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Dynamics and Structural Breaks in Tourist Arrivals in Australia

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Abstract

This paper analyses the effects of the real exchange rate and world income on aggregate international tourism in Australia. This study uses Auto Regressive Distributed Lag (ARDL) modelling to develop a dynamic structure of tourism demand. Using monthly post-float data from 1984:01 to 2015:01, it has been found that a 1 % real appreciation of the Australian dollar reduces tourist arrivals by 1.23 % while a 1 % rise in world income increases tourist arrivals by 2.26 % in the long-run. The deviation from the long-run equilibrium is corrected by nearly 9 % over a month. One of the endogenously determined structural break dates was negative and statistically significant indicating non-linearity in the Australian aggregate tourist demand function.

Keywords

Tourism demand, endogenous structural breaks, unit-root, error correction, ARDL

Introduction

Tourism is a major part of the Australian economy as highlighted by the Australian Bureau of Statistics (ABS) Catalogue No. 5249.0 Tourism Satellite Account. Tourism accounted for $10.6 billion of total GDP in 20014-15, an increase of four per cent in real terms over the 2013-14 period. The inbound tourism industry share of GDP was 0.9 per cent in 2014-15. Total tourism consumption represented 10 per cent of the country's total exports of goods and services in 2014-15. The tourism industry employed 497,800 people in 2014-15, an increase of three per cent on 2013-14. Tourism's share of total employment remained steady around its trend value of approximately four per cent.

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Despite the importance of tourism in the Australian economy, there is a shortage of in-depth studies on the determinants of tourist arrivals in Australia. In order to meet this need, this paper focuses on the determinants of tourism in Australia from 1984:01 to 2015:01 by using a flexible and robust methodology known as Autoregressive Distributed Lag (ARDL) modelling. The rest of the paper is organised as follows: A review of literature is provided in Section 2. The analytical framework is outlined in Section 3. In Section 4, the time-series properties of the variables in the presence of endogenous structural breaks in data are tested by using the Third Generation Unit-Root Test of Lee and Strazicich (2003). In Section 5, this study estimates the model by using the Auto Regressive Distributed Lag (ARDL) modelling. The main advantage of ARDL modelling lies in its flexibility; it can be applied when the variables are of different order of integration (Pesaran, Shin, & Smith, 2001). ARDL typically outperforms alternative approaches to cointegration (such as FMOLS) when the sample size is small. This is particularly true of the size-power performance of the tests on the long-run parameter. Discussion on short-run dynamics and adjustment toward long-run equilibrium is reported and analysed in Section 5. Section 6 contains the summary and conclusion of the findings.

Literature Review

The literature such as Crouch (1994), Lim (1997), and Li, Song and Witt (2005) have extensively investigated tourism demand for different countries. However, only five studies have examined the factors affecting Australian tourism. These studies are by Divisekera (1995, 2003), Kulendran (1996), Morley (1998) and Webber (2001). The first four deal with factors concerning inbound international tourism; while the latter deals with factors affecting outbound tourism. A critical appraisal of these studies is given below.

Divisekera (1995) used annual time-series data (1970-1992) to analyse the determinants of international tourists from Japan, New Zealand, the UK and the USA. By using the Johansen cointegration technique, Divesekera (1995) found airfares, prices of tourism services and income of origin countries to be the significant determinants for the international tourists to Australia. According to Divisekera (1995, p. 302), “Australia is facing a (less than perfect) price and income elastic demand from the four major visitor generating countries”.

Divisekera’s paper contains some major shortcomings. First, the use of short time-series annual data (23 observations) renders the parameter estimates unreliable and unstable. Lim (1997, p. 837) highlights the “small sample problem” and argues that: “This is a serious concern because it is generally not easy to obtain meaningful regression estimates in such circumstances and this cast doubts on the reliability of the estimation results.” Second, the use of annual data does not capture the volatile character of the tourism sector, and even the length of the time-series cannot compensate for this.

Dickey-Fuller (1981), Augmented Dickey-Fuller and Phillips-Perron unit-root tests were used to assess the time-series properties of the data. These

First-Generation unit-root tests suffer from power deficiency and may fail to reject the null hypothesis when it is false if structural breaks are present. These First-Generation unit-root tests suffer from power deficiency and may fail to reject the null hypothesis when it is false if structural breaks are present. During the sample period of 1970-1992, many important economic events took place, nationally and internationally. The collapse of the Bretton Woods System in 1973, the floating of the Australian dollar in December 1983, the recessions of the early 1980s and the 1990s are the prominent ones.

Divisekera's (2003) study is a sequel to his 1995 paper. Here an Almost Ideal Demand System (AIDS) model for international tourism was applied to the demands of the USA, the UK, Japan and New Zealand for tourism in Australia and chosen alternative destinations. In this study, Divisekera is very tentative about the results, and states: "In spite of the apparent theoretical consistency and empirically plausible nature of the results, caution should be exercised in interpreting the parameter estimates derived from this study. This is because the presence of autocorrelation cannot be ruled out (note that no well-developed diagnostic testing procedures are available to test for the presence of autocorrelation in a system of demand equations). Further bias may also be contained in the parameter estimates due to the use of a limited number of alternative destinations Divisekera" (2003, p. 46-47) (emphasis added by the author). The sample period of this study remains a mystery, because the sample period and frequency of the data used was not mentioned. However, Divisekera (2003, p.48) acknowledges using a small sample and its limitations, "There may be some unknown bias in the derived demand parameters due to the use of a small sample."

The third Australian study is by Kulendran (1996). Kulendran's study is essentially identical to Divisekera's (1995) paper. Like Divisekera, Kulendran (1996) used the Johansen (1991) cointegration procedure to estimate long-run tourist flows to Australia from Japan, New Zealand, the UK and the USA. In contrast to Divisekera (1995), Kulendran utilised quarterly data from 1975:1 to 1990:4 to derive long-run price and income elasticities for each of these origin countries. Surprisingly, the estimated elasticities (Table 2 in Kulendran, 1996) do not have their estimated standard errors or t-values and hence it is difficult to assess the statistical significance of these parameters. The only added feature of Kulendran's (1996) paper is the out-of-sampling forecasts of tourist arrivals in Australia. A careful comparison of the actual and forecast values (see Table 5 of Kulendran, 1996) reveals that in most cases the forecast values are above the actual values. The precision of these forecasts cannot be ascertained in the absence of any indicators of forecasting accuracy (for example, MAPE and so on).

Morley (1998) developed and estimated a non-linear diffusion tourist demand model from seven major tourist sources to Australia including Canada, Germany, Japan, Malaysia, New Zealand, the UK and the USA. Once again the estimation was based on a small sample of 21 annual time-series observations from 1972 to 1992. One of the key findings of this study is the importance of income as a prime determinant of international tourism to Australia. This study found that income elasticity coefficient is inversely related to the income of the origin country. However, the estimated income-elasticities are much lower than the above-mentioned studies.

Webber (2001) investigated the long-run demand for Australian outbound leisure tourism during the period 1983:1 to 1997:4 for nine major tourism destinations, including Indonesia, Japan, Malaysia, Philippines, Singapore, Thailand, New Zealand, the UK and the USA, and found the exchange rate volatility to be a significant determinant of long-run tourism demand in 50 per cent of estimates. Real disposable income and substitute prices were found to have inelastic long-run effects on tourism, while the long-run relative price elasticity tended to differ widely across countries. These results were obtained by two methods: (1) the Engle-Granger (EG) (1987) two-step procedure and (2) the Johansen Maximum Likelihood cointegration procedure (1995).

A few comments are worth mentioning regarding the sample and methodology of the above study. First, the sample period covered 1983:1 to 1997:4. During that period the Australian exchange rate remained pegged until it was floated completely in December 1983. The sample period followed the recession of 1982-83 and included the "recession we had to have" in 1991 followed by the 1996-97 Asian Financial Crisis. These events cast doubts on the results obtained, particularly when trying to assess the impact of exchange rate volatility on outbound tourism. Most Asian destinations were subjected to the contagion of the Asian Financial Crisis in 1996-97, and this exacerbated the two recorded recessions in the sample period. Clark, Tamirisa, and Wei (2004) note that on an average, during the 1970s, 1980s and 1990s the volatility of fixed exchange rates was approximately the same as that of floating rates. The same study found that "Overall, if exchange rate volatility has a negative effect on trade, this effect would appear to be fairly small and is by no means a robust, universal finding". Clark et al. (2004, p. 6) conclude, "These results suggest that, from the perspective of enhancing trade, exchange rate volatility is probably not a major policy concern."

The robustness of parameter estimates due to the small sample size is highlighted by Webber (2001, p. 401-402), "…. to obtain reliable estimates of the number of long-run relationships and the corresponding coefficient estimates, the JP (Johansen Procedure) requires a large number of observations. Since this study will be using 59 quarterly observations, it is on the borderline for concern about this small sample problem. One of the ways that this problem will manifest itself is in the robustness of the estimated long-run parameters."

The Engle-Granger Procedure (EGP) (1987), used in checking the robustness of the Johansen Procedure (1988) estimates, has further econometric limitations. First, low powers and biases are associated with cointegration tests (Banerjee, Dolado, Hendry, & Smith, 1986). Second, the possibility of more than one cointegrated vector highlights the most important weakness of the EGP, because the underlying assumption of EGP allows for only one cointegrating relationship. This is not the case, as shown in Table 3 in Webber (2001, p. 403), where two cointegrating vectors are found for Malaysia, Philippines and Singapore while three cointegrating vectors were found for New Zealand.

The preceding discussion did not comment on the choice of the explanatory variables in the international tourism demand model, mindful of the quote from Crouch (1994, p. 21), "It is apparent from the wide variety of results that a narrative review of the research, as presented here, cannot adequately reveal the underlying nature of the relationships between the demand for international tourism and its determinants." One common theme that ran through all these studies was the ex post use of dummy variables to capture the effects of seasonality and special events (America's Cup, Australian Bicentennial and Expo, and the Pilots' Strike) and these can be regarded as "data mining" by the authors. Another common element in the literature is the application of the Johansen cointegration procedure (1995) utilising small samples with the exception of Morley (1998). The Johansen likelihood ratio (LR) tests (1995) are derived from asymptotic results and statistical inferences in finite samples may not be appropriate. Cheung and Lai (1993, p. 324) demonstrate (emphasis added by the author), *"It is found that Johansen's tests are biased toward finding cointegration more often than what asymptotic theory suggests. Moreover, the finite sample bias magnifies as the dimension of the estimated system or the lag length increases."* Lastly, Divisekera (1995), Kulendran (1996) and Webber (2001) attempt to incorporate the short and long-run dynamic behaviour of international tourism, but none of these studies either mentions or quantifies the speed of adjustment towards equilibrium.

So far this paper has focussed solely on the methodological aspects of these studies and has only provided a succinct critique of the cited works. The discussion above clearly exposes the weaknesses in the existing literature. In view of the paucity of studies on Australian tourism, we now attempt to overcome the weaknesses in the existing literature with a new study that specifically examines tourism demand for Australia from January 1984 to the latest available data until January 2015. This study employ a flexible methodology with a long, high frequency data set that yields more robust results.

The Conceptual Framework

Theory and variables

The choice of a travel destination is a complex and dynamic process. Within tourism many interlinked processes operate, such as economic demand and social demand. Psychological factors, such as time availability and the need to escape from the daily chores of life, also play important roles. Psychological considerations can explain a great deal of recent changes in tourist patterns, and are an important aspect for explaining tourism demand.

From a purely economic viewpoint, the choice of tourist destination is one of consumer's constrained utility maximising problems subject to prices and income. The aggregate demand function that captures the tourist arrivals (TA) in Australia in time period t can be written as:

$$TAt = f(p,Y,O) \tag{1}$$

where, p is a vector of the prices of all consumption goods, Y is aggregate foreign income and O is a vector of exogenous (non-economic) determinants of demand such as seasonal factors, risk factors (external and internal conflicts, and ethnic tension) coupled with socio-economic variables. We assume that tourists have complete information about the exogenous (seasonal, risk, socio-economic factors and so on) elements at the destination. This assumption is intuitive, because tourists are becoming better informed through using the internet and sharing experience with friends who have travelled to their intended destination.

Most variables within the demand function do not have simple empirical counterparts. This study uses the number of tourist arrivals at the destination country as a measure for tourism demand. These data are easily available and accessible and free from ambiguities (Witt & Witt, 1995).

The vector of prices in the tourism demand function is often difficult to measure, because tourist price indices are typically unavailable, so we used the real exchange rate as a measure of relative prices. The use of the real exchange rate, which is the nominal exchange rate adjusted for inflation in both the origin and the destination countries, better accounts for the changes in actual cost of living in both countries. A rise in the real exchange rate (real appreciation) implies that purchases in the destination are relatively more expensive for the tourists, which can be due to a combination of factors, such as a higher inflation rate in the destination compared with the origin, or the destination country's exchange rate having appreciated in nominal terms. Overseas travel is expensive, and is considered to be a luxury good, and thus is a function of discretionary income of the origin country. In the absence of a measurable discretionary income, this study used the weighted average of GDP of Japan, New Zealand, the UK and the USA as a representative of world income to measure tourist income, the weights being the tourist arrivals of the above countries.

The estimation method that this study used to examine whether tourist arrivals in Australia and the real exchange rate and world income are cointegrated was the autoregressive distributed lag (ARDL) model developed by Pesaran & Shin (1998) and further extended by Pesaran et al. (2001). The long-run model in natural logarithmic form of equation (1) is given in equation (2).

$$LnTA_t = \alpha + \beta LnR_t + \gamma LnY_t \tag{2}$$

where, TA = tourist arrivals; R = real exchange rate and Y = world income proxied by the weighted average of GDPs of Japan, New Zealand, the UK and the USA. The subscript t refers to the time period and Ln denotes the natural logarithm. Equation (2) can be analysed by performing a cointegration test. Prior to conducting the cointegration test, it is essential to check the time-series properties of the variables. If a time-series is non-stationary, the traditional regression analysis will produce spurious results. Therefore, the unit-root tests are conducted first.

Time-Series Properties In The Presence Of Structural Breaks

Data and data sources

This paper examined monthly data from 1984:01 to 2015:01, which was the latest available data. The sample period considered was the post-float period of the Australian dollar. The choice of the sample period was premised on the criterion of evaluating the effect of the free floating real exchange rate on tourism demand. The sources of data for the variables were: Tourist arrivals (TA) seasonally adjusted figures were extracted from ABS Table 3401-01: Category of Movement: Arrivals. The frequency of data was monthly. Trade-weighted real exchange rate index (R) was taken from the Reserve Bank of Australia (RBA) Table F.11: Exchange Rates: Units of Foreign Currency per A$ (end of month). The frequency of data was monthly. The methodology used by RBA for calculating the various real exchange rate indices was drawn from Ellis (2001). World real GDP (Y) (proxied by the weighted average of Japan, New Zealand, the UK and the USA GDP) index are from RBA Table I.01: Real Gross Domestic Product. Frequency of data was quarterly which was transformed into monthly figures by using the Transform Frequency option built into the EconData dX Software produced by EconData Pty Ltd. The data used in this paper were obtained from the dX database (EconData Pty Ltd.). The econometric packages used were: Microfit 5.0 (Pesaran & Pesaran, 2009); EViews 7.0 (Quantitative Micro Software, LLC); and RATS Version 7.1 (Estima).

Stationarity of data

This study applied the Augmented Dickey-Fuller (ADF) unit-root test (where the specification included a trend and intercept term) as a benchmark. A summary of the unit-root test results is given in Table 1. Because the ADF test suffers from power deficiency in the presence of structural breaks, the Lee and Strazicich (LS) (2003) minimum Lagrange Multiplier (LM) unit-root tests has been performed to determine structural breaks endogenously. The examples of policies with break consequences include frequent devaluations, deregulation of both real and financial sectors and policy regime shifts, abrupt exogenous changes such as the SARS pandemic and so. This can lead to huge forecasting errors and unreliability of the model in general.

The minimum LM unit-root test with two structural breaks endogenously determines the location of two breaks in level and trend, and also tests the null of a unit-root. LS (2003) note that accepting the alternative of the minimum LM unit-root test with two structural breaks unambiguously implies trend stationarity while not rejecting the null implies that the series possesses a unit-root either with or without structural breaks.

Lee and Strazicich (LS) (2003) Minimum LM unit-root test considers the DGP as follows:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + u_t$$

where, $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t\tilde{\delta}$ $(t = 2, \ldots T)$ and Z_t is a vector of exogenous variables defined by the data generating process; $\tilde{\delta}$ is the vector of coefficients in the regression of Δy_t on ΔZ_t respectively with Δ the difference operator; and, $\tilde{\psi}_x = y_1 - Z_1\tilde{\delta}$ with y_1 and Z_1 the first observations of y_t and Z_t respectively.

Model B in Perron (1989) is omitted from further discussion by LS (2003), because it is commonly held that most economic time-series can be adequately described by either model A or C. Perron's (1989) Model C allows for a shift in intercept and change in trend slope under the null hypothesis and is described as $Z_t = [1, t, D_t, DT_t]'$, where $DT_t = t - T_B$ for $t > T_B + 1$, and zero otherwise. Importantly, testing involves using ΔZ_t instead of Z_t. ΔZ_t is described by $[1, B_t D_t]'$ where $B_t = \Delta D_t$ and $D_t = \Delta DT_t$. Thus, and correspond to a change in the intercept and trend under the alternative, and to a one-period jump and (permanent) change in drift under the null hypothesis respectively.

The unit-root null hypothesis is described by $\phi = 0$ and the LM t-test is given by $\tilde{\tau}$, where $\tilde{\tau}$ = t-statistic for the null hypothesis $\phi = 0$. The augmented terms $\Delta\tilde{S}_{t-j}$, $j = 1,\ldots k$, terms were included to correct for serial correlation. The value of k is determined by the general-to-specific search procedure. To endogenously determine the location of the break (T_B), the LM unit-root searches for all possible break points for the minimum (the most negative) unit-root t -test statistic, as follows:

$$Inf\,\tilde{\tau}(\tilde{\lambda}) = Inf_{\lambda}\tilde{\tau}(\lambda)\text{; where } \lambda = T_B / T.$$

The two-break LM unit-root test statistic can be estimated analogously by regression according to the LM (score) principle. Here, Model A in Perron (1989) allows for two shifts in level; while Model C includes two changes in level and trend. Critical values of the endogenous two-break LM unit-root test ($T = 100$) is reported in Table 3 by LS (2003, p. 1084). LS (2003, p. 1087) concludes, "In summary, the two-break minimum LM unit-root test provides a remedy for a limitation of the two-break minimum LP test that includes the possibility of a unit-root with break(s) in the alternative hypothesis. Using the two-break minimum LM unit-root test, rejection of the null hypothesis unambiguously implies trend stationarity."

Unit-root tests for one (LS1) and two breaks (LS2) were conducted with RATS software with the code provided by Estima. The LS-Break Model (Model C) captures the change that is gradual, whereas the LS-Crash Model (Model A) picks up the change that is rapid. This study reports the results of the latter. The LS-Break Model results can be obtained from the author upon request. The ADF test suggests that all variables are non-stationary (refer to Table 1). By applying the LS1 and LS2 unit-root tests, it was found that all variables are also non-stationary. This result is surprising, because the ADF test is known to suffer from power deficiency when a structural break or breaks are present in the data.

Table 1. Unit-Root Tests in the Absence and Presence of Structural Breaks

Variable: LnTA				
Test	Time of Break 1	Time of Break 2	T_{α}=1	Decision
ADF	NA	NA	-1.8832	NS
LS1	2000:09*	NA	-1.2996	NS
LS2	2000:09*	2003:03**	-1.5014	NS

Variable: LnR				
Test	Time of Break 1	Time of Break 2	T_{α}=1	Decision
ADF	NA	NA	-3.1911	NS
LS1	1989:01**	NA	-1.6861	NS
LS2	1989:01**	2001:07	-1.7405	NS

Variable: LnY				
Test	Time of Break 1	Time of Break2	T_{α}=1	Decision
ADF	NA	NA	-1.3438	NS
LS1	1996:03**	NA	-1.7164	NS
LS2	1992:09	1996:03*	-1.8692	NS

Notes:
1. NA = not applicable; S = stationary, NS = non-stationary.
2. ADF test critical values at 1, 5 and 10 % level are -3.9896, -3.4252 and –3.1357 respectively.
3. * and ** refer to significant at 5 and 1 % level of significance.

Endogenously determined structural break dates

The estimated single structural break date, as determined by the LS1 Crash Model, corresponds to 2000:09 for *LnTA*, 1989:01 for *LnR* and 1996:03 for *LnY*. These dates are significant at the 5% level of significance. By considering the two-break LS2 Crash Model, the break dates for *LnTA, LnR* and *LnY* are (2000:09 and 2003:03); (1989:01 and 2001:07) and (1992:09 and 1996:03) respectively. The structural break dates are statistically significant for *LnTA*, while one of the break dates is not statistically significant for *LnR* and *LnY*.

The first break date of *LnTA* coincided with the Sydney Summer Olympics of September 2000. The second break date associated with *LnTA* was March 2003 due to the outbreak of SARS. The SARS pandemic between November 2002 and July 2003 had an adverse affect on global tourism, including Australia. Within weeks in early 2003, SARS spread from the Guangdong province in China to rapidly infect individuals in some 37 countries around the world.

The endogenously determined break dates in this study are plausible, considering the events occurring in the Australian economy. The behaviour of the real exchange rate shows periods of instability. One such period was centred on June 1986, the other occurred between March 1998 and June 1999. After a sustained period of depreciation, appreciations of the real exchange rate occurred during 1986-1989, so that the break date for the real exchange rate occurred in 1989:01, followed by the meltdown in 2001:07. The recession of the early 1990s in Australia (as well as in the USA) also impacted on the productivities of the two countries. The recessionary effects on World GDP were captured by the break dates of 1992:09 and 1996:03 respectively.

Empirical Findings

Econometric methodology

This section describes the use of the ARDL modelling approach for cointegration analysis. The main advantage of ARDL modelling lies in its flexibility that it can be applied "irrespective of whether the regressors are purely I(0), purely I(1) or mutually cointegrated" (Pesaran et al., 2001, p. 289-290). Another advantage of this approach is that the model takes sufficient numbers of lags to capture the data generating process in a general-to-specific modelling framework (Laurenceson & Chai, 2003, p. 28). Moreover, a dynamic error-correction model (ECM) can be derived from ARDL through a simple linear transformation (Banerjee, Dolado, Galbraith, & Hendry, 1993, p. 51). The ECM integrates the short-run dynamics with the long-run equilibrium without losing long-run information. Using the ARDL approach avoids problems resulting from non-stationary time-series data and typically outperforms alternative approaches to cointegration such as the Phillips and Hansen's Fully Modified Least Squares when the sample size is small (Laurenceson & Chai, 2003, p. 28). This is, in particular, true of the size-power performance of the tests on the long-run parameter. Finally, ARDL modelling is robust against simultaneous equation bias and autocorrelation, provided the orders of the ARDL model are adequately selected on the basis of any model selection criterion.

Thus, the error correction specification of the ARDL model pertaining to equation (2) is given in equation (3) and can be expressed as:

$$\Delta LnTA_t = \alpha_0 + \delta_1 LnTA_{t-1} + \delta_2 LnR_{t-1} + \delta_3 LnY_{t-1} + \sum_{i=1}^{p} b_i \Delta LnTA_{t-i} + \sum_{i=1}^{q} c_i \Delta LnR_{t-i} + \sum_{i=1}^{r} d_i \Delta LnY_{t-i} + \varepsilon_t \quad (3)$$

By incorporating the statistically significant structural breaks in 2000:09 and 2003:03 respectively for *TA*, two dummy variables, *D1* and *D2*, are included in equations (2) and (3) respectively, which gives us the estimable equations (4) and (5). Equation (4) shows the long-run relationship while equation (5) is its short-run error correction representation.

$$LnTA_t = \alpha + \omega D1_t + \psi D2_t + \beta LnR_t + \gamma LnY_t + \nu_t \quad (4)$$

$$\begin{aligned}\Delta LnTA_t = {} & \alpha_0 + \alpha_1 D1_t + \alpha_2 D2_t + \sum_{i=1}^{m} a_i \Delta LnTA_{t-i} + \sum_{i=1}^{n} b_i \Delta LnR_{t-i} + \sum_{i=1}^{p} c_i \Delta LnY_{t-i} \\ & + \delta_1 LnTA_{t-1} + \delta_2 LnR_{t-1} + \delta_3 LnY_{t-1} + \varepsilon_t \end{aligned} \quad (5)$$

where, the dummy variable *D1* takes on a value of zero prior to the first break date of 2000:09 (Sydney Olympics) and unity thereafter up to the second break date that occurs in 2003:03 (SARS outbreak) when *D2* takes on the value of one and zero otherwise. Equation (5) is a standard VAR model in which a linear combination of lagged-level variables are added as proxy for lagged error terms which measures the departure of the dependent variable from the independent variables in equation (4). The parameter δ_i , $i = 1$, 2, 3, are the long-run multipliers. The parameters a_i, b_i and c_i are the short-run multipliers; v_t and ε_t represent the white noise residuals. The model above is ARDL *(m, n, p,)*, where *m, n, p,* represent the lag length. In equation (5), the terms with the summation signs represent the error correction dynamics while the second part (terms with) corresponds to the long-run relationship.

The ARDL cointegration procedure for estimating equation (4) involves two stages of tests. First, this study tested the null hypothesis $(H_0\text{:}all\ \delta i = 0)$, that is, the non-existence of the long-run relationship, against the alternative of one cointegrating vector among the variables, using the *F*-test. In the second stage of the analysis, this study estimated the coefficients of the long-run relationships and made valid inferences about their values.

It is only appropriate to embark upon the second stage of analysis if cointegration among the variables is well established (Pesaran & Pesaran, 2009, p. 317). The estimated orders of an ARDL (m, n, p) model were selected by searching across number of regressions, where is the maximum number of lags used and k is the number of variables in the equation. As this study uses monthly data, 12 lags were selected as the maximum lag (l) following Pesaran & Pesaran (2009). The specification used here was the unrestricted intercept with no trend (Case III in Pesaran et al., 2001, p. 296).

Cointegration and estimation of long-run coefficients

This study investigated the long-run relationship between tourist arrivals (*TA*), real exchange rate (*R*), world GDP (*Y*), two endogenously determined structural break dummy variables *D1* and *D2* given in equation (4) by using the *'bounds test'* developed by Pesaran et al. (2001). The bounds test for examining the presence of a long-run relationship can be carried out using the *F*-test, where the null hypothesis tests the joint significance of $\delta_1 = \delta_2 = \delta_3 = 0$ in equation (5). The *F*-test has a non-standard distribution and is contingent on: (1) whether variables in the ARDL model are *I(0)* or *I(1)*; (2) the number of regressors; (3) whether the model has an intercept and/or a trend; and (4) the sample size. Pesaran et al. (2001) computed two sets of critical values which classified regressors into pure *I(1), I(0)* and mutually cointegrated categories. If the computed *F-statistic* is greater than the upper critical bound (UCB), the regressors are *I(1)*; if the *F-statistic* is less than the lower critical bound (LCB), the regressors are *I(0)*; and if the *F-statistic* falls within the interval of LCB and UCB, inference is inconclusive, and the order of integration between the underlying variables are required for a conclusive inference (Pesaran et al., 2001, p. 299).

Table 2. Bounds Test for Cointegration Analysis

Computed F-Statistics (F_{Bounds})	7.96	
Critical bounds (10 %)	LCB: 3.17♠	UCB: 4.14♠
	LCB: 4.35♣	UCB: 5.32 ♣
Critical bounds (5 %)	LCB: 3.79♠	UCB: 4.85♠
	LCB: 5.17♣	UCB: 6.18 ♣

Notes:
1. LCB = lower critical bound and UCB = upper critical bound.
2. ♠ Critical bounds are from Pesaran et al. (2001:300) Table CI (iii) Case III.
3. ♣ Critical bounds are from Pesaran & Pesaran (2009).

Based on the bounds test (given in Table 2), the computed F-statistic is 7.96, which is above the upper critical bound (UCB) at the 5 % significance level. This provides conclusive evidence of a long-run relationship between tourist arrivals and the relevant macroeconomic variables, namely the real exchange rate and real GDP. Given the existence of a long-run relationship, in the next step the study used the ARDL cointegration method to estimate the parameters of equation (5) with maximum order of lag set to 12. The optimal ARDL model in levels, using order (5, 4, 0) as selected by the Akaike Information Criterion (AIC) model selection criteria is given in Table 3. Judge, Griffiths, Hill, Lutkepohl, and Lee (1985, p. 869) clearly show how the most common model selection criteria (for example, Schwarz Bayesian criterion and Hannan-Quinn criterion) not considered here, are variations of one another and are asymptotically equivalent.

According to this model, a 1 % increase in the real exchange rate (appreciation) will lead to 1.23 % decrease in tourist arrivals in the long-run. The sign of the estimated coefficient is negative and is statistically significant. This finding is consistent with a priori expectation, because the price effect due to real exchange rate movement is expected to be negative. The magnitude of the estimated coefficient exceeds unity indicating elastic demand.

Table 3. Estimated Long-run Coefficients

Dependent Variable is: $LnTA_t$

Regressors	Coefficient	Standard Error	T-Ratio	P-value
LnR_t	-1.230	0.347	-3.546	0.000
LnY_t	2.261	0.241	9.400	0.000
$D1_t$	-0.132	0.041	-3.204	0.002
$D2_t$	-0.066	0.049	-1.362	0.920
Intercept	3.140	0.918	3.422	0.174

Note: The long-run results are derived from the estimated ARDL (5, 4, 0) model given in Table 4.

According to this model, a 1 % increase in world income will lead to a 2.26 % increase in tourist arrivals in Australia. This result supports the fact that tourism is a luxury good, with income elasticity in excess of unity. The estimated income elasticity lies within Divisekera's (1995, p. 298) lower bound value of 1.494 (for the USA) and the upper bound value of 3.561 (for Japan). The income elasticity coefficient is also consistent with the findings of Kulendran (1996). However, Morley (1998, p. 78) estimates the income elasticities of demand to be less than unity for Canada, Malaysia, New Zealand, the UK and the USA – with the exception of Germany and Japan, where the income elasticity coefficients were estimated at 1.3 and 2.94 respectively.

Ryan (2003) argues that tourism is susceptible to variations in macroeconomic growth. In times of recession tourism appears to be income inelastic, while in times of growth tourism becomes income elastic. This asymmetry can be explained as follows: when economies grow, levels of disposable income usually rise. A relatively large part of discretionary income will typically be spent on tourism. On the other hand, a tightening of the economic situation will often result in a decrease in tourism spending.

The results found that dummy variable *D1* was negative and statistically significant while *D2* was also negative but statistically insignificant. Since the Sydney Olympics in R^2 = 2000:09, tourist numbers declined considerably, compounded by the 9/11 incident in 2001, which subsequently led to severe restrictions on air travel worldwide bringing down tourist arrivals as well. This downward trend was further aggravated by the outbreak of the SARS pandemic in late 2002. Tourism plummeted due to SARS, and its deleterious effects continued on till the end of the sample period in 2009:01.

Table 4 shows that the overall goodness of fit of the estimated model (equation 5) is extremely high, showing an . In addition, the joint significance of all regressors is statistically significant at the 1 % level. To ascertain the appropriateness of the ARDL model, various diagnostic analyses for serial correlation, heteroskedasticity, normality of residuals and model adequacy tests were conducted, and are reported in Table 4. These tests indicate that the specified model passes all the diagnostic tests. Following Pesaran & Pesaran (2009), this study used the Brown, Durbin, and Evans (1975) stability testing technique. This technique is also known as the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) test. The CUSUM and CUSUMSQ statistics are updated recursively and plotted against the break points. If the plots of CUSUM and CUSUMSQ statistics stay within the critical bounds of 5 % level of significance, then the null hypothesis of all coefficients in the given regression are stable and cannot be rejected. The CUSUM and CUSUMSQ plot to check the stability of short-run and long-run coefficients in the ARDL error correction model are given in Figures 1 and 2. They are within the critical bounds, indicating that all coefficients in the ARDL error correction model are stable.

Table 4. Autoregressive Distributed Lag Estimates
ARDL (5, 4, 0) selected based on Akaike Information Criterion

Dependent Variable is: $LnTA_t$

Regressors	Coefficient	Standard Error	T-Ratio	P-value
$LnTA_{t-1}$	0 .702	0.059	11.822	0.000
$LnTA_{t-2}$	0.264	0.073	3.630	0.000
$LnTA_{t-3}$	-0.059	0.075	0.791	0.430
$LnTA_{t-4}$	-0.160	0.73	-2.200	0.029
$LnTA_{t-5}$	0.162	0.058	2.790	0.006
LnR_t	-0.070	0.069	-1.020	0.309
LnR_{t-1}	0.081	0.097	0.841	0.401
LnR_{t-2}	0.043	0.097	0.449	0.654
LnR_{t-3}	-0.023	0.968	-0.240	0.811
LnR_{t-4}	-0.143	0.070	-2.061	0.040
LnY_t	0.207	0.066	3.126	0.002
$D1_t$	-0.012	0 .004	2.696	0.007
$D2_t$	-0.006	0.005	-1.178	0.240
Intercept	0.287	0.075	3.497	0.001

R-Squared	0.99490	R -Bar-Squared	0.99466
S.E. of Regression	0 .014749	F -stat. F(13, 275) 4126.1	[0.000]
Mean of Dependent Variable	5.4545	S.D. of Dependent Variable	0.2018
Residual Sum of Squares	0.059824	Equation Log-likelihood	815.6883
Akaike Info. Criterion	801.6883	Schwarz Bayesian Criterion	776.0233
DW-statistic	2.0418		

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (12) = 18.72 [.051]	F(12, 263) = 1.52 [.028]
B: Functional Form	CHSQ (1) = 0.921 [0.337]	F(1, 274) = 0.876 [.350]
C: Normality	CHSQ (2) = 21.881 [.000]	Not applicable
D: Heteroscedasticity	CHSQ (1) = 0.107 [.743]	F(1, 287)= 0.106 [.744]

A: Lagrange multiplier test of residual serial correlation
B: Ramsey's RESET test using the square of the fitted values
C: Based on a test of skewness and kurtosis of residuals
D: Based on the regression of squared residuals on squared fitted values

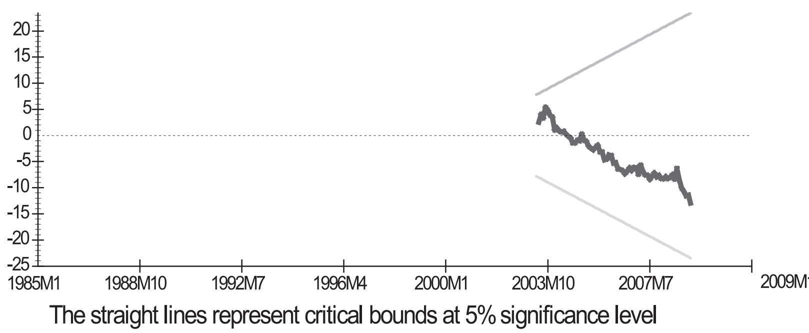

Figure 1: Plot of Cumulative Sum of Recursive Residuals

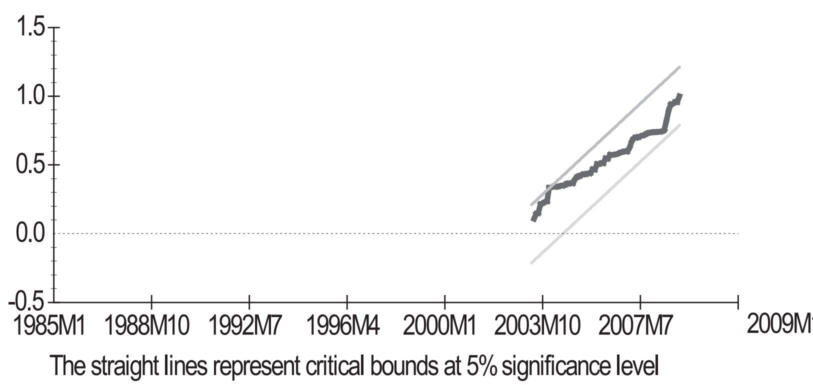

Figure 2: Plot of Cumulative Sum of Squares of Recursive Residuals

Short-run dynamics

Having estimated a stable long-run tourist arrivals equation, this study then estimated a dynamic (short-run) model. Table 5 presents the error correction estimation. The empirical results are based on the re-parameterisation of the estimated ARDL(5, 4, 0) model. The short-run adjustment process is measured by the error correction term ECM_{t-1}, which indicates how quickly variables adjust and return to equilibrium. The coefficient of ECM_{t-1} should carry the negative sign and be statistically significant. In a study, Kremers, Erickson, and Dolado (1992) assert that the significance of the error correction term is an efficient and a useful way of establishing cointegration. This substantiates the earlier finding of cointegration via the bounds test. As shown in Table 5, the estimated coefficient for ECM_{t-1} is equal to -0.09 for the specified model and highly significant, indicating that the deviation from the long term equilibrium path is corrected by nearly 9% over the following month. In other words, the speed of adjustment process is high.

Table 5

Error Correction Representation for ARDL (5, 4, 0)

Dependent Variable is: $\Delta LnTA_t$

Regressor	Coefficient	Standard Error	T-Ratio	P-value
$\Delta LnTA_{t-1}$	-0.207	0.058	-3.556	0.000
$\Delta LnTA_{t-2}$	0.575	0.060	0.964	0.336
$\Delta LnTA_{t-3}$	-0.001	0.060	-0.026	0.979
$\Delta LnTA_{t-4}$	0.162	0.058	-2.790	0.006
ΔLnR_t	-0.070	0.069	-1.020	0.309
ΔLnR_{t-1}	0.123	0.069	1.794	0.074
ΔLnR_{t-2}	0.167	0.069	2.412	0.017
ΔLnR_{t-3}	0.143	0.700	2.061	0.040
ΔLnY_t	0.207	0.066	3.126	0.002
$\Delta D1_t$	-0.012	0.004	2.696	0.007
$\Delta D2_t$	-0.006	0.005	-1.178	0.240
ECM_{t-1}	-0.091	0.023	-3.999	0.000

R-Squared	0.1685	R-Bar-Squared	0.1292	
S.E. of Regression	0.0147	F-stat. F(12, 276)	4.6452	0.000
Mean of Dependent variable	0 .0025	S.D. of Dependent Variable	0.0158	
Residual Sum of Squares	0.0598	Schwarz Bayesian Criterion	776.0233	
Akaike Info. Criterion	801.6883	DW-statistic	2.0418	

Conclusion

This paper adds new insights to the literature on the determinants of international tourism in Australia. This research differs from previous studies in many ways: First, this study estimates an aggregate tourist demand function for Australia by utilising high frequency monthly data from 1984:01 till 2015:01. Previous studies (Divisekera, 1995 & 2003; Kulendran, 1996; Morley, 1998) used short sample periods to estimate a pair-wise tourist function for Australia. Second, it conducted unit-root testing with the Lee and Starzicich (2003) test procedure in the presence of two endogenous structural breaks. No previous studies on tourism have used the third-generation unit-root test procedures. Third, the estimated break dates were found to be plausible with the events in Australia and elsewhere. These breaks were subsequently incorporated as dummies in the model to capture the non-linearity in the tourism demand model. Previous studies imposed the special events dummies in an ex post fashion. Fourth, this study modelled tourism demand in Australia by the application of ARDL modelling, which is flexible and robust to estimate long and short-term relationships among relevant variables.

The empirical results support the view that a strong, negative link exists between the real exchange rate and tourist arrivals in Australia from the period 1984:01 to 2015:01. The model shows that a 1% real appreciation of the Australian dollar will lead to a 1.23 decrease in tourist arrivals in Australia in the long-run. These findings are in conformity with those of Toh, Khan, and Goh (2006), where Japanese tourists to Singapore were found to be sensitive to the exchange rate and income. Similarly, Eilat and Einav (2006) found that exchange rates matter for tourism revenue in developed countries. The results also highlight the key role that income has in explaining international tourism to Australia: a 1 % increase in world income will increase tourist arrivals by 2.26 % in the long-run. Webber (2001, p. 404) also asserts the importance of national income on out-bound tourism of Australia, "…. alterations in national income are the single most important determinant of tourism, with seasonality running a close second. National income is likely to have close to a one-for-one percentage impact on tourism."

It was found that one of the two endogenously determined structural break dummy variables was negative and significant (2000:09 Sydney Olympics), while the second dummy variable (2003:03 SARS pandemic) was found to be negative but insignificant. Considering the significant negative effect of structural breaks on tourist arrivals, non-linearity exists in the tourist demand function of Australia since the Sydney Olympics. Last but not the least, it was found that the speed of adjustment towards the equilibrium path was high, with short-run disequilibrium correcting by approximately 9 % a month. These results hold some general lessons for countries wanting to expand tourism and tourism revenue. The real exchange rate should not be misaligned so that Australia loses its competitive advantage. Australia must maintain its international price competitiveness to encourage tourist arrivals. Finally, tourism demand can be expected to expand as incomes rise around the world, suggesting that the tourism industry will continue to attract investment in the future.

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