Monthly Variations in Seasonally Adjusted and Unadjusted International Tourism to Australia

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Abstract: Tourist arrivals series from Hong Kong, Malaysia and Singapore to Australia exhibit strong seasonality. For purposes of data and policy analysis, it is useful to obtain seasonally adjusted data for international tourism from the respective origin countries. In this paper, the traditional moving average technique for estimating the seasonal components of time series is applied to monthly tourist arrivals time series data to Australia for the period 1975(1) to 1996(12). The autocorrelation and partial autocorrelation functions, the Lagrange multiplier test for the absence of serial correlation, and model selection criteria, namely the Akaike Information Criterion and Schwarz Bayesian Criterion, are used to examine which time series processes best describe international tourist arrivals data for Australia.

1. Introduction

Seasonality, or intra-year fluctuations in the data, is a widely known but relatively unappreciated facet of tourism time series data. In general, tourist seasonality can be defined as "the tendency of tourist flows to become concentrated into relatively short periods of the year" (Allcock, 1989, p. 387). More generally, Hylleberg (1992, p.4) defines seasonality as follows: "Seasonality is the systematic, although not necessarily regular, intra-year movement caused by changes of the weather, the calendar, and timing of decisions, directly or indirectly through the production and consumption decisions made by the agents of the economy. These decisions are influenced by the endowments, the expectations and the preferences of the agents, and the production techniques available in the economy."

Much effort has been made by both the private and public sectors to reduce seasonality in destination countries because it contributes to the "problem of maximising the efficient operation of tourism facilities and infrastructure, and results in unnecessary excess capacity for most of the year in most destinations" (Butler, p. 338). Hence, seasonality has significant implications for employment and capital investment in the tourist industry, and potentially destabilizing effects on other sectors of the tourist-receiving economy.

In general, there are two types of seasonality in tourism, namely 'natural' and 'institutional' seasonality. Natural seasonality is related to the regular and recurring temporal changes in natural phenomena at a particular destination, which is usually associated with climate and seasons of the year. Institutional seasonality is the result of religious, cultural, ethnic and social factors. The most important form of this seasonality is the school vacations in summer. Related to these two types of seasonality, four types of international tourism have been developed:

1. Summer tourism associated with sun-seeking holidays;
2. Winter sports tourism;
3. Cultural tourism (museum, cathedrals, and other tourist sights) and pilgrimages;
4. Business and conference tourism.

The major tourism season is in summer because of the lengthy school holidays. Historically, the long summer vacation stemmed from the need for children's help during the agricultural harvest, which is no longer required in Europe. However, the tradition of observing the summer school holidays remains, and continues to dominate the tourist industry, since "the bulk of world tourism is generated by the western industrial countries" (Butler, p. 333). Suggestions and efforts have been made by tourist promotion boards in various countries to expand off-season tourism, including: the introduction of a 'shoulder' season, in one or all of spring, autumn or winter; and providing activities which are not related to the weather, such as conferences or festivals (art exhibitions in museums), which can be held outside the main tourist season. Incentives such as off-season discounts on airfares, hotels and package tours are used to discourage tourism in the high season, or to entice people to consider taking a second vacation, which is becoming increasingly popular in many industrialised countries.

Seasonal or intra-year variations are evident in international tourism to Australia. Concentrating on annual figures only, Australia experienced an impressive average annual growth rate of 9.83% in international tourist arrivals between 1980 and 1994, which far exceeded the growth rate over the same period of the world's top 10 tourist-destination countries in 1994 (World Tourism Organisation, 1996). Between 1990 and 1995, Australia experienced the largest average annual percentage growth in tourist arrivals from Asia (31%), which far exceeded the average annual percentage growth rate (12%) of all tourist arrivals in the country (Australian Bureau of Statistics, 1996). Tourists from Hong Kong, Malaysia and Singapore, which are considered the major tourist markets in Asia apart from Japan, represented 4%, 3% and 6%, respectively, of international tourist arrivals to Australia in 1996. In terms of the international tourism market share of the three countries, Singapore is Australia's fifth major market, followed by Hong Kong and Malaysia, which occupy seventh and eighth places, respectively. However, since international tourism from these countries has strong seasonal components, it would be useful to obtain seasonally adjusted data for international tourism from the respective origin countries for purposes of data and policy analysis.

The purpose of the paper is to examine and estimate the monthly seasonal patterns in international tourism time series and the seasonal concentration of tourist arrivals in Australia from three major Asian markets, namely Hong Kong, Malaysia and Singapore, during the period 1975(1)-96(12). International tourism demand is usually measured by proxies such as tourist expenditures or the number of tourist arrivals from a particular source country to a foreign destination. In this paper, tourist arrivals series are chosen for the analysis of international tourism to Australia, as they are available on a monthly basis from the Australian Bureau of Statistics. Tourist expenditures are obtained by surveys which are conducted on a quarterly basis, and are published by the Australian Bureau of Tourism Research.

The plan of the paper is as follows. In Section 2, the application of the moving average technique will be discussed, followed by the application of alternative time series models in Section 3. Concluding remarks are given in Section 4.

2. The Moving Average Technique

The traditional and frequently used technique to smooth a time series and to estimate the seasonal component is the moving average method, which is carried out without recourse to a formal statistical model. The technique is computationally convenient as it involves straightforward calculations. In this approach, it is assumed that a moving average expresses satisfactorily the trend and cyclical components of the series. It is also assumed that the seasonal structure remains constant from year to year, which means that the peaks and troughs generally occur in the same intra-year period. A centred twelve-month moving average of monthly tourist arrivals, for example, can be calculated by applying the following transformation:

$$(1)\ MA_t = \left[A_{t+6} + 2\sum_{x=1}^{11}(A_{t+6-x}) + A_{t-6} \right] \Big/ 24$$

where

MA_t = the centred moving average of tourist arrivals for month t;

A_t = number of tourist arrivals in month t.

Figures 1-3 display the centred moving averages and the logarithms of short-term international tourist arrivals for short-term international tourist arrivals from Hong Kong, Malaysia and Singapore, respectively, for the period 1975(1)-1996(12). Short-term tourists include persons travelling to Australia, which is not their usual residence, for a period not exceeding twelve months, for holiday, business and other purposes. The movements in each of the series display strong seasonal patterns. Moreover, the series appear to be non-stationary in the mean, with the respective means rising over time. Figures 1-3 show clearly that the seasonal patterns are multiplicative, namely additive in the logarithms of the variables. The most prominent features of the series are, therefore, increasing trends and strong multiplicative seasonal patterns in the original series.

Prior to the 1990s, the trends in the three series rise slowly for tourist arrivals from all three tourist-generating countries, but the situation changes dramatically in the 1990s. The signing of the Joint Declaration between the UK and Chinese Governments in 1984 (concerning the handover of Hong Kong to China on 1 July, 1997) fuelled the growth of inbound tourism from Hong Kong, which reflected a trend related to subsequent immigration. A downward trend can be observed for tourist arrivals from Malaysia in the late 1980s. The dramatic growth of inbound tourism from the three origin countries in the 1990s can be attributed largely to the dynamic economic growth experienced by each of these countries during this period.

Ratios of observation-to-moving average, P_t, are obtained by dividing the original tourist arrivals by the corresponding moving average figure for each month and expressing it in percentage form, as follows:

$$P_t = \frac{A_t}{MA_t} * 100 .$$

These ratios, often referred to as "ratio-to-moving averages", are intended to eliminate the trend and cyclical components, thereby resulting in a series that contain seasonal and irregular movements. The calculated ratio-to-moving averages are then averaged by months after deleting the lowest and highest values, to eliminate the irregular movements and to isolate the seasonal components. This procedure removes the influence of extreme values which Hamburg (1977, p. 475) argued "tend to be atypical because of erratic or irregular factors such as strikes, work stoppages, or other unusual occurrences." If outliers are important, there are clear benefits involved in the adjustment procedure to accommodate these problems.

Using the average monthly seasonal indices estimated for tourist arrivals in levels, as shown in Table 1, information about the seasonal concentrations of tourist arrivals from these origin countries can be obtained. These seasonal patterns are qualitatively similar regardless of whether the moving average method is applied to the levels or logarithms of tourist arrivals. Tourism seasons are defined as months for which the corresponding average seasonal indices exceed 1.0, which means that the seasonal factors increase tourist arrivals above the trend and cyclical components.

Based on the seasonal indices obtained from the levels of international tourist arrivals, a number of observations are pertinent. During 1975(1)-96(12), on average over 53% of tourists from Hong Kong arrived in Australia, predominantly in February, July and December. About 13% of the annual total arrived in the peak month of February, with the lowest months being May and September. The seasonal range, namely the difference between the highest and the lowest monthly indices, is 0.899, and the seasonal ratio, namely the highest seasonal value divided by the lowest, is 2.368.

During the same period, about 54% of tourists from Malaysia arrived in the tourism seasons of February-April and November-December. The peak month of November accounts for about 13% of the annual total arrivals, with the lowest month of tourist arrivals from Malaysia being June. Statistically, the seasonal range is 0.842 and the seasonal ratio is 2.322.

About 48% of tourist arrivals from Singapore fluctuated above the trend during February, June, and November-December during 1975-96. Over 17% of the annual total arrived in the peak month of December, with the lowest months being January and July. The seasonal range is 1.432 and the seasonal ratio is 3.196.

Among the three tourist-generating countries, Singapore has by far the largest average concentration of tourist arrivals in the peak month of December, the largest seasonal range, and the largest seasonal ratio. Malaysia has the highest concentration of tourists during the tourism season, followed closely by Hong Kong. Both of these countries have similar seasonal ranges and ratios. However, on the whole, there is not an excess concentration of tourist arrivals from these three countries to Australia during the tourism season.

3. Alternative Time Series Models: Estimation and Testing

In time series analysis, there are two simple and useful models for representing the behaviour of observed time series processes, namely the autoregressive (AR) and moving average (MA) models. The AR model is used to describe a time series in which the current observation depends on its preceding values, whereas the moving average (MA) model is used to describe a time series process which is a linear function of current and previous random errors.

It is possible that a stationary time series will contain a mixture of autoregressive and moving average components, in which case the series is said to be generated by an autoregressive moving average process of order (p, q), where p and q are the orders of the AR and MA components, respectively. If a particular time series, A_t, is not stationary, it can be transformed into a stationary series by successive differencing. The general formulation suggested by Box and Jenkins (1970) as an autoregressive moving average process, often referred to as an ARMA (p, q) model, can be written as:

$$(2)\ (1-\phi_1 L-\ldots-\phi_p L^p)A_t$$
$$= C+(1-\theta_1 L-\ldots-\theta_q L^q)\varepsilon_t,\ \ t = 1, \ldots, n$$

and

$$C = (1-\phi_1-\ldots-\phi_p)\mu$$

where

A_t = number of tourist arrivals from a particular origin country to a destination at time t;
μ = time series observation mean;
ϕ_i = autoregressive parameter (i = 1, ..., p);
θ_j = moving average parameter (j = 1, ..., q);
L = backward shift operator;
ε_t = normally and independently distributed error term.

Logarithmic transformations are applied to each of the monthly tourist arrivals data to Australia from Hong Kong, Malaysia and Singapore for the period 1975(1)-1996(12). The logarithmic transformation is used to enable the log-linear model to capture the multiplicative effects in the levels of the variables. Moreover, as discussed in Lim (1997), the log-linear model has other key features as follows: "it has variable marginal effects and constant elasticities; it yields a steady-state growth path; it permits straightforward testing of whether the dependent variable should be expressed in nominal or real values; it imposes non-negative restrictions upon variables; and it permits the random errors in the equation to be normally distributed."

Graphical representations of the natural logarithmic transformations of tourist arrivals from Hong Kong, Malaysia and Singapore, given in Figures 1-3, display clear trends. The time paths of the tourist arrivals series could be governed by either a linear deterministic trend, or a stochastic trend, or perhaps both. Visual examinations of the correlograms suggest that the logarithmic tourist arrivals series from these three countries are not stationary, since the sample autocorrelations are declining gradually without tapering off. On the contrary, the sample autocorrelations remain moderately large for high lags, which would seem to suggest that the tourist arrival series are not stationary.

Augmented Dicker-Fuller (ADF) tests for unit root are used for the three logarithmic tourist arrival series over the full sample period, with and without a deterministic trend. The time trend is included in the auxiliary regression model when the ADF statistics, with and without a deterministic trend, are substantially different. Such differences are evident in the three logarithmic tourist arrival series. The ADF auxiliary regression is given as follows:

$$\Delta y_t = \alpha+\delta t+\beta y_{t-1}+\sum_{i=1}^{k}\psi_i \Delta y_{t-i}+u_t$$

where y_t is the natural logarithm of tourist arrivals at time t, α is the constant term in the regression, t is the deterministic trend, Δy_{t-i} are the lagged values first differences, which are included to accommodate correlated error processes, u_t is the error term, and δ, β and ψ are the remaining parameters to be estimated. In the ADF tests of the null hypothesis of a unit root (that is, β = 0), the t-ratio of the OLS estimate of β does not have the standard asymptotic normal distribution. In order to determine k, an initial lag length of ten is used in the ADF regression, and the tenth lag is tested for significance using the asymptotic t-ratio. If the tenth lag is insignificant, the lag length is reduced successively until a significant lag length is obtained.

Table 2 presents the results of the ADF test for the three logarithmic tourist arrivals series. The ADF test statistics are compared with the critical values from the non-standard Dickey-Fuller distribution with trend at the 5% significance level. Since the ADF statistics for the Hong Kong and Singapore tourist arrivals series are less (that is, more negative) than the critical value of -3.429, the null hypothesis of a unit root is rejected at the 5% level, implying that the series are stationary, or integrated of order zero, I(0). For the Malaysia tourist arrivals series, the unit root hypothesis is not rejected, which suggests that the series are non-stationary, or integrated of order one, I(1). However, the results for Malaysia are highly sensitive to the lag structure of the ADF auxiliary regression. When smaller lag lengths, such as 9 to 5, are used for the ADF regression, the ADF statistics are less than the critical value at the 5% level, thereby leading to the rejection of the unit root hypothesis.

Various models are fitted to determine whether the monthly tourist arrivals data for 1975(1)-96(12) can be described by the simple autoregressive (AR) or moving average (MA) process, or the autoregressive moving average (ARMA) process. To keep the analysis manageable, different orders for p and q from 0 to 4 are used. A twelfth-order autoregressive model is also fitted to take account of possible seasonal effects. For each group of inbound tourists to Australia, the sample sizes vary from 260 to 264. The appropriate model is selected for the tourist arrivals series based on the statistical significance, at the 5% level, of the AR and MA coefficients, and the absence of serial correlation, using the Lagrange multiplier test of serial correlation. If the computed F statistic exceeds the critical value given by $F_{2,200}(.05) = 3.04$, this would lead to the rejection of the null hypothesis of no serial correlation. While incorporating additional lags for a model will tend to reduce the residual sum of squares, the trade-off is the loss of degrees of freedom. A parsimonious model is generally preferred since it fits the data without including unnecessary variables. The two most commonly used model selection criteria for such a trade-off are the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC), with the decision to base the model choice being to select the model for which the appropriate criterion is smallest.

Various ARMA processes for the logarithmic tourist arrivals from Hong Kong and Singapore, which have significant estimated parameters and no serial correlation at the 5% level, include ARMA(3,0), ARMA(12,0), ARMA(0,3), ARMA(1,3), ARMA(3,1) and ARMA(3,3) for Hong Kong tourist arrivals, and ARMA(4,0) and ARMA(12,2) for Singapore tourist arrivals. Using AIC and SBC, ARMA(12,0) and ARMA(12,2) are the most suitable fitted models to explain tourist arrivals to Australia from Hong Kong and Singapore, respectively. The selected models are as follows (with absolute t-ratios in parentheses):

$$\underset{}{(1 - \underset{(2.87)}{0.14}L^5 + \underset{(3.33)}{0.16}L^9 - \underset{(11.8)}{0.59}L^{12})\log HK_t} = \underset{(70.0)}{6.20} + \underset{(23.2)}{0.01}t + \hat{\varepsilon}_{HKt} \qquad \text{(Hong Kong)}$$

$$(1 - \underset{(24.7)}{0.85}L^{12})\log S_t = \underset{(19.2)}{5.97} + \underset{(10.5)}{0.02}t + (1 - \underset{(2.67)}{0.17}L^2)\hat{\varepsilon}_{St}. \qquad \text{(Singapore)}$$

Since the ADF statistic at the tenth lag for the logarithmic tourist arrivals for Malaysia does not reject the null hypothesis of a unit root, suggesting that the series are non-stationary. By taking first differences of the logarithmic tourist arrivals, the series are transformed into a stationary series. Equation (2) can be rewritten as:

$$(3)\ (1-\phi_1 L-\ldots-\phi_p L^p)(1-L)^d A_t = C+(1-\theta_1 L-\ldots-\theta_q L^q)\varepsilon_t, \quad t = 1, \ldots, n.$$

The above formulation is often referred to as the autoregressive integrated moving average process, or ARIMA(p,d,q), and d denotes the number of times the data are differenced to obtain stationarity. The ARIMA models of the logarithmic tourist arrivals from Malaysia (when d = 1), which have significant t-ratios for the estimated parameters and no serial correlation at the 5% level, include ARIMA(0,1,4) and ARIMA(1,1,1). Since the

ARIMA(1,1,1) model has the smallest AIC and SBC, it is the most suitable fitted model for tourist arrivals from Malaysia, namely:

$$\underset{(6.58)}{(1 - 0.39L)}(1-L)\log M_t = \underset{(12.5)}{0.01} + \underset{(72.7)}{(1 + 0.98L)}\hat{\varepsilon}_{Mt}. \qquad \text{(Malaysia)}$$

One of the primary purposes of measuring seasonal variations is to remove them from the original data to examine the other components in the time series. The process of removing or adjusting for seasonal variations from a time series is known as deseasonalization. Removing seasonality is undertaken by dividing the original monthly tourist arrivals data by the computed seasonal indices, and the resulting time series are the deseasonalized or seasonally adjusted monthly time series for Hong Kong, Malaysia and Singapore, respectively. When the ADF unit root tests are used for the three logarithmic seasonally adjusted tourist arrivals series with a deterministic trend, the ADF test statistics are greater than the critical value of -3.429 at the 5% level of significance. In Table 3, the null hypothesis of a unit root is not rejected for Hong Kong and Malaysia at the tenth lag, and for Singapore, albeit marginally, at the fifth lag. These results imply that the seasonally adjusted logarithmic tourist arrivals series are non-stationary, or integrated of order one, I(1).

Three possible fitted ARIMA models for Hong Kong tourist arrivals include ARIMA(0,1,1), ARIMA(0,1,3) and ARIMA(1,1,2), in which the estimated parameters are significant and there is no serial correlation at the 5% level. Since ARIMA(0,1,3) and ARIMA(1,1,2) have the equal lowest AIC and SBC values, both are selected as the most suitable fitted models to explain tourist arrivals from Hong Kong, as follows:

$$(1 - L)\log HK_t = \underset{(4.69)}{0.011} + (1 + \underset{(20.8)}{0.92L} - \underset{(2.63)}{0.12L^3})\hat{\varepsilon}_{HK1t},$$

$$\underset{(17.8)}{(1 + 0.79L)}(1-L)\log HK_t = \underset{(6.51)}{0.012} + \underset{(15.3)}{(1 + 0.74L^2)}\hat{\varepsilon}_{HK2t}.$$

Deseasonalized tourist arrivals from Malaysia can best be described by either an ARIMA (0,1,1) or ARIMA(1,1,1) model. Both models have significant estimated parameters and no serial correlation at the 5% level. The best fitted model selected for the seasonally adjusted tourist arrivals series from Malaysia is ARIMA(1,1,1), namely:

$$\underset{(2.06)}{(1 - 0.15L)}(1-L)\log M_t = \underset{(5.50)}{0.011} + \underset{(25.7)}{(1 + 0.88L)}\hat{\varepsilon}_{Mt}.$$

ARIMA models for seasonally adjusted logarithmic tourist arrivals from Singapore, which have significant estimated parameters and no serial correlation at the 5% level, include ARIMA(0,1,1), ARIMA(0,1,3), ARIMA(0,1,4) and ARIMA(1,1,2). The best fitted model being ARIMA(0,1,1):

$$(1 - L)\log S_t = \underset{(8.88)}{0.013} + \underset{(29.6)}{(1 + 0.87L)}\hat{\varepsilon}_{St}.$$

4. Conclusion

Analysing international tourist arrivals from Hong Kong, Malaysia and Singapore to Australia is important for forecasting, marketing promotion, and planning the supply of transport and other services. Twelve-month moving averages for the estimation of seasonal patterns show that there are considerable differences in the seasonal patterns of tourist arrivals from these three tourist-generating countries. In terms of the levels of the variables, the strongest concentrations of tourist arrivals from Malaysia, Singapore and Hong Kong during the period 1975(1)-96(12) seem to work in Australia's favour, in that they do not coincide in the same months. Furthermore, the peak months of tourist arrivals from Hong Kong, Malaysia and

Singapore are February, November and December, respectively. Consequently, a redistribution of tourist arrivals from these countries to bring about a decrease in seasonal concentrations is not crucial. However, it would be beneficial for Australia to reduce the seasonal range and ratio between the peak and the trough months, through its marketing and promotional efforts.

The moving average method assumes that the seasonal patterns remain constant over time. However, seasonal patterns often change, and such can cause problems when attempts are made to separate seasonal and non-seasonal components of a series. Furthermore, since the trend and seasonal components can also be correlated, seasonal adjustments may remove not only a large proportion of seasonal fluctuations, but also some of the trend and cyclical variations which form a significant part of tourism time series data. Hence, the assumption of constant seasonal patterns over time may not be adequate to describe the behaviour of tourist arrivals to Australia.

When AR, MA or ARMA models are fitted to the tourist arrivals data, interesting and useful perspectives on the data are revealed. It is imperative that the series first be checked whether they are stationary by applying subjective judgments to the time series graphs of tourist arrivals series and to the correlogram. Individual ADF tests conducted for the logarithms of the Hong Kong and Singapore tourist arrivals series lead to the conclusion that these variables are trend stationary. However, the unit root tests and the Box-Jenkins approach using the correlogram appear to yield conflicting results for these two tourist arrival series. According to the results above, the fitted ARMA(12,0) and ARMA(12,2) models are the most appropriate descriptions of the stationary monthly tourist arrivals data from Hong Kong and Singapore, respectively, and the fitted ARIMA(1,1,1) model is the most suitable description of the non-stationary monthly tourist arrivals from Malaysia.

When seasonally adjusted data are used, the ADF tests for the three tourist arrivals series indicate that they are non-stationary. The fitted ARIMA(0,1,3) and ARIMA(1,1,2) models are the most appropriate descriptions of the non-stationary seasonally adjusted monthly tourist arrivals series for Hong Kong, and the ARIMA(0,1,1) model applies to Singapore. As for the unadjusted tourist arrivals series, the fitted ARIMA(1,1,1) model is the most suitable description of the non-stationary seasonally adjusted monthly tourist arrivals series for Malaysia.

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Table 1: Seasonal Indices for Tourist Arrivals Series from Hong Kong, Malaysia and Singapore, 1975(1)-96(12)

Month	Hong Kong	Malaysia	Singapore
January	0.988	0.865	0.652
February	1.556	1.416	1.035
March	0.948	1.103	0.996
April	1.014	1.119	0.836
May	0.657	0.894	0.816
June	0.763	0.637	1.150
July	1.383	0.731	0.659
August	1.102	0.812	0.719
September	0.665	0.715	0.771
October	0.738	0.903	0.853
November	0.852	1.479	1.429
December	1.337	1.325	2.084

Figure 1

Centred Moving Averages of the Logarithm of Short-Term Tourist Arrivals from Hong Kong, 1975-1996

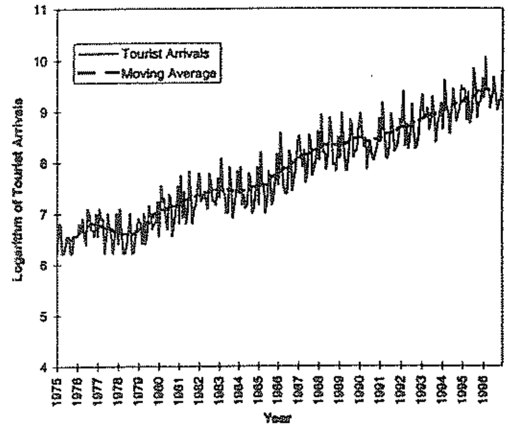

Table 2: Unit root tests of logarithmic tourist arrivals series

Origin Country	ADF lag length	ADF statistic
Hong Kong	8	-4.563*
Malaysia	10	-2.594
Singapore	10	-4.996*

Notes: A deterministic trend is included in the ADF auxiliary regression equation. The critical values at the 5% and 1% levels of significance are -3.429 and -3.998, respectively.
* denotes statistical significance at the 1% level.

Figure 2

Centred Moving Averages of the Logarithm of Short-Term Tourist Arrivals from Malaysia, 1975-1996

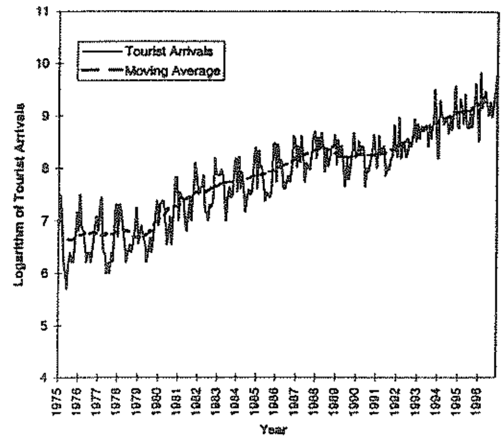

Table 3: Unit root tests of logarithmic seasonally adjusted tourist arrivals series

Origin Country	ADF lag length	ADF statistic
Hong Kong	10	-2.526
Malaysia	10	-2.075
Singapore	5	-3.428

Notes: A deterministic trend is included in the ADF auxiliary regression equation. The critical value at the 5% level of significance is -3.429.

Figure 3

Centred Moving Averages of the Logarithm of Short-Term Tourist Arrivals from Singapore, 1975-1996