Analysis of The Impact of The Covid-19 Pandemic on The Performance of Indonesian Non Oil and Gas Exports

I G B N Diksa[1], D A Srijayanti[2]

[1] South Sulawesi Province Statistics Office,
[2] Makassar City Statistics Office, Indonesia

[*]Corresponding author's e-mail: igbn.diksa@bps.go.id

Abstract. In 2020, Indonesia's exports decreased by 2.61 percent due to declining global and domestic demand during the COVID-19 pandemic. The decline in exports was not too deep due to the increase in oil exports by 16.73 percent, while non-oil exports fell by 10.10 percent. This shows the potential for non-oil exports to support the Indonesian economy during the pandemic. Seeing the impact of COVID-19 on export performance then used the ARIMA method. Based on the research, it was found that at the beginning of the COVID-19 pandemic, Indonesia experienced a slump in export performance, especially non-oil and gas. This is due to various policies regarding restrictions on mobility.

1. Introduction

Since being declared a pandemic by the World Health Organization (WHO) on March 11, 2020, the government has taken various policies to suppress the spread of COVID-19. As of August 30, 2021, there were 216,303,376 confirmed cases and 4,498,451 deaths worldwide from COVID-19. Several countries have taken policies, such as closing schools and universities, banning gatherings, closing high-risk activities such as restaurants, bars and evenings, closing non-essential activities, mandatory wearing of masks, social distancing, and travel that are considered effective in reducing the spread of the virus [1][2]. However, the implementation of these policies led to a decline in various consumption and economic activities globally [3]. Based on the April 2021 World Economic Outlook (WEO) by the International Monetary Fund (IMF), the global economy contracted by 3.3 percent in 2020, deeper than the forecast for the global economy in April 2020, which was to contract by 3 percent. This decline occurred first in Asia and then Europe, North America, and the rest of the world [4].

The implementation of social policy is closely related to international relations. The World Trade Organization (WTO) shows a decline in world export volume by 5.3 percent in 2020. Analyzed the impact of several indicators on port operations in China which showed that COVID-19 had a negative and significant effect on exports and imports, where the impact on imports is greater than the impact on exports [5]. China is a major exporter and importer in Asia and COVID-19 could negatively affect Asia [6]. The significant negative impact of COVID-19 has been shown on developing country exports [7].

In 2020, Indonesia's exports decreased by 2.61 percent due to declining global and domestic demand during the COVID-19 pandemic. The decline in exports was not too deep due to the increase in oil exports by 16.73 percent, while non-oil exports fell by 10.10 percent. This shows the potential for non-oil exports to support the Indonesian economy during the pandemic. Therefore, an analysis and forecast are needed to determine the impact of COVID-19 on non-oil exports.

2. Literature review

2.1 Autoregressive Integrated Moving Average (ARIMA)

ARIMA model (p,d,q) is an ARMA model (p,q) which is differencing as much as d so that it is stationary. Therefore, before forming the ARIMA model, the data must be stationary in terms of mean and variance first. The ARIMA model consists of Autoregressive (AR) and Moving Average (MA) elements. In identifying stationarity in the mean can use the plot of the Autocorrelation Function (ACF). If the lags drop rapidly to zero, then the data is said to be stationary in the mean. On the other hand, if the ACF lags fall slowly towards zero and many exit the interval, then the data is not stationary (Wei, 2006). Not only that, stationarity in the mean can be tested using Augmented Dickey Fuller (ADF). The testing procedure for the ADF can applied to the model $\Delta z_t = \alpha + \beta t + \gamma z_{t-1} + \delta_1 \Delta z_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$

The unit root test is the carried under the null hypothesis :

$H_0 : \delta = 0$ (Not Stationer)
$H_1 : \delta < 0$ (Stationer)
Statistic Test

$$\tau = \frac{\hat{\delta}}{se(\hat{\delta})} \tag{1}$$

If ($\tau < -\tau_{(\alpha;n-p)}$) with $-\tau_{(\alpha;n-p)}$ is Mac Kinnon's value rejecting H0, then it can be concluded that the data is stationary with a significance level 5%. If the data is not stationary in the mean, then differencing can be done. The process looks for the difference between the data period t (z_t) and the previous period (z_{t-k}) where $k = 1, 2, ..., n$

Meanwhile, time series data is said to be stationary in variance if the value of the rounded value (λ) is equal to 1 or the upper limit interval and the lower limit of the rounded value contains the number 1. Time series data that is not stationary in variance can be overcome by the Box-Cox transformation (Wei, 2006). The transformation formula in general is as follows:

$$T(z_t) = \frac{z_t^{\lambda} - 1}{\lambda}, \lambda \neq 0 \tag{2}$$

$$\lim_{\lambda \to 0} T(z_t) = \lim_{\lambda \to 0} \frac{z_t^{\lambda} - 1}{\lambda} = \ln(z_t), \lambda = 0 \tag{3}$$

with λ is the transformation parameter. There are several forms of Box-Cox transformation with corresponding values λ as shown in Table 1

Table 1 Box Cox Transformation

Value λ	**Transformation** $T(z_t)$
-1,0	$1/z_t$
-0,5	$1/\sqrt{z_t}$
0	$ln(z_t)$
0,5	$\sqrt{z_t}$
1	z_t

After the data has been stationary in terms of mean and variance, it continues to build a model which is preceded by identification of the order of the ARIMA model based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Table 2 is the form of the ACF and PACF plots of the theoretical ARIMA model

Table 2. Plot ACF and PACF ARIMA Model

Model	**Plot ACF**	**Plot PACF**
AR*(p)*	Exponentially fast dropping	Cut off after lag p
MA(*q*)	Cut off after lag q	Exponentially fast dropping
ARMA (*p,q*)	Quick drop after lag (q-p)	Quick drop after lag (p-q)

In general, the ARIMA model is like equation (4) [9].

$$\phi_p(B)(1-B)^d \dot{z}_t = \theta_0 + \theta_q(B)a_t \tag{4}$$

where

(p,d,q) = order from non-seasonal ARIMA. p is the order of AR (Autoregressive), the order of differencing is d and q is the order of MA (Moving Average)

$\phi_p(B)$ = $1-\phi_1 B-\cdots-\phi_p B^p$

$\theta_q(B)$ = $1-\theta_1 B-\cdots-\theta_q B^q$

$(1-B)^d$ = differencing operator for order d

a_t = residual value at time t that has met the assumption of white noise and is normally distributed

$\dot{z}_t$ = $\dot{z}_t - \mu$

For the ARIMA model with a seasonal pattern, it can be written as equation (5)

$$\Phi_p(B^S)(1-B^S)^D \dot{z}_t = \Theta_Q(B^S)a_t$$

(5)

where

(P,D,Q) = order from ARIMA with seasonal pattern. P is order AR , D is order differencing and order Q is order MA for seasonal pattern

S = seasonal period

$\Phi_P(B^S)$ = $(1-\Phi_1 B^S-\cdots-\Phi_P B^{PS})$, P is the order for AR for seasonal

$\Theta_Q(B^S)$ = $(1-\Theta_1 B^S-\cdots-\Theta_Q B^{QS})$, Q is the MA order for seasonal

$\left(1-B^S\right)^D$ = differencing operators for order D for seasonal patterns

If in the ARIMA model there are non-seasonal and seasonal patterns, then the multiplicative model is used ARIMA $(p,d,q)(P,D,Q)^S$. The following general equation is reflected in equation (6)

$$\phi_p(B)(1-B)^d\,\Phi_P\left(B^S\right)\left(1-B^S\right)^D\dot{z}_t=\theta_q(B)\Theta_Q\left(B^S\right)a_t \tag{6}$$

After getting an estimate from the ARIMA model, it is continued by testing the significance of the parameters ϕ and θ and using the t-test statistic.
Tests for the significance of the AR parameters are as follows:
$H_0:\phi=0$ (AR model parameter is not significant)
$H_1:\phi\neq 0$ (AR model parameter is significant)
The test statistics used is

$$t_{hitung}=\frac{\hat{\phi}}{se\left(\hat{\phi}\right)} \tag{7}$$

if the level of significance (α) is determined, then H_0 is rejected if the test statistic value is $\left|t_{hitung}\right|>t_{\frac{\alpha}{2},(n-p)}$ or *p-value* < α, where n is the number of observations, $se\left(\hat{\phi}\right)$ is the standard error of $\hat{\phi}$ and p is the number of AR model parameters.
For testing MA parameters with the following hypothesis:
$H_0:\theta=0$ (MA model parameter is not significant)
$H_1:\theta\neq 0$ (MA model parameter is significant)
The test statistics used are

$$t_{hitung}=\frac{\hat{\theta}}{se\left(\hat{\theta}\right)} \tag{8}$$

H0 is rejected if the test statistic value $\left|t_{hitung}\right|>t_{\frac{\alpha}{2},(n-q)}$ or *p-value* < α, with α is the level of significance, n is the number of observations, $se\left(\hat{\theta}\right)$ is the standard error of $\left(\hat{\theta}\right)$ and q is the number of MA model parameters.

Then proceed with testing the diagnostic model which consists of two examinations, namely the assumption of residual white noise using the Ljung & Box test and the normal distribution assumption test using the Jarque Bera test. The residual of a model is said to be white noise if the residuals are mutually independent [9].
$H_0:\rho_1=\rho_2=\cdots=\rho_k=0$ (*White Noise*)
H_1 : minimal ada satu $\rho_k\neq 0$ untuk k = 1,2,…,n (Not *White Noise*)
Statistic Ljung-Box Test :

$$Q=n(n+2)\sum_{k=1}^{n}\frac{\hat{\rho}_k^2}{(n-k)} \tag{9}$$

If α is the significance level used then reject H_0 jika $Q > \chi^2_{\alpha,(k-p-q)}$ or *p-value* < α with p value is the number of AR parameters in the model, q is the number of MA parameters in the model, $\hat{\rho}_k$ is the estimated autocorrelation of the residual lag k, n is the number of observations, and k is the maximum lag $(k \geq 1)$

Another assumption that must be met is that the residuals are normally distributed. This test can be done using the Jarque Bera test with the following hypothesis:

$H_0 : F(z) = \Phi\left(\frac{z-\mu}{\sigma}\right)$, z ϵ R (Residual is normal distribution)

$H_0 : F(z) \neq \Phi\left(\frac{z-\mu}{\sigma}\right)$, for at least one z ϵ R (Residual is not normal distribution)

Statistic test

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (10)$$

Where Φ is the cdf of the standard normal distribution and $-\infty < \mu < \infty$, and also $\sigma > 0$. In the case of known μ and σ we assume with any loss of generality $\mu = 0$ and $\sigma = 1$. S is the sample skewness and K is the sample kurtosis. H_0 has to be rejected at level α if $JB \geq \chi^2_{1-\alpha,2}$ or p-value greater than α[8].

3. Methodology

3.1 Data Sources and Research Variables

The data used in this study is secondary data regarding FOB (free on board) exports carried out by Indonesia in thousand dollars (Z). This export data includes the FOB value of non-oil exports made by Indonesia. The time period used is January 2005 to October 2020 as many as 190 data units. The source of data in this study is from Bank Indonesia which is obtained from the website https://www.bi.go.id.

3.2 Data Structure

In this study, using only 1 variable FOB value in thousand dollars from non-oil exports carried out by Indonesia in January 2005 - Oktober 2020. The data structure can be seen in Table 3.

Table 3. Indonesia's Non-Oil and Gas Export Forecast Data Structure

t	Year	Month	Z_t (thousand dollar)
1	2005	January	4.938.290
2	2005	February	5.113.290
3	2005	March	5.529.560
4	2005	April	5.304.715
5	2005	May	6.010.716
6	2005	June	5.694.923
7	2005	July	5.529.229
⋮	⋮	⋮	⋮
190	2020	October	13.773.899

4. Analysis and Discussion

4.1 ARIMA Model Formation

In this study the data is divided into two, namely training data and testing data. In the training data, an ARIMA model will be created. To see the impact, a comparison of the testing data with the forecasting results is used. In the formation of the ARIMA model, it is preceded by checking the stationarity of the training data both in the variance and in the mean. For stationary in variance it can be shown in Figure 1.

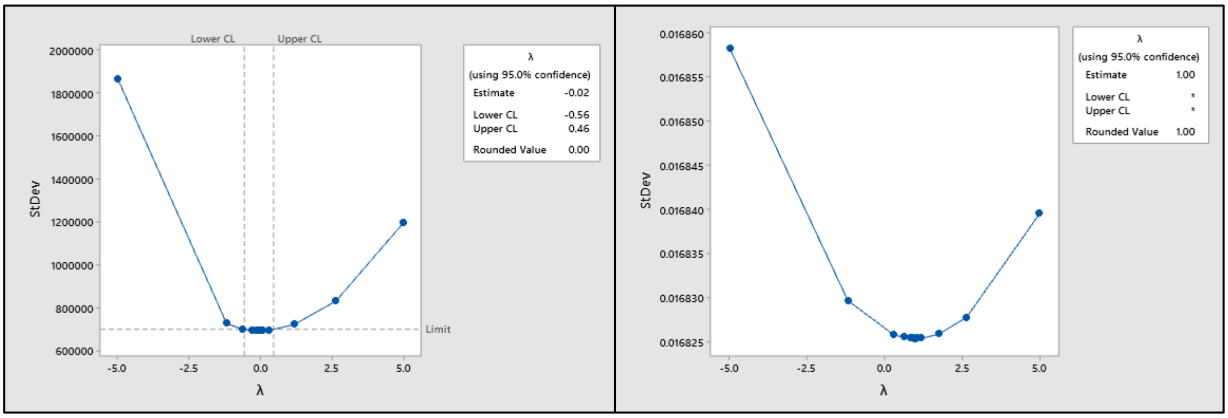

Figure 1. Stationarity Test In Variance

Based on Figure 1, it can be seen that the data is not stationary in variance. This can be seen in the value of the rounded value which is zero. Then the natural logarithm transformation is carried out to make the variance stationary. Then check for stationarity in the mean which can be seen in Figure 2.

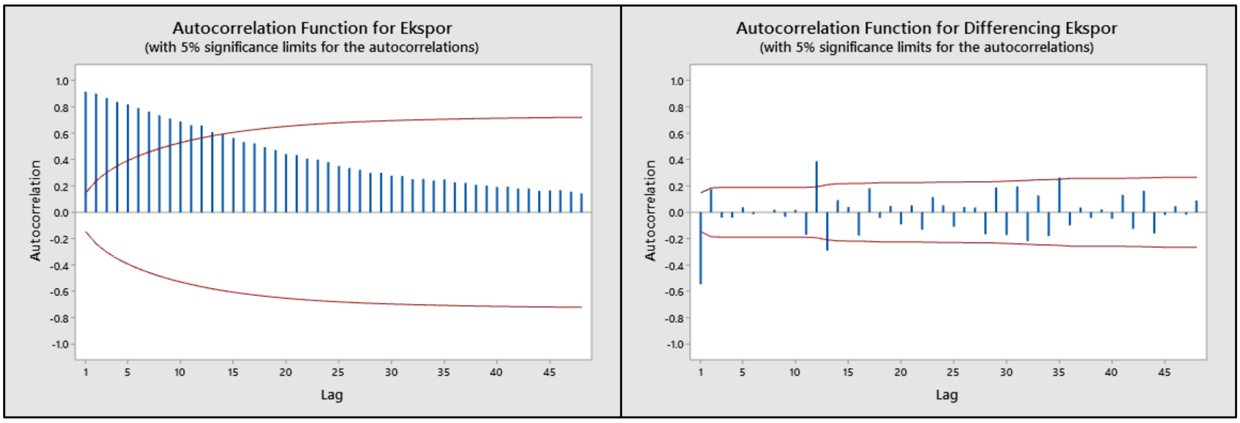

Figure 2. Stationarity Test In Mean

From Figure 2, it can be seen in the graph that ACF Exports has a downward movement slowing towards 0. This can indicate that the data is not stationary. This is reinforced by the p value of the ADF test which is 0,5647 which can be concluded that it failed to reject H0 (data not yet stationary). Furthermore, differencing is performed at lag 1 so that the ACF plot data pattern has dropped sharply to 0 with the p-value of the ADF test of 0,01, which means that H0 is rejected (the data is stationary at the mean). If the data is stationary, it can be continued by looking at the AR and MA orders on the ACF and PACF plots.

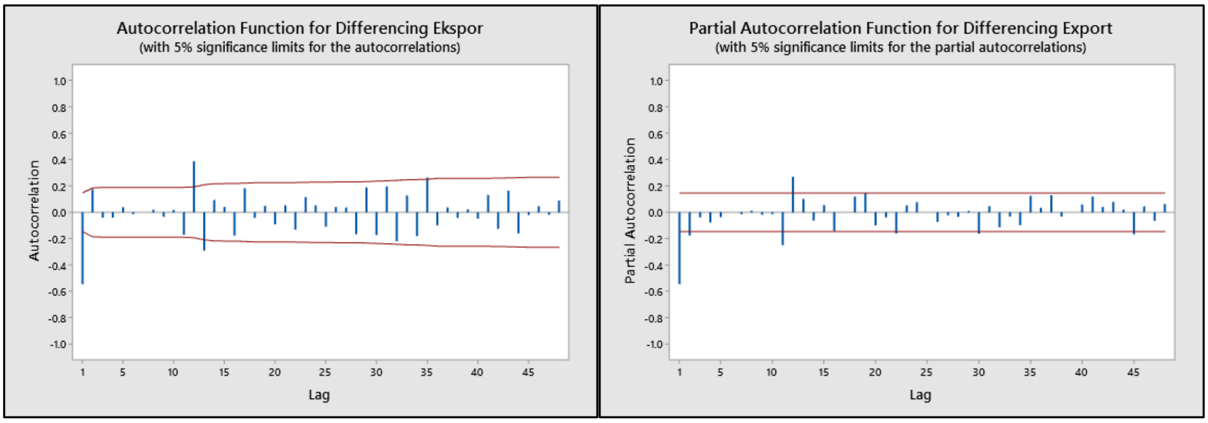

Figure 3. Plot ACF and PACF

Based on Figure 3, the AR order to be used can be seen on the PACF plot and the MA order to be used can be seen from the ACF plot. Based on the figure, the suspected AR orders are lag 1, 2, 12, 13, 22 and 30. For the MA orders that are thought to be 1, 12, 13 and 35. Then a model is formed from the combination of the second order parameters, namely AR and MA. which can be seen in Table 4.

Table 4. ARIMA Model Parameter Estimation

Parameter	Lag	Estimation	Standard Error	*T-Value*	*P-Value*	Conclusion
ARIMA ((2,[12],[13],[22],[45]),1,([1],[12]))						
ϕ_1	1	-1,1327	0,088316	-12,8256	0,000000	Significant
ϕ_2	2	-0,36117	0,061156	-5,9057	0,000000	Significant
ϕ_{12}	12	0,599433	0,058902	10,1768	0,000000	Significant
ϕ_{13}	13	0,382615	0,052371	7,3059	0,000000	Significant
ϕ_{22}	22	-0,10893	0,023145	-4,7066	0,000025	Significant
ϕ_{45}	45	-0,09492	0,030006	-3,1633	0,001560	Significant
θ_1	1	0,6874	0,089219	7,7046	0,000000	Significant
θ_{12}	12	-0,30881	0,081358	-3,7957	0.000147	Significant
ARIMA ((2,[12],[13),1,1)						
ϕ_1	1	-1,430160	0,056939	-25,1176	0,000000	Significant
ϕ_2	2	-0,465920	0,058731	-7,93300	0,000000	Significant
ϕ_{12}	12	0,366648	0,059400	6,17250	0,000000	Significant
ϕ_{13}	13	0,386917	0,057982	6,67300	0,000000	Significant
θ_1	1	1,000000	0,029966	33,3716	0,000000	Significant
ARIMA (([1],[12],[45]),1,1)						
ϕ_1	1	-0,35962	0,089471	-4,0194	0,000000	Significant

Parameter	Lag	Estimation	Standard Error	*T-Value*	*P-Value*	Conclusion
ϕ_{12}	12	0,351904	0,062639	5,618	0,000000	Significant
ϕ_{45}	45	-0,14883	0,067257	-2,2129	0,026910	Significant
θ_1	1	-0,23129	0,106387	-2,1741	0,029700	Significant

Based on Table 2, with a significance level of 5 percent, all models have significant parameters in the model. Therefore, the three models are continued in the diagnostic test process of the model. The test results are presented in Table 5

Table 5. ARIMA Model Diagnostic Test

Lag	statistic (Q)	p-value	decision	p-Value	decision
ARIMA ((1,2,[12],[13],[22],[45]),1,([1],[12]))					
12	4,297505	0,367238	*White Noise*	0,05302	Normal Distribution
24	20,29953	0,207032			
30	23,76126	0,359867			
36	39,94381	0,066893			
48	53,50462	0,074952			
ARIMA ((2,[12],[13),1,1)					
12	5,989718	0,54095	*Not White Noise*	0,02021	Not Normal Distribution
24	24,28235	0,185544			
30	29,58062	0,240377			
36	45,52326	0,044749			
48	60,54555	0,039853			
ARIMA (([1],[12],[45]),1,1)					
12	3,709972	0,882297	*White Noise*	0,00008	Not Normal Distribution
24	19,30966	0,501787			
30	23,68162	0,594165			
36	46,93306	0,042996			
48	59,83782	0,056016			

Based on the diagnostic test, namely the white noise and normality test, the ARIMA model (((2,[12],[13],[22],[45]),1,([1],[12])) is the best model because it has fulfilled both assumptions test. Furthermore, the ARIMA model can be described ((1,2,[12],[13],[22],[45]),1,([1],[12])) into the following equation:

$$\phi_{45}(B)\phi_{22}(B)\phi_{13}(B)\phi_{12}(B)\phi_2(B)(1-B)^1 z_t = \theta_1(B)\theta_{12}(B)a_t$$

$$(1-\phi_{45}B^{45})(1-\phi_{22}B^{22})(1-\phi_{13}B^{13})(1-\phi_{12}B^{12})(1-\phi_1 B-\phi_2 B^2)(1-B)^1 z_t = (1-\theta_1 B)(1-\theta_{12}B^{12})a_t$$

$$(1+0,09492B^{45})(1+0,10893B^{22})(1-0,382615B^{13})(1-0,599433B^{12})(1+1,1327B+0,36117B^2)$$

$$(1-B)^1 z_t = (1-0,6874B)(1+0,30881B^{12})a_t$$

4.2 Impact of the COVID-19 Pandemic on Indonesia's Non-Oil and Gas Exports

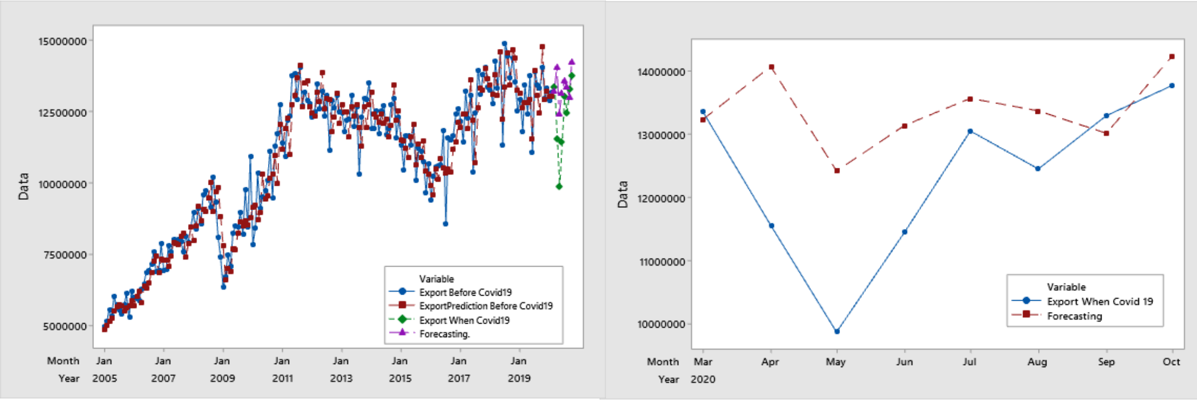

Figure 4. Indonesian non-oil forecasting results

Based on Figure 4. the forecasting results for March 2020 – June 2021 have different movement patterns with the FOB value of Indonesia's non-oil exports. At the beginning of the COVID pandemic in March - August 2020 the FOB value of non-oil and gas exports was smaller than the forecast results. This indicates that Indonesia's export performance has been severely impacted by the COVID-19 pandemic. Entering the COVID-19 pandemic phase in March 2020, six world agricultural commodities experienced a decline in trade value. PSBB policies and lockdowns in many countries are the main factors in the decline in trade values. This condition was exacerbated by the contraction of the world economy, causing people's purchasing power to decline. In April 2020, exports fell for some food products, especially for high-value products, such as fresh produce, dairy, and meat. In addition, perishable and high-value agricultural products transported by air have been particularly hard hit by the COVID-19 pandemic. The emergence of new regulations for flights with sudden restrictions on passenger traffic and reducing air transport capacity has caused transportation costs to increase. In addition, rubber and coffee commodities experienced a decline in export value in January-May 2020.

5. Conclusion

Based on the research results that the best forecasting model is ARIMA ((1,2,[12],[13],[22],[45]),1,([1],[12])). Based on the comparison of forecasting results with actual data ,it can be said that at the beginning of the COVID-19 pandemic, Indonesia experienced a slump in export performance, especially non-oil and gas. This is due to various policies regarding restrictions on mobility.

References

[1] Yacong B, Cui G, Chanqin L, Yiqian Z, Hao B L, Yumiao Z, Hossain Md S, Jimmy W M C, David W Y, Kin O K, Samuel Y S W, Alexis K H L and Xiang Q L 2021 Effectiveness of Non-Pharmaceutical Interventions on COVID-19 Transmission in 190 Countries from 23 January to 13 April 2020 *International Journal of Infectious Diseases* **102** 247–53

[2] Brauner J M, Mindermann S, Sharma M, Johnston D, Salvatier J, Gavenciak T, Stephenson A B, Leech G, Altman G, Mikulik V, Norman A J, Monrad J T, Besiroglu T, Ge H, Hartwick M A, Teh Y W, Chindelevitch L, Gal Y and Kulveit J 2020 Inferring the Effectiveness of Government Interventions Against COVID-19 *Science* **371** (651)

[3] CPB Netherlands Bureau for Economic Policy Analysis 2021 The Effect of the Pandemic and Non-Pharmaceutical Interventions on Household Consumption

[4] United Nations ECLAC 2020 The Effects of The Coronavirus Disease (COVID-19) Pandemic on International Trade and Logistics

[5] Xu L, Yang S, Chen J and Shi J 2021 The Effect of COVID-19 Pandemic on Port Performance: Evidence from China *Ocean and Coastal Management* **209** (2021) 105660

[6] Hassani K and Dost S 2020 Impact of COVID-19 on International Trade and China's Trade

Turkish Economic Review **7** (2) 103–10

[7] Hayakawa K, Mukunoki H 2021 The Impact of COVID-19 on International Trade: Evidence from The First Shock *Journal of The Japanese and International Economies* **60**(2021) 101135

[8] Paper, W. (2004), “www.econstor.eu.”

[9] Wei, W. W. (2006). Time Series Analysis: Univariate and Multivariate Methods, 2nd Edition. New York: Pearson.