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Modelling and forecasting Australian domestic tourism

George Athanasopoulos*, Rob J. Hyndman

Department of Econometrics and Business Statistics, Monash University, Melbourne, Vic. 3800, Australia

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Abstract

In this paper, we model and forecast Australian domestic tourism demand. We use a regression framework to estimate important economic relationships for domestic tourism demand. We also identify the impact of world events such as the 2000 Sydney Olympics and the 2002 Bali bombings on Australian domestic tourism. To explore the time series nature of the data, we use innovations state space models to forecast domestic tourism demand. Combining these two frameworks, we build innovations state space models with exogenous variables. These models are able to capture the time series dynamics in the data, as well as economic and other relationships. We show that these models outperform alternative approaches for short-term forecasting and also produce sensible long-term forecasts. The forecasts are compared with the official Australian government forecasts, which are found to be more optimistic than our forecasts.

Keywords: Australia; Domestic tourism; Exponential smoothing; Forecasting; Innovations state space models

1. Introduction

The Australian tourism industry can be divided into three major segments: (i) international inbound tourism; (ii) domestic tourism; and (iii) outbound tourism. Of these, domestic tourism is the largest financial contributor to the Australian economy. In 2005, domestic tourism contributed an estimated $55.5 billion to the Australian economy, more than three times the contribution of international arrivals (Tourism Forecasting Committee, 2005). Despite this, the main focus of Australian academic tourism research has been on international tourism (see, for example, Kulendran & King, 1997; Kulendran & Witt, 2003; Lim & McAleer, 2001a, 2002; Morley, 1998; Morris, Wilson, & Bakalis, 1995); worldwide tourism research has had a similar focus (see Li, Song, & Witt, 2005 for a comprehensive survey).

Domestic tourism also plays a significant role in maintaining and improving tourism infrastructure, especially in regional Australia. An Australian tourist is much more likely than an international tourist to visit regional and remote areas of Australia that are not internationally promoted. Thus, Australian domestic tourism is an important topic that is in need of careful study and analysis.

To the best of our knowledge, the only forecasts available for the Australian domestic tourism market are those produced by the Tourism Forecasting Committee (TFC) and published by Tourism Research Australia (TRA). TRA is a business unit under the umbrella of Tourism Australia, which is an Australian federal government statutory authority. Tourism Australia was established after the initiatives of the Tourism White Paper (2003) which intended to strengthen the tourism industry.

Following the white paper, the TFC was also established as an independent body. The committee comprises experts from both the private and government sectors in the tourism and finance industry. Current members are: Tourism Australia, Australian Standing Committee on Tourism, Australian Tourism Export Council, Department of Industry Tourism and Resources, Australian Bankers Association, Tourism and Transport Forum Australia, Property Council of Australia (representing major property investors), Qantas and Queensland Tourism Industry Council. The TFC produces consensus forecasts for

*Corresponding author.
E-mail addresses: George.Athanasopoulos@buseco.monash.edu.au (G. Athanasopoulos), Rob.Hyndman@buseco.monash.edu.au (R.J. Hyndman).

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international, domestic and outbound tourism activity which are published by TRA. The forecasts produced by the TFC in October 2005 for the third quarter of 2005 and beyond show steady growth in the domestic market. In contrast, our forecasts show that the Australian domestic market is in decline, and it seems that it will remain this way at least in the short-term.

We develop three different statistical models for forecasting Australian domestic tourism. First, to help in understanding and capturing some of the economic relationships important to the domestic tourism market, we construct a regression model of tourism demand. This modelling framework identifies some useful economic relationships and significant events influencing the Australian domestic tourism market. However, as these models are static, they are unable to capture the dynamic properties of the data.

The second approach adopted is to use pure time series models to capture these dynamics. The models employed are single source of error (or innovations) state space models (see Aoki, 1987; de Silva, Hyndman, & Snyder, 2006; Hannan & Deistler, 1988; Ord, Koehler, & Snyder, 1997; Snyder, 1985). These have been extremely successful when applied to data from forecasting competitions (e.g., Hyndman, Koehler, Snyder, & Grose, 2002; Makridakis et al., 1982; Makridakis & Hibon, 2000), and have numerous advantages over the more common form multiple source of error structural time series models (STSM) (as outlined in Ord, Snyder, Koehler, Hyndman, & Leeds, 2005). However, they have never previously been applied to tourism data.

The third modelling approach we take is to include exogenous variables in the innovations state space models. These models combine the advantages of each of the above modelling frameworks. Hence, they capture the significant economic relationships and events identified in the regression models, and combine these with the time series properties of the innovations state space models. Although other formulations of state space models with exogenous variables exist (see Harvey, 1990), this is the first time that the innovations state space formulation with exogenous variables has been published. A two-step estimation procedure is proposed. The estimated models produce accurate short-term forecasts and sensible long-term forecasts.

The data are introduced in Section 2. Section 3 describes the three models and compares them based on within-sample fits and out-of-sample forecast performance. The out-of-sample forecast evaluation also includes forecasts produced by the TFC. Section 4 presents and analyses the long-run forecasts from the three models and those from the TFC. We summarize our conclusions in Section 5.

2. Data

The Australian domestic tourism data were obtained from the National Visitor Survey, managed by TRA. Data is collected by computer-assisted telephone interviews from approximately 120,000 Australians aged 15 years and over on an annual basis (Tourism Research Australia, 2005). We use the number of visitor nights (VN) as the indicator of tourism activity. We disaggregate the data based on the main purpose of travel: holiday (Hol), visiting friends and relatives (VFR), business (Bus) and other (Oth). The available sample spans from the first quarter of 1998 to the second quarter of 2005. Hence, there are a total of $n = 30$ quarterly observations (see Fig. 1).

Fig. 2 shows the total number of visitor nights (the aggregate of the series in Fig. 1). Also shown are the forecasts produced for this series by the TFC in Tourism Forecasting Committee (2005). The annual TFC forecasts show a steady average growth of 0.9% per annum from 2006 to 2014. In contrast, there is no noticeable trend in the historical data from 1998 to 2005.

3. Statistical models

3.1. Regression models

The proposed tourism demand function is

$$VN_t^i = f(t, DEBT_t, DPI_t, GDP_t, BALI_t, OLYMP_t, MAR_t, JUN_t, SEP_t, \varepsilon_t), \quad (1)$$

where $i = \{Hol, VFR, Bus, Oth\}$; VN_t^i is the number of visitor nights per capita travelling for purpose i; t the time period; $DEBT_t$ is real personal debt (by all lenders) per capita included as a proxy to consumer confidence; DPI_t the price index for domestic holiday travel and accommodation reflecting the price movement of domestic travel; GDP_t the real gross domestic product per capita included as an income variable; $BALI_t$ is a dummy variable capturing the effect of the bombings in Bali ($BALI_t = 1$ during the fourth quarter of 2002 and beyond), $OLYMP_t$ is a dummy variable capturing the effect of the Sydney 2000 Olympic games ($OLYMP_t = 1$ in the fourth quarter of 2000, which is the quarter following the games, and 0 otherwise), MAR_t, JUN_t and SEP_t are seasonal dummy variables, and ε_t is a random error term. Full descriptions of the data, the data sources and projections of the regressors used for forecasting are provided in Appendix A.

We considered many other economic variables of interest including petrol prices, prices of competing goods (e.g., car sales), audio equipment and others. However, due to the small sample size and the lack of variation in many of these variables, they were found to be statistically insignificant. The small sample size also prevented us testing for non-linear relationships such as threshold effects for the variables of interest.

Visual inspection of the dependent variables (see Appendix B for plots of the per capita data) suggests that stationarity tests are required. Table 1 presents the results from three unit root tests: the augmented Dickey Fuller

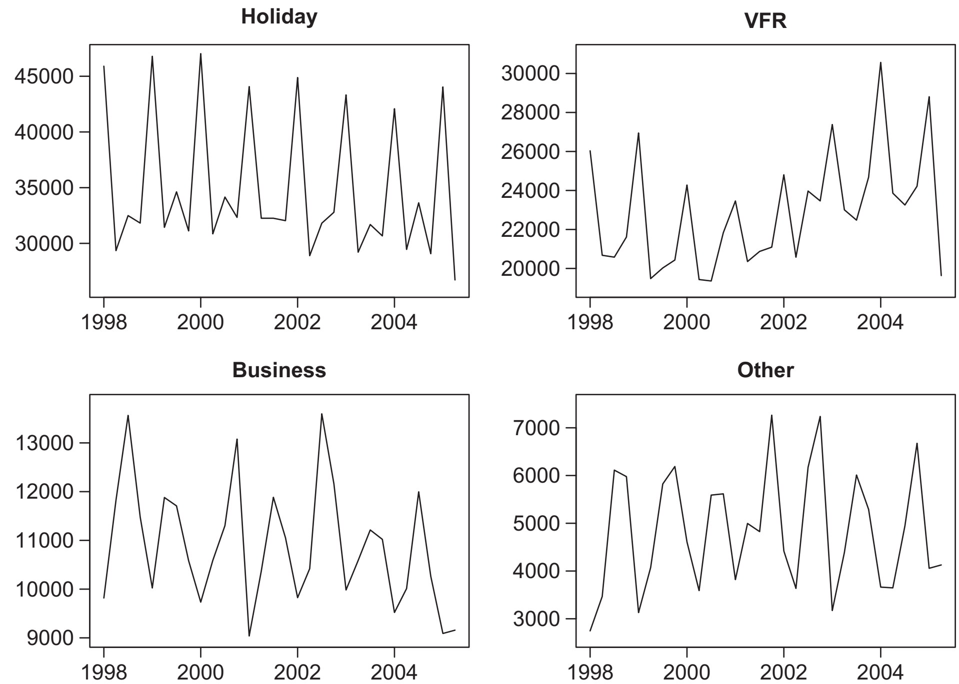

Fig. 1. Quarterly observations for Australian domestic tourism: visitor nights (*VN*).

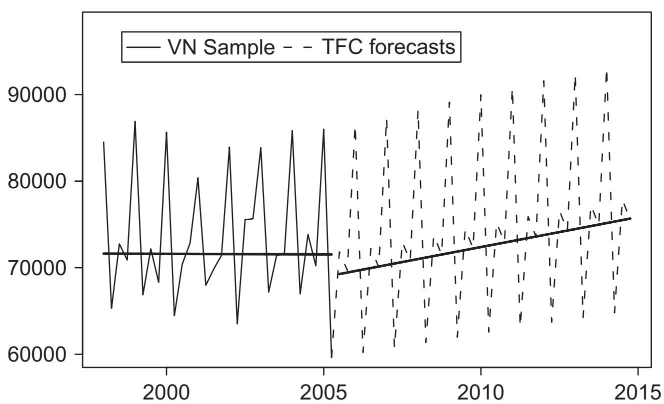

Fig. 2. Linear trend lines fitted to the sample of total visitor nights and the TFC forecasts.

Table 1
Unit root tests

Seasonally adjusted series	ADF	KPSS	MZ_a
$\ln VN_t^{Hol}$	-5.44^a	0.13^a	-14.88^b
$\ln VN_t^{VFR}$	-2.47	0.22^a	-10.98^a
$\ln VN_t^{Bus}$	-4.97^a	0.10^a	-16.47^b
$\ln VN_t^{Oth}$	-6.43^a	0.14^a	-8.14^a

The data generating processes assumed for $\ln VN_t^{Hol}$ and $\ln VN_t^{Bus}$ contain both an intercept and a deterministic trend. The data generating processes assumed for $\ln VN_t^{VFR}$ and $\ln VN_t^{Oth}$ contain only an intercept.
[a]The test finds no unit root at the 5% level of significance.
[b]The test finds no unit root at the 10% level of significance.

(ADF) test (Dickey & Fuller, 1979, 1981), the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) and the Modified Phillips–Perron (MZ_a) test due to Ng and Perron (2001). Ng and Perron (2001) consider modified versions of four existing unit root tests. Their Monte-Carlo simulation results indicate that these tests have superior size and power to any existing test. The results presented here are robust to the choice of the test. In general, the hypothesis testing framework for unit roots can be simply presented by considering an autoregressive process such as

$$y_t = \rho y_{t-1} + \mathbf{z}_t'\boldsymbol{\delta} + \varepsilon_t, \tag{2}$$

where $\mathbf{z}_t$ is a set of exogenous regressors which may contain a constant and a time trend. In the ADF and MZ_a tests, the null hypothesis is that the series contains a unit root (i.e., $H_0 : |\rho| = 1$ versus $H_1 : |\rho| < 1$). The KPSS tests the null hypothesis that the series does not contain a unit root (i.e., $H_0 : |\rho| < 1$ versus $H_1 : \rho = 1$). Before applying these tests, each series was seasonally adjusted (see Fig. 3) using an additive moving average method (e.g., Makridakis, Wheelwright, & Hyndman, 1998). The test results presented in Table 1 indicate that none of the four series contains a unit root.

However, at least two of the response variables are clearly trending (this is especially apparent in Fig. 3 where the seasonal variation has been removed). Consequently, a deterministic trend and the growth rates of the explanatory variables are employed in the regression model; the growth rates are calculated as $(100 \times \Delta \ln(Z))$ for variable Z. We include up to one lag of each regressor. Given the quarterly frequency of the data, we have also tested for lags two, three and four of each regressor (one lag of each regressor at a time due to the small sample size) but these were not found to be significant. After eliminating variables found to be statistically insignificant at a 10% level of significance across all four equations, the general demand model

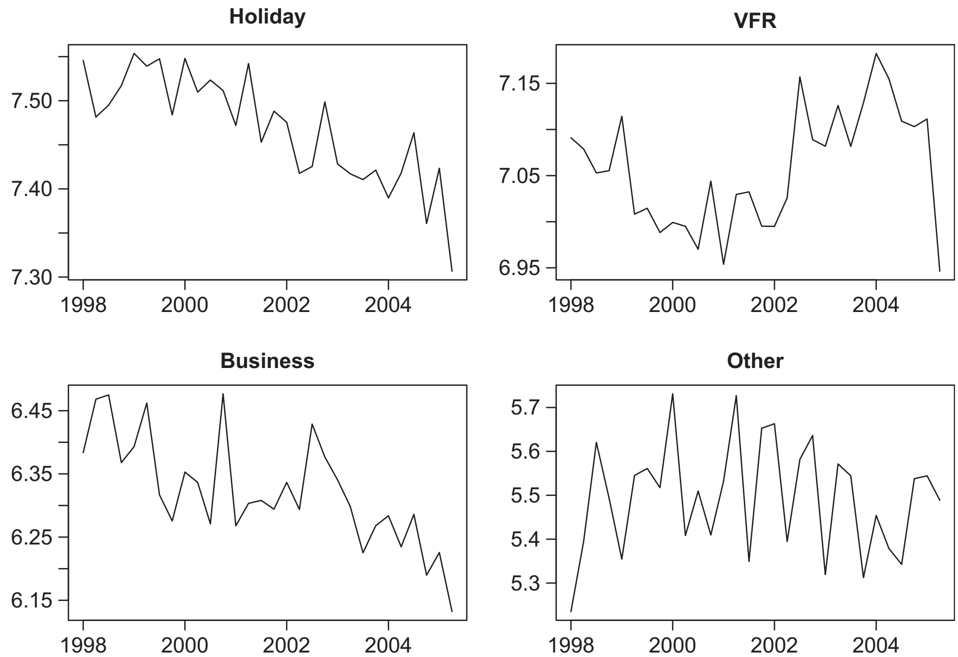

Fig. 3. Seasonally adjusted natural logarithms of visitor nights per capita, i.e., seasonally adjusted ln VN_t^i.

employed is

$$1000 \ln VN_t^i = c + \delta t + \beta_1 D_{t-1} + \beta_2 P_{t-1} + \beta_3 Y_t + \beta_4 BALI_t + \beta_5 OLYMP_t + s_1 MAR_t + s_2 JUN_t + s_3 SEP_t + \varepsilon_t, \quad (3)$$

where D_{t-1} is the lag of the growth rate of $DEBT_t$; P_{t-1} the lag of the growth rate of DPI_t; Y_t the growth rate of GDP_t; and the remaining variables are as described in Eq. (1). The response variable was scaled up by 1000 to avoid very small estimated coefficients.

Table 2 shows the demand equations estimated one at a time using ordinary least squares (OLS). In this setting, the OLS estimator is equivalent to the generalized least squares (GLS) estimator employed in a seemingly unrelated regression (SUR) framework, as the equations contain identical regressors (refer to Green, 2000, p. 616, for proof). The equations show a satisfactory fit with R^2 values ranging from 0.82 for the "Other" variable to 0.98 for the "Holiday" variable. The diagnostic tests at the bottom of the table show that the residuals of each equation satisfy the basic OLS assumptions of no serial correlation, homoscedasticity and normality. Also the RESET test results indicate that the model is appropriately specified.

We simplified the models by eliminating insignificant variables one at a time, selecting the coefficient with the highest p-value among all insignificant coefficients at the 5% level of significance. Then, because we expect that the errors across equations will be contemporaneously correlated and because not all equations include the same regressors, the system was estimated efficiently using the SUR estimation method (Zellner, 1963). The estimation results are presented in Table 3.

The estimated coefficient for the exponential trend is negative and statistically significant in the "Holiday" and "Business" equations. Hence, these results show a significant long-term decline in visitor nights per capita where travel is for holiday and business purposes.

The estimated coefficient of the lag of the growth of *DEBT* is positive and statistically significant in the "Holiday" and "Business" equations. This variable can be considered a proxy for consumer confidence. An increase in the growth rate of borrowing in the last quarter (i.e., a rapid growth in consumer confidence in the previous quarter), results in an increase in domestic travel for both "Holiday" and "Business" purposes.

The lag of the growth in the domestic travel price index, *DPI*, has mixed results across equations. In the "Holiday" equation, the coefficient of *DPI* is negative and statistically significant. This suggests that as prices for domestic travel grew faster (or declined more slowly) in the previous quarter, domestic holiday travel decreased. However, the coefficient in the "Business" equation is positive and statistically significant. This may suggest that domestic travel prices have been driven up by an increase in economic activity. An increase in economic activity should also result in an increase in domestic travel for business purposes, leading to the positive relationship between the lag of the growth rate of *DPI* and business travel.

The coefficient of *GDP* growth was found to be negative across all equations, but was only statistically significant in the "Holiday" equation. The negative coefficient suggests that an increase in the growth of *GDP* results in a significant decline in visitor nights for holiday purposes, and vice versa. Perhaps the explanation for this is that during periods of increasing economic activity, domestic

Table 2
Estimated coefficients of the unrestricted demand model of Eq. (3)

Regressor	Holiday	*VFR*	Business	Other
Intercept	7493.33[a]	7041.23[a]	6472.51[a]	5823.92[a]
	(16.71)	(34.61)	(30.39)	(80.78)
t	−5.14[a]	−2.21	−8.04[a]	6.04
	(0.91)	(1.88)	(1.65)	(4.38)
D_{t-1}	4.34[a]	4.84[b]	7.88[a]	−3.88
	(1.30)	(2.70)	(2.37)	(6.29)
P_{t-1}	−5.45[a]	1.81	8.04[a]	−5.89
	(1.88)	(3.89)	(3.42)	(9.08)
Y_t	−39.09[a]	−14.80	−21.10	−67.23
	(9.61)	(19.91)	(17.48)	(46.48)
$BALI_t$	−14.20	108.02[a]	35.70	−168.23[a]
	(16.31)	(33.80)	(29.67)	(78.88)
$OLYMP_t$	31.60	26.78	118.17[b]	−292.65
	(38.99)	(80.77)	(70.92)	(188.52)
MAR_t	342.68[a]	156.95[a]	−180.97[a]	−563.63[a]
	(13.40)	(27.76)	(24.37)	(64.79)
JUN_t	−39.62[a]	−56.84[a]	−40.34	−510.12[a]
	(13.52)	(28.01)	(24.59)	(65.37)
SEP_t	31.13[a]	−48.22	46.07[b]	−141.28[a]
	(14.35)	(29.74)	(26.11)	(69.41)
R^2	0.98	0.82	0.88	0.82
$\bar{R}^2$	0.97	0.75	0.82	0.73
QN[c]	0.23	0.40	0.57	1.07
QSC_{lags}[d]	1.12_2	2.09_2	4.97_2	9.61_3[e]
QHT[f]	11.27	15.65	15.34	7.71
QRR[g]	0.51	1.19	1.76	1.76

Standard errors are shown in parentheses beneath each coefficient.
[a]Significant at the 5% level.
[b]Significant at the 10% level.
[c]Jarque and Bera (1980) χ^2 test for normality.
[d]Breusch (1978) and Godfrey (1978) Lagrange multiplier χ^2 test for serial correlation.
[e]These residuals showed some weak third order serial correlation which was ignored.
[f]White (1980) χ^2 test for heteroscedasticity.
[g]Ramsey (1969) RESET χ^2 test for misspecification.

Table 3
Estimated coefficients of the demand model of Eq. (3) after eliminating insignificant parameters

Regressor	Holiday	*VFR*	Business	Other
Intercept	7505.57[a]	7020.25[a]	6441.09[a]	5771.92[a]
	(13.33)	(21.03)	(22.84)	(47.28)
t	−5.91[a]		−6.17[a]	
	(0.50)		(0.88)	
D_{t-1}	4.41[a]		5.91[a]	
	(1.23)		(2.00)	
P_{t-1}	−4.11[a]		7.58[a]	
	(1.64)		(2.89)	
Y_t	−43.71[a]			
	(8.14)			
$BALI_t$		56.61[a]		
		(17.75)		
$OLYMP_t$			148.00[a]	
			(51.26)	
MAR_t	338.09[a]	170.33[a]	−170.83[a]	−540.23[a]
	(13.06)	(26.87)	(24.28)	(64.74)
JUN_t	−43.19[a]	−71.36[a]	−42.57[b]	−460.75[a]
	(12.40)	(26.87)	(24.51)	(64.74)
SEP_t	27.78[b]	−33.73	55.03[a]	−109.13
	(14.01)	(27.84)	(25.57)	(66.86)
R^2	0.98	0.79	0.86	0.77
$\bar{R}^2$	0.98	0.75	0.82	0.74

Standard errors are shown in parentheses beneath each coefficient.
[a]Significant at the 5% level of significance.
[b]Significant at the 10% level of significance.

holiday travel decreases significantly as Australians choose to travel to overseas destinations instead. Tourism Forecasting Committee (2005) shows that for Australian residents, short-term departures to overseas destinations have grown at approximately 4% per annum on average between 1995 and 2004.

The dummy variable for the Sydney Olympics captures a positive and statistically significant increase of business travel in the December quarter of 2000. This is the quarter following the Sydney Olympic games, which suggests that business travel was put on hold for the Olympic games and took place immediately afterwards.

The dummy variable for the Bali 2002 bombings captures a positive and statistically significant mean shift in the *VFR* series. After the Bali bombings, Australians reverted to visiting friends and relatives more than before.

The coefficient estimates for the seasonal dummy variables are consistent with what would be expected for Australian domestic travel. The March quarter has the highest holiday and *VFR* travel, but the lowest business travel. This is the summer quarter for Australia and includes the longest period of school holidays. The lowest level of holiday and *VFR* travel is found in the June quarter which includes the first semester of all levels of schooling.

3.2. Exponential smoothing via innovations state space models

Exponential smoothing was proposed in the late 1950s (see the pioneering works of Brown, 1959; Holt, 1957; Winters, 1960) and has motivated some of the most successful forecasting methods. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation the higher the associated weight. For example, consider the simple (or single) exponential smoothing method (Brown, 1959). The recursive formulae for computing a h-step-ahead forecast $\hat{y}_{t+h}$, using all data up to time t, are

$$\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1}, \tag{4}$$

$$\hat{y}_{t+h|t} = \ell_t, \tag{5}$$

where ℓ_t denotes the level of the series at time t and α is a smoothing coefficient usually $0<\alpha<1$. By repeatedly substituting for ℓ_{t-1} in (4) we get

$$\hat{y}_{t+h} = (1-\alpha)^t \ell_0 + \alpha \sum_{i=0}^{t-1} (1-\alpha)^i y_{t-i}. \tag{6}$$

Hence, the forecasted value $\hat{y}_{t+h}$ is a weighted average of all observations (for which the associated weights decrease exponentially) and the initial level ℓ_0. The weight associated with each observation depends on α. If α is large we place a lot of weight on recent observations and in the extreme case that $\alpha = 1$ we do not learn anything from history. If α is small more weight is placed on historical information and in the extreme case where $\alpha = 0$ we do not learn anything from new information as our forecast is always equal to ℓ_0. More general exponential smoothing methods include trend and seasonal terms.

Recently, a statistical framework for such forecasting methods has been developed (Hyndman et al., 2002; Ord et al., 1997). Innovations state space models encapsulate the notion of exponential smoothing in a state space framework, and allow maximum likelihood estimation, model selection and prediction intervals to be derived. Their general form is

$$y_t = \boldsymbol{w}'\boldsymbol{x}_{t-1} + \varepsilon_t, \tag{7}$$

$$\boldsymbol{x}_t = \boldsymbol{F}\boldsymbol{x}_{t-1} + \boldsymbol{g}\varepsilon_t, \tag{8}$$

where y_t is an observation at time t, $\boldsymbol{x}_t$ is a vector of unobserved components which can be a mixture of a level, growth and a seasonal component, ε_t is Gaussian white noise with mean zero and variance σ^2, $\boldsymbol{w}$ is a vector containing elements of zeros and ones, $\boldsymbol{F}$ is a transition matrix containing zeros, ones and possibly model parameters, and $\boldsymbol{g}$ is a vector of unknown parameters which determine the impact of the random noise on the unobserved components of the series. Eq. (7) is referred to as the *measurement* (or *observation*) equation and describes the relationship between the unobserved states and observation y_t. Eq. (8) is referred to as the *transition* (or *state*) equation and describes the evolution of the states over time.

Notice that, unlike structural time series models (Harvey, 1990), innovations state space models only involve a single source of error. For example, the model that underlies the simple exponential smoothing method of Eqs. (4) and (5) is known as the local level model:

$$y_t = \ell_{t-1} + \varepsilon_t, \tag{9}$$

$$\ell_t = \ell_{t-1} + \alpha\varepsilon_t. \tag{10}$$

Hyndman, Koehler, Ord, and Snyder (2005) show that the optimal forecasts from innovations state space models are identical to those obtained using exponential smoothing methods.

Exponential smoothing methods have been previously applied to tourism data. Law (2000), Burger, Dohnal, Kathrada, and Law (2001), Lim and McAleer (2001b) and Cho (2001, 2003) directly implement exponential smoothing methods to forecast tourism demand. The general theme of these papers is that exponential smoothing methods perform quite well although the choice of exponential smoothing methods is very subjective (i.e., not based on any proper selection criteria) and in some cases we believe that the selected method is not the most appropriate.

A more common form of state space model is the formulation of Harvey (1990) known as structural time series models. These models give approximately the same forecasts as the innovations state space models. In contrast to the single source of error innovations state space models, structural time series models are sometimes referred to as multiple source of error models, as each equation carries its own independent error term. These types of models have been successfully applied in the tourism literature. González and Moral (1996), Kulendran and King (1997) and Kulendran and Witt (2001) only consider basic structural models (often referred to as the non-causal model as it does not include any explanatory variables). González and Moral (1995), García-Ferrer and Queralt (1997), Greenidge (2001), Turner and Witt (2001) and Kulendran and Witt (2003) also consider causal structural time series models. The results in these papers indicate that the structural time series models produce quite accurate forecasts. So much so that Li et al. (2005) in their extensive literature survey, list structural time series models alongside time-varying parameter models as the models that perform consistently well. Furthermore it seems that explanatory variables do not help in forecasting tourism demand. In general, the non-causal basic structural models out-forecast the causal structural time series models. Finally, du Preez and Witt (2003) consider a multivariate basic structural model. This is outperformed by the univariate model.

The modelling strategy we follow in this paper is a restricted version of the Hyndman et al. (2002) methodology for innovations state space models, which is based on the taxonomy proposed by Pegels (1969), extended by Gardner (1985) and advocated by Makridakis et al. (1998). In this study, only additive seasonal models are considered. The models considered are listed in Table 4. All three models have additive errors and an additive seasonal component and may contain no trend, an additive trend or a damped trend. We refer to this class of models as "ETS" (for Error-Trend-Seasonal) models. The damped trend model was proposed by Gardner and McKenzie (1985) as a modification to Holt's linear model. This modification comes through the parameter ϕ which dampens the trend. When $0<\phi<1$, the forecasts produced by the model converge to $\ell_n + b_n/(1-\phi)$ as $h \to \infty$ where n is the time of the last observation. Thus, the short-run forecasts are trended but the long-run forecasts are constant.

Treating this as a time series modelling exercise, the dependent variable considered is visitor nights instead of visitor nights per capita. The parameters are restricted to $0<\alpha<1$, $0<\beta<\alpha$, $0<\gamma<1$ and $0<\phi<0.98$. The damping parameter ϕ is restricted to a maximum of 0.98 to ensure

Table 4
Innovations state space additive models with seasonal component

No trend	Additive trend	Damped trend
$y_t = \ell_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{y}_{t+h\mid t} = \ell_t + s_{t+h-m}$	$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{y}_{t+h\mid t} = \ell_t + hb_t + s_{t+h-m}$	$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{y}_{t+h\mid t} = \ell_t + (1 + \phi + \cdots + \phi^{h-1})b_t$ $+ s_{t+h-m}$

ℓ_t denotes the level of the series at time t; b_t denotes the slope at time t; s_t denotes the seasonal component at time t; m is the number of seasons in a year; $\hat{y}_{t+h\mid t}$ denotes a forecast of y_{t+h} based on all the data up to time t.

that the damped model gives noticeably different forecasts from the additive trend model. Section 3.3 includes further discussion on the damped trend model.

The models are estimated by maximising the likelihood function using the R package "forecast" (Hyndman, 2006), and the Akaike information criterion (AIC) is employed as the model selection criterion. The Bayesian information criterion (BIC) was also considered but was found to be too restrictive. The selected models and estimated coefficients are presented in Table 5. The model selected for the "Holiday", "Business" and "Other" series is the damped trend model, while a no-trend model is selected for *VFR*. The seasonal smoothing parameter, γ, is zero for all models, indicating a fixed and unchanging seasonal pattern.

Table 5
Models and estimated parameters

Model parameter	Holiday Damped trend	*VFR* No trend	Business Damped trend	Other Damped trend
α	0.10	0.52	0.00	0.00
β	0.08		0.00	0.00
γ	0.00	0.00	0.00	0.00
ϕ	0.85		0.98	0.34

3.3. Innovations state space models with exogenous variables

The two modelling approaches described so far have contrasting advantages and disadvantages. The regression models identified some very useful economic relationships, such as the positive relationship between consumer confidence and domestic holiday travel. The effects of significant world events such as the Sydney Olympic games and the Bali bombings were also highlighted. These relationships are important to policy makers (such as Tourism Australia). However, the regression model does have some disadvantages. For example, if the model is used for forecasting, forecasts of the regressors are required. Furthermore, the regression model is static—it does not explore the dynamic properties of the data. In contrast, time series models such as the ETS capture the dynamic characteristics of the data and use these to forecast the future.

In this section, a combination of these two modelling strategies is proposed, giving ETS models with exogenous variables or "ETSX" models. These models are estimated via a two-step procedure. First, we identify the exogenous variables to be included in the model. These are the variables found to be statistically significant for each equation in the SUR estimation results, as presented in Table 3. In the second step, the fully specified model is estimated by maximising the likelihood function.

The dependent variable employed is visitor nights per capita, i.e., y_t is VN_t^i as defined in Eq. (1). Because the seasonal component in each of the time series models was deterministic, we model seasonality using seasonal dummies in the set of exogenous variables.

A damped trend model is used for all series. Including the exogenous variables in the observation equation, the ETSX model is

$$y_t = \ell_{t-1} + b_{t-1} + \mathbf{z}_t'\boldsymbol{\delta} + \varepsilon_t, \tag{11}$$
$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t,$$
$$b_t = \phi b_{t-1} + \beta\varepsilon_t,$$
$$\hat{y}_{n+h} = \ell_n + (1 + \phi + \cdots + \phi^{h-1})b_n + \hat{\mathbf{z}}_{n+h}'\hat{\boldsymbol{\delta}}, \tag{12}$$

where $\mathbf{z}_t$ is a vector of the exogenous variables not including the constant and the time trend. When $0<\phi<1$, the forecasts produced by model (12) converge to $\ell_n + b_n/(1-\phi) + \hat{\mathbf{z}}_{n+h}'\hat{\boldsymbol{\delta}}$ as $h \to \infty$. Thus, the short-term forecasts produced by this model are largely affected by the final trend estimate b_n. However, as we forecast further into the future, this effect diminishes (i.e., the trend is damped). This allows long-term forecasts to be largely driven by the forecasts of the exogenous variables. This type of model has important policy implications as long-term forecasts (in this case tourism demand) can reflect the beliefs/views of policy makers about the future of the exogenous variables.

The estimated models are presented in Table 6. The smoothing parameters are restricted as in Section 3.2. The estimates of the coefficients of the exogenous variables seem to be consistent with the corresponding estimates in the regression framework of Section 3.1.

Table 6
Estimates of the ETSX models

	Holiday	*VFR*	Business	Other
Parameter				
α	0.13	0.00	0.47	0.01
β	0.01	0.00	0.00	0.00
ϕ	0.98	0.97	0.98	0.76
Variable				
D_{t-1}	6.79		3.78	
P_{t-1}	−7.25		4.21	
Y_t	−67.67			
$BALI_t$		132.09		
$OLYMP_t$			104.05	
MAR_t	661.69	213.54	−95.78	−129.18
JUN_t	−65.52	−72.54	−21.25	−116.15
SEP_t	48.64	−31.95	32.91	−27.51

Table 7
In-sample accuracy measures for the three models

	Regr	ETS	ETSX	Regr	ETS	ETSX
	RMSE			ME		
Holiday	814.0	1173.1	974.5	8.5	−244.4	−182.0
VFR	1216.7	1266.6	1196.1	36.6	56.7	−55.4
Business	510.4	688.8	541.6	12.5	0.0	−28.6
Other	583.4	548.3	581.2	34.7	0.0	−24.3
Total	1649.2	2264.9	1714.8	92.3	−187.7	−290.2
	MAE			MAPE		
Holiday	665.7	994.2	757.8	1.9	2.9	2.2
VFR	930.8	949.7	899.9	4.0	4.2	3.9
Business	395.5	548.8	450.6	3.5	4.9	4.1
Other	481.6	454.4	473.2	10.4	9.5	10.4
Total	1352.0	1649.0	1421.4	1.9	2.3	2.0

3.4. In-sample evaluation of the three models

We evaluate how well the three models fit the data by computing some in-sample accuracy measures. The accuracy measures employed are the root mean squared error (*RMSE*), the mean error (*ME*), the mean absolute error (*MAE*) and the mean absolute percentage error (*MAPE*) (see Makridakis et al., 1998, for definitions). The results are presented in Table 7.

For each error measure, the first four rows summarize the error produced by each of the three models when fitted to the individual series. The final row labelled "Total" summarizes the aggregated errors produced by each model for the total of visitor nights. The mean error provides a measure of the bias in the fitted models, and the other three measures describe the accuracy of the models in fitting the data.

Let us concentrate on the MAPE results presented on the lower right corner of the table. The regression model provides the best fit for the "Holiday" and "Business" series. For these cases the regression model included a deterministic trend. The fit of the ETSX models approached the fit of the regression models as the damping parameter ϕ approached one. For the "*VFR*" case, where no deterministic trend was included in the regression model, the fit of the ETSX model was best. In the case of the "*Other*" series the ETS model performed best. This is not surprising because this series is the most difficult to model via economic relationships as it contains travel for very diverse purposes.

3.5. Forecast evaluation of the three models and TFC

The in-sample evaluation of the models has shown that the models fit the data quite well. Although this is useful when modelling domestic tourism, it does not mean that the models can forecast well. In order to get some indication of the forecasting performance of the models, we also conduct an out-of-sample forecast performance evaluation.

Due to the short sample size available, the period September 2004–June 2005 is selected as the "holdout" sample. Thus, the models are estimated using the first 26 observations (March 1998–June 2004) and 1–4 step-ahead forecasts are produced.

The forecast error measures are presented in Table 8. For each measure, the first four rows show the error produced by each model for each individual series. The "Total" row gives the forecast error produced by each model for the total aggregate of visitor nights. The final "*Average*" row gives the error of each model, averaged across the four individual series.

Again, we will focus on the most popular forecast error measure, the *MAPE*, presented in the lower right corner of Table 8. The three models developed in this study seem to be competitive in forecasting the individual series. Forecasting the total visitor nights, the ETSX models perform best producing the lowest *MAPE* of 4.20%.

There is only one instance where the TFC forecasts outperform any of the models. This is for the "Business" series where the TFC forecasts outperform the ETS model. The average improvement that can be achieved by tourism analysts in implementing our ideas is highlighted in

Table 8
Forecast error measures calculated for the holdout sample: September 2004–June 2005

	Regr	ETS	ETSX	TFC	Regr	ETS	ETSX	TFC
	RMSE				ME			
Holiday	680.8	1633.1	1761.0	2255.6	185.8	−383.7	−71.7	−286.1
VFR	1925.9	1625.4	1892.0	2449.9	−919.5	−422.4	−1067.2	−1718.9
Business	1787.0	1081.5	857.7	748.2	−363.4	−919.3	−612.6	−397.0
Other	535.4	468.5	536.0	1056.3	−122.3	−173.6	−171.7	73.1
Total	3746.6	3696.0	3826.7	4233.5	−1219.5	−1898.9	−1923.1	−2328.9
Average	1232.3	1202.1	1261.7	1627.5	−304.9	−474.7	−480.8	−582.2
	MAE				MAPE			
Holiday	1856.7	1426.8	1528.3	2186.1	5.8	4.8	5.0	7.0
VFR	954.2	1131.9	1118.8	1882.2	4.8	5.2	5.5	8.5
Business	507.5	919.3	612.6	731.9	5.2	9.5	6.4	7.4
Other	380.5	316.1	371.0	906.2	7.7	6.5	7.6	17.6
Total	2960.5	2757.6	2657.6	3126.9	4.5	4.3	4.2	4.9
Average	924.7	948.5	907.7	1426.6	5.9	6.5	6.1	10.1

the "Average" row. Here the TFC average *MAPE* is between 60% and 70% larger than that for any of our models.

4. Comparing long-run forecasts from the three models and TFC

Fig. 4 plots the long-term visitor nights forecasts (aggregated to annual), produced by each of the models. Also plotted are the forecasts produced by the TFC (Tourism Forecasting Committee, 2005). The annual percentage growth values in these forecasts are shown in Table 9. All three models predict an overall decrease in visitor nights for the year 2005. This is also predicted by the TFC. The largest decline is predicted by the ETS models (a drop of 3.74% in comparison to 2004) followed by the TFC forecast (a drop of 3.27%). However, from 2006, the forecasts produced by the models tell a very different story about the future of Australian domestic tourism compared to the TFC forecasts.

The regression model driven by deterministic trends (in the "Holiday" and "Business" series) predicts a continuous decline in visitor nights. The average predicted decline over the 2005–2014 period is 0.48% per annum. The rate of decline diminishes further the forecasts are into the future, due to the nature of the exponential trend. If the forecast horizon was extended enough, one would see the forecasts approach an asymptote parallel to the horizontal axis. This is an important implication of the exponential (instead of linear) trend on the forecasts produced by these models. It shows that this type of model does not forecast negative visitor nights at some point in the future, as would be the case if a linear trend was employed.

The ETS models predict the lowest number of domestic visitor nights with not one increase for the period 2005–2014. Given that three of the series are modelled by a damped trend model the rate of decline is damped. The average percentage decrease in visitor nights over the period 2005–2014 is 0.55%. However, the average decrease for the period 2005–2008 is 1.17% compared to 0.13% for the period 2009–2014.

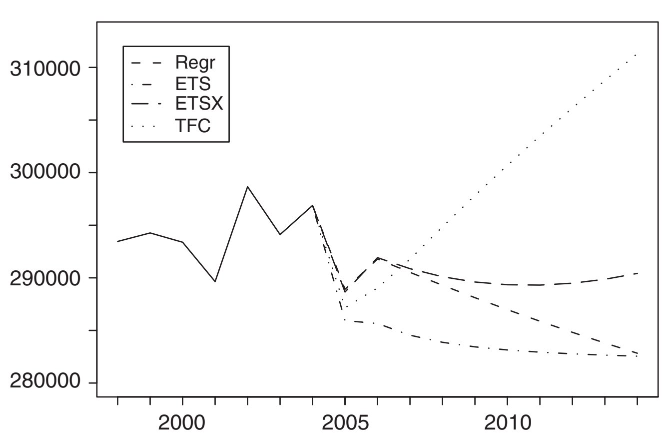

Fig. 4. Long-run annual forecasts for total visitor nights from the three models and the TFC.

Table 9
Percentage growth/decline in visitor nights from 1998 to 2014

	Actual	Regr	ETS	ETSX	TFC
Period					
98–99	0.28				
99–00	−0.30				
00–01	−1.27				
01–02	3.11				
02–03	−1.52				
03–04	0.94				
04–05		−2.68	−3.74	−2.77	−3.27
05–06		0.99	−0.19	1.13	0.66
06–07		−0.43	−0.45	−0.36	0.95
07–08		−0.42	−0.30	−0.26	1.05
08–09		−0.41	−0.22	−0.17	1.01
09–10		−0.40	−0.17	−0.09	0.96
10–11		−0.38	−0.14	−0.01	0.93
11–12		−0.37	−0.12	0.06	0.88
12–13		−0.36	−0.11	0.13	0.85
13–14		−0.34	−0.10	0.19	0.83
Average growth					
99–04	0.21				
05–10		−0.56	−0.84	−0.42	0.23
05–14		−0.48	−0.55	−0.22	0.48
Total growth					
98–04	1.16				
04–10[a]		−3.34	−5.01	−2.54	1.29
04–14[a]		−4.73	−5.45	−2.17	4.86
05–14[b]		−2.11	−1.78	0.61	8.41

[a]Total growth from the last actual observation to the forecast period stated.
[b]Total growth over the forecasted periods.

The most optimistic of our forecasts come from the ETSX models. Recall that these models are a combination of the ETS damped trend model and the exogenous variables. The characteristics of the forecast function of this model (discussed in Section 3.3) can be now seen in operation. From 2006 to 2011, the models predict a decline in the visitor nights, but this decline is rapidly damped. Beyond 2011, the trend is damped enough for the growth in the exogenous variables (such as the growth in the Australian population, the growth in *GDP*, etc.) to dominate and produce an overall growth in visitor nights. For the whole period 2005–2014 these models predict an average decline of 0.22%.

In contrast to the forecasts from any of the three models, the TFC predict a steady growth in visitor nights for the period 2005–2014. The average predicted growth over 2005–2014 is 0.48%. This means that domestic visitor nights are predicted to increase by 8.41% over the next 10 years. This is a much greater total increase than that predicted by any of the three statistical models. The regression and ETS models predict a total decline of 2.11% and 1.78%, respectively. The ETSX models predict a small total growth of 0.61%.

Fig. 5 presents the annual forecasts (from the three models and the TFC) for the disaggregated series by purpose of travel. This figure highlights where the TFC

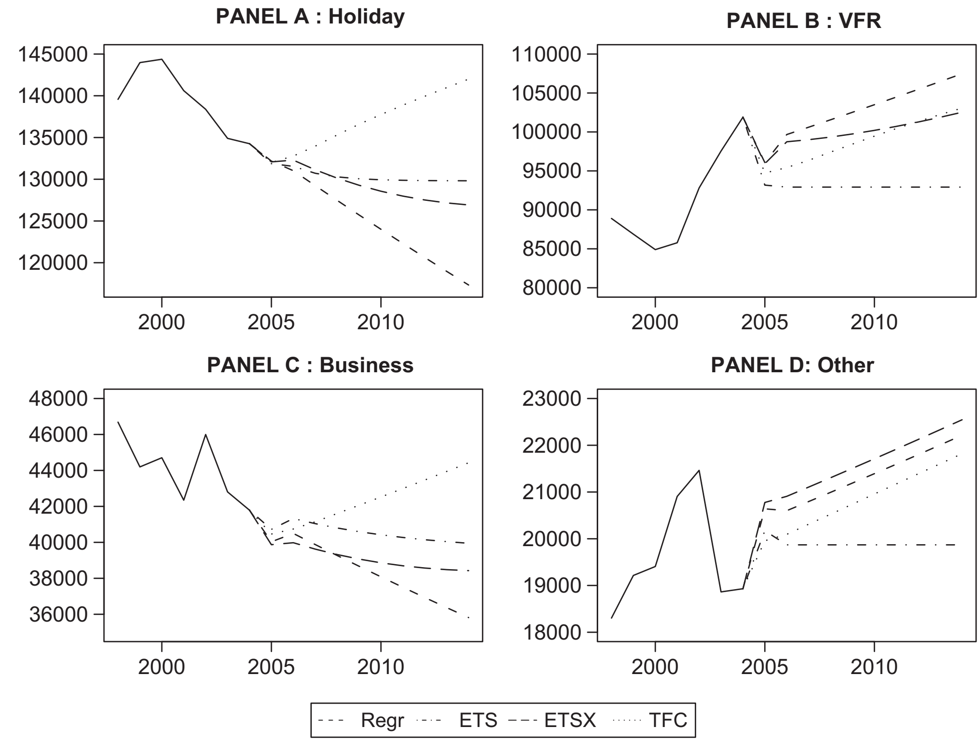

Fig. 5. Long-run annual forecasts for each of the four travel purpose components of visitor nights, from the three models and the TFC.

seem to have been over-optimistic. For two of the four series, namely "*VFR*" and "Other", the forecasts produced by the models and the TFC are fairly similar (the exception being ETS for both cases which has a flat forecast function). However, there is a noticeable discrepancy between the models and the TFC forecasts for the other two series. The largest component of the total visitor nights is "Holiday" travel. Panel A highlights the significant divergence between the models and the TFC in the long-term forecasts for this series. There is also a divergence between the models and the TFC forecasts for the "Business" component as shown in Panel C. The forecasts of these two components are the primary source of the overly optimistic TFC forecasts for total visitor nights.

5. Conclusion

We have modelled Australian domestic tourism demand using three statistical models. The first approach used regression models. The estimated regression models have identified significant economic relationships for domestic tourism. This analysis has also highlighted the impact of world events on Australian domestic tourism such as the increase in business travel immediately after the 2000 Sydney Olympic games, and the significant increase in visiting friends and relatives after the 2002 Bali bombings. In order to take advantage of the time series properties of the data, we also consider time series modelling and implement innovations state space models (for the first time in the tourism literature). We combine the properties of the regression and the innovations state space models by proposing innovations state space models with exogenous variables.

All three statistical models are shown to outperform the TFC published forecasts for short-term demand of Australian domestic tourism. The long-term forecasts produced by the models indicate that the TFC long-term forecasts may be optimistic. In particular, the models suggest that TFC forecasts of the "Holiday" and "Business" travel components of Australian domestic tourism have been optimistic. The statistical models show that Australian domestic tourism is on the decline.

The proposed statistical models are clearly of substantial benefit to policy makers. In particular, we recommend the use of innovations state space models with exogenous variables (the ETSX models), which can capture time series dynamics as well as economic and other relationships, and which out-performed the other models based on both the MAE and MAPE error measures.

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Appendix A. Descriptions and projections of regressors

DEBT: Total real personal finance commitments per capita from all lenders in Australia in $A thousands (seasonally adjusted, aggregated monthly series by averaging across the months of each quarter, series 5671-P1A from the DX database, Australia).

DPI: Domestic holiday travel and accommodation price index (seasonally adjusted by additive method, Australian Bureau of Statistics, series ID A2329356K).

GDP: Real Gross Domestic Product per capita in constant 03–04 $A billions (seasonally adjusted, series AUS.EXPGDP.LNBQRSA from the DX database, Australia).

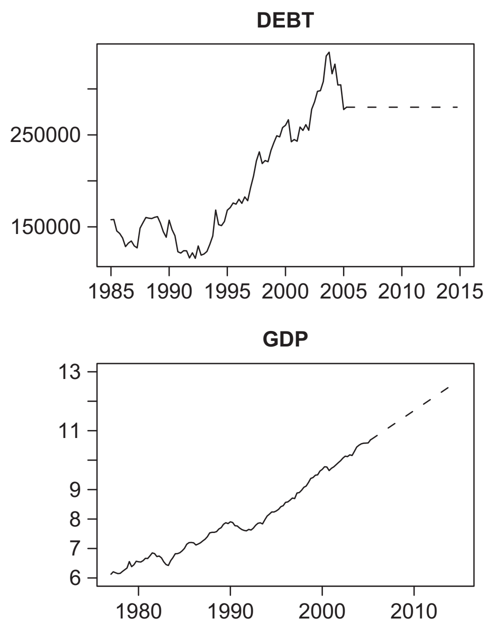

Fig. A.1. Levels of the regressors and their projections.

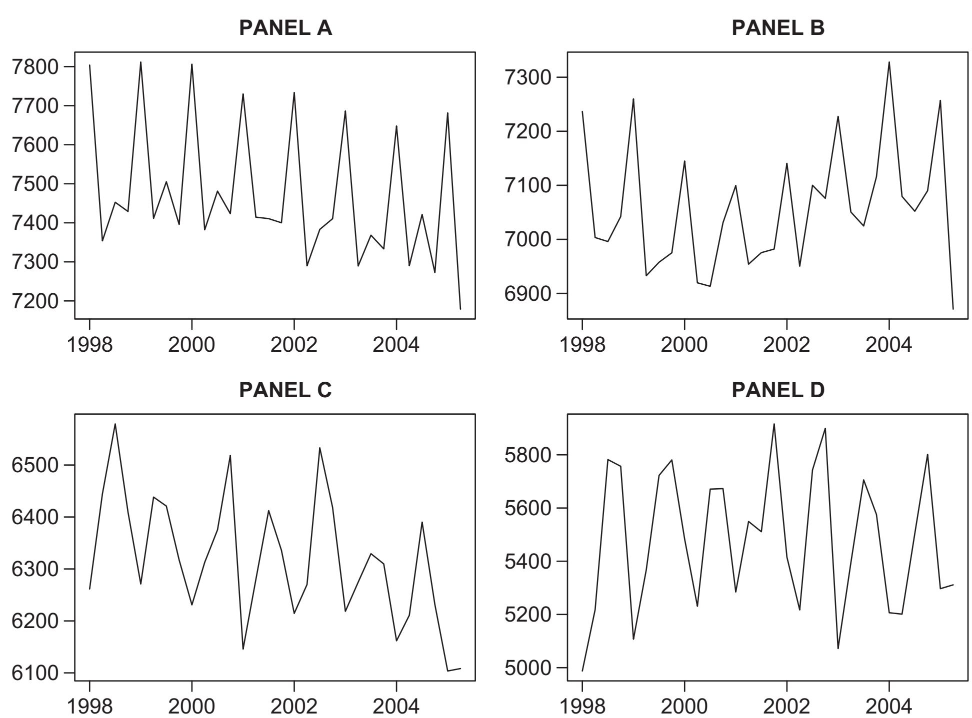

Fig. B.1. These are the visitor nights per capita series as defined in Eq. (3): Panel A: $\ln VN_t^{Hol} \times 1000$; Panel B: $\ln VN_t^{VFR} \times 1000$; Panel C: $\ln VN_t^{Bus} \times 1000$; Panel D: $\ln VN_t^{Oth} \times 1000$.

POP: Australian population and population projections as provided by the Australian Bureau of Statistics: Series B Population Projections, Australia 2004–2101, ABS cat. no. 3222.0.

The forecasts for *GDP*, *DPI* and *DEBT* were produced using the R package "forecast" (Hyndman, 2006) (Fig. A.1). The models selected by minimizing the AIC are: additive trend, additive trend and no-trend, respectively. The forecasts for *POP* are the population projections supplied by the Australian Bureau of Statistics.

Appendix B. Visitor nights per capita series

The visitor nights per capita series according to Eq. (3) is given in Fig. B.1.

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