

Analysis of wholesale price indexes with the vector error correction model (VECM) approach

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Abstract:

To obtain the wholesale price index (WPI) model and see the causal relationship between variables with the VECM approach based on the period January 2000 to August 2019. In this study, 3 variables are used; (i) Agriculture, (ii) Industry and (iii) Oil and Gas. This research begins with the stationarity test by looking at the plot and unit root test. When the variables are not stationary, a differencing is necessarily needed. The lag assessment is performed by observing at the smallest Aikake Information Criteria (AIC) and Schwarz Information Criteria (SIC). A cointegration test using Johansen test is conducted to find whether there is a long-term relationship between WPI variables as a condition to proceed to VECM modeling. To see the dynamic behavior of the VECM model the Impulse Response Function (IRF) is used. The best model obtained in this study is VECM(3) and based on the Granger causality analysis we obtained that Industry is affected by Oil and Gas, and Oil and Gas is affected by Industry and Agriculture.

Keywords: Analysis, VECM, wholesale price index

I INTRODUCTION

A wholesale price index (WPI) is an index that measures and tracks the changes in the price of goods in the stages before the retail level – that is, goods that are sold in bulk and traded between entities or businesses instead of consumers. In other words, WPI is used to measure price variance before a product or service release to a consumer. WPI is an easy and convenient method to calculate inflation. Inflation rate is the difference between WPI calculated at the beginning and the end of a year. The percentage increase in WPI over a year gives the rate of inflation for that year.

In Indonesia, wholesale price data collected from 33 provincial capital cities and 111 other potential cities/towns, assumed to have major companies and traded varied goods. Respondents are selected from companies considered representative enough on trading commodities, so that all commodities covered could represent the Wholesale Price for each province. The data is

collected directly from respondents every month, by direct interview. (“Indonesia - Wholesale Price Index”, 2019).

In this paper we analyze the WPI data of Agriculture, Industry and Oil and Gas sectors in Indonesia from January 2000 to August 2019 using vector error correction model (VECM). The VECM is a method of estimating dynamic models that do not refer to structural models based on theoretical concepts, but instead use the basic assumptions of economic theory, meaning that this model is more of a model that adapts to the current economic phenomenon.

II LITERATURE REVIEW

According to Pankratz (1991), time series analysis is an analysis that studies interrelationships over times. The goal in time series analysis is to find a model to express the structured time relationship between several variables which can further forecast one or more variables. To quantitatively analyze time series

data by involving more than one variable or multivariate time series, the method used is Vector Autoregressive (VAR). The VAR model plays an important role in modern analytical techniques, especially in economics and finance (Hamilton, 1994; Kirchgassner and Wolters, 2007). In 1980, Christopher A. Sims introduced the VAR model as an alternative in macroeconomic analysis. The VAR model has a simpler model structure with a minimal number of variables where all variables are endogenous variables and the independent variable are their lags.

A detail discussion of VAR model with integrated regressors, cointegration, and structural VAR modeling can be seen in Asteriou (2007). Asteriou discussed the development of methods that address the "unit root" problem in a multivariate model and present a simple approach that can help researchers infer in the VAR model. A discussion of "unit root" can also be seen in Dickey and Fuller (1979); Elliot and Stock (1992). Unit root restructuring, cointegration and structural changes can be studied in Maddala and In-Moo (2004). Roots and cointegration units in multivariate time series can be seen in Hamilton (1994). Hamilton also discussed the hypothesis testing for unit roots and cointegration in multivariate time series. The VAR model is designed for stationary variables that do not contain trends. Stochastic trends in data indicate that there are long-run and short-run components in time series data. Research on stochastic trends in economic variables continues to develop. In 1987, Engle and Granger developed the concept of cointegration and error correction. Then in 1990, Johansen and Juselius developed the VECM concept. VECM offers an easy working procedure for separating long-term components and short-term components from the data formation process. Thus, VECM is different from VAR where VECM can be used to model cointegrated and non-stationary time series data (Sinay, 2014).

Multivariate Time Series

Statistical analysis for time series data has helped many studies in various fields of science, especially in modeling. The application of this field of statistics has greatly helped the development of economic and social sciences. Time series data that has two or more variables is called a multivariate time series. The multivariate time series model involves several variables that are not only coherent but also correlate each other (Montgomeri et al., 2008). Multivariate time series analysis takes together a number of time series data. Generally, multivariate time series analysis is more complicated than univariate time series analysis when the number of data studied is large. In learning multivariate time series analysis, it includes dynamic relationships between variables and increases the prediction accuracy of the data to be analyzed. For example the data will be predicted y_{T+1} based on the data $\{y_1, \dots, y_T\}$, the model obtained is:

$$\hat{y}_{T+1} = g(y_T, y_{T-1}, \dots, y_1)$$

where:

\hat{y}_{T+1} : Prediction of y_T

$g(\cdot)$: the corresponding function

The purpose of multivariate time series analysis is to determine the function $g(\cdot)$ is based on data available (Tsay, 2014).

Stationarity

Stationary means there is no drastic change in the data. Data fluctuations are around a constant average value, independent of the time and variance of these fluctuations. The assumption of stationarity in time series data analysis is fundamental and must be checked before analyzing data. Several methods are available to check stationarity of time series data, based on data plots or through the test Augmented Dickey-Fuller (ADF). The ADF test process is as follows, for example y_1, y_2, \dots, y_n becomes a time series, assuming that $\{y_t\}$ follows the AR(p) model with the given μ :

$$y_t - \mu = \phi_1(y_{t-1} - \mu) + \dots + \phi_p(y_{tp} - \mu) + \varepsilon_t \quad (1)$$

where:

ε_t is the white noise average 0 and variance σ^2 , and $\varepsilon_t \sim N(0, \sigma^2)$.

Testing non-stationary data in equation (1) using the ADF test or tau test (τ) is carried out as follows:

$H_0 : \phi_1^* = 0$ (there are root units or non-stationary time series)

$H_1 : \phi_1^* < 0$ (no root units or stationary time series)

Test statistics:

ADF test

$$(\tau) = \frac{\hat{\phi}_1^*}{\widehat{se}_{\phi_1^*}}$$

for significance level ($\alpha = 0.05$), reject H_0 if $\tau < -2.57$ or if p-value < 0.05 (Brockwell and Davis (2002); Tsay. (2005)).

Determination of Lag Length

Lag is a distance or interval between two interrelated events (Kirchgassner and Wolters, 2007). The optimal length lag variable is needed to capture the effect of each variable on other variables in the VAR system. The selected length lag can be seen through the minimum value of each criterion. Some criterion information that is often used is as follows:

i) Final Prediction error (FPE)

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

ii) Akaike Information Criteria (AIC)

$$AIC(p) = \ln|\Sigma_{\hat{u}\hat{u}}(p)| + (k + pk^2) \frac{2}{T}$$

iii) Bayesian Criterion of Gideon Schwarz (SC)

SC =

$$\ln|\Sigma_{\hat{u}\hat{u}}(p)| + (k + pk^2) \frac{2 \ln \ln(T)}{T}$$

iv) Hannan-Quinn Criterion (HQ)

$$HQ = \ln|\Sigma_{\hat{u}\hat{u}}(p)| + (k + pk^2) \frac{\ln \ln(T)}{T}$$

where $|\Sigma_{\hat{u}\hat{u}}(p)|$ is the determinant of the covariance matrix of the VAR model (p), where k

is the number of variables, T is the number of observations of p is the length of lag the VAR model (Kirchgassner and Wolters., 2007).

Vector Autoregressive (VAR) Model

To quantitatively analyze data time series by 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 lagged value of the dependent variable as a representation of the autoregressive nature in the model. The VAR model (p) can be written in the following equation:

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

where:

Γ_i = matrix coefficient of size nxn coefficient of the endogenous variable -i

y_{t-1} = vector of endogenous variables with lag to -1 size n x 1

ε_t = error vector size n x 1

If the data used is stationary at the same differencing level and if there is cointegration, the VAR model will be combined with the error correction model into the Vector Error Correction Model (VECM) (Asteriou and Hall, 2007).

VAR Stability

If y_t is a VAR(p) process, VAR(1) has the dimension K_p corresponding to:

$$Y_t = v + AY_{t-1} + U_t$$

can be defined, where:

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}, v = \begin{bmatrix} v \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \begin{matrix} (K_p \times 1) \\ (K_p \times 1) \end{matrix}$$

$$A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_K & 0 & \dots & 0 & 0 \\ 0 & I_K & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_K & 0 \end{bmatrix}, \quad U_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

(K_p x K_p)
(K_p x 1)

Y_t is stable if:

$$\det(I_{K_p} - Az) \neq 0 \text{ for } |z| \leq 1$$

with,

$$\det(I_{K_p} - Az) = \det(I_{K_p} - A_1 z - \dots - A_p z^p)$$

Based on the definition of a polynomial characteristic of a matrix, we call this polynomial characteristic, the opposite of the VAR(p) process. Thus, the process is stable if the polynomial characteristics of the converse do not have roots in and in complex unit circles. Then y_t stable if:

$$\det(I_{K_p} - A_1 z - \dots - A_p z^p) \neq 0 \text{ for } |z| \leq 1$$

This condition is called the condition of stability (Lutkepohl, 2005).

Vector Error Correction Model (VECM)

VAR is a special form of the simultaneous equation system. The VAR model can be applied if all variables used are stationary, but if the variables in the vector y_t are not stationary, the model used is the VECM provided that there is one or more cointegration relationships between the variables. VECM is a VAR that has been designed for use on non-stationary data and has a cointegration relationship (Enders., 2015).

According to Mustofa et al. (2017) VECM is a time series modeling that can directly estimate the level of variables brought back to equilibrium after the shock of other variables. VECM is very useful for estimating short-term effects for both variables and long-term effects from time series data. VECM (p) with cointegration rank r ≤ k is as follows:

$$\Delta y_t = \alpha \beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon_t \quad (3)$$

where:

- Δ = operators differencing, with Δy_t = y_t - y_{t-1}
- α = vector adjustment sized n x r
- β = cointegration vector size n x r
- y_{t-1} = endogenous variable vector with lag 1st size n x 1
- Γ_i = coefficient matrix size n x n coefficient of the endogenous variable -i
- ε_t = error vector size n x 1

Multivariate Cointegration Test: Johansen Test

VECM form contains information concerning the short and long term variables as stated by parameters Γ_i and Π. Suppose the component of the vector Y_t is a single-order integration or written I(1), Πy_{t-1} is a linear combination of Y_{t-1} that produces a close correlation with Δy_{t-1} which is a stationary element, Johansen uses the properties from the matrix Π:

1. If Rank (Π) = 0, then there are no variables cointegrated with each other.
2. If Rank(Π) = m, (m number of variables in the VAR model), then all the variables are cointegrated with each other.
3. If 0 < Rank(Π) < m, then Rank(Π) states the number of variables cointegrated between 0 and m.

The matrix Π can be decomposed into Π = αβ^T where α is the speed of adjustment and β is the coefficient matrix such that long-term β^TY_{t-1} is a cointegration relationships that ensure that Y_t achieve long-term balance. Furthermore, rank (αβ^T) can be determined by calculating the Eigen value of matrix αβ^T. For example the estimated Eigen value of matrix αβ^T is λ₁ ≥ λ₂ ≥ ... ≥ λ_k. For example, the rank for the matrix αβ^T we assume is r₀, so to test the hypothesis is done sequentially with the hypothesis carried out sequentially with the following hypothesis.

$$H_0 : r = r_0$$

$$H_1 : r_0 = r_{0+1}$$

The test can be used to test the statistics likelihood ratio of the Eigen values as follows:

$$\text{Likelihood ratio } (r_0) = \lambda_{\max}(r_0) = -T \ln \left(\frac{1 - \hat{\lambda}_{r_0+1}}{1 - \hat{\lambda}_{r_0+1}} \right)$$

Furthermore, the test statistics are compared with a critical point at a certain significant level, for example 5%. If the value likelihood ratio is greater than the critical point, then reject H_0 (Juanda and Junaidi., 2012).

Granger Causality

The Granger causality test in both VAR and VECM modeling aims to look at the short-term relationship in the form of reciprocal variables in the vector. The long-term causality can be seen through the t test statistic value in the Ordinary Least Square (OLS) method, and the short-term causality can use Granger causality test (Sinay, 2014).

The relationship between variables does not prove the existence of causality or influence, so to examine whether there is a one-way or two-way influence a causality test is needed. If an event x occurs before y, then it is possible that x affects y but it is not possible to reverse it, this is the idea in applying the Granger Causality Test (Gujarati., 2003). If the X variable causes the Y variable, it means that the Y value in the current period can be explained by the Y value in the previous period and the X value in the previous period. Granger's causality only tests the relationships between variables and does not estimate the model.

Full Granger causality model:

$$y_t = \alpha_0 + \alpha_n Y_{t-1} + \dots + \alpha_n Y_{tn} + \beta_1 X_{t-1} + \dots + \beta_n X_{tn} + \varepsilon_1$$

Reduce Granger causality model:

$$y_t = \alpha_0^* + \alpha_0^* Y_{t-1} + \dots + \alpha_n^* Y_{tn} + \varepsilon_1^*$$

to test the hypothesis:

$$H_0 = \beta_1 = \dots = \beta_n = 0$$

$$H_1 = \text{at least one } \beta_i \text{ is not zero}$$

test statistic:

$$F = \frac{Nk \text{SSE}_{\text{Limited}} - \text{SSE}_{\text{Full}}}{q \text{SSE}_{\text{Full}}}$$

F is distributed with degrees of freedom q and N-k, where

N = number of observations

k = number of full model parameters

q = number of restricted model parameters

H_0 is rejected if $F > F_{\text{table}}$ or p-value < 0.05 . If

H_0 is rejected, then at least one β_i is not zero.

Impulse Response Function (IRF)

IRF is a method used to see the response of an endogenous variable to shock given by other variables (Pindyck & Rubinfeld, 1998). IRF can help to explain the dynamic structure of the VAR / VECM model that is to find out the effect of shock between other dependent variables and by itself. This means that IRF describes the rate of shock from one variable to another at a certain time, so that it can be seen the duration of the shock effect of that variable. IRF describes the response of the dependent variable to shocks in error terms with the standard deviation values in the VAR / VECM system (Gujarati, 2004).

III RESEARCH METHODOLOGY

Data Analysis Process

1. At this stage, stationarity test will be carried out that is visible through plots time series, charts Autocorrelation Function (ACF) and unit root tests.
2. After data is stationary, it is determined the length of lag optimum based on several criteria; AIC, SC, FPE, and HQ, where the optimum lag is shown with an asterisk (*).
3. Then cointegration testing is tested, and to test the cointegration the method used is the Johansen test.
4. Estimation of the selected VECM model uses the smallest FPEC, AIC, SBC, and HQC criteria. Based on the best VECM(p) parameters that have been selected, an estimation of the VECM model(p) will be obtained by forming a cointegration coefficient matrix (Π) then forming a variable matrix differencing (Γ).

5. Furthermore, the feasibility test of the model is carried out, it can be seen from the feasibility of each variable which is analyzed univariately using ANOVA table.
6. Granger causality testing to see the relationship between variables.
7. IRF analysis to determine the effect of shock between other dependent variables and by itself.

IV RESULTS AND DISCUSSION

Stationary Testing

The first step that must be taken is the data stationarity test. Stationary testing can be done in three ways, which are by viewing the time series plot, using the Autocorrelation Function (ACF) graph, and the unit root test.

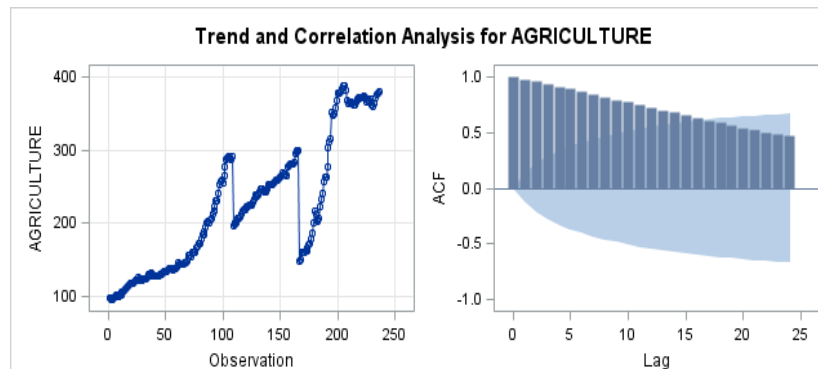


Fig. 1. Plot time series and ACF Agricultural Variables.

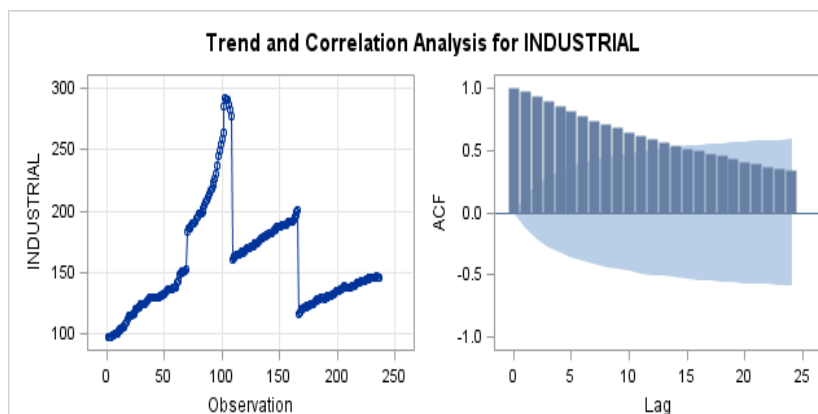


Fig. 2. Plot time series and ACF Industrial Variables.

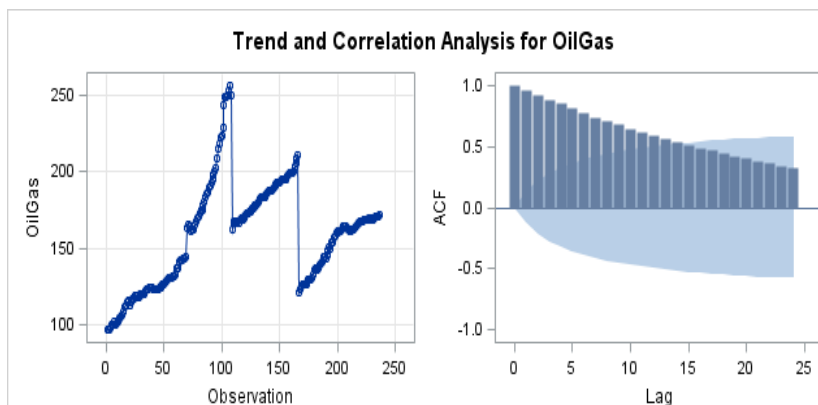


Fig. 3. Plot time series and ACF Oil and Gas Variables.

Based on Figure 1 to Figure 3, it can be seen that the three data are not stationary in the average or variety because they have a tendency pattern. Next, looking at the ACF graphs from the three

images also shows the instability because it has an exponentially declining pattern slowly approaching zero. Then finally, stationary testing with unit root test can be showed in Table 1.

Table 1
Dickey-Fuller Unit Root Tests.

Variable	Type	Rho	Pr <Rho	Tau	Pr <Tau
Agriculture	Zero Mean	0.7796	0.8712	0.87	0.8960
	Single Mean	-2.5128	0.7150	-1.00	0.7518
	Trend	-15.7134	0.1534	-2.66	0.2533
Industry	Zero Mean	-0.2901	0.6163	-0.28	0.5830
	Single Mean	-10.0151	0.1306	-2.32	0.1634
	Trend	-9.7272	0.4478	-2.25	0.4567
Oil and Gas	Zero Zero	0.0642	0.6971	0.08	0.7079
	Single Mean	-9.4652	0.1495	-2.35	0.1561
	Trend	-10.2208	0.4134	-2.28	0.4431

Hypothesis Testing:

H_0 : has a unit root (not stationary)

H_1 : no unit root (stationary)

Based on Table 1, it is seen in the statistical p -value of Tau (τ) for all types of testing for each variable is greater than the significant level used that is $\alpha = 0.05$, so it does not reject H_0 which means the data is not stationary.

Since no variable is stationary, differencing must be performed on the data, and then stationary testing is performed again using time series plots, ACF charts and unit root tests.

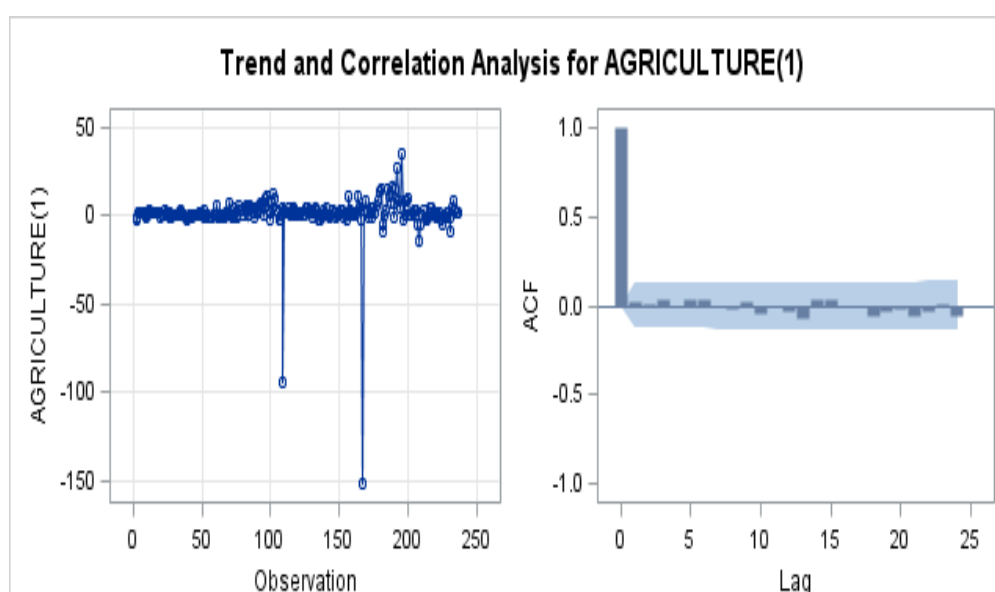


Fig. 4. Plot time series and ACF of 1st differences of Agriculture price index

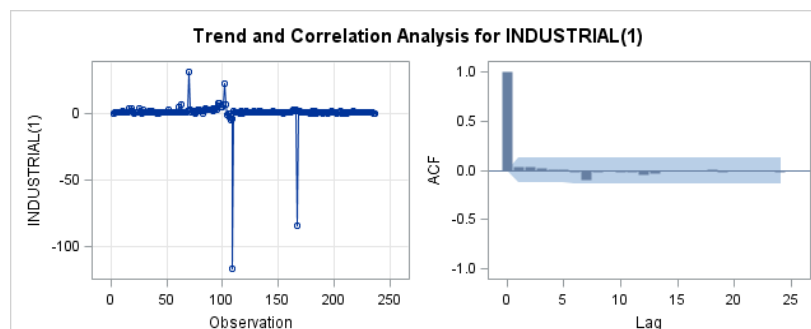


Fig. 5. Plot time series and ACF of 1st differences of Industrial Price Index

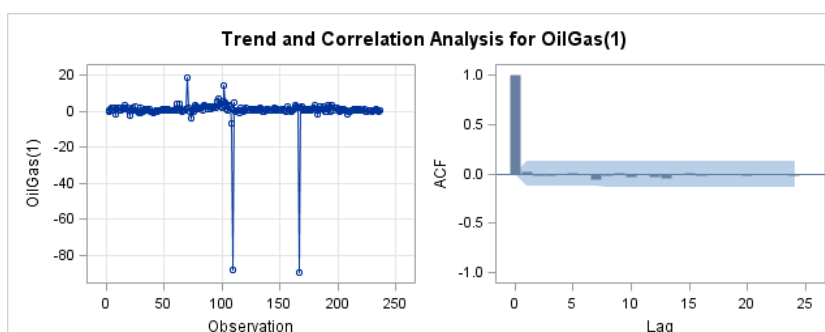


Fig. 6. Plot time series and ACF of 1st differences of Oil and Gas Price Index

Based on Figure 4 to Figure 6 it shows that the data is stationary in average and variety because it

does not have a tendency pattern, then subsequently testing stationary with unit root test.

Table 2
Unit root test of all variables after differencing 1

Variable	Type	Rho	Pr <Rho	Tau	Pr <Tau
Agriculture	Zero Mean	-194.243	0.0001	-7.19	<.0001
	Single Mean	-209.294	0.0001	-7.33	<.0001
	Trend	-209.703	0.0001	-7.32	<.0001
Industry	Zero Mean	-195.490	0.0001	-7.21	<.0001
	Single Mean	-196.204	0.0001	-7.20	<.0001
	Trend	-201.158	0.0001	-7.24	<.0001
Oil and Gas	Zero Mean	-245.040	0.0001	-7.64	<.0001
	Single Mean	-248,533	0.0001	-7.65	<.0001
	Trend	-253.505	0.0001	-7.67	<.0001

Hypothesis Testing:

H_0 : has a unit root (not stationary)

H_1 : has no unit root (stationary)

Conclusion:

Based on Table 2, for the p-value statistical Tau (τ) all types of testing for each variable is greater than the significant level used, $\alpha = 0.05$, so reject H_0 which means the data is stationary[1-20].

Optimum Lag Testing

Determination of the optimum lag for the VAR model of endogenous variables (Agriculture, Industry, Oil & Gas) by looking for lags is significant from each of the criteria information used and the following results are obtained:

Table 3
Lag VAR model for all variables

Lag	AICC	HQC	AIC	SBC	FPEC
1	8.567177	8.619762	8.566178	8.699075	5251.045
2	8.43125	8.534673*	8.427166	8.69377*	4569.689
3	8.43074*	8.583117	8.421346*	8.822475	4543.544*
4	8.481996	8.681298	8.464917	9.001398	4746.667
5	8.55387	8.79791	8.52657	9.199237	5049.911
6	8.604141	8.890561	8.563909	9.373607	5244.23

Table 3 shows that from all the criteria used, the smallest AIC and FPEC is in lag 3, so that cointegration testing will use lag 3.

Cointegration Test

Cointegration test used in this study is examined by using the Johansen Test with the help of software SAS 9.4 and the following results are obtained:

Table 4
Cointegration test for all variables

H0: Rank k = r	H1: Rank > r	Eigenvalue	Trace	Pr> Trace	Drift in ECM	Drift in Process
0	0	0.3424	175.9836	<.0001	NOINT	Constant
1	1	0.1682	78.7363	<.0001		
2	2	0.1437	35.9987	<.0001		

Hypothesis Testing:

H_0 : Rank = r (no cointegration)

H_1 : Rank > r (there is cointegration)

Conclusion:

Table 4 gives the p -value for rank =2 is smaller than the significant level $\alpha = 0.05$, meaning reject H_0 . It indicates there is cointegration between variables with rank = 3. Since the data are cointegration correlation, a model that will be used next is VECM(p).

Estimation of VECM Parameters (3) with Cointegration rank = 3

After the cointegration relationship between

research variables has been found, the next step is to form a VECM model. An important procedure in estimating VECM equations is the selection of lag optimum. The selection procedure lag optimum in VECM can use information criteria of AIC and FPEC. In testing the length, it is found that the lag optimum obtained is lag 3, so the estimated form of the VECM equation is VECM(3). Thus, the form of equality in VECM (3) is as follows:

Table 5
Parameter Estimation ($\alpha\beta'$)

Variable	AGRICULT URE	OFINDUS TRY	OIL&G AS
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AGRICULTURE	0.08672	2.72871	-4.66897
INDUSTRY	0.49191	1.41164	-3.42513
OILGAS	0.49574	1.92308	-3.90109

Table 6
Estimation of the AR coefficient parameter model at differentiated lag ($\Gamma\Delta y_{t-1}$)

Equation	Parameter	Estimate	Standard Error	t Value	Pr> t	Variable
D_AGRICULTURE	AR2_1_1	-1.25470	0.24688	-5.08	0.0001	D_Agriculture(t-1)
	AR2_1_2	-3.20202	0.63465	-5.05	0.0001	D_Industry(t-1)
	AR2_1_3	5.42163	0.96074	5.64	0.0001	D_Oil & Gas(t-1)
	AR3_1_1	-0.62150	0.21379	-2.91	0.0040	D_Agriculture(t-2)
	AR3_1_2	-1.33713	0.49776	-2.69	0.0078	D_Industry(t-2)
	AR3_1_3	2.45310	0.78740	3.12	0.0021	D_Oil & Gas(t-2)
D_INDUSTRY	AR2_2_1	-1.08898	0.17668	-6.16	0.0001	D_Agriculture(t-1)
	AR2_2_2	-3.27478	0.45418	-7.21	0.0001	D_Industry(t-1)
	AR2_2_3	5.26194	0.68754	7.65	0.0001	D_Oil & Gas(t-1)
	AR3_2_1	-0.38612	0.15300	-2.52	0.0123	D_Agriculture(t-2)
	AR3_2_2	-1.15529	0.35622	-3.24	0.0014	D_Industry(t-2)
	AR3_2_3	1.94534	0.56349	3.45	0.0007	D_Oil & Gas(t-2)
D_Oil&Gas	AR2_3_1	-0.92839	0.15612	-5.95	0.0001	D_Agriculture(t-1)
	AR2_3_2	-2.61946	0.40135	-6.53	0.0001	D_Industry(t-1)
	AR2_3_3	4.29242	0.60757	7.06	0.0001	D_Oil & Gas(t-1)
	AR3_3_1	-0.32724	0.13520	-2.42	0.0163	D_Agriculture(t-2)
	AR3_3_2	-0.90460	0.31478	-2.87	0.0044	D_Industry(t-2)
	AR3_3_3	1.55822	0.49795	3.13	0.0020	D_Oil & Gas(t-2)

Based on Table 5 and Table 6, the VECM(3) model is obtained as follows:

$$\Delta \begin{bmatrix} y_{t1} \\ y_{t2} \\ y_{t3} \end{bmatrix} = \begin{bmatrix} 0.08672 & 2.72871 & -4.66897 \\ 0.49191 & 1.41164 & -3.42513 \\ 0.49574 & 1.92308 & -3.90109 \end{bmatrix} \begin{bmatrix} y_{t1-1} \\ y_{t2-1} \\ y_{t3-1} \end{bmatrix} + \begin{bmatrix} -1.25470 & -3.20202 & 5.42163 \\ -1.08898 & -3.27478 & 5.26194 \\ -0.92839 & -2.61946 & 4.29242 \end{bmatrix} \begin{bmatrix} \Delta y_{t1-1} \\ \Delta y_{t2-1} \\ \Delta y_{t3-1} \end{bmatrix} + \begin{bmatrix} -0.62150 & -1.33713 & 2.45310 \\ -0.38612 & -1.15529 & 1.94534 \\ -0.32724 & -0.90460 & 1.55822 \end{bmatrix} \begin{bmatrix} \Delta y_{t1-2} \\ \Delta y_{t2-2} \\ \Delta y_{t3-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \\ \varepsilon_{t3} \end{bmatrix}$$

where y_{t1} = Agriculture, y_{t2} = Industry, and y_{t3} = Oil and Gas.

Model Feasibility Test

Model feasibility test is from the feasibility of each endogenous variable analyzed univariately

by using software SAS 9.4 and the following results are obtained.

Table 7
Diagnosis of univariate models with ANOVA.

Variable	R-Square	Standard Deviation	F Value	Pr> F
AGRICULTURE	0.5521	11.99651	24.54	<.0001
INDUSTRY	0.6094	8.58645	31.06	<.0001
OIL&GAS	0.5990	7.58932	29.74	<.0001

All models of endogenous variables from table 7 have p-values smaller than significant level ($\alpha = 0.05$). This means that all models of endogenous variables are feasible to use.

Model Stability Test

VECM models are said to have high stability when the roots of the characteristic polynomial AR have a modulus of ≤ 1 :

Table 8
Characteristic roots of AR polynomials.

Index	Real	Imaginary	Modulus	Radian	Degree
1	0.63524	0.00000	0.6352	0.0000	0.0000
2	0.59786	0.00000	0.5979	0.0000	0.0000
3	0.17709	0.35080	0.3930	1.1033	63.2145
4	0.17709	-0.35080	0.3930	-1.1033	-63.2145
5	-0.18818	0.56828	0.5986	1.8906	108.3220
6	-0.18818	-0.56828	0.5986	-1.8906	-108.3220
7	-0.19826	0.30473	0.3636	2.1476	123.0476
8	-0.19826	-0.30473	0.3636	-2.1476	-123.0476
9	-0.45419	0.00000	0.4542	3.1416	180.0000

Table 8 shows that the modulus of the characteristic roots in all lags is ≤ 1 . So that it is concluded that VECM(3) is feasible to use because of the high stability in feasibility.

Granger Causality Test

Granger causality test is to find a reciprocal relationship between variables, whether each variable in the past has a significant effect on other variables, or only affects itself. By using software SAS 9.4 the following results are as follows.

Table 9
Granger Causality Test.

Test	Variable Group	Pr> Chi Sq	H ₀	Decision
1	Group 1: AGRICULTURE	0.8624	AGRICULTURE is only affected by itself and not by INDUSTRY	H ₀ not rejected

Group 2: INDUSTRY				
Group 1:				
2	AGRICULTURE	0.1010	AGRICULTURE is only affected by itself and not by the OIL & GAS	H_0 is not rejected
Group 2: OILGAS				
Group 1: INDUSTRIAL				
3	Group 2: AGRICULTURE	0.6530	INDUSTRY affected only by himself and not by AGRICULTURE	H_0 is not rejected
4	Group 1: INDUSTRIAL	0.0001	INDUSTRY affected only by himself and not by OIL & GAS	H_0 rejected
Group 2: OIL & GAS				
Group 1: OIL & GAS				
5	Group 2: AGRICULTURE	0.0290	OIL & GAS is only affected by itself and not by AGRICULTURE	H_0 rejected
Group 1: OIL & GAS				
6	Group 2: INDUSTRY	0.0011	OIL & GAS is only affected by itself and not by INDUSTRY	H_0 denied

The results of the test 1 on table 9 shows that H_0 is not rejected, which means JCI in the agricultural sector is only affected by itself and not by industrial sector. Then in the second test shows the H_0 is not rejected, which means agriculture is only affected by itself and not by the oil and gas sector. The test 3 shows H_0 is not rejected, which means only the industrial sector affected by itself and is not affected by the agricultural sector. Then in test 4 it shows that H_0

is rejected, which means the sector of industry is affected by the oil and gas sector. Then in test 5 shows H_0 is rejected, which means oil and gas sector is affected by the agricultural sector. Moreover, in test 6 also shows H_0 is rejected, which means oil and gas sectors affected by the industrial sector. From the results above, the causal relationship model can be described as follows:

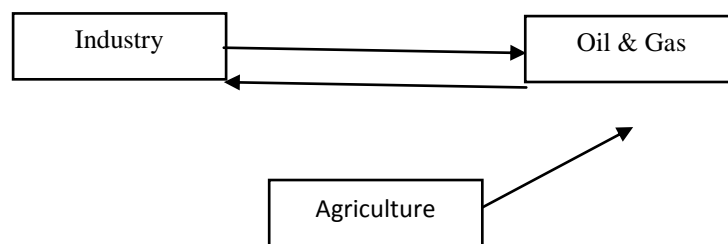


Fig. 7. Graph of Granger Causality on Variables.

Impulse Response Function (IRF)

To find out a variable responding to shock another variable, the IRF graph can be used, while

the results of this analysis can be used as long-term information. Using software SAS 9.4 the following results are presented.

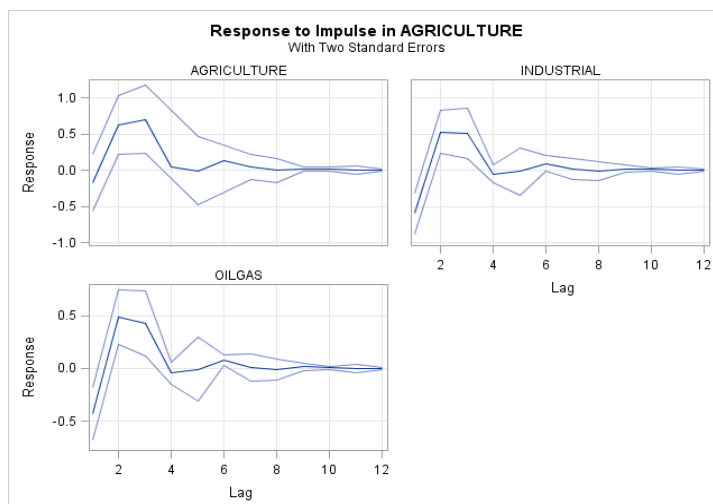


Fig. 8. IRF for the Agriculture variable.

Figure 8 is a graph of the IRF, if there is a shock of 1 standard deviation on the Agriculture and its impact on the Agriculture itself, Industry and Oil and Gas. If the IRF chart moves near the equilibrium point or returns to the original equilibrium (zero), this means that the response of one variable to another variable's shock disappears, so that the shock does not leave a permanent effect on the variable. Shock equal to one standard deviation in the agriculture variable, this causes Agriculture to give a negative response in the first month of -0.16799 then in the second month to the fourth month to give a positive response that is 0.61838, 0.70123, 0.04406 after

the fourth month until then move closer to the equilibrium point (zero). Shock equal to one standard deviation in the agricultural variable, this causes the Industry to give a negative response in the first month of -0.59706 then the response in the second and third months is 0.52381, 0.51189 after the fourth month until it moves closer to the equilibrium point (zero). Furthermore, shock equal to one standard deviation in the agriculture variable, this causes Oil and Gas to give a negative response in the first month of -0.43265 then the response in the second and third months is 0.48766, 0.43149 after the fourth month until it moves closer to the equilibrium point (zero).

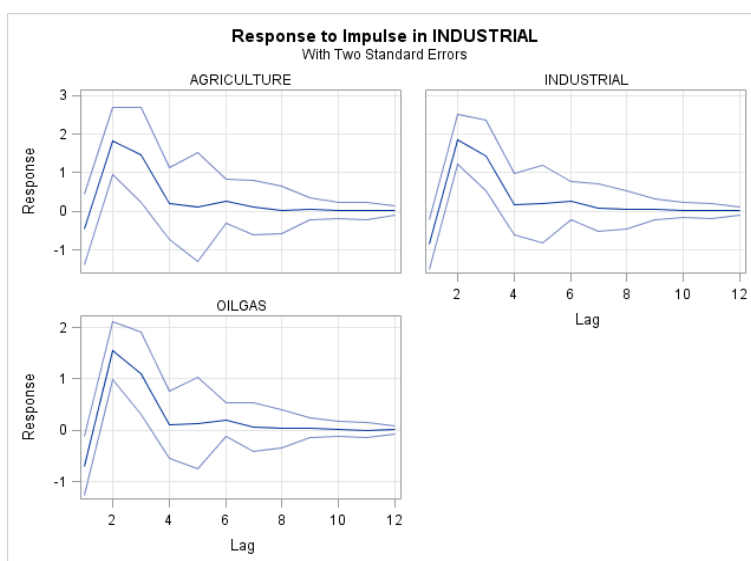


Fig. 9. IRF for Industry variable.

Figure 9 is a graph of the IRF, if there is a shock of 1 standard deviation on the Industry and its impact on the Industry itself, Agriculture and Oil and Gas. If the IRF chart moves near the equilibrium point or returns to the original equilibrium (zero), this means that the response of one variable to another variable's shock disappears, so that the shock does not leave a permanent effect on the variable. Shock equal to one standard deviation in the Industry sector, this causes Agriculture to give a negative response in the first month of -0.47331. Then in the second to the fourth month it gives a positive response of 1.82879, 1.47165, 0.19815 after the fourth month

until next it moves closer to the equilibrium point (zero). As shock of one standard deviation of the Industry, this causes the Industry itself to give a negative response in the first month of -0.86314 then the response in the second and fourth months is 1.86797, 1.44898, 0.18394 after the fourth month until next it moves closer to the equilibrium point (zero). And shock equal to one standard deviation of the Industry variable, this causes Oil and Gas to give a negative response in the first month of -0.69638 then the response in the second and third months of 1.55181, 1.11100 after the fourth month until next it moves closer to the equilibrium point (zero)[21-25].

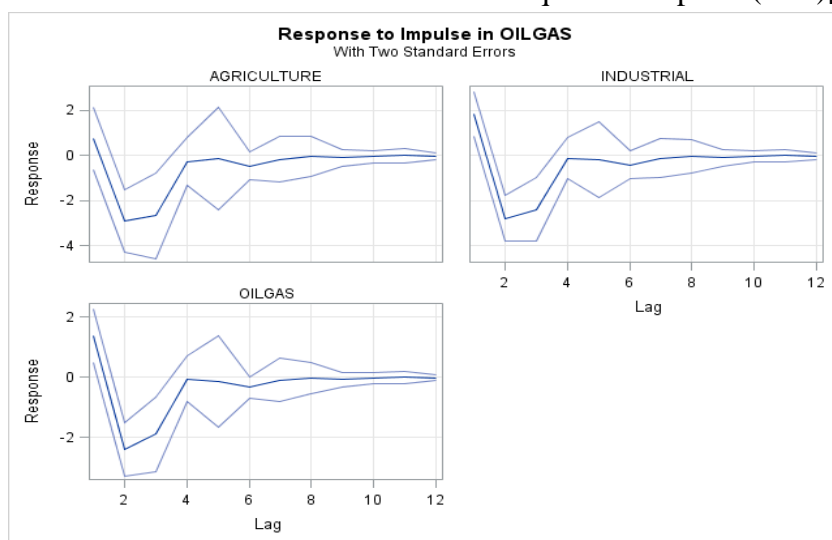


Fig. 10. IRF for Oil and Gas variables.

Figure 10 is a graph of the IRF, if there is a shock of 1 standard deviation on the Oil and Gas variable and its impact on the Agriculture, Industry and Oil and Gas itself. If the IRF chart moves near the equilibrium point or returns to the original equilibrium (zero), this means that the response of one variable to another variable's shock disappears, so that the shock does not leave a permanent effect on the variable. Shock equal to one standard deviation of the agricultural variable, this causes Agriculture to give a positive response in the first month of 0.75267 then in the second month to the fourth month to give a negative response that is -2.91714, -2.67673 after the fourth month until then move closer to the equilibrium point (zero). Shock equal to one

standard deviation of the Oil and Gas variable, this causes the Industry to give a positive response in the first month of 1.83681 then the response in the second and third months is -2.79579, -2.39699 after the fourth month until next it moves closer to the equilibrium point (zero). And shock equal to one standard deviation of the Oil and Gas variable, this causes Oil and Gas to give a positive response in the first month of 1.39134 then the response in the second and third months of 2.40315, -1.89464 after the fourth month until next it moves closer to the equilibrium point (zero).

V CONCLUSION

From results and discussion, it therefore can be concluded into two considerations as follows;

1. Model formed is VECM(3) with rank = 3 as follows:

$$\Delta \begin{bmatrix} y_{t1} \\ y_{t2} \\ y_{t3} \end{bmatrix} = \begin{bmatrix} 0.08672 & 2.72871 & -4.66897 \\ 0.49191 & 1.41164 & -3.42513 \\ 0.49574 & 1.92308 & -3.90109 \end{bmatrix} \begin{bmatrix} y_{t1-1} \\ y_{t2-1} \\ y_{t3-1} \end{bmatrix} + \begin{bmatrix} -1.25470 & -3.20202 & 5.42163 \\ -1.08898 & -3.27478 & 5.26194 \\ -0.92839 & -2.61946 & 4.29242 \end{bmatrix} \begin{bmatrix} \Delta y_{t1-1} \\ \Delta y_{t2-1} \\ \Delta y_{t3-1} \end{bmatrix} + \begin{bmatrix} -0.62150 & -1.33713 & 2.45310 \\ -0.38612 & -1.15529 & 1.94534 \\ -0.32724 & -0.90460 & 1.55822 \end{bmatrix} \begin{bmatrix} \Delta y_{t1-2} \\ \Delta y_{t2-2} \\ \Delta y_{t3-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \\ \varepsilon_{t3} \end{bmatrix}$$

2. As the Granger casualty analysis, it is revealed that the causal relationship formed is industry sector which is dependent on oil and gas sector, while oil and gas is affected by industry and agriculture sector.

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