Full Length Research Paper

Interventions affecting air transport passenger demand in Taiwan

Jennifer C. H. Min[1]*, Hsien-Hung Kung[2,3] and Hsiang Hsi Liu[4]

[1]Department of International Business, Ming Chuan University, No.250, Sec. 5, Zhongshan N. Rd., Taipei City, 11103, Taiwan, R.O.C.
[2]Department of Marketing and Distribution Management, Hsing Wu College, Taipei, Taiwan, R.O.C.
[3]National Sun Yat-Sen University, Institute of china and Asia-Pacific Studies, No. 70, Lianhai Rd., Kaohsiung City 804, Taiwan, R.O.C.
[4]Graduate Institute of International Business, National Taipei University, No.151, Daxue Rd., Sanxia Township, Taipei County 237, Taiwan, R.O.C.

All around the world, air travel has become a vital element in people's lives, one that stimulates national economies, global trade and tourism. Nevertheless, the airline industry is highly vulnerable to exogenous shocks. The objectives of this study, therefore, are to apply Autoregressive Integrated Moving Average (ARIMA) with intervention model (also known as intervention analysis) to evaluate the impact of different local, regional and global incidents of a man-made, natural and health character, in Taiwan over the last decade. The incidents used in this study are the Asian financial crisis starting in mid-1997, the September 21st earthquake in 1999, the September 11th terrorist attacks in 2001, and the outbreak of Severe Acute Respiratory Syndrome (SARS) in 2003. Empirical results revealed that the SARS illness had a significant impact, whereas the Asian economic crisis, the September 21st earthquake, and the September 11th terrorist attacks showed no significant effect on air movements. Based on the results, implications and recommendations are provided, and future research possibilities are also noted.

Key words: Tourism, intervention analysis, catastrophic events, air movement, airline industry.

INTRODUCTION

All around the world, air travel has become a vital element in people's lives, one that stimulates national economies, global trade and tourism. As well, the air transport industry has experienced significant growth over the past few decades. Due to its outstanding economic performance in the Asia-Pacific region since the 1980s, the island state of Taiwan has developed into one of this region's wealthiest areas, and has been planning to become an Asia-Pacific operations center. Consequently, there has been a substantial growth in air traffic in Taiwan as more people take the opportunity to fly for both business and private purposes.

Nevertheless, the airline industry is highly vulnerable to exogenous shocks. External negative events and crisis situations, such as the Persian Gulf crisis during 1990 - 1991, the September 11th terrorist attacks, the wars in Afghanistan and the Arabian Gulf, and the Severe Acute Respiratory Syndrome (SARS) outbreak, have certainly had a significant impact on the demand for air travel (Alderighi and Cento, 2004; Annelies, 2006; Coshall, 2003; Coy, 2005; Gillen and Lall, 2003; Inglada and Rey, 2004; Lai and Lu, 2005; Lee et al., 2005; Mason, 2005; Rossiter and Dresner, 2004).

Due to the nature of services in the transportation industry, accurate forecasts of demand and impact assessments of exogenous changes or extreme events are crucial for better management and planning of services, and are something which governments, academics, and practitioners cannot ignore. It is also essential to pay sufficient attention to establishing a forecasting model for the aftermath of such events, since the

---

*Corresponding author. E-mail: jennifer_min.tw@yahoo.com.tw. Tel: 886-2-28824564 ex2830. Fax: 886-2-28809751.

impact of exceptional external misfortunes can cause the mean levels of air transport demand in a time series to change radically. Such models would allow decision makers to evaluate the pattern and duration of the effects of unexpected catastrophic events.

OBJECTIVES AND SCOPE

Various forecasting techniques in the airline industry have been developed during the last three decades. A significant ingredient in forecasting is the system of air passenger volume estimation, which provides essential information to civil aviation authorities in all planning activities, such as adding additional flights on routes (Grosche et al., 2007). Less attention, however, has been paid to the results derived from different possible events affecting air movements. Comparison of the recovery status of air passenger demand from disastrous events has not ever been examined or discussed in the air transport management literature. The objectives of this study, therefore, are to apply one forecasting approach, the Autoregressive Integrated Moving Average (ARIMA) with intervention model (also known as intervention analysis), to evaluate the impact of different local, regional and global incidents of a man-made, natural and health character, in Taiwan over the last decade. The incidents used in this study are the Asian financial crisis starting in mid-1997, the September 21st earthquake in 1999, the September 11th terrorist attacks in 2001, and the outbreak of SARS in 2003. It is imperative for travel practitioners, policy makers, and academic researchers to understand how passengers are affected by these calamities in order to enable prompt and adequate responses to be developed for future such circumstances, which appear to have increased in frequency and severity in recent years.

LITERATURE REVIEW

Since the study by Box and Jenkins (1976), time series analysis has been popularly adopted for the modeling of dependent, sequential observation. Two useful representtations express the behavior of observed time series processes, namely, the autoregressive (AR) and the moving average (MA), which describe the behavior of stochastic and dynamic systems (Box et al., 1994). Time series analysis has outperformed other forecasting models because of its well-established theoretical foundation and the ease of estimation (Karlaftis and Vlahogianni, 2009) and its value regardless of a stationary or nonstationary time series, and with or without seasonal components (Lim and McAleer, 2002; Min, 2008a). It has therefore been successfully and overwhelmingly applied for modeling and forecasting in the transportation management literature, such as air

transportation (Inglada and Rey, 2004; Lepak, 1997; Pitfield, 2007,2008; Smith et al., 2002), safety issues (Foreman, 1993; Males, 2007; McLeod and Vingilis, 2008; Wagenaar et al., 2007), the modeling of freight and transportation demand (Babcock and Lu, 2002; Batchelor et al., 2007; Cervero, 1985; Godfrey and Powell, 2000; Pitfield, 1993), and air quality and transportation emissions (Gokhale and Khare, 2004; Issarayangyun and Greaves, 2007; Lau et al., 2009; Sharma and Khare, 1999, 2000 and 2001).

Intervention analysis is a transfer function stochastic model and may be understood as an extension to the ARIMA set of time series models. In terms of intervention, such an analysis has been used to study the impact of exceptional external events, including natural disasters, political or economic policy initiatives or changes, technological changes, strikes, sales promotions, advertising, and like (Liu, 2006). Box and Tiao (1975) provided a procedure, known as intervention analysis, for analyzing a time series in the presence of external events. It exhibits a useful stochastic modeling tool that can rigorously analyze the impact and represent two distinct components: an underlying disturbance term and the set of interventions in the series.

The pioneering application of intervention analysis was a study by Box and Tiao (1975), which provided an analytical framework for examining the effect of two interventions in Los Angeles: the opening of the Golden State Freeway, and the enforcement of a new law concerning oxidant data. Over the years, the technique has been widely employed and successfully applied in different fields in the physical and social sciences. Although intervention analysis has been well-documented in various disciplines, this approach has not attracted much attention from researchers and academics in air travel demand. One study by Coshall (2003) applied the intervention model to assessing the impact of three interventions—the U.S. bombing of Libya in 1986, the Lockerbie air disaster in 1988, and the Persian Gulf crisis during 1990-1991 on the flow of U.K. air passengers to a variety of destinations. Lee et al. (2005) employed intervention analysis to assess the status of recovery after the September 11th terrorist attacks on US air passenger transport demand. Empirical results showed that the demand for US air passenger transport had not yet fully recovered from the attacks but the demand had appeared to be increasing gradually. In Pitfield (2007), the ARIMA with intervention model was used to examine the influence of airline alliances on the traffic of constituent airlines for five routes to the US from European hubs (Frankfurt and Paris). A similar methodology was applied by Pitfield (2008) to estimate the impact of the so-called "Southwest Effect" on traffic and market share for key domestic air routes in the USA, where Southwest had started its service. Lai and Lu (2005) compared the SARIMA with intervention model with different techniques; the results showed that it outperformed

all other techniques when significant intervention in the series existed.

RESEARCH QUESTIONS

This article attempts to go further than the above reviewed research by employing intervention model on the major events in Taiwan over last decade. As noted previously, the associated consequences of uncertainty or a deteriorating economy may influence passengers' intentions to take a flight or visit Taiwan. In fact, the profound influences on air movements from different tragedies are not well documented in the literature. The current study intends to shed more light on these issues, and specifically raises the following research questions:

Research Question 1: Was air travel demand in Taiwan affected by these events, and what was the extent of the change in passenger demand?
Research Question 2: Does the status of the recovery from catastrophe have a temporary or long-term impact on air passenger demand?

METHODOLOGY

Data

In the air travel industry, passenger flows from a source to a destination represent a statistical time series adopted monthly, quarterly, or yearly numbers of air passengers. In this study, the variable is the number of air passengers moving monthly through both Taoyuan and Kaohsiung international airports in Taiwan for the period from January 1981 to December 2008.

The set of data obtained from the database of the Advanced Retrieval and Econometric Modeling System (AREMOS), published by the Taiwan Economic Data Center, is the indicator chosen in this analysis. The analysis was carried out using the statistical package SAS/ETS 9.1.

The intervention model approach

Traditionally, once a time series is subjected to a natural or man-made intervention at a particular period in time, its impact in changing the mean level of the series is determined by using a two-sample t-test. Nevertheless, the t-test is valid only if the two observations before and after the intervention being considered vary according to the means normally, with constant but not necessarily equal variance, and independently. Box and Tiao (1975), therefore, formalized intervention analysis by presenting a suite of step and pulse responses that characterized the response of a time series to a known intervention in time, and express a deterministic influence on the time series. The advantages of using an intervention analysis are to provide a means of measuring the impact of the intervention that cannot be obtained by merely inspecting a plot of the data, or that may be clouded by underlying patterns such as trends and seasonal variations in the data (Narayan and Considine, 1989). The goal of finding a good model is to represent the process-generating mechanism adequately. In the intervention model, it can be expressed as (Box and Jenkins, 1975):

$$z_t = f(k, \xi, t) + N_t \tag{1}$$

in which z_t is the interval of the observed series; $f(k, \xi, t)$ is the fixed effect of the exogenous variable in time t, which includes the time function of a group of unknown parameter k; and N_t is the unknown intervening time item. If the intervening item is in accordance with the ARIMA, the model can be expressed as:

$$\phi(B)N_t = \theta(B)a_t \tag{2}$$

in which B is the backward operation factor; a_t is the white noise process with an expected value of 0 and an independent normality variance of σ^2, where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ are the B autoregressive moving average polynomial item of exponential p and q with the root of $\phi(B)$ and $\theta(B)$ located on or outside the unit circle. The sample Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) are examined to identify the AR and MA models. If the series presents as nonstationary, it can become stationary after d times of difference. The intervention model was generated using a cycling process of trial and error on the ARIMA and the transfer function model. The procedure included three stages. First, the ARIMA model with a pre-intervening item was established. Second, the intervention model was built by identifying the substantial meaning of the intervention's occurrence, knowing the existence and time of the intervening factor, and using that to judge the impact form. Finally, the intervention function and intervening model were combined to estimate the parameters of the intervention model simultaneously. If the parameters are not statistically significant, a new model identification is needed to discover its reasons prior to another around of analysis. According to Box and Tiao (1975), the dynamic model of affected exogenous variable ξ is expressed as:

$$f(\delta, \omega, \xi, t) = \sum_{j=1}^{k} Z_{ij} = \sum_{j=1}^{k} \left[\frac{\omega_j(B)}{\delta_j(B)} \right] \tag{3}$$

whereas $\delta_j(B) = 1 - \delta_{1j}B - \cdots - \delta_{rj}B^r$ and $\omega_j(B) = 1 - \omega_{1j}B - \cdots - \omega_{sj}B^s$ are the B polynomial of exponential r and s with roots located outside the unit circle. The exogenous variable ξ_t can be transferred to Z_t with difference equation and expressed as:

$$z_t = Z_t + N_t = \left[\frac{\omega(B)}{\delta(B)} \right] \xi_t + \left[\frac{\theta(B)}{\phi(B)} \right] a_t \tag{4}$$

Z_t is the dynamic system of virtual variable response at a step of time and thus can be defined as $\xi_t = S_t^{(T)}$ with $\dfrac{\omega(B)}{\delta(B)}$:

$$S_t^{(T)} = \begin{cases} 0 & t < T, \\ 1 & t \geq T. \end{cases} \tag{5}$$

T is the exogenous impact point of time. When Z_t is a time pulse inside the dynamic system of its virtual variable response, it can be defined as:

$$P_t^{(T)} = \begin{cases} 0 & t \neq T, \\ 1 & t = T. \end{cases} \tag{6}$$

in which, T is the time point of exogenous impact. Note that $P_t^{(T)} = S_t^{(T)} - S_{t-1}^{(T)} = (1-B)S_t^{(T)}$ and they are correlated; pulse functions therefore can be expressed in terms of step functions. Some typical transfer functions for step and pulse response patterns were illustrated as shown in Figure 1.

Modeling

Strictly speaking, there is no such thing as "the best" forecasting model. Thus, the most important problem to be solved in forecasting is that of trying to match the appropriate forecasting model to the pattern of the available time series data. Box and Jenkins (1976), therefore, proposed three practical stages for finding a good model, namely identification, estimation and diagnostic checking.

Identification

The initial step in model identification is to undertake a graphical analysis of the data that would suggest whether a series is likely to be stationary or nonstationary. In addition, the results can be supported by a correlogram, which displays the estimated autocorrelation and partial autocorrelation functions of the residuals. An air passenger series is said to be stationary if the mean, variance, and covariance of the series remain constant over time. The unit root test is a formal method of testing the stationarity of a series.

The time series y_t has a stochastic trend when y_t is tested for a unit root. Ignoring the problem of the unit root will cause an error with the statistical inference (Nelson and Plosser, 1982). The most commonly used method to examine the unit root is the Augmented Dickey-Fuller (ADF) Test. If the null hypothesis is tested to show that y_t has a unit root, the alternative hypothesis of y_t is stationary. The hypotheses $H_0 : \beta_1 = 0$ and $H_1 : \beta_1 < 0$ can be tested in the following regression equation:

$$\Delta y_t = \beta_0 + \alpha t + \beta_1 y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{7}$$

in which the middle part ($\beta_1 y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i}$) of the equation is

the augmented part of the ADF test, where y_t is the natural logarithm of air passengers at time t, β_0 is the constant term in the regression, t is the deterministic trend, Δy_{t-i} represents the lagged first differences, ε_t is the error term, and α, β_1, and γ are the remaining parameters to be estimated. In order to determine p, an initial lag length of 12 is used in the Δy_t regression, and the $12th$ lag is tested for significance using the standard asymptotic t-ratio. If the $12th$ lag is insignificant at the 5% level, the lag length is reduced sequentially until a significant lag length is obtained. If the null hypothesis of a unit root is not rejected, the time series is said to be nonstationary. Appropriate regular and/or seasonal differencing is determined to transform the data to a stationary series.

Estimation

In this stage, least squares and maximum likelihood are always adopted for estimating the parameters $\phi, \Phi, \theta, \Theta$ in equation (8). If all of the important statistical relations in the stationary time series have been embodied in the SARIMA model, the ACF function for the residuals would ideally have statistically zero autocorrelation coefficients.

$$\phi(B)\Phi(B^s)\nabla_s^D \nabla^d z_t = \theta(B)\Theta(B^s)a_t \tag{8}$$

Diagnostic checking

After parameter estimation, diagnostic checking is employed by examining the residuals from the fitted model to see if the model specification is adequate. The basic assumption is that the $\{a_t\}$ are white noise. The Ljung-Box Q-statistic is often adopted to test the adequacy of a model, and can be expressed as follows:

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

where T is the sample size, $\hat{\rho}_j$ is the sample autocorrelation at lag j, and k is the number of lags being tested. Q is asymptotically χ^2 distribution with $j-p-q$. If $Q < \chi^2_{\alpha(j-p-q)}$, an accept model is reasonable; if $Q > \chi^2_{\alpha(j-p-q)}$, a reject model is reasonable. Tests at the diagnostic checking stage ensure that residuals are statistically small, that their variance does not change with time, and that residuals should be statistically independent random noise. The iterative cycle of identification, estimation and diagnostic checking is repeated until a suitable representation is found.

ANALYSIS AND RESULTS
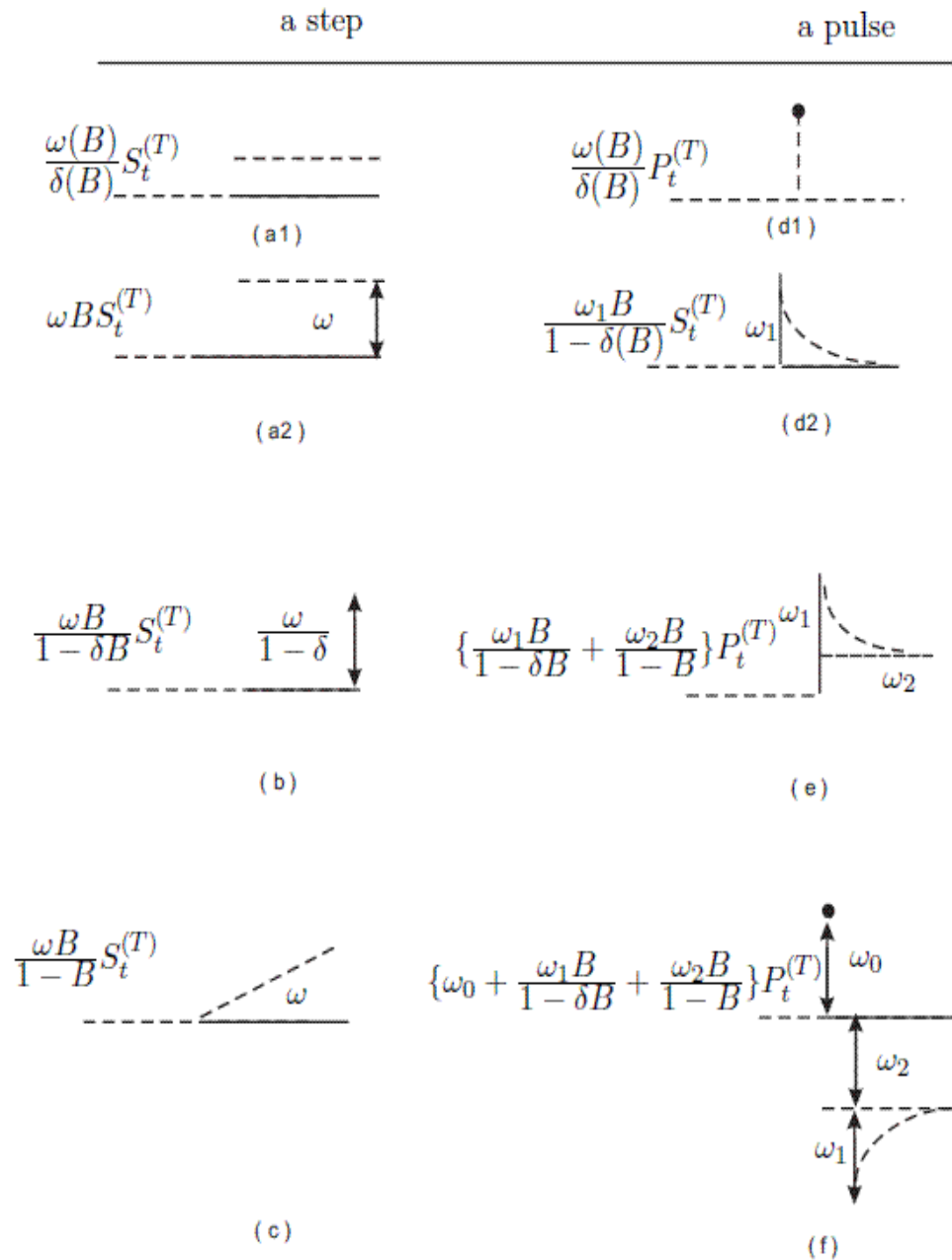
The data series in this study consisted of the monthly

Figure 1. Intervention functions.

aggregate air passengers in and out of Taiwan during the 28-year period from January 1981 to December 2008. The first aspect of a time series analysis was to plot the data, and this has been done in Figure 2. Data displays in various features were an essential tool in the analyses of the series. The plot revealed irregular variations, as well as upward and downward trends. The pattern revealed a clearly observable decline at the time of the SARS outbreak in April, 2003. In an intervention analysis, a substantial amount of data was required for the pre- and

post-intervention observations to identify the noise component N_t (Box and Tiao, 1975; Enders, 2004).

The Pre-intervention model

The appropriate model for N_t was identified prior to the known intervention, and the first 198 observations, from January 1981 to June 1997, were used for the identification process. Logarithmic transformations were
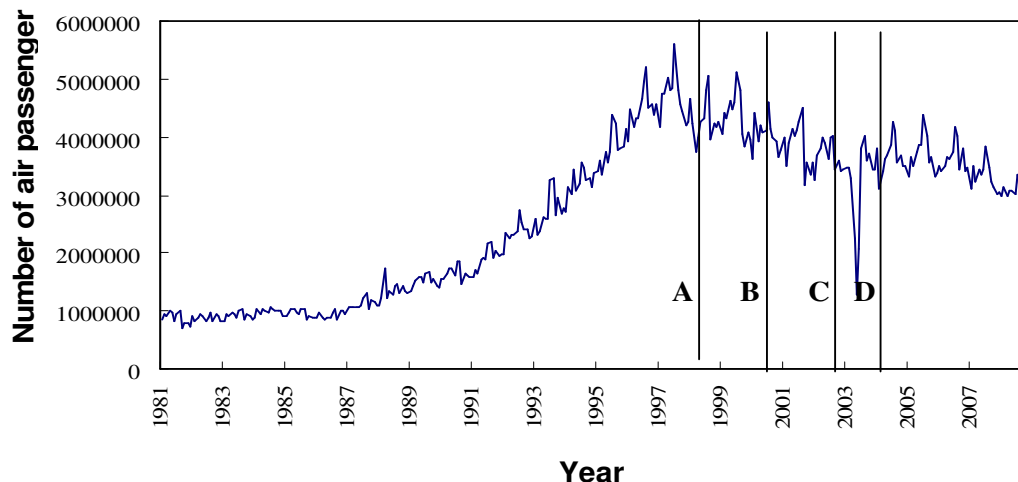
Figure 2. Time series plot from 1981 to 2008. A: Asian financial crisis. B: 9/21 earthquake. C: 9/11 terrorist attacks. D: SARS

Table 1. Unit root tests of the air passengers (1981:01-1997:06).

Variable	ADF lag length	ADF statistics	5% critical value
log z_t	13	-1.682721	-3.431368
Δ log z_t	12	-4.007376	-3.431368

applied to the series 1981/01–1997/06, and the ADF for a unit root was used to check for intercept and deterministic trends. As examined, the results of the ADF tests illustrated in Table 1 indicated that the air passenger series shows typical of a nonstationary series, because the ADF statistic for the series was -1.682721 larger than the critical value of -3.431368 at 5% significance level, indicating that the null hypothesis of a unit root was not rejected. After the first difference, the null hypothesis of a unit root was rejected, since the ADF statistic for the series was -4.007376 less than the critical value of -3.431368 at 5% significance level.

In addition, the ACF at lags 12, 24 and 36 showed the most distinct seasonal effect, indicating the presence of seasonality in the given time series. Obviously, seasonal differencing was called for. However, the seasonally differenced $(1-B^{12})$ series alone was not stationary either, as indicated by the slow die-out behavior. In view of the above indications, it became desirable to employ both the non seasonal and seasonal differencing operators in the multiplicative form $(1-B)(1-B^{12})$ to achieve stationarity. The appropriate pre-intervention model was determined by checking the diagram of the ACF and the Ljung-Box Q statistic. The tentative pre-intervention model and the estimate for the first 198 air passengers were obtained by maximum likelihood estimation as:

$$(1-B)(1-B^{12})z_t = (1-0.63231B)(1-0.74225B^{12})a_t \quad (10)$$

Twenty-four lags of the sample ACF of the residuals are computed and displayed in Figure 3, and the sample ACF appears to be 'clean', indicating the residuals approximate white noise. Thus, the fitted pre-intervention model is appropriate.

The Intervention model

The air passenger series indicated that July 1997 was the first month that the Asian financial crisis (ξ_{t1}) started to take effect. Other events included the September 21st earthquake in 1999 (ξ_{t2}), the September 11th terrorist attacks in 2001 (ξ_{t3}) and the SARS outbreak in 2003 (ξ_{t4}). An intervention model of the form was set as $\omega_0 - \omega_1 B$ and $\dfrac{\omega_0 - \omega_1 B}{1-\delta B}\xi_t$. The full intervention model and the estimates became:

$$(1-B)(1-B^{12})\Delta \log z_t =$$

$$(1-B)(1-B^{12})\left[(\omega_{01}-\omega_{11}B)\xi_1 + (\omega_{02}-\omega_{12}B)\xi_2 + (\omega_{03}-\omega_{13}B)\xi_3 + \left(\frac{\omega_{04}-\omega_{14}B}{1-\delta B}\right)\xi_4\right]$$

$$+(1-\theta_1 B)(1-\theta_{12}B^{12})a_t$$

or

```
                         Autocorrelation Plot of Residuals

Lag    Covariance      Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error
  0    0.0037194        1.00000       |                    |********************|          0
  1   -0.0001537        -.04131       |              .    *|  .              |      0.073521
  2    0.00010521       0.02829       |              .     |* .              |      0.073647
  3    0.00024277       0.06527       |              .     |* .              |      0.073706
  4   -5.9005E-6        -.00159       |              .     |  .              |      0.074017
  5   -0.0002166        -.05823       |              .    *|  .              |      0.074017
  6    0.00019175       0.05155       |              .     |* .              |      0.074265
  7    0.00048257       0.12974       |              .     |***              |      0.074458
  8   -0.0003112        -.08367       |             .**    |  .              |      0.075670
  9    0.00026489       0.07122       |              .     |* .              |      0.076169
 10    0.00004464       0.01200       |              .     |  .              |      0.076528
 11    0.00011818       0.03177       |              .     |* .              |      0.076538
 12    0.00009126       0.02454       |              .     |  .              |      0.076609
 13    0.00007280       0.01957       |              .     |  .              |      0.076652
 14    0.00032901       0.08846       |              .     |**.              |      0.076679
 15    0.00005100       0.01371       |              .     |  .              |      0.077228
 16   -0.0001741        -.04681       |            . *     |  .              |      0.077241
 17    0.00003143       0.00845       |              .     |  .              |      0.077394
 18   -0.0002277        -.06121       |            . *     |  .              |      0.077399
 19   -0.0001102        -.02962       |            . *     |  .              |      0.077661
 20   -0.0001841        -.04951       |            . *     |  .              |      0.077722
 21   -0.0000314        -.00843       |              .     |  .              |      0.077892
 22   -0.0000815        -.02191       |              .     |  .              |      0.077897
 23   -0.0002168        -.05828       |            . *     |  .              |      0.077930
 24    0.00005547       0.01491       |              .     |  .              |      0.078165
```

Figure 3. Residual autocorrelation of the pre-intervention model.

$$\Delta \log z_t = \left[(\omega_{01} - \omega_{11}B)\xi_{t1} + (\omega_{02} - \omega_{12}B)\xi_{t2} + (\omega_{03} - \omega_{13}B)\xi_{t3} + \left(\frac{\omega_{04} - \omega_{14}B}{1 - \delta B} \right)\xi_{t4} \right]$$

$$+ \frac{(1 - \theta_1 B)(1 - \theta_{12}B^{12})}{(1 - B)(1 - B^{12})} a_t$$

The estimate values for parameters were substituted as,

$$\Delta \log z_t = \left[\begin{array}{l} (0.01521 - 0.11588B)\xi_{t1} + (-0.06398 - 0.03936B)\xi_{t2} \\ + (-0.20057 + 0.10423B)\xi_{t3} + \left(\dfrac{-0.49956 - 0.86897B}{1 - 0.43856B} \right)\xi_{t4} \end{array} \right]$$

$$+ \frac{(1 - 0.60585B)(1 - 0.78329B^{12})}{(1 - B)(1 - B^{12})} a_t$$

Table 2 presents the results of the estimation and shows that only the SARS variable estimate parameters were significant with a very small p-value. The plot of the estimated residuals ACF illustrated in Figure 4 looked like "white noise," indicating that the residuals were random and the autocorrelations were within the 95% confidence interval. The impacting effect transfer function I_t of the total air passenger series was considered in the intervention model as follows:

$$I_t = (\omega_{01} - \omega_{11}B)\xi_{t1} + (\omega_{02} - \omega_{12}B)\xi_{t2} + (\omega_{03} - \omega_{13}B)\xi_{t3} + \left(\frac{\omega_{04} - \omega_{14}B}{1 - \delta B} \right)\xi_{t4}$$

$$= (\omega_{01} - \omega_{11}B)\xi_{t1} + (\omega_{02} - \omega_{12}B)\xi_{t2} + (\omega_{03} - \omega_{13}B)\xi_{t3} + (\omega_{04} - \omega_{14}B)(1 + \delta B + \delta^2 B + \cdots)\xi_{t4}$$

$$= (\omega_{01} - \omega_{11}B)\xi_{t1} + (\omega_{02} - \omega_{12}B)\xi_{t2} + (\omega_{03} - \omega_{13}B)\xi_{t3} + \omega_{04}\xi_{t4} + (\omega_{04}\delta - \omega_{14})\xi_{t4-1} + \delta(\omega_{04}\delta - \omega_{14})\xi_{t4-2} + \cdots$$

(11)

A graphic presentation of the percentage of post-intervention effects is given in Figure 5. The ARIMA model with intervention provided a useful stochastic modeling tool to quantify the consequences of the impact of the four interventions on the Taiwan air transport passenger demand; the strength and structure of an effect could also be quantified in terms of its duration (temporary or permanent) and speed (gradual or immediate).

Empirical results revealed that the SARS illness had a significant impact, whereas the Asian economic crisis, the September 21st earthquake, and the September 11th terrorist attacks showed no significant effect on air movements. The SARS outbreak, which was the last intervention variable in the study, caused a dramatic reduction in the number of air passengers. The figures showed an over 37% decline in air passengers
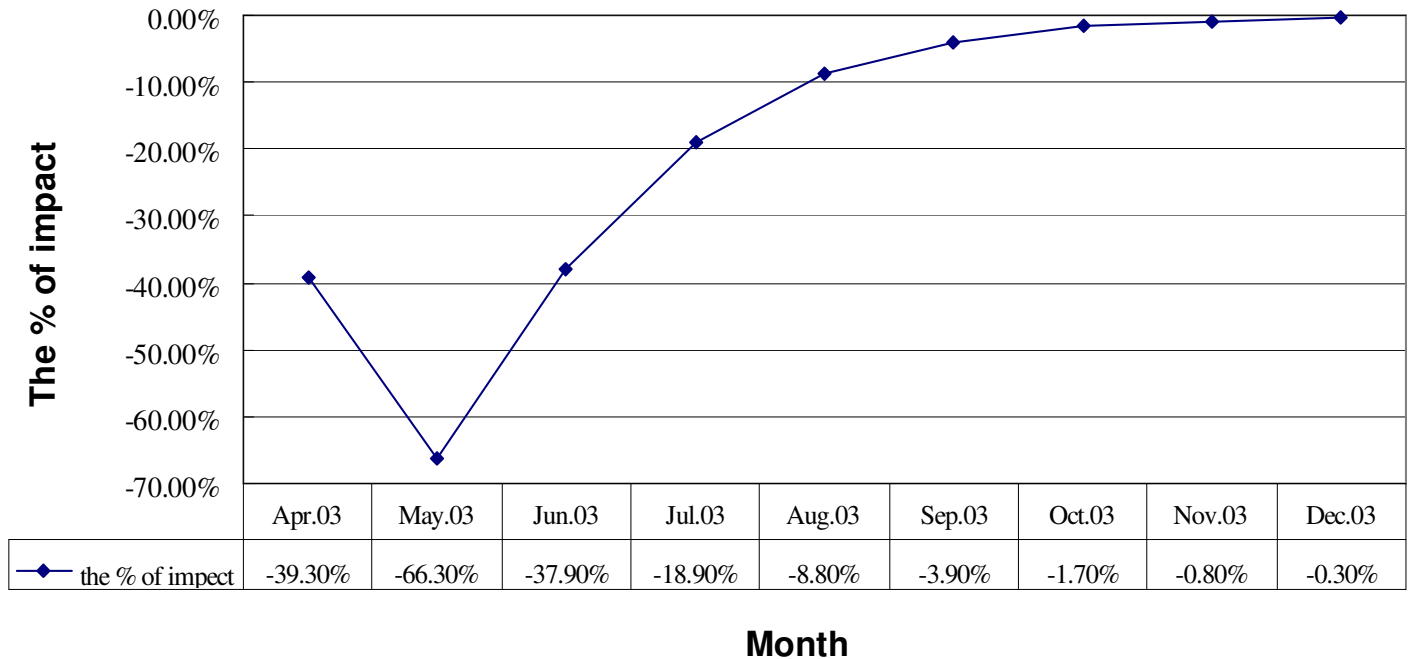
Table 2. Full-intervention model estimation.

Parameter	Estimate	Standard error	t value	Approx Pr> |t|	Lag	Variable	Shift
θ_1	0.60585	0.04502	13.46	< 0.0001	1	MA(1)	0
θ_{12}	0.78329	0.04174	18.77	< 0.0001	12	MA(12)	0
ω_{01}	0.01521	0.05524	0.28	0.7830	0	Asian financial crisis	0
ω_{11}	0.11588	0.05526	2.10	0.0360	1	Asian financial crisis	0
ω_{02}	-0.06398	0.05550	-1.15	0.2490	0	9/21 earthquake	0
ω_{12}	0.03936	0.05539	0.71	0.4774	1	9/21 earthquake	0
ω_{03}	-0.20057	0.05554	-3.61	0.0003	0	9/11 terrorist attacks	0
ω_{13}	-0.10423	0.05551	-1.88	0.0604	1	9/11 terrorist attacks	0
ω_{04}	-0.49956	0.05283	-9.46	< 0.0001	0	SARS	0
ω_{14}	0.86897	0.05758	15.09	< 0.0001	1	SARS	0
δ	0.43856	0.04181	10.49	< 0.0001	1	SARS	0

```
                          Autocorrelation Plot of Residuals

Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error
 0     0.0035380      1.00000       |                      |******************|             0
 1    -0.0002041      -.05770       |                   .*|  .                 |      0.055728
 2     0.00014458     0.04087       |                   . |*.                  |      0.055913
 3     0.00030453     0.08608       |                   . |**                  |      0.056006
 4     0.00001998     0.00565       |                   . | .                  |      0.056415
 5    -0.0000631      -.01783       |                   . | .                  |      0.056417
 6     0.00023523     0.06649       |                   . |*.                  |      0.056434
 7     0.00038066     0.10759       |                   . |**                  |      0.056677
 8    -1.0181E-7      -.00003       |                   . | .                  |      0.057308
 9     0.00025717     0.07269       |                   . |*.                  |      0.057308
10     0.00005515     0.01559       |                   . | .                  |      0.057593
11     0.00037550     0.10614       |                   . |**                  |      0.057607
12    -0.0000336      -.00951       |                   . | .                  |      0.058211
13     0.00018411     0.05204       |                   . |*.                  |      0.058216
14     0.00030969     0.08753       |                   . |**                  |      0.058360
15     0.00013722     0.03879       |                   . |*.                  |      0.058766
16     0.00015852     0.04481       |                   . |*.                  |      0.058846
17     0.00023419     0.06619       |                   . |*.                  |      0.058951
18    -0.0000240      -.00678       |                   . | .                  |      0.059182
19     0.00011379     0.03216       |                   . |*.                  |      0.059184
20    -0.0000852      -.02409       |                   . | .                  |      0.059238
21     0.00005570     0.01574       |                   . | .                  |      0.059269
22     0.00007268     0.02054       |                   . | .                  |      0.059282
23    -0.0000949      -.02683       |                   .*|  .                 |      0.059304
24     0.00011750     0.03321       |                   . |*.                  |      0.059342
```

Figure 4. Residual autocorrelation of the intervention model.

	Apr.03	May.03	Jun.03	Jul.03	Aug.03	Sep.03	Oct.03	Nov.03	Dec.03
the % of impect	-39.30%	-66.30%	-37.90%	-18.90%	-8.80%	-3.90%	-1.70%	-0.80%	-0.30%

Month

Figure 5. Post-intervention effects on air passengers (%).

during the April - June quarter, and particularly severe in May, to the lowest level since 1988. The SARS virus was new and easy to transmit, which in turn would affect travelers' intention because of its rapid spread through international air travel, as well as extensive and exaggerated media coverage. Taiwan had to cope with the third-largest SARS outbreak. In March 2003, the World Health Organization (WHO) came up with the following suggestions: (1) travelers were advised to notice the symptoms; (2) advice to airlines was issued; and (3) national authorities were recommended to implement a heightened surveillance for cases of SARS (World Health Organization, 2003). These travel advisories were aimed at limiting the rapid spread of the virus through air travel. By May, the WHO had placed Taiwan on the travel advisory list; this was the harshest travel warning in WHO history. The fast spread of the SARS virus caused fear and uneasiness for local residents and travelers from the beginning of the outbreak, though the government devoted much effort to infection control procedures to prevent the disease from spreading further. It was obvious that the sharp declines were attributed to the detrimental effects of the SARS virus. In June, the WHO removed Taiwan from the SARS travel advisory list, and traffic flows rebounded gradually. Taiwan was removed from the list of areas with recent local transmission in July and an increased flow of air passengers became evident almost immediately. Obviously, the reduction in air passengers from this tragedy represented a significant, pulse, and temporary impact on air movement.

Conclusion

This study identified both the significance and duration of four events on air passenger demand in Taiwan by employing an intervention analysis. The four incidents were the Asian financial crisis ignited in 1997, the September 21st earthquake in 1999, the September 11th terrorist attacks in 2001, and the SARS outbreak in 2003. It not only measured the impact of these four exceptional external events, but also incorporated the intervention into the air passenger time series to improve the robustness of the model to estimates. An overriding finding from the applications of intervention model in the three occasions—the Asian economic crisis, the 1999 Earthquake, and the attacks of 9/11 yielded insignificant interventions, while the SARS epidemic had a significant impact on Taiwan air travel demand. Although, the SARS adversity impeded the air passenger flows, air movement returned to pre-catastrophe levels following the pandemic's destructive impact, indicating that the effect of the disaster on air travel passenger movement presented only temporarily.

The contribution of the current study would be to use the ARIMA intervention approach to see if the air transport passenger demand in Taiwan was affected by the above four negative events. Overall, it is argued that intervention analysis is a powerful tool in the study of travel demand. Not only does it establish and measure the significance of impacts on passenger flows, but it can also assess the form of decay of the impact, be it temporary, gradual, or permanent. Additionally, the

findings of the study provide some insight for decision makers to help the industry respond to the impact of an exogenous shock and a sudden downturn in air travel demand. The study presents the first attempt at adopting intervention analysis through these four real-life misfortunes in the literature of air travel management.

The findings of this study must be considered in light of certain limitations. First, the study considered only passenger volume and did not take into account air passengers' motivations for traveling (visiting friends and relatives, holidays, or business, for example). Tourism researchers can thus conduct more in-depth studies incorporating these factors, which affect air transport passenger demand. Second, it is difficult to base an accurate assessment of improvements in passenger flows on the adopted monthly data alone. Future studies may therefore use weekly data to more precisely classify the recovery.

A number of issues require attention from future researchers. Forecasting is useful for its ability to enable government authorities and airline practitioners to make operational, tactical, and strategic decisions (Law and Au, 1999; Min, 2008b; Wang and Lim, 2005). A comparative study would thus be beneficial in assessing whether the intervention model produces better forecasts of air move-ments in comparison with other forecasting techniques, such as regression and econometric models, both of which are often adopted in the air travel demand literature. Improvements in the worldwide economic downward trend which began in September, 2008 may encourage the travel industry to react positively. However, there are still a number of uncertainties, such as unemployment and increasing public deficits, which may continue to impact the air passenger demand (World Tourism Organization, 2009). The WTO further reported that the global economic crisis, combined with the uncer-tainty caused by the A(H1N1) outbreak, turned 2009 into one of the toughest years for the tourism and travel sector. Fortunately, the recovery is underway, and even somewhat earlier and at a stronger pace than initially expected (World Tourism Organization, 2010). Future studies can employ the model and methodology used in this study in the above occurrences to identify any potential adverse effects on the flow of air passengers. On the other hand, potential increases in travel demand generally accompany major international events. Whether coming events such as the Shanghai World Exposition in China or the FIFA World Cup in South Africa will lead to a continued boost in the industry could provide a basis for further study.

REFERENCES

Alderighi M, Cento A (2004). European airlines conduct after September 11. J. Air. Transp. Manage., 10(2): 97-107.
Annelies W (2006). The severe acute respiratory syndrome: impact on travel and tourism. Travel. Med. Infect. Dis., 4(2): 53-60.
Babcock MW, Lu X (2002). Forecasting inland waterway grain traffic. Transport. Res. E-Log., 38(1): 65-74.
Batchelor R, Alizadeh A, Visvikis I (2007). Forecasting spot and forward prices in the international freight market. Int. J. Forecasting., 23(1): 101-114.
Box GEP, Jenkins GM (1976). Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day Inc.
Box GEP, Jenkins GM, Reinsel GC (1994). Time Series Analysis: Forecasting and control. 3rd edition, Prentice Hall: Englewood Cliffs, New Jersey.
Box GEP, Tiao GC (1975). Intervention analysis with applications to economic and environmental problems. J. Am. Stat. Assoc., 70: 70-74.
Cervero R (1985). Short-run forecasting of highway gasoline consumption in the United States. Transport Res A: Gen, 19(4): 305-313.
Coshall JT (2003). The threat of terrorism as an intervention on international travel flows. J. Travel. Res., 42(1): 4-12.
Coy S (2005). Management of airline arrival performance before and after September 11, 2001 in US domestic markets. J. Air. Transp. Manage., 11(4): 219-230.
Enders W (2004). Applied Econometrics Time Series. New York: John Willey & Sons, Inc.
Foreman SE (1993). An application of Box-Jenkins ARIMA techniques to airline safety data. Logist Transport Rev., 29(3): 221-240.
Gillen D, Lall A (2003). International transmission of shocks in the airline industry. J. Air. Trans. Manage., 9(1): 37-49.
Godfrey GA, Powell WB (2000). Adaptive estimation of daily demands with complex calendar effects for freight transportation. Transport. Res. B-Meth, 34(6): 451-469.
Gokhale S, Khare M (2004). A review of deterministic, stochastic and hybrid vehicular exhaust emission models. Int. J. Transp. Manage., 2(2): 59-74.
Grosche T, Rothlauf G, Heinzl A (2007). Gravity models for airline passenger volume estimation. Int. J. Transp. Manage., 13(4): 175-183.
Inglada V, Rey B (2004). Spanish air travel and the September 11 terrorist attacks: a note. Int. J. Transp. Manage., 10(6): 441-443.
Issarayangyun T, Greaves S (2007). Analysis of minute-by-minute exposure to fine particulates inside a car – a time-series modelling approach. Transport Res D-Tr E, 12(5): 347-357.
Karlaftis MG, Vlahogianni EI (2009). Memory properties and fractional integration in transportation time-series. Transport Res C-Emer, 17(4): 444-453.
Lai SL, Lu WL (2005). Impact analysis of September 11 on air travel demand in the USA. J. Air. Transp. Manage., 11(6): 455-458.
Lau JC, Hung WT, Yuen DD, Cheung CS (2009). Long-memory characteristics of urban roadside air quality. Transport Res D-Tr E, 14(5): 353-359.
Law R, Au N (1999). A neural network model to forecast Japanese demand for travel to Hong Kong. Tourism Manage, 20(1): 89-97.
Lee S, Oh C, O' Leary JT (2005). Estimating the impact of the September 11 terrorist attacks on the US air transport passenger demand using intervention analysis. Tourism Anal, 9(4): 355-361.
Lepak GM (1997). Airline deregulation and the impact on stock prices of major surviving carriers. Transport Res E-Log, 33(2): 107-115.
Lim C, McAleer M (2002). Time series forecasts of international travel demand for Australia. Tourism Manage., 23(4): 389-396.
Liu LM (2006). Time Series Analysis and Forecasting. 2nd edition, Scientific Computing Associations Corp.
Males M (2007). California's graduated driver license law: effect on teenage drivers' deaths through 2005. J. Safety. Res., 38(6): 651-659.
Mason KJ (2005). Observations of fundamental changes in the demand for aviation services. J. Air. Transp. Manage., 11(1): 19-25.
McLeod I, Vingilis ER (2008). Power computations in time series analyses for traffic safety interventions. Accident Anal Prev., 40(3): 1244-1248.
Min J (2008a). Intervention analysis of inbound tourism: a case study of Taiwan. Advances Hospitality Leisure, 4: 53-74.
Min J (2008b). Forecasting Japanese tourism demand in Taiwan using an intervention analysis. Int. J. Cult. Tourism. Hospitality. Res., 2(3): 197-216.

Narayan J, Considine J (1989). Intervention analysis to assess the impact of price changes on ridership in a transit system: a case study. Logist. Transport. Rev., 25(1): 53-62.

Nelson C, Plosser C (1982). Trends and random walks in macroeconomic time series. J. Monetary. Econ., 10(2): 139-162.

Pitfield DE (1993). Predicting air-transport demand. Environ. Plann., 25(4): 459-466.

Pitfield DE (2007).The impact on traffic, market shares and concentration of airline alliances on selected European—US routes. J. Air. Transp. Manage., 13(4): 192-202.

Pitfield DE (2008). The Southwest effect: a time-series analysis on passengers carried by selected routes and a market share comparison. J. Air. Trans. Manage., 14(3): 113-122.

Rossiter A, Dresner M (2004). The impact of the September 11th security fee and passenger wait time on traffic diversion and highway fatalities. J. Air. Transp. Manage., 10(3): 225-230.

Sharma P, Khare M (1999). Application of intervention analysis for assessing the effectiveness of CO pollution control legislation in India. Transport Res D-Tr E, 4(6): 427-432.

Sharma P, Khare M (2000). Real-time prediction of extreme ambient carbon monoxide concentrations due to vehicular exhaust emissions using univariate linear stochastic models. Transport Res. D-Tr E, 5(1): 59-69.

Sharma P, Khare M (2001). Short-term, real-time prediction of the extreme ambient carbon monoxide concentrations due to vehicular exhaust emissions using transfer function-noise model. Transport. Res. D-Tr E, 6(2): 141-145.

Smith BL, Williams BM, Oswald RK (2002). Comparison of parametric and nonparametric models for traffic flow forecasting. Transport. Res. C-Emer., 10(4): 303-321.

Wagenaar AC, Maldonado-Molina MM, Ma L, Tobler AL, Komro KA (2007). Effects of legal BAC limits on fatal crash involvement: analyses of 28 States from 1976 through 2002. J. Safety. Res., 38(5): 493-499.

Wang Y, Lim C (2005). Assessing forecasting models for outbound Japanese travelers to Australia and China. J Appl Econ. Manage., 3(1): 1-15.

World Health Organization (WHO) (2003). World health organization issues emergency travel advisory. Retrieved March 15, 2003, from http://www.who.int/csr/sars/archive/2003_03_15/en/

World Tourism Organization (2009). UNWTO world tourism barometer. Retrieved August 1, 2009, from http://unwto.org/facts/eng/pdf/barometer/UNWTO_Barom09_1_en_excerpt.pdf

World Tourism Organization (2010). International tourism on track for a rebound after an exceptionally challenging 2009. Retrieved March 1, 2010, from http://www.unwto.org/media/news/en/press_det.php?id=5361