Nonconstant reputation effect in a dynamic tourism demand model for Spain*

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Abstract

Following the ideas of the Tourism Area Life Cycle (TALC) theory, we propose a dynamic econometric model for tourism demand where the reputation effect (the effect of the lagged demand on current tourism demand) is not constant, but dependent on congestion. We test the model using panel data from Spanish regions during the period 2000-2013. Two estimations are performed depending on whether the tourists' origin is domestic or international. The results show a satisfactory performance. The reputation effect is not constant in both estimates, supporting the idea that tourism congestion influences tourist arrivals in Spain. However, the analysis also shows that the effect of congestion on reputation differs in both estimates (domestic vs international tourists)

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1 Introduction

Research in tourism economics has been dominated by demand analysis (Sinclair, Blake and Sugiyarto, 2003). Li, Song, and Witt (2005), Song and Li (2008) and Song, Dwyer, Li and Cao (2012) review the diversity of methods used to analyze tourism demand. Since the 1990s demand modelling studies have shifted from the use of static regression models to more sophisticated dynamic specifications. Dynamic models aim to avoid potential problems such as spurious regression, poor predictions and structural instability (Witt and Song,

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2000, and Song and Turner, 2006), and take into account important factors like repeat visits, habit persistence, and word-of-mouth recommendations or reputation, among others (Morley, 2009).

The most common way to incorporate dynamics into the model is to include the lagged demand in a linear fashion as an explanatory variable (Salman, 2003, Croes and Vanegas, 2005, Garín-Muñoz, 2006, among others). However, this may not be sufficient to account for the dynamics of tourism demand (Morley, 1998, 2009). The simple inclusion of the lagged demand assumes a constant reputation effect, which is not in agreement with the Tourism Area Life Cycle (TALC) theory (Butler, 1980). TALC theory, the most popular one on tourism evolution, suggests that the word-of-mouth or reputation effect changes as the level of occupation approaches the destination carrying capacity. According to the TALC theory, tourism destinations experiment a growth pattern with several phases, from exploration to stagnation. During the first stages, the number of visitors increases at an increasing speed. However, as it approaches the carrying capacity the process slows down. The theory suggests a nonconstant reputation effect.

Lundtorp and Wanhill (2001, 2006) show that the TALC model might be satisfactorily approximated assuming that the number of tourists arriving in the country follows the pattern of a logistic growth model. In this model the reputation effect depends on congestion, understood as the ratio of visitors over the carrying capacity. Following this idea, we propose an econometric demand model which improves the literature in two ways. First, specifying a non linear relationship between current and lagged demand allows a nonconstant reputation effect. Second, according to the TALC theory, it considers the tourism congestion as the key to this nonlinearity.

We test the model with panel data from Spanish regions during the period 2000-2013. We perform two different estimates depending on the origin, domestic or international, of the tourists. The results show a satisfactory performance. The reputation effect is not constant in both estimates, supporting the idea that congestion influences tourist arrivals in Spain.

Panel data have been used in recent studies on tourism demand. However, they simply include the lagged demand in a linear fashion to take into account habit persistence or reputation. As examples, we have the work by Maloney and Montes Rojas (2005) for tourist demand in Caribbean destination, Naudé and Saayman (2005) for tourist demand in 43 African states, Garín-Muñoz (2006, 2007 and 2009) for tourism demand in different Spanish destinations, Garín-Muñoz and Montero-Martín (2007) for tourism demand in Balearic Islands (Spain), Massidda and Etzo (2012) for domestic tourism in Italy, and Rodríguez et. al. (2012) for academic tourism demand in Galicia (Spain). All these studies assume a constant reputation effect. Our econometric specification is more flexible as it allows the reputation effect to vary with congestion. Furthermore, it allows us to analyze the influence of tourism congestion on a destination's appeal. To the best of the authors' knowledge, there are few empirical studies analyzing this supply-side factor.

The paper is organized as follows. Section 2 provides the theoretical foundations of the model. Section 3 assesses the congestion in Spain, as a tourist destination. Section 4 presents the data and variables used in our estimates. Section 5 provides the empirical model and describes the econometric methods used for estimation. Section 6 contains the results of our estimations and their interpretations. Finally, Section 7 offers some conclusions.

2 A nonlinear dynamic demand model

Econometric models studying tourism demand are based on the classical economic theory which postulates that income and price-type factors are likely to play a central role in determining the demand. Moreover, theoretical and empirical studies suggest that the behavior of tourism demand may also be affected by dynamic elements (Morley 2009). Accordingly, most tourism demand modelers have included the lagged demand as an explanatory variable (Salman, 2003, Song and Witt, 2003, Croes and Vanegas, 2005, Garín-Muñoz 2006, Garín-Muñoz and Montero-Martín 2007, among others). These models assume a habit persistence and word-of-mouth or reputation effect that boosts current demand. There are two reasons for this: the less uncertainty associated with holidaying at a known destination and the spreading of the knowledge about destinations as people talk about their holidays (Garín-Muñoz, 2006).

The standard dynamic econometric model formally obeys the specification

$$T_t = \beta_0 + \beta_1 T_{t-1} + \gamma' \cdot X_t + \varepsilon_t \tag{1}$$

where T_t is demand for tourism during period t, T_{t-1} is the lagged demand, β_0 is the constant and $X_t' = (x_t^1, x_t^2, ...x_t^k)$ is the vector of the remaining k explanatory variables (price, income, etc) which can also include lagged explanatory variables and dummy variables. The regression error term is ε_t. Parameter β_1 measures the word-of-mouth or reputation effect and $\gamma^{'} = (\gamma_1, \gamma_2, .., \gamma_k)$ is a vector of the remaining k parameters. The demand for tourism, T_t, is measured as the number of nights, number of visitors or tourism expenditures. See Song et. al. (2010) for a recent review of tourism demand measures. The dependent and explanatory variables can be measured with logarithms.

Equation (1) assumes an exponential trend for tourism demand, modified by the evolution of the explanatory variables X_t.[1] Variables growing exponentially grow unboundedly, at an increasing speed and at a constant growth rate. The reason for this is that

$$\frac{\partial T_t}{\partial T_{t-1}} = \beta_1 \text{ is constant.} \tag{2}$$

[1] Note that, from (1),

$$T_t = \delta + T_0 \beta_1^t + \gamma' \cdot \sum_{j=1}^{t} \beta^{t-j} X_j + \hat{\varepsilon}_t,$$

where δ is a constant, T_0 the initial demand and $\hat{\varepsilon}_t$ the error term. The term β_1^t drives an exponential growth for T_t.

That is, this model assumes that the reputation effect is constant (lagged demand has a constant effect on the current demand). If variable T_t measures the logarithm of tourism demand, equation (2) means that the elasticity of current tourism demand with respect the lagged demand is constant.

However, the theoretical literature argues that this effect may not be constant (Butler, 1980, 2009, 2011; Morley, 1998, 2000, 2009). Morley suggest a diffusion model, which shares some properties with Butler's (1980) tourism area life cycle (TALC) model. The TALC theory is one of the most accepted descriptions of the temporal evolution of tourism areas. The theory argues that resorts evolve over an S-shape curve. Lundtorp and Wanhill (2001) show that this evolution might be satisfactorily approximated by the logistic growth model[2]

$$T_t - T_{t-1} = \sigma T_{t-1}\left(1 - \frac{T_{t-1}}{CC}\right) \tag{3}$$

where parameter σ is the intrinsic rate of tourism growth, assumed as positive, and CC refers to the carrying capacity.

The S-shape pattern is due to the interaction of two opposite effects. First, the word-of-mouth or reputation effect leads to a positive autocorrelation of past visitors and current tourists. Secondly, the subsequent congestion has a negative effect on arrivals.

Rearranging the terms in equation (3) gives

$$T_t = \beta_1 T_{t-1} + \beta_2 \frac{T_{t-1}^2}{CC}, \tag{4}$$

with $\beta_1 > 0$, $\beta_2 < 0$. Mathematically, equation (4) is a Riccati equation with constant coefficients, which has been used to describe diffusion processes. Note that, from equation (4)

$$\frac{\partial T_t}{\partial T_{t-1}} = \beta_1 + 2\beta_2 \frac{T_{t-1}}{CC}. \tag{5}$$

That is, contrary to (2), the word-of-mouth or reputation effect is not constant. There exists a positive but diminishing marginal effect of past number of visitors, T_{t-1}, on current tourism, T_t. This reputation effect decreases with the amount of past tourism.

The non-constant effect (5) is essential for TALC theorists. If the carrying capacity is constant, as the number of visitors grows, the speed of growth decreases. That is, tourism areas "...carry with them the potential seeds of their own destruction, as they allow themselves to become more commercialized and lose their qualities which originally attracted tourists" (Plog 1974:58).

Traditionally, tourism carrying capacity has been considered as a given and static value. However, several authors argue that it can be subject to change. (Saveriades, 2000; Cole, 2012, Albaladejo and Martínez-García, 2014). Carrying

[2] Although Lundtorp and Wanhill (2001) formulated the model in continuous time, here we present its discrete version, to fit the econometric analysis better.

capacity, CC_t, could evolve along time due to changes in tourists' preferences, tourism supply, or the evolution of environmental or social restrictions. Moreover, destinations can expand their capacity simply by rejuvenating the products and services, by investing in developing new ones, opening up to new markets or improving the communication infrastructures.

Taking into account both ideas, the tourism area life cycle theory and a dynamic carrying capacity, the econometric model we propose to analyze the tourism demand is

$$T_t = \beta_0 + \beta_1 T_{t-1} + \beta_2 \frac{T_{t-1}^2}{CC_{t-1}} + \gamma' \cdot X_t + \varepsilon_t. \tag{6}$$

Likewise in Morley (1998, 2000, 2009), the model (6) is a quadratic form where the square of lagged demand is divided by a time-dependent variable, in our case, the carrying capacity. Moreover, according to (6),

$$\frac{\partial T_t}{\partial T_{t-1}} = \beta_1 + 2\beta_2 \frac{T_{t-1}}{CC_{t-1}}, \tag{7}$$

which means that the word-of-mouth or reputation effect is not constant, but is affected by the ratio T_{t-1}/CC_{t-1}, which is the lagged congestion. Not only lagged demand, like in (5), but also past carrying capacity, which is not given in this specification, can modify the reputation effect. Note that, if tourism demand is measured with logarithms, equation (7) means that the elasticity of tourism demand with respect to lagged demand is not constant but dependent on lagged congestion.

Alleviating tourism congestion requires purposive efforts from entrepreneurs and governments (Albaladejo and Martínez-García, 2014). As is illustrated in the following section, Spain, as a tourist destination, has expanded the number of tourism spots throughout its territory, which can be interpreted as an enlargement of the country's tourism carrying capacity. We shall study to what extent this policy has had positive effects on tourism demand.

3 The tourism congestion in Spain

In order to define the tourism congestion of a destination, a measure of its carrying capacity must be given. There are many definitions of carrying capacity in tourism. In its most traditional sense, it is understood as the maximum number of tourists or tourist use that can be accommodated within a specific geographic destination (O'Reilly, 1986). This capacity has been identified in terms of limits of environmental, social, economical or physical factors (Butler, 1980; Saveriades, 2000; Cole, 2009; Diedrich and García-Buades, 2009). However, a measure of the carrying capacity of a destination is difficult to define, there are many factors involved and they are not all quantifiable.

Traditionally, the main reason tourists come to Spain was a sunny climate close to the coast, the so-called "sun and beach" tourism. Over the past 10 or 15 years, the preferences of tourists are changing and they are showing a desire for more activities and alternative forms of tourism (Aguiló et al, 2005). This heterogeneity of the demand has given rise to an increase and diffusion of the supply with new alternatives being developed in the coast areas but also in other regions and in many cities of Spain (Ivars, 2004). The spread of the supply through Spain from 2001 to 2013 can be seen in Figures 6 and 7. In 2001, the number of tourism spots is considerably lower than in 2013 and they are mainly situated on the coasts of the Mediterranean and Atlantic as well as of its two archipelagoes. In 2013, all regions have some tourism spot.

Figure 4: Tourism spots in Spain on 2001

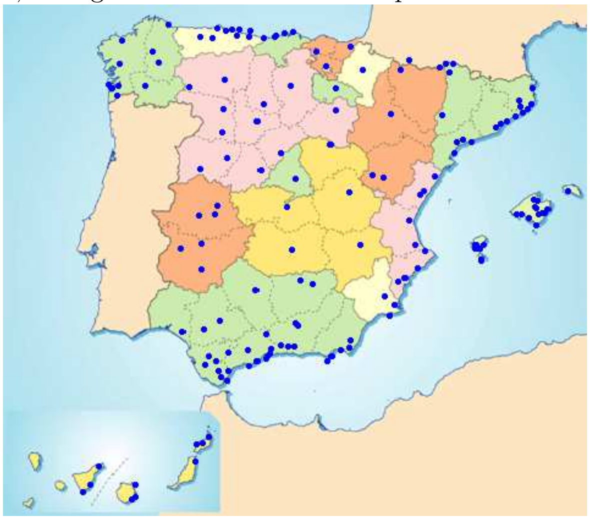

Figure 5: Tourism spots in Spain on 2013

The number of tourism spots is a quantitative measure of the tourism supply of a destination but also of the space distribution of the services offered. In Spain, the INE identifies as "tourism spot" a municipality where the concentration of tourism supply -not only lodgings- is significant. All of them count on some important tourism attraction (beaches, monuments, etc) or are near to an attraction; the greater the number of tourism spots, the larger the spatial dispersion of supply and therefore the higher the chance to accommodate visitors, that is, lower congestion. The number of tourism spots in Spain can therefore be used as a proxy of its carrying capacity from a physical point of view. The advantages of using this measure is that its homogeneous character allows for comparison among the several destinations.

In this paper, the tourism congestion of a destination at time t is taken as

$$\frac{T_t}{CC_t} = \frac{\text{number of tourists in the destination at time } t}{\text{number of tourism spots in the destination at time } t}$$

The congestion of a destination moves due to changes in the number of tourists and/or in the number of tourism spots. In addition, it increases when the number of tourists grows or when the number of tourism spots decreases.

4 Data and variables

In order to analyze the main determinants of Spanish tourism demand, we estimate the model proposed in Section 2 (equation 6) using data from foreign and domestic visitants arriving to Spain. Spain is an important destination for foreign tourists but also for domestic tourists. In fact, in 2013 approximately half of the tourists in Spain were domestic (51% of tourists who chose hotels as accommodation). However, their evolution has varied greatly over the period studied (Figures 1 and 2). In both cases, tourism rose sharply from 2002 to 2007. After that, a decline is observed in both types of tourists in 2008 and 2009, as a result of the global financial crisis and economic recession. In 2010, a recovery occurs but after of this year the demand for foreign and domestic tourists has opposite behaviors. The number of foreign tourists seems to experiment a new growth phase while the domestic tourists continues to decrease, in accordance with the 2008–2014 Spanish financial crisis.

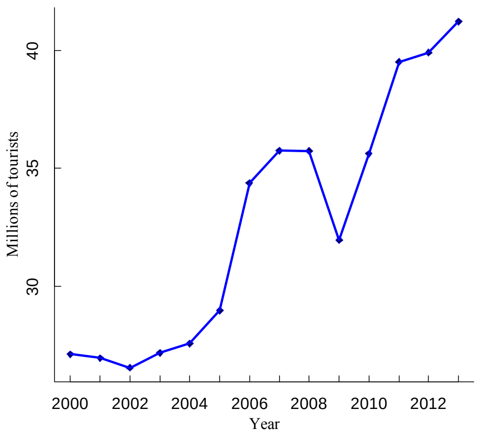

Figure 1: Evolution of number of foreign visitants that stay one or more nights in a hotel of Spain 2001-2013. Source: INE

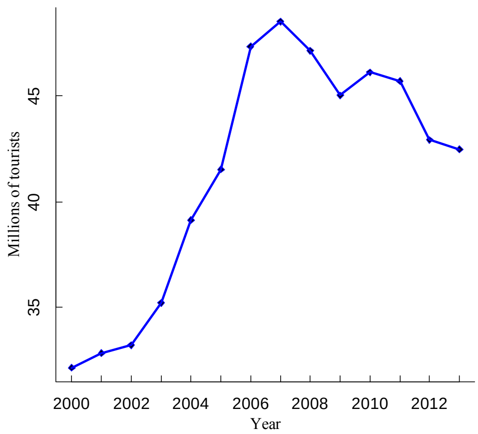

Figure 2: Evolution of number of domestic visitants that stay one or more nights in a hotel of Spain 2001-2013. Source: INE

Moreover, tourism arrivals in Spain are not equally distributed between regions either in terms of volume and composition: domestic versus international. The regions of the Mediterranean (Catalonia, Andalusia, Valencia and Murcia), the two archipelagos (the Balearic Islands and the Canary Islands) and Madrid account for almost 80% total tourism (Figure 3). In most Spanish regions domestic tourism is greater than international one. However, the Balearic Islands, Canary Islands and Catalonia, receive a higher percentages of foreign tourists than domestic. Respectively, 86.8%, 76.2% and 63.3% are foreign tourists.

Figure 3: Percentage of visitors that stay one or more nights in a hotel in Spain by autonomous communities.

Two models, one for domestic tourism and another for international tourism, are estimated using data disaggregated by region of destination. We use a balanced panel data set consisting of the 17 Autonomous Communities of Spain for the period 2000-2013. The panel data has some advantages over cross sectional or time series data. One is that it enables us to control for unobservable cross sectional heterogeneity which is common in regional data. Time series and cross section studies not controlling this heterogeneity run the risk of obtaining biased results. Moreover, panel data usually give a large number of data points, increasing the degrees of freedom, reducing the collinearity among explanatory variables and improving the efficiency of econometric estimates (Hsiao, 2003 and Baltagi, 2008).

The models include economic demand variables, such as income and prices, and a quadratic form to capture the effect of the lagged demand. Our quadratic relationship allows the positive word-of-mouth or reputation effect to be non constant, but dependent on the past congestion (equation 7).

According to which the model, the dependent variable is the number of domestic or international tourists (DT and IT, respectively) who chooses hotels and similar establishments as accommodation. Data are taken from the Encuesta de Ocupación Hotelera (EOH) of the Instituto Nacional de Estadística of Spain (INE). Two traditional economic factors are included between the explanatory variables: origin income and price. To measure origin income, we use the per capita real GDP of Spain ($GDPSP$) in the domestic tourism model and the per capita real GDP of UE 28 ($GDPUE$) in the international tourism model. Both variables were taken from the OCDE. The price variable included in our model reflects the costs of living of tourists in the different destinations relative to the cost of living in the origin country. We construct two relative price variables, one for domestic demand model (DP) and one for international demand model (IP) :

$$\begin{aligned} DP_{it} &= \frac{CPI_{it}}{CPI_{SPt}} \qquad\qquad i = 1, ..., 17 \\ IP_{it} &= \frac{CPI_{it}}{CPI_{UE28t} \cdot EX_t} \qquad i = 1, ..., 17 \end{aligned}$$

where CPI_{it}, CPI_{SPt} and CPI_{UE28t} are the consumer price indices (CPIs) for each of the 17 destinations considered, Spain and UE-28, respectively; EX_t is the nominal effective exchange rate Spain vs UE28. Data on exchange rates and CPIs for Spain and UE-28 were collected from Eurostat. Data on CPI for the 17 regions in Spain were collected from the National Statistics Institute of Spain (INE).

Our dynamic econometric model also includes the lagged carrying capacity, CC_{t-1}, which, as defined in section 3, is the number of tourism spots in a region. They were collected from the Encuesta de Ocupación Hotelera (EOH) of the Instituto Nacional de Estadística of Spain (INE).

5 Methodology and model specification

Following the model proposed in Section 2 and considering the variables defined in Sections 3 and 4, the econometric models have the representation:

$$DT_{it} = \eta_i + \beta_1 DT_{i,t-1} + \beta_2 \frac{DT^2_{i,t-1}}{C_{i,t-1}} + \beta_3 GDPSP_{i,t} + \beta_4 DP_{it} + \varepsilon_{it} \tag{8}$$

$$IT_{it} = \eta_i + \beta_1 IT_{i,t-1} + \beta_2 \frac{IT^2_{i,t-1}}{CC_{i,t-1}} + \beta_3 GDPUE_{i,t} + \beta_4 IP_{it} + \varepsilon_{it} \tag{9}$$

where the subscripts i ($i = 1, ..., 17$) and t ($t = 2000 - 2013$) denote the destination region and time period, respectively. η_i is the unobserved regional-specific variable (or fixed effects) that varies across regions but is invariable within a region over time, and ε_{it} is a disturbance term. A key assumption throughout this paper is that the disturbance ε_{it} is uncorrelated across regions, but regional heteroskedasticity and serial correlation is allowed for. The number of domestic and international tourists, per capita real GDPs and prices are in logs, and therefore coefficients are elasticities. Given a specific time period t, the origin incomes $GDPSP_t$ and $GDPUE_t$ are common to the various destination regions. Therefore, these variables only vary throughout time, while the rest vary both throughout time and across regions.

As discussed in Section 2, the relation between current and past tourism depends on β_1, β_2 and the previous level of congestion[3]. Since a positive sign is expected for β_1, a negative β_2 would imply that the elasticity between current and past tourism is positive but decreasing with the previous congestion, while a positive β_2 would imply an increasing elasticity. If β_2 is zero, the elasticity is constant. As usual in demand models, we expect a positive sign for β_3 and a negative sign for β_4.

A generalized method of moments (GMM) panel data estimation (Arellano and Bond, 1991) was applied to conduct our empirical analysis. Ordinary Least Squares (OLS) is not appropriate to estimate dynamic panel models with the lagged dependent variable among its regressors. The lagged dependent variable is correlated with the unobserved regional effect (η_i) which gives rise to "dynamic panel bias" (Nickell, 1981). The within groups (WG) and random effects estimators do not eliminate the "dynamic panel bias" and they are also biased and inconsistent. To solve this problem Arellano and Bond (1991) suggest first-differencing the model to remove the unobserved fixed effects (η_i). As the first-differenced lagged dependent variable is still potentially endogenous, it is instrumented with its past values to solve the problem of autocorrelation. If the ε_{it} are not serially correlated, we can use lags 2 and up of the endogenous variable as instruments.

We use the two-step difference GMM estimator to the models (8) and (9)[4]. Because the usual formulas for coefficient standard errors in two-step GMM tend to be downward biased when the instrument count is high, we use the Windmeijer (2005) standard errors correction. A crucial assumption for the validity of GMM is that the instruments are exogenous. We conduct two diagnostic tests: Hansen (1982) J tests of the over identifying restrictions for the GMM estimators[5], and the Arellano and Bond (1991) test for autocorrelation in the disturbance term, ε_{it}. This autocorrelation test is important because if the ε_{it} are serially correlated of order 1, then second lag of the endogenous variable would make an invalid instrument. Arellano and Bond test is applied to the residuals in differences. To check for first order serial correlation in levels, we look for second-order correlation in differences.

[3] When we refer to congestion in the domestic model it means the ratio between the number of domestic tourists and the number of tourism spots. Likewise, congestion in the international model means the ratio between the number of international tourists and the number of tourism spots.

[4] One-step difference GMM estimator is based on the assumption that the ε_{it} are i.i.d. The two-step difference GMM estimator is built on the more realistic assumption that errors are correlated within regions, not across them (Roodman, 2009a).

[5] The Hansen statistics is a chi-squared test to determine if the residuals are correlated with the instrument variables. If nonsphericity is suspected in the errors, the Hansen overidentification test is theoretically superior to the Sargan (1958) test.

6 Results

This section presents and discusses the results of our analysis. We show two different GMM estimates: GMM-DIFF (I) and GMM-DIFF (II) for each model. In GMM-DIFF (I) the lag of the dependent variable is treated as endogenous. In GMM-DIFF (II) the lag of the dependent variable and the quadratic term are treated as endogenous. Due to the small number of regions, all the estimates are obtained using only the second lag of each endogenous variable as instrument[6].

Tables 1 and 2 reports the estimated results and some associated statistic to check the validity of the models (8) and (9), respectively. The lagged dependent variable and the quadratic term are significant for all estimation models, implying a non constant elasticity of past tourism on current tourism. This indicates that if the quadratic term is not taking into account, the elasticity of the lagged dependent variable is not properly estimated. Additionally, the results reveal a general satisfactory performance of the econometric models. The autocorrelation tests (Arellano and Bond, 1991) do not detect any serial correlation problem in the residuals. As expected, the residuals in differences are autocorrelated of order 1, while there is no autocorrelation of second order. In addition the Hansen (1982) J-test does not reject the null for joint validity of the instruments.

Table 1: *Estimation results for domestic tourism model, 2000-2013*

Dependent variable: DT_{it}	GMM-DIFF(I)		GMM-DIFF(II)	
Explanatory variables	Coefficients	SE	Coefficients	SE
$DT_{i,t-1}$	0.480***	0.071	0.531***	0.045
$\frac{DT^2_{i,t-1}}{CC_{t-1}}$	-0.0009**	0.0005	-0.0007*	0.0004
$GDPSP_{i,t}$	1.339***	0.297	1.299***	0.221
DP_{it}	-		-	
Instruments	$DT_{i,t-2}$		$DT_{i,t-2}$ $\frac{DT^2_{i,t-2}}{CC_{t-2}}$	
Hansen test (p-value)	0.135		0.782	
AR(1) (p-value)	0.006		0.005	
AR(2) (p-value)	0.304		0.290	
Number of observations	204		204	
Number of groups	17		17	

Note: standard errors were calculated using Windmeijer (2005) correction. *,**,*** denote significant at the 10%, 5% and 1% level respectively. All estimations are made by using the xtabond2 command in STATA10 (Roodman, 2009a).

[6] Roodman (2009b) argues that finite sample problems caused by a large number of instruments are of two sorts. First, numerous instruments can overfit instrumented variables, biasing coefficient estimates towards those from non-instrumenting estimators. Second, instrument proliferation can take two-step GMM far from the theoretically efficient ideal, and it can weaken the Hansen test.

Table 2: *Estimation results for international tourism model, 2000-2013*

Dependent variable: IT_{it}	GMM-DIFF(I)		GMM-DIFF(II)	
Explanatory variables	Coefficients	SE	Coefficients	SE
$IT_{i,t-1}$	0.275***	0.068	0.287***	0.067
$\frac{IT^2_{i,t-1}}{CC_{t-1}}$	0.0008*	0.0004	0.0009*	0.0005
$GDPUE_{i,t}$	3.041***	0.444	3.184***	0.413
IP_{it}	-1.858***	0.569	-2.032***	0.491
Instruments	$IT_{i,t-2}$		$IT_{i,t-2}$ $\frac{IT^2_{i,t-2}}{CC_{t-2}}$	
Hansen test (p-value)	0.135		0.783	
AR(1) (p-value)	0.014		0.016	
AR(2) (p-value)	0.904		0.982	
Number of observations	204		204	
Number of groups	17		17	

Note: standard errors were calculated using Windmeijer (2005) correction. *,**,*** denote significant at the 10%, 5% and 1% level respectively. All estimations are made using the xtabond2 command in STATA10 (Roodman, 2009a).

Table 1 shows estimation results for domestic tourism model (equation 8). We find that all variables are significant except relative price. So, we estimate the model without price. Both estimates (GMM-DIFF(I) and GMM_DIFF(II)) show a positive sign for β_1 and a negative sign for β_2 and yield similar results. Since estimated β_1 (0.480 and 0.531) is large relative to estimated β_2 (–0.0009 and -0.0007) it is clear that, for current levels of tourists and tourism spots, the previous tourism demand elasticity is positive and decreases slowly with the previous congestion. Our result, in line with the TALC theory, implies a positive but decreasing word-of-mouth or reputation effect. Finally, the estimated income elasticity (1.339 and 1.299) is positive and significant, showing that the national demand for tourism in Spanish regions depends positively on the wealth of Spain.

Table 2 shows estimated results for international tourism model (equation 9). All variables are significant. Both estimates (GMM-DIFF(I) and GMM_DIFF(II)) yield similar results. They show a positive sign for β_1 and β_2, suggesting that the elasticity of international tourism with respect to its previous value is positive and increasing with the previous congestion. As regards the estimated income and price elasticities, the results are consistent with economic theory. As expected, a positive elasticity is estimated for per capita real GDP with values of 3.041 and 3.184, suggesting that the international demand for tourism in Spanish regions depends heavily on the wealth of the European Union. Conversely, a negative coefficient of the relative price suggests that international tourism is sensitive to price fluctuations.

The estimated income elasticity is larger for international demand than for domestic demand. This finding is also supported by Garín-Muñoz (2009) and

Taylor and Arigoni (2009). Besides, contrary to what happens when we use data from domestic tourism, the quadratic term has a positive impact on international tourist arrivals. Despite this, the estimates β_1 (0.275 and 0.287) and β_2 (0.0008 and 0.0009) indicate that the positive word-of-mouth or reputation effect is smaller for international than for domestic demand.

To summarize, we focus on the lagged dependent variable, includes in a quadratic form. The significant and positive estimated coefficient of the lagged dependent variable indicates that word-of-mouth or reputation effect has played an active role in regional Spanish tourism. Besides, in both demand models the quadratic term is significant, revealing a nonconstant reputation effect. This effect depends differently on the previous congestion in each model. While in the international demand model it is positively affected by this ratio, the domestic model exhibits a decreasing word-of-mouth or reputation effect. This unequal effect of the congestion agrees with related studies. In particular, Santana-Jiménez and Hernández (2011) analyze the influence of the tourist perception of overcrowding on the tourist affluence. Using the population density to measure overcrowding in a tourist area, they estimate a tourism demand model with data of tourists coming from UK and Germany to the Canary Islands. Their results show opposite signs of the density effect on demand across the different islands and origin countries, revealing that the tourist perception of overcrowding depends on consumer characteristics and destination.

7 Concluding remarks

There is general agreement on the desirability of taking into account the reputation of a destination among the factors explaining tourism demand. Up to date, most empirical studies on tourism demand include the lagged demand to measure this word-of-mouth effect in a linear fashion. These specifications assume a reputation effect constant over time, that is independent of variables, like the level of tourist congestion, that could affect tourist arrivals. This assumption disagrees with accepted theories on tourism, like the TALC theory.

In this paper, we follow the TALC theory to propose a new dynamic specification to estimate demand elasticities. Our tourism demand model includes a quadratic form of the lagged demand and allows a nonconstant reputation effect which depends on congestion.

We use a panel data of tourists arrivals to the 17 Spanish regions during the period 2000-2013 to test the proposed model. The analysis was performed separately for domestic tourist arrivals and international arrivals, using the GMM difference estimator for dynamic panel data models. In both cases the econometric model includes traditional economic factors, such as income and relative prices, and the quadratic function of the lagged demand. Our dynamic specification is more flexible than that used elsewhere. The reputation effect is not fixed but depends on congestion, defined as the ratio between the number of tourists and the number of tourism spots at the destination. Nonetheless, the number of tourism spots quantifies the supply but also its spatial dispersion at the destination. To the best of our knowledge, there are few contributions that include the tourism congestion in their model specification, and none in the way we do.

The results indicate the positive effect of reputation on arrivals. Moreover, the reputation effect is not constant. The opposite sign of the quadratic term in the two estimates reveals that the reputation effect varies differently with the level of previous congestion for domestic than international tourists. For international tourists there is a growing reputation effect, whereas for domestic tourists it decreases with previous level of congestion. This unequal effect of the congestion on the reputation effect of domestic and foreign visitors opens up new lines of research. Is this result due to the fact that for most Spanish regions domestic tourism is considerably larger than the international? Do international tourists look for a different tourism product than domestic tourists? In the future it would be interesting to conduct a similar study for those Spanish regions where international tourism has higher weight: Balearic Islands, Canary Islands and Catalonia. Would we obtain a different conclusion? Moreover, new measures of congestion should be proposed in further research.

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