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MODELING SEASONAL VARIATION IN TOURISM FLOWS WITH CLIMATE VARIABLES

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The purpose of this article is to model and forecast the seasonal variation, the fluctuations in tourist numbers from season to season in Australian inbound holiday tourism, using climate variables such as maximum temperature, humidity, and hours of sunshine. For estimation purposes this study uses quarterly data on arrivals from the US, UK, Japan, and New Zealand to Australia from September 1975 to September 2009. Seasonal variation, which is the respective and predictable movement of visitation around the trend line, was first extracted from the quarterly holiday tourist arrivals time-series using the Basic Structural Model (BSM) approach. Subsequently, the influence of climate variables on seasonal variation in different seasons was identified using the average Euclidean minimum distance (AD) statistics. The AD statistics show that climate variables shape the characteristic of seasonal variation of tourism flows but the effect tends to vary between seasons and countries. A time-series model was estimated with climate variables to forecast seasonal variation. The forecasting comparison result shows that climate variables improve the forecasting performance. The approach can be replicated to help destination managers and forecasters determine if climate variables influence tourism flows between other origins and destinations globally.

Key words: Seasonal variation; Climate variables; Average Euclidean distance statistics; ARCH modeling; Australian tourism

Introduction

Climate is important to international tourism because it attracts tourists who expect favorable weather conditions in their holiday destination. Climate plays a major role in the marketing of holiday tourism to destinations. Tourism Australia jointly with the government, the state/territory, and the travel industry promotes “Discover Australia in Different Seasons” by publicizing activities and

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things to do in Australia in different seasons. Seasonal holiday tourism is motivated by destination climate conditions, such as temperature, hours of sunshine, humidity, and environmental variables, and each has been identified as important in models of destination competitiveness (Dwyer & Kim, 2003). A change in the mean value of climate variables including temperature, humidity, and rainfall in different seasons can influence the seasonal variation in holiday tourist arrivals. To our knowledge, no attempt has been made to model the seasonal variation in holiday tourist arrivals using climate variables such as temperature, humidity, hours of sunshine, and rainfall. Modeling and forecasting of the seasonal variation in tourism flows is important to tourism stakeholders in both the private and public sectors for planning day to day operations, managing risk, and for design of tourism facilities to maintain destination competitiveness into the future, particularly given the impacts that climate change is likely to have on such variables.

Seasonal variation in tourism flows for any destination can be measured as the fluctuation in tourist numbers from season to season. A definition of seasonality in economies generally has been proposed by Hylleberg (1992) stating that: "Seasonality is the systematic, although not necessarily regular, intra-year movement caused by the 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 endowments, the expectations, and preferences of the agents" (p. 4). The factors that cause the seasonal movement in tourism flows can be classified into two factors: *Natural factors* relate primarily to the destination's climate including considerable variations throughout each year in the hours of daylight and of sunshine, the maximum and minimum temperatures, wind, fog, rainfall, humidity, snow, etc. *Institutional factors* include calendar effects (timing of religious festivals such as Christmas, Easter, Ramadan, etc.) and timing decisions (school vacations, industry vacations, etc.). Institutional factors may not change for a long period but natural factors are less stable. Weather is the mix of events that happen each day in our atmosphere including temperature, rainfall, and humidity. In contrast, we use the word "climate" to refer to the average weather pattern in different seasons in a place over many years.

In this article we distinguish between visitor flows affected by climate seasonality and those affected by climate variation. The former refers to seasonal movement/seasonal variation mainly caused by variations in mean weather conditions. Thus, a resort hotel or entire destination may experience different visitation over the different quarters of the year with the greatest difference between visitation in the summer and winter. Climate variation, on the other hand, can affect visitor flows within any given season. A particularly cold or rainy winter (what are often referred to as unseasonal conditions) for example, may adversely affect visitor levels driving them below the seasonal average.

Seasonality in tourism is caused by a combination of natural and institutional conditions. Koenig-Lewis and Bischoff (2005) reviewed past tourism seasonality studies and found that "natural and institutional" factors are the two major causes of tourism seasonality. Past studies (Amelung & Viner, 2006; Amelung, Nicholls, & Viner, 2007; Dwyer & Kim, 2003; Gomez, 2005; Hamilton & Lau, 2004; Stern, Hoedt, & Ernst, 2000) have recognized the link between climate variables and seasonal variation but no attempt has been made to quantify the impact of maximum temperature, hours of sunshine, and humidity on seasonal variation using a time-series model. The importance of adopting a quantitative approach in seasonality research has recently been emphasized (Koenig-Lewis & Bischoff, 2005).

To date, tourism demand modeling studies (Crouch, 1995; Lim, 2006; Witt & Witt, 1995) have largely been silent on the potential effects of climate variables on destination choice. Lise and Tol (2002) stated that: "While climate is obviously an important factor for determining seasonal tourism demand (measured by number of tourist arrivals), very few tourism demand studies have identified the link with climate. Yet, it is not known just how important climate is for the destination choice of tourists" (p. 429).

Studies that have recently attempted to measure the effects of climate on tourism flows include Lise and Tol (2002), who estimated the impact of climate on total tourist arrivals and departures on world travel to Canada, France, Germany, Italy, Japan, Netherlands, the UK, and the US. Using regression analysis for the estimation procedure, the authors found that climate variables (represented by temperature and precipitation) will have an increasingly strong effect on tourism demand. In another study, Goh, Law, and Mok (2008) used both the rough sets algorithms approach and econometric analysis consisting of both quantitative economic factors and qualitative noneconomic factors to measure the impact of leisure time and climate on annual Hong Kong inbound tourism demand. Focusing on long-haul US and UK tourism demand for Hong Kong, their study showed that leisure time and climate have stronger impacts on tourist arrivals than the economic factors. Hamilton, Maddison, and Tol (2005) simulated international tourist flows using 1995 data on arrivals and departures for 207 countries and the impact on arrivals and departures through changes in population, per capita income, and climate variable, which was measured by annual average temperature. The study found that, in the medium to long term, tourism will grow; however, the change due to climatic factors was smaller than that from population and income changes. Hamilton and Tol (2007) further extended their work on the Hamburg Tourism Model (HTM) to downscale by region for Germany, the UK, and Ireland. They found that the impact of climate variable on national tourism is different to that for regional tourism. Berrittela, Bigano, Rosen, and Tol (2006) studied the economic implications of climate variations in tourism demand using a world computable general equilibrium (CGE) model. This study considered the minimal temperature variation as a climate variable to estimate the impact on aggregate tourism expenditure, highlighting the losers and gainers among countries experiencing climate change. Taylor and Ortiz (2009) employed panel data techniques on regional tourist and climate data in the UK to estimate the influence of temperature, precipitation, and sunny conditions on domestic tourism. The study found that the climate variables have a significant impact on domestic tourism.

To measure the impact of climate variables on tourism, some studies (Goh et al., 2008; Matzarakis, 2001a, 2001b; Mieczkowski, 1985; Skinner & De Dear, 2001) have attempted to construct a tourism climate index to capture weather information relevant to specific tourist activities at a particular destination. Key variables considered in these studies are temperature, hours of sunshine, humidity, wind speed, and solar radiation. Mieczkowski (1985) constructed a Tourism Climate Index (TCI) based on six subindices: Daytime comfort index (CID), which is measured by maximum daily temperature (°C) and minimum daily relative humidity (%); Daily comfort index (CIA), which is measured by mean daily temperature (°C) and mean daily relative humidity (%); Precipitation (R) (mm); Sunshine (S), measured by daily duration of sunshine (hours); and Wind speed (W) (m/s or KM/h). The index is weighted and computed as follows: Tourism Climate Index = 4CID + CIA + 2R + 2S + W, indicating that more weight is given to the day time comfort index followed by precipitation and sunshine. However, there are some drawbacks in the construction of a climate index. Amelung and Viner (2006) and Amelung et al. (2007) argue that the TCI applies only to sightseeing, shopping, and more general forms of tourism activity, and it is not applicable to more climate-dependent activities such as winter sport. Different climatic variables are required for different types of climate, dependent on the type of tourism activity, and different locations. For example, beach holiday activity requires warm climate conditions while winter skiing holidays require cooler climatic conditions. Moreover, the assignment of weights by researchers to climatic variables is a subjective process and may change according the tourist activity. Assigning weights to beach holiday tourism is different to light tourism activity such as sightseeing and shopping activity because beach tourism requires a much warmer and less humid climate than those other activities. Another problem is that since a TCI measures the impact of a weighted average of climatic variables on seasonal tourism demand, it is not useful for discerning the effects of the individual components of the index. To overcome the problems commonly associated with published climate change indexes as a determinant of tourism demand; this study attempts a more disaggregative approach that involves estimating the impact of individual climatic variables on tourism flows.

Despite the relatively large number of Australian tourism demand studies to date (Crouch, Schultz, & Valerio, 1992; Divisekera, 2003; Kulendran, 1996; Kulendran & Divisekera, 2007; Kulendran & Dwyer, 2009; Lim & McAleer, 2001), no attempt has been made to measure the impact of climate variables such as temperature, sunshine, and humidity on the seasonal tourism demand for inbound tourism. Focusing as they have on variables such as origin country income, tourism price, cost of travel and special events, and marketing and migration stocks and flows, these studies are vulnerable to the criticism of Lise and Tol (2002) that they " have short time horizon, assuming that the climate at the tourist destination is constant. In the longer term, however, climate is not constant" (p. 429).

The drawback to previous studies that have included climate variables in their tourism demand model is that, in their emphasis on climate variation impacts in total tourism flows or tourism expenditure, they have ignored its effects on the seasonal variation in tourist flows. Thus, if a destination becomes warmer due to climate change and guaranteed sunshine and heat for the holiday makers, it is likely to have a positive impact on the seasonal variation in holiday tourist arrivals to that destination. While the researchers have emphasized that temperature, hours of sunshine, and humidity are the important factors for determining the seasonal variations, in the past no attempt has been made to model the seasonal variation using the climate variables.

This study quantifies the impact of temperature, hours of sunshine, and humidity on seasonal variations in Australian inbound holiday tourism. In tourism, the inclusion of a seasonal variation in the climate variables impact study has several advantages. First, this study is the first attempt to estimate the impact of maximum temperature, hours of sunshine, and humidity on the seasonal variation in tourism flows, enabling us to identify which climatic variables most strongly influence the seasonal variation for different seasons. The reason for taking the maximum temperature not the minimum temperature is that it can be considered as a proxy for the distribution of day time temperature where most tourism activity occurs. Second, it enables us to model and forecast seasonal variation with climate variables determinants. Specifically, this study considers the influence of climatic variables maximum temperature, hours of sunshine, and relative humidity on the seasonal variation in holiday tourist arrivals to Australia from four major source markets: New Zealand (NZ), US, UK, and Japan, using a time-series modeling approach.

The structure of the article is as follows. Section 2 provides an outline of how seasonal variation was extracted from the quarterly tourist arrivals time-series. Section 3 discusses the method of constructing the climate variables for Australian tourism. Section 4 identifies the link between seasonal variation and variation in maximum temperature, hours of sunshine, and humidity by quarters using the average Euclidean minimum distance approach. Section 5 estimates the impact of maximum temperature, hours of sunshine, and humidity on seasonal variation and discusses the usefulness for forecasting of the time-series models incorporating climate variables. The final section discusses some of the policy implications of the study.

Extraction of Seasonal Variation From Seasonal Tourism Demand

To estimate the impact of climate variables on seasonal variation, this study first extracted the seasonal variation from the quarterly holiday tourist arrivals time-series. Seasonal variation is a component of a tourist arrivals time-series defined as the repetitive and predictable movement around the trend line. It is detected by measuring the tourist arrivals in quarters. Seasonal variation exhibits in both monthly and quarterly tourist arrivals time-series but the focus here is only the seasonal variation in quarterly tourist arrivals time-series.

Figure 1 shows the seasonal variation and the trend in quarterly tourist arrivals to Australia from US, UK, Japan, and NZ. Figure 1 shows that the Japan quarterly tourist arrivals to Australia exhibit a downward trend, which may be due to their changing propensity to travel. Tourism Australia (2009) stated that "In 2002, Japan began to emerge from a prolonged 15 year economic recession that heralded significant labor market restructuring. In the process, traditional social norms weakened, new consumer markets developed and consumer behavior within key market segments changed.

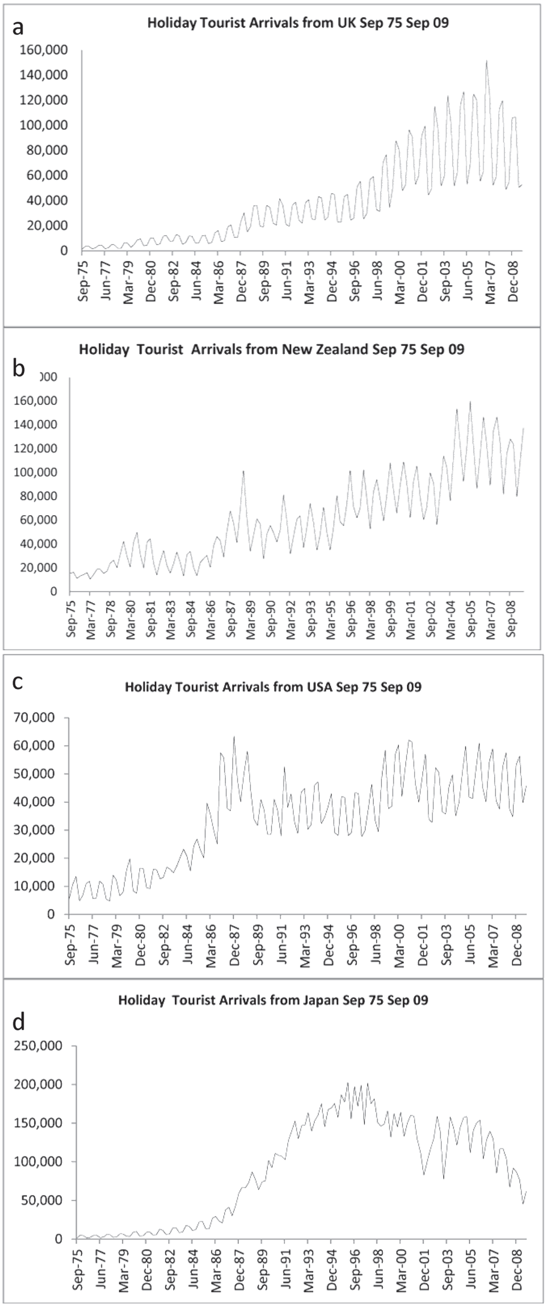

Figure 1. Holiday arrivals to Australia 1975 September quarter to 2009 September quarter from (a) UK, (b) New Zealand, (c) US, and (d) UK.

These changes were arguably most evident in the changing travel attitudes of young Japanese adults" (p. 7).

Quarterly tourist arrivals time-series has four components: Trend (T), Seasonal (S), Cyclical (C), and Irregular (ε). To extract the seasonal (S) variation from the quarterly tourist arrivals time-series, the BSM approach (Harvey 1989) was employed. Quarterly holiday tourist arrivals time-series to Australia from the US, Japan, UK, and NZ for the period from the September quarter 1975 to September quarter 2009 were obtained from ABS Catalog No: 3401.0. The BSM approach assumes that a time-series possesses some structure, which is the sum of the unobserved components: trend, seasonal, and irregular. The unobserved components model for quarterly tourist arrivals can be written as: $Y_t = T_t + S_t + \varepsilon_t$ where Y_t is the quarterly tourist arrivals series (measured in numbers), T_t is the Trend component (long-term relatively smooth pattern or direction that the quarterly time-series exhibits), S_t is a Seasonal component (systematic pattern that occurs in the four traditional season), ε_t is an Irregular component (irregular changes in quarterly time-series caused by random events), which is normally distributed with $(0, \sigma_\varepsilon^2)$. The cyclical component was not considered because main purpose of using BSM approach is to extract the seasonal variation from the quarterly time-series. The BSM of Harvey (1989) was estimated by the STAMP (5.0) program. Figure 2 shows the extracted seasonal variation S_t (measured in numbers of seasonal tourist arrivals) (where $S_t = Y_t - T_t - \varepsilon_t$) in holiday tourist arrival to Australia from the US, UK, Japan, and NZ which exhibits increasing seasonal variation.

Table 1 and Figure 3 show the mean values of the extracted seasonal variation from quarterly holiday tourist arrivals to Australia from the US, UK, Japan, and NZ. The March quarter has the lowest seasonal mean value and September quarter has the highest seasonal mean value for NZ. The March quarter seasonal mean value is −18.56, which means that on average March quarter tourist arrivals numbers from NZ would reduce by 18,560. The September quarter mean value 16.90 indicates that on average September quarter tourist arrivals from NZ would increase by 16,900. The June quarter seasonal mean values for NZ, UK, US, and Japan are 0.26, −14.37, −6.02, and −13.01, respectively, which is low for all four countries. On average, June quarter tourist arrivals numbers from NZ

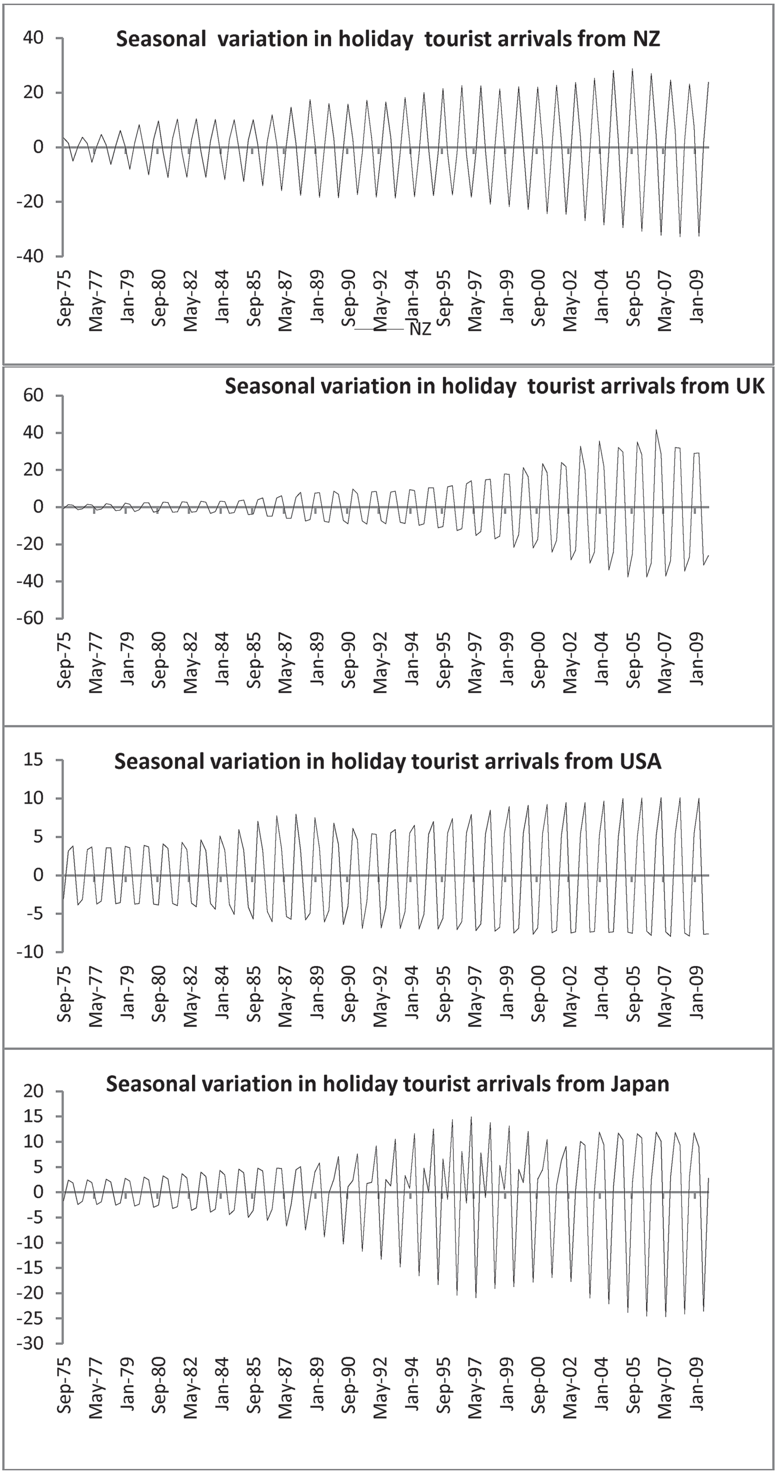

Figure 2. Extracted seasonal variation from holiday tourist Arrivals to Australia from NZ, UK, US, and Japan using the BSM modeling approach from 1975 September quarter to 2009 September quarter.

Table 1
Extracted Seasonal Component Mean Values of Visitor Flows to Australia by Origin and by Season (in ’000s’ Visitors)

	NZ	UK	US	Japan
March	–18.56	11.82	6.19	7.63
June	0.26	–14.37	–6.02	–13.01
September	16.90	–11.52	–5.52	0.78
December	1.26	13.58	5.30	4.36

would increase by 261 and from the UK, US, and Japan would decrease by 14,370, 6,020, and 13,010, respectively. June quarter seasonal mean value is low for all four countries. This may be due to low temperature and hours of sunshine and high humidity, conditions that may not be suitable for outdoor activity.

Construction of Climate Variables

To construct the climate variables such as maximum temperature, hours of sunshine, and relative humidity for Australia, this study combined the Melbourne airport, Brisbane airport (Brisbane Aero), and Sydney airport maximum temperature (°C), hours of sunshine, and relative humidity % data. Sydney, Melbourne, and Brisbane are the major city gateways into Australia together receiving over 95% of inbound tourism to Australia. Data on Melbourne airport, Brisbane Aero, and Sydney airport maximum temperature (°C), hours of sunshine, and relative humidity % data were obtained from the Australian Bureau of Meteorology Melbourne. The average maximum temperature, humidity, and hours of sunshine for the period September quarter 1975 to September quarter 2009 are given in Table 2 and displayed in Figure 4. These climate variables have been adjusted based on the tourism market share 0.253 of Victoria, 0.292 Queensland, and 0.455 New South Wales. Figure 5 shows the maximum temperature, humidity, and hours of sunshine indices which are adjusted by the market shares.

Table 2 and Figure 4 show the mean values of maximum temperature, humidity, and hours of hours of sunshine for the different seasons in Australia. Different quarters have different mean values for climate variables. The September quarter has the lowest maximum temperature mean value and March quarter whereas March quarter has the highest maximum temperature mean value. The June quarter has the lowest mean value for hours of sunshine and the highest value for humidity percentage.

Comparison of Seasonal Variation and Climate Variables by Seasons

The comparison of average mean values of seasonal variation and climatic variables in Tables 1 and 2 indicate that, prima facie, there is a link between the seasonal variation in tourist arrivals

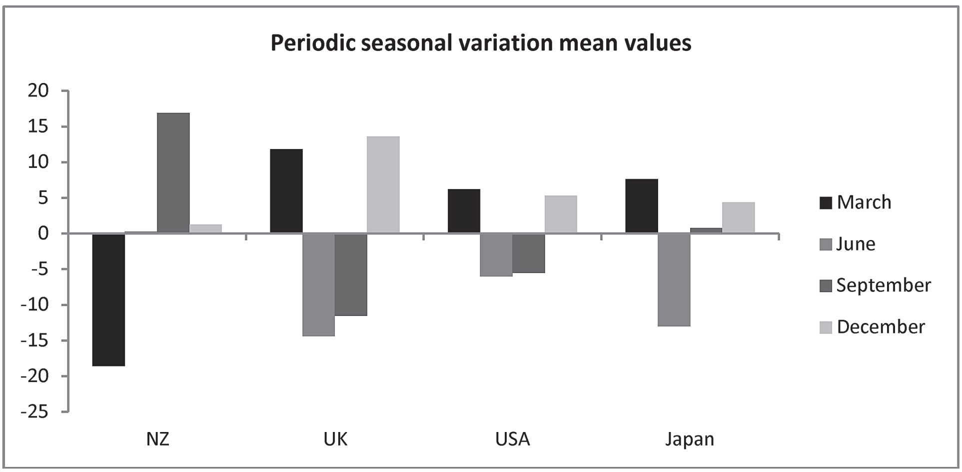

Figure 3. Quarterly seasonal variation mean values by countries.

Table 2
Average Maximum Temperature, Average Humidity, and Average Hours of Sunshine, Period: September 1975 to September 2009, Australia (Cities: Sydney, Melbourne, Brisbane)

	Temperature	Humidity	Hours of Sunshine
March	26.84	61.50	7.58
June	20.40	63.49	6.56
September	18.80	58.50	7.55
December	24.51	59.72	8.12

Source: Australian Bureau of Meteorology Melbourne.

and variation in maximum temperature, humidity, and hours of sunshine by seasons. For example, for the UK, US, and Japan, the December and March quarter seasonal variation mean values are high, which is consistent with high maximum temperature values in Australia in these two quarters. Similarly for the UK and US, the June and September quarter seasonal variation mean values are low, consistent with low maximum temperatures in the major Australian gateways. On the other hand, NZ is the only origin market that delivers fewer tourists in the second hottest quarter, while Japan and NZ are the only origins that deliver more tourists in the second coolest September quarter. In the case of NZ, the lower numbers of tourists coming in the summer months to Australia may be related to the fact that NZ, as a Southern Hemisphere destination, shares its seasons with Australia reducing the attractiveness of holidaying in Australia during its summer. In the case of Japan, the attractiveness of Australia seems to be particularly low during the Australian winter.

Having established the link between variations in the climatic variables and the seasonal variation pattern in Australian inbound tourism there is a need to identify which climatic variables have the greatest effect on seasonal variation in each quarter to develop policy and marketing strategy for major Australian inbound high yield tourism markets. This section identifies the link between each component of the climatic variables (temperature variation, humidity percentage variation, and hours of sunshine variation) and seasonal variation in four different seasons: namely March quarter, June quarter, September quarter, and December quarter. There are two methods available: the Granger Causality test and the Euclidean distance method.

The Granger Causality test identifies the direction of causality between each component of the

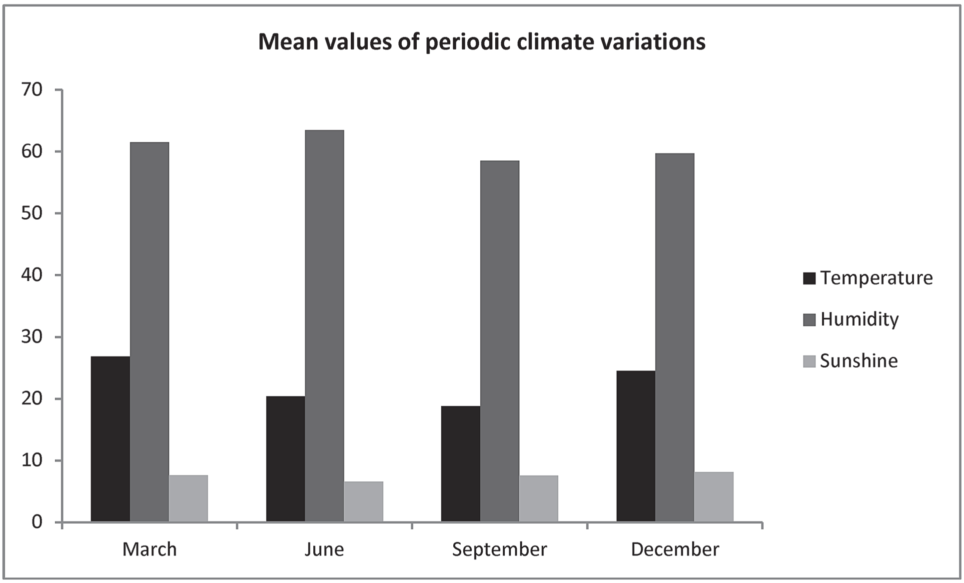

Figure 4. Variation in maximum temperature, humidity, and hours of sunshine, September 1975 to September 2009, Australia (cities: Sydney, Melbourne, and Brisbane). Source: Australian Bureau of Metrology Melbourne.

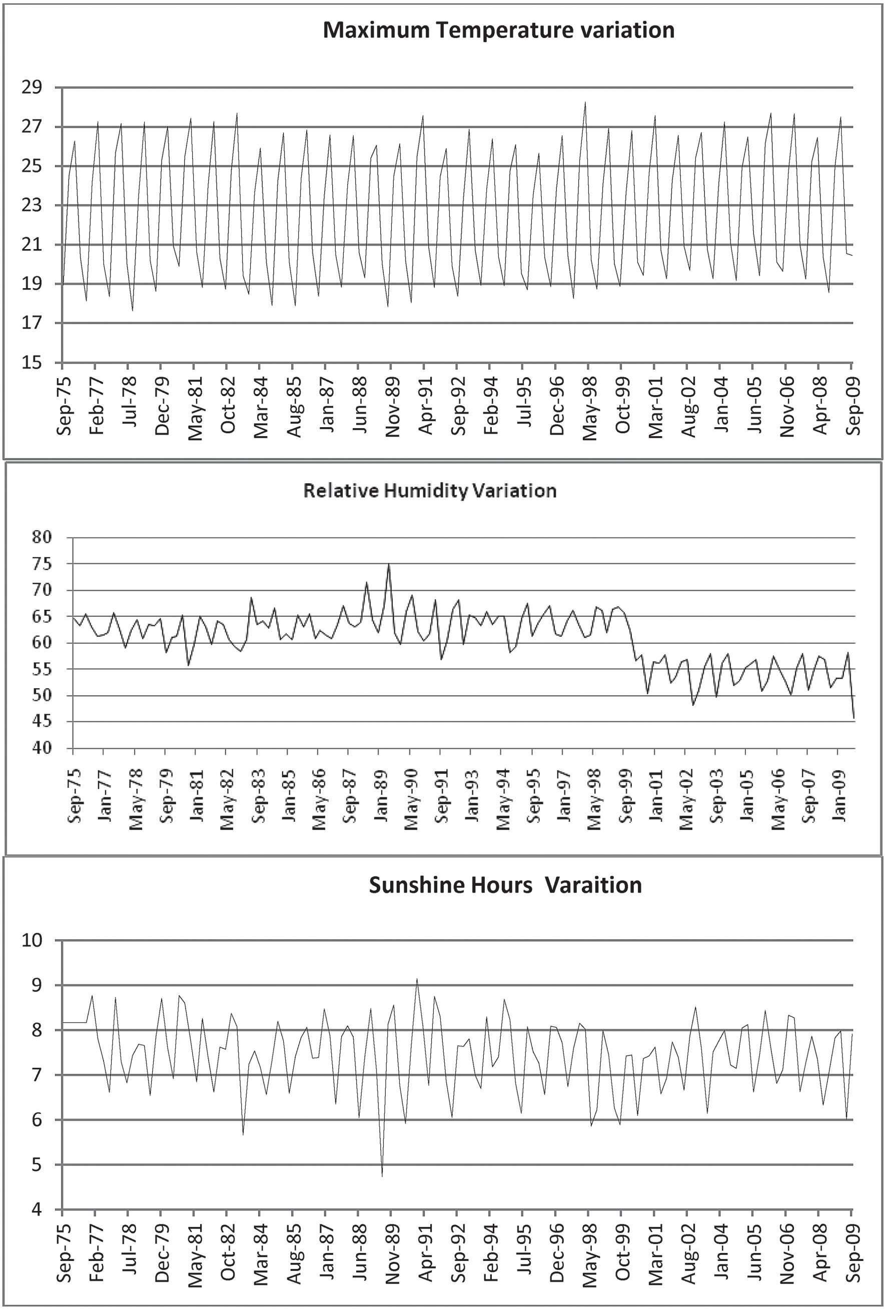

Figure 5. Maximum temperature, relative humidity, and hours of sunshine from 1975 September quarter to 2009 September quarter.

climatic variables and seasonal variation in different seasons. The advantage of using the Euclidean distance approach (http://mathworld.wolfram.com/Distance.html) is that this method identifies the climatic variable that plays the dominant role in shaping the characteristic of the seasonal variation in different season. The Euclidean distance approach measures the deviation between climatic variable variation and seasonal variation in different season. The smallest deviation provides the following useful information. First, it shows the greater similarity pattern between a climatic variable variation and seasonal variation; second, it shows the dominant role of a climatic variable in shaping the characteristic of seasonal variation. The Euclidean distance approach measures the deviation (D) between points p and q is the length of the line segment $\overline{pq}$. Cartesian coordinates, if $p = (p_1, p_2, \ldots, p_n)$ and $q = (q_1, q_2, \ldots, q_n)$ are two points in Euclidean n-space, the distance from p to q is given by:

$$D(p,q) = \sqrt{\begin{array}{l}(p_1 - q_1)^2 + (p_2 - q_2)^2 \\ +\ldots\ldots\ldots + (p_n - q_n)^2\end{array}}$$

$$D(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$$

The average Euclidean distance (AD) statistics can provide a good index of spatial dispersion because this statistics can be interpreted easily. The AD statistics can be written as:

$$AD(p,q) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - q_i)^2}$$

The AD statistics were considered to measure the average deviation between every climate variables and seasonal variation in each quarter. Climate variables and seasonal variations are usually measured in different units. Thus, the measurement of temperature is (°C), humidity is in percent, and hours of sunshine in hours and seasonal demand are measured in number of tourist arrival. In order to apply the AD statistics and to measure the deviation between temperature and seasonal variation, humidity and seasonal variation, hours of sunshine and seasonal variation in each quarter, both seasonal and climatic variations must be standardized. The AD statistics for standardized climate variables and standardized seasonal variation is given as

$$AD(seasonal, climate) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(seasonal_i - climate_i)^2}$$

where $i = 1, 2, 3 \ldots n$, AD is the average Euclidean distance between standardized seasonal variation and standardized climate variables. The smaller the AD statistic (closer to zero), the greater the dominant role of a climatic variable in shaping the characteristic of seasonal variation. Numbers in Tables 3, 4, and 5 show the measures of AD statistics indicating the average deviation between standardized climate variables maximum temperature , humidity percentage, and hours of sunshine and standardized seasonal variation for the period 1975–2009 by season and country.

To analyze the link between climate variables and seasonal variation in tourism demand in different seasons this section first compares the temperature variable and seasonal variation using the AD statistics measures. The numbers in Table 3 are the measure of AD statistics between the standardized temperature variable and standardized seasonal variation by season and country. For example, in the case of NZ the measure of AD statistics between temperature and seasonal variation in March, June, September, and December quarters are 1.472, 1.213, 0.946, and 1.213, respectively. For NZ the smallest measure of AD statistics (0.946) occurs in the September quarter. This implies that, compared to all other quarters, the September quarter temperature plays a dominant role in shaping the number of seasonal tourist arrivals in the September quarter. Any changes in the Australian temperature in the September quarter will influence the number of seasonal tourist arrivals in the September quarter from NZ. Low temperature in the September quarter may well have motivated New Zealanders to escape their cool season and to visit Australia in the September quarter. For the UK and US, the smallest measure for AD statistics is in the June quarter and the numbers are 1.130 and 1.125, respectively. This means that the June quarter temperature plays

Table 3
Measure of AD Statistics (Average Deviation) Between the Standardized Temperature Variable and Standardized Seasonal Variation in Tourism Demand by Season and by Origin Country

	NZ	UK	US	Japan
March	1.472	1.278	1.267	1.447
June	1.213	1.130	1.125	1.203
September	0.946	1.754	1.709	1.226
December	1.213	1.172	1.501	1.093

Table 4
Measure of AD Statistics (Average Deviation) Between the Standardized Humidity% Variable and Standardized Seasonal Variation in Australian Tourism Demand by Season and by Origin Country

	NZ	UK	US	Japan
March	0.839	1.717	1.712	1.469
June	0.916	1.310	1.308	1.212
September	1.729	0.732	0.900	1.461
December	1.604	1.846	1.322	1.784

a dominant role in shaping the number of seasonal tourist arrivals in the June quarter from the UK and US. In Australia, the June quarter average temperature is 20°C (refer to Table1), which is low compared to the sunny and warmer climate in Northern Hemisphere. Due to this reason, Australia becomes less attractive to UK and US tourists in the June quarter. Japan has the smallest measure of AD statistics (1.093) in the December quarter, meaning that warm temperature in the December quarter plays a dominant role in shaping the number of seasonal tourist arrivals in the December quarter. Winter in Japan and summer in Australia appears to motivate Japanese tourists to visit Australia in the December quarter. Overall findings from the smallest value of measure of AD statistics shows the Australian temperature plays a dominant role in shaping the seasonal tourist arrivals in different quarters from the US, UK, Japan, and NZ. For example, Australian hot temperatures in summer plays a dominant role in shaping the number of seasonal tourist arrivals from Japan in the December quarter, whereas the cool temperature in winter plays a dominant role in shaping the number of seasonal tourist arrivals from the UK and US in the June quarter. Temperature in the September quarter plays dominant role is shaping the seasonal tourist arrivals from NZ in the September quarter.

The numbers in Table 4 are the measures of AD statistics between the standardized humidity percentage and standardized seasonal variation in tourism demand by season and country. The measures of AD statistics between standardized humidity percentage variable and standardized seasonal variation in the March quarter for NZ, the UK, US, and Japan are 0.839, 1.717, 1.712, and 1.469, respectively. The smallest measure of AD statistics for NZ occurs in the March quarter; for the UK and US in the September quarter; and for Japan in the June quarter. This implies that for NZ, the March quarter humidity plays a dominant role of shaping the number of seasonal tourist arrivals in the March quarter. For the UK and US, September quarter humidity plays a dominant role of shaping the number of seasonal tourist arrivals in the September quarter. For Japan, June quarter humidity affects the June quarter seasonal variation. Japan has the lowest seasonal mean value (refer Table 2) in the June quarter because of high humidity levels and low temperature in Australia compared to the warm and sunny season in Japan, Europe, and the US.

We can also compare variation in the hours of sunshine in Australia with seasonal variation in tourism demand. Table 5 contains measures of AD statistics between the variation in hours of sunshine and seasonal variation by season and country. The measures of AD statistics between hours of sunshine and seasonal variation in the June quarter for NZ, UK, US, and Japan are 1.195, 1.121, 1.142, and 1.208, respectively. The smallest measure of AD statistics for NZ, the UK, and Japan occurs in the June quarter whereas for the US it is in the September quarter. June quarter hours of sunshine play a dominant role in shaping the number of seasonal tourist visitor arrivals from NZ, the UK, and Japan. September quarter hours of sunshine are an important influence on the September quarter seasonal variation in US seasonal demand. June quarter low hours of sunshine, combined with high humidity and low temperature compare to Europe, US, and Japan is important in shaping the seasonal variation in NZ, the UK, and Japan seasonal demand in the June quarter. In the winter season (from June to August for most of the country)

Table 5
Measures of AD Statistics (Average Deviation) Between Standardized Hours of Sunshine and Standardized Seasonal Variation in Tourism Demand by Season and by Origin Country

	NZ	UK	US	Japan
March	1.429	1.258	1.306	1.461
June	1.195	1.121	1.142	1.208
September	1.548	1.179	1.068	1.483
December	1.225	1.501	1.423	1.369

compared to Europe, Australia has the low hours of sunshine, low temperature, and high humidity level which can restrict the numbers of day time tourism activity in Australia as the result seasonal tourist arrivals during this period is very low (refer to Table 1).

Table 6 summarizes the quarters that have the minimum AD statistics for the following comparisons: temperature versus seasonal variation; humidity versus seasonal variation; and hours of sunshine versus seasonal variation. It shows which climate variables have the greatest effect on seasonal variation from the Australian major tourism markets NZ, US, UK, and Japan. The last row identifies seasons when the seasonal variation is linked to more than one climate variable. For example, in the case of the UK, the June quarter seasonal tourist arrivals is linked to more than one climate variable such as temperature and hours of sunshine. The last column identifies the highest frequency season across the major tourism markets within a particular climate variable. For example, Australian temperature has the greatest effect on June quarter seasonal variation from the US and UK. The implication of the finding is that Australian seasonal tourism demand in June and September quarters from major source market is linked to more than one climate variables. If Australian climate variation changes in June and September quarters, it could affect the number of seasonal tourist arrivals in these quarters from NZ, US, UK, and Japan.

Modeling Seasonal Variation With Climate Variables

Following the Hylleberg (1992) definition of seasonality, the seasonal variation in Australian inbound holiday seasonal demand can be modeled by climatic variables such as maximum temperature, humidity percentage, and hours of sunshine and institution factors include Christmas and Easter holidays and special events. That is: Seasonal variation = f (maximum temperature, hours of sunshine, humidity, Easter Holiday, Christmas Holiday, special events).

Tourism demand determinants such as tourist income, price of tourism, cost of transportation, and prices at the substitute destination are not included in the determinant of seasonal variation. These economic variables show only the trend and unlike climate variables do not exhibit seasonal variation pattern in different seasons.

This section considers the logarithmic transformation of seasonal variation [(ln(seasonal variation)] that was obtained from the $\ln(Y_t)$ [logarithmic transform tourist arrivals (measured in numbers)] time-series using the STAMP program. Logarithmic transformation is often preferred to stabiles the variance and to interpret the coefficient as elasticity.

To measure the impact of current and lagged values of maximum temperature, humidity percentage, and hours of sunshine variation on seasonal variation this section introduces the following regression model.

$$\ln(\text{seasonal variation})_t = \beta_0 + \beta_1 D_2 \times T + \beta_2 D_3 \times T + \beta_3 D_4 \times T + \beta_4(D_{o2000}) + \beta_5(D_{sept11}) + \beta_6(D_E) + \beta_7(D_c)$$
$$\sum_{i=0}^{4}\gamma_i \ln(\max Temp)_{t-i} + \sum_{i=0}^{4}\delta_i \ln(Humdity)_{t-i} +$$
$$\sum_{i=0}^{4}\lambda_i \ln(Sunshinehours)_{t-i} + u_t$$

where, u_t is the error term and ln is the logarithmic transformation. The dependent variable is the

Table 6

Quarters Showing the Minimum Average Euclidean Distance Between Climate Variation and Seasonal Variation, for Each Origin

Climate	NZ	UK	US	Japan	Selected Highest Frequent Quarter
Temperature	Sept	June	June	Dec	June
Humidity	March	Sept	Sept	June	Sept
Hours of sunshine	June	June	Sept	June	June
Selected quarter that is linked to more than one climate variable	Nil	June	Sept	June	

seasonal variation, which is measured by number of seasonal tourist arrivals. The independent variables are: maximum temperature variation measured by (°C); humidity measured in percentage; and hours of sunshine measured in hours. There is no multicollinerarity problem. Correlation between maximum temperature and humidity percentage is 0.032; correlation between maximum temperature and hours of sunshine is 0.375; correlation between hours of sunshine and humidity percentage is 0.381. D_2, D_3, and D_4 are seasonal dummy variables where $D_2 = 1$ when June quarter (Jq) = 1, and 0 otherwise. $D_3 = 1$ when September quarter (Sq) = 1, and 0 otherwise. $D_4 = 1$ when December quarter (Dq) = 1 and 0 otherwise. T is the time trend. Figure 5 shows that the seasonal variation in the US, UK, Japan, and NZ holiday seasonal tourism demand exhibits an increasing seasonal variation and increasing by quarter. To model an increasing seasonal variation, seasonal dummy variables D_2, D_3, and D_4 are multiplied by a trend component ($s_2 = D_2 \times T$, $s_3 = D_3 \times T$ and $s_4 = D_4 \times T$, where T is the trend, D_2 = Jq, D_3 = Sq, and D_4 = Dq). This method of modeling the increasing seasonal variation is based on that developed by Frances and Koehler (1998). To capture the impact of holiday periods on seasonal variation two dummy variables, Easter Holiday (falls in April) dummy variable ($D_E = 1$, when Jq = 1 and 0 otherwise) and Christmas Holiday dummy variable ($D_C = 1$, when Dq = 1 and 0 otherwise), were included. Two special events dummy variables were also included to represent the 2000 Olympic Games in Sydney ($D_{o2000} = 1$, when t = Sept. 2000 and t = Dec. 2000) and September 11, 2001 ($D_{sept11} = 1$, when t = Sept. 2001) incident in the United States.

The OLS method cannot be used to estimate the seasonal variation regression model because the regression model error term (u_t) does not have the constant error variance and exhibits the heteroskedasticity problem. The test for Autoregressive Conditional Heteroskedasticity (ARCH) effect in the error term (u_t) as discussed in Maddala (2001, p. 468) confirmed the ARCH effect. Therefore, to model the seasonal variation in quarterly time-series, this study considered the ARCH modeling approach (Engle, 1982) with four (4) lags. The rationale for introducing the ARCH (4) model is to add a second equation $\sigma_t^2 = \alpha_0 + \alpha_1 (u_{t-1})^2 + \alpha_2 (u_{t-2})^2 + \alpha_3 (u_{t-3})^3 + \alpha_4 (u_{t-4})^2$ to the standard regression model. The conditional variance equation plausibly depends on the squared residuals ($u^2_{t-1} \ldots u^2_{t-2} \ldots$). The ARCH modeling approach allows for simultaneous estimation of conditional means and conditional variances overtime.

It is recognized that there are some limitations in this study. Stochastic seasonality is assumed to be stationary. Only three climate variables were considered. It terms of calculation of climate variables the origin country climate variables were not considered.

The above time-series model was estimated from 1975 Q1 to 2009 Q3 with Eviews (7.0) using the method of maximum likelihood. The estimated time-series model for the US, UK, Japan, and NZ are presented in Table 7. The adj. R^2 goodness of fit, LM (4) test for fourth order serial correlation, DW for first order serial correlation, White test for constant error variance, and JB tests for normality confirmed these estimated models are valid.

Table 8 shows the impact of current and lagged values of maximum temperature, humidity percentage, and hours of sunshine on seasonal variation (measured in number of seasonal tourist arrivals) for the US, UK, NZ, and Japan. Current season maximum temperature ($Temp_t$) has the positive sign except for NZ. A 1% increase in current season maximum temperature would increase the seasonal variation/number of seasonal tourist arrivals by 0.387%, 0.773%, and 0.534% for the US, UK, and Japan, respectively. A 1% increase in current season humidity percentage (Hum_t) would increase the seasonal tourist arrivals by 0.116% and 0.277% for the US and UK, respectively. A 1% increase in current season hours of sunshine (Sun_t) would increase the seasonal variation/seasonal tourist arrivals by 0.167% for NZ. Lagged season's maximum temperature, humidity percentage, and hours of sunshine also impact on seasonal variation and the impact varies by countries and seasons. Previous year maximum temperature also impacts on seasonal variation for the US, UK, and NZ. Seasonal variation in NZ seasonal tourism demand is influenced by current, lagged, and previous year seasons' maximum temperature. Seasonal variation in the US, UK, and NZ seasonal tourism demand is influenced by current and previous year season maximum temperature. Australia's Christmas holiday has a positive impact on seasonal variation in

Table 7

Estimated Time Series Seasonal Variation Model (1975–2009)

US $\ln(\text{Seasonal})_t = -0.877 + 0.0004\,S_2 - 0.001S_4 + 0.182\,D_C - 0.144D_E + 0.387\ln\text{Temp}_t - 0.373\ln\text{Temp}_{t-2}$
(z = −1.41) (z = 5.227) (z = −10.228) (Z = 11.621) (Z = −16.76) (z = 4.25) (z = −4.68)
$+ 0.286\,\ln\text{Temp}_{t-4} + 0.116\ln\text{Hum}_t - 0.126\ln\text{Hum}_{t-2}$
(z = 4.64) (Z = 3.69) (Z = −3.38)
$\sigma^2 = 0.0001 + 0112(U_{t-1})^2 + 0135\,(U_{t-2})^2 - 0.056(U_{t-3})^2 + 0.646(U_{t-4})^2$
(z = 2.262) (z = 1.527) (z = 1.259) (z = −2.113) (z = 2.905)
Adj. $R^2 = 0.917$, DW = 2.25, JB(2) = 3.915, LM(4) = 0.957, WH(46,84) = 1.4184

UK $\ln(\text{Seasonal})_t = -5.504 - 0.00038S_3 + 0.196D_C - 0.291D_E + 0.773\ln\text{Temp}_t + 0.847\text{Tln}\text{Temp}_{t-4}$
(z = −25.04) (z = −3.47) (z = 23.41) (z = −24.86) (z = 9.81) (z = 11.73)
$+ 0.277\ln\text{Hum}_t - 0.091\ln\text{Hum}_{t-2} - 0.133\ln\text{Sun}_{t-4}$
(z = 6.153) (z = −1.96) (Z = −3.79)
$\sigma^2 = 0.0005 - 0.0242(U_{t-1})^2 - 0.061(U_{t-2})^2 - 0.016(U_{t-3})^2 + 0.670(U_{t-4})^2$
(z = 3.312) (z = −0.518) (z = −1541) (z = −0.286) (z = 2.947)
Adj R^2=0.988, DW = 1.908, JB(2) = 2.932, LM(4) = 0.148, WH(39,93) = 1.861

NZ $\ln(\text{Seasonal})_t = -0.0748 - 0.0008\,S_2 + 0.0004S_4 + 0.147D_E - 0.220\,\text{LnTemp}_t - 0.421\text{LnTem}_{t-1}$
(z=-0.173) (z=-4.79) (z=3.76) (z=7.151) (z=-2.61) (z=-7.53)
$+ 0.753\ln\text{Tem}_{t-2} + 0.277\ln\text{Tem}_{t-3} - 0.427\ln\text{Tem}_{t-4} + 0.167\ln\text{Sun}_t + 0.098\ln\text{Sun}_{t-1} - 0.186\ln\text{Sun}_{t-2}$
(z = 12.29) (z = −4.94) (z = −7.160) (z = 4.86) (z = 4.51) (z = −6.35)
$\sigma^2 = 0.0006 - 0.035(U_{t-1})^2 + 0.141(U_{t-2})^2 + 0.075(U_{t-3})^2 + 0.666(U_{t-4})^2$
(z = 2.916) (z = −2.346) (z = 1.903) (z = 1.638) (z = 2.932)
Adj $R^2 = 0.946$, DW=2.41, JB(2) = 0.543, LM(4) = 0.354, WH(73,59) = 0.248

Japan $\ln(\text{Seasonal})_t = 0.140 + 0.0036S_2 + 0.0032S_3 - 0.005\,S_4 + 0.399D_C - 0.188DE + 0.534\ln\text{Temp}_t$
(z = −0.099) (z = 10.01) (z = 7.639) (z = −9.32) (z = 10.67) (z = −5.57) (z = 2.60)
$- 1.014\ln\text{Tem}_{t-2} - 0.572\ln\text{Hum}_{t-1} + 0.778\ln\text{Hum}_{t-3} - 0.352\ln\text{Sun}_{t-1} + 0.551\ln\text{Sun}_{t-3}$
(z = −4.94) (z = −3.22) (z = 4.68) (z = −3.10) (z = 4.66)
$\sigma^2 = 0.003106 - 0.0543(U_{t-1})^2 + 0.0985(U_{t-2})^2 + 0.0247(U_{t-3})^2 + 0.5550(U_{t-4})^2$
(z = 1.96 (z = −1.76) (z = 0.728) (z = 0.328) (z = 2.159)
Adj $R^2 = 0.769$, DW = 1.99, JB(2) = 5.56, LM(4) = 1.52, WH(65,68) = 0.89

Note: $S_2 = D_2{*}T$, $S_3 = D_3{*}T$, $S_4 = D_4{*}T$, D_E = Easter Dummy, D_C = Christmas Dummy.

the US, UK, and Japan seasonal tourism demand. Easter holidays have positive impact on seasonal variation in NZ seasonal tourism demand and negative impact on seasonal variation in the US, UK, and Japan seasonal tourism demand.

Out-of-Sample Forecast Comparison

This section identifies whether the climate variables improves the forecasting performance of time-series models. The estimated time-series models

Table 8

Estimated Impact of Maximum Temperature, Humidity, and Hours of Sunshine on Seasonal Variation

Country	Temperature	Humidity	Hours of Sunshine	D_c	D_e
US	0.387 (Temp_t) –0.373 (Temp_{t-2}) 0.286 (Temp_{t-4})	0.116 (Hum_t) –0.126 (Hum_{t-2})		0.182	–0.144
UK	0.773 (Temp_t) 0.847 (Temp_{t-4})	0.277 (Hum_t) –0.091 (Hum_{t-2})	–0.133 (Sun_{t-4})	0.196	–0.291
NZ	–0.220 (Temp_t) –0.421 (Temp_{t-1}) 0.753 (Temp_{t-2}) 0.277 (Temp_{t-3}) –0.427 (Temp_{t-4})		0.167 (Sun_t) 0.098 (Sun_{t-1}) –0.186 (Sun_{t-2})		0.147
Japan	0.534 (Temp_t) –1.014 (Temp_{t-2})	–0.572 (Hum_{t-1}) 0.778 (Hum_{t-3})	–0.352 (Sun_{t-1}) 0.551 (Sun_{t-3})	0.399	–0.188

Note: D_c is Christmas dummy, D_e is Easter dummy.

with climate variables and seasonal dummies for the US, UK, Japan, and NZ were reestimated for the period 1975 Q1 to 2004 Q4 to generate out-of-sample forecasts for the period 2005 Q1 to 2009 Q3. Then the out-of-sample forecasting performances of these models were compared with time-series models with only seasonal dummies. To assess the out-of-sample forecasting performance, the following measures were considered: mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) (Table 9).

This study compared only the one-step ahead out-of-sample forecasts instead of multisteps because the purpose is to find out whether climate variables improve the forecasting performances. Eview 7.0 output provided measures of accuracy MAPE and RMSPE values for both static and dynamic models but these values are similar. The out-of-sample forecasting comparison shows that based on the measures of accuracy RMSPE and MAPE, the time-series model with seasonal dummies, and climate variables provides better forecast than time-series model with seasonal dummies.

Conclusions

This study has proposed a new approach to identify the relationship between climate variables such as maximum temperature, relative humidity, and hours of sunshine, and seasonal variation, defined as the repetitive and predictable movement around the trend line in holiday tourism demand. The context was seasonal variation in holiday tourism demand to Australia from the US, UK, Japan, and NZ. First, the seasonal variation in holiday tourism demand to Australia was extracted using the BSM modeling approach. Second, the average Euclidean minimum distance statistics was used to measure the deviation between the climate variation and seasonal variation to identify the similarity in the pattern. The advantage of using the seasonal variation is that it allows the comparison of maximum temperature, relative humidity, and hours of sunshine/seasonal variation by season. It enables us to develop a forecasting model with the climate variables determinants to predict the seasonal variation (the fluctuation of tourist numbers from season to season), which is required by destination managers for planning and investment purposes.

The empirical results show that the climate variables shape the seasonal variation in holiday tourism demand. Any changes in climate variables will alter the seasonal variation pattern in holiday tourism demand. The effects of climate variables on seasonal variation tend to vary between season and origin countries. The AD statistics show the link between climate variables such as temperature, humidity percentage, and hours of sunshine and seasonal variation in different seasons and origins. Australian temperature (weighted average of main cities Melbourne, Sydney, and Brisbane) play a dominant role in shaping the number of seasonal tourist arrivals from the US in the June quarter, UK in the June quarter, Japan in the December quarter, and New Zealand in the September quarter. Australian humidity percentage (weighted average of main cities Melbourne, Sydney, and Brisbane) play a dominant role in shaping the number of seasonal tourist arrivals from the US in the September quarter, UK in the September quarter, Japan in the June quarter, and NZ in the March quarter. Australian hours of sunshine (weighted average of

Table 9
Forecast Accuracy in Terms of RMSPE and MAPE

Forecast Horizon	Forecasting Method	Origin Country US	UK	Japan	NZ
RMSPE					
1 quarter	Model with dummies and climate variables	1.95(1)	3.62(1)	16.90(1)	4.46(1)
	Model with dummies	6.15(2)	13.33(2)	N/A	21.83(2)
MAPE					
1 quarter	Model with dummies and climate variables	8.99(1)	7.91(1)	102.58(1)	53.31(1)
	Model with dummies	29.36(2)	36.71(2)	N/A	147.25(2)

N/A: For Japan Eview7.0 does not provide RMSPE and MAPE values due to negative values in the calculation.

main cities Melbourne, Sydney, and Brisbane) play a dominant role in shaping the number of seasonal tourist arrivals from the US in the September quarter, UK in the June quarter, Japan in the June quarter, and NZ in the June quarter. In the Australian main cities (Melbourne, Sydney, and Brisbane), the June and September quarters climate is cool, whereas Northern Hemisphere countries are warm and sunny. June and September quarters low temperature, combined with high humidity percentage level, and low hours of sunshine is identified as important in shaping the characteristic pattern of the seasonal variation in the UK, US, and Japan seasonal demand in the June and September quarters.

Climate variables are important determinants of seasonal variation which is the fluctuation in tourist numbers from season to season. Other tourism demand determinants such as income, price of tourism, cost of transportation, and cost of living at the destination were not considered here because, unlike climate variables, these economic variables do not exhibit seasonal variation in different seasons. The overall impact of current and past season's climate variables such as maximum temperature, humidity, and hours of sunshine on seasonal variation varies by country. US and UK seasonal variation is influenced by maximum temperature and humidity. NZ seasonal variation is influenced by maximum temperature and hours of sunshine. Japan's seasonal variation is influenced by temperature and past season's humidity percentage and hours of sunshine. The estimated elasticity of maximum temperature is high for all countries which is the most important determinant of seasonal variation in holiday tourism. The impact of Australian temperature on seasonal variation cannot be generalized to all tourist origin countries. Australian temperature has a positive impact on countries that share different seasons and a negative impact on countries sharing the same season.

The out-of-sample forecasting comparison shows that adding climate variables does improve the forecasting performance of the time-series models. The one-step ahead forecasting comparison based on MAPE and RMPSE shows that the time-series models with seasonal dummies and climate variables provide better forecasts than time-series models only with seasonal dummies. The forecasting practitioners can consider time-series model with climate variables determinant to obtain the accurate forecast seasonal variation which is the fluctuations in tourist numbers from season to season for planning and risk management purposes.

Much of the analysis is exploratory. However, the findings are interesting enough to extend the analysis to other contexts. It would be particularly interesting to replicate the approach to determine if the addition of climate variables to tourism demand models influences tourism flows between other origins and destinations globally. Such cross-country comparisons would be useful to destination managers. Not only would additional research in this area add to our knowledge of the influence of these climate variables on seasonal variation in different seasons for different countries, but would address a hitherto neglected variable in the demand modeling and forecasting literature.

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