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Multi Input Intervention Model for Evaluating the Impact of the Asian Crisis and Terrorist Attacks on Tourist Arrivals

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Abstract The objective of this research is to study the impact of the Asian financial crisis and terrorist attacks Bali on the number of tourist arrivals by using a multi input intervention model. The focus is on the development of a model that could be used to explain the magnitude and periodic impacts of the Asian financial crisis since July 1997 and terrorist attacks referring to the Bali bombings on October 12th 2002 and October 1st 2005, respectively. Monthly data comprising the number of tourist arrivals in Indonesia via Soekarno-Hatta airport are used as the data for this case study. The results show that the Asian financial crisis and Bali bombings yield negative impacts on the number of tourist arrivals to Indonesia via Soekarno-Hatta airport. Generally, the Asian financial crisis gives a negative permanent impact after seven month delay. The first and second Bali bombings also yield negative impacts which were temporary effect after six and twelve months delay respectively. In addition, this research also discusses how to assess the effect of an intervention in transformation data.

Keywords Asian crisis; terrorist attacks; tourist arrivals; intervention model; transformation data.

1 Introduction

International tourist arrivals have been affected due to disruptions caused by a range of events that may occur in the destination itself, in competing destinations, original markets, or they may be remote from either. In recent years, major disruptions that have affected the international tourist arrivals include the Gulf War in 1991, the Asian financial crisis in 1997, the terrorist attack on September 11, 2001 on the US, the SARS and avian flu in 2003 as well as natural disasters such as hurricanes, tsunamis, and earthquakes [42, 29, 49, 44].

The tourism industry in Indonesia is an important component as well as a significant source of foreign exchange revenue for the Indonesian economy. However, tourism in this country is also subject to the effects of natural and man-made disasters. Some of natural disasters that have taken place are: the 26 December 2004 Aceh tsunami, 27 May 2006 and 30 September 2009 earthquakes in Yogyakarta and Padang respectively on, and the bird flu epidemic in 2005. Besides these natural disasters, man-made disasters caused by terrorist attacks and bombings such as the incidents on 12 October 2002 and 1 October 2005 in Bali, 5 August 2003 at the Jakarta's Marriot Hotel, 9 September 2004 in the Australian embassy in Jakarta and more recently, the 17 July 2009 bomb attacks of JW Marriot and Ritz-Carlton hotels in Jakarta.

This paper examines the impact of the Asian financial crisis and terrorist attacks on tourism in Indonesia as a way to establish a better understanding of how these changes and trends affect international tourism. This research focusses on the use of a time series approach, particularly the intervention analysis as a way to study the impact of the disasters on tourism.

The paper is organized as follows: a brief literature review about the impact of the different crisis and terrorism on tourism based on a time series approach, data description and the modeling method, results based on the model, evaluations of the the impact due to the interventions, and conclusions.

2 Literature Review

The relationship between tourism and terrorism or political instability has been investigated extensively by many researchers since 1980s. [46] did a comprehensive literature review focusing on the relationship between these phenomena during 18 years, i.e. from 1980-1998.

Generally, researchers have relied on two main approaches for evaluating the effect of crisis or terrorism to the tourism industry by focussing on the impact of these events on micro-tourist preferences using individual tourist data or focussing on estimating the aggregate effects using time series data. The first approach could be seen in [53] who analyzed the personal experience in contributing to the different patterns of response to rare terrorist attacks. [2] studied the short-run impacts of the September 11 attacks in New York on tourist preferences for competing destinations in the Mediterrnean and the Canary Islands, and [44] who studied about perceived travel risks regarding terrorism and disease in Thailand.

This research focusses on the second approach that utilizes a time series analysis for assessing the impact of crisis or terrorism on tourism. [13] and [15] were among the first researchers who used time series approach for analyzing the negative impacts of terrorism on tourism revenues in Spain and other European countries. The research can be used to support substitution effects between these countries as a result of the tourist's goal of minimizing the risk of facing a terror attack. Similar results were also found by [12] who studied the regional effects of terrorism on tourism in three Mediterranean countries.

In another study by [40] who analyzed the severity and frequency of the terror events and found that they have a negative correlation with tourism demand. This result is further supported by [28] who studied the effects of atrocious events on the flow of tourism to Israel. In addition, [41] also showed that the frequency of terror acts had caused a larger decline in demand than the severity of those visits for Israel tourism. Similarly, [11] applied an intervention analysis to explore the dynamics of the impact of terrorism events on those visiting United Kingdom and UK tourists going abroad. His research showed that the expenditure for foreign travel was robust in the 80s, and it rapidly resumed its expenditure norm after the crisis. In a recent study by [26] who studied the impact of the first Bali bombing to tourism industry. They found that there was a distinct decrease of the occupancy rate at the five star hotels in Bali.

Other studies investigating the impact of the Asian financial crisis on tourism have determined that the crisis had significantly affected the tourism industry. [43] showed that the Asian financial crisis had significantly impacted the Australian tourism. [18] studied the impact of the Asian financial crisis and the bird flu epidemic on tourism demand using data from ten arrival series to Hong Kong. Besides that, [34] investigated how the stock market crash in 1987 and the Asian financial crisis in 1997 impacted the number of Japanese tourists traveling to Australia from 1976 to 2000. [10] used the Asian financial crisis and the September 11 attacks as examples of economic and political shocks to analyze the accuracy of using a fractionally integrated ARIMA model to predict tourist arrivals to Singapore. More recently, [49] analyzed the impact of crisis events and macroeconomic activity on Taiwan's international inbound tourism demand. His research showed that the number of inbound tourism arrivals suffered the worst decline during the outbreak of severe acute respiratory syndrome (SARS) followed by the 21st September 1999 earthquake and 11th September 2001 attacks. In comparison to these incidents, the impact of the Asian financial crisis is considered to be relatively mild.

One of the models commonly used these researches is an intervention analysis. This is a special type of time series models usually used to evaluate the internal and/or external impacts in time series dataset. Studies using this intervention model for evaluating the impact of certain interventions is not new. [8] were among the first researchers who used this intervention model for economics and environmental problems. Similarly, this model has also been applied to various problem domains such as transportation [4, 3, 25, 23, 38, 31, 45], business and economics [8, 36, 37, 1, 48, 14, 5, 22, 33, 47, 17, 30], environmental management [8, 9, 27], medical research [21, 19, 24, 16, 39, 35, 54], and tourism research [51, 20, 18, 34, 11, 26].

3 Data

The number of tourist arrivals in Indonesia via Soekarno-Hatta airport from January 1989 until December 2009 is used in this study. The data are 252 monthly records of the arrivals published by Badan Pusat Statistik (BPS-Statistics Indonesia) in *www.bps.go.id*. Figure 1 illustrates the data in a time series plot.

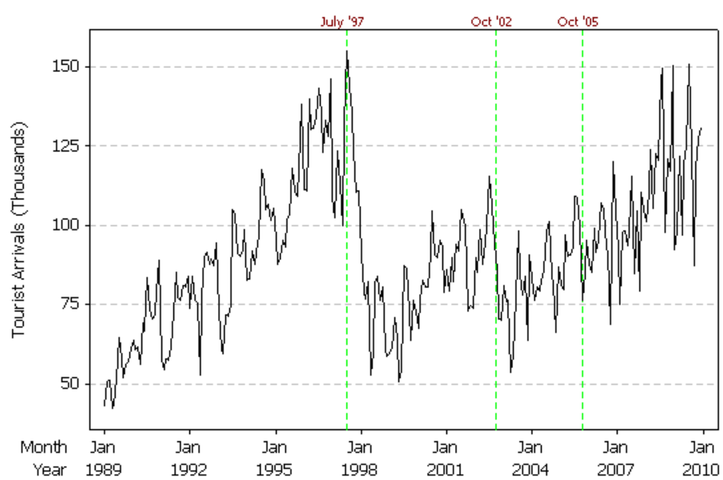

Figure 1: Monthly tourist arrivals to Indonesia via Soekarno-Hatta airport from January 1989 – December 2009

During this period, there were three interventions which may have affected the number of tourist arrival in Indonesia via Soekarno-Hatta airport. These interventions are the Asian financial crisis which occurred from July 1997 until December 2009 (Prideaux et al., 2003) and the Bali bombings which occurred in October 12, 2002 and October 1, 2005. In this analysis, the Asian financial crisis is the step function intervention variable, whereas the Bali bombings are the pulse functions. From the graph, we could see that the data decline dramatically according to the period when the Asian financial crisis occurred which was in July 1997. The graph also shows that the number of tourist arrivals dropped slightly after the first Bali bombings, and remained constant during the second attacks.

4 Modeling Method

There are two common types of intervention, namely step and pulse functions. Detailed explanations of intervention analysis can be found in [6], [52], [50], and [7]. An intervention model can be written as

$$Y_t = \frac{\omega_s(B)B^b}{\delta_r(B)} X_t + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t, \tag{1}$$

where Y_t is a response variable at time t and X_t is a binary indicator variable that shows the existence of an intervention at time t. X_t can be the step function S_t or the pulse function P_t. Then, $\omega_s(B)$ and $\delta_r(B)$ are defined as

$$\omega_s(B) = \omega_0 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s,$$

and

$$\delta_r(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r.$$

B is the back shift operator, $\theta(B)$ is the moving-average operator, and $\phi(B)$ is the autoregressive operator, represented as a polynomial in the back shift operator.

Eq. (1) shows the magnitude and period of intervention effect according to b, s, and r. The delay time is b, while s gives information about the time which is needed for an effect of intervention to be stable, and r is the pattern of the intervention effect. The equation illustrating the impact of an intervention model on a time series dataset (Y_t^*) is

$$Y_t^* = \frac{\omega_s(B)B^b}{\delta_r(B)} X_t. \tag{2}$$

A step function is an intervention type which occurs over a long term and is written as

$$S_t = \begin{cases} 0, & t < T \\ 1, & t \geq T, \end{cases} \tag{3}$$

where the intervention starts at T. This step function single input intervention model comprising of $b = 2$, $s = 1$, and $r = 1$ can be obtained by substituting Eq. (3) with Eq. (1),

$$Y_t = \frac{(\omega_0 - \omega_1 B)B^2}{1 - \delta_1 B} S_t + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t. \tag{4}$$

Therefore, the effect of this step function single input intervention will be

$$Y_t^* = \frac{(\omega_0 - \omega_1 B)B^2}{1-\delta_1 B} S_t. \tag{5}$$

If $|\delta_1| < 1$, then

$$Y_t^* = \omega_0 S_{t-2} + (\omega_0\delta_1 - \omega_1)S_{t-3} + (\omega_0\delta_1^2 - \omega_1\delta_1)S_{t-4} + \cdots . \tag{6}$$

The effect of this intervention effect on Eq. (6) can also be written as

$$Y_t^* = \begin{cases} 0, & t < T+2 \\ \sum_{i=2}^{k} \omega_0\delta_1^{i-2} - \sum_{j=3}^{k} \omega_1\delta_1^{j-3}, & t = T+k, \text{ and } k \geq 2. \end{cases} \tag{7}$$

An intervention which occurs only at a certain time (T) is called a pulse intervention and is written as

$$P_t = \begin{cases} 0, & t \neq T \\ 1, & t = T. \end{cases} \tag{8}$$

To explain this single input intervention effect with pulse function, a similar calculation as the step function interventions in Eq. (4)–(7) can be used.

4.1 Multi input intervention model

With reference to Eq. (1), the multi input intervention model [7] is

$$Y_t = \sum_{i=1}^{k} \frac{\omega_{s_i}(B)B^{b_i}}{\delta_{r_i}(B)} X_{i,t} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t. \tag{9}$$

Eq. (9) shows that there are k events that have affected the time series dataset. As an illustration, consider a multi input intervention with two events, namely a pulse function occurring at $t = T_1 = 40$ with ($b_1 = 1$, $s_1 = 2$, $r_1 = 0$) which is followed by a step function at $t = T_2 = 60$ with ($b_2 = 1$, $s_2 = 1$, $r_2 = 1$), thus

$$Y_t = [(\omega_{0_1} - \omega_{1_1}B - \omega_{2_1}B^2)B^1]P_{1,t} + \frac{(\omega_{0_2} - \omega_{1_2}B)B^1}{1-\delta_{1_2}B} S_{2,t} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t. \tag{10}$$

The impact is

$$\begin{aligned} Y_t^* &= \omega_{0_1}P_{1,t-1} - \omega_{1_1}P_{1,t-2} - \omega_{2_1}P_{1,t-3} + \omega_{0_2}S_{2,t-1} \\ &\quad + (\omega_{0_2}\delta_{1_2} - \omega_{1_2})S_{2,t-2} + (\omega_{0_2}\delta_{1_2} - \omega_{1_2})\delta_{1_2}S_{2,t-3} + \cdots \end{aligned} \tag{11}$$

which can also be written as

$$Y_t^* = \begin{cases} 0, & t \leq T_1 \\ \omega_{0_1}, & t = T_1 + 1 \\ -\omega_{1_1}, & t = T_1 + 2 \\ -\omega_{2_1}, & t = T_1 + 3 \\ 0, & t = T_1 + k \leq T_2, \text{ and } k \geq 4 \\ \omega_{0_2}\sum_{i=1}^{m} \delta_{1_2}^{i-1} - \omega_{1_2}\sum_{i=2}^{m} \delta_{1_2}^{i-2}, & t \geq T_2 + m, \text{ and } m \geq 1. \end{cases}$$

The illustration of Eq. (10) and its impact are represented in Figure 2 where $\omega_{0_1} = -25$, $\omega_{1_1} = 10$, $\omega_{2_1} = 5$, $\omega_{0_2} = -15$, $\omega_{1_2} = 4$, and $\delta_{1_2} = 0.5$. The first intervention that affected the data at $t = 41$, with a magnitude of -25. The pulse function intervention had an effect that lasted for 3 periods beyond $t = T_1 = 40$ with magnitude effects of -10 and -5 on the second and third after the intervention, respectively. After that, the effect of this pulse intervention will be equal to zero. The second intervention began at $t = T_2 = 60$. This step intervention was detected at $t = 61$ and its impact was -15. From $t = 62$ to $t = 65$ the impacts of this step intervention were -26.5, -32.25, -36.5, and -37.3, respectively. It is noted that the impact did not increase beyond -38.

Viewing this from another multi input intervention model, where the step function intervention occurred at $t = T_1 = 40$ with $(b_1 = 1,\ s_1 = 2,\ r_1 = 0)$ as its first intervention and followed by a pulse function intervention at $t = T_2 = 60$ with $(b_2 = 1,\ s_2 = 1,\ r_2 = 1)$ the model is

$$Y_t = [(\omega_{0_1} - \omega_{1_1}B - \omega_{2_1}B^2)B^1]S_{1,t} + \frac{(\omega_{0_2} - \omega_{1_2}B)B^1}{1 - \delta_{1_2}B}P_{2,t} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d}a_t,$$

and the impact is

$$\begin{aligned} Y_t^* &= \omega_{0_1}S_{1,t-1} - \omega_{1_1}S_{1,t-2} - \omega_{2_1}S_{1,t-3} + \omega_{0_2}P_{2,t-1} \\ &\quad + (\omega_{0_2}\delta_{1_2} - \omega_{1_2})P_{2,t-2} + (\omega_{0_2}\delta_{1_2} - \omega_{1_2})\delta_{1_2}P_{2,t-3} + \cdots . \end{aligned}$$

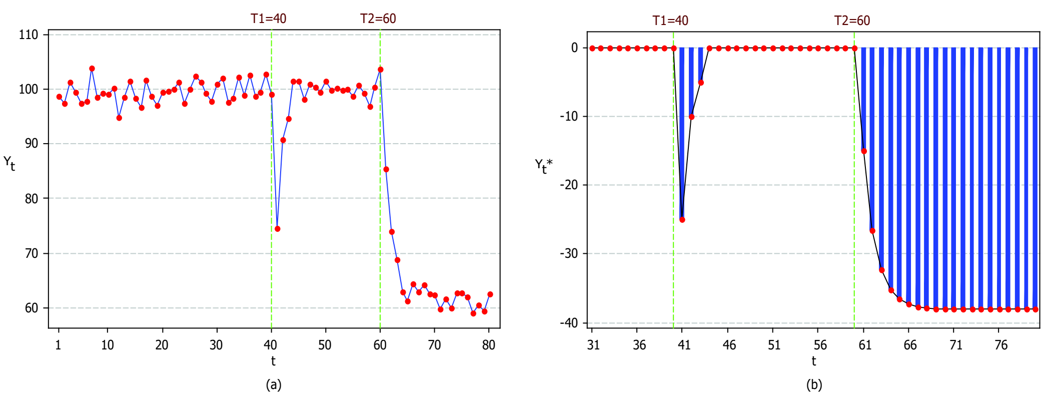

Figure 2: (a) Simulation of the Intervention Model, (b) Intervention effect of Multi Input Intervention where Pulse Function $(b_1 = 1,\ s_1 = 2,\ r_1 = 0)$ occurred at $t = 40$ and followed by the Step Function $(b_2 = 1,\ s_2 = 1,\ r_2 = 1)$ at $t = 60$

The first intervention as the step function intervention, started to affect the data for a period of time after the intervention event occurred. The impact was ω_{0_1}. This impact would be $(\omega_{0_1} - \omega_{1_1})$ during the second period. From the third period until $t = T_2$, the impact was $(\omega_{0_1} - \omega_{1_1} - \omega_{2_1})$. One period after $t = T_2$ which was the second intervention, namely the pulse function intervention, gives additional impact to the time series dataset, ω_{0_2}. Therefore, the net impact would be $(\omega_{0_1} - \omega_{1_1} - \omega_{2_1} + \omega_{0_2})$. The second and third periods after $t = T_2$ had the following impacts $(\omega_{0_1} - \omega_{1_1} - \omega_{2_1} + \omega_{0_2}\delta_{1_2} - \omega_{1_2})$ and $(\omega_{0_1} - \omega_{1_1} -$

$\omega_{2_1} + \omega_{0_2}\delta_{1_2}^2 - \omega_{1_2}\delta_{1_2}$). Following this, the impact decreased gradually to zero. Eventually, the impact will return to $(\omega_{0_1} - \omega_{1_1} - \omega_{2_1})$.

Figure 3 shows the simulation of a multi input intervention where the first intervention is a step function and the second intervention is a pulse function. The initial value for this simulation were $\omega_{0_1} = -25$, $\omega_{1_1} = 10$, $\omega_{2_1} = 5$, $\omega_{0_2} = -15$, $\omega_{1_2} = 4$, and $\delta_{1_2} = 0.5$. The first intervention, which occurred at $t = T_1 = 40$, started to affect the data when $t = 41$, and the impact was -25. There was a rapid decrease in the intervention effect (see Figure 3(b)) from $t = 42$ to $t = 44$, but the effect remained constant at 40 between $t = 45$ and $t = 60$. The second intervention occurred at $t = T_2 = 60$ and started to affect the data at $t = 61$. This effect became 40 (result of the first intervention) from $t = 65$ onwards.

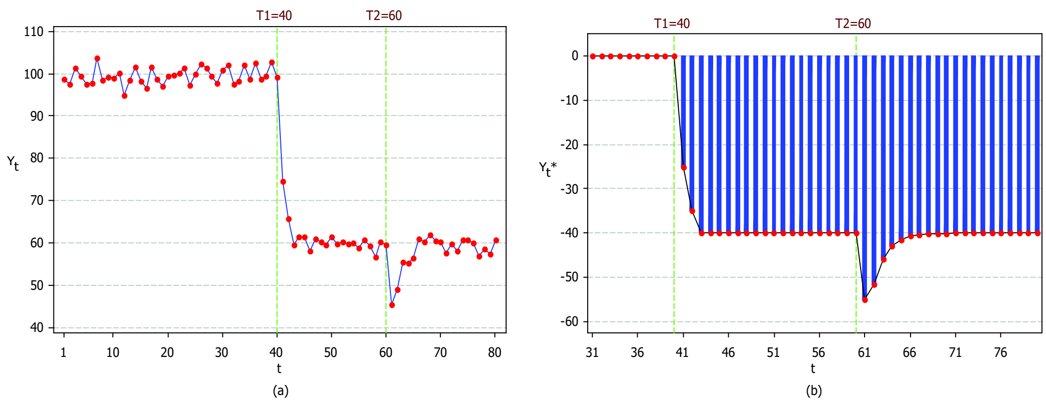

Figure 3: (a) Simulation of an Intervention Model, (b) Intervention effect of Multi Input Intervention where the Step Function ($b_1 = 1$, $s_1 = 2$, $r_1 = 0$) occurred at $t = 40$ and followed by the Pulse Function ($b_2 = 1$, $s_2 = 1$, $r_2 = 1$) at $t = 60$

The intervention model is defined as

$$Y_t = \frac{\omega_s(B)}{\delta_r(B)} X_{t-b} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d} a_t. \tag{12}$$

Eq. (12) can be rewritten as

$$\delta_r(B)\phi_p(B)(1-B)^d Y_t = \omega_s(B)\phi_p(B)(1-B)^d X_{t-b} + \delta_r(B)\theta_q(B)a_t, \tag{13}$$

or

$$c(B)Y_t = d(B)X_{t-b} + e(B)a_t$$

where

$$c(B) = \delta_r(B)\phi_p(B)(1-B)^d = (1 - c_1B - c_2B^2 - \cdots - c_{p+r}B^{p+r})(1-B)^d,$$
$$d(B) = \omega_s(B)\phi_p(B)(1-B)^d = (d_0 - d_1B - d_2B^2 - \cdots - d_{p+s}B^{p+s})(1-B)^d,$$
$$e(B) = \delta_r(B)\theta_q(B) = 1 - e_1B - e_2B^2 - \cdots - e_{r+q}B^{r+q}.$$

Thus, we have

$$a_t = \frac{c(B)Y_t - d(B)X_{t-b}}{e(B)}. \tag{14}$$

The nonlinear least square estimation to estimate the unknown parameters can be found by minimizing

$$S(\delta, \omega, \phi, \theta | b) = \sum_{t=t_0}^{n} a_t^2, \tag{15}$$

where $t_0 = \max(p + r + 1, b + p + s + 1)$ and a_t are the residuals under the white noise assumption and Normal distribution. The parameters of this multi input intervention can be obtained by replacing Eq. (12) with Eq. (9) and following the same minimization procedure as Eq. (13)–(15).

4.2 Building the Model

[32] showed that the intervention response or Y_t^* is easily formulated using the response values chart for determining the order of intervention model using b, s, and r. The intervention response denoted as $Y_t^*$is basically residual or error which is the difference between the actual data and the ARIMA model forecasts based on the data before the intervention. A complete procedure of the intervention model building can be used to evaluate these k intervention functions at time $T_1, T_2, \ldots, T_k$ as according to the following procedures.

Procedure 1: Dividing the dataset into $k + 1$ parts.

Part 1: The data before the first intervention, as many as n_0 time periods, i.e. $t = 1, 2, \ldots, T_1 - 1$. Denoted as Y_{0_t}.

Part 2: The data from the first intervention until just before the second intervention, as many as n_1 time periods, i.e. $t = T_1, T_1 + 1, T_1 + 2, \ldots, T_2 - 1$. Denoted as Y_{1_t}.

⋮

Part $k + 1$: The data from the kth intervention until the end of data analysis based on as many as n_k time periods, i.e. $t = T_k, T_k + 1, T_k + 2, \ldots, n$. Denoted as Y_{k_t}.

Procedure 2: Modeling of the first intervention.

Step 1: ARIMA model building for time series data before the first intervention occurs (Y_{0_t}), so we have

$$Y_{0_t} = \frac{\theta_q(B)}{\phi_p(B)(1 - B)^d} a_t.$$

Forecasting of Part 2 dataset (Y_{1_t}) using the ARIMA model. In this step, we get the forecast data, i.e.

$$\hat{Y}_{T_1}, \hat{Y}_{T_1+1}, \ldots, \hat{Y}_{T_1+n_1-1}.$$

Step 2: Calculate the response values of the first intervention or $Y_{1_t}^*$. These are the residuals of the data for $t = T_1, T_1 + 1, T_1 + 2, \ldots, T_2 - 1$, based on the forecasting of the ARIMA model in the first step. This step produces response values of the first intervention, i.e.

$$Y_{T_1}^*, Y_{T_1+1}^*, \ldots, Y_{T_2-1}^*.$$

Determination of b_1, s_1, r_1 from the first intervention by using the plot of response values $Y^*_{T_1}, Y^*_{T_1+1}, \ldots, Y^*_{T_2-1}$ and a confidence interval of width, i.e. $\pm 3\,\hat{\sigma}_{a_0}$, where $\hat{\sigma}_{a_0}$ is Root Mean Square Error (RMSE) of the previous ARIMA model. This interval is based on the determination of control chart bounds during statistical quality control for detecting outlier observations.

Step 3: Estimate the parameter and test the significance for the first intervention model. Conduct a diagnostic check to examine the residual assumption, i.e. white noise and normality distribution. In this step, we have the first input intervention model, i.e.

$$Y_t = \frac{\omega_{s_1}(B)B^{b_1}}{\delta_{r_1}(B)} X_{1_t} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d}\, a_t. \tag{16}$$

Procedure 3: Modeling of the mth Intervention Model, where $m = 2, 3, \ldots, k$.

Step 1: Forecast Data $m+1$ (Y_{m_t}) based on the mth intervention model. In this step, we will obtain the forecasted values from the mth intervention model

$$\hat{Y}_{T_m}, \hat{Y}_{T_m+1}, \ldots, \hat{Y}_{T_m+n_m-1}.$$

Step 2: Calculate the mth intervention responses $(Y^*_{m_t})$ which is the residual of the data for $t = T_m, T_m+1, \ldots, T_{m+1}-1$. This is based on the forecasting of the $(m-1)$th intervention model. These response values are denoted as

$$Y^*_{T_m}, Y^*_{T_m+1}, \ldots, Y^*_{T_{m+1}-1}.$$

Identify b_m, s_m, r_m from the mth intervention model from the plot of response values $Y^*_{T_m}, Y^*_{T_m+1}, \ldots, Y^*_{T_{m+1}-1}$, and the confidence interval of width $\pm 3\,\hat{\sigma}_{a_{m-1}}$.

Step 3: Estimate the parameter and conduct a significance test for the m^{th} intervention model. Conduct a diagnostic check to examine the residual assumption inclusive of white noise and normality distribution. The result of this step is

$$Y_t = \sum_{j=1}^{m} \frac{\omega_{s_j}(B)B^{b_j}}{\delta_{r_j}(B)} X_{j,t} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d}\, a_t. \tag{17}$$

This procedure is done iteratively until the last (kth) intervention. As a result of these steps, eventually we would obtain the following multi input intervention model

$$Y_t = \sum_{j=1}^{k} \frac{\omega_{s_j}(B)B^{b_j}}{\delta_{r_j}(B)} X_{j,t} + \frac{\theta_q(B)}{\phi_p(B)(1-B)^d}\, a_t.$$

5 Results, Analysis and Evaluation

All the results and models reported in this study were estimated using Statistical Analysis System (SAS) and the graphs were produced by MINITAB. The following sections will outline the results of the pre-intervention model using the Box-Jenkins procedure and the first, second and third intervention models.

5.1 Pre-intervention model results

The Box-Jenkins procedure [7] was utilized for this research which included the identification, parameter estimation, diagnostic checking, and forecasting to find the best ARIMA model before the first intervention, i.e. the Asian financial crisis since July 1997. The identification step showed that the data was not stationary both in variance and mean. Based this on Box-Cox transformation, a natural log was employed to cause the variance data to be stationary as shown in Figure 4.

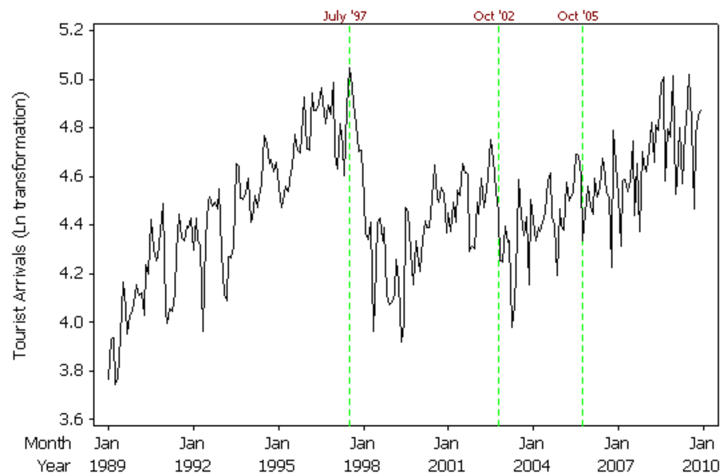

Figure 4: Natural log transformation of the Monthly Tourist Arrivals in Soekarno-Hatta airport from January 1989 – December 2009

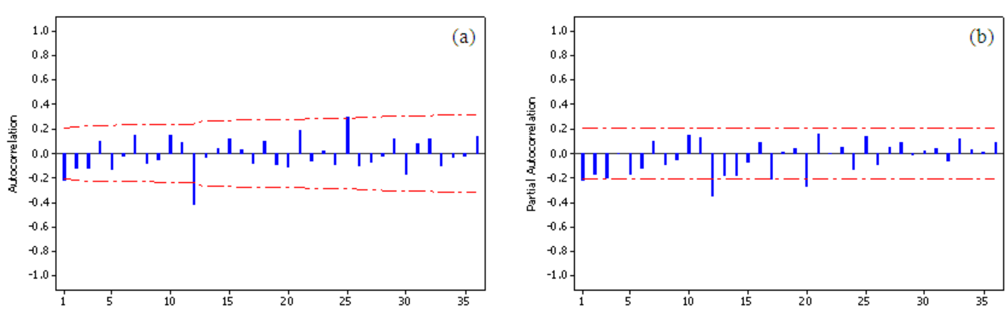

Figure 5: (a) Plot of ACF and (b) PACF of the Stationary Data before the First Intervention after Regular and Seasonal differencing ($d = 1$, and $D = 1$, $S = 12$)

Then, regular and seasonal differencings were applied to convert the stationary data into the mean. The graph based on the ACF and PACF stationary data are shown in Figure 5. There are several non seasonal lags (lag $1, 2, \ldots, 8$), and the ACF tends to be cut off after lag 1 whereas PACF diminishes dies down. On the other hand, ACF and PACF at seasonal lags (lag $12, 24, \ldots$) tend to cut off after lag 12. Hence, there are 2 possible appropriate orders of this ARIMA model, i.e. $(0,1,1)(0,1,1)^{12}$ and $(0,1,1)(1,1,0)^{12}$.

Table 1 shows the results of the parameter estimation, parameter significance test, and diagnostic checking. From this table, we know that both models are appropriate as a means for forecasting the monthly tourist arrivals via Soekarno-Hatta airport before Asian financial crisis. The comparison of the mean square errors (MSE) showed that ARIMA$(0,1,1)(0,1,1)^{12}$ yielded less MSE than ARIMA$(0,1,1)(1,1,0)^{12}$. Thus, the best ARIMA model for data before the first intervention is ARIMA$(0,1,1)(0,1,1)^{12}$, i.e.

$$\ln Y_t = \frac{(1-0.4592B)(1-0.8555B^{12})}{(1-B)(1-B^{12})}\, a_t. \tag{18}$$

Table 1: Results of Parameter Estimation, Parameter Significance Test, and Diagnostic Checking for ARIMA$(0,1,1)(0,1,1)^{12}$ and ARIMA$(0,1,1)(1,1,0)^{12}$ Models

ARIMA Model	Parameter	Coef.	SE Coef.	t	P-value	MSE
$(0,1,1)(0,1,1)^{12}$	$\hat{\theta}_1$	.4592	.0923	4.98	.000	.009280*
	$\hat{\Theta}_1$	.8555	.0878	9.74	.000	
$(0,1,1)(1,1,0)^{12}$	$\hat{\theta}_1$	−.2263	.1021	−2.22	.029	.011005*
	$\hat{\Phi}_1$	.6951	.1115	6.23	.000	

* = residual has satisfied the white noise and normal distribution assumptions

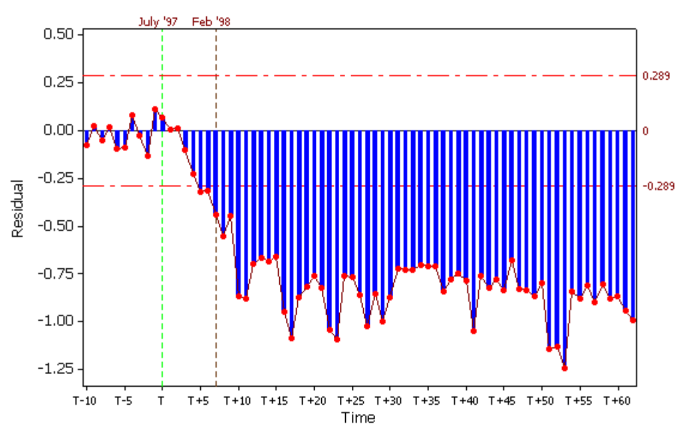

Figure 6: Response Values on the Number of Tourist Arrivals via Soekarno-Hatta airport (in Natural Log) after the First Intervention and Prior to the Second Intervention

5.2 The first intervention model results

This section present the results of the intervention model by illustrating the impact of the first step function intervention, namely the Asian financial crisis from July 1997 until December 1999 or at the time $t = 103, 104, \ldots, 132$. Its function could be written as

$$S_{1,t} = \begin{cases} 0, & t \leq 102 \\ 1, & t = 103, 104, \ldots, 132. \end{cases}$$

The first step in this modeling is to determine the order b, s, and r for the first step function intervention model. This is done to determine the order of the intervention model and to explain the decrease in the number of tourist arrivals via Soekarno-Hatta airport due to the Asian financial crisis. A residual chart is as in Figure 6 is used to show this step.

Figure 6 shows that the response values at time $T+6$, $T+8$,..., $T+62$ (where $T = 103$ is time when the Asian financial crisis starts occur) have greater absolute values than the confidence intervals. This graph also illustrates that the values at $T + 7$ until $T + 9$ are close to the confidence interval. Hence, there are 2 appropriate presume orders of the first intervention model from which $b_1 = 7$, $s_1 = (3)$, $r_1 = 0$ and $b_1 = 10$, $s_1 = 0$, $r_1 = 0$. The results of these parameter estimation and significance test show that the second model by eliminating order $s_1 = (1, 17)$ yields the best fit. Thus, the order for the first intervention model is $b_1 = 10$, $s_1 = 0$, $r_1 = 0$. The SAS output for these parameter estimation, significance test and diagnostic checking for this model could be seen in Figure 7.

The ARIMA Procedure
Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1,1	0.34501	0.08039	4.29	<.0001	1	y	0
MA2,1	0.67678	0.06881	9.84	<.0001	12	y	0
NUM1	-0.18544	0.07781	-2.38	0.0185	0	S1t	10

Variance Estimate	0.01555
Std Error Estimate	0.1247
AIC	-185.297
SBC	-176.43
Number of Residuals	142

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9.11	4	0.0584	0.045	-0.099	-0.106	0.103	-0.157	0.056
12	14.29	10	0.1602	-0.028	-0.042	-0.079	0.156	-0.006	0.018
18	23.52	16	0.1004	-0.055	0.021	0.038	0.088	-0.205	0.042
24	26.79	22	0.2194	0.045	-0.040	0.008	0.066	-0.105	0.011

Figure 7: SAS Output from the First Intervention Model

The output at Figure 7 shows that all the model parameters are significant (at the 5% significance level). Diagnostic checking of the model shows that the first step function intervention model has satisfied the assumptions of the white noise and normally distributed residuals. In this case, the intervention model for the number of tourist arrivals via Soekarno-Hatta airport after the first step function intervention and prior to the second pulse function intervention can be written as

$$\ln Y_t = -0.18544 S_{1,t-10} + \frac{(1 - 0.34501B)(1 - 0.67678B^{12})}{(1 - B)(1 - B^{12})} a_t. \tag{19}$$

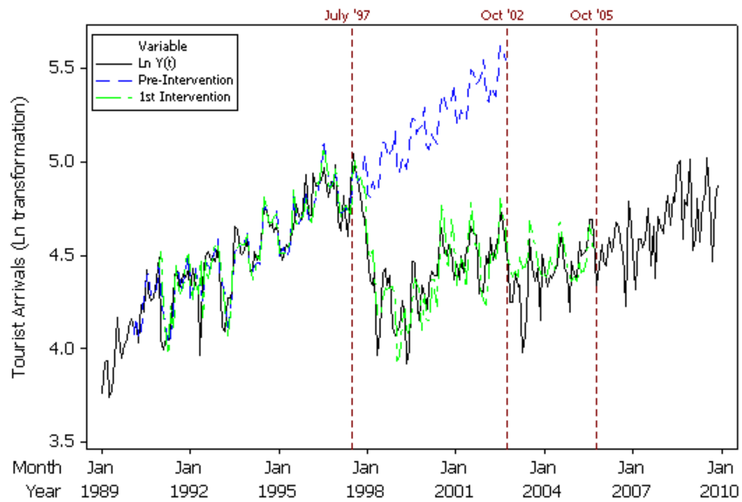

Figure 8: The Effect Reconstruction and Forecasts of the First Intervention Model

Based on the model presented in Eq. (19), the interpretation of the impact of the Asian financial crisis is not direct as it was delayed for 10 months or it started only on May 1998 when there were riots, killings, and destruction of commercial districts in Java, particularly the anti-Chinese sentiment riots in Jakarta. The reconstruction of the first intervention model effect and the forecast values start at the second intervention until a month before the third intervention period can be seen in Figure 8.

5.3 Results from the Second Intervention Model

After modeling the first intervention based on the intervention model due to the Asian financial crisis, another analysis of the second pulse function intervention was conducted. This was based on the October 12, 2002 Bali bombing at which is equated with $t = T = 166$. Thus, the pulse function is written as

$$P_{2,t} = \begin{cases} 0, & t \neq 166 \\ 1, & t = 166. \end{cases}$$

The first step in this analysis is to determine the order of the second intervention model. Figure 9 shows a chart of the residuals to determine the order of b, s, and r used in the intervention model. The residuals will be used to model the decrease of tourist arrivals due to the first Bali bombing.

Figure 9 shows that the response values at time $T + 6$ has greater absolute values than the confidence interval. This graph also illustrates that the values at $T + 7$ is close to the confidence interval. This means that there are 2 possible sets of orders for the second pulse function intervention model. The first set order is $b_2 = 6$, $s_2 = 0$, $r_2 = 0$ and the second is $b_2 = 6$, $s_2 = (1)$, $r_2 = 0$. Parameter estimation and significance tests show that both set of the model orders yield significant parameters and residuals that satisfy the white noise and

Normal distribution assumptions. The comparison of SBC criteria show that the second model yields better result than the first. The results in Figure 10 are shown using the SAS output.

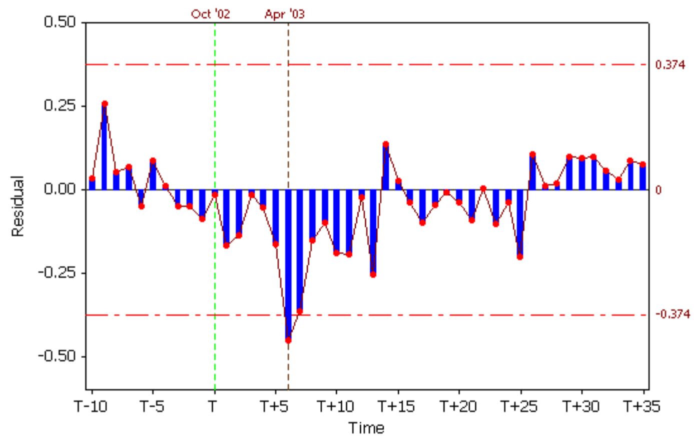

Figure 9: Response Values of the Number of Tourist Arrivals after the Second Intervention and Prior to the Third Intervention

The ARIMA Procedure

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1,1	0.38514	0.07103	5.42	<.0001	1	y	0
MA2,1	0.67123	0.05911	11.35	<.0001	12	y	0
NUM1	-0.19725	0.07162	-2.75	0.0065	0	S1t	10
NUM2	-0.33103	0.09693	-3.42	0.0008	0	P1t	6
NUM1,1	0.24758	0.09697	2.55	0.0115	1	P1t	6

Variance Estimate	0.014181
Std Error Estimate	0.119084
AIC	-247.47
SBC	-231.561
Number of Residuals	178

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.18	4	0.1268	0.038	-0.071	-0.086	0.080	-0.133	0.033
12	12.20	10	0.2721	-0.031	-0.017	-0.095	0.120	-0.002	0.041
18	19.67	16	0.2353	-0.073	0.018	0.027	0.082	-0.157	0.001
24	21.01	22	0.5203	0.049	-0.018	0.014	0.052	-0.031	0.002

Figure 10: SAS Output for the Second Intervention Model

Based on the results listed in Figure 10, an intervention model for the number of tourist arrivals via Soekarno-Hatta airport after the second pulse function intervention and prior to the third pulse function intervention can be written as

$$\begin{aligned}\ln Y_t &= -0.19725 S_{1,t-10} - 0.33103 P_{2,t-6} - 0.24758 P_{2,t-7} \\ &\quad + \frac{(1-0.38514B)(1-0.67123B^{12})}{(1-B)(1-B^{12})}\, a_t.\end{aligned} \tag{20}$$

The effects from the reconstruction of the second intervention model can be seen in Figure 11.

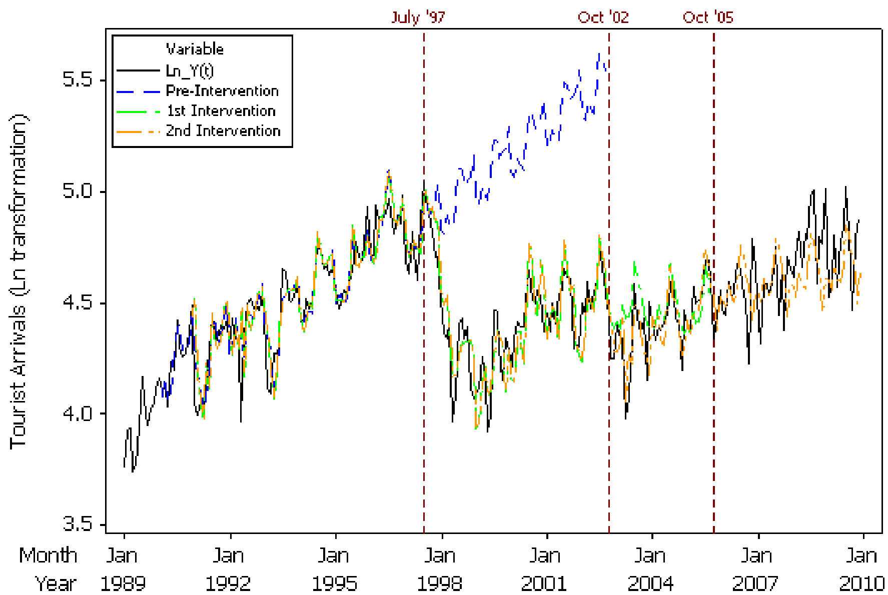

Figure 11: Chart of the Effects of the Reconstruction and Forecasts of the First and Second Intervention Model

5.4 Results from the Third Intervention Model

The final analysis of the third pulse intervention function based on the second Bali bombing which took place on October 1, 2005 is equated with $t = T = 202$. So, the pulse function in this intervention could be written as

$$P_{3,t} = \begin{cases} 0, & t \neq 202 \\ 1, & t = 202. \end{cases}$$

As described in the previous section, the first step is to determine the order of the third intervention model. Figure 12 shows a chart of the residuals to determine the order of b, s, and r for the third intervention model based on the second Bali bombing.

From Figure 12, we can see that the response values at time $T, T+1, \ldots, T+12$ have less absolute values than the confidence interval. This graph also illustrates that only the values at $T + 12$ is close to the lower confidence interval. Thus, there is 1 possible set of order for the second pulse function intervention model, i.e. $b_3 = 12$, $s_3 = 0$, $r_3 = 0$. Parameter estimation and significance tests show that this model order yields significant parameters from this third intervention. Figure 13 presents the SAS output based on the final multi input intervention model.

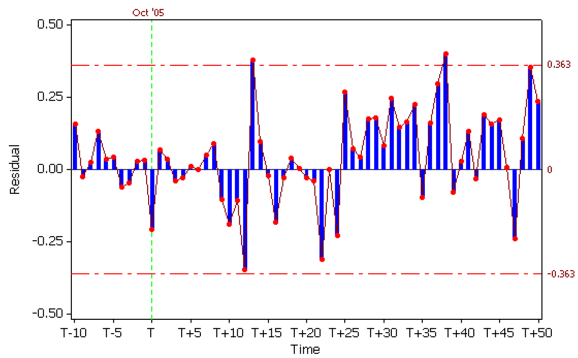

Figure 12: Response Values of the Number of Tourist Arrivals after the Third Intervention

The ARIMA Procedure
Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1,1	0.54205	0.05753	9.42	<.0001	1	y	0
MA2,1	0.65221	0.05537	11.78	<.0001	12	y	0
NUM1	-0.18565	0.06856	-2.71	0.0073	0	S1t	10
NUM2	-0.33741	0.10294	-3.28	0.0012	0	P1t	6
NUM1,1	0.26559	0.10299	2.58	0.0106	1	P1t	6
NUM3	-0.29516	0.10108	-2.92	0.0039	0	P2t	12

Variance Estimate	0.015736
Std Error Estimate	0.125443
AIC	-292.343
SBC	-271.793
Number of Residuals	227

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	3.21	4	0.5226	0.039	-0.021	-0.103	-0.001	0.022	0.028
12	8.70	10	0.5609	0.037	-0.039	-0.128	0.042	0.005	0.044
18	13.74	16	0.6178	-0.048	-0.073	0.074	-0.024	-0.083	-0.006
24	16.21	22	0.8055	0.062	0.026	0.004	-0.061	0.016	-0.035

Figure 13: SAS Output for the Final Intervention Model

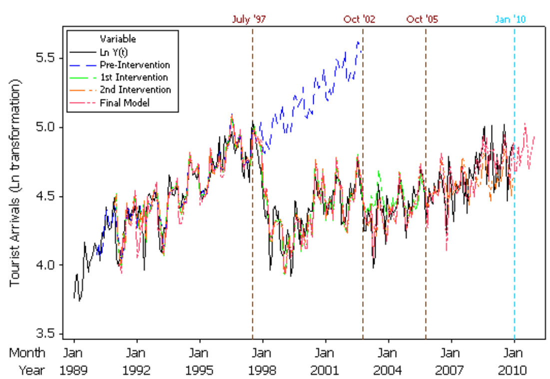

Figure 14: Effect Reconstruction and Forecasts of the First, Second and Third Intervention models (at Transformation Data)

The SAS output shown in Figure 13 shows that the final multi input intervention model for the number of tourist arrivals in Indonesia via Soekarno-Hatta airport after the third pulse intervention function can be written as

$$\ln Y_t = -0.8565S_{1,t-10} - 0.33741P_{2,t-6} - 0.26559P_{2,t-7} - 0.29516P_{3,t-12} + \frac{(1-0.54205B)(1-0.65221B^{12})}{(1-B)(1-B^{12})}a_t, \tag{21}$$

where $S_{1,t}$ the step function of the Asian financial crisis, $P_{2,t}$ is the pulse function of the first Bali bombing, and $P_{3,t}$ is the second Bali bombing. The effect from the reconstruction and the forecast of the final intervention model as the for transformation data (natural log data) are presented in Figure 14.

5.5 Model Evaluation

An evaluation of the impact for each intervention could not be done directly based on the model of Eq. (21). This has caused the data are not in origin scale, so the effect of each intervention could not be directly used as the estimated parameters. The rational for this statement is based on the assumption that the intervention model that we want to evaluate is as follows

$$Y_t = Y_t^* + n_t$$

where Y_t is the actual data, Y_t^* is the intervention effect, and n_t is the ARIMA model for error (data without intervention effect). Besides that, the next assumption is that the intervention effect follows the simplest model, i.e. $Y_t^* = \omega_0 P_t$, where P_t is the pulse function at a certain T. In this case, the effect of the intervention at $t = T$ is

$$Y_T^* = Y_T - n_T = \omega_0.$$

Thus, we could directly use the estimated parameters to measure the impact of an intervention.

On the other, we can assume that the variance data is not stationary and we must transform this data by using natural log. Thus, we have $\tilde{Y}_t = \ln Y_t$ and the intervention model is

$$\tilde{Y}_t = \tilde{Y}_t^* + n_t.$$

If $\tilde{Y}_t^* = \omega_0 P_t$, where P_t is the pulse function at a certain T, then the effect of this intervention at $t = T$ on the transformation data is

$$\tilde{Y}_T^* = \tilde{Y}_T - n_T = \omega_0.$$

Hence, the impact of this intervention on the original data is

$$Y_T^* = e^{\tilde{Y}_T^* + n_T} - e^{n_T} \neq e^{\tilde{Y}_T^*}.$$

This result shows that the estimated parameters of this intervention model at transformation data could not be interpreted directly due to the magnitude of the effects of an intervention. Therefore, the effect of the intervention on the transformation data at a certain time must be calculated by using the difference between the forecast of this intervention and the pre-intervention models.

Following this, we can transform the data to the original scale to examine the impact and the result of each intervention as shown in Figure 15. Based on this conversion to the original data scale, the impact of the first, second and third interventions are summarized in the following sections.

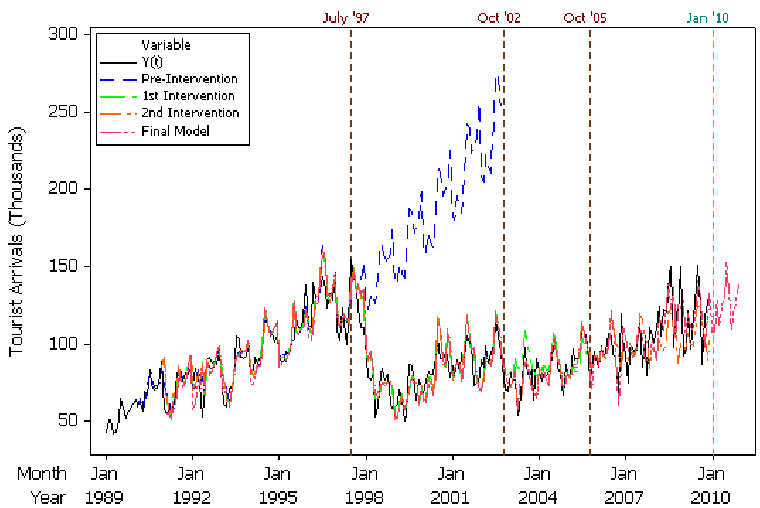

Figure 15: Effects of the Reconstruction and Forecasts of the First, Second and Third Intervention Models (Original Data)

5.5.1 Impact of the Asian financial crisis

Based on the model Eq. (21), it could be interpreted that the impact of the Asian financial crisis has been delayed for 10 months as it only started in May 1998. At that time, there were riots, killings, and destruction of commercial districts in Java, particularly the anti-Chinese sentiment riots in Jakarta. This riot was viewed with concern by many Asian markets and this could be the most likely reason for the decline of tourist arrivals in Bali beginning May 1998 [42]. Mathematically, this model shows that the period for the greatest drop in the number of tourist arrivals in Bali was in May, June and July 1998, $t = 103+10, 103+11, \ldots$ or $t = 113, 114, \ldots$. Table 2 presents the magnitude of the effects (Y_T^*) of the Asian financial crisis during those months as depicted based on the original data scale. In this table, $\hat{Y}_T$ is forecast value based on the final intervention model, and $\hat{n}_T$is forecast value based on the pre-intervention model. From this table, we could see that the decreasing number of tourist arrivals in Bali on May, June, and July 1998 were 59670, 74646, and 91147, respectively.

Based on the calculation effect results of the transformation data shown in above, we would suggest and recommend using the original data to explain the impact of certain interventions. At the moment, there has yet to be a book or journal which has extensive discussions on how to interpret the impact of an intervention on the time series dataset with transformation.

Table 2: Magnitude of the Effects of the Asian Financial Crisis on the Number of Tourist Arrivals via Soekarno-Hatta airport (original data in thousands)

t	Time	$\hat{Y}_T$	$\hat{n}_T$	Y_T^*
T_1+10	May 1998	66.148	125.819	−59.670
T_1+11	Jun 1998	68.438	143.084	−74.646
T_1+12	Jul 1998	73.548	164.695	−91.147
⋮	⋮	⋮	⋮	⋮

5.5.2 Impact of the First Bali Bombing

The final intervention model Eq. (21) shows that the first Bali bombing on October 12th 2002 only affected the decrease of tourist arrivals via Soekarno-Hatta airport after 6 and 7 month or at April and May 2003, i.e. 0.33741 and 0.26559 (in natural log) respectively. It means that the first Bali bombing have no direct effect for tourist arrival via Soekarno-Hatta airport, even though this attack was the deadliest act of terrorism in the history of Indonesia, killing 202 people from which 152 were foreigners (including 88 Australians) and 38 were Indonesian citizens.

This model also illustrates that the largest decrease of tourist arrivals, i.e. 0.33741 (in natural log) was in April 2003, a 6 month after the attack. The decrease in tourist arrivals continued for only one month more, i.e. May 2003. At that time, issue about the SARS and avian flu in Jakarta in April 2003 could be the most likely reason for the decline of tourist arrivals in Indonesia via Soekarno-Hatta airport in Jakarta [42].

The magnitude of the effect (Y_T^*) of this terrorist attack in April and May 2003 in the original data scale is presented in Table 3. In this table, $\hat{Y}_T$ is the forecast values based on the final intervention model, and $\hat{Y}_T^1$ is forecast values based on the first intervention model. It can be seen that the decrease number of tourist arrivals in Bali in April 2003 is more compared to May 2003 with the 26735 and 10776 tourists respectively.

Table 3: The Magnitude Effects of the First Bali Bombing on the Number of Tourist Arrivals via Soekarno-Hatta airport (original data in thousands)

t	Time	$\hat{Y}_T$	$\hat{Y}_T^1$	Y_T^*
T_2+6	Apr 2003	57.111	83.846	−26.735
T_2+7	May 2003	73.532	84.308	−10.776

5.5.3 Impact of the Second Bali Bombing

From Eq. (21), this could be interpreted that the second Bali bombing also has no directly affected and contributed to the decrease of tourist arrivals via Soekarno-Hatta airport.

Moreover, this model has also been used to illustrate the same impact due to the first attack. The impact that took place only at 12 month after the attack, October 2006, was 0.29516 (in natural log). As the first attack, at that time the issue about the avian flu in Jakarta in October 2006 could be the most likely reason for the decline of tourist arrivals in Indonesia via Soekarno-Hatta airport in Jakarta.

However, the bombing incident had killed 20 and injured 109 people inclusive of the three bombers who killed themselves during the attack. The number of casualties in this attack was less than the first bombing. This condition was the likely explanation for the fewer declines and shorter periods impact of tourist arrivals to Bali for the second attack. Table 4 illustrates the magnitude effects (Y_T^*) of this terrorist attack in October 2006 based on the original data scale. $\hat{Y}_T$ is the forecast value based on the final intervention model, and $\hat{Y}_T^2$ is the forecast value based on the second intervention model. From this table, we could see that the decrease in the number of tourist arrivals to Indonesia via Soekarno-Hatta airport on October 2006 was 36417 tourists.

Table 4: Magnitude Effects of the Second Bali Bombing on the Number of Tourist Arrivals via Soekarno-Hatta airport (original data in thousands)

t	Time	$\hat{Y}_T$	$\hat{Y}_T^2$	Y_T^*
$T_3 + 12$	November 2005	60.529	96.946	$-$ 36.417

In summary, this research has found that the impact of the Asian financial crisis on tourist arrivals to Indonesia via Soekarno-Hatta airport is more significant as compared to terrorist attacks Bali. This research also shows that any impact affecting safety translates to negative tourist arrivals. The impact of the first and second Bali bombings on the decrease of tourist arrivals via Soekarno-Hatta airport was not directly as the decrease of tourist arrivals in Bali. This result indicates that the local issue about the SARS and avian flu in Jakarta has more affected the decrease of tourist arrivals via Soekarno-Hatta airport.

6 Conclusion

Studying the impact due to unexpected disruptions such as the Asian financial crisis and terrorist attacks on tourism is important for forecasters, planners, investors and operators. This paper provides an analysis of the impact of three interventions, namely the Asian financial crisis and the two Bali bombings on the number of tourist arrivals in Indonesia via Soekarno-Hatta airport.

The Asian financial crisis that occurred from July 1997 to December 1999 did not directly affect the decrease of tourist arrivals in Indonesia via Soekarno-Hatta airport but it did cause a delayed reaction after 10 months when the constant impact was felt since May 1998. The impact took place due to the riots, killings, and destruction of commercial districts in Java, especially in Jakarta. The decrease of tourist arrivals in Bali was due to these crises and the number of tourists in May, June and July 1998 were 59670, 74646, and 91147 respectively. In addition, the first and second Bali bombing also had delay reaction to the decrease of tourist arrivals. The first attack had a negative impact on 6 and 7 months after the attack whereas the second one had an impact only on 12 months after the attack. Moreover, the reduced numbers of tourist arrivals via Soekarno-Hatta airport at that time more due to the issue about the SARS and avian flu in Jakarta.

This paper also shows that the interpretation of an intervention model for transformation data could not be done directly based on estimated model parameters. Further research is needed to understand the precise impact of the interventions on other forms of data transformation.

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