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# Application of Vector Autoregressive with Exogenous Variable: Case Study of Closing Stock Price of PT INDF.Tbk and PT ICBP.Tbk

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**Abstract.** Multivariate time series are widely used in various fields such as finance, economics, and the stock market. One analysis model that is widely used for multivariate time series data is the VAR model. Vector autoregressive (VAR) is a model used to describe the relationship between several variables. The VAR model provides an alternative approach that is very suitable for forecasting purposes and is very suitable for solving economic data problems. The variables used in this study consisted of endogenous variables with closing prices of ICBP and INDF shares and exogenous variables with exchange rates collected from January 2017 to July 2020. In this study, the best model, VARX (1,0), was obtained. also the relationship between variables through the impulse response function and granger causality. Furthermore, forecasting is also carried out for the next 30 days using the best model, VARX (1,0).

**Keyword:** vector autoregressive with exogenous variable, granger causality, impulse response function, forecasting..

## 1. Introduction

Covid-19 (Corona Virus Disease 2019) is a disease caused by SARSCov-2 (Severe Acute Respiratory Syndrome Coronavirus 2) or better known as Corona Virus. The Covid-19 case was first discovered in Wuhan Province, China in December 2019. This virus is not only in its home country, but the virus has spread throughout the world, including Indonesia. Of course this outbreak has had a negative impact on several sectors, one of which is the Indonesian economy and also has a significant impact on the stock market value of various sectors. In this study, the value of shares from the consumer sector is used because this sector is one of the sectors whose products are still used by the people in the midst of this pandemic and exchange rates are also used, namely the price of a currency from a country that is measured or expressed in currency. other money. Exchange rates play an important role in spending decisions, because they allow us to translate prices from various countries into the same language. Financial data or economic data collected in the same time interval is often referred to as time series



data. Multivariate time series are very popular in various fields such as finance, economics, stock market, and earth science, for example, meteorology [1]. In a multivariate time series analysis, not only the nature of the individual series but also the possible cross relations between time series data are discussed. The application of an autoregressive vector model (VAR) has been widely discussed by [2-4]. The VAR model can be used for structural analysis. In structural analysis, certain assumptions are imposed on the causal structure of the data being examined, and the causal impact resulting from unexpected shock or innovation for certain variables is studied. This causal impact is usually summarized in Granger causality and impulse response function (IRF) [5-7]. VAR provides an alternative approach that is very suitable for forecasting purposes. This model can be called an approach to the reduced form of a simultaneous structured system of equations. The VAR model is based on the historical data provisions of the variables to be predicted [8]. In this study involving exogenous variables, this model is extended to VAR with exogenous variables or VARX [[6],[9]].

## 2. Statistical Model

Multivariate time series data are considered as multiple time series data simultaneously. This is a branch of multivariate statistical methods, but is related to dependent data [4]. The main objectives of multivariate time series analysis to study the dynamic relationship between or between variables and to improve the accuracy of predictions [9-12]. In multivariate time series, k-dimensional time series data or vector time series data are used [13]. One of the multivariate time series data analysis is the Vector Autoregressive (VAR) model. The VAR model, for example  $X_t$  with  $t = 0, 1, \dots$ , becomes the p-component, full rank, zero average, covariance stationarity process. It is shown that the stationary process with full rank has a representation of the one-sided moving average or a unique Moving Average of the form [14]

$$X_t = \epsilon_t + \Gamma_1 \epsilon_{t-1} + \Gamma_2 \epsilon_{t-2} + \dots \quad (1)$$

Where  $\epsilon_t$  is component  $p$  zero which means that that the process orthogonal. Under general condition, (1) can be written as

$$(1 - \psi_1 L - \psi_2 L^2 - \dots) X_t = \epsilon_t \quad (2)$$

Or equivalent to

$$X_t = (\psi_1 L - \psi_2 L^2 - \dots) + \epsilon_t \quad (3)$$

$$= \begin{bmatrix} \psi_{11}(L) & \dots & \psi_{1p}(L) \\ \vdots & \ddots & \vdots \\ \psi_{p1}(L) & \dots & \psi_{pp}(L) \end{bmatrix} X_t + \epsilon_t \quad (4)$$

[15] where  $L$  is lag operator  $LX_t = X_{t-1}$  and

$$\psi_{ij}(L) = \sum_{k=1}^{\infty} \psi_{ijk} L^k \quad (5)$$

### 2.1. VAR (p) and VARX (p,q) Models

Vector autoregressive (VAR) is a model used to describe the relationship between several variables. This model is a generalization form of the univariate AR model. All variables in VAR are arranged symmetrically by including equations that explain the development of each variable based on its own lag and the lag of all other variables in the model. The general model for VAR (p) is as follows [11],

$$\begin{aligned} \dot{y}_t &= \Phi_1 \dot{y}_{t-1} + \dots + \Phi_p \dot{y}_{t-p} + a_t \\ \dot{y}_t &= \sum_{i=1}^p \Phi_i \dot{y}_{t-i} + a_t \\ \Phi(B) \dot{y}_t &= a_t \end{aligned} \quad (6)$$

where,

$\dot{y}_t$  =  $m \times 1$  vector variable at time  $t$ , with  $\dot{y}_t = y_t - \mu$

$\Phi_p$  =  $m \times m$  matrix of order  $p$ ,

$a_t$  =  $m \times 1$  vector residuals at time  $t$ .

VARX is Vector Autoregressive model with exogenous variable involve in the model. VARX Model ( $p, q$ ) is defined as follows:

$$\dot{y}_t = \sum_{i=1}^p \Phi_i \dot{y}_{t-i} + \sum_{i=1}^q \Theta_i^* x_{t-i} + a_t$$

$$\Phi(B) \dot{y}_t = \Theta_i^*(B) x_t + a_t \quad (7)$$

where,

$$\Phi(B) = I_k - \Phi_1 B - \dots - \Phi_p B^p$$

$$\Theta_i^*(B) = I_k - \Theta_1^* B - \dots - \Theta_q^* B^q$$

$$\dot{y}_t = ((y_{1t} - \mu), \dots, (y_{kt} - \mu))'$$

$$a_t = (a_{1t}, \dots, a_{kt})'$$

$$x_t = (x_{1t}, \dots, x_{rt})'$$

$\Phi_i$  is  $k \times k$  matrix and  $\Theta_i^*$  is  $k \times r$  matrix parameters.

### 2.2. Condition for Stationary

The stationarity of multivariate time series data can be tested by looking at the data graph whether the data fluctuates around a certain number or not; if not, then the data is not stationary. Statistically, we can check stationary data using the augmented dickey fuller test (ADF Test) or unit root test. In addition, it can also check the autocorrelation function (ACF) graph; if ACF decay very slowly, it can be said that the data is not stationary. In Unit-Root Test with lag- $p$ , the model with constants is defined as follows:

$$\Delta X_t = \alpha + \phi X_{t-1} + \sum_{i=1}^{p-1} \phi_i^* \Delta X_{t-i} + u_t \quad (8)$$

Where  $\Delta X_t = X_t - X_{t-1}$  and  $u_t$  is white noise. The null hypotheses is  $H_0 : \phi = 0$  against the alternative hypotheses  $H_a : \phi < 0$ . The test statistics is  $\tau$  (tau) with the distribution approximately  $t$ -distribution [9]. For significant level ( $\alpha = 0.05$ ),  $H_0$  is rejected if  $\tau < -2.57$  or if  $P - value < 0.05$  [10][16]. The test statistics is as follows:

$$ADF \tau = \frac{\phi}{se(\phi)} \quad (9)$$

### 2.3. Test for Granger Causality

Granger causality is used to look at the inter-dependency structure of the system that underlies multivariate time series [17-19]. The concept of Granger causality was introduced by Granger [11], the Granger variable causes other variables to increase if the coefficients are positive in the model (10). In a multivariate time series, the other observed variables are included in two autoregressive vector models (VAR) for  $Y$ . The econometric test of the observed data, for example,  $Y$  Granger Cause  $X$ , can be based on the following model [6]:

$$X_t = c_1 + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \dots + \alpha_p X_{t-p} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + u_t \quad (10)$$

### 2.4. Impulse Response Function

VAR Model can be written as vector MA ( $\infty$ ) as follows:

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

So that, matrix  $\Psi_s$  has an interpretation as follows:

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

Row  $i$ , column  $j$  of the element  $\Psi_s$  indicates the consequences of the increase one unit in innovation variable  $j$  at time  $t$  ( $u_{jt}$ ) for the value of variable  $i$ th at time  $t+s$  ( $X_{i,t+s}$ ), assuming that all other innovation are constant. If the first element  $u_t$  is changed as big as  $\delta_1$ , at the same time, the second element is changed as big as  $\delta_2, \dots$ , and the  $n$ th element is changed as big as  $\delta_n$ , then the join effects of those changed on the vector value ( $X_{t+s}$ ) become

$$\Delta X_{t+s} = \frac{\partial X_{t+s}}{\partial u_{1t}} \delta_1 + \frac{\partial X_{t+s}}{\partial u_{2t}} \delta_2 + \dots + \frac{\partial X_{t+s}}{\partial u_{nt}} \delta_n = \Psi_s \delta \quad (11)$$

Plot of the row  $i$ , column  $j$  of the element  $\Psi_s$

$$\frac{\partial X_{i,t+s}}{\partial u_{jt}}$$

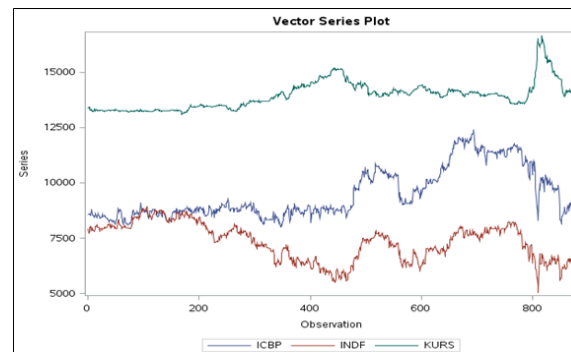
The function  $s$  is called as Impulse Response Function [4].

### 2.5. Forecasting

Forecasting is one of the main objectives in multivariate time series data analysis. Forecasting in the VAR ( $p$ ) model is basically similar to the estimate in the univariate AR ( $p$ ) model. First, the basic idea in the forecasting process is that the best VAR model must be identified using certain criteria to choose the best model. After the model is found, it can be used for estimation. Therefore, forecasting will be obtained from the best VARX ( $p, q$ ) model [4].

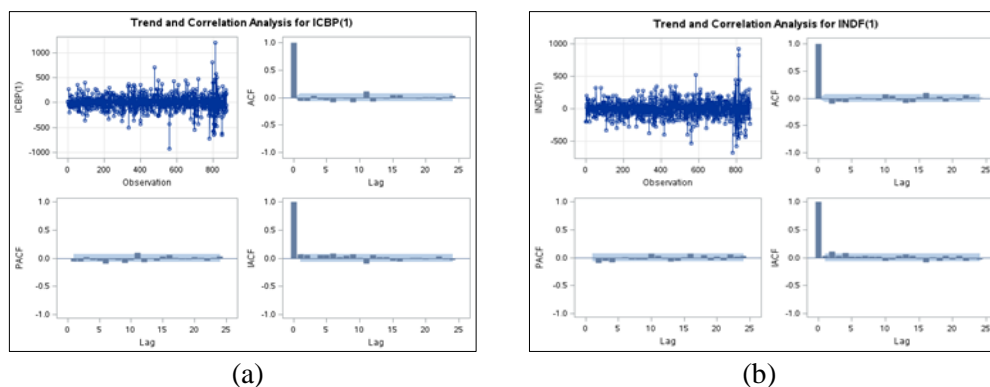
### 3. Result and Discussion

The data used in this study are ICBP and INDF stock closing price data taken from the January 2017 to July 2020 period and exchange rate data also taken from the January 2017 to July 2020 period. ICBP and INDF [20] [21] data are taken from Yahoo Finance and the value of the exchange rate is taken from Bank Indonesia. The plot of the data can be seen in Figure 1. The text of your paper should be formatted as follows:



**Figure 1.** Plot of Exchange rate, ICBP, and INDF from January 2017 to July 2020

In Figure 1. It can be seen that ICBP, INDF, and KURS data are not stationary. The exchange rate data from the first day to the 200th day of the chart looks flat, from the 200th to 400th data the trend rises slowly and fluctuates and from the 400th day the trend declines and fluctuates until the 800th day and then on the 10th day 800 graphs show a trend to increase dramatically and decrease slowly again. ICBP data from the first day fluctuated until the 450th day and increased from 450th to the 550th day and then on the 550th day increased again until the 700th day and the data tended to decrease and fluctuate until the last day. INDF data from the first day fluctuated until the 450th day and decreased from the 450th day to the 550th day and then on the 550th day increased again until the 700th day and the data tended to decrease and fluctuate until the last day. Next, a stationary test was performed on the data using the ADF test.



**Figure 2.** Residual plot, ACF, PACF, and IACF after differentiation with  $d = 1$  for (a) ICBP, (b) INDF

Figure 2 (a) and Figure 2 (b) are plots of the ADF test results after differencing. It can be seen that, after differencing data fluctuates around certain numbers. This shows that after differencing the data becomes stationary. This can also be seen in Table 1. Namely the ADF test results that show the p-value of the ICBP and INDF data of  $p < 0.0001$ . Therefore, it can be concluded that this data is stationary on the first differencing.

**Table 1.** Augmented Dickey Fuller Unit Root test for data ICBP and INDF before and after differentiation ( $d=1$ ).

Variable	Type	Before differentiation				After Differentiation			
		Rho	P value	Tau	P value	Rho	P value	Tau	P value
ICBP	Zero Mean	-0.0477	0.6720	-0.10	0.6487	-1045.53	0.0001	-22.82	<.0001
	Single Mean	-8.0345	0.2152	-2.04	0.2704	-1045.72	0.0001	-22.81	<.0001
	Trend	-14.4198	0.2042	-2.49	0.3323	-1046.37	0.0001	-22.81	<.0001
INDF	Zero Mean	-0.2937	0.6161	-0.56	0.4760	-1066.45	0.0001	-23.06	<.0001
	Single Mean	-10.8308	0.1100	-2.29	0.1763	-1066.83	0.0001	-23.05	<.0001
	Trend	-14.8710	0.1879	-2.73	0.2251	-1066.86	0.0001	-23.04	<.0001

Furthermore, to get the best model, it was selected using the AICC, HQC, AIC, and SBC information criteria from each model. The best model is the model that has the smallest value of the information criteria and the results of the analysis are presented in Table 2. Based on Table 2. The best model with SBC criteria is VARX (1,0) with a minimum value of 19,54635, with HQC criteria, namely VARX (2,0) with a minimum value of 19.50884, and the AICC and AICC criteria are VARX (4,0) with a minimum value of 19.4761 and 19.47556.

**Table 2.** Comparison of the criteria for VARX (1,0)–VARX (5,0) models

	Information Criteria			
	AICC	HQC	AIC	SBC
VARX (1,0)	19.50267	19.51933	19.50258	19.54635*
VARX (2,0)	19.48389	19.50884*	19.4837	19.54941
VARX (3,0)	19.4792	19.51241	19.47885	19.56655
VARX (4,0)	19.4761*	19.51755	19.47556*	19.58528
VARX (5,0)	19.47936	19.52901	19.47858	19.61036

After obtaining several candidate best models, VARX (1,0), VARX (2,0), and VARX (4,0). Judging from the schematic representation of the estimated parameters of each of these models. It can be seen in Table 3. There are 2 parameters and 3 significant parameters in AR1 for the VARX (1,0) and VARX (4,0) models and there are 5 significant parameters in AR1-2 for the VARX (2,0) model, and there are no significant parameters in AR3 and AR4. So the best model used is the VARX model (1,0).

**Table 3.** Schematic representation of parameter estimates for VARX (1,0), VARX (2,0), and VARX (4,0) models

Model	Variable/lag	C	XL0	AR1	AR2	AR3	AR4
VARX (1,0)	ICBP	.	.	+			
	INDF	+	-	+			
VARX (2,0)	ICBP	.	.	+	..		
	INDF	+	-	++	-.		
VARX (4,0)	ICBP	.	.	+	..	..	..
	INDF	.	.	++	..	..	..

+ is > 2\*std error, - is < -2\*std error, . is between, \* is N/A

**Table 4.** Statistical test for the parameters used in model

Equation	Parameter	Estimate	Standard Error	t Value	Pr >  t	Variable
ICBP	CONST1	371.53411	283.85174	1.31	0.1909	1
	XL0_1_1	-0.01272	0.01636	-0.78	0.4368	KURS(t)
	AR1_1_1	0.99221	0.00546	181.86	0.0001	ICBP(t-1)
	AR1_1_2	-0.01626	0.01192	-1.37	0.1726	INDF(t-1)
INDF	CONST2	656.11496	236.68721	2.77	0.0057	1
	XL0_2_1	-0.03171	0.01364	-2.33	0.0203	KURS(t)
	AR1_2_1	0.00180	0.00455	0.40	0.6920	ICBP(t-1)
	AR1_2_2	0.96834	0.00994	97.46	0.0001	INDF(t-1)

Based on Table 4. VARX(1,0) model can be written as follows:

$$\Gamma_t = \begin{pmatrix} 371.53411 \\ 656.11496 \end{pmatrix} + \begin{pmatrix} 0.99221 & -0.01626 \\ -0.00180 & 0.96834 \end{pmatrix} \Gamma_{t-1} + \begin{pmatrix} -0.01272 \\ -0.03171 \end{pmatrix} \Psi_t + \varepsilon_t \quad (12)$$

Where  $\Psi_t = \text{ExR values}$ . VARX(1,0) model is also can be written as two univariate model as follows:

$$\Gamma_{1t} = 371.5341 + 0.99221 \Gamma_{1t-1} - 0.01626 \Gamma_{2t-1} - 0.03171 \Psi_t + \varepsilon_{2t} \quad (13)$$

and

$$\Gamma_{2t} = 656.11496 - 0.00180 \Gamma_{1t-1} + 0.96834 \Gamma_{2t-1} - 0.01272 \Psi_t + \varepsilon_{1t} \quad (14)$$

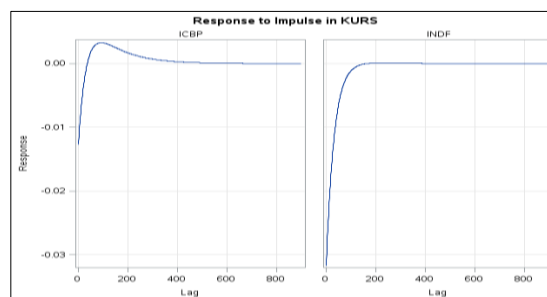
The results of the statistical test of the parameters VARX(1,0) model is given in Table 4, and for model (13) and (14) are given in Table 5. The results of the test for model  $\Gamma_{1t}$  (ICBP) is very significant with p-value<0.0001 and R-square 0.9802 this means that 98.02% variation of ICBP can be accounted for variables lag  $\Gamma_{1t-1}$ ,  $\Gamma_{2t-1}$  and  $\Psi_t$  (Exchange rate values). The results for the test statistic model  $\Gamma_{2t}$  (INDF) is very significant with p-value<0.0001 and R-square 0.9744 this means that 97.44% variation of INDF can be accounted for variables lag  $\Gamma_{1t-1}$ ,  $\Gamma_{2t-1}$  and  $\Psi_t$  (Exchange rate values). With high values of R-squares, this indicates that the VARX(1,0) model is fit with the data.

**Table 5.** Univariate Model ANOVA Diagnostics checks  
for the parameters used in model

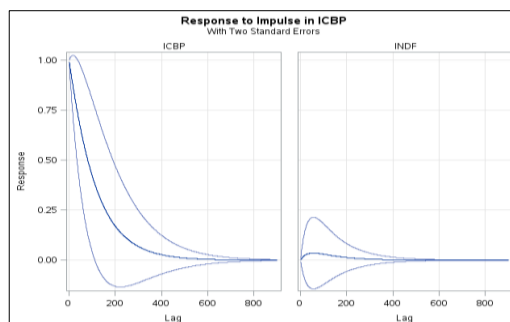
Variable	R-Square	Standard Deviation	F Value	Pr > F
ICBP	0.9802	159.13415	21481.8	<.0001
INDF	0.9744	133.05888	16552.0	<.0001

### 3.1. Impulse Response Function

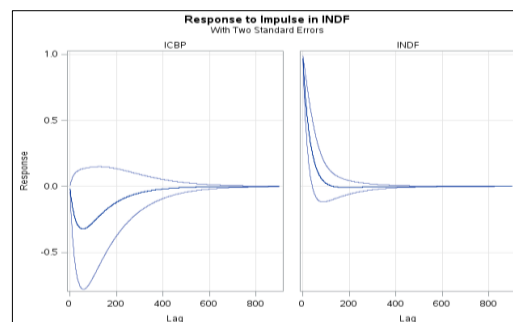
In this study, IRF is used to describe how economics reacts to exogenous impulses, commonly referred to by economists as shock or shocks and models in the context of VAR. Figure 4. Shows IRF shock in the exchange rate. A standard deviation of the exchange rate causes the ICBP to respond negatively for about 100 days and the minimum effect (first day) with a value of around -0.01 but after that it shifts to zero (stable condition) to around 770 days. Whereas the exchange rate causes INDF to respond negatively for about 150 days and after that it is in a stable condition which is in the 0 to 3 years period.



**Figure 3.** Impulse Response Function in Exchange Rate



**Figure 4.** Impulse Response Function in ICBP



**Figure 5.** Impulse Response Function in INDF

Figure 4. Shows IRF shock at ICBP with one standard deviation at ICBP causing ICBP to respond positively and have significance for about 3 months, whereas from the third to the 14th month the response moves to zero (stable condition). Thus, stable conditions were reached until the 14th month onwards. Behavior at confidence intervals between the third and 14th months is very interesting when there is high volatility. Impulses in ICBP appear to have an effect on INDF volatility. The IRF plot for INDF shows that INDF responded positively about 7 months ago to stabilize around zero when volatility is high up to a year after the ICBP shock, which shows that the closing price of the INDF stock fluctuated within the year after the ICBP shock. And Figure 5. Shows IRF shock at INDF with one standard deviation at INDF causing ICBP to respond positively for about 14 months, after which it returned to a stable condition, which is at 0. From the behaviour of the confidence interval on the ICBP plot, it can be observed that the volatility is very high. Therefore, it can be concluded that in this horizon, closing



prices after the INDF shock fluctuate significantly. The impact of impulses in INDF causes INDF to respond positively and has significance for about 3 months then the response moves to 0 (stable condition). Thus, stable conditions were achieved until the following months.

### 3.2. Granger Causality

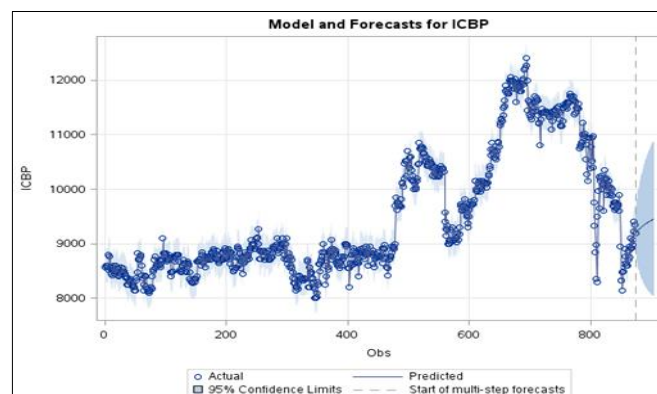
In Table 6. Test 2 shows the p-value of 0.1916 which means that ICBP only affects itself and does not affect INDF and so does Test 5 show that even INDF does not affect ICBP and only affects itself with p-value 0.4157. And in Test 7. Obtained significant test results namely the ICBP variable and the INDF variable is influenced by the exchange rate with p-value 0.0047 ( $<0.05$ ).

**Table 6.** Granger Causality Wald Test

Test	Group	DF	Chi-Square	Pr > ChiSq
2	Group 1 variables: ICBP Group 2 variables: INDF	1	1.71	0.1916
5	Group 1 variables: INDF Group 2 variables: ICBP	1	0.66	0.4157
7	Group 1 variables: KURS Group 2 variables: ICBP INDF	2	10.74	0.0047

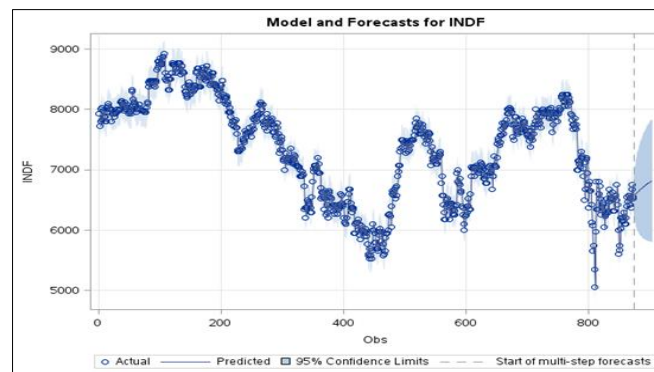
### 3.3. Forecasting

Forecasting is a process that allows the estimation of unknown future values that are used to predict forecast values in the time series data. In this study, the VARX (1,0) model was used to predict 30 values from ICBP and INDF data. Figure 6. Shows that the VARX (1,0) model for ICBP is very compatible with the original data. The circle represents the original data and the lines describe the model. Below is a predictive value with a 95% confidence interval. Accordingly, ICBP prediction data for the next 30 days appear to be increasing slightly.



**Figure 6.** Prediction and Forecasting of ICBP

In Figure 7. shows that the VARX(1,0) model for INDF is also very close to the original data. As for the INDF data, the circle represents the original data and the lines describe the model. Below is a predictive value with a 95% confidence interval. Thus, ICBP prediction data for the next 30 days seem to form an increasing trend.



**Figure 7.** Prediction and Forecasting of INDF

#### 4. Conclusion

Based on the results of the analysis of the relationship between endogenous variables namely ICBP and INDF and exogenous variables namely exchange rates, the best model for the relationship between these variables is the VARX(1,0) model. And univariate model obtained from the VARX(1,0) model is very significant. Based on the results of the IRF analysis, it can be concluded that if there is a shock in the exchange rate, then and through the Granger Causality test the results show that the exchange rate affects the ICBP and INDF. The univariate model for forecasting is very significant and the predictive value is very close to observation. This shows that this model is very reliable to be used for forecasting, forecasting results for the next 30 days do not fluctuate too much, but the confidence interval is greater as the period of prediction gets farther.

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