Impact of earthquakes on the number of airline passenger arrivals and departures: A case study of West Nusa Tenggara Province, Indonesia

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This study investigates the impact of earthquakes on the number of airline passenger arrivals and departures in West Nusa Tenggara Province, Indonesia. The monthly data of airline passengers at Lombok International Airport (Lombok), Sultan M. Kaharuddin Airport (Sumbawa), and Sultan M. Salahudin Airport (Bima) from January 2008 to December 2018 were used to conduct this study. The time series regression model was used to examine two scenarios, namely the global and partial effect of each earthquake event. The results showed that the impact of earthquakes on the number of airline passenger arrivals and departures was not evident globally. However, there was a significant negative impact on the partial effects, especially for the earthquakes that occurred in August 2018 and December 2018. The real and predicted effects of an earthquake in the month that it occurs have the same value when measured with the best model, thereby indicating the accuracy of the model in predicting the earthquake's effects in the month of its occurrence. However, this study shows that the real effect after a month of occurrence is usually more significant than the estimated effect. Therefore, future research can focus on analysing the disaggregated data by region or airport and determine other variables that better describe the impact of earthquakes.

Introduction

Indonesia is an archipelago at a high risk of natural disasters, namely earthquakes, volcanic eruptions, floods, and tsunamis. The geographical and geological conditions of this country, which is situated at the junction of three giant plates – Eurasia, Indo-Australia, and Pacific – and the Pacific Ring of Fire, have made the Indonesian archipelago prone to disasters, especially earthquakes. One of the provinces in Indonesia that is prone to earthquakes is West Nusa Tenggara. Due to the geographical, climatological, topographical, and sociological conditions, this province is a disaster-prone area spread across the islands of Lombok and Sumbawa (Local Government of West Nusa Tenggara Province 2019). West Nusa Tenggara is an archipelago and has tremendous potential in the tourism sector with several tourist destinations, such as the Mandalika Special Economic Zone, Mount Rinjani Geopark, and Pesona Gili-Gili. Furthermore, the West Nusa Tenggara province is dependent on the transportation sector, which plays a significant role in the distribution of goods and services as well as in population mobility (Statistics Indonesia West Nusa Tenggara Province 2020). The transportation sector also promotes the development of the economy, and is a driving force of the regional potential, especially for the tourism sector (Yudana 2016). According to Toth et al. (2013), the existence of the tourism sector depends on transportation, which is one of the primary preconditions. Moreover, transportation plays an important role in the socio-economic sector (Novak–Varsanyi 2011, Álvarez-Díaz et al. 2017, Nezdei 2020, Tsiotas et al. 2020) and supports all aspects of life (Statistics Indonesia 2020).

In the short term, natural disasters create direct costs including damage to infrastructure, decline in capital and human resources, loss of crops and livestock; and indirect costs, such as input and investment losses and those with a macroeconomic impact (Chhibber–Laajaj 2008). The damage to infrastructure, especially that of transportation, disrupts the sector's performance, thereby having a negative impact on the local economy (The World Bank 2019). Concerns arising from natural disasters also lead to negative sentiments in the areas experiencing the disaster, such as in the cases of the eruption of Mount Agung in Bali (Saputra et al. 2018) and a series of earthquakes that occurred in the West Nusa Tenggara province in July 2018 (Said et al. 2020). This led to the issuance of travel warnings from the tourists' country of origin and delay or cancellation of airline departures.

It is still debated whether natural disasters have a negative or a positive impact on macroeconomic indicators in the long term. Chhibber–Laajaj (2008) state four different scenarios of the impact on per capita gross domestic product (GDP), and each scenario is associated with a certain type of disaster. An earthquake has a negative impact in the short term, followed by a form of reconstruction that leads to expansion and technological change, which is considered a positive impact in the long term. In contrast, natural disasters, such as droughts, have a negative impact in the long term. Ahlerup (2013) empirically stated that natural disasters have a positive association with economic performance. This is inconsistent with the empirical studies carried out by Hochrainer (2013) and Lee et al. (2018), which stated that natural disasters have a negative impact on growth on average. These impacts tend to become more pronounced depending upon the size and intensity of the shock. In addition to aggregate macroeconomic indicators, the response of the tourism sector, especially that of inbound tourists, to the impact of natural disasters has been widely investigated by several previous studies as well, such as those by Min (2008), Rindrasih et al. (2019), Tangkudung (2019), Rossello et al. (2020), and Ma et al. (2020).

In this study, we adopted a different approach from that of the previous studies related to the impact of natural disasters. Rather than directly investigating the impact of natural disasters on aggregate macroeconomic indicators, such as GDP or the widely used tourism sector, this study examined the impacts of earthquakes on the transportation sector, including the number of airline passenger arrivals and departures in the West Nusa Tenggara province. The hypothesis testing to determine whether earthquakes had a positive or a negative impact on the number of airline passengers from 2008 to 2018 was conducted using an analysis mechanism, namely the time series regression (TSR), while the event served as a dummy variable. TSR modelling was comprehensively conducted on the number of airline passenger arrivals and departures simultaneously to test whether earthquakes had a significant effect on these two indicators of the transportation sector using two scenarios, thus testing the impact of this disaster globally and the effect of each event in a certain month. Finally, the best model was obtained, and the earthquake's impact on the number of airline passenger arrivals and departures was measured.

The remaining part of this study is organised as follows. In Section 2, we review the literature related to this study. In addition, the cases, methods, and results from previous studies are explored. In Section 3, we review the data sources and modelling procedures, including the scenarios used to produce the best TSR model and the techniques used to measure the impact of an earthquake on the number of airline passenger arrivals and departures. The results of this empirical study and the conclusions and suggestions are presented in Sections 4 and 5, respectively.

Literature review

In time series analysis, inconsistent observations with relatively higher or lower values are often detected due to interruptive events that influence them. However, assuming that the cause of the interruptive event is known, the impact can be measured using an intervention model (Wei 2006). According to Box–Jenkins (1976), the intervention model is an extension of the Box–Jenkins ARIMA, which is widely used to measure the impact of certain events, such as government policies in pricing, tourism promotion, disaster events, outbreaks, pandemics, acts of terrorism, or economic crises, on the time series data of a variable. The impact of an event on the time series data occurs in two forms, namely a pulse function, when the impact is only felt at a specific time ($t = T$); and a step function, when it is felt at a certain time interval ($t \geq T$).

In previous studies, intervention models were widely used to measure the impact of certain events on the tourism sector's performance. Lee–Suhartono (2010) used an intervention model to measure the impact of the financial crisis in Asia, which occurred in July 1997, as well as the first and second Bali bombings on October 12, 2002 and October 1, 2005, respectively. Min (2008) used the same model to measure the impact of the earthquake that occurred on September 21, 1999 and the SARS outbreak in 2003 on the number of foreign tourists visiting Taiwan. Atmanegara et al. (2019) used an intervention model to measure the impact of the second Bali bombing, which occurred on October 1, 2005, and the Sarinah bombing in January 2015, on the number of foreign tourists travelling from Bahrain to Indonesia. This model was also used to measure the impact of the closure of gambling locations in Batam in June 2005 and the promotion of sharia tourism in October 2013 on the number of foreign tourists travelling from Singapore to Indonesia. In addition, Ismail et al. (2009) used an intervention model to measure the impact of the first Bali bombing on the occupancy rate of Bali's five-star hotel rooms. These studies indicate that such events have a negative impact on the observed time series variables.

Based on descriptive analysis, Rindrasih et al. (2019) investigated the relationship between disaster events and the tourism sector's performance measured by the number of foreign tourist visits, income generated from the sector, and the occupancy rates of hotel rooms. They also assessed the impact of disaster spillovers on this sector in Indonesia. The results showed that over the past 18 years, disasters had affected the tourism sector's performance differently in terms of the scale of damage, location, and type of disaster. Natural disasters in Indonesia affected the tourism sector through the resulting impacts, such as damage to facilities and infrastructure and reduced tourist visits. A study carried out in Turkey shows that tourism demand affects regional sector employment (Fernandez-Crehuet et al. 2020, Kirca–Ozer 2021). Based on the literature review and descriptive analysis of official statistical data produced by Statistics Indonesia, Tangkudung (2019) measured the impact of the earthquakes that occurred in July and August 2018 on several macroeconomic indicators, namely gross regional domestic product, number of foreign tourists visiting, sea and air transport passengers, exports, imports, net exports, room occupancy rates of star and non-star hotels, open unemployment rates, and inflation. In general, all these indicators, except inflation, experienced a sharp decline in performance after the earthquake.

Additionally, intervention models have been used to measure the impact of certain events on other sectors. In the transportation sector, Wiradinata et al. (2017) used an intervention model to measure the impact of forest and peatland fires on the number of domestic air passengers in the Riau province. Worthington–Valadkhani (2004) used an intervention model to measure the impact of hurricanes, floods, cyclones, earthquakes, and forest fires on prices in the Australian stock market. The result showed that cyclones and forest fires had the most significant negative impact on stock prices. Gilmour et al. (2006) used an intervention model to measure the impact of heroin shortage in Australia in 2001, which caused a spike in the prices of heroin and its substitutes, such as cocaine. One of the visible impacts was that cocaine ownership increased rapidly in the first two months after the scarcity of heroin began. However, there was a gradual decrease in ownership until it reached the normal level after 15 months. Meanwhile, heroin ownership experienced a sharp decline in the same month when the scarcity began.

The econometric approach and the ARIMA model with dummy variables are also widely used to measure the impact of certain events. Rossello, Becken, and Santana-Gallego (2020) used a gravity model to determine the impact of droughts, earthquakes, tsunamis, floods, industrial accidents, forest fires, storms, and volcanic eruptions, which was measured by the number of deaths and lives affected including the economic losses experienced due to a reduction the number of foreign tourists visiting from 17 countries between 1995 and 2013. The model used macroeconomic variables, such as GDP, population and crime rates at the destination, and the existence of regional trade agreements (RTAs) between two countries. The result showed that GDP, the population of tourist destinations, and RTAs have a positive impact on foreign visits. However, crime rate and disasters have a significant negative impact on economic losses. Mukherjee–Hastak (2018) used a panel data model to investigate the impact of disasters on economic growth. The result showed that natural hazard-induced disasters affect countries' or regions' economic growth, although the effect varies over time. Flood is the most devastating disaster which tends to affect economic growth. The developed econometric model helps in making government policies and decisions related to investment needs for pre-disaster and post-disaster risk mitigation and response planning strategies to protect the country and minimise the negative economic impact effectively.

Sridharan et al. (2003) applied several procedures, such as linear regression with and without ARIMA errors, ARIMA models with dummy variables, and structural time series models, to measure the impact of government policies, namely the abolition of parole and renewal of sentences for all perpetrators of crimes committed on or after January 1, on the crime rate report in Virginia. The ARIMA model with a dummy variable was also used by Sahin–Yavuz (2015) to measure the impact of natural disasters on macroeconomic indicators, such as inflation, industrial sector production index, and the unemployment rate in four member countries of the Organisation for Economic Cooperation and Development.

Disaster events either have positive or negative impacts, and the severity varies based on the country's level of preparedness. Ma et al. (2020) used a linear regression model to determine the impact of earthquakes and terrorist attacks in the world's eight most competitive countries on the number of foreign tourists and travel experiences obtained from online reviews through TripAdvisor. It was found that earthquakes had a more significant impact on the tourism sector than terrorist attacks. Loayza–Olaberri (2012) used a panel data analysis model to measure the impact of drought, floods, storms, and earthquakes on the economic growth of the agricultural, industrial, and service sectors of 68 developing and 26 developed countries. The results showed that disasters do not always have a negative impact. However, severe disasters tend to have a more negative impact on the economic growth of developing countries than on that of the developed ones.

Methodology

This study uses monthly data of the number of airline passenger arrivals and departures in West Nusa Tenggara province, Lombok International Airport (Lombok), Sultan M. Kaharuddin Airport (Sumbawa), and Sultan M. Salahudin Airport (Bima) from January 2008 to December 2018 (132 observations). The data were obtained from Statistics Indonesia (Badan Pusat Statistik), West Nusa Tenggara province. Consequently, rather than using separate data to investigate the impact of earthquakes on the number of airline passenger arrivals and departures in each airport, this study focuses only on the global impact.

The procedure of modelling earthquakes was carried out using the TSR model reported in previous studies by Suhartono et al. (2010) and Wulansari et al. (2014). The step-by-step analysis or procedure is as follows:

1. Determine the variables that show a linear trend, i.e., $t = 1, 2, \ldots, 132$.
2. Determine dummy variables that show monthly seasonal patterns from January to December, i.e., $M_{1,t}, M_{2,t}, \ldots, M_{12,t}$, respectively.
3. Determine the dummy variable for earthquake events using two scenarios. In the first scenario, the global earthquake dummy variable, $G_{i,t} = 1$, is used when an earthquake occurs in month t and $G_t = 0$, assuming there is no occurrence. In the second scenario, the earthquake dummy variable for each event, $G_{i,t} = 1$, is used when the i-th earthquake occurs in month t and $G_{i,t} = 0$ is used for others with $t = 1, 2, \ldots, 8$ which is regarded as the sequence of events during the study.
4. The TSR model is estimated as follows:
$$y_t = \beta_1 G_t + \beta_2 t + \alpha_1 M_{1,t} + \cdots + \alpha_{12} M_{12,t} + N_t \tag{1}$$
for the first scenario and
$$y_t = \beta_1 G_{1,t} + \cdots + \beta_8 G_{8,t} + \beta_9 t + \alpha_1 M_{1,t} + \cdots + \alpha_{12} M_{12,t} + N_t \tag{2}$$
for the second scenario.

5. Perform diagnostic checking whether the residual N_t meets the white noise assumption. Conversely, supposing no white noise is detected, input the lag variable y_t into the model, based on the significant lag information from the autocorrelation function (ACF) plot of the residual N_t. Therefore, the TSR model is stated as follows:
$$y_t = \beta_1 G_t + \beta_2 t + \alpha_1 M_{1,t} + \cdots + \alpha_{12} M_{12,t} + \sum_j \phi_j y_{t-j} + \varepsilon_t \quad (3)$$
for the first scenario and
$$y_t = \beta_1 G_{1,t} + \cdots + \beta_8 G_{8,t} + \beta_9 t + \alpha_1 M_{1,t} + \cdots + \alpha_{12} M_{12,t} + \sum_j \phi_j y_{t-j} + \varepsilon_t \quad (4)$$
for the second scenario. Repeat from step four to re-estimate the TSR model. The residual ε_t is a white noise process.
6. Perform the normality test for the residual ε_t using the Kolmogorov–Smirnov (KS) analysis. Supposing it does not follow the normal distribution, incorporate the outlier as a dummy variable, i.e., $I_t^{(T)} = 1$ when $t=T$ and $I_t^{(T)} = 0$ assuming $t \neq T$, into the model till the residual ε_t follows the normal distribution. The TSR model without variable selection is obtained after the residuals have met the white noise assumptions and have followed the normal distribution.
7. The TSR model with variable selection is obtained by testing each parameter's significance without variable selection. Backward elimination is performed for each parameter with the largest *P-value* until only the significant ones are left in the model. Conversely, re-check the white noise and the normal distribution assumption as stated in Steps 5 and 6.
8. In accordance with the procedures above, four models were obtained for the number of airline passenger arrivals and departures. Subsequently, the best model for the number of airline passenger arrivals and departures was determined based on the values of the root mean square error (RMSE), Akaike information criterion (AIC), and Schwarz Bayesian criterion (SBC). The RMSE formula is stated as follows:
$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n-p}} \quad (5)$$
where n is the number of observations and p is the number of parameters in the model.

In addition, this study also estimated the best model without involving the earthquake dummy variables, G_t and $G_{i,t}$. The objective of this study is to measure the earthquake's effect on the number of airline passenger arrivals and departures. The real effect is measured by the difference between the actual data, y_t and the forecast results without the earthquake dummy variable, $\hat{y}_{-G,t}$. The estimated effect is measured by the difference between the forecast results with the earthquake dummy variable, $\hat{y}_t$, and the forecast results without the earthquake dummy variable, $\hat{y}_{-G,t}$.

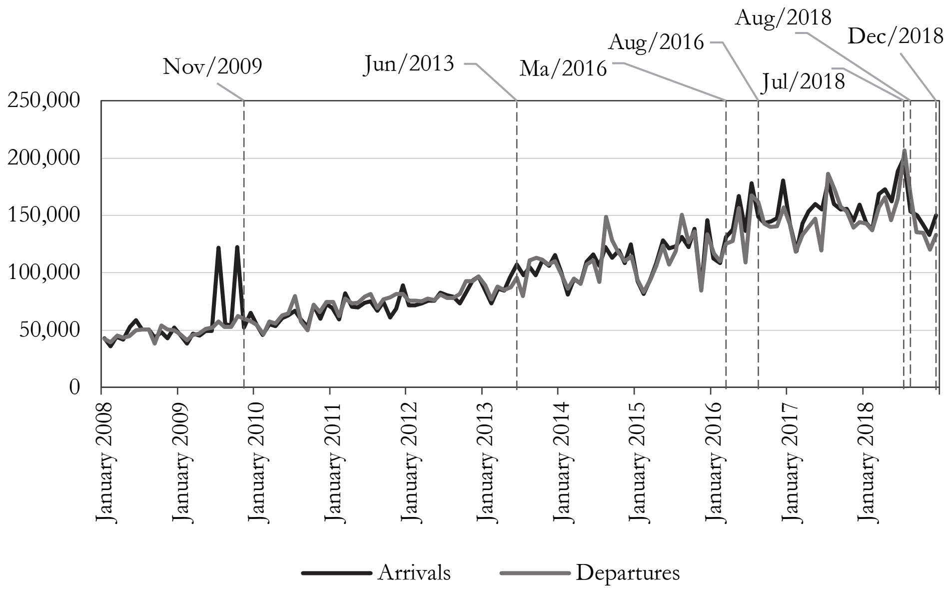
Results and discussion

Identification of seasonal trends and patterns

First, the seasonal trends and patterns of data are identified, such as the number of airline passenger arrivals and departures. The two series data have a positive linear trend, as shown in Figure 1. This means that the number of airline passenger arrivals and departures at the three airports in West Nusa Tenggara province keeps increasing over time.

Figure 1

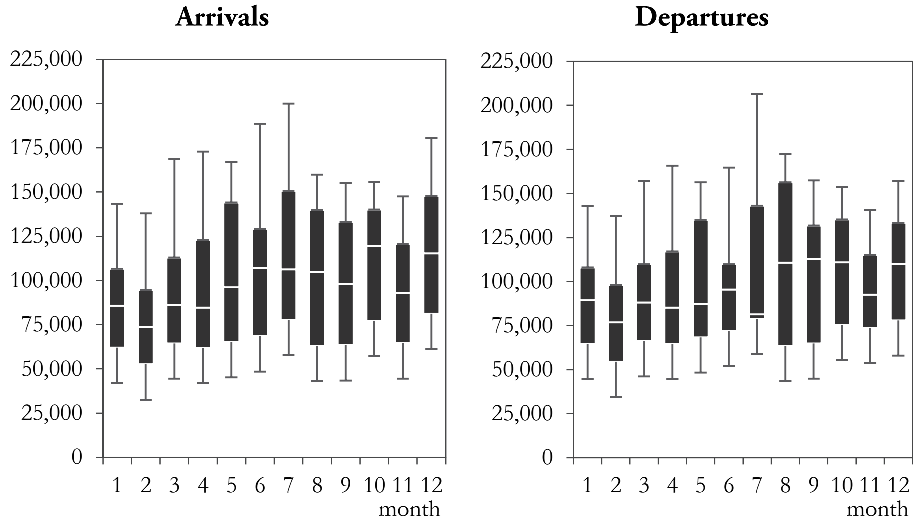
Time series plots of the monthly number of airline passenger arrivals and departures and earthquake events in the West Nusa Tenggara Province



Note: earthquake events (vertical line).

The monthly seasonal pattern is displayed by the boxplot pattern of the series data shown in Figure 2. The two series data have similar boxplot patterns that decreased in February and August, and increased in July (school holidays) and December (Christmas and New Year holidays).

Figure 2
Boxplot of monthly number of airline passenger arrivals and departures in the West Nusa Tenggara Province

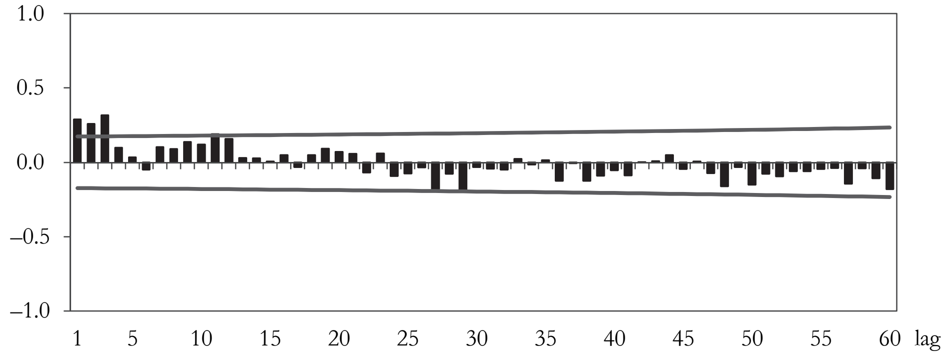


Estimation of TSR model

TSR model for airline passenger arrivals in the first scenario

The initial estimation results of the TSR model without variable selection for the number of airline passenger arrivals show that the residuals do not meet the white noise assumption. Therefore, the lag variables were included in the model based on the significant one in the ACF plot of residual, namely the 1st, 2nd, and 3rd lag, as shown in Figure 3.

Figure 3
ACF plot of residual from the TSR model for airline passenger arrivals in the first scenario and without variable selection



After re-estimating the model, it was discovered that the residuals already met the white noise assumption. Therefore, the normality test was performed with the KS analysis. The result shows that the residual already follows the normal distribution with statistical and P-values of 0.073 and 0.092, respectively. The complete estimation results of the TSR model for airline passenger arrivals in the first scenario and without variable selection are shown in Table 1.

Table 1

Estimation results of the TSR model for airline passenger arrivals in the first scenario and without variable selection

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
G_t	−1,463	0.7818	$M_{8,t}$	11,891	0.0790
t	392.1613	0.0025	$M_{9,t}$	7,011	0.2963
$M_{1,t}$	3,374	0.6128	$M_{10,t}$	17,024	0.0101
$M_{2,t}$	−2,497	0.6838	$M_{11,t}$	4,909	0.4218
$M_{3,t}$	12,696	0.0361	$M_{12,t}$	26,025	<.0001
$M_{4,t}$	16,828	0.0022	Y_{t-1}	0.1976	0.0393
$M_{5,t}$	25,505	<.0001	Y_{t-2}	0.1378	0.1422
$M_{6,t}$	21,248	0.0005	Y_{t-3}	0.2646	0.0054
$M_{7,t}$	30,380	<.0001			

The results are stated in the following equation:

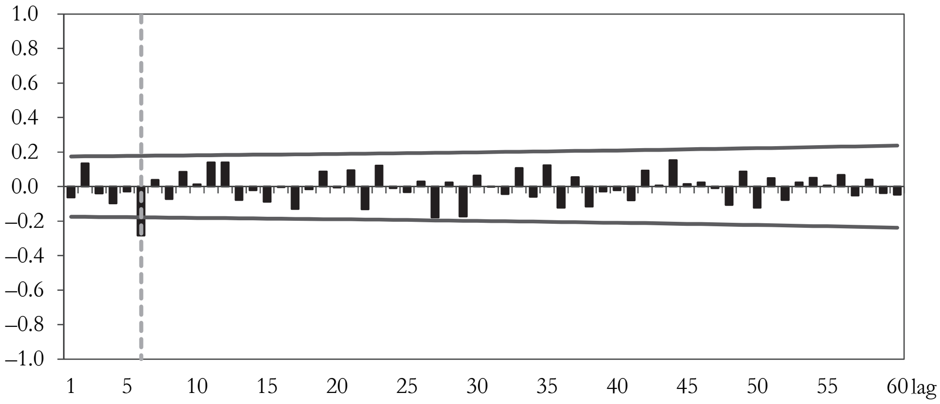
$$\begin{aligned}\hat{y}_t = {} & -1{,}463G_t + 392.1613t + 3{,}374M_{1,t} - 2{,}497M_{2,t} + 12{,}696M_{3,t} + 16{,}828M_{4,t} \\ & + 25{,}505M_{5,t} + 21{,}248M_{6,t} + 30{,}380M_{7,t} + 11{,}891M_{8,t} + 7{,}011M_{9,t} \\ & + 17{,}024M_{10,t} + 4{,}909M_{11,t} + 26{,}025M_{12,t} + 0.1976y_{t-1} \\ & + 0.1378y_{t-2} + 0.2646y_{t-3}\end{aligned} \quad (6)$$

The variable selection process was conducted using the backward elimination method with the α = 0.05 level based on the above estimation results. It is worth noting that the earthquake dummy variable was not excluded from the model even when it was not statistically significant. This is because the dummy variable was the main variable used to measure the earthquake's effect on the number of airline passenger arrivals. After selecting the variables, the next step is to test for the white noise assumption on the residuals. The Ljung–Box test results show that the residuals do not meet the white noise assumption. Therefore, the lag variable was included in the model based on the significant one from the residual's ACF plot, namely the 6th lag, as shown in Figure 4.

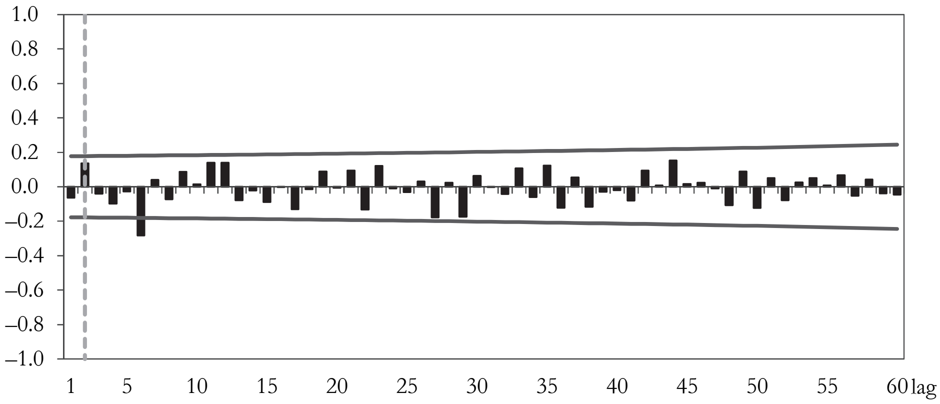
Figure 4

ACF plot of residual from the TSR model for airline passenger arrivals in the first scenario and with variable selection before and after the lag variable y_{t-6} is added

Before



After



However, after the second estimate, the dummy variable for October $M_{10,t}$ becomes insignificant and needs to be excluded from the model. The third estimate results show that the residuals do not meet the white noise assumptions because there is a significant lag from the ACF plot, that is the 2nd lag, as shown in Figure 4. Therefore, the lag variable y_{t-2} is included in the model and re-estimated afterward. The result shows that the residual meets the white noise assumption and follows the normal distribution with statistical and P-values of 0.053 and > 0.150, respectively. The complete estimation result of the TSR model for airline passenger arrivals in the first scenario with variable selection is shown in Table 2.

Table 2

Estimation results of the TSR model for airline passenger arrivals in the first scenario using a variable selection

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
G_t	−2,255	0.6610	$M_{12,t}$	23,431	<.0001
t	341.1914	0.0007	Y_{t-1}	0.2227	0.0041
$M_{4,t}$	16,464	0.0008	Y_{t-2}	0.1557	0.0469
$M_{5,t}$	23,963	<.0001	Y_{t-3}	0.5334	<.0001
$M_{6,t}$	19,228	<.0001	Y_{t-6}	−0.2325	0.0051
$M_{7,t}$	24,445	<.0001			

The results are stated as follows:

$$\hat{y}_t = -2{,}255G_t + 341.1914t + 16{,}464M_{4,t} + 23{,}963M_{5,t} + 19{,}228M_{6,t} + 24{,}445M_{7,t} + 23{,}431M_{12,t} + 0.2227y_{t-1} + 0.1557y_{t-2} + 0.5334y_{t-3} - 0.2325y_{t-6} \quad (7)$$

TSR model for airline passenger arrivals in the second scenario

A similar procedure was adopted in the TSR modelling. The estimation result without variable selection for airline passenger arrivals in the second scenario is shown in Table 3. Based on the results, the only earthquake dummy variable that is statistically significant at $\alpha = 0.05$ is the one obtained for August 2018 ($G_{7,t}$).

Table 3

Estimation results of the TSR model for airline passenger arrivals in the second scenario and without variable selection

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
$G_{3,t}$	12,374	0.2278	$M_{9,t}$	−1,752	0.7631
$G_{4,t}$	8,162	0.4261	$M_{10,t}$	11,316	0.0400
$G_{5,t}$	−11,027	0.3299	$M_{11,t}$	1,205	0.8389
$G_{6,t}$	11,970	0.2645	$M_{12,t}$	24,272	<.0001
$G_{7,t}$	−32,618	0.0035	Y_{t-1}	0.3337	0.0018
$G_{8,t}$	−15,204	0.1723	Y_{t-2}	0.1293	0.1267
t	425,5567	0.0135	Y_{t-3}	0.0758	0.4149
$M_{1,t}$	3,126	0.6021	Y_{t-6}	−0.1149	0.1451
$M_{2,t}$	−6,745	0.1912	Y_{t-11}	0.0965	0.1967
$M_{3,t}$	12,614	0.0193	Y_{t-12}	0.0903	0.2384
$M_{4,t}$	9,748	0.0764	Y_{t-17}	−0.0939	0.2046
$M_{5,t}$	15,594	0.0053	Y_{t-23}	0.1443	0.0588
$M_{6,t}$	8,885	0.1715	$I_t^{(95)}$	−40,221	0.0001
$M_{7,t}$	11,395	0.0455	$I_t^{(130)}$	−24,242	0.0273
$M_{8,t}$	7,088	0.1985			

The results are stated in the following equation:

$$\begin{aligned}\hat{y}_t = {} & 12{,}374G_{3,t} + 8{,}162G_{4,t} - 11{,}027G_{5,t} + 11{,}970G_{6,t} - 32{,}618G_{7,t} - 15{,}204G_{8,t} \\ & + 425{,}5567t + 3{,}126M_{1,t} - 6{,}745M_{2,t} + 12{,}614M_{3,t} + 9{,}748M_{4,t} \\ & + 15{,}594M_{5,t} + 8{,}885M_{6,t} + 11395M_{7,t} + 7088M_{8,t} - 1{,}752M_{9,t} \\ & + 11{,}316M_{10,t} + 1{,}205M_{11,t} + 24{,}272M_{12,t} + 0.3337y_{t-1} \\ & + 0.1293y_{t-2} + 0.0758y_{t-3} - 0.1149y_{t-6} + 0.0965y_{t-11} \\ & + 0.0903y_{t-12} - 0.0939y_{t-17} + 0.1443y_{t-23} - 40{,}221I_t^{(95)} \\ & - 24242I_t^{(130)}\end{aligned} \quad (8)$$

Furthermore, the variable selection process was also performed. The final model obtained has a residual that follows the normal distribution. However, it does not meet the white noise assumption because it contains an autoregressive (AR) component, observed from the significant lag in the partial autocorrelation function (PACF) plot, as shown in Figure 5. The complete estimation result is shown in Table 4. Consequently, after the variable selection process, two significant earthquake dummy variables were obtained, namely those for August and December 2018 ($G_{7,t}$ and $G_{8,t}$).

Figure 5

PACF plot of residual from the TSR model for airline passenger arrivals in the second scenario and with variable selection

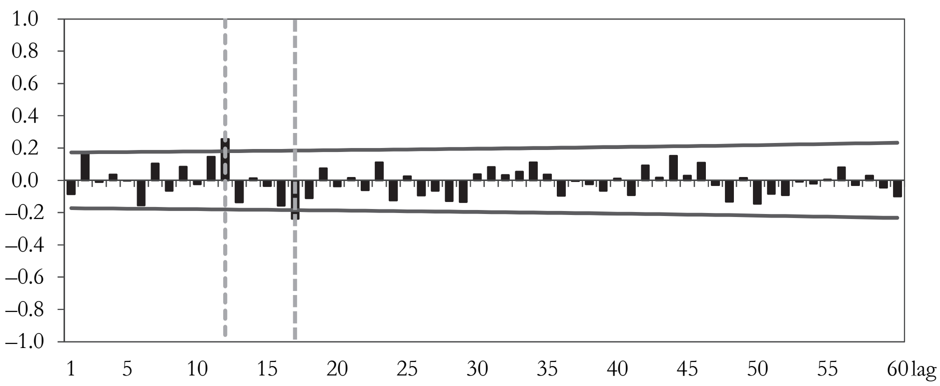


Table 4

Estimation results of the TSR model for airline passenger arrivals in the second scenario with variable selection

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
$G_{3,t}$	10,781	0.2966	$M_{6,t}$	9,339	0.0201
$G_{4,t}$	6,256	0.5454	$M_{7,t}$	16,779	<.0001
$G_{5,t}$	−10,000	0.3446	$M_{8,t}$	11,492	0.0045
$G_{6,t}$	13,314	0.2000	$M_{10,t}$	15,271	<.0001
$G_{7,t}$	−32,265	0.0027	$M_{12,t}$	26,930	<.0001

(Table continues next page.)

(Continued)

Variable	Estimated parameter	P-value	*Variable*	Estimated parameter	P-value
$G_{8,t}$	−24,248	0.0251	Y_{t-1}	0.4275	<.0001
t	444.9875	0.0001	Y_{t-23}	0.2198	0.0006
$M_{3,t}$	14,906	0.0001	$I_t^{(95)}$	−40,656	<.0001
$M_{4,t}$	7,557	0.0353	$I_t^{(130)}$	−27,679	0.0096
$M_{5,t}$	15,333	<.0001			

The results are stated in the following equation:

$$\begin{aligned}\hat{y}_t = {} & 10{,}781G_{3,t} + 6{,}256G_{4,t} - 10{,}000G_{5,t} + 13{,}314G_{6,t} - 32{,}265G_{7,t} - 24{,}248G_{8,t} \\ & + 444.9875t + 14{,}906M_{3,t} + 7{,}557M_{4,t} + 15{,}333M_{5,t} + 9{,}339M_{6,t} \\ & + 16{,}779M_{7,t} + 11{,}492M_{8,t} + 15{,}271M_{10,t} + 26{,}930M_{12,t} \\ & + 0.4275y_{t-1} + 0.2198y_{t-23} - 40{,}656I_t^{(95)} - 27{,}679I_t^{(130)}\end{aligned} \quad (9)$$

TSR model for airline passenger departures in the first scenario

The modelling procedure for airline passenger departures is the same as that reported earlier. The TSR model estimation result without variable selection in the first scenario is shown in Table 5. This is similar to the TSR modelling for airline passenger arrivals, where the global earthquake dummy variable is also not statistically significant.

Table 5

Estimation results of the TSR model for airline passenger departures in the first scenario and without variable selection

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
G_t	1,157	0.8007	$M_{10,t}$	22,424	0.0022
t	575.4469	0.0070	$M_{11,t}$	13,596	0.0448
$M_{1,t}$	24,573	0.0003	$M_{12,t}$	18,349	0.0042
$M_{2,t}$	11,242	0.0985	Y_{t-1}	0.2764	0.0042
$M_{3,t}$	17,241	0.0066	Y_{t-2}	0.1241	0.1676
$M_{4,t}$	17,719	0.0077	Y_{t-6}	−0.0991	0.3058
$M_{5,t}$	21,935	0.0007	Y_{t-11}	0.3929	0.0001
$M_{6,t}$	18,575	0.0094	Y_{t-12}	0.3979	0.0002
$M_{7,t}$	21,992	0.0021	Y_{t-13}	−0.5036	<.0001
$M_{8,t}$	27,774	<.0001	Y_{t-22}	−0.2038	0.0493
$M_{9,t}$	17,257	0.0201			

The results are stated in the following equation:

$$\begin{aligned}\hat{y}_t = {} & 1{,}157G_t + 575.4469t + 24{,}573M_{1,t} + 11{,}242M_{2,t} + 17{,}241M_{3,t} \\ & + 17{,}719M_{4,t} + 21{,}935M_{5,t} + 18{,}575M_{6,t} + 21{,}992M_{7,t} \\ & + 27{,}774M_{8,t} + 17{,}257M_{9,t} + 22{,}424M_{10,t} + 13{,}596M_{11,t} \\ & + 18{,}349M_{12,t} + 0.2764y_{t-1} + 0.1241y_{t-2} - 0.0991y_{t-6} \\ & + 0.3929y_{t-11} + 0.3979y_{t-12} - 0.5036y_{t-13} - 0.2038y_{t-22}\end{aligned} \quad (10)$$

Conversely, after the variable selection process, it was discovered that the residual already met the white noise assumption and followed the normal distribution with the statistical and *P-values* of 0.075 and 0.098, respectively. Therefore, the lag variable was not included in the model. The complete estimation result with variable selection in the first scenario is shown in Table 6. However, even after the variable selection process, the global earthquake dummy variable is still not statistically significant.

Table 6

Estimation results of the TSR model for airline passenger departures in the first scenario with variable selection

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
G_t	−349.0492	0.9366	Y_{t-2}	0.0715	0.0044
$M_{1,t}$	3,935	0.0159	Y_{t-11}	0.0733	<.0001
$M_{8,t}$	3,695	0.0386	Y_{t-12}	0.0769	<.0001
Y_{t-1}	0.0845	0.0003	Y_{t-13}	0.0941	<.0001

The results are stated in the following equation:

$$\hat{y}_t = -349.0492G_t + 3{,}935M_{1,t} + 3{,}695M_{8,t} + 0.0845y_{t-1} + 0.0715y_{t-2} + 0.0733y_{t-11} + 0.0769y_{t-12} + 0.0941y_{t-13} \quad (11)$$

TSR model for airline passenger departures in the second scenario

The TSR model estimation result without the variable selection in the second scenario is shown in Table 7. One of the earthquake dummy variables is statistically significant, namely the one obtained for December 2018 ($G_{8,t}$).

Table 7

Estimation results of the TSR model without variable selection for airline passenger departures in the second scenario

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
$G_{3,t}$	9,963	0.4259	$M_{7,t}$	13,552	0.1093
$G_{4,t}$	14,062	0.2640	$M_{8,t}$	19,862	0.0134
$G_{5,t}$	11,939	0.4228	$M_{9,t}$	6,625	0.4726
$G_{6,t}$	21,975	0.1104	$M_{10,t}$	15,203	0.0693
$G_{7,t}$	−12,258	0.3825	$M_{11,t}$	6,372	0.4497
$G_{8,t}$	−27,685	0.0400	$M_{12,t}$	18,692	0.0161
t	47.8607	0.8554	Y_{t-1}	0.0936	0.3999
$M_{1,t}$	17,155	0.0288	Y_{t-2}	0.0291	0.7682
$M_{2,t}$	5,063	0.5324	Y_{t-6}	−0.1229	0.2511
$M_{3,t}$	13,521	0.0641	Y_{t-9}	0.2209	0.0547
$M_{4,t}$	9,850	0.2269	Y_{t-11}	0.1988	0.0988
$M_{5,t}$	12,687	0.1107	Y_{t-12}	0.2993	0.0157
$M_{6,t}$	6,407	0.4616	Y_{t-23}	0.2399	0.0830

The results are stated in the following equation:

$$\begin{aligned}\hat{y}_t = {} & 9{,}963G_{3,t} + 14{,}062G_{4,t} + 11{,}939G_{5,t} + 21{,}975G_{6,t} - 12{,}258G_{7,t} - 27{,}685G_{8,t} \\ & + 47.8607t + 17{,}155M_{1,t} + 5{,}063M_{2,t} + 13{,}521M_{3,t} + 9{,}850M_{4,t} \\ & + 12{,}687M_{5,t} + 6{,}407M_{6,t} + 13{,}552M_{7,t} + 19{,}862M_{8,t} + 6{,}625M_{9,t} \\ & + 15{,}203M_{10,t} + 6{,}372M_{11,t} + 18{,}692M_{12,t} + 0.0936y_{t-1} \\ & + 0.0291y_{t-2} - 0.1229y_{t-6} + 0.2209y_{t-9} + 0.1988y_{t-11} \\ & + 0.2993y_{t-12} + 0.2399y_{t-23}\end{aligned} \tag{12}$$

In addition, after the variable selection process, the TSR model's estimation result with variable selection in the second scenario is shown in Table 8. The earthquake dummy variable obtained for December 2018, which was significant initially, became insignificant. Therefore, the residual of this model met the white noise assumption. However, the assumption that it follows the normal distribution was not fulfilled irrespective of whether the dummy variable was included as an additive outlier.

Table 8

Estimation results of the TSR model with variable selection for airline passenger departures in the second scenario

Variable	Estimated parameter	*P-value*	Variable	Estimated parameter	*P-value*
$G_{2,t}$	4,087	0.6146	Y_{t-13}	−0.3169	0.0003
$G_{3,t}$	6,462	0.4267	$I_t^{(68)}$	23,247	0.0052
$G_{4,t}$	10,237	0.2185	$I_t^{(80)}$	24,197	0.0046
$G_{5,t}$	645.8018	0.9418	$I_t^{(95)}$	−40,155	<.0001
$G_{6,t}$	1,582	0.8622	$I_t^{(101)}$	22,732	0.0066
$G_{7,t}$	−12,834	0.1347	$I_t^{(107)}$	28,888	0.0013
$G_{8,t}$	−15,608	0.0737	$I_t^{(119)}$	−22,124	0.0082
Y_{t-1}	0.2312	0.0029	$I_t^{(129)}$	−36,726	<.0001
Y_{t-2}	0.1449	0.0144	$I_t^{(130)}$	−21,945	0.0133
Y_{t-11}	0.3296	<.0001	$I_t^{(131)}$	−24,116	0.0061
Y_{t-12}	0.6811	<.0001			

The results are stated in the following equation:

$$\begin{aligned}\hat{y}_t = {} & 4{,}087G_{2,t} + 6{,}462G_{3,t} + 10{,}237G_{4,t} + 645.8018G_{5,t} + 1{,}582G_{6,t} - 12{,}834G_{7,t} \\ & - 15{,}608G_{8,t} + 0.2312y_{t-1} + 0.1449y_{t-2} + 0.3296y_{t-11} \\ & + 0.6811y_{t-12} - 0.3169y_{t-13} + 23{,}247I_t^{(68)} + 24{,}197I_t^{(80)} \\ & - 40{,}155I_t^{(95)} + 22{,}732I_t^{(101)} + 28{,}888I_t^{(107)} - 22{,}124I_t^{(119)} \\ & - 36{,}726I_t^{(129)} - 21{,}945I_t^{(130)} - 24{,}116I_t^{(131)}\end{aligned} \tag{13}$$

Performance comparison of the TSR models

The process of determining the best model for the number of airline passenger arrivals and departures based on the values of RMSE, AIC, and SBC shows different results as shown in Table 9. The TSR model without variable selection for forecasting the number of airline passenger arrivals in the second scenario generated the smallest RMSE value. The model without variable selection produced a smaller RMSE value than the one with variable selection, in both scenarios. This shows that the variable selection process decreases forecasting accuracy. Therefore, the least value is generated by the TSR model with variable selection based on AIC and SBC in the second scenario. The residuals of this model did not meet the white noise assumption and follow the normal distribution. The unfulfilled white noise assumption is due to the presence of an AR component of the residuals that was not modelled using the TSR model.

Based on forecasting the number of airline passenger departures, the smallest RMSE value is also generated by the TSR model with variable selection in the second scenario. However, the model's value with variable selection is smaller than that of the other model without variable selection, in both scenarios. This means that in modelling the number of airline passenger departures, the variable selection process produces a more accurate model. These results differ from the results obtained from modelling the number of airline passenger arrivals. However, the least value is generated by the TSR model without variable selection based on AIC and SBC in the first scenario.

Table 9

RMSE, AIC, and SBC values of the TSR models

Var.	Scenario	Variable selection	Number of para-meters	RMSE	AIC	SBC	Residual
Arrivals	First	No	17	12,994.04	2,825.70	2,874.31	WN, Normal
		Yes	11	13,206.09	2,759.15	2,790.35	WN, Normal
	Second	No	29	9,387.61*	2,327.69	2,405.74	WN, Normal
		Yes	19	9,646.26	2,326.45*	2,377.59*	not WN, Normal
Departures	First	No	21	10,553.31	2,368.99*	2,425.70*	WN, Normal
		Yes	8	10,493.55	2,548.95	2,571.19	WN, Normal
	Second	No	26	11,487.18	2,369.70	2,439.68	WN, Normal
		Yes	21	8,064.81*	2,497.48	2,555.84	WN, not Normal

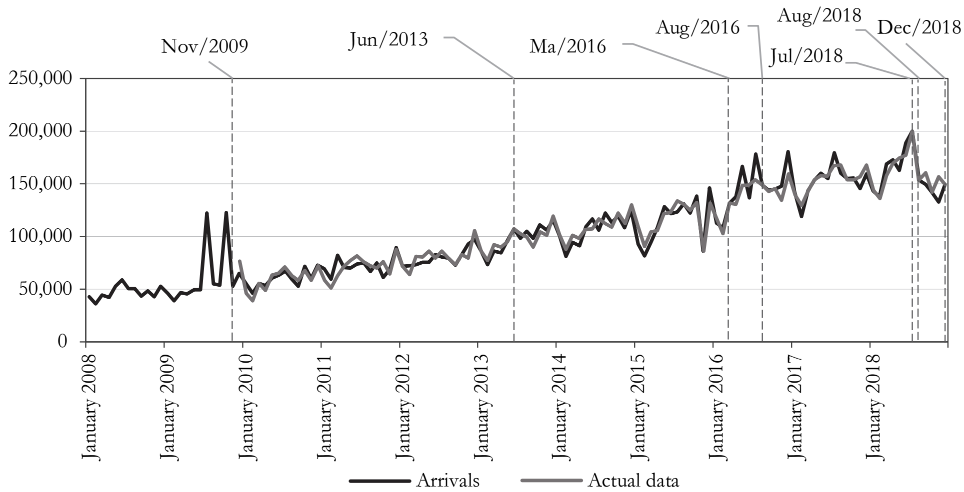
Note: *– the least value; WN – white noise.

The best model in this study was determined based on the value of the RMSE since accurate forecasting results are assumed to be used significantly to measure the effect of an earthquake on the number of airline passenger arrivals and departures. Therefore, the best model for predicting the number of airline passenger arrivals is the TSR model without variable selection in the second scenario. Furthermore, the best model for predicting the number of airline passenger departures is the model with variable selection in the second scenario. The plot of actual data and forecasting results obtained with the best TSR models are shown in Figure 6.

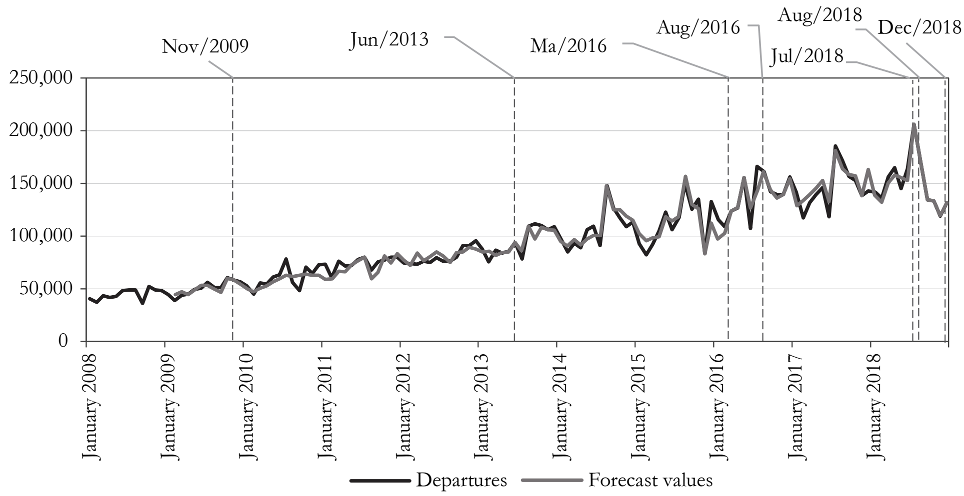
Figure 6

Plot of actual data and forecasted value of airline passenger arrivals and departures from the best TSR model

Arrivals



Departures



Note: earthquake events (vertical line).

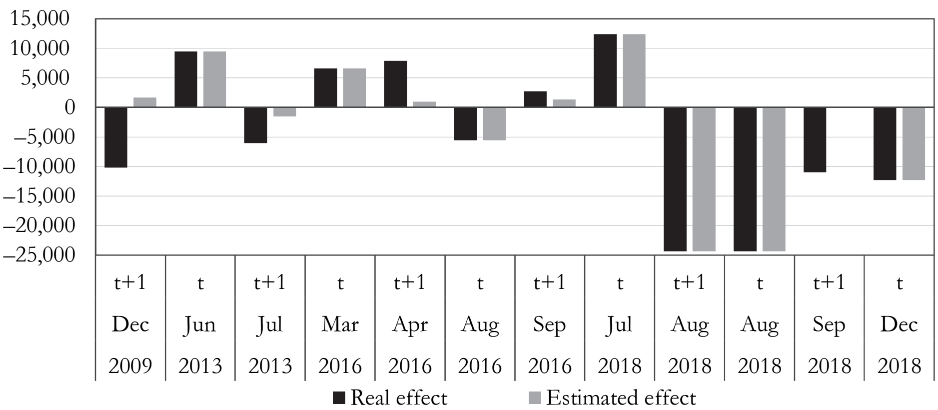
Measuring the effect of earthquakes on the number of airline passenger arrivals and departures

Before measuring the earthquake's effect on the number of airline passenger arrivals and departures at three airports in the West Nusa Tenggara province, forecasts were made using the best models without the earthquake dummy variables. The results of measuring the real and estimated effects of earthquakes in month *t* and month *t*+1 are shown in Figure 7. The real effect shows the extent of increase or decrease in the number of airline passenger arrivals or departures. However, the estimated effect is the presumed increase or decrease in the number of arrivals or departures. This is used to estimate the effect of an earthquake that occurs in a certain month outside of the reference time of this study.

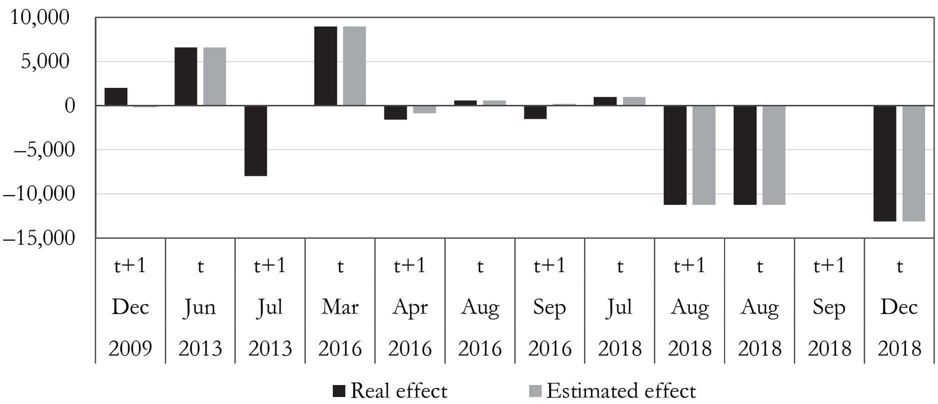
Figure 7

Measurement of the real effect and estimated effect of an earthquake on the number of airline passenger arrivals and departures

Arrivals



Departures



The real and estimated effects of an earthquake on the number of airline passenger arrivals in a particular month have similar values, as shown in Figure 7. One month after an earthquake, the real effect tends to be greater than the estimated effect. Based on the empirical results, earthquakes do not always have a negative effect, as shown in the month of June 2013, March 2016, and July 2018. This is supported by the earthquake dummy variable, which is not statistically significant in these months, except in August 2018. This month recorded 1,658 occurrences of earthquakes and had the highest frequency for the period 2009 to 2019 (Sabtaji 2020) with the largest magnitude of 7.0. Therefore, the damage caused is also great, even after an earthquake, which occurred in September 2018, showed a decrease in the real effect. This pattern is different compared to the impact pattern generated by the earthquakes that occurred in March and August 2016 where negative real and estimated effects were not experienced at one month after the earthquake. The earthquake that occurred in June 2013, March 2016, and July 2018 had positive real and estimated effects since it occurred in the end of the month, i.e. in June 22nd, March 31st, and July 29th.

Generally, similar results are also obtained from the measurements of the real and estimated effects of earthquakes on the number of airline passenger departures, as shown in Figure 7. The only difference is that none of the earthquake dummy variables are statistically significant. However, only the earthquake dummy variable obtained for December 2018 had the least *P-value* of 0.737. This was observed by the most significant negative effect that occurred due to the magnitude of the earthquake in that month. The effects were discovered to be more significant than the negative effects of the earthquake that occurred in August 2018.

Conclusion

Based on the empirical results, there are several conclusions and suggestions for future studies:

1. The two scenarios used to observe the effect of the earthquake dummy variable on the number of airline passenger arrivals and departures showed different results. In the first scenario, which was on a global level, the earthquake had no significant effect on the number of airline passenger arrivals and departures. Whereas in the second scenario, the earthquake affected the number of airline passenger arrivals and departures, particularly in August and December 2018.
2. The best model for assessing the number of airline passenger arrivals is the TSR model without variable selection in the second scenario. The variable selection process in this TSR modelling reduces the accuracy of forecasting. However, the best model for assessing the number of airline passenger departures is the TSR model with variable selection in the second scenario.

Contrary to the aforementioned results, for the number of airline passenger arrivals, the variable selection process tends to improve forecasting accuracy. This means that a more complex model does not always provide accurate forecasts, such as the results from M3 (Makridakis–Hibon 2000) and M4-Competitions (Makridakis et al. 2018, Hyndman 2020).

3. The real and estimated effects of the month when an earthquake occurred had a similar value. This indicates that the best model is effective for estimating the effect of an earthquake in the month of occurrence. However, one month after the earthquake occurred, the real effect tends to be greater than the estimated impact. This indicates that the best model is ineffective for estimating the earthquake's effects in the subsequent month.
4. Earthquakes do not always have a negative effect on the number of airline passenger arrivals and departures. The events even have a positive effect in certain months with insignificant earthquake dummy variables. These results are consistent with those of previous studies (Rossello et al. 2020, Loayza–Olaberri 2012, Sahin–Yavuz 2015). Based on the number of airline passenger arrivals, the biggest negative effect was experienced in August 2018 and was supported by a significant dummy variable. However, the biggest negative effect on the number of airline passenger departures was experienced in December 2018. This effect was even greater than the impact of the magnitude of the earthquake experienced in August 2018.
5. However, future studies need to use other variables that effectively describe earthquake events, such as the number of occurrences, magnitude, and the resulting impact, e.g. the number of deaths, lives affected, and economic losses, as reported by Rossello et al. (2020). Furthermore, the use of data was disaggregated by region, such as the number of airline passenger arrivals and departures at each airport, which can capture the effects of earthquakes in each individual area effectively.

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