Available online at http://scik.org
J. Math. Comput. Sci. 2022, 12:105
https://doi.org/10.28919/jmcs/7181
ISSN: 1927-5307

# PREDICTION OF EXPORT AND IMPORT IN INDONESIA USING VECTOR AUTOREGRESSIVE INTEGRATED (VARI)

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**Abstract:** This study aims to analyze the VARI model on the data of Indonesia's exports and imports from January 2015 to March 2021. The data from September 2020 to March 2021 became the out sample to measure the success of the VARI model in predicting exports and imports, which is measured by the value of MAPE (mean absolute percentage error). The R shiny program was developed to estimate the model parameter. Based on the Granger test, there was a causal relationship between exports and imports, so that past information on the export value can be used to predict the import values, and vice versa. The results of the analysis of the VARI model showed that simultaneously exports and imports in the previous period have a significant effect on the export and import value in the period of $t$.

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Received January 15, 2022

Based on the diagnostic test, the residuals have met the white noise assumption, and based on the MAPE value, the prediction results of the export and import values from October 2020 to March 2021 yielded a good result.

**Keywords:** export; import; Granger causality; VARI; MAPE.

**2010 AMS Subject Classification:** 37M10.

## 1. INTRODUCTION

Export is shipments of goods or services from a country to abroad for sale to obtain foreign currency from the buying country, while import is an activity of bringing goods and services for sale from another country into a country which results in an outflow of foreign currency. Based on Central Bureau of Statistics (BPS) data, Indonesia's exports in March 2021 reached US$18.35 billion, an increase of 20.31% compared to exports in February 2021. Meanwhile, imports in March 2021 reached US$16.79 billion, a rise of 26.55% compared to March 2021 [1]. The increase in import values was higher than the rise in the export values.

Exports and imports in various sectors will have an impact on the balance of trade of Indonesia [2], [3]. The three provinces that most largely contributed to the national export values during January-March 2021 were West Java, East Java, and Riau. The three countries that supplied the most non-oil and gas imports were China, Japan, and South Korea. In the same period, China was also the most dominant export destination with 21.36%, followed by the United States with 11.8%, and Japan with 7.91%. The main commodities exported to China are iron/steel, coal, and palm oil. Export activities will influence Indonesia's foreign exchange reserves which can be used to pay foreign debts, import needs, and the stability of the Rupiah currency [4].

Exports and imports have a role in the Indonesian economy as measured by gross domestic product, where in the first quarter of 2021, exports and imports contributed 19.18% and 18.09%, respectively. To see how the value of Indonesia's exports and imports looks like in the future, the Vector Autoregressive Integrated (VARI) model is used. The VAR model was initially introduced by C.A. Sims (1972) which was developed from the idea of Granger (1969) [5]. Granger suggested that if two variables, such as and $y$, have a causal relationship where $x$ affects $y$, then the past information on $x$ can help predict $y$.

In this study, R Shiny was developed to analyze the VARI model of the export and import data from January 2015 to March 2021. R Shiny can be developed by utilizing several available packages to facilitate users in data processing and statistical analysis [6]. Many researchers have worked to make the R package more user-friendly. A user can visualize data in a quick and customizable manner using the app [6], [7]. This research uses R shiny to predict and analyze export and import in Indonesia using vector autoregressive integrated model.

## 2. METHOD

The data used in this study were collected from the website of the Central Bureau of Statistics (BPS). The variables are the export and import values from January 2015 to March 2021. VAR was firstly introduced by Christopher A. Sims (1972) [5]. This model does not require distinguishing endogenous and exogenous variables [5], [8]. The VAR model is a widely-used dynamic linear model to forecast economic variables either in the long or in the medium to long term. In addition, the VAR model can also be used to determine causal relationships. Several strengths of the VAR model include [9]: 1) Researchers do not need to distinguish between endogenous and exogenous variables because all VAR variables are endogenous; 2) The estimation method is simple, namely, the least-squares method and separate models can be made for each endogenous variable; 3) the results of prediction using this model are in many cases better than those of even complex simultaneous equation models [10]. The VAR model with $k$ variables and the order of $p$ or known as VAR(p) can be written as follows [11], [12]:

$$\mathbf{Z}_{\mathrm{t}} = \mathbf{\Phi}_0 + \mathbf{\Phi}_1\mathbf{Z}_{\mathrm{t}-1} + \cdots + \mathbf{\Phi}_{\mathrm{p}}\mathbf{Z}_{\mathrm{t}-\mathrm{p}} + \mathbf{a}_{\mathrm{t}} \tag{1}$$

using backward shift operator B, the equation (1) is written as:

$$\mathbf{\Phi}_{\mathrm{p}}(\mathrm{B})\mathbf{Z}_{\mathrm{t}} = \mathbf{\Phi}_0 + \mathbf{a}_{\mathrm{t}} \tag{2}$$

with,

$$\mathbf{a}_{\mathrm{t}} \overset{iid}{\sim} \mathrm{VWN}\,(\mathbf{0}, \mathbf{\Sigma})$$

$$\boldsymbol{\Phi}_{\mathrm{p}}(\mathrm{B}) = \mathbf{I} - \boldsymbol{\Phi}_1 \mathrm{B} - \ldots - \boldsymbol{\Phi}_{\mathrm{p}} \mathrm{B}^{\mathrm{p}}$$

$\mathbf{Z}_{\mathrm{t}}$ : $\left(\mathrm{Z}_{1,\mathrm{t}}, \mathrm{Z}_{2,\mathrm{t}}, \ \ldots, \ \mathrm{Z}_{\mathrm{k},\mathrm{t}}\right)^{\mathrm{T}}$, is vector of $\mathrm{Z}_{\mathrm{t}}$ sized $k \times 1$

$\boldsymbol{\Phi}_{\mathrm{i}}$ : matrices sized $k \times k$, and $i = 1, 2, \ldots, p$

$\boldsymbol{\Phi}_0$ : $(\Phi_{10} \ \ \Phi_{20} \ldots \ \Phi_{\mathrm{k}0})^{\mathrm{T}}$

$\boldsymbol{\alpha}_{\mathrm{t}}$ : $\left(\mathrm{a}_{1,\mathrm{t}}, \mathrm{a}_{2,\mathrm{t}}, \ \ldots, \ \mathrm{a}_{\mathrm{k},\mathrm{t}}\right)^{\mathrm{T}}$, is an error vector sized $k \times 1$ that is assumed white noise.

The VAR (1) model is a Vector Autoregressive model with order of 1. The VAR(1) model with two variables can be written as [13]:

$$\mathbf{Z}_{\mathrm{t}} = \boldsymbol{\Phi}_0 + \boldsymbol{\Phi}_1 \mathbf{Z}_{\mathrm{t}-1} + \mathbf{a}_{\mathrm{t}}$$
$$\mathrm{Z}_{1,\mathrm{t}} = \phi_{10} + \phi_{11}\mathrm{Z}_{1,\mathrm{t}-1} + \phi_{12}\mathrm{Z}_{2,\mathrm{t}-1} + \mathrm{a}_{1,\mathrm{t}}$$
$$\mathrm{Z}_{2,\mathrm{t}} = \phi_{20} + \phi_{21}\mathrm{Z}_{1,\mathrm{t}-1} + \phi_{22}\mathrm{Z}_{2,\mathrm{t}-1} + \mathrm{a}_{2,\mathrm{t}} \tag{3}$$

expressed in a matrix, thus:

$$\mathbf{Z} = \mathbf{W}\,\boldsymbol{\Phi} + \mathbf{A} \tag{4}$$

with,

$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_{1,2} & \mathbf{Z}_{2,2} \\ \mathbf{Z}_{1,3} & \mathbf{Z}_{2,3} \\ \vdots & \vdots \\ \mathbf{Z}_{1,n} & \mathbf{Z}_{2,n} \end{bmatrix}_{(\mathbf{n}-\mathbf{1})\mathbf{x2}} \qquad \mathbf{W} = \begin{bmatrix} \mathbf{1} & \mathbf{Z}_{1,2-1} & \mathbf{Z}_{2,2-1} \\ \mathbf{1} & \mathbf{Z}_{1,3-1} & \mathbf{Z}_{2,3-1} \\ \vdots & \vdots & \vdots \\ \mathbf{1} & \mathbf{Z}_{1,n-1} & \mathbf{Z}_{2,n-1} \end{bmatrix}_{(\mathbf{n}-\mathbf{1})\mathbf{x3}}$$

$$\boldsymbol{\Phi} = \begin{bmatrix} \boldsymbol{\phi}_{10} & \boldsymbol{\phi}_{20} \\ \boldsymbol{\phi}_{11} & \boldsymbol{\phi}_{21} \\ \boldsymbol{\phi}_{12} & \boldsymbol{\phi}_{22} \end{bmatrix}_{\mathbf{3x2}} \qquad \mathbf{A} = \begin{bmatrix} \mathbf{a}_{1,2} & \mathbf{a}_{2,2} \\ \mathbf{a}_{1,3} & \mathbf{a}_{2,3} \\ \vdots & \vdots \\ \mathbf{a}_{1,n} & \mathbf{a}_{2,n} \end{bmatrix}_{(\mathbf{n}-\mathbf{1})\mathbf{x2}}$$

The lag in the VAR model can be determined using several criteria, such as Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ), Schwarz Information Criterion (SC), and Final Prediction Criterion (FPE) [5], [12], [14]. This study uses the HQ criteria in determining the optimum lag, indicated by the model with the smallest HQ value. If the data underwent the first differencing process to produce stationary data, the form of the VARI(1,1) model can be written as:

$$\mathbf{Z}_{1,t} - \mathbf{Z}_{1,t-1} = \boldsymbol{\phi}_{10} + \boldsymbol{\phi}_{11}(\mathbf{Z}_{1,t-1} - \mathbf{Z}_{1,t-2}) + \boldsymbol{\phi}_{12}(\mathbf{Z}_{2,t-1} - \mathbf{Z}_{2,t-2}) + \mathbf{a}_{1,t}$$
$$\mathbf{Z}_{2,t} - \mathbf{Z}_{2,t-1} = \boldsymbol{\phi}_{20} + \boldsymbol{\phi}_{21}(\mathbf{Z}_{1,t-1} - \mathbf{Z}_{1,t-2}) + \boldsymbol{\phi}_{22}(\mathbf{Z}_{2,t-1} - \mathbf{Z}_{2,t-2}) + \mathbf{a}_{2,t}$$

or,

$$
\begin{aligned}
\Delta \mathbf{Z}_{1,t} &= \boldsymbol{\phi}_{10} + \boldsymbol{\phi}_{11}\Delta \mathbf{Z}_{1,t-1} + \boldsymbol{\phi}_{12}\Delta \mathbf{Z}_{2,t-1} + \mathbf{a}_{1,t} \\
\Delta \mathbf{Z}_{2,t} &= \boldsymbol{\phi}_{20} + \boldsymbol{\phi}_{21}\Delta \mathbf{Z}_{1,t-1} + \boldsymbol{\phi}_{22}\Delta \mathbf{Z}_{2,t-1} + \mathbf{a}_{2,t}
\end{aligned} \tag{5}
$$

One of the assumptions of the VAR model is stationary [14]. Stationary checking can be conducted using the unit root test of the Augmented Deckey Fuller Test (ADF Test) [5]. A process is said to be non-stationary in the mean if there is a trend in the data, while it is said to be non-stationary in the variance if there is heteroscedasticity in the movement of the data. Non-stationary data in the mean can be solved by differencing the data [15]. Meanwhile, to stabilize the variance, transformation should be performed to the data that has not undergone the differencing process. The first step in the estimation of the model using ordinary least squares (OLS) is to determine the function of the sum of the squares of errors by transforming the matrix $\mathbf{Z}$, $\mathbf{W\Phi}$, and $\mathbf{A}$ into vectors.

$$
\vec{\mathbf{Z}} = \begin{bmatrix} \mathbf{Z}_{1,1} \\ \mathbf{Z}_{1,2} \\ \vdots \\ \mathbf{Z}_{1,n} \\ \mathbf{Z}_{2,1} \\ \mathbf{Z}_{2,2} \\ \vdots \\ \mathbf{Z}_{2,n} \end{bmatrix}_{\mathbf{2nx1}} \quad \vec{\boldsymbol{\phi}} = \begin{bmatrix} \boldsymbol{\phi}_{10} \\ \boldsymbol{\phi}_{11} \\ \boldsymbol{\phi}_{12} \\ \boldsymbol{\phi}_{20} \\ \boldsymbol{\phi}_{21} \\ \boldsymbol{\phi}_{22} \end{bmatrix}_{\mathbf{6x1}} \quad \vec{\mathbf{a}} = \begin{bmatrix} \mathbf{a}_{1,1} \\ \mathbf{a}_{1,2} \\ \vdots \\ \mathbf{a}_{1,n} \\ \mathbf{a}_{2,1} \\ \mathbf{a}_{2,2} \\ \vdots \\ \mathbf{a}_{2,n} \end{bmatrix}_{\mathbf{2nx1}}
$$

$$
\begin{aligned}
\mathbf{V} &= \mathbf{I}_{\mathbf{2x2}} \otimes \mathbf{W}_{\mathbf{nx3}} \\
&= \begin{bmatrix} \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} \end{bmatrix} \times \begin{bmatrix} \mathbf{1} & \mathbf{Z}_{1,2-1} & \mathbf{Z}_{2,2-1} \\ \mathbf{1} & \mathbf{Z}_{1,3-1} & \mathbf{Z}_{2,2-1} \\ \vdots & \vdots & \vdots \\ \mathbf{1} & \mathbf{Z}_{1,n-1} & \mathbf{Z}_{2,n-1} \end{bmatrix} \\
&= \begin{bmatrix}
\mathbf{1} & \mathbf{Z}_{1,2-1} & \mathbf{Z}_{2,2-1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\
\mathbf{1} & \mathbf{Z}_{1,3-1} & \mathbf{Z}_{2,3-1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\mathbf{1} & \mathbf{Z}_{1,n-1} & \mathbf{Z}_{2,n-1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\
\mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{Z}_{1,2-1} & \mathbf{Z}_{2,2-1} \\
\mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{Z}_{1,3-1} & \mathbf{Z}_{2,3-1} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} & \mathbf{Z}_{1,n-1} & \mathbf{Z}_{2,n-1}
\end{bmatrix}_{\mathbf{2(n-1)x6}}
\end{aligned}
$$

Equation (4) can be written as:

$$\vec{\mathbf{Z}} = \mathbf{V}\vec{\boldsymbol{\phi}} + \vec{\mathbf{a}} \tag{6}$$

The equation for the sum of the squared errors is as follows:

$$\begin{aligned}
\mathbf{S} &= \sum_{i=1}^{2}\sum_{j=1}^{n} \mathbf{a}_{ij}^{2} \\
&= \begin{bmatrix} \mathbf{a}_{1,1} & \mathbf{a}_{1,2} & \cdots & \mathbf{a}_{1,n} & \mathbf{a}_{2,1} & \mathbf{a}_{2,2} & \cdots & \mathbf{a}_{2,n} \end{bmatrix} \times \begin{bmatrix} \mathbf{a}_{1,1} \\ \mathbf{a}_{1,2} \\ \vdots \\ \mathbf{a}_{1,n} \\ \mathbf{a}_{2,1} \\ \mathbf{a}_{2,2} \\ \vdots \\ \mathbf{a}_{2,n} \end{bmatrix} \\
&= \mathbf{a}^{t}\mathbf{a} \\
&= \left(\vec{\mathbf{Z}} - \mathbf{V}\vec{\boldsymbol{\phi}}\right)^{\mathbf{T}}\left(\vec{\mathbf{Z}} - \mathbf{V}\vec{\boldsymbol{\phi}}\right) \\
&= \vec{\mathbf{Z}}^{\mathbf{T}}\vec{\mathbf{Z}} - 2\vec{\mathbf{Z}}^{\mathbf{T}}\mathbf{V}\vec{\boldsymbol{\phi}} + \vec{\boldsymbol{\phi}}^{\mathbf{T}}\mathbf{V}^{\mathbf{T}}\mathbf{V}\vec{\boldsymbol{\phi}}
\end{aligned} \tag{7}$$

The subsequent step is to subtract the square function partially to the parameter $\vec{\phi}$ :

$$\begin{aligned}
\frac{\mathbf{dS}}{\mathbf{d}\vec{\boldsymbol{\phi}}} &= \frac{\mathbf{d}(\vec{\mathbf{Z}}^{\mathbf{T}}\vec{\mathbf{Z}} - 2\vec{\mathbf{Z}}^{\mathbf{T}}\mathbf{V}\vec{\boldsymbol{\phi}} + \vec{\boldsymbol{\phi}}^{\mathbf{T}}\mathbf{V}^{\mathbf{T}}\mathbf{V}\vec{\boldsymbol{\phi}})}{\mathbf{d}\vec{\boldsymbol{\phi}}} \\
&= -2\vec{\mathbf{Z}}^{\mathbf{T}}\mathbf{V} + 2\vec{\boldsymbol{\phi}}^{\mathbf{T}}\mathbf{V}^{\mathbf{T}}\mathbf{V}
\end{aligned} \tag{8}$$

Once the first derivative of squared error for $\vec{\phi}$ is obtained, the first derivative function should equal to zero. Parameter estimation $\Phi$ using OLS can be written as:

$$\boldsymbol{\Phi}_{\mathbf{OLS}} = (\mathbf{V}^{\mathbf{T}}\mathbf{V})^{-1}\mathbf{V}^{\mathbf{T}}\vec{\mathbf{Z}} \tag{9}$$

To ensure that the error squared function has a minimum, the second derivative of the squared error function must be positive. Equation (8) is then derived for $\vec{\phi}^{T}$:

$$\begin{aligned}
\frac{\mathbf{d^2S}}{\mathbf{d}\vec{\boldsymbol{\phi}}\,\mathbf{d}\vec{\boldsymbol{\phi}}^{\mathbf{T}}} &= \frac{\mathbf{d}(-2\vec{\mathbf{Z}}^{\mathbf{T}}\mathbf{V} + 2\vec{\boldsymbol{\phi}}^{\mathbf{T}}\mathbf{V}^{\mathbf{T}}\mathbf{V})}{\mathbf{d}\vec{\boldsymbol{\phi}}^{\mathbf{T}}} \\
&= 2\mathbf{V}^{\mathbf{T}}\mathbf{V}
\end{aligned}$$

Because the second derivative of the sum squared error function is positive, the first derivative produces a parameter estimate that minimizes the error function. The estimation of the VARI model using the OLS method was performed using equation (9) where the data used was data that had been stationary. The model that had been estimated using the OLS method was then used for forecasting. Before forecasting, the causality relationship between variables must be tested.

Granger states that if two variables, $x$ and $y$, have a causal relationship where $x$ affects $y$, then the past information on $x$ can help predict $y$ [5]. Furthermore, in addition to the assumption of stationarity, the resulting residuals should fulfill the assumption of white noise. The development of shiny R for the VARI model in this study focused on data with two variables, and the data processed were stationary data. The packages used in the present study involved Shiny, Shiny dashboard, Vars, Forecast, Tseries, MVN, and Metrics. The stages of R Shiny developed had complied with the stages in the analysis of the VAR model, as follows:

1. Conducting stationarity test in the variance and checking the mean of each variable.
2. Transforming and differencing non-stationary data.
3. Saving stationary data.
4. Creating ACF and PACF plots to identify the model.
5. Determining optimum lag.
6. Conducting causality test using Granger Causality.
7. Estimating parameters of the model using the OLS method.
8. Performing diagnostic check on residuals using the assumption of white noise.

R Shiny consists of UI (user interface) and server. The function of UI is for displaying all input and output, while the function of the server is for processing input into output. Here is the framework in R shiny [6], [16]:

```
  library(shiny)
  ui <- fluidPage( # or other layout function
    # contents of ui.R file
  )
  server <- function(input, output) {
    #contents of server.R file
  }
shinyApp(ui = ui, server = server)
```

## 3. RESULTS AND DISCUSSION

The first step that should be performed before VAR modeling on export and import data is to check the stationarity of the data. This test is required to obtain stationary data. Stationary checks can be done through inspection of the plot. The plot of export and import data can be seen in Figure 1.

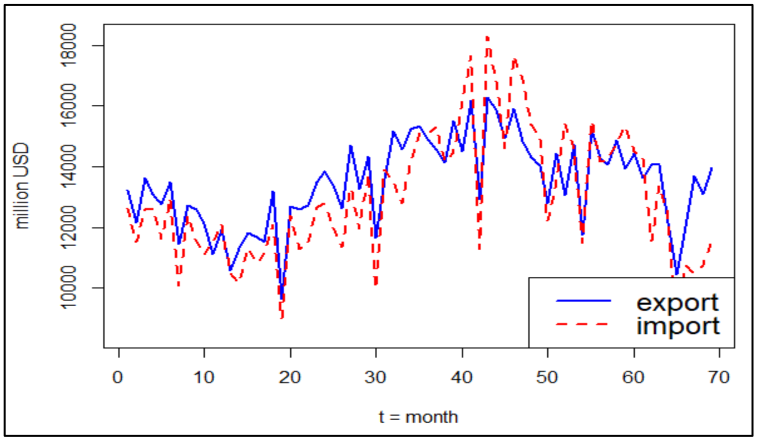


**Figure 1.** Plot of export and import data

Based on the plot in Figure 1, it can be seen that neither exports nor imports are stationary. This can be seen from the data pattern that is not around the mean. To determine whether the data is stationary or not, it is necessary to test the hypothesis. One of the hypothesis tests for stationary detection is the ADF-Test.

**Table 1.** ADF-Test and Box-Cox

| Variable | ADF-*Test* | *p-value* | $\lambda$ Box-Cox |
|---|---|---|---|
| Export | -1.697 | 0.6983 | 0.999959 |
| Import | -0.92848 | 0.9425 | 0.1631205 |

From the results of the ADF-Test in Table 1, it can be seen that the p-value of exports and imports is larger than the significance level ($\alpha$=5%). Thus, it can be concluded that both exports and imports are not stationary in the mean. From the $\lambda$ Box-Cox value, it can be seen that the value for exports is close to 1, meaning that the data of exports are stationary in the variance, while the $\lambda$ value for imports is less than 1, meaning that the data of imports are non-stationary in the variance. Therefore, it is necessary to handle stationarity in the data through transformation and differencing.

The following table provides the results of ADF-Test and Box-Cox on the data of exports and imports after transformation and differencing.

**Table 2.** ADF-Test and Box-Cox of Transformation and Differencing

| Variable | ADF-*Test* | *p-value* | $\lambda$ Box-Cox |
|---|---|---|---|
| Export | -4.281 | 0.01 | 0.9999339 |
| Import | -3.8938 | 0.01976 | 0.9999339 |

The stationary data were used to build the VARI(p,1) model. The first step is to determine the lag $p$ in the model. Lag can be determined through inspection on the ACF and PACF plots, as well as the frequently-used criteria, namely Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ), Schwarz Information Criterion (SC), Final Prediction Error (FPE). The followings are the plots of ACF, PACF, and the results of the lag selection.

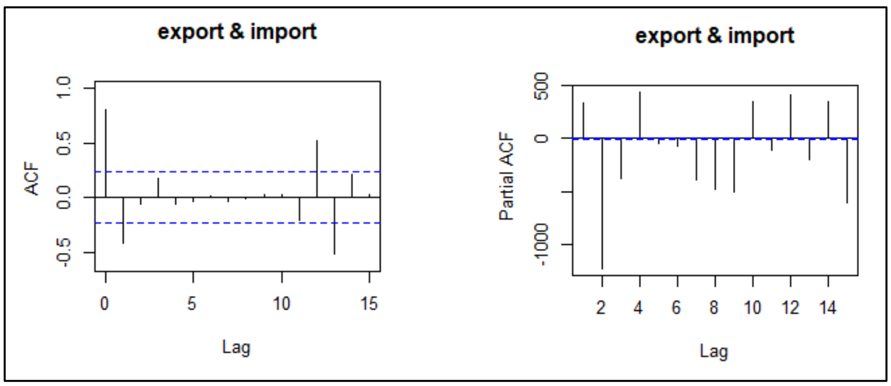


**Figure 2.** ACF and PACF Plot.

**Table 3.** ADF-Test and Box-Cox of Transformation and Differencing

| Criteria | Lag |
|---|---|
| AIC | 14 |
| HQ | 2 |
| SC | 2 |
| FPE | 14 |

The ACF plot showed that the highest autocorrelation is at lag 0, while the PACF plot indicated that the highest partial autocorrelation is at lag 2. According to the HQ and SC criteria, lag 2 is selected, so the model to be used is the VARI(2,1) model. Furthermore, the VARI(2,1) model is estimated using the OLS method with the following results:

$$\Delta \text{export}_t = -8.39 - 0.52\Delta \text{export}_{t-1} - 361.53\,\Delta \text{import}_{t-1} + 0.35\Delta \text{export}_{t-2} - 1268.492\,\Delta \text{import}_{2,t-2}$$

$$\Delta \text{import}_t = -0.026 + 0.0001\Delta \text{export}_{t-1} - 0.903\Delta \text{import}_{t-1} + 0.0003\Delta \text{export}_{t-2} - 0.9461\Delta \text{import}_{2,t-2}$$

**Table 4.** Estimation of VARI(2,1) for Δexport

| | Estimate | Std. Error | t value | p-value |
|---|---|---|---|---|
| $\Delta Export_{t-1}$ | -0.5225 | 0.1810 | -2.888 | 0.005 |
| $\Delta Import_{t-1}$ | -361.5291 | 331.2414 | -1.091 | 0.279 |
| $\Delta Export_{t-2}$ | 0.3504 | 0.1835 | 1.909 | 0.061 |
| $\Delta Import_{t-2}$ | -1268.4919 | 335.2825 | -3.783 | 0.000 |
| Const | -8.3942 | 128.2693 | -0.065 | 0.948 |
| **$R^2$** | **0.5205** | | | |
| **$R^2$ adj** | **0.489** | | | |
| **p-value F-stat** | **0.000** | | | |

**Table 5.** Estimation of VARI(2,1) for Δimport

| | Estimate | Std. Error | t value | p-value |
|---|---|---|---|---|
| $\Delta Export_{t-1}$ | 0.0001022 | 0.00009049 | 1.129 | 0.263 |
| $\Delta Import_{t-1}$ | -0.9033 | 0.1656 | -5.453 | 0.000 |
| $\Delta Export_{t-2}$ | 0.0003370 | 0.00009179 | 3.671 | 0.000 |
| $\Delta Import_{t-2}$ | -0.9461e | 0.1677 | -5.643 | 0.000 |
| Const | -0.02642 | 0.06.414 | -0.412 | 0.682 |
| **$R^2$** | 0.5632 | | | |
| **$R^2$ adj** | 0.5346 | | | |
| **p-value F-stat** | 0.000 | | | |

The estimation results using the OLS method showed that simultaneously exports and imports in the previous period have a significant effect on the value of exports and imports in period t. The $R^2$ values are 0.5205 and 0.5632, respectively, which means that the model can explain 52.05% of the variance in the ΔExport value and 56.32% of the variance in the ΔImport value, while the remaining variance is explained by other variables. The results of examining the assumption of white noise on the residuals using the Ljung-Box show that the probability value is greater than alpha 0.05 so that the residuals have white noise. The results of the Granger causality test indicated that exports and imports have a causal relationship at lag = 2. Thus, the VARI(2,1) model can be used to predict the value of Indonesian imports and exports in September 2020-March 2021. The following table presents the prediction results obtained along with Mean Absolute Percentage Error (MAPE):

**Table 6.** Prediction Results

| Month | Export | Import |
|---|---|---|
| Oct-2020 | 13014.04 | 10227.72 |
| Nov-2020 | 13575.65 | 11058.63 |
| Dec-2020 | 13526.57 | 10874.25 |
| Jan-2021 | 13318.69 | 10618.26 |
| Feb-2021 | 13538.13 | 10869.17 |
| Mar-2021 | 13441.22 | 10709.12 |
| **MAPE = 17.21%** | | |

MAPE is a measure used to determine whether the predicting results are good or not [17]–[19]. If the prediction results have a MAPE below 10% then the prediction results will be very accurate, $10\% \leq MAPE < 20\%$ then the prediction results are in the good category, $20\% \leq MAPE < 50\%$ then the prediction results are still in the reasonable category, and lastly if forecasting results have a MAPE of more than 50% then the forecasting results are very inaccurate [17]. Based on the MAPE results in table 6, the prediction results of the value of exports and imports in Indonesia using the vector autoregressive integrated model have predictive results in a good category.

The development of R shiny in the analysis of the VARI model is specified for the data with two variables. The processed data is those that had been stationary. The results of the development of R Shiny can be accessed via https://statistikterapan.shinyapps.io/VAR_/. This tool facilitates users in processing data, offers efficient and accurate results because it can minimize errors in formulating R code in the analysis of the VAR or VARI models. Users can access it freely because it is built using open-source R software, and this tool facilitates the user in transforming and differencing non-stationary data. Users can directly analyze the results of VAR(1) and VAR(p) modeling using four criteria, namely AIC, HQ, SC, and FPE. This tool does not facilitate users who analyze the VAR and VARI models of more than two variables, and the parameters are estimated using the OLS method only. In the application, there is an R code that can be used by the user if the data processing is more than two variables. Due to the fact that R is a free piece of software with an open source code, it can be shared and improved by users who wish to do so [6], [7].

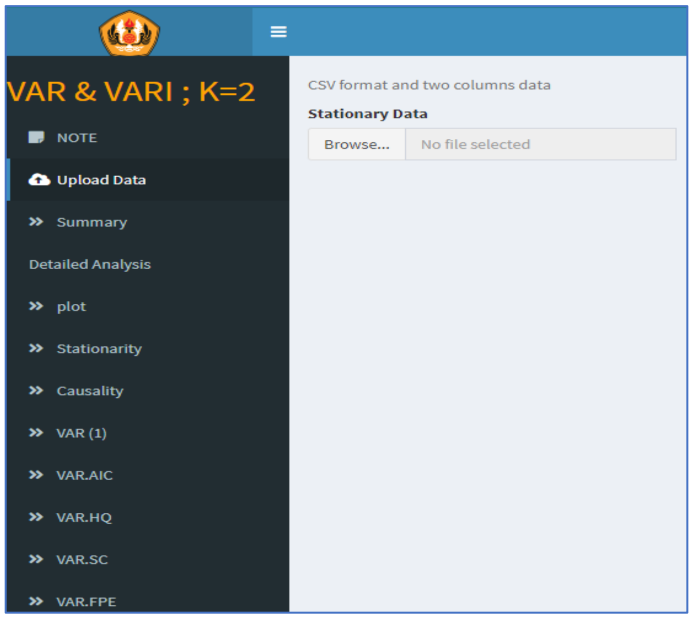


**Figure 3.** R shiny development result

## 4. CONCLUSION

The import and export values need a single-time differencing process to meet the stationarity assumption. The selection of lag based on the HQ criteria is order 2, so the suitable model to use is the VARI(2,1) model. Based on the diagnostic results, the residuals have met the white noise assumption, and the Granger causality test revealed a causal relationship between imports and exports. The prediction of the export and import values produces a good result as they have a MAPE value of 17.21%. R Shiny can be developed for both the VAR and VARI model analysis, where the data used is those that fulfilled stationarity assumption.

## ACKNOWLEDGMENTS

The authors would like to thank the Rector of Universitas Padjadjaran who had provided financial support to disseminate research reports of students and lecturers under the Academic Leadership Grant with the grant number: 1959/UN6.3.1/PT.00/2021 and Studies Center for Modeling and Computation Unpad.

## CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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