Forecasting international quarterly tourist flows using error-correction and time-series models

N. Kulendran a, Maxwell L. King b,*

aDepartment of Applied Economics, Victoria University of Technology, Victoria, Australia
bDepartment of Econometrics, Monash University, Clayton, Victoria 3168, Australia

Abstract

This paper compares a range of forecasting models in the context of predicting quarterly tourist flows into Australia from the major tourist markets of USA, Japan, UK and New Zealand. Models considered include the error-correction model, the autoregressive model, the autoregressive integrated moving average model, the basic structural model and a regression based time series model. Seasonality is an important feature of these series that requires careful handling. The relative performance of each model varies from country to country. The main conclusion is that relative to the time-series models, the error correction models perform poorly. This may be caused by the way in which decisions on how best to model nonstationarity and seasonality are made. © 1997 Elsevier Science B.V.

Keywords: Unit roots; Seasonality; Tourism demand; Cointegration; Forecast comparison

1. Introduction

Recently, Martin and Witt (1989) and Witt and Witt (1995) compared the forecasting performance of econometric and time-series models within the context of predicting tourist arrivals. Martin and Witt's (1989) econometric model involved the use of least squares regression to model the level of tourist arrivals in a particular country as a linear function of the factors (such as income, price, airfare and special events, etc.) that influence arrivals. Remaining autocorrelation was corrected using the Cochrane-Orcutt procedure. Others who have also used regression analysis to model the level of tourist arrivals include Loeb (1982); Uysal and Crompton (1984); Witt and Martin (1987); Crouch et al. (1992) and Morris et al. (1995).

Our concern in this paper is with forecasting quarterly tourist arrivals into Australia from four separate parts of the world; namely Japan, New Zealand, United Kingdom—Ireland and USA. These four time-series each have strong trends and seasonal components. Through the blossoming literature on spurious regression and cointegration analysis (see for example Granger and Newbold, 1974 and Engle and Granger, 1987, 1991), we now know that considerable care has to be taken when conducting...
regression analysis on such data to avoid the problem of estimating a spurious regression. In fact, the above-mentioned analyses may be criticised on the grounds that they did not guard against this possibility. This point was addressed in a recent paper by Kulendran (1996) who applied cointegration analysis to the problem of modelling tourist arrivals. This involves identifying long-run relationships between the economic variables and then fitting an appropriate error correction model (ECM).

Our aim is to fit a range of different time-series forecasting models to the four tourist arrival series and to compare the forecasting accuracy of these models with that of the estimated ECMs. The types of models fitted include seasonal autoregressive integrated moving average (ARIMA) models, Harvey's (1990) basic structural models (BSM), simple autoregressive (AR) models and regression based time series models. Throughout a major issue is how to model the seasonality.

The plan of the paper is as follows. Section 2 discusses the economic factors which influence the demand for international tourism and the data used in this study are also discussed. Section 3 reports the use of cointegration analysis to estimate ECMs for each of the series under study. Section 4 outlines the various time series models fitted to each of the series. The results of the comparison of the forecasting performance of each of the estimated models are discussed in Section 5. Some concluding remarks are made in the final section.

2. Economic factors and data

The first step in econometric model building is to identify appropriate explanatory variables. In any demand study, price and income are always likely candidates.

The price of international tourism can be divided into two components: the cost of living at the destination and the cost of transport. For tourists from the USA and the UK, we took the cost of living component to be Australian prices relative to American prices. This is based on the assumption that American tourists compare living costs of a holiday in Australia with those of a domestic holiday in say California or Hawaii. For UK tourists, we are assuming they compare living costs of a holiday in Australia with those for a similar long-haul destination such as California or Hawaii. New Zealand is geographically close to Australia so it is natural for New Zealanders to compare the costs of a domestic holiday with one in Australia. For these tourists we took the cost of living component to be Australian prices relative to New Zealand prices. For Japanese tourists, we compared Australian living costs with those in Hawaii. For Japanese looking for sandy beaches and a good climate, Queensland and Hawaii have a lot in common including their distance from Japan.

Real personal disposable income is clearly the most appropriate measure of income for our purposes. Unfortunately we were unable to obtain quarterly observations on such variables and had to resort to the use of other measures of income such as gross domestic product (GDP) for the UK and gross national product (GNP) for the USA and Japan. These were obtained from the OECD publication Main Economic Indicators and are in seasonally adjusted form. In the case of New Zealand we used production based real GDP (obtained from the New Zealand Department of Statistics and not seasonally adjusted). The four respective income series are denoted IUK, IUS, IJA and INZ in the next section.

The cost of transport was measured by the real cost in the origin country's currency, of the one-way economy airfare from London to Sydney (FUK), Tokyo to Sydney (FJA), Auckland to Sydney (FNZ), San Francisco to Sydney (FUS) and Tokyo to Honolulu (FHA). This data was obtained from the ABC World Airways Guide.

Japanese tourists are typically "group-package" tourists who purchase a package tour which includes airfare, accommodation and transport within Australia. Consequently they can be assumed to be more aware of the cost of package tours than the cost of flights to Australia and the cost of living in Australia. For the Japanese model, we therefore combined these two costs to calculate a relative price of tourism (PJA) for an Australian package tour as:

$$ PJA = \frac{0.6FJA + 0.4CL\text{Aus}}{0.6FHA + 0.4CL\text{USA}} $$

where $FJA$ and $FHA$ are the real costs of airfares
from Tokyo to Sydney and Tokyo to Honolulu, respectively, and $CL_{AUS}$ and $CL_{USA}$ are the relative cost of living within Australia and the USA, respectively. For Australia, $CL_{AUS}$ is calculated as

$$CL_{AUS} = \frac{CPI_{AUS}}{CPI_{JAP}E_{AUS/JAP}}$$

where $CPI_{AUS}$ and $CPI_{JAP}$ are respective consumer price indices of Australia and Japan and $E_{AUS/JAP}$ is an index of Australian dollars per Japanese yen.

There are a number of special events that have influenced tourist arrivals into Australia. These were modelled by four different dummy variables whose value is zero except where indicated. Dummy variable $D_{It}$ (= 1 for 1985(1) to 1986(4)) was included in the USA model to represent the set of events that occurred throughout the mid 1980s to make Australia more popular with American tourists. This included increased exposure of Australian films and music, the winning of the America’s Cup yacht race and more vigorous advertising by the Australian Tourist Commission (ATC). In June 1987, the Japanese government announced a new policy aimed at nearly doubling the amount of Japanese overseas travel from 5.5 million trips for 1986 to 10 million trips by 1991 (Nozawa, 1992). This policy shift is represented by dummy variable $D_{2t}$ (= 1 for 1987(3) onwards) in the Japanese model. All models included dummy variable $D_{3t}$ (= 1 for 1988(2) and 1988(3)) to represent the effect of the World Expo hosted in Brisbane in 1988 and dummy variable $D_{4t}$ (= 1 for 1989(4)) to represent the effect of the 1989 Australian airline pilots’ strike.

Finally the dependent variables in this study are the number of quarterly tourist arrivals from Japan (denoted TJA), from New Zealand (TNZ), from the UK and Ireland (TUK) and from the USA (TUS). These data were obtained from Australian Bureau of Statistics publications. Because our aim is to compare the forecasting performance of different models of these four variables, all model identification, estimation and diagnostic testing was carried out on the 64 observations over the period 1975(1) to 1990(4). This allowed 16 quarterly observations from 1991(1) to 1994(4) to be used to evaluate the out-of-sample forecasting performance of the different approaches. All models were estimated using logs of tourist arrivals.

### 3. Cointegration analysis

In this section, we provide a brief outline of the application of cointegration analysis to construct the ECM’s used in the forecast comparison. Fuller details may be found in Kulendran (1996).

We used the test proposed by Hylleberg et al. (1990) (HEGY) to test for unit roots (seasonal and nonseasonal) in the log of TJA, TNZ, TUK and TUS. The test was also applied to the log of quarterly income and the log of relevant price variables for Japan, New Zealand, the United Kingdom and the USA. For a series $\{x_t\}$, the test involves various $t$ and $F$ tests of the coefficients of the regression

$$y_{4t} = \pi_1y_{1t-1} + \pi_2y_{2t-1} + \pi_3y_{3t-2} + \pi_4y_{3t-1} + \mu_t + \epsilon_t$$

where $y_{1t} = (1 + B + B^2 + B^3)x_t$, $y_{2t} = -(1 + B^2 - B^3)x_t$, $y_{3t} = -(1 - B^2)x_t$, $y_{4t} = -(1 - B^4)x_t$, in which $B$ is the backward shift operator and $\mu_t$ is a deterministic component. We used four different deterministic components. These were (i) an intercept, (ii) an intercept and seasonal dummies, (iii) an intercept and a time trend and (iv) an intercept, seasonal dummies and a time trend. The component $F$ and $t$ tests need the disturbances of (1) to be uncorrelated. We checked this using a general fourth-order Lagrange multiplier test for autocorrelation and added lagged values of $y_{4t}$ when required in order to remove autocorrelation.

The results of the HEGY tests suggest that quarterly tourist arrivals from the USA and New Zealand have unit roots at the zero and seasonal (both biannual and annual) frequencies. The analogous series for the UK appears only to have one unit root which is non-seasonal. Our testing suggests the Japanese series has unit roots at the zero frequency
and one seasonal (annual) frequency. We also found all income, price and airfare series to have one nonseasonal unit root. Consequently, before any relationships are estimated, all variables need to have the same order of integration, namely I(1). This was achieved by removing seasonal unit roots as follows. The seasonal filter \( S_1(B) = (1 + B + B^2 + B^3) \) (see Engle et al., 1989) was applied to tourist arrivals from the USA and New Zealand and the seasonal filter \( S_2(B) = (1 + B^2) \) was applied to the Japanese tourist arrivals series.

Johansen’s (1988) full-information maximum likelihood method was used to estimate the long-run relationships between tourist arrivals and the factors that influence these arrivals such as income, price and airfare. We tested for the possibility of multiple long-run relationships using Johansen and Juselius’ (1990) test but in each case only one relationship was found. The Mircofit 286 program was used to estimate the following relationships:

\[
S_1(B) \log TUS_t = 2.13 \log IUS_t - 3.02 \log PUS_t \\
+ 0.64 \log FUS_t + \hat{u}_{1t} \\
(0.96) \quad (13.51) \quad (1.57)
\]

\[
S_2(B) \log TJA_t = 4.65 \log IJA_t - 0.95 \log PJA_t \\
+ 0.335D_{2t} + \hat{u}_{2t} \\
(11.32) \quad (11.37) \quad (9.50)
\]

\[
\log TUK_t = 2.16 \log IUK_t - 0.98 \log PUK_t \\
- 2.89 \log FUK_t + \hat{u}_{3t} \\
(11.57) \quad (23.94) \quad (10.24)
\]

\[
S_1(B) \log TNZ_t = 1.30 \log INZ_t - 1.16 \log PNZ_t \\
- 0.937 \log FNZ_t + \hat{u}_{4t} \\
(7.82) \quad (6.86) \quad (8.37)
\]

The numbers in brackets are ratio statistics for the test that the associated parameter value is zero. Its asymptotic critical values come from the chi-square distribution with one degree of freedom. For Japan, UK and New Zealand, the estimated parameters have their expected signs and are highly significant. For the USA, the estimated parameters have their expected signs but only the price coefficient is significant at the 1% level. Although their coefficients were found to be insignificant, the income and airfare variables were retained in this cointegrating relationship on the grounds of economic arguments. It is only the error terms of these equations that are used in ECMs presented below. Note that the estimated coefficients give estimates of the long-run elasticities with respect to their corresponding independent variables.

Below we report the estimated ECMs for each of the arrivals series. In each case, up to four lags of the arrivals, income, price and airfare series were included, but only significant terms were retained for final estimation with the least significant terms being deleted first. Similarly, where appropriate, the special event dummy variables discussed above and seasonal dummy variables were included with only significant terms being retained. \( V = (1 - B) \) and \( V_4 = (1 - B^4) \) denote the first and fourth difference operators, respectively. Observe that \( V S_1(B) = V_4 \). \( D_t \) and \( D_{Dt} \) denote quarterly seasonal dummy variables for the June (second) and December (fourth) quarters, respectively. Also \( \hat{u}_{n-1} \) is the error correction term, being the lagged residual from the corresponding long-run equation given above. It measures how far things are from the long-run equilibrium path. DW and LM(4) are the Durbin–Watson test statistic and the Lagrange multiplier test statistic for general fourth-order autocorrelation, respectively. Significance of the DW test can be judged against the usual Durbin–Watson tables (see King and Wu, 1991) while LM(4) is chi-square with 4 degrees of freedom for independent errors. Standard errors are given in parentheses.

\[
V_4 \log TUS_t = 1.764 + 1.024V \log PUS_{t-1} \\
+ 0.295V \log TUS_{t-1} \\
(0.308) \quad (0.302) \quad (0.098)
\]

\[
+ 0.165D_{3t} - 0.260\hat{u}_{1t-1} \\
(0.075) \quad (0.046)
\]
\[ \hat{R}^2 = 0.547, \quad F(4, 54) = 18.55, \]
\[ DW = 2.11, \quad LM(4) = 6.9 \]

\[ \nabla(S(B)) \log TJA_t = -5.76 + 0.589 \nabla(S(B)) \log TJA_{t-2} \\
(1.74) (0.114) \]
\[ - 0.328 \nabla(S(B)) \log TJA_{t-4} \\
(0.126) \]
\[ - 0.291 \nabla \log PJA_{t-2} - 0.217 \hat{u}_{t-1} \\
(0.115) (0.065) \]

\[ \hat{R}^2 = 0.480, \quad F(4, 52) = 14.28, \]
\[ DW = 2.44, \quad LM(4) = 5.73 \]

\[ \nabla \log TUK_t = -0.047 - 0.325 \nabla \log TUK_{t-4} \\
(0.027) (0.120) \]
\[ - 0.458 D_{D_t} + 0.304 D_{D_t} \\
(0.083) (0.092) \]
\[ - 0.156 \hat{u}_{3t-1} \\
(0.049) \]

\[ \hat{R}^2 = 0.939, \quad F(4, 54) = 224.63, \]
\[ DW = 2.43, \quad LM(4) = 7.96 \]

\[ \nabla_4 \log TNZ_t = 2.41 + 0.413 \nabla_4 \log TNZ_{t-1} \\
(0.684)(0.099) \]
\[ + 0.195 \nabla_4 \log TNZ_{t-3} \\
(0.088) \]
\[ - 0.958 \nabla \log PNZ_{t-3} - 0.304 \hat{u}_{4t-1} \\
(0.283) (0.086) \]

\[ \hat{R}^2 = 0.744, \quad F(4, 49) = 39.52, \]
\[ DW = 2.35, \quad LM(4) = 9.0 \]

4. Time series models

In order to provide some benchmarks to compare the quality of forecasts from these ECMs, we also fitted the following time-series models to the four quarterly tourist arrivals series. As an important issue is the correct modelling of the trends and seasonality of these series, we applied the methodology developed and typically used for each different approach. Thus our focus is on what the methodology as typically applied produces, rather than on what the model is capable of producing. As we shall see this provides some interesting insights. In each case, the model was fitted to the log of the arrivals series.

4.1. Autoregressive models

The simplest approach we considered was the fitting of an AR model to a transformation of the series that is nearly stationary. Because each of the series exhibits trend and seasonality, we considered a range of difference operators to make the series more stationary. We decided to apply the \( \nabla_4 \) operator bearing in mind that \( \nabla_4 S(B) \) and \( \nabla_4 \) can remove both stochastic and deterministic trend while \( S_1(B) \) is a seasonal filter.

Two AR models were fitted. The first was a purposely overfitted AR(12) model which is denoted AR(12) in the next section. The second involved using the Schwarz Bayesian Criterion (SBC) to choose an AR(p) model for each series from the range \( p = 1, \ldots, 12 \) and then checking the resultant model residuals for autocorrelation. In all four cases, the AR(1) model was chosen by SBC but in the case of Japanese arrivals, the estimated AR(1) model exhibited fourth-order autocorrelation in its residuals. In order to overcome this problem, we choose to fit an AR(4) model to the Japanese data.

4.2. Seasonal ARIMA models

For more than two decades, Box–Jenkins’ models have been providing benchmark forecasts in many contexts. For this reason, standard Box and Jenkins (1976) methods were used to fit seasonal ARIMA models to each of the four arrivals series. For the USA, Japan, UK and New Zealand; ARIMA(2,1,0)(0,1,0)\( _4 \), ARIMA(1,1,0)(1,1,0)\( _4 \), ARIMA(1,1,0)(1,1,0)\( _4 \) and ARIMA(1,1,0)(0,1,1)\( _4 \) models, respectively, were identified and estimated using the SAS (see SAS, 1988, p.99) program. A number of intervention variables were included in the seasonal ARIMA models. The World Expo variable, \( D_{3t} \), has a significant (at the 5% level) and positive coefficient in the USA and New Zealand models. The Japanese policy variable, \( D_{2t} \), has a significant positive coefficient in the Japanese model. All calculated \( Q \) test
statistics for autocorrelation in the residuals are not significant.

4.3. Simple regression model with ARMA errors

An alternative approach to handling trends (both stochastic and deterministic) and seasonality to those used above is to take first differences and use seasonal dummy variables to model the remaining seasonality and finally fit a seasonal ARMA model to the residual term that remains. This approach was applied to each of the arrival series using the SAS program. The fitted error models were ARMA(2,0,0)(0,0,0)\(^4\) for the USA, ARMA(3,0,0)(1,0,0)\(^4\) for Japan, ARMA(2,0,0)(0,0,0)\(^4\) for the UK and ARMA(1,0,0)(0,0,0)\(^4\) for New Zealand. In addition, the same intervention variables as used in the seasonal ARIMA models were also included. All calculated Q test statistics for autocorrelation in the residuals of the fitted models are not significant at the 5% level. These models are denoted RM (for regression model) in the discussion below.

4.4. Structural time-series models

Recently, Gonzalez and Moral (1995) analysed the external demand for Spanish tourist services using Harvey’s (1990) structural time-series modelling approach. Their estimated model includes explanatory variables, a stochastic trend representing changes in tourists’ tastes and a stochastic seasonal component. Note that a structural time-series model with explanatory variables is a generalization of the regression model with a linear deterministic time trend and seasonal component in addition to the explanatory variables. Also observe that in the ECMs, the lagged dependent variables can be regarded as capturing some of the effects of changes in tourists’ tastes.

Basic structural models with intervention explanatory variables were fitted to each of the tourist arrivals series using the computer program STAMP (see Harvey, 1990, p.15). The same intervention variables as used in the RM and seasonal ARIMA models were again found to be significant with appropriately signed coefficients. All calculated Q test statistics for autocorrelation in the residuals of the fitted models were not significant at the 5% level. These models are denoted BSM in the following discussion.

5. Analysis of forecasting performance

The estimated ECMs and time series models outlined above were used to generate forecasts for quarterly tourist arrivals from the USA, Japan, UK and New Zealand for the post-sample period 1991(1)–1994(4). For each model, one-step, two-step, four-step and eight-step ahead forecasts were calculated and compared with the actual values of the series. We considered forecasts both with and without re-estimation of the model using all available data at the time of the forecast.

Forecasting accuracy was assessed using mean absolute percentage error (MAPE), root mean square percentage error (RMSPE) and root mean square error (RMSE). Each of these measures was used to rank the 6 forecasting models for each series and lead time. These rankings are given in Table 1 together with Theil’s U statistic which gives some idea of the magnitude of the differences in performance between the different approaches.

The first obvious feature is that almost always the AR model outperforms the overfitted AR(12) model and in some instances there is a very large difference, particularly for longer lead times. Because they are similar in most respects, except in the way they handle trends and seasonality, it is interesting to compare the forecasting performance of the RM, ARIMA and AR models. As might be expected and observed by Witt and Witt (1995) in their review, which model performs best depends on the country of origin. For example, the RM is best overall for the USA but arguably the worst predictor for the UK and New Zealand. To a lesser extent, which model is best depends on the lead time. For example, the ARIMA models show a clear tendency to be relatively less accurate than other procedures as the lead time increases. On the other hand, the AR model improves with increasing lead time and provides the best 8 period forecasts for 3 of the 4 countries. This does suggest that simple fourth-order differencing provides better long-term forecasts than the double differencing used in the ARIMA models.
or the combination differencing and seasonal dummy variables used in the RM, at least for our series.

Turning to the BSMs and ECMs, the former perform relatively well for smaller lead times while the latter perform relatively poorly in the short term and improve their relative standing as the lead time increases (the UK series being an exception). The Japanese ECM performs particularly well for lead times of 2 or longer, but for the other countries the ECM is somewhat disappointing.

Overall the RM is the best model for forecasting tourist arrivals from the USA, while for the UK the AR model is best. For tourist arrivals from New Zealand, the ARIMA model provides the best short-term forecasts and the AR model is best for 4-step-ahead and 8-step-ahead forecasts. For Japanese tour-

<table>
<thead>
<tr>
<th>Forecasting Method</th>
<th>USA</th>
<th>Japan</th>
<th>UK</th>
<th>NZ</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ranking</td>
<td>Theil's U</td>
<td>Ranking</td>
<td>Theil's U</td>
</tr>
<tr>
<td>One-step (without re-estimation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>4 3 4</td>
<td>0.24</td>
<td>3 1 1</td>
<td>0.52</td>
</tr>
<tr>
<td>BSM</td>
<td>2 2 2</td>
<td>0.23</td>
<td>2 2 2</td>
<td>0.68</td>
</tr>
<tr>
<td>AR</td>
<td>3 4 3</td>
<td>0.28</td>
<td>5 6 5</td>
<td>1.49</td>
</tr>
<tr>
<td>AR(12)</td>
<td>6 6 6</td>
<td>1.42</td>
<td>4 5 6</td>
<td>1.44</td>
</tr>
<tr>
<td>RM</td>
<td>1 1 1</td>
<td>0.18</td>
<td>1 3 3</td>
<td>0.68</td>
</tr>
<tr>
<td>ECM</td>
<td>5 5 5</td>
<td>0.36</td>
<td>6 4 4</td>
<td>1.21</td>
</tr>
<tr>
<td>One-step (with re-estimation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>2 2 2</td>
<td>0.25</td>
<td>3 1 1</td>
<td>0.54</td>
</tr>
<tr>
<td>BSM</td>
<td>5 3 4</td>
<td>0.29</td>
<td>2 2 2</td>
<td>0.80</td>
</tr>
<tr>
<td>AR</td>
<td>3 4 3</td>
<td>0.28</td>
<td>5 5 5</td>
<td>1.52</td>
</tr>
<tr>
<td>AR(12)</td>
<td>6 6 6</td>
<td>0.76</td>
<td>4 6 6</td>
<td>1.61</td>
</tr>
<tr>
<td>RM</td>
<td>1 1 1</td>
<td>0.18</td>
<td>1 3 3</td>
<td>0.82</td>
</tr>
<tr>
<td>ECM</td>
<td>4 5 5</td>
<td>0.32</td>
<td>6 4 4</td>
<td>1.04</td>
</tr>
<tr>
<td>Two-step (with re-estimation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>3 3 3</td>
<td>0.31</td>
<td>2 2 2</td>
<td>0.74</td>
</tr>
<tr>
<td>BSM</td>
<td>4 2 2</td>
<td>0.29</td>
<td>1 4 4</td>
<td>1.02</td>
</tr>
<tr>
<td>AR</td>
<td>5 5 5</td>
<td>0.56</td>
<td>5 5 5</td>
<td>2.13</td>
</tr>
<tr>
<td>AR(12)</td>
<td>6 6 6</td>
<td>1.38</td>
<td>6 6 6</td>
<td>2.95</td>
</tr>
<tr>
<td>RM</td>
<td>1 1 1</td>
<td>0.15</td>
<td>3 3 1</td>
<td>0.84</td>
</tr>
<tr>
<td>ECM</td>
<td>2 4 4</td>
<td>0.32</td>
<td>4 1 3</td>
<td>0.89</td>
</tr>
<tr>
<td>Four-step (with re-estimation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>5 5 5</td>
<td>0.64</td>
<td>2 5 4</td>
<td>1.55</td>
</tr>
<tr>
<td>BSM</td>
<td>4 3 3</td>
<td>0.33</td>
<td>4 2 2</td>
<td>1.43</td>
</tr>
<tr>
<td>AR</td>
<td>2 2 2</td>
<td>0.26</td>
<td>5 4 5</td>
<td>1.31</td>
</tr>
<tr>
<td>AR(12)</td>
<td>6 6 6</td>
<td>2.14</td>
<td>6 6 6</td>
<td>7.46</td>
</tr>
<tr>
<td>RM</td>
<td>1 1 1</td>
<td>0.21</td>
<td>1 3 3</td>
<td>1.43</td>
</tr>
<tr>
<td>ECM</td>
<td>3 4 4</td>
<td>0.33</td>
<td>3 1 1</td>
<td>0.68</td>
</tr>
<tr>
<td>Eight-step (with re-estimation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARIMA</td>
<td>5 4 4</td>
<td>2.50</td>
<td>5 5 4</td>
<td>4.02</td>
</tr>
<tr>
<td>BSM</td>
<td>4 5 5</td>
<td>2.91</td>
<td>3 2 5</td>
<td>1.52</td>
</tr>
<tr>
<td>AR</td>
<td>1 1 1</td>
<td>0.29</td>
<td>4 3 3</td>
<td>1.44</td>
</tr>
<tr>
<td>AR(12)</td>
<td>6 6 6</td>
<td>4.12</td>
<td>6 6 6</td>
<td>18.63</td>
</tr>
<tr>
<td>RM</td>
<td>2 2 2</td>
<td>0.49</td>
<td>2 4 4</td>
<td>3.43</td>
</tr>
<tr>
<td>ECM</td>
<td>3 3 3</td>
<td>0.33</td>
<td>1 1 1</td>
<td>0.59</td>
</tr>
</tbody>
</table>
ist arrivals it is much harder to be clear-cut about which model is best. Certainly for the longer forecast horizon, the ECM provides the best forecasts. For the shorter lead times, the best model varies between the ARIMA model and the RM.

6. Conclusions

In many ways our findings are similar to those of Witt and Witt (1995) who recently reviewed the literature on forecasting tourism demand. As already mentioned, a feature of the results is the relatively disappointing forecasting performance of the ECMs. We feel they should perform better than they do, particularly for longer lead times. This is because, unlike the other time-series models, they use exogenous variables. In our study we used actual known values of these exogenous variables to calculate forecasts; in practice one would have to use predicted values for longer lead times. An obvious question is why do our ECMs perform so poorly?

One possible answer is the use of hypothesis testing to choose the level of differencing and seasonal differencing. This method was not used on any of the other models. There is a growing consensus in the literature (see for example Schwert (1989)) that tests for unit roots can lack power and therefore favour the null hypothesis. Like Granger et al. (1995), we wonder if hypothesis testing is the most appropriate tool for these model selection decisions. Of course there may be other reasons why our ECMs perform so poorly. However, it would be nice to be able to rule out the possibility that problems are caused by the over use of hypothesis testing to make decisions in the model building process. We therefore conclude that the effect of modelling methodology on forecasting performance, particularly in the context of constructing ECMs from nonstationary data, is an important topic for further research.

Acknowledgments

We are grateful to the editor and two referees for constructive comments on an earlier version of this paper.

References


Biographies: Nadarajumuthali KULENDRAN is a senior lecturer in the Department of Applied Economics at the Victoria University of Technology, Melbourne, Australia. He is currently teaching in the areas of operations research and forecasting and recently completed his doctoral research on forecasting Australian tourist flows at Monash University.

Maxwell L. KING is Professor of Econometrics and head of the Department of Econometrics at Monash University. He has held visiting appointments at the University of Southampton, University of Auckland and University of California, San Diego. He has published widely in a range of econometrics and statistics journals. His research interests include hypothesis testing, regression analysis, model selection, time-series analysis and forecasting.