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Article

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Analysis Forecasting of Gasoline Prices in Some ASEAN Countries by Using State Space Representation on Vector Autoregressive Model

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ABSTRACT

Research on the price of gasoline has become a topic of research that has been carried out by many researchers. The topic is interesting because the price of gasoline has a relationship with many aspects of people's lives. This study aims to examine the relationship pattern of gasoline prices in several ASEAN countries: Indonesia, Malaysia, and Vietnam, and to make gasoline price forecasting in these three countries for the next 12 months. This study uses a multivariate time series approach; first, the best vector autoregressive (VAR(p)) model will be built based on Akaike's Information Criterion (AIC). Based on the best VAR(p) model, granger-causality analysis is discussed, and for forecasting gasoline prices, a state space model will be developed based on the best VAR(p). State vectors are built based on canonical correlation analysis. Based on the results of granger causality analysis, gasoline prices in Indonesia are affected by past gasoline prices in Vietnam; gasoline prices in Malaysia are affected by past gasoline prices in Indonesia and Vietnam. The results of forecasting analysis for the next 12 months using the state space model show that gasoline prices in Indonesia for the next 12 months tend to have a downward trend; gasoline prices in Malaysia for the next 12 months tend to have an upward trend; and the price of gasoline in Vietnam for the next 12 months tends to have an upward trend for the first 6 months and then has a downward trend for the next 6 months.

Keywords: Vector Autoregressive, Granger-causality Test, State Vector, State Space Model, Forecasting
JEL Classifications: E31, E39, Q47.

1. INTRODUCTION

Many researchers are interested in studying the retail price of gasoline and how it relates to numerous other factors because it affects many different aspects of daily living. Some of the studies include research on the relationship between the price of gasoline and the number of accidents, the price of gasoline and public transportation, the relationship between the price of gasoline and housing development, and research on forecasting the price of gasoline. Many studies have discussed the factors that influence the variation in gasoline prices. Most research studies discuss asymmetric price behavior. Pricing asymmetry occurs when the time lag it takes for prices to react to a change in upstream prices is different for a price decrease than for a price increase. Several studies have concluded that gasoline prices generally respond more quickly to increases in crude oil prices than to decreases, perhaps because retailers seek to gain larger profit margins as input prices fall (Chen, et al., 2005; Davis, 2007; Grasso and Manera, 2007; Deltas, 2008;). Other studies (Bachmeier and Griffin, 2003; Galeotti et al., 2003; Douglas, 2010; Angelopoulou and Gibson, 2010) argue that there is little evidence of an asymmetric response to price shocks. Karrenbrock (1991) concluded that despite evidence of price asymmetry in response to changes in wholesale prices, consumers ultimately benefit from reduced prices as fully as they do from increases. Fullerton et al. (2015) discuss various factors that cause patterns of gasoline price movements, namely variables: Wholesale gasoline price, local economics, weather and cross - border economics.

Wilson et al. (2015) discussed the relationship between the impact of declining gasoline prices on motor vehicle fatalities and injuries. Wilson et al. (2015) concluded from their research results that declining gasoline prices may result in an increase in fatal and non-fatal injuries from motor vehicle crashes in several OECD countries. Burke and Nishitateno (2014) examined the relationship between gasoline prices and road fatalities. This study utilizes data from 144 countries from 1991 to 2010 to present the first international estimates of the gasoline price elasticity of road fatalities. Existing evidence from many studies in the United States indicates that higher gasoline prices reduce road fatalities or crashes (Chi et al., 2010; 2011; 2012; 2013a; 2013b; Grabowski and Morrisey 2004, 2006; Montour 2011).

Several studies have looked for determinants by analyzing the response of retail prices to changes in wholesale prices (Karrenbrock, 1991; Tsuruta, 2008) or crude oil prices (Radchenko, 2005). Eckert and West (2004) concluded that retail gasoline prices may vary between cities due to differences in market structure and the level of competition. Smart (2014) in his research discussed the relationship between gasoline prices and the willingness to invest public money in improving mass transportation. Smart (2014) hypothesized that volatility in fuel prices was a determining factor in supporting more mass transit funding. With the increasing volatility of gasoline prices, the public should support investment in mass transportation. Smart (2014) also concluded that from the results of his study, there is a strong influence of price volatility on consumers' willingness to support transit spending.

Rodriguez (2013) discusses the relationship between gasoline prices and real estate development in suburban and out-of-town areas in the United States. The development of residential subdivisions far from the city center has increased driving distances. The gradual and then dramatic rise in oil prices from 2003 to 2008 triggered gasoline price shock. The convergence of rising gasoline prices and an abundance of newly built low-density tract housing led to an equally dramatic decline in new housing developments in areas far from the city center and older suburbs. While the gasoline price shock affected the number of new homes, the recession was responsible for falling house prices; the two concepts act independently of each other. By correlating gasoline prices, housing developments in rural areas compared to city centers, vehicle efficiency, and vehicle mileage data cause the demand for sprawl developments to decline substantially as gasoline prices increase over time.

Hamilton (2009) discusses the relationship between the price of gasoline and the price of crude oil, stating that because crude oil represents about half the cost of gasoline, consumers expect that a 10% increase in the price of crude oil will be associated with a 5% increase in the price of gasoline. Hamilton (2009) also stated that the price elasticity of demand for crude oil should be about half of the price elasticity of retail gasoline.

Forecasting is an important concept in business and economics. The ability to predict prices allows economic actors to make optimal decisions for the present and future. Anderson et al. (2011) stated the importance of forecasting both in the production of new energy, research related to energy, and the manufacture of durable goods that use energy, all of which depend heavily on the quality of predictions on future energy prices. Unqualified predictions can cause losses in investments.

In this study, we investigate how gasoline prices in several ASEAN countries can predict gasoline price using a multivariate time series analysis approach, namely the State Space model.

2. STATISTICAL MODEL

The first step before we analyze time series data is to check the assumption of stationarity and cross correlation among the variables, these assumptions are very fundamental in multivariate time series analysis (Hamilton, 1994; Brockwell and Davis, 2002; Tsay, 2010; Virginia et al., 2018; Warsono et al., 2019a; 2019b; 2020; Russel et al., 2022; 2023). In this study, to check or test the stationarity of the time series data can be done by checking the behavior of the plot of the data and by testing using the Augmented Dickey-Fuller test (ADF test) (Wei, 2006; 2019; Tsay, 2010; 2014). To check that there is a cross correlation between the variables, the correlation is tested with the t-test and stated in the schematic representation of cross correlation (Wei, 2006; 2019; Tsay, 2010; 2014). To test whether the data meet the stationary assumptions using the Augmented Dickey-Fuller (ADF-test) and it is conducted by the following model:

$$\Delta z_t = c + \beta_t + \delta z_{(t-1)} + \sum_{(i=1)}^{m} \alpha_i \Delta z_{(t-1)} + e_t \quad (1)$$

The null and alternative hypotheses are as follows:

H_0: δ=0 and H_1: δ<0

In the statistical test, to test the null hypothesis, we use the test- or Dickey-Fuller test as follows:

$$\tau = \frac{\delta}{S_\delta} \quad (2)$$

The null hypothesis is rejected if the P-value ≤ α, for α=0.05, (Enders, 2015; Virginia et al., 2018, Warsono et al., 2019a; 2019b.).

2.1. Model Vector Autoregressive (VAR)

According to Tsay (2014), to analyze data multivariate time series that involve more than one variable, we can use one of the models, for example, the vector autoregressive (VAR) model. The VAR(p) model can be written as follows:

$$Z_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i Z_{t-1} + a_t \quad (3)$$

where Z_t is nx1 vector time series, Φ_0 is nx1 vector constant, Φ_i is $n \times n$ matrix of parameters(for i > 0, $\Phi_p \neq 0$), is vector shock with mean vector zero, and a_t variance covariance matrix is Σ_a.

2.2. Granger Causality Test

One of the most popular causality tests used in various multivariate time series data studies is the Granger Causality Test. According to (Hamilton, 1994; Lütkepohl, 2005; Warsono et al., 2020; Russel, et al., 2022; 2023), the Granger causality test is used to determine the short-term relationship in the form of reciprocity between variables under study. Suppose that we analyze the Granger causality between variables X and Y and the model for Granger Causality Test is:

$$x_t = c_1 + \alpha_t x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_p y_{t-p} + u_t \tag{4}$$

Based on the assumption of ordinary least squares (OLS), the null hypothesis to be tested is as follows:

H_0: $\beta_1 = \beta_2 = \cdots = \beta_p = 0$ (Y is not Granger Causal X) against H_1: at least one of $\beta_p \neq 0$ (Y Granger Causal X). The statistic test is as follows:

$$\text{F Test} = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T-2p-1)} \tag{5}$$

Reject the null hypothesis if F-Test > $F_{(\alpha,\ p,\ T\text{-}2p\text{-}1)}$ or if P < 0.05 (Hamilton, 1994).

Where to calculate the residual sum of squares 1 or RSS_1 using the shocks of model (4) is calculated as follows:

$$RSS_1 = \sum_{t=1}^{T} \hat{u}_t^2 \tag{6}$$

Under the null hypothesis the model (4) is written as follows:

$$x_t = c_0 + \gamma_t x_{t-1} + \gamma_2 x_{t-2} + \ldots + \gamma_p x_{t-p} + e_t \tag{7}$$

And to calculate the residual sum of squares 0 or RSS_0 by using the shocks of model (7) is calculated as follows:

$$RSS_0 = \sum_{t=1}^{T} \hat{e}_t^2 \tag{8}$$

2.3. Model State Space

A state space model is an approach to simultaneously model and predict much time series data that are interconnected, where the variables have dynamic interactions. The state space representation is explained through the state equation:

$$Y_{t+1} = AY_t + GX_{t+1} \tag{9}$$

The output equation is

$$Z_t = HY_t \tag{10}$$

Where Y_t is kx1 state vector, A is a transition matrix $k \times k$, G is kxn input matrix, X_t is nx1 vector input with nx1 dimension, Z_t is the mx1 output vector, and H is the mxk matrix observation or output (Wei, 2006).

2.4. Canonical Correlation Analysis

Canonical correlation analysis is a statistical analysis used to see the relationship between a group of dependent variables and a group of independent variables. According to Akaike (1974; 1975; 1976) and Wei (2006), the state vector is uniquely determined through the analysis of canonical correlations between a set of current and previous observations and a set of observations of current and future events. A discussion of the canonical correlation can be seen in Wei (2006). A canonical correlation analysis is simply performed between data spaces:

$$D_n = (Z'_n, Z'_{n-1}, \ldots, Z'_{n-p})' \tag{11}$$

And predictor space:

$$F_n = (Z'_n, Z'_{n+1|n}, \ldots, Z'_{n+p|n})' \tag{12}$$

The choice of the order p for VAR model is obtained from the optimal fit of the data to the VAR(p) model, which is determined based on the smallest AIC (Akaike's Information Criterion) value. The canonical correlation analysis refers to the matrix Block Hankel of the covariance sample:

$$\hat{\Gamma} = \begin{bmatrix} \hat{\Gamma}(0) & \hat{\Gamma}(1) & \cdots & \hat{\Gamma}(p) \\ \hat{\Gamma}(1) & \hat{\Gamma}(2) & \cdots & \hat{\Gamma}(p+1) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\Gamma}(p) & \hat{\Gamma}(p+1) & \cdots & \hat{\Gamma}(2p) \end{bmatrix} \tag{13}$$

where $\hat{\Gamma}(j)$ is the covariance matrix sample defined as follows:

$$\hat{\Gamma}(s) = \frac{1}{n} \sum_{t=1}^{n-s} (Z_t - \bar{Z})(Z_{t+s} - \bar{Z})' \tag{14}$$

The smallest canonical correlation of (j) is used to select the components of the state vector.

2.5. Parameter Estimation

Based on the model state space

$$Y_{t+1} = AY_t + GX_{t+1}$$

where X_t-iid N (0, Σ). The order of observation Z_t composes m main components of Y_t so that $Z_t = HY_t$ where H is a matrix $[I_m, 0]$ with the order of $m \times k$. According to Wei (2006) after the state space model is selected, the estimation of the parameters of the state space model is conducted using the maximum likelihood estimation method. Given the likelihood function:

$$L(Z_1, Z_2, \cdots, Z_n \mid A, G, \Sigma) = (2\pi)^{-\frac{n}{2}} \Sigma^{-\frac{n}{2}} e^{-\frac{1}{2} trace\, S(A,G)} \tag{15}$$

So that the log likelihood function is:

$$\ln L(Z_1, Z_2, \cdots, Z_n \mid A, G, \Sigma) = \ln\ (2\pi)^{-\frac{n}{2}} \Sigma^{-\frac{n}{2}} e^{-\frac{1}{2} trace\, S(A,G)}$$

$$\ln L(Z_1, Z_2, \cdots, Z_n \mid A, G, \Sigma) = -\frac{n}{2} \ln |\sum| - \frac{1}{2} trace \sum^{-1} S(A,G) \tag{16}$$

Where

$$S(A,G)=\sum_{t=1}^{n} X_t X_t^{'}$$

2.6. Forecasting

The Kalman filter is the most common approach to approximate and estimate statistics on state space models. In this case, the Kalman filter can handle changes in model parameters and variances. According to Welch and Bishop (2001), at the forecasting stage, the estimated value is generated for the current state and the error covariance value is used as initial guess information for the next step. The Kalman filter is a recursive renewal procedure that consists of forming the initial estimation of the state and then revising the estimation by adding a correction to the initial estimation. The basic recursive formula is used to update averages and covariance matrices (Wei, 2006). Consider the state space model given in (9) and (10), once the state space model is constructed, the l-step ahead forecasts from the forecast origin time t can be calculated as follows (Wei, 2006):

$$\hat{Y}_t(l)=E(Y_{t+1}\,|Y_j,\ j\le t)$$

$$=A\hat{Y}_t(l-1)$$

$$=A.A\hat{Y}_t(l-2)$$

$$=A^l\,\hat{Y}_t\ . \tag{17}$$

Hence,

$$\hat{Z}_t(l)=E(Z_{t+l}\,|\,Z_j,j\le t)$$

$$=H\hat{Y}_t(l)$$

$$\hat{Y}_t$$

Where

$$\hat{Y}_t=E(Y_t\,|\,Y_j,\ \ j\le t)=Y_t \tag{18}$$

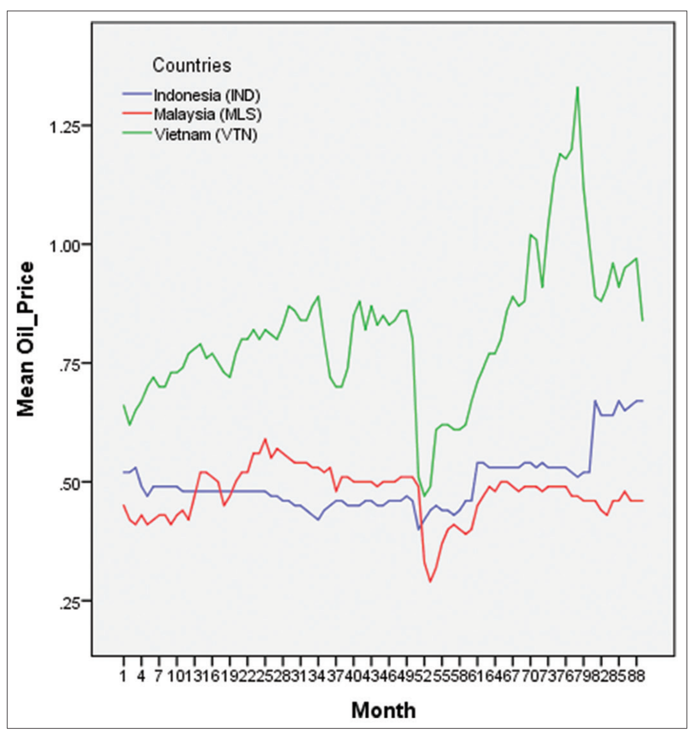
Clearly, from (17), the accuracy of the forecasts $\hat{Z}_t(l)$ depends on the quality of the estimate $\hat{Y}_t$ of the state vector Y_t, which summarizes the information from the past that is needed to forecast the future. To improve forecasts, when a new observation is available, it has to be used to update the state vector and hence to update the forecast. For this purpose, the Kalman Filter method is available, which is a recursive procedure used to make inferences about the state vector Y_t (See: Wei, 2006; Gomez, 2016).

3. RESULTS AND DISCUSSION

Gasoline price data in three ASEAN countries: Indonesia (IND), Malaysia (MLS), and Vietnam (VTN), from January 2016 to May 2023 are discussed in this study. Data source is from Tradingeconomic.com and from the Government of Indonesia, Government of Malaysia, and Government of Vietnam. Figure 1 shows the pattern of gasoline price movements in the three ASEAN countries. The price of gasoline in Indonesia has an increasing trend from 2016 to 2017, and from January 2018 to December 2019, it has downward trend. At the beginning of 2020, there was a significant decline in gasoline prices in all three countries. From May 2020 to June 2021, the price of gasoline in Indonesia has an upward trend, and from June 2021 to May 2023 the trend has decreased slightly. The trend of gasoline in Malaysia from 2016 to 2020 is stable and fluctuating, and from January 2021 to May 2023, the trend is rising and fluctuating. Gasoline prices in Vietnam from January 2016 to December 2019 trended up and fluctuated, and from January 2020 to May 2020 there was a significant price decrease and from June 2020 to September 2022 there was a sharp and fluctuating price increase, and from October from 2022 to May 2023 there will be a significant downward trend. From Figure 1 and the description above, it can be concluded that gas price data in Indonesia, Malaysia, and Vietnam from January 2016 to May 2023 are not stationary Table 1. The Dickey fuller unit root tests before differencing showed that the gasoline price data in Indonesia, Malaysia and Vietnam were not stationary, and after differencing the results of the unit root test (ADF test) showed that the data were stationary and that after differencing the data met the assumptions stationary.

To check whether the vector time series gasoline price data in Indonesia, Malaysia, and Vietnam from 2016 to May 2023 have a cross correlation by using a multivariate time series analysis approach, it is necessary to check whether there is a cross correlation of the three variables. From the results of the cross-correlation analysis in Tables 2 and 3, it shows that the time series gasoline price data has a significant and positive cross correlation

Figure 1: Plot data gasoline prices in Indonesia, Malaysia, and Vietnam from January 2016 to May 2023



between Indonesian and Vietnamese gasoline prices and between Malaysia and Vietnam, and there is a negative cross correlation between Indonesian and Malaysian. and these results are consistent with the results in Figure 1. With the existent of cross correlation, the vector time series modeling approach should use multivariate time series modeling.

Table 4 results from the minimum analysis of the Information Criterion Based on AICC suggesting that the minimum value occurs at AR2 (−20.5989), based on these results, the model to be used is vector autoregressive with order 2 (VAR (2)).

3.1. Model VAR(2)

$$Z_t = C + \Phi_1 Z_{t-1} + \Phi_2 Z_{t-2} + \varepsilon_t \quad (19)$$

The estimation model VAR(2) is:

$$\begin{pmatrix} IND_t \\ MLS_t \\ VTN_t \end{pmatrix} = \begin{pmatrix} 0.0026 \\ -0.0013 \\ 0.0013 \end{pmatrix} + \begin{bmatrix} -0.1956 & 0.0923 & -0.0338 \\ 0.3626 & -0.0596 & 0.1775 \\ 0.1563 & -0.0787 & 0.2291 \end{bmatrix} \begin{pmatrix} IND_{t-1} \\ MLS_{t-1} \\ VTN_{t-1} \end{pmatrix} + \begin{bmatrix} -0.0922 & -0.0216 & -0.1176 \\ 0.1345 & -0.0676 & 0.1115 \\ 0.1229 & -0.0733 & -0.1195 \end{bmatrix} \begin{pmatrix} IND_{t-2} \\ MLS_{t-2} \\ VTN_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix}$$

with covariance innovation

$$Cov \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix} = \begin{bmatrix} 0.0005 & 0.0001 & -0.0001 \\ 0.0001 & 0.0005 & 0.0002 \\ -0.0001 & 0.0002 & 0.0040 \end{bmatrix}$$

Model parameter estimates and testing are given below:

Table 1: Dickey-fuller unit root tests

Before differencing						After differencing					
Variable	Type	Rho	P−value	Tau	P-value	Variable	Type	Rho	P-value	Tau	P-value
IND	Zero Mean	0.29	0.7507	0.81	0.8850	IND	Zero Mean	−103.82	0.0001	−7.12	<0001
	Single Mean	−0.38	0.9334	−0.12	0.9431		Single Mean	−106.02	0.0001	−7.16	<0001
	Trend	−5.27	0.7928	−1.43	0.8439		Trend	−121.03	0.0001	−7.62	<0001
MLS	Zero Mean	−0.09	0.6594	−0.15	0.6282	MLS	Zero Mean	−86.70	<.0001	−6.55	<0001
	Single Mean	−16.86	0.0197	−2.92	0.0472		Single Mean	−86.74	0.0008	−6.51	<0001
	Trend	−17.38	0.0965	−2.99	0.1416		Trend	−87.27	0.0003	−6.50	<0001
VTN	Zero Mean	−0.17	0.6427	−0.19	0.6149	VTN	Zero Mean	−93.09	<.0001	−6.58	<0001
	Single Mean	−13.12	0.0547	−2.63	0.0908		Single Mean	−93.54	0.0008	−6.54	<0001
	Trend	−16.43	0.1185	−2.75	0.2180		Trend	−93.60	0.0003	−6.52	<0001

Table 2: The cross - correlation of dependent series gasoline prices of Indonesia, Malaysia and Vietnam

Cross Correlations of Dependent Series									
Lag	Variable	IND	MLS	VTN	Lag	Variable	IND	MLS	VTN
0	IND	1.0000	-0.0792	0.4366	5	IND	0.5808	−0.0209	0.3972
	MLS	−0.0792	1.0000	0.4184		MLS	−0.2256	0.4092	0.2220
	VTN	0.4366	0.4184	1.0000		VTN	0.4890	0.0514	0.5225
1	IND	0.8978	-0.0277	0.4417	6	IND	0.5209	−0.0358	0.3730
	MLS	−0.1209	0.8814	0.3566		MLS	−0.2605	0.3641	0.1844
	VTN	0.4388	0.4336	0.9108		VTN	0.4990	0.0108	0.4500
2	IND	0.8105	-0.0125	0.4401	7	IND	0.4538	−0.0239	0.3400
	MLS	−0.1483	0.7224	0.3010		MLS	−0.2811	0.2902	0.1455
	VTN	0.4322	0.3605	0.7863		VTN	0.5088	−0.0242	0.3973
3	IND	0.7298	-0.0085	0.4308	8	IND	0.3779	−0.0206	0.3022
	MLS	−0.1650	0.5769	0.2610		MLS	−0.3037	0.1989	0.0965
	VTN	0.4663	0.2367	0.6805		VTN	0.4956	−0.0695	0.3401
4	IND	0.6642	-0.0166	0.4095	9	IND	0.2901	−0.0282	0.2790
	MLS	−0.1983	0.4802	0.2430		MLS	−0.3290	0.1102	0.0507
	VTN	0.4729	0.1256	0.6020		VTN	0.4770	−0.1404	0.2661

Table 3: Schematic representation of cross correlations

Schematic representation of cross correlations										
Variable/Lag	0	1	2	3	4	5	6	7	8	9
IND	+.+	+.+	+.+	+.+	+.+	+.+	+.+	+.+	+.+	+.+
MLS	.++	.++	.++	.++	.++	-++	-+.	-+.	-.	-.
VTN	+++	+++	+++	+++	+.+	+.+	+.+	+.+	+.+	+.+

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

Table 4: MSinimum information criterion based on AICC

Lag	AR0	AR1	AR2	AR3	AR4	AR5
AICC	−15.5788	−20.4507	−20.5989	−20.5637	−20.3905	−20.1645

From Table 5, the pattern of significant relationships can be described as follows:

Figure 2 shows that the price of gasoline in Indonesia at time t (IND_t) is significantly influenced by information on gasoline prices in Indonesia at time t-1 (IND_{t-1}) and information on gasoline prices in Vietnam at time-(t-2) (VTN_{t-2}); Gasoline prices in Malaysia at time t (MLS_t) are significantly influenced by information on gasoline prices in Vietnam at time t-1(IND_{t-1}) and information on gasoline prices in Vietnam at time-(t-2) (VTN_{t-2}); Gasoline prices in Vietnam at time t (VTN_t) are significantly influenced by information on gasoline prices in Vietnam at time t-1 (VTN_{t-1}).

3.2. Granger Causality Test

From the results of the Granger Causality analysis (Table 6), Test 2, which has a Null Hypothesis (Ho), Gasoline price in Indonesia (IND) is influenced by itself and unaffected by the past information of gasoline price of Vietnam (VTN), with a p value = 0.0127 < 0.05. So Ho in Test 2 is rejected, so the gasoline price in Indonesia (IND) is influenced not only by itself but also by the past and present information of the gasoline price of Vietnam (VTN). Test 3, which has a null hypothesis (Ho), Gasoline price in Indonesia (IND) is influenced by itself and unaffected by past information on the gasoline price of Malaysia (MLS), with a P-value of 0.0929 <0.10. Therefore, Ho in Test 3 is rejected at a significant level of 0.10, so the gasoline price in Indonesia (IND) is influenced not only by itself but also by the past and present information of the gasoline price of Malaysia (MLS). Test 4, which has a Null Hypothesis (Ho), Gasoline price in Malaysia (MLS) is influenced by itself and unaffected by past information on the gasoline price of Vietnam (VTN), with a P-value of 0.0001 <0.05. So Ho on Test 4 is rejected. Gasoline prices in Malaysia (MLS) are influenced not only by themselves but also by past and present information on gasoline prices in Vietnam (VTN). From the granger causality test, Test 1, Test 5, and Test 6 were not significant because they each had P-values of 0.6863, 0.8647, and 0.9419, so Ho Test 1, Test 5, and

Table 5: Model parameter estimates and tests

Equation	Parameter	Estimate	Standard Error	t Value	P-value	Variable
IND	CONST1	0.00263	0.00234	1.12	0.2645	1
	AR1_1_1	−0.19567	0.10835	−1.81	0.0748	IND (t-1)
	AR1_1_2	0.09231	0.10399	0.89	0.3774	MLS (t-1)
	AR1_1_3	−0.03387	0.03903	−0.87	0.3881	VTN (t-1)
	AR2_1_1	−0.09223	0.11203	−0.82	0.4128	IND (t-2)
	AR2_1_2	−0.02167	0.08985	−0.24	0.8100	MLS (t-2)
	AR2_1_3	−0.11792	0.04419	−2.67	0.0092	VTN (t-2)
MLS	CONST2	−0.00135	0.00248	−0.54	0.5885	1
	AR1_2_1	0.36265	0.11479	3.16	0.0022	IND (t-1)
	AR1_2_2	−0.05965	0.11017	−0.54	0.5897	MLS (t-1)
	AR1_2_3	0.17747	0.04134	4.29	0.0001	VTN (t-1)
	AR2_2_1	0.13458	0.11868	1.13	0.2602	IND (t-2)
	AR2_2_2	−0.06761	0.09519	−0.71	0.4796	MLS (t-2)
	AR2_2_3	0.11154	0.04681	2.38	0.0196	VTN (t-2)
VTN	CONST3	0.00127	0.00694	0.18	0.8558	1
	AR1_3_1	0.15635	0.32165	0.49	0.6283	IND (t-1)
	AR1_3_2	−0.07877	0.30870	−0.26	0.7993	MLS (t-1)
	AR1_3_3	0.22915	0.11585	1.98	0.0514	VTN (t-1)
	AR2_3_1	0.12298	0.33256	0.37	0.7125	IND (t-2)
	AR2_3_2	−0.07327	0.26673	−0.27	0.7843	MLS (t-2)
	AR2_3_3	−0.11956	0.13117	−0.91	0.3648	VTN (t-2)

Table 6: Test granger causality

Test	Group variables	Ho	Chi-Squares	P-value	Granger-cause
1	Group 1 Variable : IND Group 2 Variable : MLS	Gasoline price in Indonesia (IND) is influenced by itself and unaffected by past information on the gasoline price of Malaysia (MLS).	0.75	0.6863	Non-significant
2	Group 1 Variable : IND Group 2 Variable : VTN	Gasoline price in Indonesia (IND) is influenced by itself and unaffected by past information on the gasoline price of Vietnam (VTN).	8.74	0.0127	Significant
3	Group 1 Variable : MLS Group 2 Variable : IND	Gasoline price in Malaysia (MLS) is influenced by itself and unaffected by past information on gasoline prices in Indonesia (IND).	4.75	0.0929	Non-significant
4	Group 1 Variable : MLS Group 2 Variable : VTN	Gasoline price in Malaysia (MLS) is influenced by itself and unaffected by past information on the gasoline price of Vietnam (VTN).	20.88	<.0001	Significant
5	Group 1 Variable : VTN Group 2 Variable : IND	Gasoline price in Vietnam (VTN) is influenced by itself and unaffected by past information on gasoline prices in Indonesia (IND).	0.29	0.8647	Non-significant
6	Group 1 Variable : VTN Group 2 Variable : MLS	Gasoline price in Vietnam (VTN) is influenced by itself and unaffected by past information on gasoline prices in Malaysia (MLS).	0.12	0.9419	Non-significant

Table 7: Canonical correlation analysis

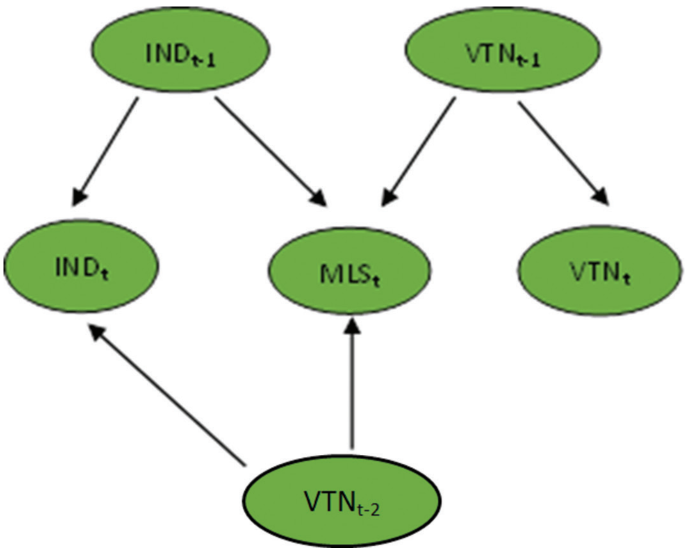
State vector	Canonical Correlation	IC	Chi-Square	DF
IND_t, MLS_t, VTN_t, $IND_{t+1\|t}$	1, 1, 1, 0.3070	−3.1882	8.5747	6
IND_t, MLS_t, VTN_t, $MLS_{t+1\|t}$	1, 1, 1, 0.4979	3.3634	24.5085	6
IND_t, MLS_t, VTN_t, $MLS_{t+1\|t}$, $VTN_{t+1\|t}$	1, 1, 1, 0.5066, 0.2107	−5.9564	3.9300	5
IND_t, MLS_t, VTN_t, $MLS_{t+1\|t}$, $MLS_{t+2\|t}$	1, 1, 1, 0.5288, 0.1929	−6.6257	3.2795	5

IND_t: Gasoline price in Indonesia at time t, MLS_t: Gasoline price in Malaysia at time t, VTN_t: Gasoline price in Indonesia at time t, and IC: Information Criterion

Table 8: parameters estimate of the state space model

Parameter	Estimate	Standard Error	t Value	Parameter	Estimate	Standard Error	t Value
F (1,1)	0.8393	0.0532	15.76	F (4,1)	0.0163	0.0355	0.46
F (1,2)	−0.1188	0.0610	−1.95	F (4,2)	−0.4830	0.1561	−3.09
F (1,3)	0.0473	0.0240	1.97	F (4,3)	−0.0217	0.0162	−1.34
F (3,1)	0.1141	0.1242	0.92	F (4,4)	1.4106	0.1736	8.12
F (3,2)	−1.0242	0.4800	−2.13	G (4,1)	0.1481	0.0821	1.80
F (3,3)	0.8643	0.0577	14.96	G (4,2)	0.9020	0.0992	9.09
F (3,4)	1.1577	0.5386	2.15	G (4,3)	0.1676	0.0370	4.53

Figure 2: The arrows (X→Y) indicate significant effects from variable X to variable Y



Test 6 were not rejected. From Test 1 we can conclude that the price of gasoline in Indonesia (IND) is not affected by past and present gasoline prices in Malaysia (MLS); From Test 5 we can conclude that the price of gasoline in Vietnam (VTN) is not affected by past and present gasoline prices in Indonesia (IND); From Test 6 we can conclude that the price of gasoline in Vietnam (VTN) is not affected by past and present gasoline prices in Malaysia (MLS).

3.3. Canonical Correlation Analysis

The best model for multivariate time series data IND, MLS, and VTN is vector autoregressive with order 2 VAR(2). Based on this best model, a state space approach for forecasting is being conducted. Using the canonical correlation approach, the state vector is built. In determining the state vector, we use the approach suggested by Wei (2006) and the process of determining the state vector follows the method given by Akaike (1976), that is by using canonical correlation. The choice state vector is based on the value of Information Criterion (IC), where the negative value of IC <0, then the minimum canonical correlation (ρ_{min}) is considered zero (Wei, 2006); otherwise, it is considered greater than zero.

From Table 7, for the first step, we consider the set of state vector: IND_t, MLS_t, VTN_t, $IND_{t+1|t}$ and for this set of state vector, the value of IC is negative (−3.1882). Therefore, we exclude the variable $IND_{t+1|t}$ into the state vector. Second step, we consider the set of state vector: IND_t, MLS_t, VTN_t, $MLS_{t+1|t}$, and for this set of state vector, the value of IC is positive (3.3634). Therefore, we include the variable $MLS_{t+1|t}$ into the state vector. In the third step, we consider the set of state vector: IND_t, MLS_t, VTN_t, $MLS_{t+1|t}$, $VTN_{t+1|t}$, and for this set of state vector, the value of IC is negative (−5.9564). Therefore, we exclude the variable $VTN_{t+1|t}$ into the state vector. In the fourth step, we consider the set of state vector: IND_t, MLS_t, VTN_t, $MLS_{t+1|t}$, $MLSt_{+2|t}$, and for this set of state vector, the value of IC is negative (−6.6257). Therefore, we exclude the variable $MS_{t+2|t}$ in the state vector. Based on the analysis above, at the second step, the IC value is positive. Therefore, based on the analysis of the canonical correlation, the component of the state vector is as follows:

$$Y_t = \begin{bmatrix} IND_{t|t} \\ MLS_{t|t} \\ VTN_{t|t} \\ MLS_{t+1|t} \end{bmatrix} \tag{20}$$

3.4. State Space Model

Based on the results of canonical analysis (Table 7) and from parameter estimation of transition matrix A and input matrix G (Table 8), the state space model can be written as follows:

$$Y_{t+1} = AY_t + GX_{t+1} \tag{21}$$

$$\begin{bmatrix} IND_{t+1|t+1} \\ MLS_{t+1|t+1} \\ VTN_{t+1|t+1} \\ MLS_{t+2|t+1} \end{bmatrix} = \begin{bmatrix} 0.8393 & -0.1188 & 0.0473 & 0 \\ 0 & 0 & 0 & 1 \\ 0.1141 & -1.0242 & 0.8643 & 1.1577 \\ 0.0163 & -0.4830 & -0.0217 & 1.4106 \end{bmatrix} \begin{bmatrix} IND_{t|t} \\ MLS_{t|t} \\ VTN_{t|t} \\ MLS_{t+1|t} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0.1481 & 0.9020 & 0.1676 \end{bmatrix} \begin{bmatrix} \alpha_{t+1} \\ \beta_{t+1} \\ \gamma_{t+1} \end{bmatrix}$$

Where

$$Var\begin{bmatrix}\alpha_{t+1}\\ \beta_{t+1}\\ \gamma_{t+1}\end{bmatrix}=\begin{bmatrix}0.00073 & -0.00003 & 0.00000\\ -0.00003 & 0.00049 & 0.00018\\ 0.00000 & 0.00018 & 0.00374\end{bmatrix}$$

3.5. Forecast

In this study forecasting gasoline prices in Indonesia (IND), Malaysia (MLS), and Vietnam (VTN) where forecasting will be carried out using the Fitted State Space Model and carried out using the Kalman Filter techniques. Estimation of the state space model given in model (21), which will be used for forecasting the next 12 months of gasoline prices in Indonesia, Malaysia and Vietnam. Figure 3 shows that the State Space model that was built is very fit with real data where the data and prediction values are very close together, this shows that this model is very reliable for use in forecasting for several future periods. From the forecasting results for the next 12 months for gasoline prices in Indonesia presented in Table 9 and Figure 3, it shows that in the next 12 months gasoline prices in Indonesia will have a downward trend; From the forecasting results for the next 12 months for gasoline prices in Malaysia (MLS) presented in Table 9 and Figure 3, it shows that in the next 12 months gasoline prices in Malaysia will have an upward trend; From the forecasting results for the next 12 months for the price of gasoline in Vietnam (VTN) presented in Table 9 and Figure 3, it shows that in the next 12 months the price of gasoline in Vietnam in the first 6 months has an increasing trend, and the following 6 months has a decreasing trend.

Figure 3: The plot of gasoline price data in Indonesia, Malaysia, and Vietnam, and predicted and forecasting values for the next 12 months

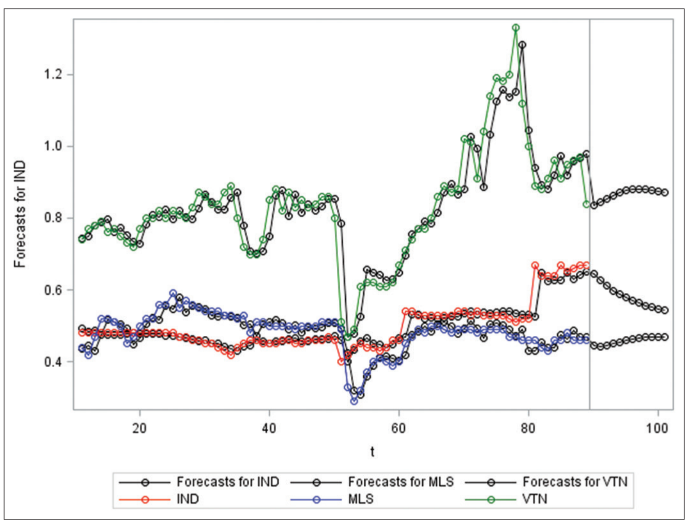


Table 9: Forecasting data gasoline price for the next 12 months

Month	IND	MLS	VTN
June 2023	0.64551	0.44513	0.83695
July 2023	0.62658	0.44241	0.84359
Agus 2023	0.61133	0.44541	0.85343
Sept 2023	0.59864	0.45050	0.86302
Oct 2023	0.58783	0.45578	0.87075
Nov 2023	0.57850	0.46034	0.87608
Dec 2023	0.57038	0.46389	0.87905
Jan 2024	0.56329	0.46642	0.87999
Feb 2024	0.55707	0.46807	0.87932
Mar 2024	0.55163	0.46905	0.87746
Apr 2024	0.54686	0.46955	0.87481
May 2024	0.54267	0.46972	0.87167

4. CONCLUSION

Gasoline price behavior data in several ASEAN countries: Indonesia (IND), Malaysia (MLS), and Vietnam (VTN), are interesting to be analyzed because they can influence the prices of other commodities and the cost of living of the population. In this study, the pattern of the relationship between gasoline prices in Indonesia, Malaysia and Vietnam, the results of the granger-causality analysis show that the price of gasoline in Indonesia is affected by the past price of gasoline in Vietnam, and this result is consistent with the results of the VAR(2) model analysis, where the price of gasoline in Indonesia was affected by the price of gasoline in Vietnam 1 and 2 months earlier; the results of the granger-causality analysis show that gasoline prices in Malaysia are affected by past gasoline prices in Indonesia and Vietnam, and these results are consistent with the results of the VAR(2) model analysis, where gasoline prices in Malaysia are influenced by gasoline prices in Indonesia, namely the price of one the previous month as well as 1 and 2 month gasoline prices in Vietnam.

The results of forecasting analysis for the next 12 months using the state space model show that gasoline prices in Indonesia for the next 12 months tend to have a downward trend; gasoline prices in Malaysia for the next 12 months tend to have an upward trend; and the price of gasoline in Vietnam for the next 12 months tends to have an upward trend for the first 6 months and then has a downward trend for the next 6 months.

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