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Modeling Multivariate Time Series by Vector Error Correction Models (VECM) (Study: PT Kalbe Farma Tbk. and PT Kimia Farma (Persero) Tbk)

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Abstract. Time series analysis (time series) is one method with the aim to find out events that will occur in the future based on data and past circumstances. Time series are widely used in economics, business, environmental science, and finance. The analytical tool that is widely used to answer quantitative research problems is the Autoregressive Vector (VAR). The VAR model is used if the data is stationary. If the variable has cointegration and stationary at the first difference value, the VAR model is modified to become the Error Correction Model (VECM). Then we can find out the influence of variables with other variables by looking at the Impulse Response Function and Granger Causality. In this research, PT Kalbe Farma Tbk's stock data will be analyzed. (KLBF) and PT Kimia Farma (Persero) Tbk (KAEF). The data used are weekly data from January 2010 to June 2020. Based on data analysis, it is known that the data is not stationary and there are unit roots. Furthermore, first differencing is done to make the data stationary. Because there was cointegration, a VECM analysis was performed and a VECM (p) was obtained with a lag of p = 4. So the best model for this research is VECM (4) with rank = 2. Causal relationships between variables using Granger Causality showed that KLBF influenced KAEF in the past. Based on IRF analysis, each variable gives a fluctuating response with itself and with other variables.

Keywords: VAR model,VECM, cointegration, Granger Causality, Impulse Response Function

1. Introduction

Time series analysis is one method with the aim to find out events that will occur in the future based on data and past circumstances. In general, the time series econometrics model is a structural model because it is based on existing economic theories. In 1980 Christopher A. Sims introduced the VAR model as an alternative in macroeconomic analysis. The analytical tool commonly used to answer quantitative research problems is the Autoregressive Vector (VAR). The VAR model is used to explain the simultaneous variables that have influence on each other. The VAR model is used if the data is stationary at the level. The data is not stationary at the level but stationary at the first difference value we will use the Autoregressive Vector in Difference (VARD) if all variables do not have

cointegration. When the variables have cointegration and stationary at the first difference value, then the Error Correction Model (VECM) is used. In this applied statistical research various cases of multivariate time series data will be examined. Modeling that will be used for multivariate time series data is the Error Correction Model (VECM) Vector, which will then be seen the causal relationship between time series variables using Granger Causality, to see the effect of the shock of a variable against other variables will be used Impulse Response Function (IRF)). Discussed the relationship and forecasting between the price indexes of two oil companies in Indonesia using VAR [1].

In this research, modeling will be carried out on the stock data of PT Kalbe Farma Tbk. (KLBF) and PT Kimia Farma (Persero) Tbk (KAEF). PT Kalbe Farma Tbk., with its subsidiaries, develop, manufacture, and trade pharmaceutical products in Indonesia. It operates in four segments: Prescription Pharmacy, Consumer Health, Nutrition, and Distribution and Logistics. The company was founded in 1966 and based in Jakarta, Indonesia. PT Kalbe Farma Tbk. is a subsidiary of PT Gira Sole Prima. PT Kimia Farma (Persero) Tbk manufactures and sells medicines, herbal medicines, iodine, salt, quinine and its derivative products, and vegetable oils in Indonesia, throughout Asia, Europe, Australia, Africa and New Zealand. The company operates through the manufacturing, distribution, retail and other services segments. The company was founded in 1817 and based in Jakarta, Indonesia. Both of these variable data are time series data. So that time series analysis can be done to make multivariate modeling that can be used for the future. The objectives of this study are (1) Formulating a Multivariate Time series data model with the Vector Error Correction Model (VECM) approach. (2) Review the behavior of Multivariate data with Granger Causality. (3) Assess how the behavior of one variable with respect to other variables in the event of shock and how long the equilibrium will occur.

2. Literature Review

2.1 *Test Cointegration*

The concept of cointegration was introduced by Engle and Granger and the development of practical and inferential estimation methods was given by Johansen. In much of the literature, the time series Xt is said to be integrated with the sequence process 1, I (1), if (1-B) Xt is stationary and cannot be reversed. If the time series data is stationary and can be reversed, it says process I (0). In general, univariate time series Xt is process I(d), if $(1-B)^d$Xt stationary and non invertable [2],[3],[4]. Burke and Hunter proposed the procedure of Johansen's for estimation and inferencial [5]. If there is cointegration between variables, then we must test the cointegration ranking. Some cointegration rank testing methods are as follows: Trace test and Test the maximum eigenvalue. In the cointegration test Johansen cointegration test is used as follows: It is known that the model $VAR\ (p)$ is

$$y_t = A_t y_{t-1} + \cdots + A_p y_{t-p} + B x_t + \varepsilon_t$$

where y_t is a vector with k non stationary variable I (1), xt is a vector with d deterministic variable, εt is an error vector. The equation $VAR\ (p)$ can also be written as

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

where

$$\Pi = \sum_{i=1}^{p} A_i + I, \qquad \Gamma_i = -\sum_{i=1}^{p} A_j$$

For testing the hypotheses can be used the trace test :

$$LR_{tr}(\text{r|k}) = -\text{T} \sum_{i=r+1}^{k} \log (1 - \lambda_i)$$

And statistical test for maximum eigen value

$$\text{LRmax(r|r + 1)} = -\text{T} \log(1 - \lambda_{r+1})$$
$$= LR_{tr}(\text{r|k}) - LR_{tr}(\text{r + 1|k})$$

for $r = 0, 1, \ldots, k - 1$, with the null hypotheses is H_0 : there is r cointegration equation.

At the significance level (1 - α) 100%, H_0 is accepted if the trace test statistic and the maximum eigenvalue are smaller than the critical value when α, or p-value is greater than the significance value

α [6]. If there is cointegration between variables, the representation the error-correction VAR model was modified, so the model became a VECM model [7] [8].

2.2 *Vector Autoregressive* (Var)

Vector Autoregressive (VAR) is a special form of simultaneous equation system. The VAR model can be applied if all variables used are stationary, but if the variables in the Y_t vector are not stationary then the model used is the Vector Error Correction Model (VECM) provided that there is one or more cointegration relationships between the variables. VECM is a limited VAR that is designed to be used in non-stationary data which is known to have a cointegration relationship [9].

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{p-1} + \varepsilon_t$$

where,

y_t : is vector of observation,
A : matrix of parameter,
ε_t : vektor error

If the data used is stationary at the same differencing level and there is cointegration, then the VAR model will be combined with the error correction model into the Vector Error Correction Model (VECM) [7].

2.3 *Vector Error Correction Model (VECM)*

VECM is a limited VAR model designed to be used in non-stationary time series but has a cointegration relationship between variables. VECM is very useful because it can estimate the short-term effects between variables and the long-term effects of time series data. The general form of VECM (p) where p is the lag of endogenous variables with cointegration rank r $\leq$ k is as follows [2]:

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

where:

Δ = operator *differencing,* where $\Delta y_t = y_t - y_{t-1}$,
y_{t-1} = vector variable endogenous with *lag* 1,
ε_t = kx1 vector residuals,
D_t = kx1 vektor constant,
Π = matrix coefficient of cointegration ($\Pi = \alpha \beta^t$; α = vector *adjustment*, kxr matrix and β = matrix cointegration (*long-run parameter*) (k $\times$ r))
Γ_i = kxk matrix coefficient the ith variable endogenous.

2.4 *Test For Normality Of Residuals*

Residual normality test is used to determine the residual normality in a multivariate model. The normality test is carried out using the Jarque-Bera (JB) Test of Normality. This test uses a measure of skewness and kurtosis. Jarque-Bera (JB) used in the normality test on the residual model where the calculation is done by adding indicators of the number of independent variables or predictors, JB calculation is as follows:

$$JB = \left[\frac{N}{6} b_1^2 + \frac{N}{24} (b_2 - 3)^2 \right]$$

Where:

N = number of sample size,
$b_1 = Expected\ Skewness$
$b_2 = Expected\ Excess\ Kurtosis$
where *Jarque-Bera* (JB) *Test of Normality* with *chi-square* x^2 distribution with degrees of freedom 2 [10].

2.5 *Granger Causality*

Granger causality is used to see short-term relationships in the form of reciprocity between variables in a vector. A stable VAR is defined as follows:

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

y_t is consist of vector y_{1t} and y_{2t}. y_{2t} is not grager causality for y_{1t} if coefficient matrix of parameter VAR namely $A_{21,i} = 0$ for i=1,2,..., p[2].

The Granger Causality Test is based on the F test which attempts to determine if there is a change in one variable due to a change in another variable. A variable X is said to be a Granger Cause variable Y, if the previous value of X can predict the current Y value.
VAR Model:

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

If all the coefficients $\emptyset$ on the lag value of y are significant then X Granger Causal Y. If X Granger Causal Y and not vice versa, it is called indirect causality. If causality is found in both, from X to Y and from Y to X, then it is called bidirectional causality [11] [12] [13].

2.6 *Impulse Response Function* (IRF)
The Impulse Response Function is a method used to see the response of an endogenous variable to shock given by another variable. A Vector Autoregressive (VAR) can be written in the form of a Vector Moving Average (VMA) that allows us to see various responses from veriable in the VAR system. The VAR model can be written in the MA vector (∞) as

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

And the matrix has an interpretation as follows:

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

Row i, column j element identifies the consequence of increasing one unit in the innovation of variable j on the date t (μ_{jt}) for the value of the i variable at time t + s (X_i, t + s), holding all other innovations at all constant dates. If the first μ_t element is changed by δ_1, at the same time, the second element is changed by δ_2, .., and element n by δ_n, then the combined effect of this change on the vector value X_{t+s} will

$$\Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}} \delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}} \delta_2 + \dots + \frac{\partial X_{t+s}}{\partial u_{nt}} \delta_n = \Psi_s \delta$$

Plot of row I, column j element of Ψs is called Impulse Response Function (IRF).

3. Results And Discussion
The first step that must be passed to get the VECM estimate is to test the stationarity of each variable's data. Stationary data is needed to influence the results of the VECM estimation test. In this study, to detect whether or not the stationary variable of each variable data, it can be seen with a time series plot, ACF graph (Autocorrelation Function), and Augmented Dickey-Fuller Unit Root Test.
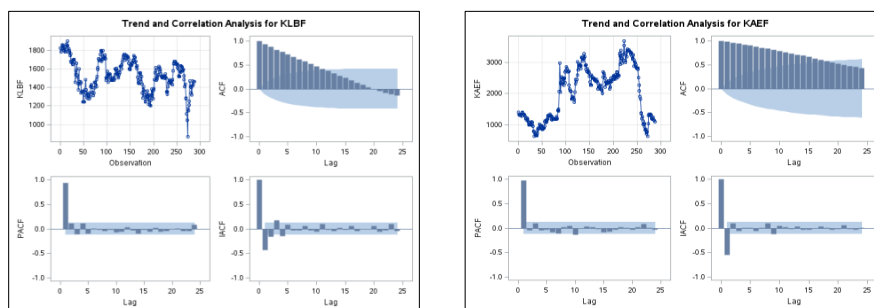

Figure 1. Trend and correlation analysis for KLBF and for KAEF

Table 1. Augmented Dickey Fuller Unit Roots Test

Variable	Type	lags	ρ	Pr $< \rho$	Tau	Pr $<$Tau
Kurs KLBF	Zero mean	3	-0.4354	0.5837	-0.68	0.4204

	Single mean	3	-19.7479	0.0113	-3.20	0.0215
	trends	3	-21.6944	0.0454	-3.26	0.0747
Kurs KAEF	Zero mean	3	-0.6201	0.5441	-0.58	0.4652
	Single mean	3	-3.7952	0.5605	-1.32	0.6227
	trends	3	-2.7430	0.9466	-0.85	0.9589

From Figure 1, the time series plot shows that the two variables above are not stationary because they still contain elements of trend. Furthermore, the instability of the data is also shown by the ACF graph where from lag 1 to the next lag falls slowly linearly near zero, this shows that the coefficient of autocorrelation is significantly different from zero. From table 1, all variables contain unit roots or are not stationary at the level. This can be seen in the p value of the statistical value Tau (τ) all types of testing for each variable is greater than the significance limit used, namely $\alpha = 0.05$, so the data is not stationary (there is a unit root). Thus it can be said that all the variables above contain unit roots or are not stationary. Since all veriabels are not stationary at the level level, the first differencing is performed on the data, then checked again using time series plots, ACF charts and unit root tests.
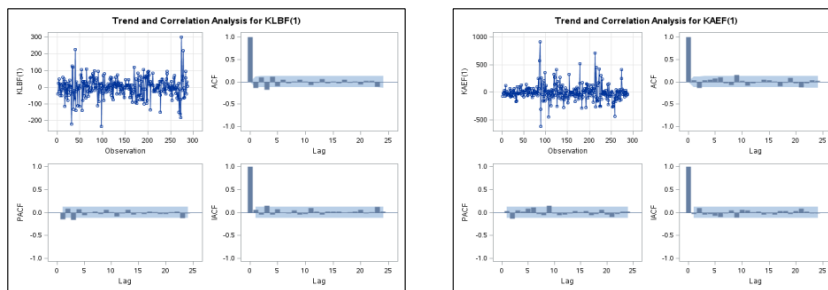

Figure 2. Trend and correlation analysis for KLBF and for KAEF

Table 2. Augmented Dickey Fuller Unit Roots Test

Variable	Type	lags	ρ	$Pr < \rho$	Tau	$Pr < Tau$
Kurs KLBF	Zero mean	3	-462.644	0.0001	-11.24	<.0001
	Single mean	3	-464.561	0.0001	-11.23	<.0001
	trends	3	-466.902	0.0001	-11.23	<.0001
Kurs KAEF	Zero mean	3	-305.689	0.0001	-9.91	<.0001
	Single mean	3	-305.725	0.0001	-9.89	<.0001
	trends	3	-314.081	0.0001	-9.97	<.0001

From Figure 2 in the time series plot it can be seen that the two variables are stationary to the mean and variance because they no longer contain an element of trend. Furthermore, the stationarity of the data is also shown by the ACF graph where from lag 0 to the next lag it slowly decreases exponentially to zero. So it can be concluded that the five variables above are stationary to the mean and variance. From Table 2, all variables no longer contain unit or stationary roots in the 1st Differencing. This can be seen in the p value of statistical Tau all types of testing for each variable is smaller than the significance limit used, $\alpha = 0.05$, so that the data is stationary (there is no unit root). Thus it can be said that all of the above variables do not contain unit roots or stationary data.

3. 1 *Test for Lag Optimal*
VECM estimates are very sensitive to the lag length of the data used. The length of the lag is used to determine the time needed for the effect of each variable on its past variable. In this study, determining the length of the lag is done by looking at the smallest value of the information criteria. Determination of the optimum lag as follows:

Table 3. Lag Optimal

Information criterion	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AICC	17.36952	17.36942	17.3686	17.35107*	17.36112

HQC	17.38788*	17.39994	17.41118	17.40565	17.42762
AIC	17.36939	17.36908	17.36793	17.34995*	17.35944
SBC	17.41668*	17.448	17.47856	17.4924	17.53379
FPEC	34948784	34938002	34897684	34276010*	34603014

Based on table 3, it can be seen that the optimal lag length lies in lag 4. The selection of lag 2 as the optimal lag is based on the smallest values of AICC, AIC, and FPEC. So cointegration testing will be carried out in lag 4.

3.2 *Test Cointegration*

Cointegration testing is used to determine the long-term relationship of each variable. The requirement in estimating VECM is that there is a cointegration relationship in it. If there is no cointegration relationship, then the VECM estimate is canceled, but must use the VAR (Vector Atouregression) model. The cointegration test used in this study is the Johansen cointegration test.

Table 4. Table cointegration

H_0: Rank=r	H_1: Rank>r	Eigenvalue	Trace	Pr > Trace
0	0	0.1979	227.9709	<.0001
1	1	0.1807	108.2325	<.0001

ased on Table 4, it can be seen that the p value for rank = 1 is smaller than the significance limit used, namely $\alpha = 0.05$, so there is not enough evidence to reject H1: rank> r. Thus it can be said that there is a cointegration relationship between variables with rank = 2. Because the data used there is a cointegration relationship, the VAR (p) model used is VECM (p) with rank = 2.

3.3 *Selection of VECM(p)*

Selection of VECM(p) based on the information criterion of AICC, HQC, AIC, SBC and FPEC, the best VECM(p) is as follows:

Table 5. Selection VECM(p)

Information criterion	VECM(1)	VECM(2)	VECM(3)	VECM(4)	VECM(5)
AICC	17.36952	17.36942	17.3686	17.35107*	17.36112
HQC	17.38788*	17.39994	17.41118	17.40565	17.42762
AIC	17.36939	17.36908	17.36793	17.34995*	17.35944
SBC	17.41668*	17.448	17.47856	17.4924	17.53379
FPEC	34948784	34938002	34897684	34276010*	34603014

Based on Table 5 it can be seen that the smallest values of AICC, AIC, and FPEC are found in VECM (4). So that VECM (4) was chosen as the best model.

3.4 *The estimation Parameter of VECM(4) with rank r=2*

Based on the above analysis, VECM (4) was selected as the best model with rank r = 2. Next, we will estimate the model for VECM (4) as follows:

Table 6. Long-Run Parameter Beta Estimates when RANK=2

Variable	1	2
KLBF	0.04208	0.01324
KAEF	-0.00844	0.01620

Table 7. Adjustment Coefficient Alpha
Estimates When RANK=2

Variable	1	2
KLBF	-23.09162	-10.51971
KAEF	14.39345	-50.96496

Table 8. Parameter Alpha *
Beta' Estimates

Variable	KLBF	KAEF
KLBF	-1.11094	0.02450
KAEF	-0.06902	-0.94739

Table 9. Model Parameter Estimates

Equation	Parameter	Estimate	Standard Error	t Value	Pr > |t|	Variable
D_KLBF	AR1_1_1	-1.11094	0.09739			KLBF(t-1)
	AR1_1_2	0.02450	0.04034			KAEF(t-1)
	AR2_1_1	0.00790	0.08104	0.10	0.9224	D_KLBF(t-1)
	AR2_1_2	0.00962	0.03526	0.27	0.7851	D_KAEF(t-1)
	AR3_1_1	-0.02219	0.06415	-0.35	0.7296	D_KLBF(t-2)
	AR3_1_2	-0.03383	0.02925	-1.16	0.2479	D_KAEF(t-2)
	AR4_1_1	-0.13230	0.04263	-3.10	0.0020	D_KLBF(t-3)
	AR4_1_2	-0.05164	0.02018	-2.56	0.0108	D_KAEF(t-3)
D_KAEF	AR1_2_1	-0.06902	0.21217			KLBF(t-1)
	AR1_2_2	-0.94739	0.08788			KAEF(t-1)
	AR2_2_1	0.11690	0.17653	0.66	0.5081	D_KLBF(t-1)
	AR2_2_2	-0.08981	0.07681	-1.17	0.2428	D_KAEF(t-1)
	AR3_2_1	-0.02170	0.13974	-0.16	0.8767	D_KLBF(t-2)
	AR3_2_2	-0.04961	0.06371	-0.78	0.4365	D_KAEF(t-2)
	AR4_2_1	-0.00970	0.09288	-0.10	0.9168	D_KLBF(t-3)
	AR4_2_2	-0.04136	0.04396	-0.94	0.3472	D_KAEF(t-3)

Based on the parameter estimation results, the VECM estimation (4) is obtained, i.e.

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Gamma_1 \Delta Y_{t-3} + \varepsilon_t$$

$$\Delta Y_t = \begin{bmatrix} -1.11094 & 0.02450 \\ -0.06902 & -0.94739 \end{bmatrix} Y_{t-1} + \begin{bmatrix} 0.00790 & 0.00962 \\ 0.11690 & -0.08981 \end{bmatrix} \Delta Y_{t-1} \\ + \begin{bmatrix} -0.02219 & -0.03383 \\ -0.02170 & -0.04961 \end{bmatrix} \Delta Y_{t-2}$$

$$+ \begin{bmatrix} -0.13230 & -0.05164 \\ -0.00970 & -0.04136 \end{bmatrix} \Delta Y_{t-3} + \begin{bmatrix} \varepsilon_{t1} \\ \varepsilon_{t2} \end{bmatrix}$$

**Table 10.** Schematic Representation of Cross Correlations of Residuals

Variable/Lag	0	1	2	3	4	5	6	7	8	9	10	11	12
KLBF	++	..	..	..	..	..	..	..	..	..	..	..	..
KAEF	++	..	..	..	..	..	..	..	.-	.+	..	..	..

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

Table 11. Portmanteau Test for Cross Correlations of Residuals

Up To Lag	DF	Chi-Square	Pr > ChiSq
5	4	5.86	0.2099
6	8	8.06	0.4272
7	12	9.46	0.6636
8	16	17.40	0.3604
9	20	24.82	0.2082
10	24	25.74	0.3663
11	28	26.92	0.5227
12	32	30.73	0.5308

3.5 *Normality Residual*
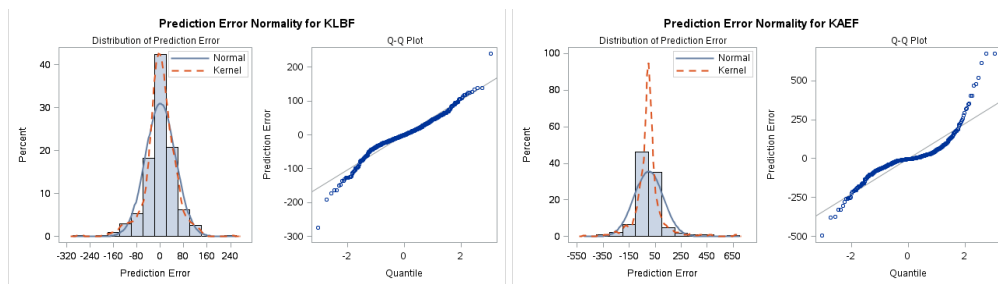
Figure 3. Prediction Error Normality for KLBF and for KAEF

Table 12. Univariate Model White Noise Diagnostics

Variable	Durbin Watson	Normality		ARCH	
		Chi-Square	Pr > ChiSq	F Value	Pr > F
KLBF	1.98909	241.34	<.0001	4.57	0.0330
KAEF	2.00446	2234.35	<.0001	41.99	<.0001

Table 13. Univariate Model AR Diagnostics

Variable	AR1		AR2		AR3		AR4	
	F Value	Pr > F	F Value	Pr > F	F Value	Pr > F	F Value	Pr > F
KLBF	0.02	0.8993	0.01	0.9877	0.03	0.9941	0.03	0.9986
KAEF	0.00	0.9566	0.00	0.9976	0.00	0.9999	0.00	1.0000

Tables 12 and 13 are used to examine residual white noise on the condition of a univariate equation. The table shows a statistical test for distribution normality using the Jarque Bera normality test. Table 12 shows the p-values for KLBF and KAEF <0.05, meaning that the residuals are normally distributed. From Figure 3 it can be seen that the residual is approaching the normality line.

3.6 *Test for Stability Model*
The model stability test is used to see whether the model is stable or not.

Table 14. Roots of AR Characteristic Polynomial

Index	Real	Imaginary	Modulus	Radian	Degree
1	0.48209	0.03817	0.4836	0.0790	4.5274
2	0.48209	-0.03817	0.4836	-0.0790	-4.5274
3	0.04416	0.65159	0.6531	1.5031	86.1226
4	0.04416	-0.65159	0.6531	-1.5031	-86.1226
5	-0.00620	0.38205	0.3821	1.5870	90.9301
6	-0.00620	-0.38205	0.3821	-1.5870	-90.9301
7	-0.50635	0.00000	0.5064	3.1416	180.0000
8	-0.67399	0.00000	0.6740	3.1416	180.0000

Based on Table 14, you can see the modulus value <1. So that VECM (4) is a model that is feasible to use.

3.7 *Test for fit the Model*
The model fit test can be seen from the ANOVA table of the univariate model to determine the significance of the model. Based on the equation of the VECM model (4) written univariately, the model feasibility test is as follows:

Table 15. Univariate Model ANOVA Diagnostics

Variable	R-Square	Standard Deviation	F Value	Pr > F
KLBF	0.5688	48.41149	32.32	<.0001
KAEF	0.5423	18.57153	29.03	<.0001

Based on Tabel 15, the univariate F-test are 32.32 and 29.03 with p-values <0.0001 for both KLBF and KAEF respectively.

3.8 *Analisys of Granger-Causality*

Granger-Causality Test is intended to determine the causal relationship of each independent variable on the dependent variable. The Granger-Causality test is based on the wald-test with the chi-square distribution or F-test. The null hypothesis in the Granger-Causality test is where group one is influenced by itself not by group two.

Table 16. Granger Causality Wald Test

Test	Group Variables	Pr > ChiSq	Conclusion
1	Group 1 Variables : KLBF Group 2 Variables : KAEF	0.0056	Reject H_0
2	Group 1 Variables : KAEF Group 2 Variables : KLBF	0.5926	Not enough evidence to reject H_0

Based on table 16, in test 1, the p-value <0.05 reject H0 means that KLBF is affected by KAEF. In test 2, p-value> 0.05 was obtained, it means that there was not enough evidence to reject H0. So in the second test, KAEF is affected only on itself and not on KLBF.

3.9 *Impulse Response Function (IRF)*
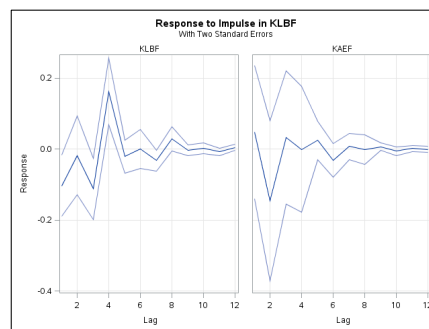
Figure 4. Response to Impulse in KLBF

Based on Figure 4, if the Impulse Response Function (IRF) graph experiences a shock of one standard deviation it will affect the KAEF variable and itself. If the IRF chart approaches the point of equilibrium or returns to the zero line, it means that the response of the variable to show other variables is getting lost so that the shock does not leave a permanent effect on the variable. Shock one standard deviation at ITMA, because ITMA gives a fluctuating response from the first week to the ninth week. In the first week to the second week the response is negative. The third and fourth weeks provide positive responses. The fifth and sixth week gives positive responses. The seventh and eighth week gives positive responses. The ninth week onwards the response begins to approach the point of balance and positive response. Shock one standard deviation at ITMA, because ELSA gives a positive fluctuating response from the first week to the seventh week. In the first week and second week negative responses. In the third week and the fourth week the value dropped but the response was positive. In the fifth week and the sixth week the response is negative. Then in the seventh week it starts to strike a balance point.
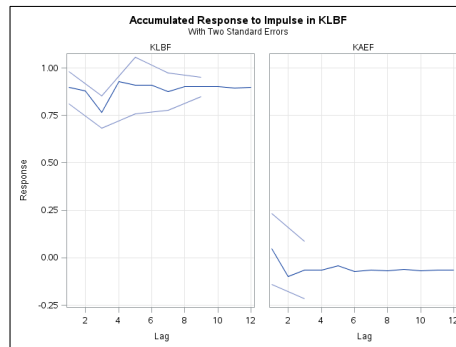
Figure 5. Response to Impulse in KAEF

Based on Figure 5, if the Impulse Response Function (IRF) graph experiences a shock of one standard deviation it will affect the KAEF variable and itself. If the IRF chart approaches the point of equilibrium or returns to the zero line, it means that the response of the variable to show other variables is getting lost so that the shock does not leave a permanent effect on the variable. Shock one standard deviation at KAEF, because KLBF gives a fluctuating response from the first week to the third week. Then in the fourth week onwards it does not fluctuate and gives a positive response because it is above point 0. Shock one standard deviation at KLBF, because KAEF gives a fluctuating response from the first week to the third week. Then in the fourth week and so on it does not fluctuate but gives a negative response because it is below the 0 point.

4. Conclusion

Based on the analysis of KLBF and KAEF time series data per week during January 2010-June 2020. This study examines the relationship between KLBF and KAEF, there is a cointegration relationship between KLBF and KAEF stock data with rank = 2. Based on the cointegration test and the smallest value of the information criteria, the best model is VECM (p) with lag p = 2. Meanwhile, the granger causality test explains that in test one a p-value of <0.05 starting with H_0 means that KLBF is affected by KAEF. Whereas in the second test, there was not enough evidence to reject H_0, meaning that KAEF stock data was affected only by itself and not by KLBF stock data. Based on IRF analysis, each variable gives a fluctuating response with itself and with other variables.

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