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Assessing impacts of SARS and Avian Flu on international tourism demand to Asia

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Abstract

The purpose of this paper is to investigate the impacts of infectious diseases including Avian Flu and severe acute respiratory syndrome (hereafter SARS) on international tourist arrivals in Asian countries using both single datasets and panel data procedures. An autoregressive moving average model together with an exogenous variables (ARMAX) model are used to estimate the effects of these diseases in each SARS- and Avian Flu-infected country, while a dynamic panel model is adopted to estimate the overall impact on the region of these two diseases. The empirical results from both approaches are consistent and indicate that the numbers of affected cases have a significant impact on SARS-affected countries but not on Avian Flu-affected countries. However, since the potential damage arising from the Avian Flu and subsequent pandemic influenza is much greater than that resulting from the SARS, the need to take the necessary precautions in the event of an outbreak of Avian Flu and pandemic influenza warrants further attention and action. Therefore, the empirical findings of this study could add to the knowledge regarding the relationship between tourism and crisis management, especially in so far as the management of transmissible diseases is concerned.

Keywords: SARS; Avian Flu; International travel; ARMAX; Dynamic panel model

1. Introduction

The global tourism industry has been significantly affected by disasters and crises. Page, Yeoman, Munro, Connell, and Walker (2006) pointed out that the recent disasters or crises including 9/11 and Hurricane Katrina in the US, the outbreaks of foot and mouth disease in the UK, the severe acute respiratory syndrome (SARS) epidemic in the Asian countries, and the devastation caused by the Indian Ocean tsunami had a huge adverse impact on international tourism. For example, following the 2004 Indian Ocean tsunami, the number of international arrivals in Phuket, Thailand’s second international gateway, dropped by 67.2% in the first half of 2005, and an estimated 500 tourism companies, employing more than 3000 people, collapsed during these months with predictions of further job losses (Henderson, 2007). Wilder-Smith (2006) noted that there was a drop of 12 million arrivals in Asian and Pacific countries following the outbreak of the Avian Flu epidemic. The World Travel and Tourism Council (2003) estimated that approximately 3 million people in the tourism industry lost their jobs following the outbreak of SARS in the most severely affected countries of China, Hong Kong, Vietnam and Singapore, which resulted in losses of over $20 billion in terms of GDP.

However, there is a new disease, namely Avian Flu and the pandemic influenza that would emerge from it, that could cause much greater damage to the global tourism industry than all the above disasters or crises once it emerges into a pandemic influenza (Page et al., 2006). Since this Avian Flu is still in its relatively early stages, its impact on tourism has so far been relatively moderate. Nonetheless, it is in our interests to estimate its impact on the tourism sector and to compare it to other crisis/disaster level diseases, such as SARS, so that people can learn from
these former outbreaks and be well prepared to limit such a deadly disease’s potential damage.

Much of the development of the relationship between tourism and crisis management can be credited to Faulkner (2001). Faulkner defines a crisis as an event which disrupts an organization’s (or destination’s) functioning, and of which a large part of its effects can be prevented or reduced by human efforts. On the other hand, a “disaster” has been used to refer to the situation where a destination is confronted with unpredictable catastrophic change over which it has little control. In this sense, the current Avian Flu epidemic is more of a crisis than a disaster. Meanwhile, Page et al. (2006) pointed out the importance of comparing the post-crisis analysis with the pre-crisis analysis (e.g., Beirman, 2003; Ritchie, 2004; Glaeber, 2005). Comparing the post-crisis analysis of SARS with the pre-crisis analysis of Avian Flu can form a strategic framework that will combat the transmissible diseases. Meanwhile, Page et al. (2006) pointed out the global spread of Avian Flu was taking place at such a speed that its geographical distribution was changing weekly and that the simulated data in their paper would certainly be overtaken. Thus, this paper follows the suggestion by Page et al. (2006) that updated data be used to analyze Avian Flu.

Avian Flu has recently been found in nearly 50 countries. Meanwhile, about 200 cases of humans who have been infected by Avian Flu have been confirmed, and the mortality rate of 59% (WHO, 2006) has been high. Avian Flu has a potential global reach in that it can spread through international travel, but a short- to medium-term slowdown could result in the shutdown of the tourism sector (Page et al., 2006). Thus, international tourism will be seriously affected or even restricted to prevent the spread of Avian Flu and pandemic influenza. Brahmbhatt (2005) estimates that the 2004 Avian Flu outbreak in Vietnam led to a 1.8% decline in GDP, where a 5% decline in tourist arrivals could lead to a 0.4% decline in GDP. Furthermore, the World Bank estimated that the global economic influence of an outbreak of Avian Flu could be US $800 billion, equal to 2% of world economic output (Brahmbhatt, 2005).

To estimate the impacts of two infectious diseases, SARS and Avian Flu, on tourism demand in Asia’s most affected countries, two important methodologies are adopted in this study. First, we estimate the effects by implementing an autoregressive moving average model with exogenous variable (ARMAX) procedures involving a single dataset, which includes performing unit root tests for dependent and independent variables, constructing the autoregressive moving average (ARMA) models for dependent variables, and finally estimating the potential impacts by using the ARMAX models. An ARMAX model includes dynamic autoregressive and moving components in addition to theoretical explanatory variables to explain variations in endogenous variables. Bierens (1987) developed estimation and testing methodology for such a model. In the field of tourism, numerous studies have applied the models to estimate the impacts of terrorism on tourism and forecast tourism revenues. For example, Enders, Sandler, and Parise (1992) and Sloboda (2003) utilized ARMAX models to assess the effects of terrorism on tourism for various European nations and the USA. Akal (2004) found the cause–effect relationship between international tourist arrivals and tourism revenues and forecasted the future values of revenues by using ARMAX models. In order to estimate the impacts of epidemic diseases including SARS and Avian Flu on tourism demand in most Asian affected countries, the methodology of the ARMAX model is adopted in our study.

Secondly, a dynamic panel model using the generalized method of moments (GMM) estimation of Arellano and Bond is implemented in this paper to estimate the overall impact on regional tourism of SARS and Avian Flu in the infected countries. Hsiao (2003) indicated that, compared with the use of time-series or cross-section data, the utilization of pooled time-series/cross-section dataset has several advantages, such as more degrees of freedom, the mitigation of multicollinearity, a reduction in omitted variable bias, and hence an improvement in the accuracy of the parameter estimates.

The remainder of this paper is organized as follows. Section 2 introduces SARS and Avian Flu in more detail and this section can be skipped without losing the understanding of the whole paper. The dataset and econometric approach are introduced in Section 3, while the results of the empirical estimation results are addressed in Section 4. Finally, the policy implications and concluding remarks are given in Section 5.

2. SARS and Avian Flu

Richter (2003) indicated that one of the inevitable effects of globalization was increasing international travel and the emergence of infectious diseases. Numerous epidemic and pandemic diseases that have caused global concern for the World Health Organization (WHO) include SARS, Avian Flu, malaria, cholera, anthrax, tuberculosis, hepatitis and other diseases which can spread easily through international travel.

SARS, which has been caused by atypical pneumonia and has spread through close person to person contact, has generated panic all over the world since its outbreak in March 2003. Globally, the outbreak of SARS has claimed around 774 lives out of 8096 infected cases from 27 countries/areas, mostly in China, Hong Kong, Taiwan, and Singapore (WHO, 2004). In order to limit the spread of infection by international travel, WHO has advised the postponement of nonessential travel to SARS-affected areas. Asian tourism, which has mostly involved infected areas, has thus been badly affected since the outbreak of SARS in 2003. Table 1 lists the numbers of cases and deaths from SARS by country, while Table 2 lists the
numbers of confirmed human cases of Avian Flu for each country and time period.

SARS or Avian Flu can damage destination marketing, a finding that is emphasized by Buhalis (2000) and Mohsin (2005). These diseases can reduce the competitiveness of affected countries and thus give rise to a reduction in international arrivals. Page et al. (2006) pointed out that Avian Flu would cause severe shocks to tourism and a much deeper crisis of confidence in regard to travel than infectious illnesses such as SARS. Furthermore, Avian Flu might result in a high mortality rate among humans as a result of the disease being transmitted from animals to humans, but not by close person to person contact. Therefore, the travel advisories and restrictions can be much more serious for Avian Flu once it becomes easily transmitted between humans.

3. Data description and empirical methodology

3.1. Data

This study uses monthly time series data for the four SARS-infected countries/areas in Asia, namely China, Hong Kong, Singapore, and Taiwan, and two mainly Avian Flu-infected countries/areas, namely Indonesia and Vietnam. Garín-Muñoz and Pérez-Amaral (2000) indicated that international tourism demand is usually measured by proxies such as the volume of earnings generated by foreign visitors, the number of nights spent by visitors from abroad, and the number of foreign visitors. Because people face the potential danger of being infected by SARS and Avian Flu through international travel, travelers might limit nonessential travel to affected countries. Thus, we use the number of foreign visitors, namely the number of international tourist arrivals, to estimate the impacts of the two diseases on international tourism demand. The monthly data for international tourist arrivals are collected from statistical datasets for each country, and the probable numbers of SARS-infected patients and the confirmed human cases of Avian Flu are obtained from the World Health Organization (WHO, 2006). The study period for the SARS case extends from January 2001 to December 2004, while the monthly data for the Avian Flu case covers the period from October 2002 to September 2006. The econometric software applied in this study is Eviews 5.0.

Table 1
Summary of SARS cases and deaths

| Country/area      | Cases | Deaths |
|-------------------|-------|--------|
| Australia         | 6     | 0      |
| Canada            | 251   | 43     |
| China             | 5327  | 349    |
| Hong Kong         | 1755  | 299    |
| Macao             | 1     | 0      |
| Taiwan            | 346   | 37     |
| France            | 7     | 1      |
| Germany           | 9     | 0      |
| India             | 3     | 0      |
| Indonesia         | 2     | 0      |
| Italy             | 4     | 0      |
| Kuwait            | 1     | 0      |
| Malaysia          | 5     | 2      |
| Mongolia          | 9     | 0      |
| New Zealand       | 1     | 0      |
| Philippines       | 14    | 2      |
| Republic of Ireland | 1  | 0      |
| Republic of Korea | 3    | 0      |
| Romania           | 1     | 0      |
| Russian Federation | 1  | 0      |
| Singapore         | 238   | 33     |
| South Africa      | 1     | 1      |
| Spain             | 1     | 0      |
| Sweden            | 5     | 0      |
| Switzerland       | 1     | 0      |
| Thailand          | 9     | 2      |
| United Kingdom    | 4     | 0      |
| United States     | 27    | 0      |
| Vietnam           | 63    | 5      |
| **Total**         | **8096** | **774** |

Source: World Health Organization (2006).

Table 2
Numbers of confirmed human cases of Avian Flu A/(H5N1)

| Year | Cases | Deaths |
|------|-------|--------|
| 2003 | 4     | 4      |
| 2004 | 46    | 32     |
| 2005 | 97    | 42     |
| 2006 | 109   | 74     |
| **Total** | **256** | **152** |

Source: World Health Organization (2006).

Note: (1) The total number of cases includes the number of deaths. (2) WHO reports only laboratory-confirmed cases from 1 January 2003 to 6 June 2006.
Furthermore, the ARMA and ARMAX models are estimated by using nonlinear least squares estimators, while dynamic panel models are implemented by using the panel GMM technique.

Seasonality is a widely known aspect of tourism time series data (Lim and McAleer, 2001), which might lead to spurious and biased results. In order to better reveal certain non-seasonal features, seasonal adjustment is the process of estimating and removing seasonal effects from a time series. Lim and McAleer (2001) noted that the conventional and frequently-used technique for smoothing time series data is the moving average method. Hence, before estimating the effects of SARS and Avian Flu on tourism demand, the EViews software package is used to implement the process of seasonal adjustment for the tourist arrivals series in order to remove the seasonal effects by means of the multiplicative moving average method. The seasonally adjusted series for international tourism demand is then obtained to process the ARMAX models and dynamic panel data models.

### 3.2. ARMAX models for single datasets

Time series models have been applied to estimate or forecast tourism demand. An ARMAX model includes dynamic autoregressive and moving average components in addition to theoretical explanatory variables to explain variations in endogenous variables. An ARMAX model is an ARMA model for an endogenous dependent variable with additional exogenous independent variables (X). Greene (2000, p. 764) pointed out that the ARMA model is a specific case of ARMAX without explanatory variables, while Harvey (1990) and Franses (1991) considered the ARMAX problems to be an extension of ARMA model because the disturbances are generated by an ARMA process. Therefore, the ARMA model needs to be identified before constructing the ARMAX model. Furthermore, Akal (2004) indicated that the ARMAX model corrects for the shortcomings of the econometric cause-effect technique by using dynamic filters to explain the variations in dependent variables. An explanatory part is integral to the ARMA process in constructing the ARMAX model. The general ARMAX model (Bierens, 1987) can be written as:

\[
(1 - \sum_{i=1}^{p} \alpha_i L^i)y_t = \mu + \sum_{i=1}^{r} \beta_i L^i x_{t+i} + \left(1 + \sum_{i=1}^{q} \gamma_i L^i\right)\epsilon_t,
\]

where \(L\) is the lag operator, defined as \(L^i z_t = z_{t-i}\) (thus, \(L y_t = y_{t-1} - L^2 y_t = x_{t-1} - \ldots\), etc.), \(\alpha_i \in \mathbb{R}, \mu \in \mathbb{R}, \beta_i \in \mathbb{R}, \gamma_i \in \mathbb{R}\) are unknown parameters, \(y_t\) is a stationary-dependent variable, \(x_t\) is a \(k\)-dimensional vector of independent variables, the \(\epsilon_t\)’s are white noise disturbances, \(p\) denotes the lag length of the autoregressive (AR) terms, and \(q\) represents the lag length of the moving average error (MA) terms.

According to the ARMAX concept, the left side is the AR part of the model in Eq. (1), while the second term on the right-hand side represents the X part and the third expression the MA part. Franses (1991) points out that the main advantage of an ARMAX model is that it can allow an infinite lag structure with a small number of parameters, while the lag polynomial in front of \(\epsilon_t\) is invertible so as to make an ARMAX model become an ARX(\(x\)) model.

In order to investigate the impacts of epidemic diseases on tourism demand, we specifically estimate the influence of two epidemic diseases, SARS and Avian Flu, in mainly infected Asian countries. These two ARMAX models are specifically expressed as follows:

\[
(1 - \sum_{i=1}^{p} \alpha_i L^i)y_t = \mu + \sum_{i=1}^{r} \beta_i L^i S_{t+i} + \left(1 + \sum_{i=1}^{q} \gamma_i L^i\right)\epsilon_t,
\]

\[
(1 - \sum_{i=1}^{p} \rho_i L^i)y_t = \mu + \sum_{i=1}^{r} \delta_i L^i B_{t+i} + \left(1 + \sum_{i=1}^{q} \psi_i L^i\right)\epsilon_t,
\]

where \(y_t\) is tourism demand, and \(t = 1, \ldots, T\) refers to the time periods. If the ARMAX model only consists of distributed lags, the \(\beta_i\) are estimated parameters that represent the effects of the probable SARS-infected patients on tourism demand while \(S\) represents the number of the probable SARS-infected patients in Eq. (2). Similarly, the \(\delta_i\) are estimated parameters that represent the effects of the Avian Flu patients on tourism demand while \(B\) refers to the number of confirmed cases of Avian Flu in Eq. (3). On the other hand, if both distributed lags and AR terms were to be included in the ARMAX models, the coefficient that determines the impacts in each period would be calculated on the basis of the quotient of the polynomials formed by the distributed lags and by the AR polynomial lags. The process of driving the lag coefficients of the ARMAX model is shown in Appendix A. In addition, all variables included in an ARMAX model must be stationary series. Therefore, if a series is an \(I(0)\) series, the variables will be included in the ARMAX model in the levels form. On the contrary, if a series is an \(I(1)\) series, the variables will be included in the first-difference form. A detailed account of the ARMAX estimation procedures is given as follows.

The general ARMAX models that include an inevitability assumption can be estimated using nonlinear least squares and constructed by implementing the following estimation procedures. As Franses (1991) mentioned, the ARMAX model concept requires that all dependent and independent variables be stationary series. Therefore, the first step is to implement the unit root tests for stationarity. In order to make sure that all dependent and independent variables in each country are stationary, the Augmented Dickey–Fuller (henceforth ADF) test is employed to perform the unit root tests. The ADF auxiliary regressions
may be expressed as follows:

\[ \Delta y_t = a_0 + r y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + e_t, \]  

\[ \Delta y_t = a_0 + r y_{t-1} + a_2 t + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + e_t, \]

where \( y_t \) is the variable to be tested, and \( t \) is the time trend. The first equation represents the no time effect model, while the second one has a fixed time effect. The lag length, \( i \), is chosen using Akaike’s information criterion. 

MacKinnon (1991) implemented a large set of simulations and estimated the response surface using the simulation results, thereby permitting the calculation of Dickey–Fuller critical values for any sample size or for any number of right-hand variables. Therefore, MacKinnon critical values have been used to conduct the ADF test of the hypothesis of a unit root, values have been used to conduct the ADF test of the critical values for any sample size or for any number of confirmed cases of Avian Flu, are modeled without a time effect.

Secondly, before incorporating the explanatory part to construct the ARMAX model, we must identify a suitable ARMA model for the dependent variable (Franses, 1991). Various procedures are fitted to determine the appropriate lag length of the dependent variables, i.e., the monthly international arrivals series for each country, in order to conduct suitable ARMA processes. A suitable model is generally preferred since it fits the data without including unnecessary variables. The two most commonly used criteria for model selection are Akaike’s Information Criterion (AIC) and Schwartz’s Bayesian Criterion (SBC), with the decision to base the model choice being to select the model for which the appreciate criterion is the smallest.

Thirdly, these independent variables are incorporated into the ARMA model to build the initial ARMAX model, in which the lag lengths for the independent variables are determined according to the maximum lengths of the AR and MA terms. Finally, we test the hypotheses by imposing restrictions on the estimated parameters of the initial ARMAX model to obtain a simplified ARMAX model. The estimated initial ARMAX model can be used to test the hypotheses by imposing restrictions on the estimated parameters, and to evaluate the simplified model again. In our study, the simplification of the initial model is based on two criteria, the Wald test statistic for the null hypothesis where some parameters equal zero simultaneously, and \( R^2 \). Franses (1991) observed that the Wald test severely penalizes the inclusion of too many variables and therefore usually prefers the smaller model, whereas \( R^2 \) is a more conservative criterion for the larger model.

### 3.3. Dynamic panel data models for panel datasets

Garín-Muñoz (2006) pointed out that using a pooled time-series/cross-section dataset as the sample data could increase the range of variation in the variables because of substantial differences across countries in terms of the level of income and other socio-demographical characteristics. In addition, the utilization of this type of data enables us to have a relatively large number of observations and a consequent increase in degrees of freedom, hence reducing collinearity and improving the efficiency of the estimates (Song & Witt, 2000). In this study, two balanced panel datasets are used consisting of monthly data on four SARS-infected countries (i.e., China, Hong Kong, Singapore, and Taiwan) and two Avian Flu-affected countries (i.e., Indonesia and Vietnam) to investigate the overall impact of these two infectious diseases on regional tourism.

Garín-Muñoz and Pérez-Amaral (2000) suggested that tourism has a great deal of inertia, and that a dynamic model could be estimated to capture the effect of past tourism. Garín-Muñoz (2006) indicated that the estimation of the influence of other relevant variables will be overestimated if the impact of previous tourism is neglected. Hence, including previous dependent variables in a dynamic model for studying tourism demand is one of the possible strategies for handling the dynamic structure of consumer preferences where changes in taste are regarded as endogenous (Garín-Muñoz, 2006; Garín-Muñoz & Pérez-Amaral, 2000; Ledesma-Rodríguez, Navarro-Ibáñez, & Pérez-Rodríguez, 2001). In our study, the lagged dependent variables of tourism demand, which are interpreted as being based on habit formation or as interdependent preferences, are included as regressors in considering the possibility of a change in consumer preferences. Two dynamic versions of the tourism demand models are expressed as follows:

\[
y_{it} = \eta_1 + \eta_2 y_{it-1} + \eta_3 s_{it} + u_{it}, \tag{6}
\]

\[
y_{jt} = \varphi_1 + \varphi_2 y_{jt-1} + \varphi_3 B_j + \varphi_4 D_{jt} + u_{jt}, \tag{7}
\]

where \( y_{it} \) and \( y_{jt} \) represent tourism demand, \( i \) refers to SARS-infected countries, \( j \) refers to Avian Flu-infected countries, and \( t \) represents the time periods. In Eq. (6), \( u_{it} = \eta_t + \epsilon_{it} \) is the fixed effects decomposition of the error term in which \( \eta_t \) is the individual specific effect. The error component \( \epsilon_{it} \) is assumed to be uncorrelated with zero and independently distributed across countries. Moreover, in the Avian Flu-infected panel model, i.e., Eq. (7), a dummy variable \( D_{jt} \) is included to capture the possible effects of terrorism in Indonesia in October 2005. The variable takes the value of 1 in the above-mentioned month for Indonesia and 0 otherwise. A negative sign is expected for the coefficients of \( \eta_2, \varphi_2 \), and a negative one for the coefficients of \( \eta_3, \varphi_3, \varphi_4 \).

However, Garín-Muñoz (2006) indicates that when lagged dependent variables are included as regressors, not only the OLS estimator, but also the within groups (WG)
and random effects estimators are biased and inconsistent. Taking the first-difference transformation models (GMM-DIFF) and treating the lags of the dependent variables as instruments for the lagged dependent variable could solve the biased and inconsistent problems (Garin-Muñoz, 2006; Ledesma-Rodríguez et al., 2001). Therefore, the dynamic panel procedures of Garín-Muñoz (2006) were applied to investigate the impacts of SARS and Avian Flu on tourism demand.

The dynamic and first-difference versions of the tourism demand models are expressed as follows:

\[
\Delta y_{it} = \eta_1 \Delta y_{it-1} + \eta_2 \Delta y_{it-2} + \Delta u_{it}, \quad (8)
\]

\[
\Delta y_{jt} = \phi_2 \Delta y_{jt-1} + \phi_3 \Delta B_{jt} + \phi_4 \Delta D_I_{jt} + \Delta u_{jt}, \quad (9)
\]

where \(\Delta y_{it} = y_{it} - y_{it-1}\) and analogously for the other variables. It needs to be mentioned that using a dynamic panel model will generate more precise results by differencing data and removing the problem of non-stationarity (Garin-Muñoz, 2006).

4. Empirical results

4.1. ARMAX models for single datasets

4.1.1. The impact of SARS on tourism demand

Before building an ARMAX model for each SARS-infected country, the unit root tests must be implemented to ensure that the dependent variable is stationary. Table 3 presents the results of the ADF tests for the three series, including tourism demand, namely, international tourist arrivals, the probable SARS-infected patients and the number of confirmed cases of Avian Flu. The ADF test statistics are compared with the critical values from the nonstandard Dickey–Fuller distribution at the 5% significance level. If the ADF statistics are less than the critical value (i.e., MacKinnon critical values) at the 5% level, this will lead to the rejection of the unit root hypothesis, whereas the reverse results suggest that the null hypothesis of a unit root is not rejected.

Since the ADF statistics with time effects for the tourism demand series for all SARS-infected countries are greater than the critical value, the unit root hypothesis cannot be rejected, implying that the series are non-stationary. By taking the first differences of the series, the unit root can be rejected for the first differences at the 5% significance level. We may, therefore, reasonably conclude that the series in relation to the tourism demand will be included in the ARMAX model for every country in the first-difference form. On the other hand, for the series regarding the number of SARS-infected patients, the ADF results without a deterministic trend show that stationarity exists in each country. Hence, the independent variables of probable SARS-infected patients will be included in the ARMAX model for each country in the levels form.

In order to identify a suitable ARMA model for the dependent variable that has been transformed appropriately to obtain stationarity, two goodness-of-fit criteria, namely, the AIC and SBC, are used to select the most appropriate model. The results of deciding the initial ARMA model for the first-difference series of dependent variables in each country are presented in Table 4. The model involving AR(2) and MA(2) in China is the most adequate ARMA model, while the first-difference series of tourism demand for Hong Kong, Singapore, and Taiwan are represented by the ARMA(1,3) model, ARMA(1,3) model, and ARMA(1,3) model, respectively.

After selecting the ARMA model for the dependent variable, the next step is to determine the lag length of probable SARS-infected patients (\(S\)). In this study, we start with an over-parameterized model according to maximum lengths of the AR and MA terms to get an initial ARMAX model. The results of the initial ARMAX model are presented in Appendix B.

Table 5 shows the results of the simplified ARMAX model for estimating the impacts of SARS on tourism demand, namely, the estimation results of SARS on the tourism demand for China, Hong Kong, Singapore, and Taiwan. The estimated coefficients for probable SARS-infected cases (\(S_{it}, S_{it-1}, S_{it-2}, S_{it-3}\)) could be interpreted as the impacts of each SARS-infected patient on tourism demand if only distributed lags are included in the ARMAX model. For instance, the estimated results from Table 5 show that the impacts of probable SARS-infected cases on tourism demand for the current and next periods in Singapore will be significantly reduced by 798 and 1742 arrivals, respectively. However, the coefficients
that determine the impacts on each period would be calculated on the basis of the quotient of polynomials formed by the distributed lags and by the AR polynomial lags if both the distributed lags and AR terms are included in the ARMAX models. The coefficients that determine the impacts of each period for China, Hong Kong and Taiwan are shown in Table 6.

As for the impacts of probable SARS-infected patients on the tourism demand in China, we found that the change in tourism demand was reduced by 299 persons as one person became infected by SARS in the current period (or month) while in the next period the tourism demand was reduced by 355 arrivals. However, the estimation results for Hong Kong show that the impact of probable SARS-infected patients was that the tourism demand was reduced by 149 arrivals as one more person became infected with SARS in the current month. Finally, the estimation results for the impact of probable SARS-infected patients on the tourism demand in Taiwan are shown in the last column of Table 6. In Taiwan, if one more person were to be infected by SARS in the current period, there would be reductions in the tourism demand in the current and the next period of about 175 and 57 arrivals, respectively. The estimation results in Table 6 indicate that the time period for the impacts of SARS on tourism demand in Asian countries extends for about 2 months which implies that the impact of SARS on tourism demand constitutes a short-term shock.

There are certain important findings resulting from the ARMAX models for estimating the impact of SARS on tourism demand. Firstly, as expected, international tourist arrivals were negatively affected by the epidemic disease for all SARS-infected countries. We can see from above empirical results that either the current period or the previous month for each SARS-infected person (i.e. \( S_{it}, S_{it(-1)} \)) has a significantly negative impact on tourism demand. Secondly, the impact of each SARS-infected person on tourism demand in these Asian countries ranges from 175 to 1742 depending on the location. We found that the damage levels in Taiwan and China were less pronounced than those in Hong Kong and Singapore, which implies that the government’s reaction and strategies in dealing with this serious disease may result in different levels of damage.

### 4.1.2. The impact of Avian Flu on tourism demand

The results of the ADF tests for the series on tourism demand and the number of confirmed cases of Avian Flu in the mainly Avian Flu-infected countries, Indonesia and Vietnam, are shown in Table 3. Since the ADF statistics with the time effects of the series on tourism demand for the two countries are greater than the critical value, the empirical results that either the current period or the previous month for each SARS-infected person has a significantly negative impact on tourism demand.

### Table 4

| ARMA model of tourism demand for SARS countries |
|-----------------------------------------------|
| Country/area | Model  | AIC  | SBC  |
|----------------|--------|------|------|
| China          | ARMA(1,2) | 28.782 | 28.941  |
|                | ARMA(1,3) | 28.823 | 29.022  |
|                | ARMA(2,2) | 28.621 | 28.822  |
|                | ARMA(2,1) | 28.763 | 28.923  |
|                | ARMA(3,2) | 28.782 | 29.025  |
| Hong Kong      | ARMA(1,3) | 26.608 | 26.807  |
|                | ARMA(2,2) | 26.815 | 27.016  |
|                | ARMA(2,3) | 26.857 | 27.098  |
|                | ARMA(3,2) | 26.910 | 27.153  |
| Singapore      | ARMA(1,3) | 25.202 | 25.401  |
|                | ARMA(2,2) | 25.257 | 25.458  |
|                | ARMA(2,3) | 25.301 | 25.542  |
|                | ARMA(3,2) | 25.288 | 25.531  |
| Taiwan         | ARMA(1,1) | 23.617 | 23.736  |
|                | ARMA(1,2) | 23.244 | 23.403  |
|                | ARMA(1,3) | 22.904 | 23.103  |
|                | ARMA(2,1) | 23.440 | 23.600  |
|                | ARMA(2,2) | 23.239 | 23.440  |

The appropriate models are selected by using AIC and SBC.

### Table 5

| Results of simplified ARMAX model for SARS |
|-------------------------------------------|
| Variable | Coefficient (P-value) |
|---------|----------------------|
| Constant |                     |
| \( S_{it} \) | \(-298.57** (0.010) \) |
| \( S_{it(-1)} \) | \(-481.22** (0.000) \) |
| \( S_{it(-2)} \) | \(304.20** (0.008) \) |
| \( S_{it(-3)} \) | \(299.09** (0.028) \) |
| \( \Delta y_{it(-1)} \) | \(1.19** (0.000) \) |
| \( \Delta y_{it(-2)} \) | \(-0.54** (0.000) \) |
| MA(1) | \(-1.23** (0.000) \) |
| MA(2) | \(0.52** (0.012) \) |
| MA(3) | \(-0.34** (0.007) \) |
| \( \tau^2 \) | 0.209 |

*Means significantly within the 10% significance level.

**Means significantly under the 5% significance level.
unit root hypothesis cannot be rejected, implying that the series is non-stationary. By taking the first differences of the series, the unit root can be rejected for the first differences at the 5% significance level. We may therefore reasonably conclude that the series in relation to the tourism demand will be included in the ARMAX model for Avian Flu-infected countries in the first-difference form. On the other hand, as for the variable regarding the number of Avian Flu-infected patients, the ADF results without a deterministic trend show that the various series are stationary in all the countries. Hence, the independent variable for confirmed Avian Flu-infected patients will be included in the ARMAX model for each country in the levels form.

To estimate the impact of Avian Flu on the demand for tourism in Indonesia and Vietnam, an ARMAX model was adopted using a similar estimation procedure. We first implemented the AIC and SBC criteria to select a suitable ARMA model for the dependent variable for these two mainly Avian Flu-infected countries. The results of deciding which ARMA model to use for the dependent variables that have been transformed to obtain the stationary series are presented in Table 7. In Indonesia, the first-difference series of tourism demand is best represented by the ARMA(3,2) model; however, in the case of Vietnam, the MA(1) model is the most adequate ARMA model.

After selecting the ARMA model in the case of the dependent variable, we performed two estimation procedures to obtain the final ARMAX model. First, we built an over-parameterized model to serve as the initial ARMAX model. Table 8 reports the estimation results of the initial ARMAX models. Furthermore, the estimated initial ARMAX model can be used to test hypotheses to modify the initial model to obtain the simplified ARMAX model. Moreover, the results of the simplified ARMAX model used to illustrate the respective impacts of the numbers of confirmed Avian Flu-infected patients on tourism demand in Indonesia and Vietnam are also shown in Table 8. Please note that we also added a dummy variable to the ARMAX model in Indonesia to reflect the terrorism shock in October 2005. A negative sign is expected for the coefficient of the dummy variable.

The impact of the terrorism shock on the demand for tourism is significant as shown in Table 8. The results for the respective impacts of the numbers of confirmed Avian Flu-infected patients on tourism demand in Indonesia and Vietnam are shown in Table 8. As expected, international tourism demand has been negatively affected by the instability generated by terrorism in Indonesia (negative value of dummy). The changes in tourism demand due to Avian Flu are not significant, which implies that the current Avian Flu disease does not yet affect the demand for global tourism distinctly. We found that the number of affected cases had a significant impact for SARS-affected countries, but not for Avian Flu-affected countries. These results are reasonable, because SARS was able to spread from one human to another and it started as an unknown disease and so gave rise to serious panic as compared to the real damage it caused. However, the H5N1 Avian Flu virus is currently only transmitted from birds to humans and so its ability to spread among humans is still weak and the number of cases is still small.

4.2. Dynamic panel data models for panel datasets

The two dynamic models were estimated using the GMM procedure proposed by Arellano and Bond (1991), using the first-difference transformation and instrumental variables. All the estimates are obtained by using the instruments $y_{it}$ lagged up to two periods in order to reduce finite sample biases resulting from having too many instruments relative to the cross-sectional sample size. The results of a dynamic panel model for the impacts of SARS on tourism demand are shown in Eq. (10). Furthermore, the estimated results of Avian Flu on tourism demand appear in Eq. (11). The t-statistics are below each coefficient in parentheses.

$$\Delta y_{it} = 0.79\Delta y_{it-1} - 403.57\Delta S_{it} + \Delta e_{it},$$  
(10)

$$\Delta y_{it} = 0.73\Delta y_{it-1} - 221.28\Delta B_{it} - 60392.42\Delta D_{it} + \Delta e_{it},$$  
(11)

According to these results, we found tourism demand to be significantly reduced by about 403 arrivals for an additional person probably infected by SARS in the same

| Lag | China | Hong Kong | Taiwan |
|-----|-------|-----------|--------|
| 0   | -298.57 | -149.27  | -174.65 |
| 1   | -355.30 | -542.42  | -57.63  |
| 2   | 42.62   | 289.88   | 71.06   |
| 3   | 242.58  | 417.94   | 131.23  |
| 4   | 265.66  | 171.36   | 43.31   |
| 5   | 185.15  | 70.26    | 14.29   |
| 6   | 76.87   | 28.81    | 4.72    |

| Country/area | Model      | AIC   | SBC  |
|--------------|------------|-------|------|
| Indonesia    | ARMA(1,2)  | 23.964| 24.123|
|              | ARMA(2,2)  | 23.776| 23.977|
|              | ARMA(2,1)  | 23.871| 24.032|
|              | ARMA(2,3)  | 23.714| 23.955|
|              | ARMA(3,2)  | 23.679| 23.922|
| Vietnam      | ARMA(1,1)  | 23.420| 23.539|
|              | AR(1)      | 23.432| 23.512|
|              | MA(1)      | 23.408| 23.487|

The appropriate models are selected using the AIC and SBC.
period. On the contrary, tourism demand is not significantly affected by the infectious illness of Avian Flu. The results of dynamic panel models for panel datasets are consistent with the ARMAX models for single datasets so that the numbers of affected cases have significant impacts for SARS-infected countries but not for Avian Flu-affected countries. In addition, the estimated results from the single data model show that the impact of each SARS-infected person on tourism demand in these Asian countries ranged from 175 to 1742, while the average impact of regional tourism on SARS-infected countries was reduced by about 403 arrivals based on the dynamic panel model. These figures indicate that the average damage level of SARS-infected countries is around 403 but that the damage for each country is dependent upon the government’s reaction and strategies in dealing with this serious disease and may vary from 175 to 1742.

Finally, some limitations need to be addressed when \( N \) is very small in a panel model. Taylor (1980) and Hsiao (2003) have indicated that the variance component will be raised under a finite sample size. Therefore, the estimators will be less efficient than in the case of the large sample. For instance, the estimators will become more efficient when the sample size meets the condition \( T \geq 3, N-(K+1) \geq 9 \). Since our sample size regarding the number of individuals (i.e., \( N \)) is either 2 or 4, therefore, the estimator arising from the panel model may not have the asymptotic properties.

5. Policy implications and concluding remarks

Although a human-to-human influenza pandemic that could be caused by Avian Flu would be horrendous, there is still a lack of data on pandemic influenzas. A comparison of SARS and Avian Flu thus provides useful information for both disease control and tourism management. Meanwhile, clarity and sharing correct information are crucial to controlling an outbreak of either SARS or Avian Flu, both in regard to the health perspective and the travel perspective as stated by Cheng (2006). This study helps to clarify the potential situation of Avian Flu if it were to develop into a human-to-human influenza pandemic.

The literature shows if a country confronts a serious outbreak of a disease, then being better prepared can result in lower mortality during the next outbreak of the disease. Taiwan was one of the countries most seriously affected by the 2003 SARS epidemic (Liu, Hammitt, Wang, & Tsou, 2005). The Taiwan government has now learned from its experiences of SARS and is setting aside at least a US $0.65 billion budget to protect the Taiwanese people against this Avian Flu and pandemic influenza. It is also expected that Taiwan will have less in terms of loss should such a transmissible disease strike because its preparedness for a single disease can benefit its preparedness for all diseases. However, such preparedness involves relying on knowing the reaction of international travelers to the Avian Flu as shown in this study.

Ritchie (2004) pointed out that decisions taken before a crisis occurs will give rise to more effective management during a crisis, which is in the spirit of pre-crisis planning. Furthermore, Page et al. (2006) suggested that the current national tourism management authorities should formulate appropriate response strategies, so that each destination could prepare for any outbreak without adversely damaging its image as a place to visit. This study provides timely information regarding an upcoming huge and fatal crisis, and can thus serve as part of the knowledge base in the pre-crisis planning.

The major purpose of this paper has been to estimate the impacts of SARS and Avian Flu on international tourism.
The estimation results provide useful insights into how epidemic and pandemic diseases affect international tourism. Song and Witt (2000) pointed out that the static regressions of tourism demand models might emerge numerous problems, such as structural instability, forecasting failures and spurious regression. In addition, Garín-Muñoz (2007) indicates if the impact of the previous tourism was neglected, the effect of the other variables considered will tend to be overestimated. So the dynamic tourism was neglected, the effect of the other variables was considered will tend to be underestimated. The dynamic structure of consumer preference must be deliberated in the tourism demand model (Garin-Muñoz, 2006). One way to handle the dynamic structure of preferences is to consider taste change as endogenous by including previous tourism casting failures and spurious regression. In addition, the regressions of tourism demand models might emerge additional person probably infected by SARS. The figure was significantly reduced by about 403 arrivals for an additional person infected by SARS. The figure of the lag distribution of the impact of an explanatory variable can be calculated based on the ratio of the lag polynomials for the dependent and explanatory variables. The distributed lag form of the ARMAX model is

\[ y_t = \frac{\mu}{C(L)} + \frac{B(L)}{C(L)} x_t + \frac{D(L)}{C(L)} \epsilon_t. \]

The impacts of \( x_t \) on \( y_t \) can be calculated by the ratio of the polynomial \( B(L) \) and \( C(L) \). Thus,

\[ y_t = \frac{\mu}{C(L)} + \frac{Z(L)}{C(L)} x_t + \frac{D(L)}{C(L)} \epsilon_t, \]

where

\[ Z(L) = \frac{B(L)}{C(L)} = z_0 + z_1 L + z_2 L^2 + \cdots \]

Note that \( Z(L) \) is an infinite polynomial. Considering the simple case of two-period lags on both \( y_t \) and \( x_t \), the lag

\[ y_t = \frac{\mu}{C(L)} + \frac{B(L)}{C(L)} x_{t-1} + \frac{D(L)}{C(L)} \epsilon_t. \]

Ritchie (2004) noted that decisions taken before a crisis occurs will lead to more effective management during a crisis, which is in the spirit of pre-crisis planning. The government should be well prepared in each sector, especially the international tourism sector, to reduce the damage caused by Avian Flu before it becomes an inevitable disaster.

Appendix A

The general ARMAX model (Bierens, 1987) is shown in Eq. (A.1):

\[ \left(1 - \sum_{i=1}^{p} \alpha_i L^i\right) y_t = \mu + \sum_{i=1}^{r} \beta_i L^i x_{t+1} + \left(1 + \sum_{i=1}^{q} \gamma_i L^i\right) \epsilon_t. \]

(A.1)

For simplicity, we assume that a single explanatory variable included in the ARMAX model could be written as follows:

\[ C(L)y_t = \mu + B(L)x_t + D(L)\epsilon_t, \]

where the polynomials of the lag operator are defined as:

\[ C(L) = 1 - \sum_{i=1}^{p} \alpha_i L^i = 1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p, \]

\[ B(L) = \sum_{i=1}^{r} B_i L^{i-1} = B_1 + B_2 L + B_3 L^2 + \cdots + B_r L^{r-1}, \]

and

\[ D(L) = 1 + \sum_{i=1}^{q} \gamma_i L^i = 1 + \gamma_1 L^1 + \gamma_2 L^2 + \cdots + \gamma_q L^q. \]

In an ARMAX model, if both the distributed lags and AR terms were included, the coefficient that determines the impacts of each period would be calculated on the basis of the quotient of polynomials formed by the distributed lags and by the AR polynomial lags. The general form of the lag distribution of the impact of an explanatory variable can be calculated based on the ratio of the lag polynomials for the dependent and explanatory variables. The distributed lag form of the ARMAX model is

\[ y_t = \frac{\mu}{C(L)} + \frac{B(L)}{C(L)} x_t + \frac{D(L)}{C(L)} \epsilon_t. \]
### Table B.1
Results of the initial ARMAX model for SARS

| Variable | Coefficient (P-value) |
|----------|-----------------------|
|          | China | Hong Kong | Singapore | Taiwan |
| Constant | 63128.46 (0.182) | 23357.01 (0.581) | 5881.40 (0.746) | 1071.27 (0.898) |
| $S_t$    | -354.39** (0.037)  | -220.32** (0.097) | -897.30 (0.113) | -180.45** (0.005) |
| $S_{t-1}$ | -4.36 (0.982)      | -565.87** (0.000) | -1833.54** (0.002) | -23.83 (0.634) |
| $S_{t-2}$ | 275.45* (0.081)    | 427.99** (0.002)  | 1464.30** (0.015) | 102.52** (0.043) |
| $S_{t-3}$ | 236.76* (0.066)    | 749.66 (0.155)    | 73.21 (0.219)    | 0.330 (0.219)    |
| $\Delta y_{t-1}$ | 1.28** (0.000)     | 0.330 (0.219)    | 0.12 (0.709)     | 0.28 (0.181)     |
| $\Delta y_{t-2}$ | -0.59** (0.000)    | -0.01 (0.997)    | 0.01 (0.983)     | 0.07 (0.702)     |
| MA(1)    | -1.39** (0.000)    | -0.59** (0.000)  | -0.51** (0.002)  | -0.28* (0.092)   |
| MA(2)    | 0.59** (0.004)     | -0.375** (0.024) | -0.47** (0.024)  | -0.76** (0.000)  |
| MA(3)    | -0.375** (0.024)   | -0.12 (0.709)    | 0.12 (0.709)     | 0.28 (0.181)     |
| $R^2$    | 0.203             | 0.613             | 0.450             | 0.625             |

*Means significantly within the 10% significance level.

**Means significantly under the 5% significance level.

coefficients are given by the equality

$$(z_0 + z_1 L + z_2 L^2 + z_3 L^3 + z_4 L^4 + \cdots)(1 - a_1 L - a_2 L^2) = (\beta_1 + \beta_2 L + B_2 L^2).$$

By combining in the power of $L$, the lag coefficients can be expressed as follows:

$1: z_0 = \beta_1$,

$L^1: z_1 - z_0 a_1 = \beta_2$ or $z_1 = z_0 a_1 + \beta_2$,

$L^2: z_2 - z_1 a_1 - z_0 a_2 = \beta_3$ or $z_2 = \beta_1 + z_1 a_1 + z_0 a_2$,

$L^3: z_3 - z_2 a_1 - z_1 a_2 = \beta_4$ (since $\beta_4 = 0$) or $z_3 = z_2 a_1 + z_1 a_2$,

$L^4: z_4 - z_3 a_1 - z_2 a_2 = \beta_5$ and so on.

Once the estimated results for the coefficients $z_1$, $z_2$ and $\beta_1$, $\beta_2$, $\beta_3$ are found, the lag weights for $z_j$ can be calculated. The total effect in a rational lag model is $\Sigma_{j=0}^\infty z_j$.

### Appendix B

The results of the initial ARMAX model for SARS are presented in Table B.1.

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