361	-1.49	0.1264		
	Single Mean	3	-2.9328	0.6618	-1.60	0.4793	2.24	0.4991
	Trend	3	-9.3859	0.4671	-1.82	0.6913	2.14	0.7504

Table 3. ADF Test for 2020 Data

Augmented Dickey-Fuller Unit Root Tests								
Stock	**Type**	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
PALM	**Zero Mean**	3	0.1504	0.7167	0.40	0.7982		
	Single Mean	3	-19.2267	0.0116	-2.12	0.2368	2.38	0.4641
	Trend	3	-17.5139	0.1017	-2.01	0.5887	3.01	0.5757
LSIP	**Zero Mean**	3	-0.6709	0.5329	-1.16	0.2236		
	Single Mean	3	-5.1382	0.4163	-2.09	0.2507	2.42	0.4543
	Trend	3	-3.7364	0.8992	-1.25	0.8952	2.39	0.7009
SGRO	**Zero Mean**	3	-0.2830	0.6173	-1.45	0.1367		
	Single Mean	3	0.7804	0.9840	0.30	0.9778	1.13	0.7824
	Trend	3	-1.9714	0.9700	-0.62	0.9758	1.20	0.9370
SSMS	**Zero Mean**	3	-0.0094	0.6794	-0.04	0.6676		
	Single Mean	3	-4.6704	0.4623	-1.49	0.5359	1.11	0.7870
	Trend	3	-4.5276	0.8501	-1.42	0.8507	1.13	0.9499

Tables 1-3 show that data from 2018, 2019, and 2020 do not pass through the significance $\alpha = 0.05$, this means that the p-values are greater than 0.05. Thus, it is not sufficient evidence to reject Ho, so we can conclude that the data from 2018, 2019, and 2020 are nonstationary. Next, in order to make the data are stationary, we need to perform differencing on data. After the first differencing, then the stationary data can be rechecked through the tabls below.

Table 4. ADF Test for 2018 Data after the First Differencing

Augmented Dickey-Fuller Unit Root Tests								
Stock	**Type**	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
PALM	**Zero Mean**	3	-1934.64	0.0001	-8.07	<.0001		
	Single Mean	3	-2857.50	0.0001	-8.13	<.0001	33.02	0.0010
	Trend	3	-2960.23	0.0001	-8.10	<.0001	32.84	0.0010
LSIP	**Zero Mean**	3	-89.2492	<.0001	-5.22	<.0001		
	Single Mean	3	-95.7418	0.0012	-5.32	<.0001	14.13	0.0010
	Trend	3	-97.2380	0.0005	-5.31	0.0001	14.12	0.0010
SGRO	**Zero Mean**	3	-465.289	0.0001	-7.27	<.0001		
	Single Mean	3	-690.552	0.0001	-7.50	<.0001	28.15	0.0010
	Trend	3	-726.613	0.0001	-7.53	<.0001	28.36	0.0010
SSMS	**Zero Mean**	3	-94.9362	<.0001	-5.35	<.0001		
	Single Mean	3	-98.3650	0.0012	-5.38	<.0001	14.47	0.0010
	Trend	3	-98.2752	0.0005	-5.36	0.0001	14.38	0.0010

Table 5. ADF Test for 2019 Data after the First Differencing

Augmented Dickey-Fuller Unit Root Tests								
Stock	**Type**	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
PALM	**Zero Mean**	3	-248.008	0.0001	-6.70	<.0001		
	Single Mean	3	-252.229	0.0001	-6.70	<.0001	22.42	0.0010
	Trend	3	-268.015	0.0001	-6.74	<.0001	22.70	0.0010
LSIP	**Zero Mean**	3	-129.900	0.0001	-8.03	<.0001		
	Single Mean	3	-131.033	0.0001	-8.04	<.0001	32.34	0.0010
	Trend	3	-131.302	0.0001	-8.01	<.0001	32.14	0.0010
SGRO	**Zero Mean**	3	-306.768	0.0001	-12.29	<.0001		
	Single Mean	3	-307.189	0.0001	-12.25	<.0001	75.06	0.0010
	Trend	3	-307.392	0.0001	-12.21	<.0001	74.57	0.0010
SSMS	**Zero Mean**	3	-234.265	0.0001	-6.57	<.0001		
	Single Mean	3	-277.215	0.0001	-6.73	<.0001	22.68	0.0010
	Trend	3	-301.812	0.0001	-6.82	<.0001	23.28	0.0010

Table 6. ADF Test for 2020 Data after the First Differencing

Augmented Dickey-Fuller Unit Root Tests								
Stock	**Type**	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
PALM	**Zero Mean**	3	-189.928	0.0001	-6.06	<.0001		
	Single Mean	3	-191.414	0.0001	-6.06	<.0001	18.42	0.0010
	Trend	3	-215.824	0.0001	-6.21	<.0001	19.27	0.0010
LSIP	**Zero Mean**	3	-126.595	0.0001	-5.70	<.0001		
	Single Mean	3	-131.959	0.0001	-5.73	<.0001	16.43	0.0010
	Trend	3	-174.924	0.0001	-6.07	<.0001	18.44	0.0010
SGRO	**Zero Mean**	3	-227.389	0.0001	-6.47	<.0001		
	Single Mean	3	-275.118	0.0001	-6.67	<.0001	22.22	0.0010
	Trend	3	-359.712	0.0001	-6.95	<.0001	24.20	0.0010
SSMS	**Zero Mean**	3	-119.655	0.0001	-5.58	<.0001		
	Single Mean	3	-119.722	0.0001	-5.56	<.0001	15.45	0.0010
	Trend	3	-120.569	0.0001	-5.56	<.0001	15.51	0.0010

Tables 4-6 show that data from 2018, 2019, and 2020 pass through the significance $\alpha = 0.05$, this means that the p-values are not greater than 0.05. Thus, it is sufficient evidence to reject Ho, so we can conclude that the data from 2018, 2019, and 2020 are stationary.

3.2 *Cointegration Test*
Hypothesis:
H_0 = Data is not cointegrated
H_1 = Data is cointegrated

Table 7. Johansen Cointegration

Cointegration Rank Test Using Trace

Year	H0: Rank=r	H1: Rank>r	Eigenvalue	Trace	Pr > Trace
2018	**0**	**0**	**0.6470**	**540.7853**	**<.0001**
	1	**1**	**0.6203**	**384.5839**	**<.0001**
	2	**2**	**0.5783**	**239.3111**	**<.0001**
	3	**3**	**0.5190**	**109.7858**	**<.0001**
2019	**0**	**0**	**0.7279**	**618.2802**	**<.0001**
	1	**1**	**0.6882**	**423.0466**	**<.0001**
	2	**2**	**0.6124**	**248.2388**	**<.0001**
	3	**3**	**0.5070**	**106.0744**	**<.0001**
2020	**0**	**0**	**0.6637**	**459.2331**	**<.0001**
	1	**1**	**0.5688**	**305.5922**	**<.0001**
	2	**2**	**0.5434**	**186.9920**	**<.0001**
	3	**3**	**0.4185**	**76.4410**	**<.0001**

H_0 is not rejected if the value λtrace < critical values. Table 7 λtrace < Critical values in 2018, 2019, and 2020 data Thus, we can conclude that the all variables in each year have cointegration

3.3 *Model Estimation*
The first step to be taken is the VECM model to determine the optimum lag by comparing every lag to the criteria used.In the table below the minimum criteria for each information criterion value are given with star sign (*). Here are information criterion value for each year to determine the optimum lag of VECM(p) model.

Tabel 8. Information Criterion for VECM(p) Model

Year	Lag	AIC	SBC	HQC	FPEC	AICC
2018	1	22.13694*	22.458074*	22.267407*	4.11124E9*	22.142785*
	2	22.223397	22.86854	22.485508	4.48413E9	22.247768
	3	22.258744	23.230813	22.653693	4.65018E9	22.315977
	4	22.42171	23.723667	22.950709	5.4844E9	22.528061
	5	22.501565	24.136418	23.165844	5.96097E9	22.675516
2019	1	24.295844*	24.616979*	24.426311*	3.561E10*	24.301689*
	2	24.382818	25.027961	24.644929	3.886E10	24.407189
	3	24.488468	25.460537	24.883418	4.3234E10	24.545702
	4	24.534311	25.836268	25.06331	4.5354E10	24.640662
	5	24.675438	26.310291	25.339716	5.241E10	24.849389
2020	1	25.268928*	25.603539*	25.404902*	9.4229E10*	25.275554*
	2	25.277927	25.950303	25.55116	9.5122E10	25.305633
	3	25.38567	26.399013	25.797466	1.0607E11	25.450928
	4	25.439323	26.79689	25.991005	1.122E11	25.560967
	5	25.555422	27.260521	26.248333	1.2654E11	25.75506

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The table above indicates that the optimal lag for each year VECM(p) model is at lag 1, therefore the VECM(p) model used is VECM(1) for each year.

For 2018 data, the model VECM(1) is:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} -1.27844 & 0.00467 & 0.03808 & -0.02819 \\ -0.14635 & -1.00449 & 0.01351 & -0.09519 \\ -0.06397 & -0.05995 & -1.24355 & 0.06276 \\ -0.24856 & 0.17273 & -0.11893 & -1.12800 \end{bmatrix} \begin{bmatrix} Y_{t1-1} \\ Y_{t2-1} \\ Y_{t3-1} \\ Y_{t4-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}$$

For 2019 data, the model VECM(1) is:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} -1.43099 & 0.01240 & 0.00789 & -0.05430 \\ 0.24740 & -1.07110 & -0.02757 & -0.15429 \\ -1.04578 & 0.23566 & -1.25534 & -0.02919 \\ 0.22213 & -0.06016 & -0.06541 & -1.21535 \end{bmatrix} \begin{bmatrix} Y_{t1-1} \\ Y_{t2-1} \\ Y_{t3-1} \\ Y_{t4-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}$$

For 2019 data, the model VECM(1) is:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \end{bmatrix} = \begin{bmatrix} -1.09804 & 0.01673 & 0.02657 & 0.03201 \\ -0.42123 & -0.80048 & -0.13059 & 0.02852 \\ -0.32258 & 0.13501 & -1.27918 & 0.09241 \\ -0.45767 & 0.01594 & -0.00788 & -1.08631 \end{bmatrix} \begin{bmatrix} Y_{t1-1} \\ Y_{t2-1} \\ Y_{t3-1} \\ Y_{t4-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \end{bmatrix}$$

3.4 *Model Stability*

Tabel 9. Characteristic of Roots AR

		Roots of AR Characteristic Polynomial				
Year	**Index**	**Real**	**Imaginary**	**Modulus**	**Radian**	**Degree**
2018	**1**	-0.07445	0.11823	0.1397	2.1328	122.1981
	2	-0.07445	-0.11823	0.1397	-2.1328	-122.1981
	3	-0.23480	0.00000	0.2348	3.1416	180.0000
	4	-0.27079	0.00000	0.2708	3.1416	180.0000
2019	**1**	-0.00644	0.00000	0.0064	3.1416	180.0000
	2	-0.26927	0.15934	0.3129	2.6073	149.3852
	3	-0.26927	-0.15934	0.3129	-2.6073	-149.3852
	4	-0.42779	0.00000	0.4278	3.1416	180.0000
2020	**1**	0.12942	0.00000	0.1294	0.0000	0.0000
	2	-0.07509	0.15612	0.1732	2.0191	115.6858
	3	-0.07509	-0.15612	0.1732	-2.0191	-115.6858
	4	-0.24327	0.00000	0.2433	3.1416	180.0000

Table above shows that the modulus of characteristic roots for every lag is < 1 for each year. Hence, the VECM(1) model for each year has high stablility.

3.5 *Impulse Response Function*

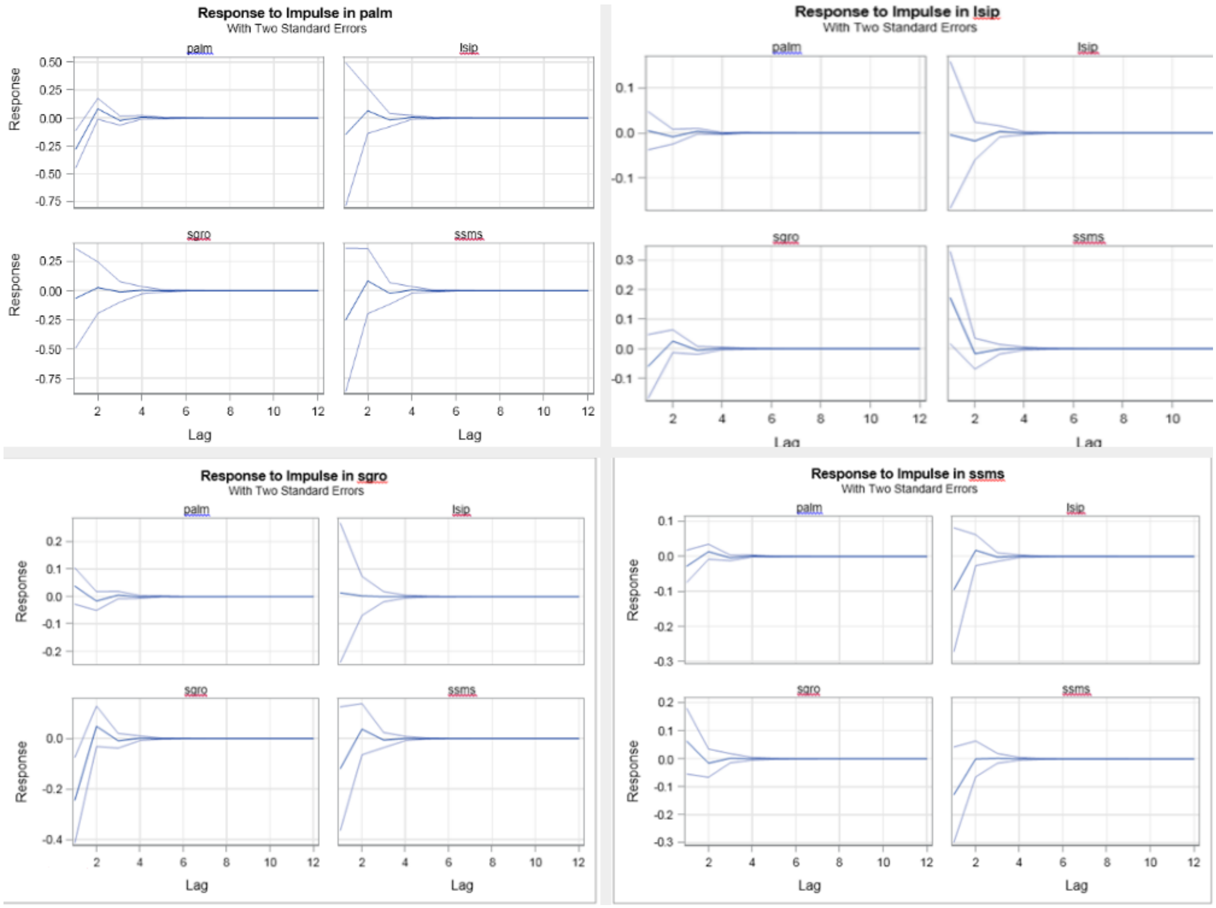

Figure 1. Graph of 2018 Data IRF

Figure 1 shows every variables impulse response to other variables in data of 2018. As shown above, the the stock prices give each other shocks, even themselves. The fluctuations of the shock reponse mostly ended in lag 4. Hence, the stock prices become stable after lag 4.

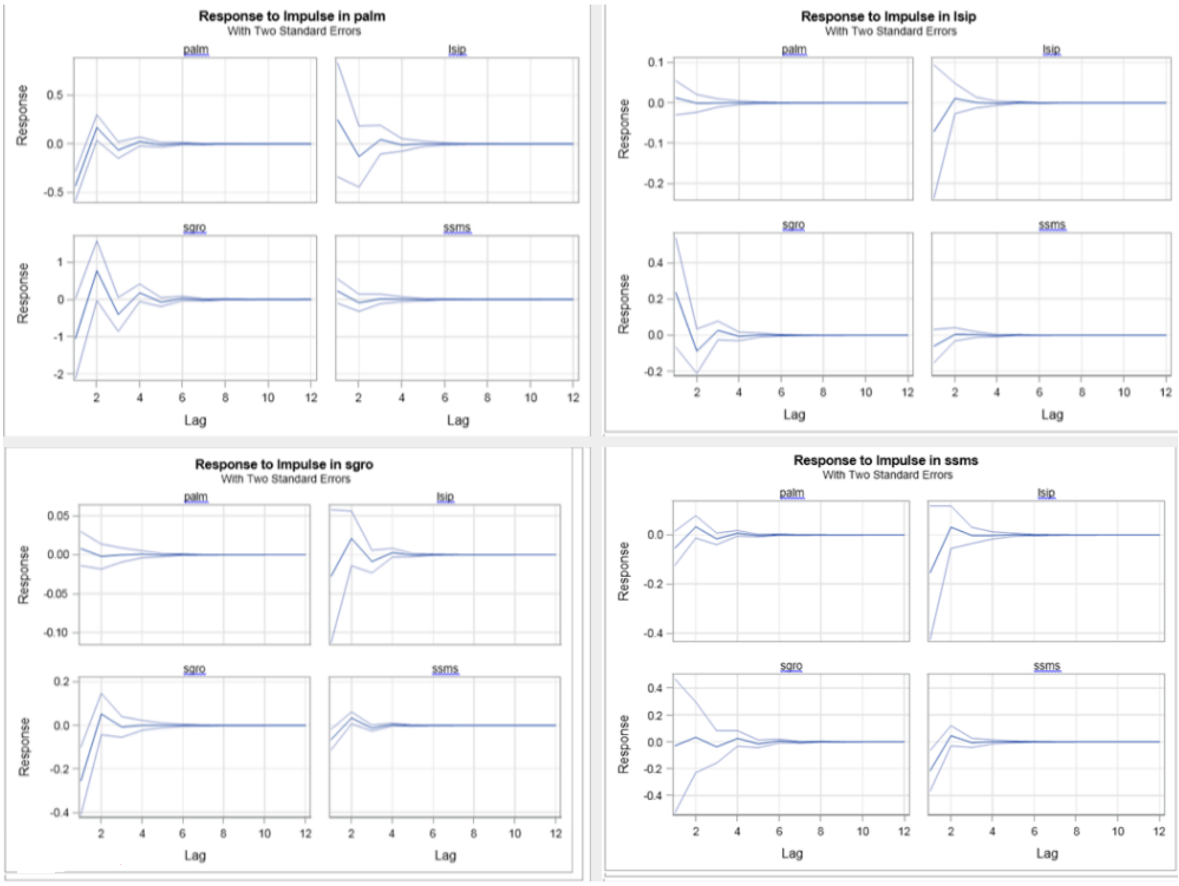

Figure 2. Graph of 2019 Data IRF

Figure 2 shows every variables impulse response to other variables in data of 2019. As shown above, the the stock prices give each other shocks, even themselves. The fluctuations of the shock reponse mostly ended in lag 4 and lag 6. Hence, the stock prices become stable after lag 4 and lag 6.

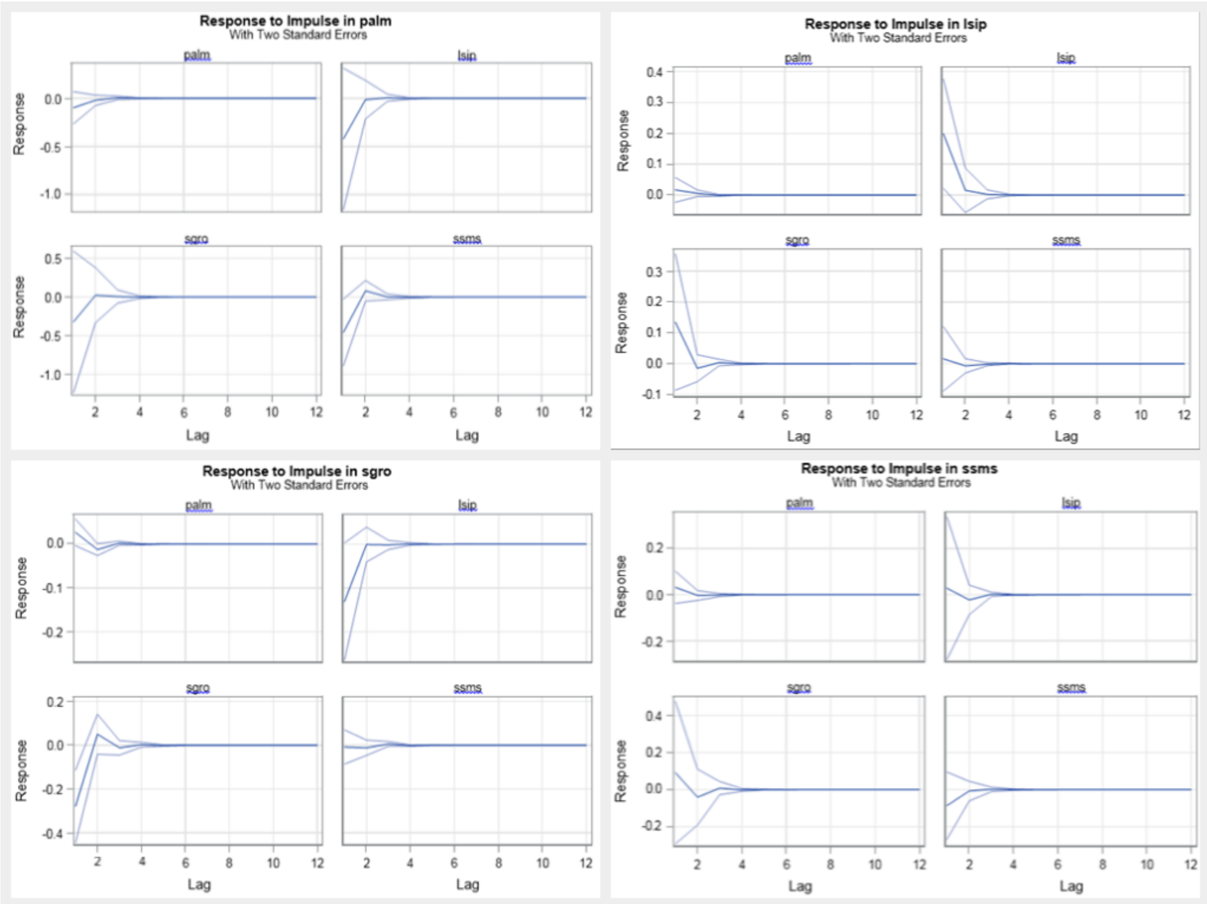

Figure 3. Graph of 2020 Data IRF

Figure 3 shows every variables impulse response to other variables in data of 2020. As shown above, the the stock prices give each other shocks, even themselves. The fluctuations of the shock reponse mostly ended in lag 4. Hence, the stock prices become stable after lag 4.

3.6 *Granger Causality*

Tabel 10. Granger Causality for 2018 Data

Test	Group Variable	Pr > ChiSq	Granger-cause
1	Group 1 Variables : PALM	<.0001	Yes
	Group 2 Variables : LSIP, SGRO, SSMS		
2	Group 1 Variables : PALM	0.0006	Yes
	Group 2 Variables : LSIP, SGRO		
3	Group 1 Variables : PALM	0.0027	Yes
	Group 2 Variables : LSIP, SSMS		
4	Group 1 Variables : PALM	<.0001	Yes
	Group 2 Variables : SGRO, SSMS		
5	Group 1 Variables : PALM	0.0006	Yes
	Group 2 Variables : LSIP		
6	Group 1 Variables : PALM	0.0007	Yes
	Group 2 Variables : SGRO		
7	Group 1 Variables : PALM	0.0923	No
	Group 2 Variables : SSMS		

8	Group 1 Variables : LSIP Group 2 Variables : PALM, SGRO, SSMS	0.0032	Yes
9	Group 1 Variables : LSIP Group 2 Variables : PALM, SGRO	0.0865	No
10	Group 1 Variables : LSIP Group 2 Variables : PALM, SSMS	0.6662	No
11	Group 1 Variables : LSIP Group 2 Variables : SGRO, SSMS	0.0491	Yes
12	Group 1 Variables : LSIP Group 2 Variables : PALM	0.3668	No
13	Group 1 Variables : LSIP Group 2 Variables : SGRO	0.1210	No
14	Group 1 Variables : LSIP Group 2 Variables : SSMS	0.9700	No
15	Group 1 Variables : SGRO Group 2 Variables : PALM, LSIP, SSMS	0.3049	No
16	Group 1 Variables : SGRO Group 2 Variables : PALM, LSIP	0.5909	No
17	Group 1 Variables : SGRO Group 2 Variables : PALM, SSMS	0.1622	No
18	Group 1 Variables : SGRO Group 2 Variables : LSIP, SSMS	0.4465	No
19	Group 1 Variables : SGRO Group 2 Variables : PALM	0.3341	No
20	Group 1 Variables : SGRO Group 2 Variables : LSIP	0.5099	No
21	Group 1 Variables : SGRO Group 2 Variables : SSMS	0.2805	No
22	Group 1 Variables : SSMS Group 2 Variables : PALM, LSIP, SGRO	0.1595	No
23	Group 1 Variables : SSMS Group 2 Variables : PALM, LSIP	0.1889	No
24	Group 1 Variables : SSMS Group 2 Variables : PALM, SGRO	0.1257	No
25	Group 1 Variables : SSMS Group 2 Variables : LSIP, SGRO	0.0832	No
26	Group 1 Variables : SSMS Group 2 Variables : PALM	0.2000	No
27	Group 1 Variables : SSMS Group 2 Variables : LSIP	0.0710	No
28	Group 1 Variables : SSMS Group 2 Variables : SGRO	0.0413	Yes

Table 10 shows that data of 2018 has 9 granger tests has p-value less than $\alpha = 0.05$, hence H_0 is rejected and group 1 variables influenced by the group 2 variables.

Tabel 11. Granger Causality Test of 2019 Data

Test	Group Variable	Pr > ChiSq	Granger-cause
1	Group 1 Variables : PALM Group 2 Variables : LSIP, SGRO, SSMS	0.0092	Yes
2	Group 1 Variables : PALM Group 2 Variables : LSIP, SGRO	0.0102	Yes
3	Group 1 Variables : PALM Group 2 Variables : LSIP, SSMS	0.0035	Yes
4	Group 1 Variables : PALM Group 2 Variables : SGRO, SSMS	0.0046	Yes
5	Group 1 Variables : PALM Group 2 Variables : LSIP	0.0024	Yes
6	Group 1 Variables : PALM Group 2 Variables : SGRO	0.9036	No
7	Group 1 Variables : PALM Group 2 Variables : SSMS	0.0016	Yes
8	Group 1 Variables : LSIP Group 2 Variables : PALM, SGRO, SSMS	0.0146	Yes
9	Group 1 Variables : LSIP Group 2 Variables : PALM, SGRO	0.8905	No
10	Group 1 Variables : LSIP Group 2 Variables : PALM, SSMS	0.0145	Yes
11	Group 1 Variables : LSIP Group 2 Variables : SGRO, SSMS	0.0051	Yes
12	Group 1 Variables : LSIP Group 2 Variables : PALM	0.6307	No
13	Group 1 Variables : LSIP Group 2 Variables : SGRO	0.9222	No
14	Group 1 Variables : LSIP Group 2 Variables : SSMS	0.0036	Yes
15	Group 1 Variables : SGRO Group 2 Variables : PALM, LSIP, SSMS	0.0626	No
16	Group 1 Variables : SGRO Group 2 Variables : PALM, LSIP	0.7215	No
17	Group 1 Variables : SGRO Group 2 Variables : PALM, SSMS	0.0687	No
18	Group 1 Variables : SGRO Group 2 Variables : LSIP, SSMS	0.0482	Yes
19	Group 1 Variables : SGRO Group 2 Variables : PALM	0.9011	No
20	Group 1 Variables : SGRO Group 2 Variables : LSIP	0.5755	No
21	Group 1 Variables : SGRO Group 2 Variables : SSMS	0.0771	No
22	Group 1 Variables : SSMS Group 2 Variables : PALM, LSIP, SGRO	0.5101	No
23	Group 1 Variables : SSMS Group 2 Variables : PALM, LSIP	0.3234	No

24	Group 1 Variables : SSMS Group 2 Variables : PALM, SGRO	0.4092	No
25	Group 1 Variables : SSMS Group 2 Variables : LSIP, SGRO	0.4910	No
26	Group 1 Variables : SSMS Group 2 Variables : PALM	0.2230	No
27	Group 1 Variables : SSMS Group 2 Variables : LSIP	0.2436	No
28	Group 1 Variables : SSMS Group 2 Variables : SGRO	0.5017	No

Table 11 shows that data of 2019 has 11 granger tests has p-value less than $\alpha = 0.05$, hence H_0 is rejected and group 1 variables influenced by the group 2 variables.

Tabel 12. Granger Causality Test of 2020 Data

Test	Group Variable	Pr > ChiSq	Granger-cause
1	Group 1 Variables : PALM Group 2 Variables : LSIP, SGRO, SSMS	0.0020	Yes
2	Group 1 Variables : PALM Group 2 Variables : LSIP, SGRO	0.2370	No
3	Group 1 Variables : PALM Group 2 Variables : LSIP, SSMS	0.1221	No
4	Group 1 Variables : PALM Group 2 Variables : SGRO, SSMS	0.0675	No
5	Group 1 Variables : PALM Group 2 Variables : LSIP	0.3360	No
6	Group 1 Variables : PALM Group 2 Variables : SGRO	0.1848	No
7	Group 1 Variables : PALM Group 2 Variables : SSMS	0.3061	No
8	Group 1 Variables : LSIP Group 2 Variables : PALM, SGRO, SSMS	0.4668	No
9	Group 1 Variables : LSIP Group 2 Variables : PALM, SGRO	0.3209	No
10	Group 1 Variables : LSIP Group 2 Variables : PALM, SSMS	0.7509	No
11	Group 1 Variables : LSIP Group 2 Variables : SGRO, SSMS	0.4564	No
12	Group 1 Variables : LSIP Group 2 Variables : PALM	0.5126	No
13	Group 1 Variables : LSIP Group 2 Variables : SGRO	0.2093	No
14	Group 1 Variables : LSIP Group 2 Variables : SSMS	0.5590	No
15	Group 1 Variables : SGRO Group 2 Variables : PALM, LSIP, SSMS	0.7649	No
16	Group 1 Variables : SGRO Group 2 Variables : PALM, LSIP	0.7259	No

17	Group 1 Variables : SGRO Group 2 Variables : PALM, SSMS	0.6393	No
18	Group 1 Variables : SGRO Group 2 Variables : LSIP, SSMS	0.9479	No
19	Group 1 Variables : SGRO Group 2 Variables : PALM	0.4237	No
20	Group 1 Variables : SGRO Group 2 Variables : LSIP	0.8359	No
21	Group 1 Variables : SGRO Group 2 Variables : SSMS	0.7456	No
22	Group 1 Variables : SSMS Group 2 Variables : PALM, LSIP, SGRO	0.0977	No
23	Group 1 Variables : SSMS Group 2 Variables : PALM, LSIP	0.0487	Yes
24	Group 1 Variables : SSMS Group 2 Variables : PALM, SGRO	0.0900	No
25	Group 1 Variables : SSMS Group 2 Variables : LSIP, SGRO	0.0831	No
26	Group 1 Variables : SSMS Group 2 Variables : PALM	0.0276	Yes
27	Group 1 Variables : SSMS Group 2 Variables : LSIP	0.0500	No
28	Group 1 Variables : SSMS Group 2 Variables : SGRO	0.6338	No

Table 12 shows that data of 2020 has 3 granger tests has p-value less than $\alpha = 0.05$, hence H_0 is rejected and group 1variables influenced by the group 2 variables.

4. Conclusions

Based on the discussion and results detailed above, we can conclude that the data of daily stock prices of PT. Provident Agro Tbk, PT. PP London Sumatera Indonesia Tbk, PT. Sampoerna Agro Tbk, and PT. Sawit Sumbermas Sarana from January to July in 2018, 2019, and 2020 have cointegration relationship and can be modeled by using Vector Error Correction Model (1). In impulse response function we can conclude that each variables give each other shock response, even themselves.

Acknowledgement

The author thank yahoo finance for providing data in this study

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