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Analysis of Data Inflation Energy and Gasoline Price by Vector Autoregressive Model

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ABSTRACT

The study of multivariate time series data analysis has become many topics of research in the fields of economics and business. In the present study, we will analyze data energy inflation and gasoline prices of Indonesia over the years from 2014 to 2020. The purpose of this study is to obtain the best model of the dynamic relationship between inflation and gasoline prices. The dynamic modeling that will be used in this research is modeling using the Vector Autoregressive (VAR) model. From the analysis results, the best model is the VAR model with order 3 (p=3), VAR(3). Based on the best model, VAR(3), further studies will be discussed with regard to Granger causality analysis, Impulse Response Function, and Forecasting.

Keywords: AICC, VAR(p) Model, Granger Causality, Impulse Response Function, Forecasting
JEL Classifications: E37, L11, Q47

1. INTRODUCTION

Currently, developments in communication technology and economic globalization have accelerated the integration of world financial markets. Price movements in one market can easily spread to other markets. Many researchers have conducted many studies in the economic field related to the energy sector, especially because of the problems that exist in the energy sector, including the scarcity of energy and renewable energy. Several studies have used cointegration and causality methods to study the relationship between crude oil prices and vegetable oil prices (Yu et al., 2006; Forero et al., 2019). The Vector Autoregressive (VAR) model has a long history as an analytical method for multivariate time series data (Quenouille, 1957). The VAR model is a model that is widely used in research in the fields of business, finance, and economics (Tsay, 2005; Kirchgassner and Wolters, 2007; Ghysels and Marcellino, 2018). Warsono et al. (2019a, 2019b) used a VAR model to discuss the relationship and price index forecasting of two Indonesian coal companies. VAR models became famous for studies in business, finance, and economic analyses when Sims (1980) suggested them as an alternative method to simultaneous equation modeling. The VAR model is often used to describe the behavior of variables over time; in this VAR model, it is assumed that the current value can be expressed as a function of the previous value and random error (Fuller, 1996; Wei, 2006). The VAR model, which can be written as a linear model, is relatively simple and very useful for multivariate time series data analysis and easy to estimate and test parameters (Fuller, 1996; Lütkepohl, 2005; Juselius, 2006). The VAR model based on the normal distribution is often a popular choice for macroeconomic time series data analysis (Juselius, 2006). The VAR model is very useful for describing and explaining the relationship and dynamic behavior of business, financial, and economic data (Lutkepohl, 2005; Wei, 2006). Forecasting is a very important goal in multivariate time series analysis. The VAR model is easy to use for forecasting and can also be applied to economic analysis (Lutkepohl, 2009). Furthermore, the VAR model can be used for structural analysis or Granger causality analysis (Hunter et al., 2017). In structural analysis, certain assumptions on the causal structure of the investigated data are applied and the impact caused by unexpected surprises or innovations on certain variables. Impulse response analysis or the decomposition of the variance of the estimated error is usually used to describe the relationship between variables in the VAR model (Lutkepohl, 2009). These causal effects are summarized in general terms in Granger causality and Impulse Response Functions (IRFs) (Hamilton, 1994; Lutkepohl, 2005, 2009; Wei, 2006).

The purpose of this study is to analyze the dynamic relationship between energy inflation and gasoline prices. The dynamic relationship between energy inflation and fuel prices will be analyzed using the VAR model. After the VAR model is obtained that matches the data, Granger causality analysis, IRF, and forecasting for the next 12 months will also be carried out.

2. STATISTICAL MODELING

Two-dimensional vector time series process, $Y_t=[Y_{1t}, Y_{2t}]'$, is stationary if the series component is a stationary univariate process and their first two moments are time-invariant. In the current study, the modeling for two-dimensional vector time series is

$$Y_t = \begin{bmatrix} Gasoline\ P_t \\ INF\_EN_t \end{bmatrix} \tag{1}$$

Stationary assumption is a fundamental assumption in multivariate time series analysis. Therefore, before we build the best model, this stationary assumption will be checked first. Stationary examination was carried out by looking at the behavior plot of the data and by using the unit root test or Augmented Dickey–Fuller test (ADF test) (Brockwell and Davis, 1991, 2002).

The most common use of the multivariate time series analysis is the VAR model. The main reasons why this model is widely used in analysis are: first, the model is easy to estimate. We can use the least squares (LS) method, the maximum likelihood (ML) method, or the Bayes method. For the VAR model, the LS estimate is asymptotically equivalent to the ML estimate (Tsay, 2014). Second, the properties of the VAR model have been intensively discussed in many studies and literatures. Third, the VAR model is similar to the multivariate multiple regression that is widely used in multivariate statistical methods (Hamilton, 1994; Pena et al., 2001; Lutkepohl, 2005; Tsay, 2014; Wei, 2019). To determine the optimal lag in the process of selecting the best model, Akaike Information Criterion Corrected (AICC) is used with the smallest AICC value being a candidate to determine the best model. Several VAR(p) models will be evaluated in an effort to obtain the best VAR(p) model. The AICC value is calculated as follows:

$$AICC = \log(|\hat{\Sigma}|) + 2r/(N - r/k) \tag{2}$$

where r is the number of parameters estimated, N is the number of observation, k is the number of dependent variables, and $\hat{\Sigma}$ is the ML estimate of Σ (Tsay, 2005; SAS/ETS 13.2, 2014).

2.1. Representation of VAR Model

Stochastic Y_T is assumed to be generated by VAR process of order p (VAR(p)) and formulated as follows:

$$Y_T=\Phi_1 Y_{T-1}+\Phi_2 Y_{T-2}+\ldots+\Phi_p Y_{T-p}+\varepsilon_T \tag{3}$$

where Φ_i(i=1,…, p) are the matrices parameters k × k, and the error process $\varepsilon_t=(\varepsilon_{1T},\ldots,\varepsilon_{KT})'$ are the white noise process with the mean zero and dimension k and its covariance matrix is $E(\varepsilon_t, \varepsilon'_t)=\sum^{\varepsilon}$ It is assumed that $\varepsilon_t \sim$ i.i.d $(0, \sum^{\varepsilon})$. The VAR(p) process is stable if

$$\det(I_k-\Phi_1 z-\ldots-\Phi_p z^p)\neq 0 \text{ for } |z| \leq 1, \tag{4}$$

namely, if all the characteristic root of polynomial is in unit circle.

2.2. Granger Causality Test

With the VAR(p) model, causality analysis can be carried out from a variable or set of variables to the dependent variable. Granger causality test allows for bidirectional causality. Consider the following models:

$$Y_t = \begin{bmatrix} \text{Gasoline P}_t \\ \text{INF\_EN}_t \end{bmatrix} = \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{bmatrix} \begin{bmatrix} \text{Gasoline P}_{t-1} \\ \text{INF\_EN}_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{bmatrix} \begin{bmatrix} \text{Gasoline P}_{t-p} \\ \text{INF\_EN}_{t-p} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \tag{5}$$

Y_t consists of vector GasolineP$_t$ and INF_EN$_t$. INF_EN$_t$ is said not to be Granger causality for Gasoline P$_t$ if the coefficient matrix of parameter δ_{21} = 0 for i=1, 2,…, p (LutkepohlLutkepohl, 2005).

2.3. Impulse Response Function

Wei (2006) and Hamilton (1994) stated that the IRF is a method used to analyze a response of a variable due to shock in another variable. Brockwell and Davis (2002) explained that the VAR(p) model can be written in the form of MA (∞) as follows:

$$Y_t=\mu+\mu_t+\phi_1 \mu_{t-1}+\phi_2 \mu_{t-2}+\ldots \tag{6}$$

It has an interpretation as follows:

$$\frac{\partial Y_{t+s}}{\partial \mu_t} = \varphi_s \tag{7}$$

The element of the ith row and jth column indicates the consequence of the increase of one unit in innovation of variable j at time t (μ_{jt}) for the i variable at time t+s ($Y_{i,\,t+s}$) and fixed all other innovation. If the element of μ_t changed by δ_1, at the same time, the second element will change by δ_2,…, and the nth element will change by δ_n, then the common effect from all of these changes on the vector X_{t+s} will become

$$\Delta Y_{t+s} = \frac{\partial Y_{t+s}}{\partial u_{1t}}\delta_1 + \frac{\partial Y_{t+s}}{\partial u_{2t}}\delta_2 + \ldots + \frac{\partial Y_{t+s}}{\partial u_{nt}}\delta_n = \varphi_s \delta \tag{8}$$

The graph of the ith row and jth column of as a function of s is called IRF.

2.4. Forecasting

To do forecasting for the next 12 months in the study, the best VAR(p) model that fits the data will be used. By using this best model, the forecasting process is carried out.

3. RESULTS AND DISCUSSION

The data used in this study are gasoline price and inflation of energy over the years from 2014 to 2020, where the gasoline price is taken from trading economics (https://id.tradingeconomics.com/indonesia/gasoline-prices) and energy inflation is taken from the Indonesian Ministry of Trade (https://statistik.kemendag.go.id/inflation-2020). The data are depicted in the Figure 1.

Figure 1 shows that gasoline price data fluctuated around 2015 and there was a slight downward trend from 2015 to December 2020. The plot of gasoline price shows that the data is stationary. Figure 1 also shows a plot of energy inflation. The energy inflation plot shows varied fluctuations up and down from January 2014 to June 2017, whereas from June 2017 to December 2020, the plot shows a flat trend and not too large fluctuations. Most of the inflation values are in the range of 0.0%–1.0%. From the results of the ADF test (Table 1), it shows that there is no unit root, and it can be concluded that the data is stationary.

Therefore, we can conclude that the assumption of stationary data is not violated by data on gasoline prices and energy inflation. Table 2 shows that there is a cross-correlation of gasoline price and energy inflation data up to lag-12. This shows that the gasoline price and energy inflation data modeling must involve autoregressive vector modeling.

Table 3 shows that the optimal lag value occurs in the Vector Autoregressive Moving Average model with orders of 5 and 1, VARMA(5,1). However, several models that are close to this model will be compared. Thus, the VAR(3), VAR(4), VAR(5), VARMA(3,1), VARMA(4,1), and VARMA(5.1) models will be compared.

From Table 4, it appears that the VAR(3) model seen from the number of parameters is significantly better than the VAR(4), VAR(5), VARMA(3,1), VARMA(4,1), and VARMA(5.1) models. In the VAR(4) model at lag-3, there are no significant parameters. In the VAR(5) model, there are no significant parameters at lag-3, lag-4, and lag-5. In the VARMA(3,1) model at lag-1, lag-2, lag-3, and MA(1), some parameters are undefined. In the VARMA(4,1) model in lag-3, lag-4 parameter is not significant. In the VAR(5) model in lag-2, lag-3, lag-4, lag-5, and MA(1), there are no significant parameters. In addition, the VAR(3) model is simpler. Therefore, for further analysis, the VAR(3) model will be used.

Table 1: Dickey–Fuller unit root test

Variable	Type	Rho	Pr<Rho	Tau	Pr<Tau
Gasoline	Zero mean	−0.35	0.6012	−0.60	0.4540
	Single mean	−16.69	0.0203	−2.88	0.0521
	Trend	−79.01	0.0003	−6.02	<.0001
INF_EN	Zero mean	−11.18	0.0179	−2.43	0.0154
	Single mean	−22.43	0.0040	−3.28	0.0191
	Trend	−31.94	0.0025	−3.91	0.0157

VAR(3) model estimate,

$$\begin{pmatrix} Gasoline\_P_t \\ INF\_EN_t \end{pmatrix} = \begin{pmatrix} 0.0920 \\ -0.3049 \end{pmatrix} + \begin{bmatrix} 0.7462 & 0.0048 \\ 2.1944 & 0.3177 \end{bmatrix} \begin{pmatrix} Gasoline\_P_{t-1} \\ INF\_EN_{t-1} \end{pmatrix} + \begin{bmatrix} -0.3425 & 0.0091 \\ -0.9422 & 0.2555 \end{bmatrix} \begin{pmatrix} Gasoline\_P_{t-2} \\ INF\_EN_{t-2} \end{pmatrix} + \begin{bmatrix} 0.3879 & 0.0184 \\ -0.4433 & 0.0571 \end{bmatrix} \begin{pmatrix} Gasoline\_P_{t-3} \\ INF\_EN_{t-3} \end{pmatrix}$$

with Covariance of Innovation

$$Var(\varepsilon_t) = \Sigma = \begin{bmatrix} 0.0009 & -0.0001 \\ -0.0001 & 0.0534 \end{bmatrix}.$$

The model parameter estimates and tests are given in Table 5.

Figure 1: Plot data gasoline price (in USD) and inflation energy

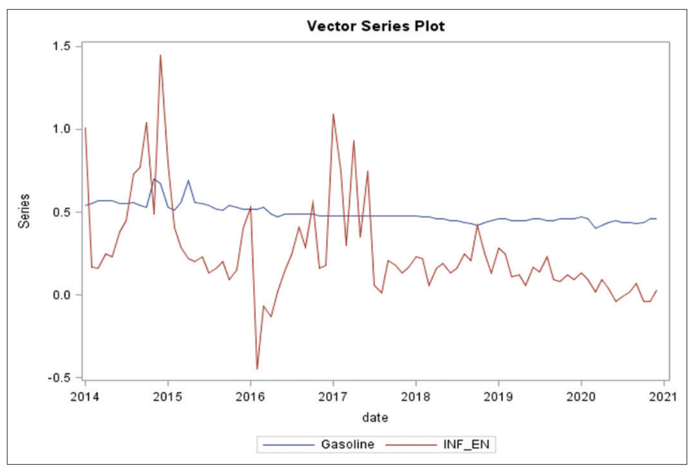


Table 2: Schematic representation of cross-correlation

Variable/lag	0	1	2	3	4	5	6	7	8	9	10	11	12
Gasoline	++	++	++	++	++	++	++	++	++	+.	+.	+.	+.
INF_EN	++	++	++	++	++	+.	+.	+.	+.	+.	+.	+.	.

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

Table 3: Test for lag optimal by using minimum information criterion based on AICC

Lag	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	−8.353355	−8.478191	−8.484103	−8.541262	−8.579243	−8.746211
AR 1	−9.586645	−9.592434	−9.805029	−9.779265	−9.742568	−9.859636
AR 2	−9.646402	−9.680577	−9.706904	−9.655664	−9.612976	−9.764643
AR 3	−9.733955	−9.782617	−9.736767	−9.718056	−9.59214	−9.649509
AR 4	−9.779322	−9.747271	−9.80743	−9.693337	−9.565316	−9.532644
AR 5	−9.70374	−9.807747	−9.783838	−9.644094	−9.509149	−9.497711

3.1. Model Diagnostic Check

Table 6 shows that in the univariate ANOVA model for the model with the independent variable gasoline price, the model is very significant with P<0.0001 and R-square=0.7208, which means that 72.08% of the variation of gasoline price is explained by the model. For the model with the independent variable energy inflation, the model is very significant with P<0.0001 and R-square=0.4221, which means that 42.21% of the variation of energy inflation is explained by the model. Table 7 shows that the Durbin–Watson test with a null hypothesis that the residuals are uncorrelated is not rejected; therefore, it can be concluded that the residuals are uncorrelated. In the Jarque–Bera normality test with the null hypothesis, the residuals are normally distributed. The null hypotheses rejected either the model univariate for independent variable gasoline price or the model univariate for independent variable inflation energy with both P<0.0001. However, Figures 2 and 3 show that the departure from normality is not too far. The test for autoregressive conditional heteroscedasticity (ARCH) to test the null hypothesis that the residuals have equal covariance is not rejected with P-values 0.5992 and 0.5827, respectively. Therefore, it can be concluded that there are no ARCH effects (Table 7). Table 8 shows that the root of AR characteristic polynomial is <1; therefore, the VAR(3) model is a stable model (Lutkepohl, 2005; Wei, 2006).

Based on the above analysis, the best model to analyze the data on the relationship between gasoline price and inflation energy is the VAR(3) model. Based on the VAR(3) model, Granger causality, IRF analysis, and forecasting will be carried out.

3.2. Granger Causality Test

Based on the results in Table 9, test 1 shows the P=0.2489 >0.05; therefore, the null hypothesis is not rejected. This means that the gasoline price is affected by the past information of gasoline price itself and not affected by the inflation energy. Test 2 shows the P=0.0395<0.05; therefore, the null hypothesis is rejected. This means that the inflation energy is affected by the past information of inflation energy itself and affected by the past and present information of gasoline price.

3.3. Impulse Response Function

From Figure 4a, if there is one unit of shock at gasoline price (or one-unit changes to gasoline price), the impact on the gasoline price lasts long up to the next 12 months, and the impact is still high and positive, where the impacts from the first to the 12th month are: 0.7462, 0.2248, 0.3268, 0.5112, 0.3893, 0.2610, 0.2880, 0.3073, 0.2550, 0.2165, 0.2146, and 0.2051, respectively. If there is one unit of shock at gasoline price (or one-unit changes to gasoline price), the impact on the inflation energy lasts long up to the next 12 months, and the impact is high and positive, where the impacts from the first to the 12th month are: 2.1944, 1.3925, 0.3499, 0.7668, 1.1267, 0.8014, 0.5656, 0.6623, 0.6880, 0.5625, 0.4909, and 0.4929, respectively. From Figure 4b, if there is one unit of shock at inflation energy (or one-unit changes to inflation energy), the impact on the gasoline price is very small, and the impact from the first to the 12th month is <0.0035. If there is one unit of shock at inflation energy (or one-unit changes to inflation energy), the impact on the inflation energy lasts long up to the next 9 months,

Table 4: Schematic representation of parameter estimate for the VAR (3), VAR (4), VAR (5), VARMA (3,1), VARMA (4,1), and VARMA (5.1) models

Model	Variable/lag	C	AR1	AR2	AR3	AR4	AR5	MA1
VAR (3)	Gasoline price	+	+•	−•	+•			
	Inflation energy	•	++	•+	••			
VAR (4)	Gasoline price	+	+•	••	••	+•		
	Inflation energy	•	++	•+	••	••		
VAR (5)	Gasoline price	•	+•	••	••	••	••	
	Inflation energy	•	++	•+	••	••	••	
VARMA (3,1)	Gasoline price	•	+•	••	••			••
	Inflation energy	•	**	**	**			**
VARMA (4,1)	Gasoline price	•	+•	− •	••	••		+•
	Inflation energy	•	••	••	••	••		••
VARMA (5,1)	Gasoline price	•	+•	••	••	••	••	••
	Inflation energy	•	••	••	••	••	••	••

+ is>2*std error, − is <−2*std error, • is between, * is N/A

Table 5: Model parameter estimates and tests for the VAR (3) model

Equation	Parameter	Estimate	Standard error	t-value	P-value|	Variable
Gasoline	CONST1	0.09200	0.03702	2.49	0.0152	1
	AR1_1_1	0.74623	0.10517	7.10	0.0001	Gasoline (t−1)
	AR1_1_2	0.00479	0.01498	0.32	0.7499	INF_EN (t−1)
	AR2_1_1	−0.34255	0.13545	−2.53	0.0136	Gasoline (t−2)
	AR2_1_2	0.00914	0.01511	0.60	0.5473	INF_EN (t−2)
	AR3_1_1	0.38799	0.10666	3.64	0.0005	Gasoline (t−3)
	AR3_1_2	0.01841	0.01410	1.31	0.1957	INF_EN (t−3)
INF_EN	CONST2	−0.30493	0.28331	−1.08	0.2853	1
	AR1_2_1	2.19446	0.80495	2.73	0.0080	Gasoline (t−1)
	AR1_2_2	0.31767	0.11461	2.77	0.0071	INF_EN (t−1)
	AR2_2_1	−0.94219	1.03668	−0.91	0.3664	Gasoline (t−2)
	AR2_2_2	0.25548	0.11565	2.21	0.0303	INF_EN (t−2)
	AR3_2_1	−0.44332	0.81633	−0.54	0.5887	Gasoline (t−3)
	AR3_2_2	0.05708	0.10792	0.53	0.5984	INF_EN (t−3)

Table 6: Univariate model ANOVA diagnostics

Variable	R-square	Standard Deviation	F value	Pr>F
Gasoline	0.7208	0.0302	31.84	<.0001
INF_EN	0.4221	0.2310	9.01	<.0001

Table 7: Univariate model white noise diagnostics

Variable	Durbin–Watson	Normality		ARCH	
		Chi-square	P-value	F value	P-value
Gasoline	2.33547	685.73	<0.0001	0.28	0.5992
INF_EN	2.00036	65.09	<0.0001	0.30	0.5827

Table 8: Root of AR characteristic polynomial

Index	Real	Imaginary	Modulus	Radian	Degree
1	0.92207	0.00000	0.9221	0.0000	0.0000
2	0.74173	0.00000	0.7417	0.0000	0.0000
3	−0.04763	0.69773	0.6994	1.6390	93.9053
4	−0.04763	−0.69773	0.6994	−1.6390	−93.9053
5	−0.25231	0.16416	0.3010	2.5648	146.9515
6	−0.25231	−0.16416	0.3010	−2.5648	−146.9515

and the impact is high and positive, where the impacts from the first to the 9th month are: 0.3176, 0.3669, 0.2815, 0.2561, 0.2067, 0.1660, 0.1484, 0.1325, and 0.1125, respectively. The impact is getting smaller after the 9th month.

3.4. Forecasting

In the current study, forecasting is based on a fitted VAR(3) model, which is the best model for the dynamic relationship between data gasoline price and inflation energy. The VAR(3) model is used to forecast data for the next 12 periods (months). From the analysis of forecasting by the VAR(3) model given in Table 10, for data gasoline price, the trend of the forecast for the next 12 months is increasing (Table 10 and Figure 5a and b); for the 1st month, the forecast is 0.4474, and at the 12th month, the forecast is 0.4599. Figure 5b also shows an increasing trend for forecasting for the next 12 months of the data gasoline price. Figure 5a also shows that the VAR(3) model fits with gasoline price data. For data inflation energy, the trend of the forecast for the next 12 months is increasing (Table 10 and Figure 6a); for the 1st month, the

Figure 2: (a and b) Prediction error normality for data gasoline price

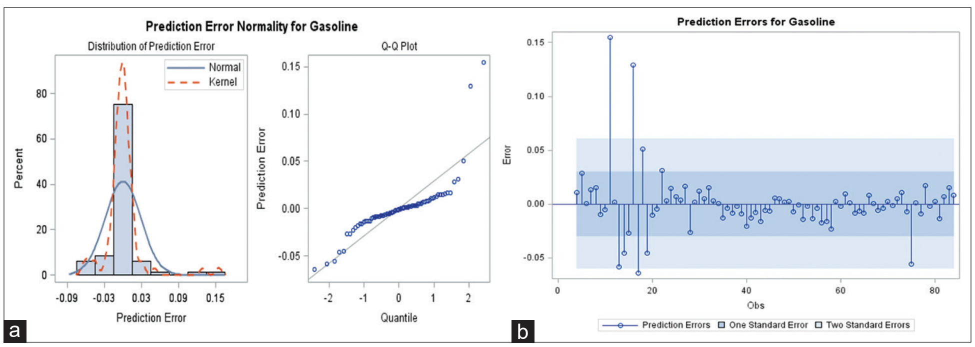


Figure 3: (a and b) Prediction error normality for data inflation energy

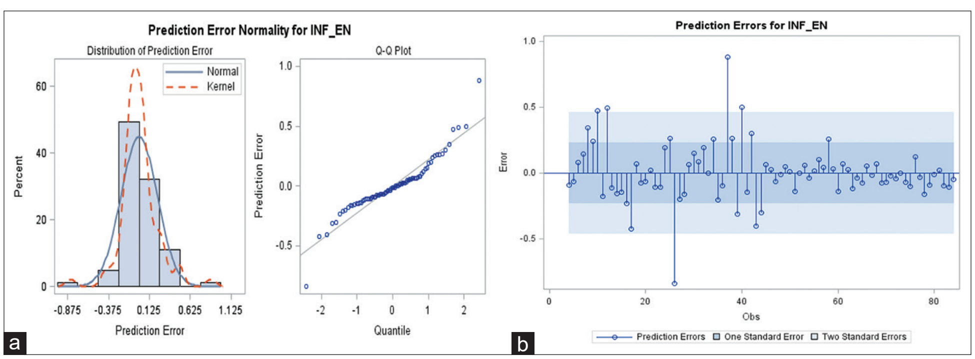


Figure 4: (a) Response to impulse in gasoline price and (b) response to impulse in inflation energy

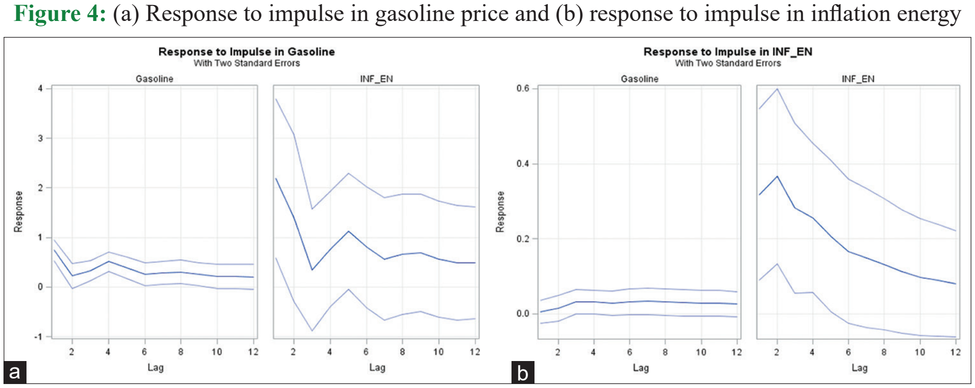


Table 9: Granger causality test

Test	Group variable	Null hypothesis	Chi-square	P-value	Granger causality
1	Group 1 variable: gasoline price Group 2 variable: inflation energy	Gasoline price is affected by itself and not by inflation energy	4.12	0.2489	Non- significant
2	Group 1 variable: inflation energy Group 2 variable: gasoline price	Inflation energy is affected by itself and not by gasoline price	8.34	0.0395	Significant

Table 10: Forecasting for the next 12 months

Variable	Obs	Forecast	Standard error	95% Confidence limits		Variable	Obs	Forecast	Standard error	95% Confidence Limits	
Gasoline	85	0.4474	0.0301	0.3882	0.5066	Inflation energy	85	0.0730	0.2310	−0.3797	0.5258
	86	0.4466	0.0376	0.3728	0.5205		86	0.0682	0.2509	−0.4236	0.5600
	87	0.4520	0.0384	0.3768	0.5273		87	0.0918	0.2679	−0.4333	0.6170
	88	0.4523	0.0403	0.3733	0.5313		88	0.1186	0.2758	−0.4220	0.6594
	89	0.4506	0.0437	0.3649	0.5363		89	0.1288	0.2830	−0.4258	0.6835
	90	0.4521	0.0457	0.3625	0.5417		90	0.1339	0.2889	−0.4323	0.7002
	91	0.4545	0.0469	0.3625	0.5465		91	0.1443	0.2924	−0.4287	0.7174
	92	0.4554	0.0483	0.3607	0.5501		92	0.1541	0.2948	−0.4237	0.7320
	93	0.4561	0.0497	0.3586	0.5535		93	0.1593	0.2970	−0.4229	0.7415
	94	0.4575	0.0507	0.3581	0.5569		94	0.1636	0.2989	−0.4222	0.7494
	95	0.4589	0.0515	0.3579	0.5600		95	0.1689	0.3002	−0.4194	0.7573
	96	0.4599	0.0523	0.3574	0.5625		96	0.1735	0.3012	−0.4169	0.7639

Figure 5: (a) Model and forecast for data gasoline price and (b) forecast for gasoline price

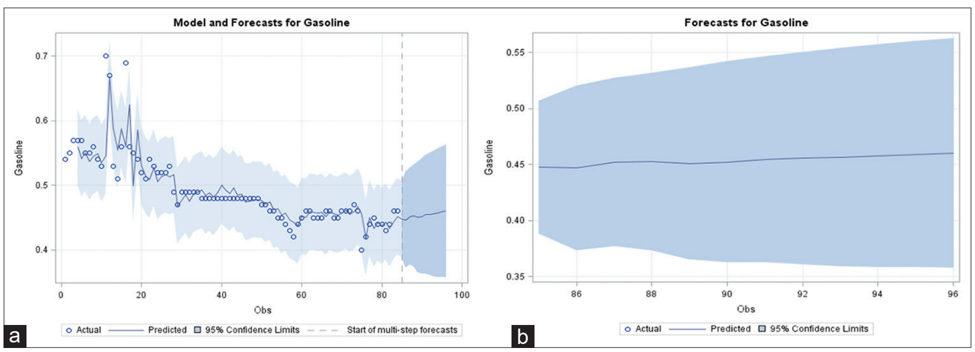
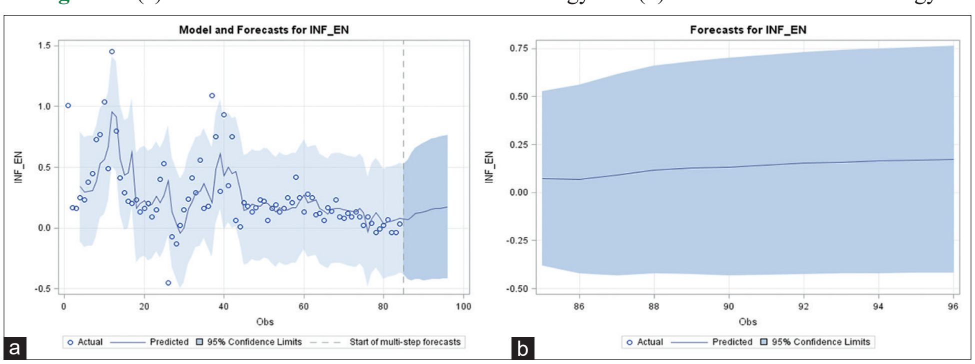


Figure 6: (a) Model and forecast for data inflation energy and (b) forecast for inflation energy



forecast is 0.0730, and at the 12th month, the forecast is 0.1735. Figure 6(b) also shows an increasing trend for forecasting for the next 12 months. Figure 6a also shows that the VAR(3) model fits with energy inflation data.

4. CONCLUSION

From the results of the analysis of the dynamic relationship between gasoline price data and energy inflation, using the AICC approach, comparison of several models, and estimation and hypothesis testing on the compared models in an effort to find the best model to describe the dynamic relationship between gasoline price data and energy inflation, then the best model is the VAR model with order p=3 (VAR(3)). Based on this best model, it is found that energy inflation is strongly influenced by gasoline price. If there is a fluctuation in gasoline prices, inflation will tend to increase. By using the VAR(3) model, the forecasting results for the next 12 months for both gasoline price data and energy inflation show an increasing trend.

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