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Investigating the effects of several intervention on supply chain behavior: Evidence from West Nusa Tenggara Province, Indonesia

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This study analyzed the impact magnitudes and patterns of several intervention events, including eight earthquakes and Covid-19 pandemic, on the number of unloading and loading goods in the three main ports and airports in West Nusa Tenggara Province during 2015-2020. The multi-input intervention models are performed for twelve series data obtained from BPS-Statistics of West Nusa Tenggara Province. The results from the estimated response values show that generally the number of unloading and loading in the three main ports and airports have experienced mixed impact, i.e., negative, and positive impacts. As the main concern in this study, the negative impacts were more experienced by the number of unloading and loading goods in airports than in ports indicating that the supply chain in airports was more vulnerable to intervention. Lombok International Airport and Sultan M Kaharuddin Airport received the most negative impact during the period. Most intervention events have delayed impact patterns that are more experienced by the three airports than the three ports. Started in March 2020, Covid-19 produced the widest and biggest negative impacts. These impacts are even bigger than the impacts produced by the severe earthquakes that occurred in August 2018.

1. Introduction

As the largest archipelago in the world that consists of more than 17,000 islands (Cribb & Ford, 2009; Indonesia, 2018; Sandee, 2016), the transportation sector plays an important role by connecting the islands in Indonesia in terms of goods, services, and people mobility. The improved regional or inter-island connectivity could lead to reduced price disparity between regions, hence boosting economic growth (Negara & Das, 2017) and lowering poverty rates (Sandee, 2016). Moreover, good connections between regions also support the tourism sector (Ahyudanari, 2021). Therefore, in November 2015 the Indonesian government started the Sea Toll Road Project to improve the connectivity from the western and central to the eastern part of Indonesia by connecting five main ports, i.e. Belawan, Tanjung Priok, Tanjung Perak, Makassar, and Sorong, with the smaller ports (Negara & Das, 2017). The availability of transportation infrastructure such as ports and also huge investment are very important to support this project. Not only sea transportation, the role of air transportation including airport infrastructure is also important to enhance the regional connectivity in Indonesia. Compared to sea transportation, this transportation has more ability to reach remote areas that are geographically challenging, support long distance connectivity, and also faster than sea transportation (Nasution, Azmi, Siregar, & Erlina, 2018). As lying at the three giant plates, i.e. Eurasia, Indo-Australia, and Pacific, Indonesia has been very prone to natural disaster, especially earthquakes (Wibowo, Ulama, Siagian, Purwa, & Wilantari, 2021). During 2009-2019, more than 70,000 earthquakes occurred in Indonesia (Sabtaji, 2020). Moreover, having several active volcanoes as a part of the Pacific Ring of Fire that spread from Sumatera, Java, Bali, Nusa Tenggara, Sulawesi, and Maluku, makes Indonesia more prone to natural disaster. More details, one of provinces in

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Indonesia with the most prone to earthquakes is West Nusa Tenggara. Only in a single month, August 2018, there were more than 1,600 earthquakes that occurred in this province. In addition, almost 7,000 earthquakes occurred during 2011-2019 making West Nusa Tenggara as the province with the fourth largest number of earthquakes (Sabtaji, 2020). The existence of geographical, topological, climatological, and sociological factors are driving factors that lead this province to having several disasters that spread throughout the region, from Lombok to Sumbawa Islands (West Nusa Tenggara Provincial Government, 2019). This prone to earthquake characteristic could potentially hamper the performance of the transportation sector in West Nusa Tenggara Province. The disastrous impact on the transportation infrastructure would affect the distribution of goods, services, and people mobility. In the post disaster, the functional failure of transportation infrastructure impairs the response to disaster and recovery, hence disrupting the socio-economic condition (Chang, Enashai, Spencer, Song, & Ouyang, 2010) and local economy (The World Bank, 2019). This condition also could lead to a decrease in the tourism market (Said, Hanafi, & Hizmi, 2019). Therefore, the impact assessment of natural disasters, i.e. earthquakes, is very important as a mitigation and disaster risk reduction for the West Nusa Tenggara Provincial and Indonesia government to face the forthcoming disaster. As stated by Sanyal and Routray (2016), the impact of disaster occurs when the potential negative effects are not managed appropriately. The economic impact has been the main objective in the impact analysis of natural disasters (Sohn, Hewings, Kim, Lee, & Jang, 2004). Several previous studies have analyzed the economic impact of natural disasters including the earthquakes on several fields that could be grouped based on the method into two groups. First, the previous studies that performed economic impact evaluation of the natural disasters using descriptive analysis by comparing the condition of several macroeconomic indicators before and after the earthquakes occurred, i.e. Tangkudung (2019) and Rindarsih, Witte, Spit, & Zoomers (2019). Second, the previous studies that evaluated the impact of natural disasters by leveraging the statistical model, i.e. Barbhuiya & Chatterjee (2020), Genc (2018), Kim & Marcouiller (2015), and Rossello, Becken, Santana, & Gallego (2020) that utilized econometric model including linear regression and panel regression to evaluate the impact of several natural disaster on macroeconomic indicator, tourism sector, total tourist arrivals, and international tourist arrivals, respectively. The studies from Mendoza et al (2002), Wu & Hayashi (2013), and Jayasinghe et al (2021) evaluate the impact of natural disasters including three earthquakes in Chile, the Great East Japan Earthquake, and tsunami, respectively on the international tourist arrivals using autoregressive integrated moving average (ARIMA) model to forecast data after intervention occurred then subtract it to the actual data to obtain the impact values. This method mechanism is quite similar with the multi-input intervention method as utilized by Mangindaan & Krityakierne (2018), Wardhani (2020) and Purwa & Atmanegara (2020) to measure the impact of volcanic eruptions and earthquakes on the international tourist arrivals. The only difference between these two methods, in the multi-input intervention model, the impact values need to be estimated in the model by first identifying the coefficients that reflect the impact magnitude and pattern.

Specifically, the impact evaluations of earthquakes in West Nusa Tenggara Province have been performed by Wibowo, Purwa, Bahri, Ulama, & Wilantari (2021) that utilized the time series approach, i.e. autoregressive integrated moving average with exogenous variables (ARIMAX) model, to measure the impact of earthquakes on the monthly consumer price index and inflation in West Nusa Tenggara Province from January 2008 to December 2018. The impact evaluation of earthquakes in the same province also performed by Wibowo et al. (2021) in the fields of transportation sector, i.e. the number of airline passenger of arrivals and departures in the three main airports: Lombok International Airport, Sultan M Kaharuddin Airport, and Sultan M Salahudin Airport, using the time series regression (TSR), with the dummy variables as representation of earthquakes.

From the latter previous study, the impact of earthquakes on the transportation sector, in terms of people mobility, has been carried out. However, the study in terms of distribution or supply chain of goods in West Nusa Tenggara Province, the impact evaluation has never been carried out based on author's knowledge. Hence this study fills that research gap by analyzed the impact of earthquakes on the number of unloading and loading goods in the three main administered ports and airports in West Nusa Tenggara Province, i.e. Lembar Port, Badas Port, Bima Port, Lombok International Airport, Sultan M Kaharuddin Airport, and Sultan M Salahudin Airport, from January 2015 to December 2020. Moreover, rather than using the time series approaches, i.e. ARIMAX and TSR model, as in the two previous studies that represented the earthquakes using the dummy variables only at the time when the earthquakes occurred, this study employs the multi-input intervention model to measure and reveal the impact pattern of earthquakes. With this mechanism, the impact of earthquakes is not only depicted at the time when the earthquakes occurred, but also several months later. In addition, the Covid-19 pandemic was also incorporated into the model. As described by SMERU (2020), the Covid-19 has disrupted the demand and supply of goods through large-scale social restriction to prevent the spread of the virus. The results of this study are expected to be a disaster mitigation supporting system and help the local government for minimizing the negative impact of earthquakes and Covid-19 pandemic on supply chain of goods.

2. Material and Methods

2.1. Data and Sources

The data of supply chain of goods, including monthly unloading and loading goods, used in this study covers three main ports and airports in West Nusa Tenggara Province, Indonesia, i.e. Lembar Port, Badas Port, and Bima Port and also Lombok International Airport, Sultan M Kaharuddin Airport, and Sultan M Salahudin Airport (Fig. 1). These data are obtained from

Transportation Statistics of West Nusa Tenggara Province, 2015-2020, published by BPS-Statistics of West Nusa Tenggara Province (BPS-Statistics of West Nusa Tenggara Province, 2016-2021). Hence there are twelve monthly series data that are analyzed in this study. During the research period, 2015-2020, each series has a different number of observations since in certain months there is data with zero value. The complete series data are found in monthly data of unloading and loading goods in Bima Port, Lombok International Airport, and Sultan MSalahud in Airport and monthly data of loading goods in Bima Port, Lombok International Airport, and Sultan M Salahudin Airport (Table 1). To overcome this issue, this study adds a constant value C to the series. This strategy would not change the pattern and variance of time series plot hence the impact magnitude of intervention events could still be captured using intervention analysis.

Source: Google Maps

Fig. 1. Location of Lembar Port (a), Badas Port (b), and Bima Port (c) and Lombok International Airport (d), Sultan M Kaharuddin Airport (e), and Sultan M Salahudin Airport (f)

Table 1
Description of Monthly Data of Loading and Unloading Goods in The Three Main Ports and Airports in West Nusa Tenggara Province

Port/Airport (Location)		Activity	Time Reference	Data with Zero Value	Number of Obs. After Adding C
Port	Lembar (Lombok Barat)	Unloading	Jan-'15 to Dec-'20	-	72
		Loading	Sep-'19 to Dec-'20	Oct-'19, Nov-'19, Dec-'20	16
	Badas (Sumbawa)	Unloading	Jan-'15 to Dec-'20	-	72
		Loading	Jan-'15 to Dec-'20	Jan-'20, Feb-'20	72
	Bima (Bima Municipality)	Unloading	Jan-'15 to Dec-'20	-	72
		Loading	Jan-'15 to Dec-'20	-	72
Airport	Lombok Int. (Lombok Tengah)	Unloading	Jan-'15 to Dec-'20	-	72
		Loading	Jan-'15 to Dec-'20	-	72
	Sultan M Kaharuddin (Sumbawa)	Unloading	Jan-'15 to Dec-'20	Jan-'15 to Jun-'15, Oct-'15, Apr-	72
		Loading	Mar-'18 to Dec-'20	Sep-'18, May-'20	34
	Sultan M. Salahudin (Bima)	Unloading	Jan-'15 to Dec-'20	-	72
		Loading	Jan-'15 to Dec-'20	-	72

Next, each series data would be analyzed using the multi-input intervention model that incorporated several intervention events, i.e. earthquakes as natural disasters and Covid-19 as a global pandemic. According to the National Agency for Disaster Management (BNPB) as provided in Indonesian Disaster Data Geoportal (BNPB, 2021), there are eight months during 2015-2020 with earthquake events. The Indonesian Task Force for Covid-19 (2020) reported the first two cases of Covid-19 in Indonesia on March, 2 2020. By the end of March, the Covid-19 case reached more than 1.500 cases. In West Nusa Tenggara Province, the first case of Covid-19 was also reported on March 24, 2020 (CNN Indonesia, 2020). Hence that March 2020 is used as a starting point for Covid-19 intervention in this study. By the end of 2020, the number of Covid-19 cases in West Nusa Tenggara Province were 5,664 cases or only 0.76% of the total cases in Indonesia, i.e. 743,198 cases. According to the time reference of data used in this study in Table 1 and months of intervention events occurred, the details of interventions events for each series data are presented in Table 2.

Table 2
Intervention Events Used in The Multi-Input Intervention Models

No.	Intervention (date)	Port						Airport					
		Lembar		Badas		Bima		Lombok Int.		Sultan M Kaharuddin		Sultan M. Salahudin	
		U	L	U	L	U	L	U	L	U	L	U	L
1	Earthquake Mar-'16	$X_{2,1}$		$X_{4,1}$	$X_{3,1}$	$X_{6,1}$	$X_{5,1}$	$X_{8,1}$	$X_{7,1}$	$X_{10,1}$		$X_{12,1}$	$X_{11,1}$
2	Earthquake Aug-'16	$X_{2,2}$		$X_{4,2}$	$X_{3,2}$	$X_{6,2}$	$X_{5,2}$	$X_{8,2}$	$X_{7,2}$	$X_{10,2}$		$X_{12,2}$	$X_{11,2}$
3	Earthquake Jul-'18	$X_{2,3}$		$X_{4,3}$	$X_{3,3}$	$X_{6,3}$	$X_{5,3}$	$X_{8,3}$	$X_{7,3}$	$X_{10,3}$		$X_{12,3}$	$X_{11,3}$
4	Earthquake Aug-'18	$X_{2,4}$		$X_{4,4}$	$X_{3,4}$	$X_{6,4}$	$X_{5,4}$	$X_{8,4}$	$X_{7,4}$	$X_{10,4}$		$X_{12,4}$	$X_{11,4}$
5	Earthquake Dec-'18	$X_{2,5}$		$X_{4,5}$	$X_{3,5}$	$X_{6,5}$	$X_{5,5}$	$X_{8,5}$	$X_{7,5}$	$X_{10,5}$	$X_{9,1}$	$X_{12,5}$	$X_{11,5}$
6	Earthquake Mar-'19	$X_{2,6}$		$X_{4,6}$	$X_{3,6}$	$X_{6,6}$	$X_{5,6}$	$X_{8,6}$	$X_{7,6}$	$X_{10,6}$	$X_{9,2}$	$X_{12,6}$	$X_{11,6}$
7	Earthquake Jul-'19	$X_{2,7}$		$X_{4,7}$	$X_{3,7}$	$X_{6,7}$	$X_{5,7}$	$X_{8,7}$	$X_{7,7}$	$X_{10,7}$	$X_{9,3}$	$X_{12,7}$	$X_{11,7}$
8	Covid-19 Mar-'20	$X_{2,8}$	$X_{1,1}$	$X_{4,8}$	$X_{3,8}$	$X_{6,8}$	$X_{5,8}$	$X_{8,8}$	$X_{7,8}$	$X_{10,8}$	$X_{9,4}$	$X_{12,8}$	$X_{11,8}$
9	Earthquake Jun-'20	$X_{2,9}$	$X_{1,2}$	$X_{4,9}$	$X_{3,9}$	$X_{6,9}$	$X_{5,9}$	$X_{8,9}$	$X_{7,9}$	$X_{10,9}$	$X_{9,5}$	$X_{12,9}$	$X_{11,9}$

Note: L (Loading); U (Unloading)

As reported by BNPB (2021), In terms of number of victims, houses and public facilities damages, the earthquakes have affected several regencies/cities in West Nusa Tenggara Province. In other words, the impact of an earthquake was not experienced by all regencies/cities but this study presumes that each earthquake would affect all regencies/cities where the port/airport is located. Furthermore, this assumption would be confirmed using the significance test in the multi-input intervention analysis.

2.2. Theoretical Model

Intervention analysis is one of the most widely used methods to measure the impact of an intervention event in various fields, such as tourism, transportation, inflation, and stock prices (Purwa & Atmanegara, 2020). Firstly proposed by Box & Tiao (1975), this method extended the most popular univariate time series method, i.e. Autoregressive Integrated Moving Average (ARIMA) model, by modelling the binary variable of intervention event. Supposed that there is a series data $t = 1,2, \ldots, T_1 - 1, T_1, \ldots, T_2 - 1, T_2, \ldots, T_k - 1, T_k, \ldots, N$ with k is number of intervention events, the first procedure to produce the multi-input intervention model is estimation of ARIMA model for series data before the first intervention event, T_1, i.e. $t = 1,2, \ldots, T_1 - 1$. Four steps of ARIMA Box-Jenkins modelling (Box, G.E.P. & Jenkins, 1976), including model identification, estimation, residual diagnostic checking, and forecasting, are performed in this first procedure. In the model identification process, the order of ARIMA models are determined based on the significant lags in the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The complete guidance to determine the ARIMA model is described in Wei (2006). This ARIMA model obtained is also called the pre-intervention model with the general form is as follows:

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^S)^D Y_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{1}$$

Where Y_t is stationary series data at time t that regularly differenced at order d using $(1-B)^d$ if contains trend and seasonally (S) differenced at order D using $(1-B^S)^D$ if contains seasonal trend, with backshift operator, B. $\phi_p(B) = \left(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p\right)$ and $\Phi_P(B^s) = (1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_P B^{PS})$ are autoregressive (AR) component with order p and AR component of seasonal period S with order P, respectively. $\theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right)$ and $\Theta_Q(B^s) = \left(1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}\right)$ are moving average (MA) component with order q and MA component of seasonal period S with order Q, respectively. A white noise process, a_t, has mean $E(a_t) = 0$, variance $Var(a_t) = \sigma_\alpha^2$, and $Cov(a_t, a_{t+k}) = 0$ for $k \neq 0$.

Next, diagnostic checking for residuals from the pre-intervention model is performed including checking for white noise and normality. If there are several alternatives of pre-intervention model, the model selection criteria, i.e. Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), or Root Mean Square Error (RMSE), could be used to choose the best pre-intervention model. Using this model, the series data $t = T_1, \ldots, T_2 - 1$ would be forecasted and obtain the response values $Y_t^* = Y_t - \hat{Y}_t$. The plot of these response value is used to identify the coefficients of the 1st intervention model, i.e. b that reflects delay time of significant impact after intervention event occurs at $t = T_1$, s is the time taken for the impact to be diminished, and r reflects the intervention event's pattern. The examples of various response value patterns along with the values of b, s, and r were described clearly by Box & Tiao (1975), Lee, Suhartono, & Sanugi (2010), and Montgomery & Weatherby (1980). Hence the formula for the first intervention model is as follows:

$$Y_t = \frac{\omega_s(B)}{\delta_r(B)} B^b X_t + \frac{\theta_q(B)\Theta_Q(B^s)}{\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^S)^D} a_t \tag{2}$$

where binary variable X_t represent the intervention event that start at $t = T$. There are two types of intervention event X_t. First, the pulse function (P_t) when an intervention event occurs at time $t = T$ and afterward as follows:

$$P_t = \begin{cases} 0, & t \neq T \\ 1, & t = T \end{cases} \tag{3}$$

Second, the step function (S_t) when an intervention event only occurs at time $t = T$ as follows,

$$S_t = \begin{cases} 0, & t < T \\ 1, & t \geq T \end{cases} \tag{4}$$

$\omega_s(B) = (\omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s)$ and $\delta_r(B) = (1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r)$. After identifying the b, s, and r, the 1st intervention model would be estimated. In this process, the estimation results of AR and MA component might be different compared to the estimation results in pre-intervention model. The diagnostic checking process for residuals also performed to obtain the adequate model.

With the same procedures, from forecasting, calculate and plot the residuals to identify the coefficients of intervention event, model estimation, and diagnostic checking, the models for the subsequent intervention events are also produced. The general formula of multi-input intervention model is as follows:

$$Y_t = \sum_{i=1}^{k} \frac{\omega_{s_i}(B)}{\delta_{r_i}(B)} B^{b_i} X_{i,t} + \frac{\theta_q(B)\Theta_Q(B^s)}{\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^S)^D} a_t \tag{5}$$

In this study, there are 12 multi-input intervention models that would be produced. The earthquakes are assumed to have the pulse function (P_t) since only occurred at $t = T$. While the Covid-19 pandemic is assumed to have the step function (S_t) since it still occurs even at the end of the time reference. By using the multi-input intervention model, the information of when the significant impact was experienced after intervention event occurred, the time taken by this impact for diminishing, and its impact magnitude would be obtained. Furthermore, the impact magnitude and pattern of an intervention event in the three main ports and airports in West Nusa Tenggara Province are summarized and compared to depict its behaviour on different ports and airports. This study utilized the statistical software Minitab 18 for producing the graphs and SAS 9 for estimating the multi-input intervention models.

3. Results

In this section, the time series plot of loading and unloading goods data for each port and airport would be visualized. Then the multi-input intervention models would be developed. To make the concise analysis results, the complete procedure to produce this model is described completely only for the unloading goods data in Lembar Port. While for others series data, the final results of multi-input intervention models are only provided.

3.1. *Intervention Model in Lembar Port*

Lembar Port is one of the administered ports in West Nusa Tenggara Province that is located in Lombok Barat Regency or in the west part of the province. This port is indirectly adjacent to the Bali Province. According to Fig. 2, the supply chain of unloading goods is bigger than loading goods with the highest number for the former is about 150,000 tons, while the highest number for the latter is only 7,000 tons. During 2015-2020, the time series plot of unloading goods in Lembar Port has no linear trend visually. The fluctuation only appears around the mean, i.e. about 100,000 tons. Regarding the intervention events (red dashed vertical line), some negative impact of intervention events at the time when the intervention occurred and/or afterward are depicted, e.g. the earthquake impact in March 2016. During 2019-2020, the time series plot of loading goods also has no linear trend. Visually, the impact of the intervention event depicted when Covid-19 started occurred in March 2020.

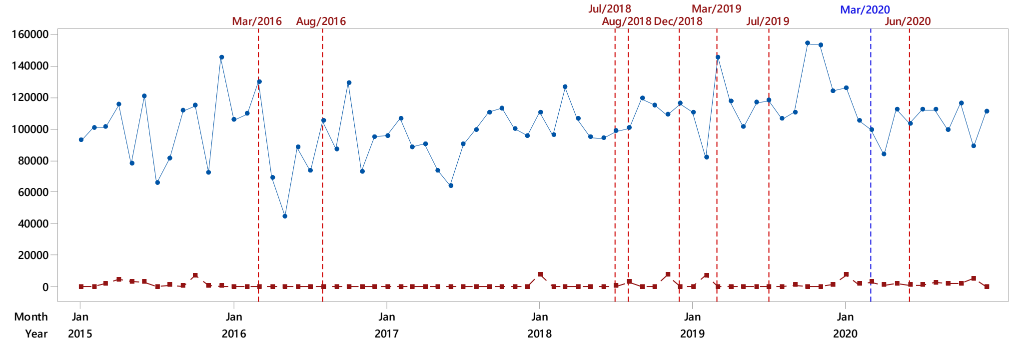
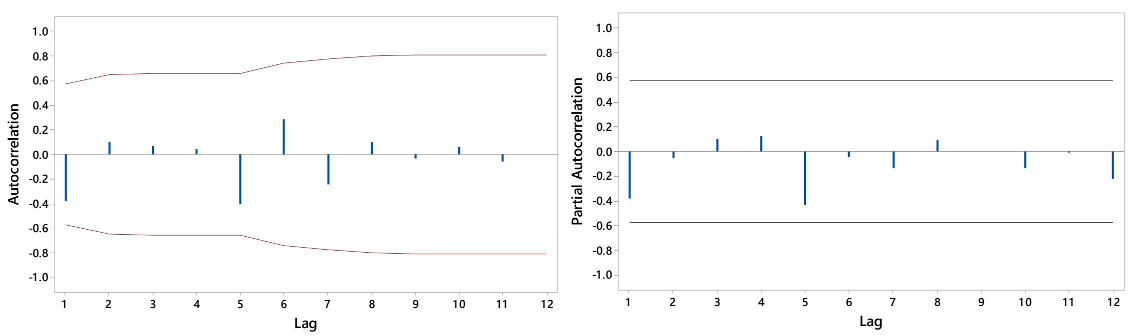


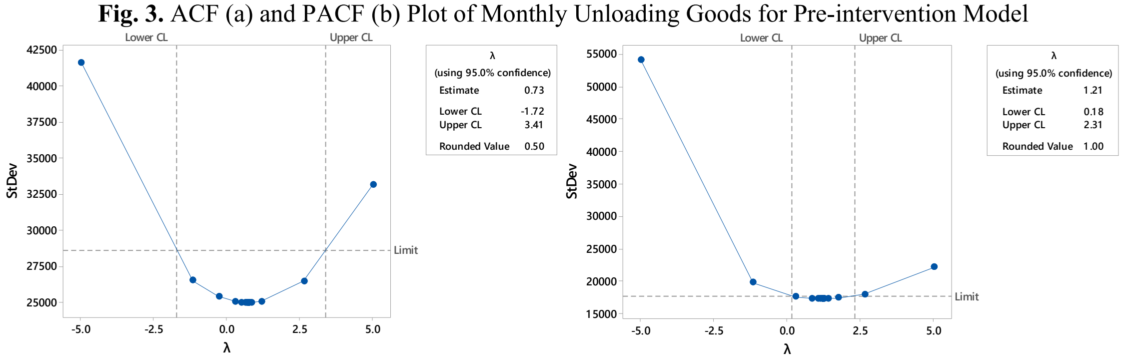
Fig. 2. Monthly Unloading (blue) and Loading (red) Goods in Lembar Port (tons), 2015-2020

For monthly unloading goods, the identification procedure of ARIMA pre-intervention model shows that the series data is already stationary in the mean and variance. The stationary in the mean indicated by ACF and PACF plots that have no slowly decaying significant plot (Fig. 3). The confidence interval of lambda value (λ) contains a unity indicates the stationary in the variance hence the transformation of the series data is not needed (Fig. 4a). According to the ACF and PACF plot, there is no significant lag then the order $p = 0$ and $q = 0$. Unfortunately, this model could not fulfil the white noise and normality assumptions in the diagnostic checking process. In other words, the model is not adequate.



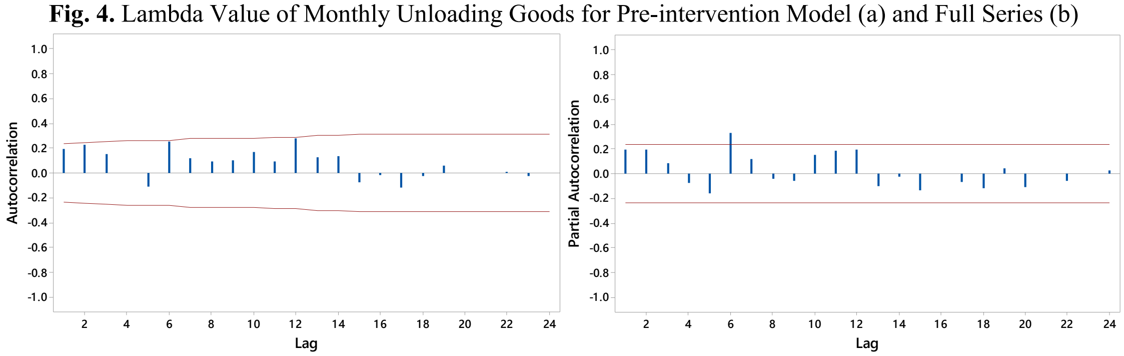
(a) (b)

Fig. 3. ACF (a) and PACF (b) Plot of Monthly Unloading Goods for Pre-intervention Model



(a) (b)

Fig. 4. Lambda Value of Monthly Unloading Goods for Pre-intervention Model (a) and Full Series (b)



(a) (b)

Fig. 5. ACF (a) and PACF (b) Plots of Full Series of Monthly Unloading Goods

This study overcomes that problem by using the full series data to identify the ARIMA model. As shown in Fig. 5, there are significant lag in ACF plot, i.e. lag 6 and 12, and significant lag in PACF plot, i.e. lag 6 (Fig. 5). From these results, there are some alternative ARIMA models. Only one model, i.e. ARIMA(0,0,[6]) that fulfils the assumption of white noise and normality. Thus, the pre-intervention model is as follows:

$$Y_{1,t} = 107459 + (1 + B^6)a_t \tag{6}$$

where μ is mean of the series data. Using this model, the series data at the time when the first intervention event occurred, i.e. earthquake in March 2016, until the time prior to the second intervention event, i.e. earthquake in August 2016, $(T_1, T_1 + 1, T_1 + 2, \ldots, T_2 - 1)$ would be forecasted to obtain the response value $Y^*_{1,t} = Y_{1,t} - \hat{Y}_{1,t}$. The plot of these residuals to identify the coefficient of the 1st intervention model is presented in Fig. 6. Based on the significant plot that exceed the confidence intervals ($\pm 2\sigma$) in this plot, the determined coefficients for the first intervention event are $b = 1$, $s = 1$, and $r = 0$. Where σ is the RMSE produced by ARIMA pre-intervention model calculated from series data $t = 1,2, \ldots, T_1 - 1$. Significant plot of response value at $T_{1,1} + 3$ and $T_{1,1} + 4$ are not included in the model since have non-significant coefficient estimates ($\alpha = 0.05$). The 1st intervention model for unloading goods in Lembar Port is as follows:

$$Y_{1,t} = -33042P_{1,t-1} - 51195P_{1,t-2} + 100080 + (1 + 0.1827B^6)a_t \tag{7}$$

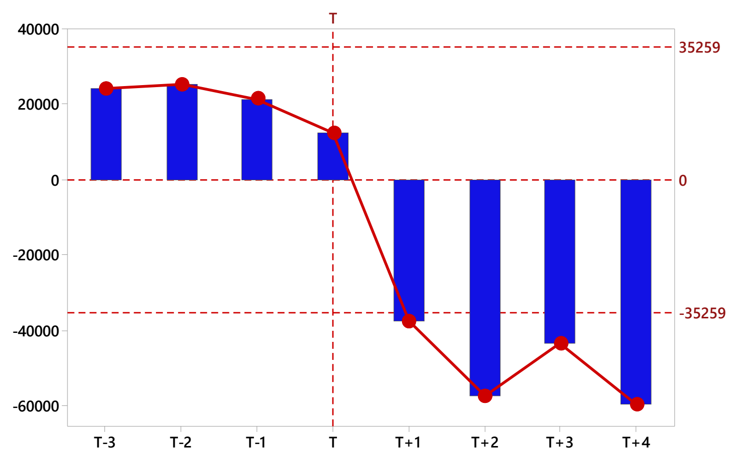


Fig. 6. Residuals plot to identify the coefficient of the 1st intervention model

With the same procedures, the 2nd until 9th intervention models would be produced. The estimation of final multi-input intervention model, i.e the 9th intervention model, is presented in Table 3. This result also can be written as follows:

$$\begin{aligned} Y_{1,t} = {} & -40796P_{1,t-1} - 49054P_{1,t-2} + 39246P_{6,t} + 53353P_{7,t-3} + 48983P_{7,t-4} + 102571 \\ & + (1 + 0.1783B^6)a_t \end{aligned} \tag{8}$$

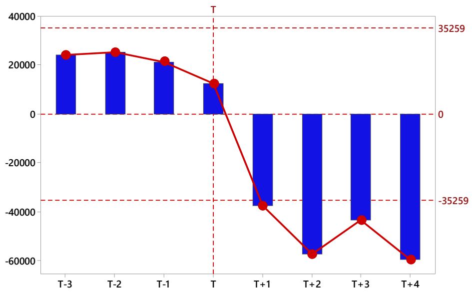
From this final model, the significant impacts are only produced by the 1st, 6th, and 7th intervention events, i.e. earthquakes occurred in March 2016, March and July 2019. This result also confirms the visual inspection of the intervention events impact in Fig. 2. The complete response values of all intervention events in Lembar Port are presented in Fig. 7.

Table 3

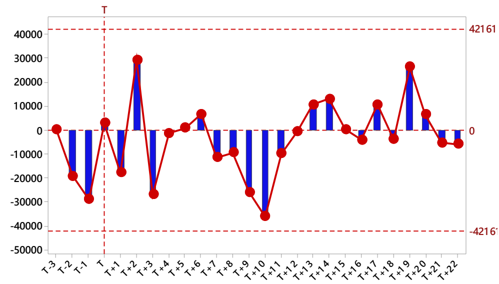
Estimation Result of The Final Intervention Model of Monthly Unloading Goods in Lembar Port

Model	Parameter	Coef.	SE Coef.	P-value
ARIMA	μ	102571	2405	<.0001
	θ_6	-0.1783	0.1330	0.1850
1st Intervention $b = 1, s = 1, r = 0$	ω_{0_1}	-40796	16545	0.0165
	ω_{1_1}	49054	16709	0.0047
6th Intervention $b = 0, s = 0, r = 0$	ω_{0_6}	39246	16519	0.0207
7th Intervention $b = 3, s = 1, r = 0$	ω_{0_7}	53353	16531	0.0020
	ω_{1_7}	-48983	16480	0.0042

The response values in Fig. 7 indicates the impact of intervention events. There are only three intervention events that produced significant impact experienced by the unloading goods in Lembar Port, i.e. earthquake that occurred in March 2016, March 2019, and July 2019. The negative impact only showed by the earthquake that occurred in March 2016. The number of unloading goods decreased around 40,000 to 60,000 tons one month after the intervention occurred. While the two other intervention events produced positive impact, i.e. at the time when the earthquake in March 2019 occurred ($T_{1,6}$) and three and four months after the earthquake in July 2019 occurred ($T_{1,7}+3, T_{1,7}+4$). Interestingly, the Covid-19 pandemic did not significantly affect the number of unloading goods in Lembar Port.

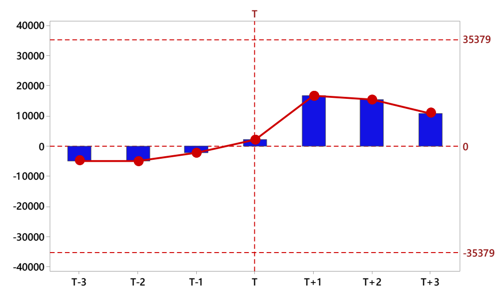


1st – Earthquake in Mar 2016

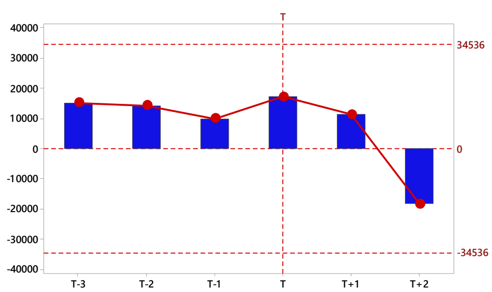


2nd - Earthquake in Aug 2016

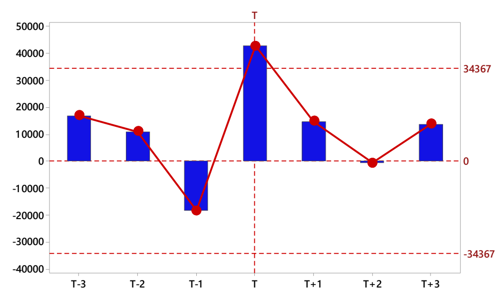
3rd - Earthquake in Jul 2018



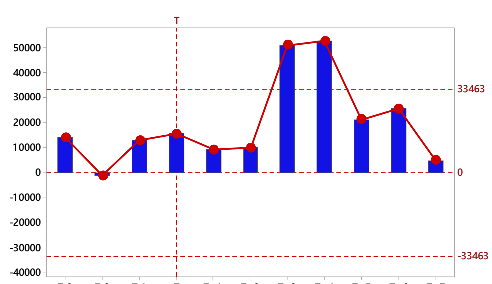
4th - Earthquake in Aug 2018



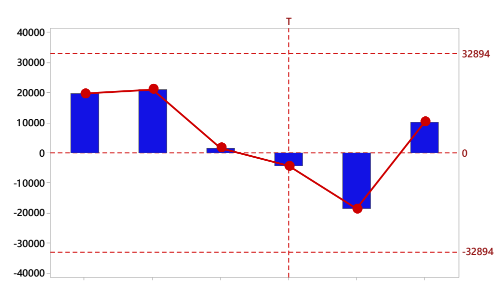
5th - Earthquake in Dec 2018



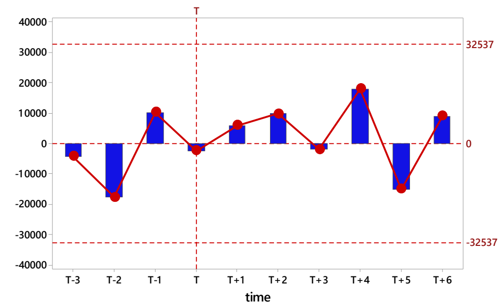
6th - Earthquake in Mar 2019



7th - Earthquake in Jul 2019



8th – Covid-19 in Mar 2020

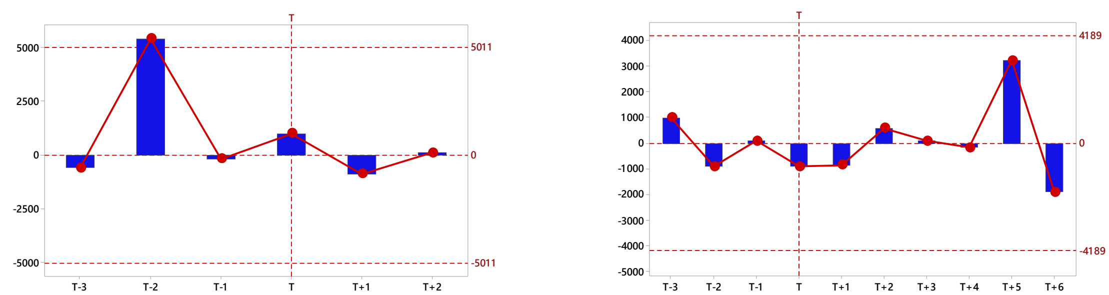


9th - Earthquake in Jun 2020

Fig. 7. Response Values of Unloading Goods in Lembar Port

As stated before, the number of loading goods in Lembar Port only has time reference started in September 2019 to December 2020 that covers only two intervention events, i.e. Covid-19 and earthquake in June 2020. Unfortunately, these two intervention events have no significant impact on this series data (Fig. 8). The final model, i.e. ARIMA model with addition of an outlier at $t = 5$, $I_t^{(5)}$, to make the residuals normally distributed is as follows:

$$Y_{2,t} = 2557 + 5752\, I_t^{(5)} + a_t \tag{9}$$



1st – Covid-19 in Mar 2020 2nd - Earthquake in Jun 2020

Fig. 8. Response Values of Loading Goods in Lembar Port

3.2. *Intervention Model in Badas Port*

The second administered port in this study, i.e. Badas Port is located in Sumbawa Regency. Compared to the other ports, Badas Port is located in the middle of Lembar Port and Bima Port. The supply chain patterns of unloading and loading goods in this port are clearly depicted in Fig. 9. Generally, the number of goods tends to be higher in April to October with an increasing pattern starting in April and decreasing pattern starting in July. While for the number of unloading goods, the opposite pattern is visible with a decreasing pattern starting in April and increasing pattern starting in May, June, or July. Similar with series data in Lembar Port, the number of unloading and loading goods in Badas Port also have no linear trend.

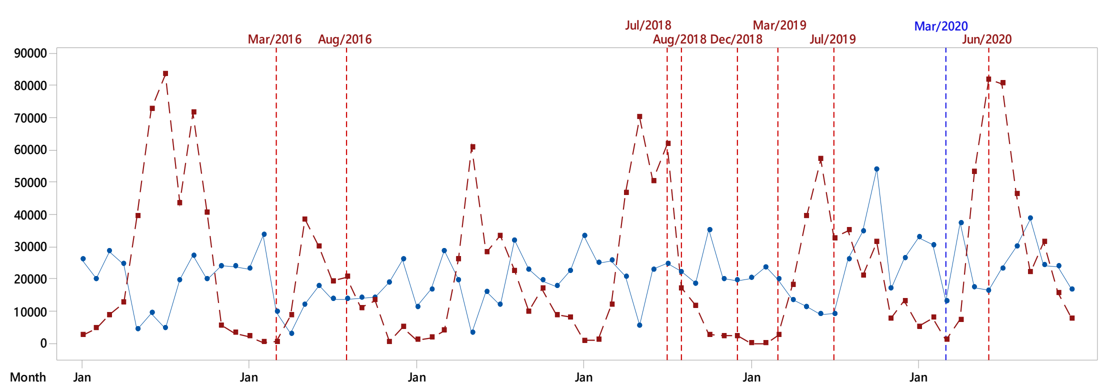


Fig. 9. Monthly Unloading (blue) and Loading (red) Goods in Badas Port (tons), 2015-2020

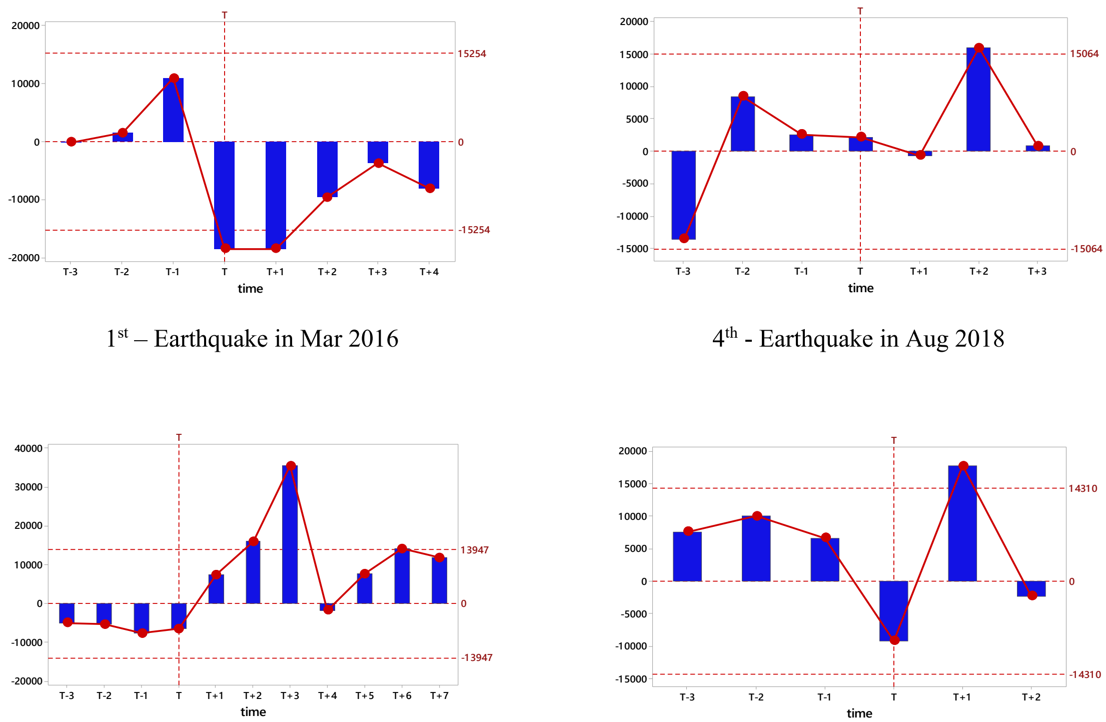
These two series data of unloading and loading goods in Badas Port cover all the intervention events. The final multi-input intervention model for these two series data are as follows:

$$Y_{3,t} = -9437P_{1,t} + 16281P_{4,t-2} + 11805P_{7,t-2} + 36257P_{7,t-3} - 13983S_{8,t} + 20236S_{8,t-1} + 19273 + (1 + 0.3767B)a_t \tag{10}$$

with the ARIMA(0,0,1) as pre-intervention model and

$$Y_{4,t} == \frac{-38508}{(1-1.0063B)}P_{4,t} + 27240P_{6,t-3} + 38850S_{8,t-2} + 32003P_{9,t} + 33430P_{9,t-1} + 33194I_t^{(6)} + 47068I_t^{(7)} + 28564I_t^{(9)} - 13934I_t^{(11)} + 18276I_t^{(29)} + 12715 + \frac{(1+0.6412B^{12})}{(1-0.9099B)}a_t \tag{11}$$

with the ARIMA(1,0,0)(0,0,1)^{12} as pre-intervention model and some additive outliers, respectively. From these two final models, the significant impacts experienced by the number of unloading goods in Badas Port are produced by earthquakes in March 2016, August 2018, July 2019, and Covid-19 pandemic started in March 2020. While for the number of loading goods, the significant impacts are produced by earthquakes in August 2018, March 2019, June 2020, and Covid-19 started in March 2020.



1st – Earthquake in Mar 2016

4th - Earthquake in Aug 2018

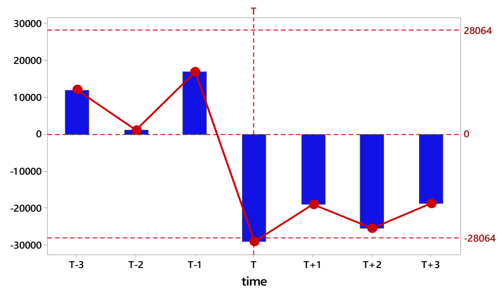
7th - Earthquake in Jul 2019

8th – Covid-19 in Mar 2020

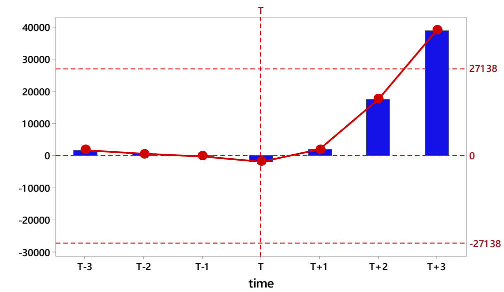
Fig. 9. Response Values of Unloading Goods in Badas Port

The impact magnitude and pattern of intervention events are represented by the response values in Fig. 9 and Fig. 10. For the number of unloading goods in Badas Port, the significant negative impact was only experienced when an earthquake occurred in March 2016. At the time when this earthquake occurred, the number of unloading goods decreased by almost 20,000 tons. While, the earthquakes that occurred in August 2018 and July 2019 actually had a significant positive impact on the number of unloading goods, i.e. two months after the former earthquake occurred ($T_{3,4} + 2$) and two, three months after the latter earthquake occurred ($T_{3,7} + 2, T_{3,7} + 3$), respectively.

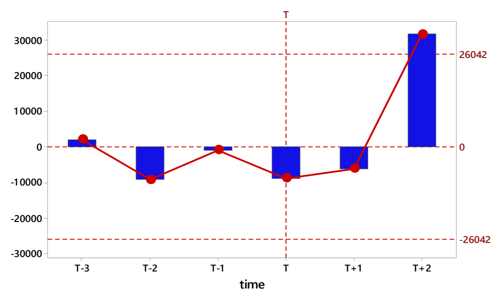
For the number of loading goods in Badas Port, the significant negative impact experienced when earthquakes occurred in August 2018 and June 2020. The number of loading goods decreased by about 30,000 tons in August 2018 ($T_{4,4}$). The decline was relatively constant until the next three months ($T_{4,4} + 1, T_{4,4} + 2, T_{4,4} + 3$). Whereas the negative impact was starting to appear three months after the earthquake in June 2020 occurred ($T_{4,9} + 3, T_{4,9} + 4, T_{4,9} + 5, T_{4,9} + 6$). The significant positive impact experienced when earthquakes occurred in March 2019 and Covid-19 that started in March 2020. The positive impact of the earthquake in March 2019 has delayed the pattern that occurred three months after this intervention event ($T_{4,6}+3$). The Covid-19 did not appear to have a significant impact on the number of loading goods, even the positive impact was felt two months after the announcement of the first two cases in Indonesia in March 2020.



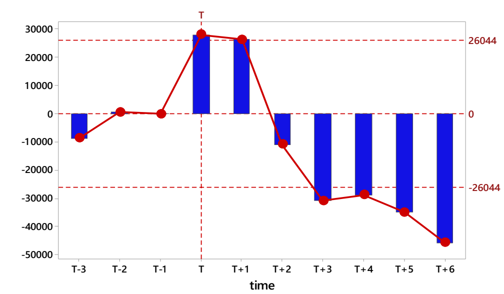
4th - Earthquake in Aug 2018



6th - Earthquake in Mar 2019



8th – Covid-19 in Mar 2020



9th - Earthquake in Jun 2020

Fig. 10. Response Values of Loading Goods in Badas Port

3.3. *Intervention Model in Bima Port*

Bima Port is located in the eastern part of West Nusa Tenggara Province, i.e. in Bima Municipality. Before the earthquake in March 2016 occurred, the number of unloading goods in Bima Port was higher than the number of loading goods. Afterward, the number of unloading and loading goods are quite similar with an average about 5,000 to 8,000 tons indicating that both series data have no linear trend.

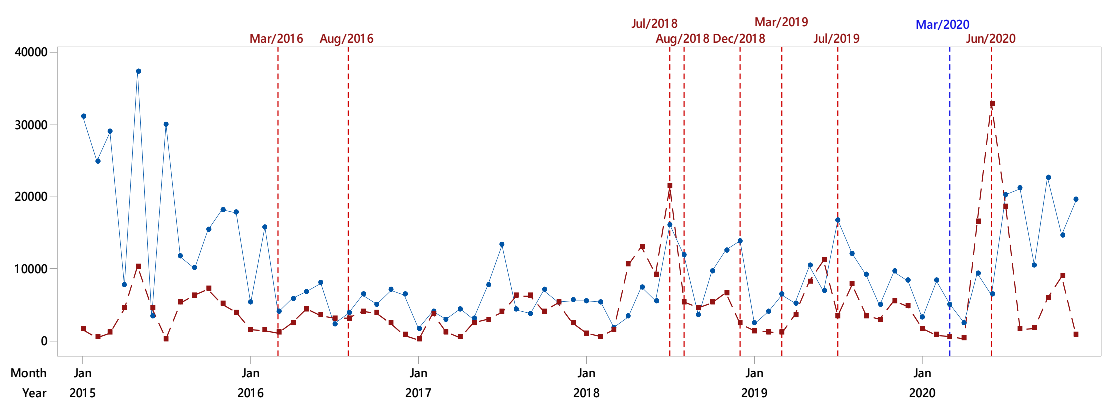


Fig. 11. Monthly Unloading (blue) and Loading (red) Goods in Bima Port (tons), 2015-2020

The final multi-input intervention model for unloading goods is as follows:

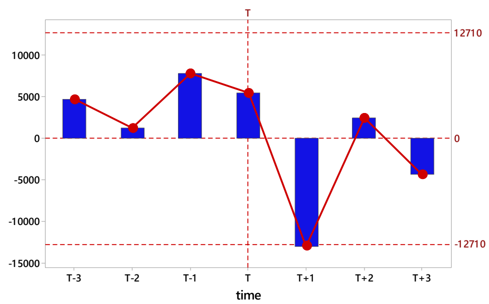
$$Y_{5,t} = 4174P_{4,t} - 9498P_{4,t-1} + \frac{12621}{(1-0.9250B)}P_{9,t-1} + 18556 + \frac{1}{(1-0.4904B^2)}\left(-10461I_t^{(6)} + a_t\right) \quad (12)$$

with the ARIMA(2,0,0) as pre-intervention model and an innovational outlier, $I_t^{(6)} = 1, t \geq 6$ and $I_t^{(6)} = 0, t < 6$. While the final multi-input intervention model for loading goods is as follows:

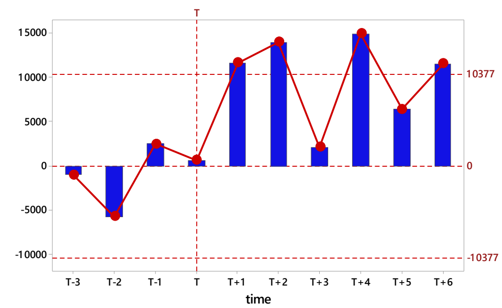
$$Y_{6,t} = 17105P_{3,t} + 2509P_{4,t} + 3557P_{6,t-3} + 7015P_{7,t-1} - 6190S_{8,t-1} + 7697S_{8,t-2} + \frac{17574}{(1-0.5453B)}P_{9,t} + 4415I_t^{(5)} + 3734I_t^{(8)} + 6879I_t^{(40)} + 5162I_t^{(41)} + 3592 + \frac{(1+0.4164B^{12})}{(1-8363B+0.6231B^2)}a_t \quad (13)$$

with the ARIMA(2,0,0)(0,0,1)^{12} as pre-intervention model and some additive outliers.

There are only two intervention events that have significant impact on the number of unloading goods, i.e. earthquake in August 2018 (4th intervention) and in June 2020 (9th intervention). The negative impact was experienced by the number of unloading goods a month after the earthquake in august 2018 occurred ($T_{5,4}+1$) with a decrease of more than 10,000 tons. In that month, there were two earthquakes with the highest magnitude compared to other earthquakes that occurred during 2015-2020, i.e. the earthquake on August 5th, 2018 with a magnitude of 7 and an earthquake on August, 19th 2018 with a magnitude of 6.9 (BMKG, 2018b, 2018a). Hence these two earthquakes caused the highest impact in terms of number of deaths, injuries, damaged houses and public facilities (BNPB, 2021). Contrary the positive impact was experienced a month after the occurrence of the earthquake in June 2020.



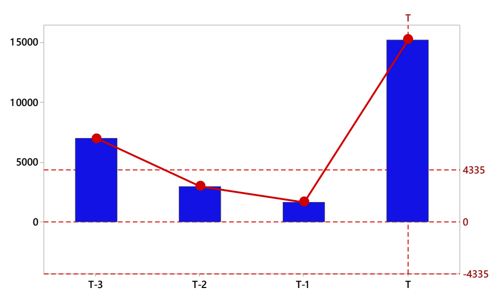
4th - Earthquake in Aug 2018



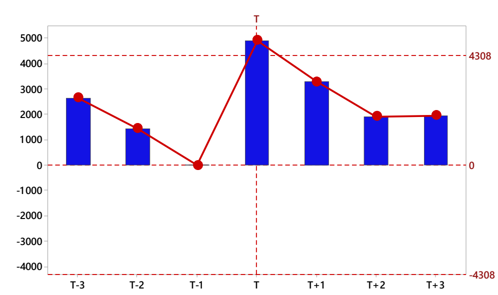
9th - Earthquake in Jun 2020

Fig. 12. Response Values of Unloading Goods in Bima Port

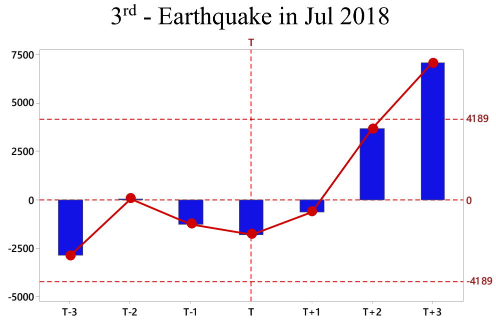
There are six intervention events that have significant impact on the number of loading goods in Bima Port, i.e. earthquake in July 2018 (3rd intervention), August 2018 (4th intervention), March 2019 (3rd intervention), July 2019, June 2020, and Covid-19. All these intervention events caused a positive impact on the number of loading goods, except Covid-19 and the earthquake in June 2020 that had a negative impact. The negative impact of Covid-19 occurred in April 2020 or a month after the first two cases were announced. The delayed impact also depicted from the response value of the earthquake in June 2020, i.e. started in two months after this intervention event occurred.



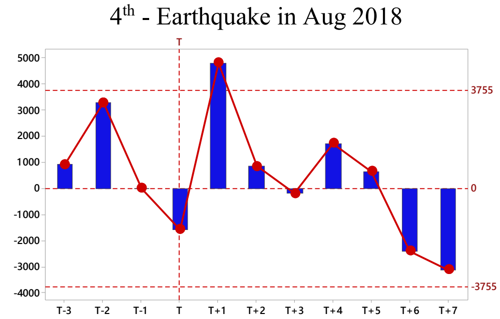
3rd - Earthquake in Jul 2018



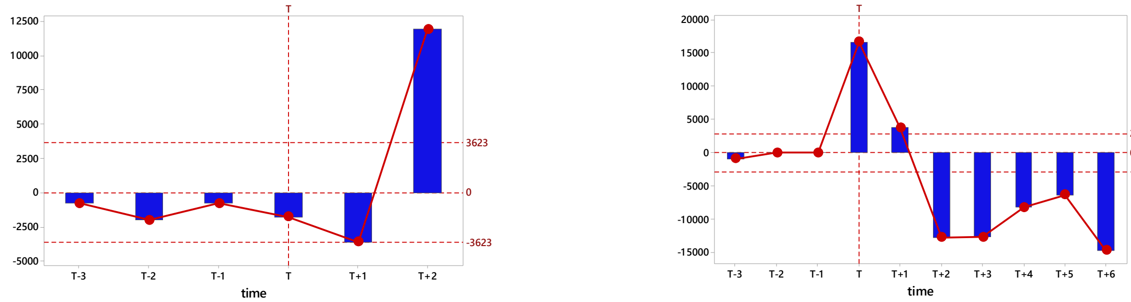
4th - Earthquake in Aug 2018



6th - Earthquake in Mar 2019



7th - Earthquake in Jul 2019



8th – Covid-19 in Mar 2020 9th - Earthquake in Jun 2020

Fig. 13. Response Values of Loading Goods in Bima Port

3.4. *Intervention Model in Lombok International Airport*

Lombok International Airport is located in Lombok Tengah Regency in the western part of West Nusa Tenggara Province, near Lembar Port in Lombok Barat Regency. During 2015-2020, the series data of unloading and loading goods in this airport have a very similar pattern of time series plot (Fig. 14). Visually, a slowly increasing trend appears from January 2015 to August 2018. Afterward, the time series plots tend to decrease until May or June 2020 then bounce back until December 2020. The negative impacts are clearly depicted at the time or after some intervention events, i.e. earthquakes in December 2018, March 2019, and Covid-19, occurred.

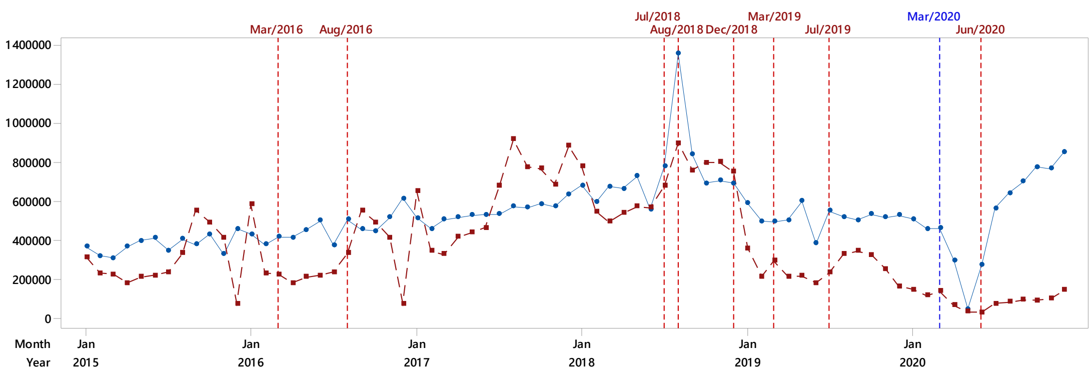


Fig. 14. Monthly Unloading (blue) and Loading (red) Goods in Lombok International Airport (tons), 2015-2020

The final multi-input intervention model for the number of unloading and loading goods in Lombok International Airport are

$$
\begin{aligned}
Y_{7,t} = {} & 64505P_{1,t-3} + 78032P_{2,t} + \frac{673083}{(1-0.2469B)}P_{4,t} - 98627P_{5,t-2} - 108941P_{6,t} + 102584P_{6,t-1} \\
& + 191020P_{6,t-3} - 39375P_{7,t-2} - 183781S_{8,t-1} + 246584S_{8,t-2} + 252624P_{9,t} \\
& + 549916P_{9,t-1} + 626848P_{9,t-2} + 687631P_{9,t-3} + 761207P_{9,t-4} + 756144P_{9,t-5} \\
& + 840879P_{9,t-6} - 58709I_t^{(11)} - 77127I_t^{(19)} + 123144I_t^{(24)} - 104699I_t^{(42)} \\
& + 76859I_t^{(43)} + 377285 + \frac{(1-0.5044B+0.4788B^4)}{(1-0.9886B)}a_t
\end{aligned}
\tag{14}
$$

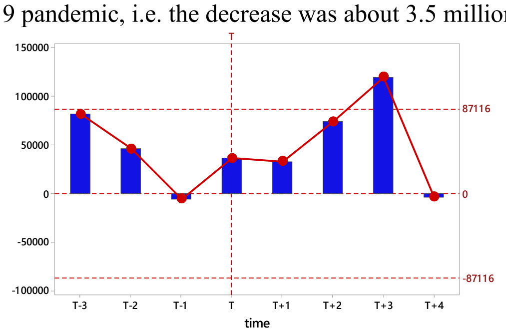
with ARIMA(1,0,[1,4]) as a pre-intervention model and

$$
\begin{aligned}
Y_{8,t} = {} & \frac{121114}{(1+0.0121B)}P_{2,t-1} - 319759P_{5,t-1} + 394867P_{5,t-2} - \frac{315861}{(1-1.0455B)}P_{6,t} \\
& + \frac{35236}{(1-1.1196B)}P_{7,t-1} + 64501S_{8,t} + 65099S_{8,t-1} + 14150S_{8,t-2} - 10708P_{9,t-2} \\
& + 3606P_{9,t-3} + 1318P_{9,t-4} - 40997P_{9,t-5} - 117562P_{9,t-6} - 360959I_t^{(12)} \\
& + 218074I_t^{(13)} - 436945I_t^{(24)} - 113596I_t^{(26)} + 239364I_t^{(32)} + 330671 \\
& + \frac{(1+0.3878B^3)}{(1-0.7100B+0.2900B^{11})}a_t
\end{aligned}
\tag{15}
$$

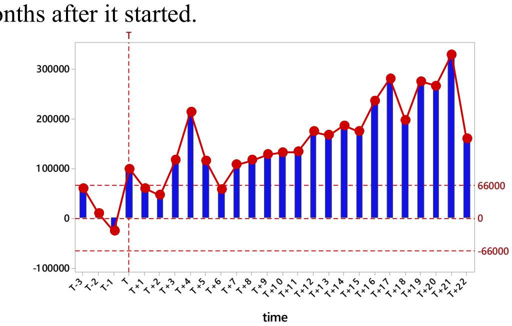
with ARIMA([1,11],0,[3]) as a pre-intervention model, respectively.

According to the final model, all the intervention events have a significant impact on the number of unloading goods, except for the earthquake in July 2018 (3rd intervention). Most of these intervention events have a negative impact with the biggest decrease experienced two months after since the Covid-19 first occurred in March 2020 ($T_{7,8}+2$). The earthquake with the highest magnitude in August 2018 (4th intervention) produced a delayed impact that started in two months after it occurred. An earthquake occurred in March 2019 (6th intervention) is the only intervention that produced a negative direct impact on the number of unloading goods.

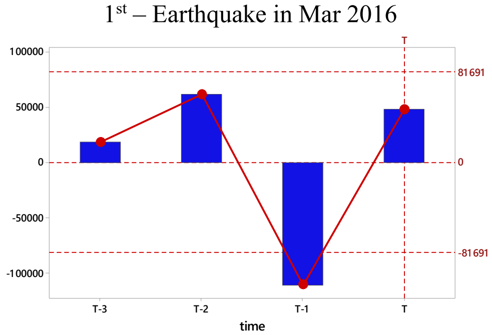
While for the number of loading goods the intervention events that have no significant impact are earthquakes in March 2016 (1st intervention), July 2018 (3rd intervention), and August 2018 (4th intervention). The response values of loading goods are quite similar compared to the response values of unloading goods, especially for the earthquakes that occurred in December 2018, March 2019, and Covid-19 that first started in March 2020. In this case, the highest magnitude earthquake in August 2018 (4th intervention) has no significant impact on loading goods. Interestingly, the biggest decrease was also caused by the Covid-19 pandemic, i.e. the decrease was about 3.5 million tons, two months after it started.



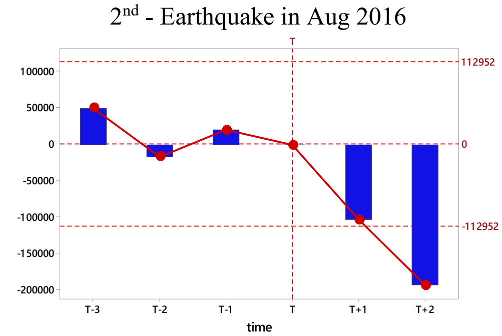
1st – Earthquake in Mar 2016



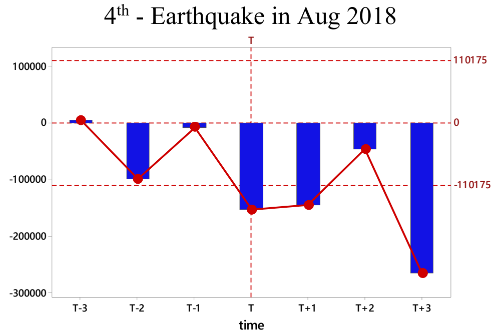
2nd - Earthquake in Aug 2016



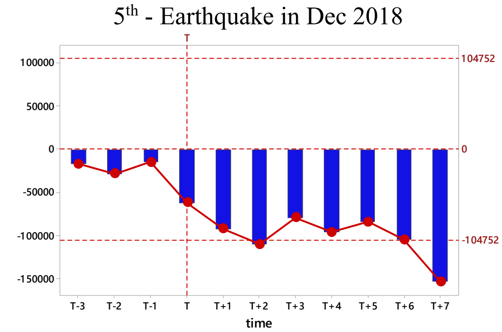
4th - Earthquake in Aug 2018



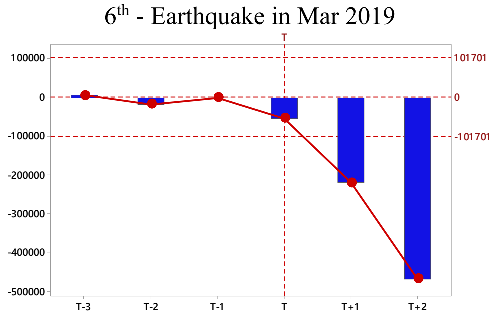
5th - Earthquake in Dec 2018



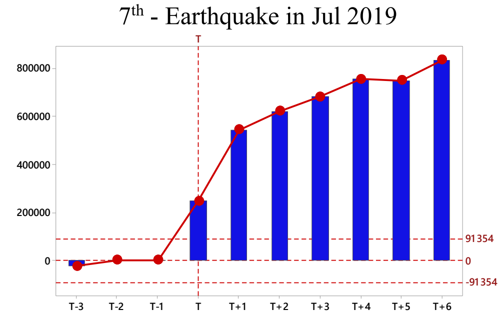
6th - Earthquake in Mar 2019



7th - Earthquake in Jul 2019

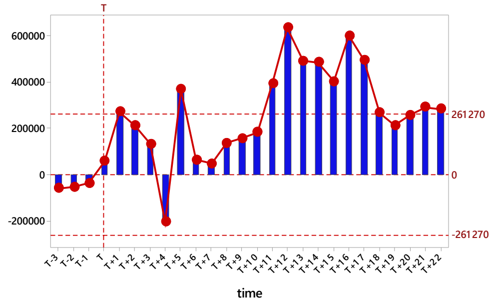


8th – Covid-19 in Mar 2020

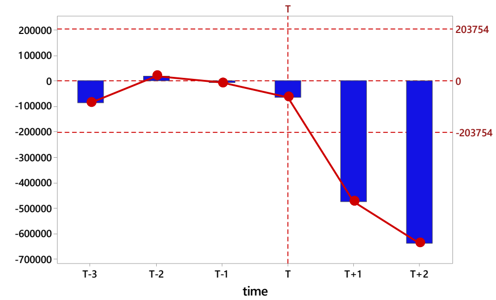


9th - Earthquake in Jun 2020

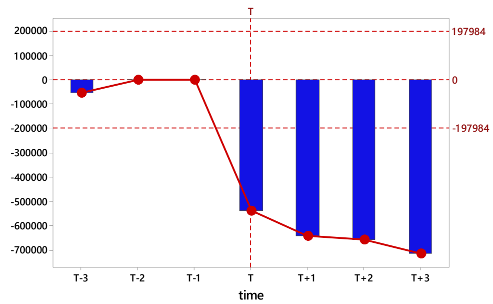
Fig. 15. Response Values of Unloading Goods in Lombok International Airport



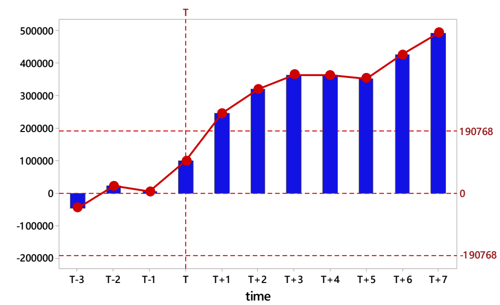
2nd - Earthquake in Aug 2016



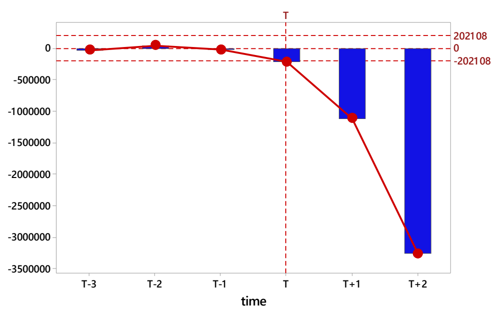
5th - Earthquake in Dec 2018



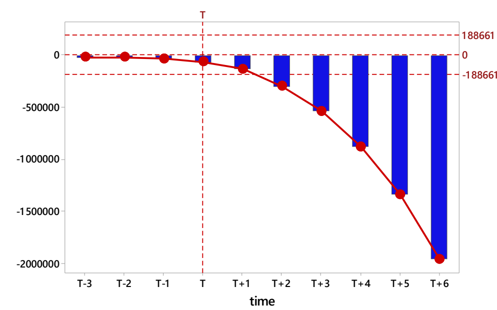
6th - Earthquake in Mar 2019



7th - Earthquake in Jul 2019



8th – Covid-19 in Mar 2020



9th - Earthquake in Jun 2020

Fig. 16. Response Values of Loading Goods in Lombok International Airport

3.5. Intervention Model in Sultan M Kaharuddin Airport

Sultan M Kaharuddin Airport is located in Sumbawa Regency in the central part of West Nusa Tenggara, near Badas Port that is also located in the same regency. Generally, the number of unloading goods in Sultan M Kaharuddin Airport is bigger than the number of loading goods. The series data of unloading goods has an increasing linear trend with the mean about 1,500 tons. While the series data of loading goods has no linear trend with the mean only about 300 tons. The visual inspection shows that the negative impact was experienced by the number of unloading and loading goods after Covid-19 pandemic occurred in March 2020 and recovered after four months.

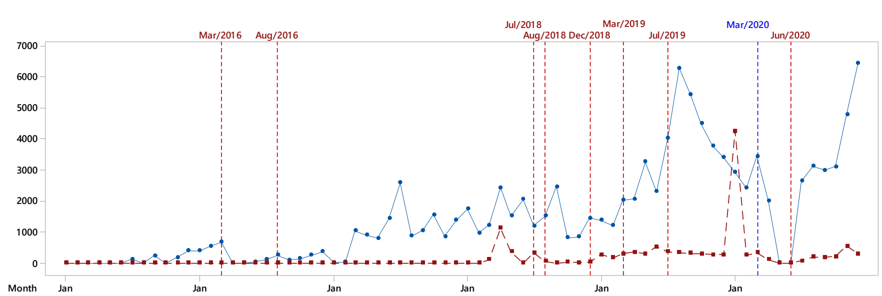


Fig. 17. Monthly Unloading (blue) and Loading (red) Goods in Sultan M Kaharuddin Airport (tons), 2015-2020

The final multi-input intervention model for the number of unloading and loading goods in Sultan M Kaharuddin Airport are as follows:

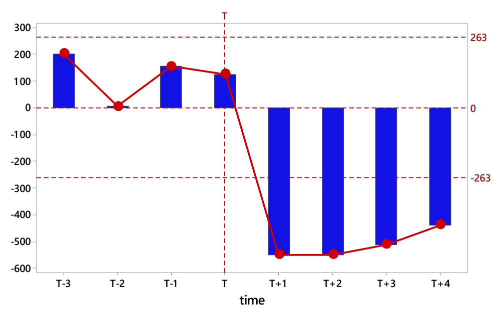
$$
\begin{aligned}
Y_{9,t} = {} & \frac{-350.0960}{(1-0.9165B)}P_{1,t-1} + \frac{813.1439}{(1-1.0277B)}P_{2,t-7} + 3.9728P_{4,t} - 870.2245P_{4,t-2} - 878.1901P_{4,t-3} \\
& - \frac{4.0097}{(1+1.3664B)}P_{5,t} + 1231P_{6,t-2} + \frac{6333}{(1-0.6923B)}P_{7,t} - 160.5727S_{8,t-1} \\
& - 3155S_{8,t-2} - 1626P_{9,t} + 1601P_{9,t-1} + 5589P_{9,t-2} + 7262P_{9,t-4} + 13822P_{9,t-6} \\
& + 1241I_t^{(31)} - 4462I_t^{(55)} + 365 + \frac{(1+0.7464B)}{(1+0.8830B)}a_t
\end{aligned} \tag{16}
$$

with ARIMA(1,0,1) as a pre-intervention model and

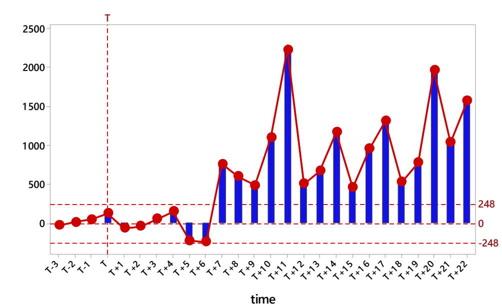
$$
\begin{aligned}
Y_{10,t} = {} & 4011P_{7,t-6} - 264.9831S_{8,t-2} + 35.9187P_{9,t-1} + 120.5242P_{9,t-2} + 58.3102P_{9,t-3} \\
& + 31.5741P_{9,t-4} + 306.4706P_{9,t-5} + 178.4281I_t^{(11)} + 160.6163I_t^{(13)} + 194.3051I_t^{(16)} \\
& - 189.2917I_t^{(26)} + 1039 + \frac{1}{(1-B)}\left(237.4306I_t^{(14)} + a_t\right)
\end{aligned} \tag{17}
$$

with ARIMA(1,0,0) as a pre-intervention model, respectively.

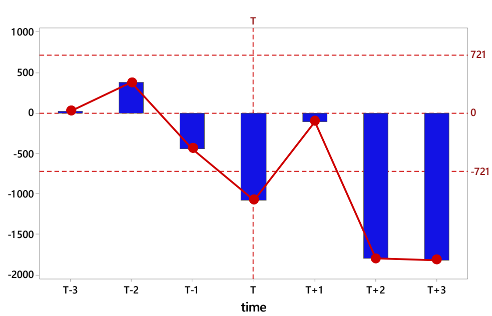
Based on the response values of the number of unloading goods, all the intervention events have significant impact, except the earthquake in July 2018 (3rd intervention). The same result was also obtained for the number of unloading goods in Lombok International Airport in the previous sub-section. Four intervention events have negative impact, i.e. earthquake in August 2018 and December 2018 that have direct impact and earthquake in March 2016 and Covid-19 that start occurred in 2020 that have delayed impact. The biggest decrease, i.e. 3,000 tons, depicted two months after Covid-19 started occurred in March 2020. The series data of loading goods in Sultan M Kaharuddin Airport only covers the last five intervention events. The significant impact appeared when earthquakes in July 2019, June 2020, and Covid-19 occurred. All of these impacts are delayed impacts with the biggest decrease produced by Covid-19 pandemic two months after it started.



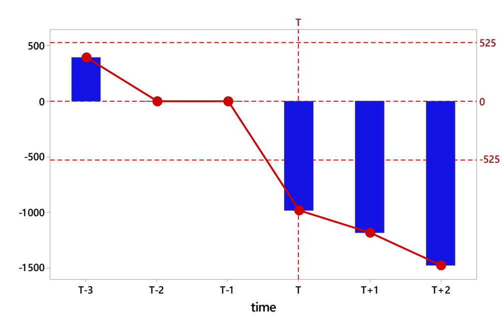
1st – Earthquake in Mar 2016



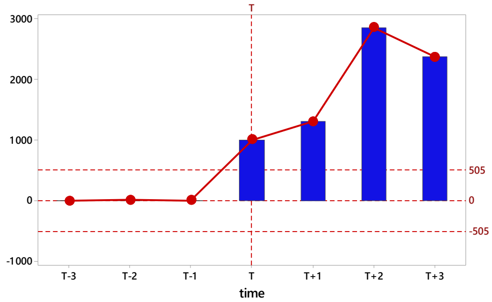
2nd - Earthquake in Aug 2016



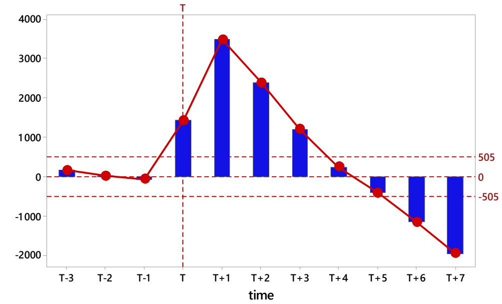
4th - Earthquake in Aug 2018



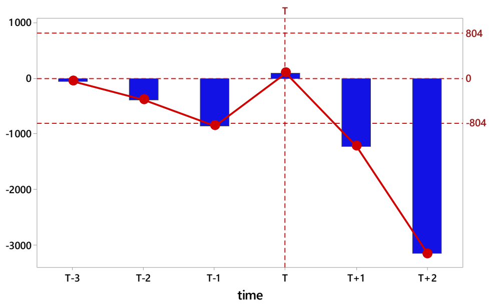
5th - Earthquake in Dec 2018



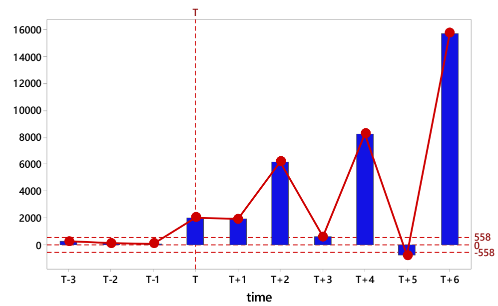
6th - Earthquake in Mar 2019



7th - Earthquake in Jul 2019

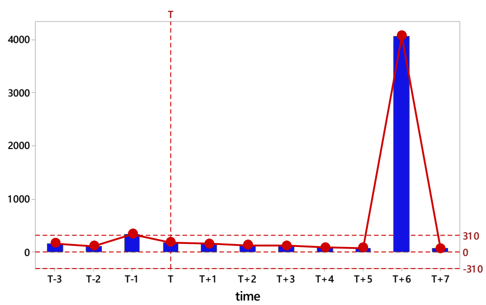


8th – Covid-19 in Mar 2020

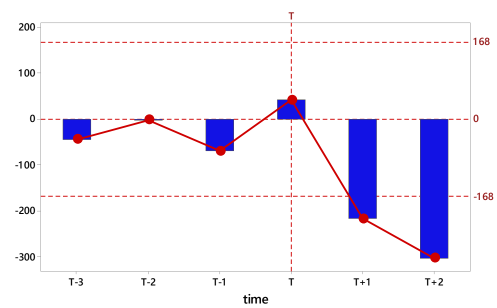


9th - Earthquake in Jun 2020

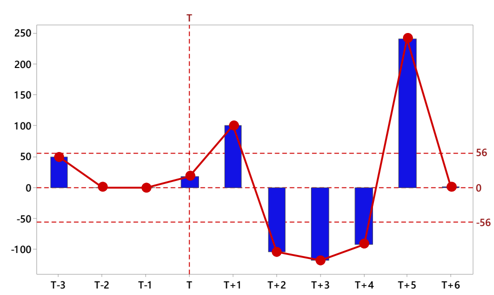
Fig. 18. Response Values of Unloading Goods in Sultan M Kaharuddin Airport



7th - Earthquake in Jul 2019



8th – Covid-19 in Mar 2020



9th - Earthquake in Jun 2020

Fig. 19. Response Values of Loading Goods in Sultan M Kaharuddin Airport

3.6. Intervention Model in Sultan M Salahudin Airport

Sultan M Salahudin Airport is located in Bima Regency in the eastern part of West Nusa Tenggara, near Bima Port. The co-movement between the number of unloading and loading goods visually appears as presented in Fig. 20. These series data have slightly increasing trend during January 2015 to December 2019 then experienced decreasing trend until May 2020 or two months after Covid-19 start occurred in March 2020. In that time, the number of unloading and loading goods in Sultan M Salahudin Airport showed the smallest value during 2015-2020, i.e. 3 and 228 tons, respectively. After the earthquake that occurred in June 2020, the number of unloading and loading goods experienced a relatively high increase. From visual inspection, the negative impact appears at the time or after some intervention events occurred, e.g. earthquake in March 2016, August 2018, December 2018, March 2019, July 2019, and Covid-19 in March 2020.

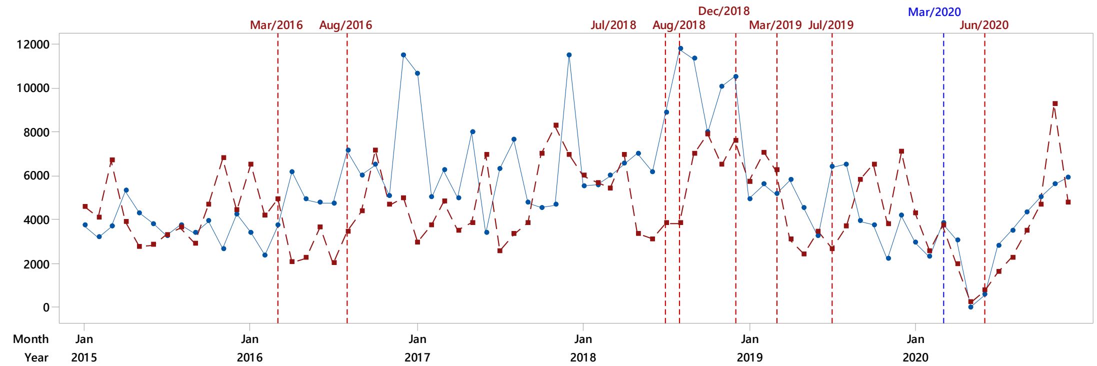


Fig. 20. Monthly Unloading (blue) and Loading (red) Goods in Sultan M Salahudin Airport (tons), 2015-2020

The final multi-input intervention model for the number of unloading and loading goods in Sultan M Salahudin airport are as follows:

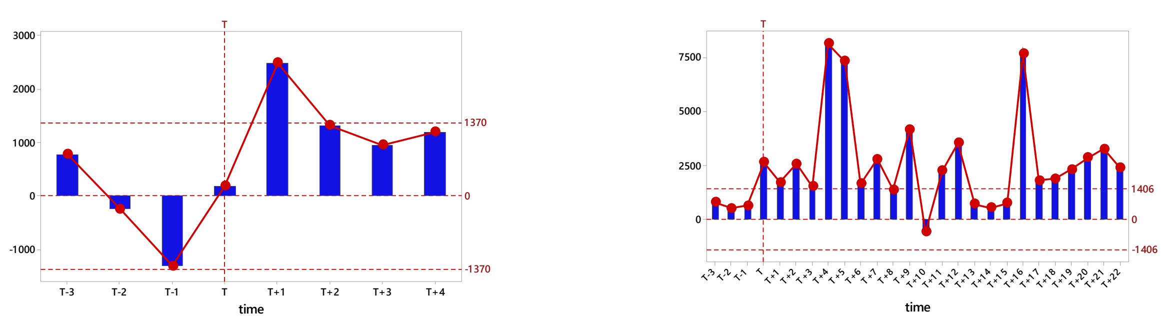
$$\begin{aligned} Y_{11,t} = {} & 2628P_{1,t-1} + 4359P_{2,t-4} + 4284P_{2,t-5} + 3874P_{4,t} + 3433P_{4,t-1} + 3601P_{4,t-3} + 3767P_{5,t} \\ & - 2393P_{6,t-2} - 2332P_{6,t-3} - 960.5738P_{7,t-7} - 3090S_{8,t-2} + \frac{2071}{(1-1.2287B)}P_{9,t-1} \\ & + 3741 + \frac{1}{(1-0.6436B+0.3863B^6-0.6463B^7)}a_t \end{aligned} \tag{18}$$

with ARIMA([1,6,7],0,0) as a pre-intervention model and

$$\begin{aligned} Y_{12,t} = {} & -1250P_{2,t-11} + 2052P_{4,t-2} + 1740P_{5,t-2} - 2135S_{8,t-2} + 4625P_{9,t-5} + 4669 \\ & + \frac{(1-1.5306B+0.8288B^2)}{(1-1.7184B+B^2)}a_t \end{aligned} \tag{19}$$

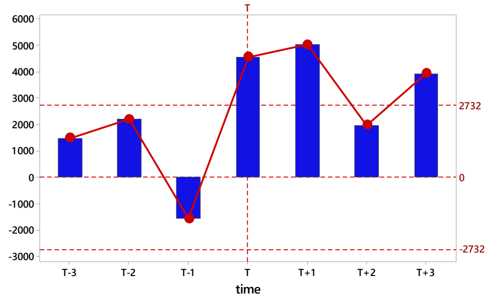
with ARIMA(2,0,2) as a pre-intervention model, respectively.

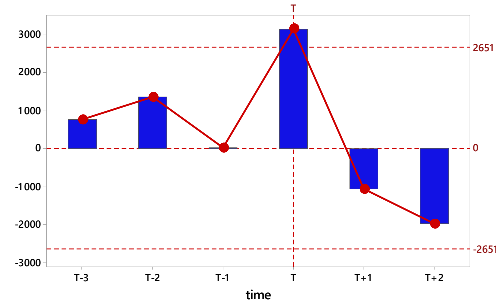
All the intervention events have a significant impact on the number of unloading goods in Sultan M Salahudin Airport, except for the earthquake in July 2018. The negative impacts were caused by the earthquake in March 2019 (6th intervention), July 2019 (7th intervention), and Covid-19 that started in March 2020 (8th intervention). All of these intervention events have delayed impact on the number of unloading goods. For the number of loading goods, there were five intervention events that had significant impact with the negative impact caused only by the earthquake in August 2016 (2nd intervention) and Covid-19 pandemic (8th intervention). These two interventions also have a delayed impact that depicts 11 months after the earthquake in August 2016 and two months after Covid-19 started in March 2020. The biggest decrease in the number of unloading and loading goods in Sultan M Salahudin Airport was caused by the Covid-19 pandemic, i.e. 5,000 and 3,000 tons, respectively, two months after it started in March 2020.



1st – Earthquake in Mar 2016

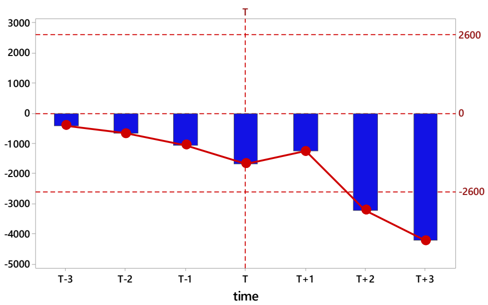
2nd - Earthquake in Aug 2016

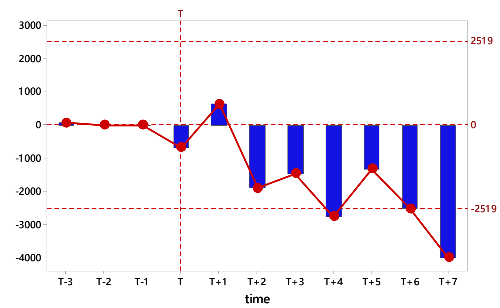




4th - Earthquake in Aug 2018

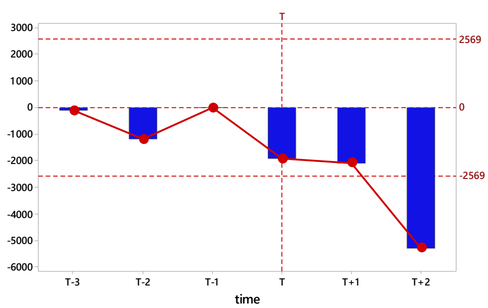
5th - Earthquake in Dec 2018

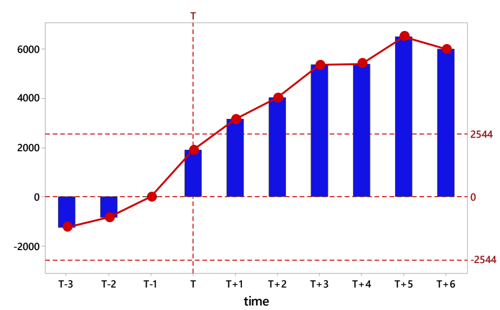




6th - Earthquake in Mar 2019

7th - Earthquake in Jul 2019

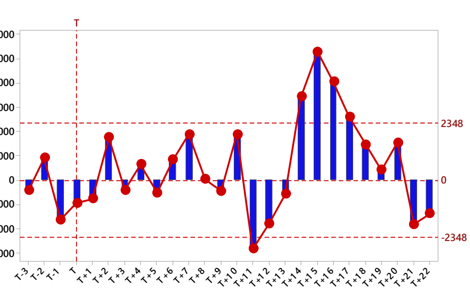


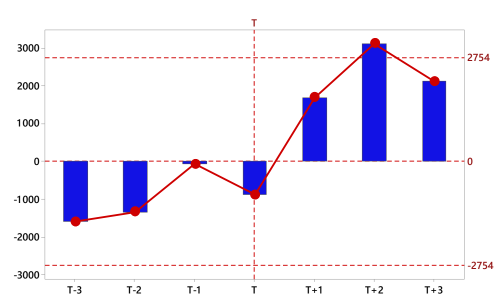


8th – Covid-19 in Mar 2020

9th - Earthquake in Jun 2020

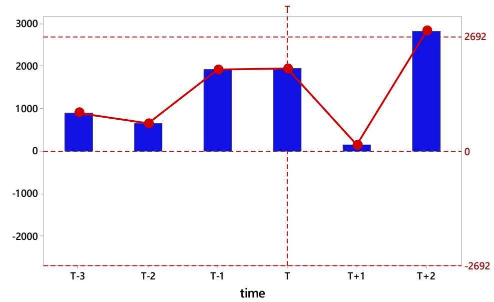
Fig. 21. Response Values of Unloading Goods in Sultan M Salahudin Airport



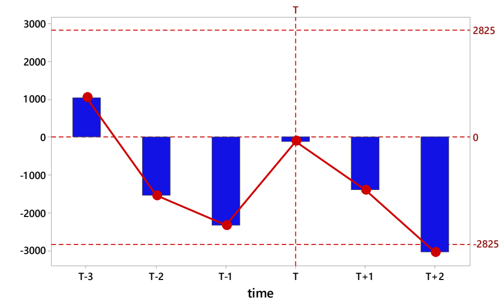


2nd - Earthquake in Aug 2016

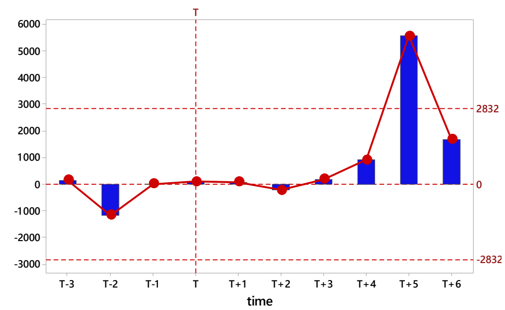
4th - Earthquake in Aug 2018



5th - Earthquake in Dec 2018



8th – Covid-19 in Mar 2020



9th - Earthquake in Jun 2020

Fig. 22. Response Values of Loading Goods in Sultan M Salahudin Airport

3.7. Summary of Intervention Event's Impact

The sign and pattern of all the significant impacts are summarized in Table 4.

Table 4
Summary of Sign and Pattern of Significant Impact

No.	Intervention (date)	Port						Airport					
		Lembar (Lombok Barat)		Badas (Sumbawa)		Bima (Bima Municipality)		Lombok Int. (Lombok Tengah)		Sultan M Kaharuddin (Sumbawa)		Sultan M. Salahudin (Bima)	
		U	L	U	L	U	L	U	L	U	L	U	L
1	Earthquake Mar-'16	D		ND	-	-	-	D	-	D		D	-
2	Earthquake Aug-'16	-		-	-	-	-	ND	D	D		D	D
3	Earthquake Jul-'18	-		-	-	-	ND	-	-	-		-	-
4	Earthquake Aug-'18	-		D	ND	D	ND	ND	-	ND		ND	D
5	Earthquake Dec-'18	-		-	-	-	-	D	D	ND	-	ND	D
6	Earthquake Mar-'19	ND		-	D	-	D	ND	ND	D	-	D	-
7	Earthquake Jul-'19	D		D	-	-	D	D	D	ND	D	D	-
8	Covid-19 Mar-'20	-	-	ND	D	-	D	D	ND	D	D	D	D
9	Earthquake Jun-'20	-	-	-	ND	D	ND	ND	D	ND	D	D	D

Notes: U and L denote for Unloading and Loading Goods, respectively. D and ND denote for Delayed and Non-delayed or direct impact pattern of intervention event, respectively. Cells with red and green colors denote negative and positive statistically significant impact ($\alpha = 0.05$), respectively. "-" denotes non-significant impact.

Generally, the intervention events did not always transmit negative impacts on the number of unloading and loading goods in the three main ports and airports in West Nusa Tenggara Province. In other fields, the mix impact of natural disasters also obtained by the previous studies by Purwa & Atmanegara (2020) and Rossello et al. (2020) for the number of international tourist arrivals, Jayasinghe, Selvanathan, & Selvanathan (2021) for Gross Domestic Product (GDP), Wibowo, Purwa, et al. (2021) for CPI and inflation, and Wibowo, Ulama, et al. (2021) for the number of airline passenger arrivals and departures. As the main concern, the negative impacts were more experienced by the three airports than the three ports. There were 19 intervention events that caused a negative impact (red colors) on the number of unloading and loading goods in the three airports. While in the three ports, negative impacts were only found in 7 intervention events. Specifically, the airports that experienced the most negative impact were Lombok International Airport, i.e. four negative impacts on each unloading and loading goods and Sultan M Kaharuddin Airport, i.e. also four negative impacts for unloading goods. The port with the most negative impacts were Badas Port, i.e. two negative impacts on loading goods, and Bima Port, i.e. also two negative impacts on loading goods. Regarding the type of activity in the three main ports and airports, the number of unloading goods experienced more negative impact than the number of loading goods in the three main airports, except in Lombok International Airport that has equal negative impacts. Whereas, in the three main ports, the negative impacts were more experienced by the number of loading goods than the number of unloading goods.

Most of the intervention events with negative impact have delayed impact patterns, i.e. 3 and 14 intervention events in the three ports and airports, respectively. There were 4 and 5 intervention events that had a direct or non-delayed impact pattern in the three ports and airports, respectively. The most delayed negative impacts were experienced by unloading goods in Lombok International Airport and Sultan M Salahudin Airport, each caused by three intervention events. While for the three ports, the most delayed negative impact was only one that was experienced by unloading goods in Lembar Port, Unloading and Loading Goods in Bima Port.

The Covid-19 pandemic was an intervention event that had the widest impact since it transmitted the negative impact on 7 series data, i.e. the number of unloading and loading goods in the three airports and number of loading goods in Bima Port. The intervention event with the second widest impact was the earthquake that occurred in June 2020. This intervention event has had a negative impact on the number of loading goods in Badas Port, Bima Port, Lombok International Airport, and Sultan M Kaharuddin airport. The earthquakes with the biggest magnitude that occurred in August 2018 only transmitted the negative impact on the number of loading goods in Badas Port, unloading goods in Bima Port, and unloading goods in Sultan M Kaharuddin Airport. While earthquakes in July 2018 have not transmitted the negative impact on the number of unloading and loading goods in the three ports and airports.

4. Discussion and Conclusions

This study utilized a multi-input intervention model to analyze the impact magnitude and pattern of intervention events, including eight earthquakes and Covid-19 pandemic, on the number of unloading and loading goods in the three main ports and airports in West Nusa Tenggara Province that occurred during 2015-2020. The results show that during that period the mix impact, i.e. negative and positive impact, were experienced by series data of unloading and loading goods. As mitigation of supply chain disruption, the statistically significant negative impacts were considered as the main concern in this study.

The negative impact of intervention events hit more the number of unloading and loading goods in the three main airports than three main ports. This result indicates that the supply chain of goods in the three main airports was more vulnerable to intervention events that consist of earthquakes and Covid-19 pandemic than supply chain of goods in the three main ports in West Nusa Tenggara Province. Specifically, the Lombok International Airport and Sultan M Kaharuddin have the most negative impact during 2015-2020. Moreover, the number of unloading goods was more vulnerable to intervention events than the number of loading goods in the airports. On the contrary, in the ports, the number of loading goods was more vulnerable to intervention events. The impact patterns of intervention events were dominated by delayed patterns. This pattern was more experienced by the three airports than the three ports in West Nusa Tenggara Province.

The Covid-19 pandemic has the widest impact followed by the earthquake that occurred in June 2020. Interestingly, the earthquake with the most fatality that occurred in August 2018 did not produce a wider impact than the two previous intervention events. This condition indicates that the Covid-19 pandemic that harmed the regional economic condition through large scale social restriction and travel restriction for foreign tourists then caused sharp decline in demand and supply of goods could produce a wider impact on the supply chain of goods than the earthquakes. The earthquakes might have a wider impact when it causes damage in the public transportation facility like ports and airports that can disrupt the supply chain of goods. Moreover, the earthquakes that caused more impact in term of number of deaths, injuries, damaged houses and public facilities presumed could give positive impact on the supply chain of goods, especially for the number of unloading goods, since it would lead to more disaster aid that enter through the ports and airports as reported in the results in the previous section. The other intervention events that were not covered in this study also could lead to a positive impact on the supply chain of goods.

Based on these results, the government and institutions related to transportation could provide policies related to mitigating the impact of intervention events on the supply chain of goods. As a province with the sea borders, the internal and external fulfilment of goods through the fluency of the supply chain of goods must be the top priority of the West Nusa Tenggara Province government. Since the supply chain of goods in airports were more prone to the intervention events, the utilization of ports as alternative transportation could be maximized. The delayed impact pattern that is experienced by most airports and ports could give more time for the government to mitigate the impact of intervention events. For future study, the addition of other intervention events that could produce positive impact should be incorporated in the multi-input intervention models. The cross-correlation between series data also needs to be considered by using other methods.

Acknowledgments

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