Tourism Management 32 (2011) 1075–1084

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Modelling Australian domestic and international inbound travel: a spatial–temporal approach

Minfeng Deng[a], George Athanasopoulos[b,*]

[a] Department of Econometrics and Business Statistics, Monash University, Clayton, VIC 3800, Australia

[b] Department of Econometrics and Business Statistics, and Tourism Research Unit, Monash University, Clayton, VIC 3800, Australia

ARTICLE INFO

Article history:
Received 19 November 2009
Accepted 6 September 2010

Keywords:
Tourism demand
Dynamic panel models
Travel flow model

ABSTRACT

In this paper Australian domestic and international inbound travel are modelled by an anisotropic dynamic spatial lag panel Origin-Destination (OD) travel flow model. Spatial OD travel flow models have traditionally been applied in a single cross-sectional context, where the spatial structure is assumed to have reached its long run equilibrium and temporal dynamics are not explicitly considered. On the other hand, spatial effects are rarely accounted for in traditional tourism demand modelling. We attempt to address this dichotomy between spatial modelling and time series modelling in tourism research by using a spatial-temporal model. In particular, tourism behaviour is modelled as travel flows between regions. Temporal dependencies are accounted for via the inclusion of autoregressive components, while spatial autocorrelations are explicitly accounted for at both the origin and the destination. We allow the strength of spatial autocorrelation to exhibit seasonal variations, and we allow for the possibility of asymmetry between capital-city neighbours and non-capital-city neighbours. Significant temporal and spatial dynamics have been uncovered for both domestic and international tourism demand. For example we find strong seasonal temporal autocorrelations, significant trends and significant spatial autocorrelations at both the origin and the destination. Moreover, the spatial patterns are found to be most significant during peak holiday seasons. Understanding these patterns in tourist behaviour has important implications for tourism operators.

© 2010 Elsevier Ltd. All rights reserved.

1. Introduction

In two of the most recent and comprehensive reviews on tourism demand modelling and forecasting, Li, Song, and Witt (2005) and Song and Li (2008) fail to identify any substantial studies using spatial methods. This finding is somewhat surprising, as tourism is a consumer product whose location of purchase and location of consumption are informative of consumer behaviour. For instance, one might reasonably expect that tourists from the same geographical region share similar values and travel interests, and that their travel patterns are similar in some way. One might also reasonably expect that tourists "package" their travels so that the number of destinations visited in one trip can be maximised. While studies of tourism demand have received much attention from a time series analytic perspective, spatial research into tourism demand has remained very limited.

In this paper, we model Australian domestic and international inbound tourism demand using a dynamic spatial panel Origin-Destination (OD) travel flow model. Time lags of the dependent variable are used to capture temporal dependencies, while contemporary spatial lags are used to capture spatial dependencies. We analyse tourism demand from an OD perspective, thus allowing spatial effects to differ between the origins of the tourists and the destinations of the tourists. Spatial OD models have traditionally been applied in a single cross-sectional setting (see for example LeSage & Pace, 2008). In this setting the spatial structure is assumed to have reached its long run equilibrium and temporal dynamics are not explicitly modelled. On the other hand, spatial effects are rarely accounted for in traditional tourism demand modelling and forecasting. Our current study is the first in formally applying spatial temporal methods in tourism research.

Before introducing our model, it is instructive to briefly review the specification and estimation of dynamic panel models, spatial panel models, and dynamic spatial panel models. An extensive literature exists on both dynamic panels and spatial panels. A small but growing literature exists on dynamic spatial panels, most notably Elhorst (2003a, 2003b, 2005), Beenstock and Felsenstein (2007), and Yu, de Jong, and Lee (2008). In dealing with dynamic panels,

* Corresponding author.
E-mail addresses: minfeng.deng@monash.edu (M. Deng), george.athanasopoulos@monash.edu (G. Athanasopoulos).

0261-5177/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.tourman.2010.09.006

difficulties arise due to the correlation between lagged dependent variables and time-invariant individual effects. In dealing with spatial panels, the simultaneity of spatially lagged dependent variables is the main obstacle. In dealing with dynamic spatial panels, both sets of difficulties must be addressed. In our current study, we argue that the ML (maximum likelihood) estimator based on a mean-deviated equation is best suited for our data and will be used.

The paper is structured as follows. In Section 2 the specification and estimation of dynamic panels, spatial panels, and dynamic spatial panels is discussed. In Section 3 we present the dynamic spatial panel OD travel flow model used in our study and in Section 4 we present and discuss the ML estimation results and policy implications for Australian tourism industry. In Section 5 we conclude the paper.

2. A review of some panel data models

In this section, we provide a summary of the specification and estimation of dynamic panels, spatial panels, and dynamic spatial panels. As the literature on these panel models is sizable, this serves only as a brief review. We intend to highlight the most salient features of these panel models, compare the relative strengths and weaknesses of various estimators, and provide justifications for the estimation method used in our study.

2.1. Dynamic panel models

A dynamic panel model can be specified as

$$Y_t = \phi Y_{t-1} + X_t\beta + \mu + \varepsilon_t, \tag{1}$$

where $t = 1, 2, \ldots, T$. Y_t is an $(N \times 1)$ vector of N cross-sectional observations at time t. X_t is an $(N \times K)$ matrix of exogenous explanatory variables observed at time t. ε_t is an $(N \times 1)$ vector of i.i.d. normal errors with $E(\varepsilon_t) = 0 \forall t$ and $E(\varepsilon_t\varepsilon_t^T) = \sigma^2 I_N \forall t$. Furthermore, the errors are assumed to be serially uncorrelated, i.e., $E(\varepsilon_t\varepsilon_s^T) = 0 \forall t \neq s$. ϕ is the first order autoregressive parameter of interest. μ is an $(N \times 1)$ vector of time-invariant individual effects, which can be specified either as fixed effects or as random effects. When they are specified as fixed effects, each cross-sectional unit is associated with a unique intercept. The standard estimator for a fixed effects panel is the LSDV (least squares dummy variable) estimator, which demeans the equation to eliminate the time-invariant fixed effects. When applied to a dynamic panel model, the demeaned equation

$$\overline{Y}_t = \phi \overline{Y}_{t-1} + \overline{X}_t\beta + \overline{\varepsilon}_t, \tag{2}$$

is estimated by OLS where $\overline{Y}_t = Y_t - 1/T\sum_{t=1}^T Y_t$, $\overline{Y}_{t-1} = Y_{t-1} - 1/T\sum_{t=1}^T Y_{t-1}$, $\overline{X}_t = X_t - 1/T\sum_{t=1}^T X_t$, and $\overline{\varepsilon}_t = \varepsilon_t - 1/T\sum_{t=1}^T \varepsilon_t$. In the presence of lagged dependent variables, this procedure becomes problematic, as the demeaned lagged dependent variable and the demeaned error term are correlated of order $(1/T)$. Nickell (1981) and Hsiao (1986) show that the estimate of ϕ is biased downwards and the extent of the bias may not be negligible for small T. Only when $T \to \infty$ does this correlation disappear and the LSDV estimator will be consistent (Baltagi, 2001; Hsiao, 1986; Nickell, 1981).

When the individual effects are specified as random effects, the variable intercepts are treated as random draws of an i.i.d. random variable. Correlation between the unobserved individual effect μ and Y_{t-1} on the right hand side makes the OLS estimator biased and inconsistent. In cases like this, where the individual effects are treated as stochastic, and in cases where T is small and the LSDV estimator is biased and inconsistent, a number of estimators have been proposed. Anderson and Hsiao (1981, 1982) suggest first-differencing the equation, thus eliminating the individual effect μ,

$$\Delta Y_t = \phi \Delta Y_{t-1} + \Delta X_t\beta + \Delta\varepsilon_t \tag{3}$$

and using either ΔY_{t-2} or Y_{t-2} as an instrument for ΔY_{t-1}. They show that their estimator for ϕ is consistent as $N \to \infty$ for any fixed T. Subsequently, Arellano and Bond (1991) and Arellano and Bover (1995) suggest using values of Y_{t-j} where $j \geq 2$ as instruments in the differenced equation. They argue that since both ΔY_{t-2} and Y_{t-2} are linear combinations of lagged values of Y_t, their Generalized Method of Moments (GMM) estimator is more efficient. In empirical studies using dynamic panels, GMM estimators of this type have been the most popular.

Hsiao, Pesaran, and Tahmiscioglu (2002) also suggest an unconditional ML estimator based on the first-differenced equation. They note that the first-differenced equation (3) is well-defined for $t \geq 2$, and they show that for $t = 1$ the differenced equation can be re-written as

$$\Delta Y_1 = \phi^m \Delta Y_{-m+1} + \sum_{j=0}^{m-1} \phi^j \Delta X_{1-j}\beta + \sum_{j=0}^{m-1} \phi^j \Delta\varepsilon_{1-j}, \tag{4}$$

where m is finite and needs to be chosen judiciously. When the distribution of ΔY_1 is completely specified, one can write down the unconditional log-likelihood function of the entire sample and estimate with ML. Strong assumptions must be made about the expected initial changes in the first period: either that they are the same for all cross-sectional units, or that the process started long ago and $E(\Delta Y_1) = 0$. Furthermore, the second term involving lagged differenced exogenous variables is also unobserved and it must be approximated following either Bhargava and Sargan (1983) or Nerlove and Balestra (1996). They show that their estimator is consistent as $N \to \infty$ for any size T.

2.2. Spatial panel models

Spatial models consist of: spatial lag models, where spatial effects are incorporated substantively via spatially lagged dependent variables; and spatial error models, where spatial autocorrelation is incorporated in the error term (Anselin, 1988). A spatial lag panel model can be specified as

$$Y_t = \rho W Y_t + X_t\beta + \mu + \varepsilon_t, \tag{5}$$

where $t = 1,2,\ldots,T$. W is an $(N \times N)$ spatial weights matrix whose ijth element specifies the spatial relationship between the ith and jth spatial unit. More specifically, W_{ij} satisfies that: $W_{ij} \geq 0$ for $i \neq j$, and $W_{ij} = 0$ for $i = j$. Therefore, nonzero W_{ij}'s are associated with cases where the ith and jth units are considered to be spatial neighbours (see Anselin, 1988, for a more detailed discussion on the specification of spatial weights matrices). ρ is known as the spatial autoregressive parameter and it specifies the extent of spatial autocorrelation. When the spatial weights matrix is row-standardised, i.e., $\sum_j W_{ij} = 1 \forall i$, which is almost always the case, WY_t gives the weighted average of spatial neighbours of Y at time t. Since the seminal work of Ord (1975) and Anselin (1988), ML is by far the most popular estimation method used in applied spatial econometric modelling. Anselin (1988) shows that the spatial lag panel model is a straightforward extension of the single cross-sectional spatial lag model and it can be consistently estimated using ML. Since the individual effect μ is not correlated with any of the right hand side variables, its presence does not introduce additional complications.

On the other hand, a spatial error panel model can be specified as,

$$\begin{aligned} Y_t &= X_t\beta + \mu + \varepsilon_t \\ \varepsilon_t &= \rho W \varepsilon_t + u_t. \end{aligned} \tag{6}$$

Baltagi and Koh (2003) consider this model, and show that this model can also be consistently estimated with ML.

Download English Version:

https://daneshyari.com/en/article/10490494

Download Persian Version:

https://daneshyari.com/article/10490494

Daneshyari.com