A disaggregated analysis of the Spanish tourism demand based on the TALC theory*

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Abstract

In this study, we propose a dynamic econometric model for tourism demand which combines the classical economic theory and the TALC theory. Unlike other dynamic models in our specification the effect of the lagged demand on the current tourism demand is not constant, but dependent on congestion. We test the model using panel data from 93 Spanish tourist cities during the period 2006-2015. The results show that the effect of tourist previous is not constant, supporting the TALC theory. Consequently, tourist congestion influences tourist arrivals in Spanish cities.
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Keywords: Tourism Area Life Cycle Model (TALC), tourism demand, tourist congestion, dynamic panel data model.

1 Introduction

Spain is one of the most important countries in terms of tourism. According to data from the World Tourism Organization (WTO), it is third (after the United States and China) in the ranking of countries by international tourism earnings worldwide with US$ 57 billion in 2015 (WTO), and also third in international tourism arrivals (after France and the United States) with 68 million tourists. Its success is due to Spain has a large number of the most appealing sun and sea tourism resorts as Marbella, Benidorm, Mallorca or Las Palmas de Gran Canaria between other, and also important cultural cities as Madrid, Barcelona, Seville or Granada competing with well-known other as Paris, London or Rome. These popular tourist destinations receive large volumes of tourist flows each year which promote the growth of Spanish economy. According to the National

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Statistics Institute (INE), in 2015 the tourism sector in Spain contributed 11.1% to the gross domestic product (GDP) and 2.49 million jobs (13% of total).

Nowadays the growth of tourism in the most important tourist cities is being related to the problems of overcrowding or congestion that many of these cities are suffering (Barcelona, London, Paris...). For example, in Barcelona the number of tourists accommodated in hotels grew by 5.4% in 2015, exceeding 8 million tourists. This positive data of tourist growth is currently under discussion because of the growing concern about the congestion in this city. Tourist flows are partly responsible for congestion of the cities, understanding that it occurs when the number of visitors is excessive in relation to the space or capacity of the destination to accommodate those tourists, especially during peak periods. In turn tourist flows can also be affected by tourist congestion of the destination. Overcrowding can damage a city's reputation and diminish its attractiveness as a tourist destination.

In the literature of tourism, the Tourism Area Life Cycle (TALC) theory (Butler, 1980), the most popular one on tourism evolution, argues for the existence of an S-shaped lifecycle in the growth of the destinations According to the TALC theory, during the first stages, the number of visitors increases at an increasing speed. However, as it approaches as the carrying capacity the process slows down. Matching this idea with the classical economic theory, we propose an econometric dynamic demand model where the effect of previous tourists is not constant but varies with the ratio between visitors and carrying capacity of the destination, interpreting it as its maximum spatial capacity. This ratio is related to congestion of the destination (Albaladejo et al., 2016).

In this paper, we use this dynamic model to analyze tourism demand in the most popular tourist cities in Spain for the period 2006 to 2015. Most common dynamic specification of the demand models include previous tourists in a linear fashion to capture the effect of word-of-mouth recommendations, and the tendency of tourists of one destination to return to the same place to spend their holidays (habit persistence) (see Garín-Muñoz, 2006, 2007 and 2009; Garín-Muñoz and Montero-Martín, 2007; Massidda and Etzo, 2012; Capacci, Scorcu and Vici, 2015, among others). They assume that the effect of previous tourists on the current tourism demand is constant (Albaladejo et al. 2016). Nevertheless, several articles have proposed alternative tourism demand dynamic specifications where more sophisticated relationships between current and lagged demand have been analyzed (see Morley 1998; Lyssiotou 2000; Rosselló at al. 2005a and 2005b; Albaladejo et al. 2016). Our model is in this line. It is a dynamic model where current and lagged demand keep a quadratic relationship, allowing the effect of previous tourists not be constant.

A system GMM dynamic panel data analysis (Blundell and Bond, 1998) is carried to estimate the model. The data are disaggregated by city of destination. We consider 93 Spanish cities chosen as tourist sites by the INE during the period 2006-2015. The empirical evidence suggests a strong habit persistence and word-of-mouth effect. The effect of previous tourists is positive and decreasing with the ratio between previous tourists and carrying capacity according to the TALC theory. Then, as a consequence the more congested cities, the lower the positive effect of the previous tourists.

The paper is organized as follows. The following section provides the theoretical foundations of our model. Section 3 presents the data and variables considered in the study. Section 4 provides the empirical model and describes the econometric method used for estimation. Section 5 contains the results and their interpretation. Finally, Section 6 draws some conclusions.

2 The theoretical framework

The TALC theory (Butler, 1980) argues for the existence of an S-shaped lifecycle in the growth of the tourism destinations with six key stages: exploration, involvement, development, consolidation and stagnation, arriving at a final post-stagnation stage where decline, rejuvenation or other intermediate solutions are possible (see Figure 2). Each stage is characterized by a different rhythm of growth.

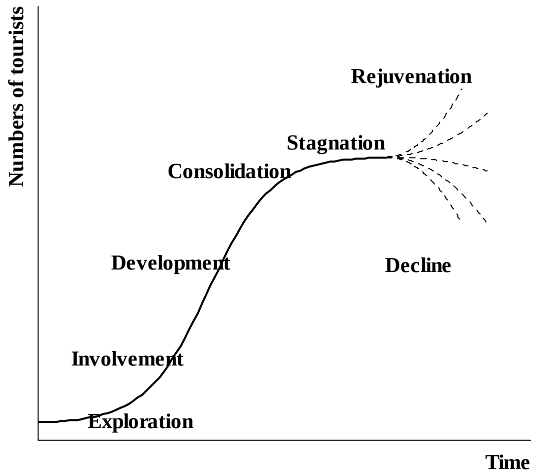

Figure 2: Evolution of tourist area according to the TALC.
Source Butler (1980).

Lundtorp and Wanhill (2001) show that a logistic curve can be quite a good theoretical representation of Butler´s lifecycle path, where the stagnation stage is determined by the carrying capacity (CC) of the tourist area destination (Figure 3). Using a discrete version of the logistic function, Albaladejo *et al* (2016) show that the S-shaped curve given by the logistic function implies a positive but diminishing marginal effect of previous tourists (T_{t-1}) on current tourism

(T_t) (see Figure 4). The impact of previous tourists on the current tourists decreases as the number of tourists approaches the destination's carrying capacity, CC. This non-constant effect is essential for TALC theorists. It is surprising, however, that much of the literature on tourism demand modeling seems to omit this TALC theory implication.

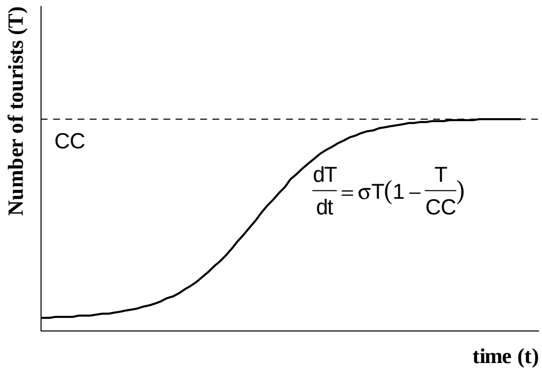

Figure 3: Logistic curve

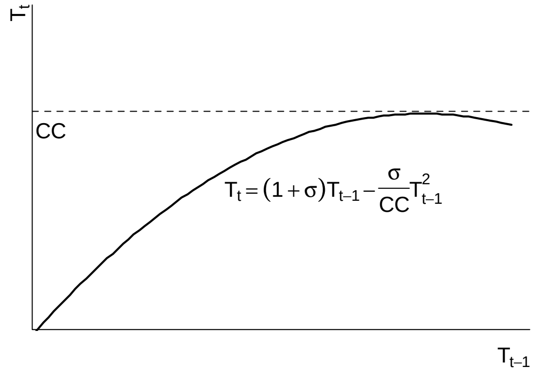

Figure 4: Marginal effect of previous tourists on current tourism

Mathematically, the discrete version of the logistic function in Figure 4 is a Riccati equation with constant coefficients. According this equation, the tourism current demand is only a function of previous visitors and carrying capacity of the destination. However, the classical economic theory assumes that tourism demand fundamentally is a function of income, prices and exchange rate (Dogru et al. 2017). Thus, a way to combine the classical economic theory and the TALC theory is to regard a expanded version of the Riccati equation to model the tourism demand

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

where q_t is a variable depending on t and which in turn can be a function of income, prices, exchange rate and other variables that define the demand.

Following this idea, the econometric model we propose to analyze the tourism demand is

$$T_{it} = \eta_i + \beta_1 T_{it-1} + \beta_2 \frac{T_{it-1}^2}{CC_i} + \gamma' \cdot X_{it} + \varepsilon_{it} \tag{2}$$

where the subscripts i and t denote the cross section and the time period, respectively. The dependent variable is T_{it}, the current number of tourists, T_{it-1} is the previous number of tourist, η_i are the fixed effects, CC_i is the carrying capacity and $X'_{it} = (x_{it}^1, x_{it}^2, ...x_{it}^k)$ is the vector of the remaining k explanatory variables (price, income, etc.), which can also include lagged explanatory variables and dummy variables.

Since the most of this studies include the previous tourists in a linear fashion, the effect of this variable on the current tourism demand is assumed to be constant over time. Our specification (2) includes a quadratic function of previous demand. Therefore, the model allows a non constant marginal effect of previous tourism. Furthermore, the relationship between previous and current tourism is influenced by the carrying capacity of the destination.

The marginal effect of T_{t-1} on T_t contains the reputation and persistence effect. It is measured by the following expression:

$$\frac{\partial T_{it}}{\partial T_{it-1}} = \beta_1 + 2\beta_2 \frac{T_{it-1}}{CC_i}, \tag{3}$$

Both the previous number of tourists and the carrying capacity can modify this marginal effect. Thus, the effect of previous tourist can be not constant. If, as expected, β_1 is positive and β_2 is negative, the quadratic function has a parabolic shape, implying a marginal effect positive but diminishing with the ratio $\frac{T_{it-1}}{CC_i}$, in line with the TALC theory. Then, the effect varies across destinations and over time. Destinations with greater ratio between tourists and carrying capacity, that is, the most congested destinations, have a lower reputation and persistence effect. In turn, given a destination, this effect does not remain stable over time. Increases in tourist arrivals decrease the marginal effect.

3 Data and variables

In this paper, we focus on the tourism demand in the Spanish cities in which the tourist influx is specifically located. We consider 93 Spanish cities chosen as tourist sites by the INE (see Encuesta de Ocupación Hotelera) during the period 2006-2015. In Spain, the INE identifies as tourist site a city where the concentration of tourism supply is significant. All these cities count on some important tourism attraction (beaches, monuments, etc.) or are near to an attraction. Tourist sites are important destinations for domestic and international tourism in Spain. In 2015, about 60 million tourists stayed at hotel in these cities, accounting for almost two thirds (63.6 %) of the total number of tourists arriving to Spain and staying in hotel (INE).[1] However, tourism is not homogeneous along the 93 Spanish tourist sites, existing important differences between them. Almost 90% of the tourist stayed at hotel are concentrated in 50 out of 93 tourist sites. According to the INE, the top 50 tourist sites represented 55% of the total number of tourists staying at hotel in Spain in 2015, equivalent to some 52 million tourists.

Figure 1 shows the evolution of the number of tourists -domestic and international- who chose hotels and similar establishments as accommodation from 2006 to 2015 in Spain, in the 93 Spanish tourist sites identified by the INE, and in the top 50 Spanish tourist sites. The evolution of tourism is very similar in the three

[1] The total number of tourists who choose hotels and similar establishments as accommodation in Spain represent 67% of total arrivals in 2015 according to the INE.

cases. Tourists increased from 2006 to 2015, but its growth is not continuous throughout the period. A decline is observed in 2009 and 2012, as a consequence of the global financial crisis and economic recession in Spain. Since 2013, the number of tourists seems to be experiencing a new growth phase.

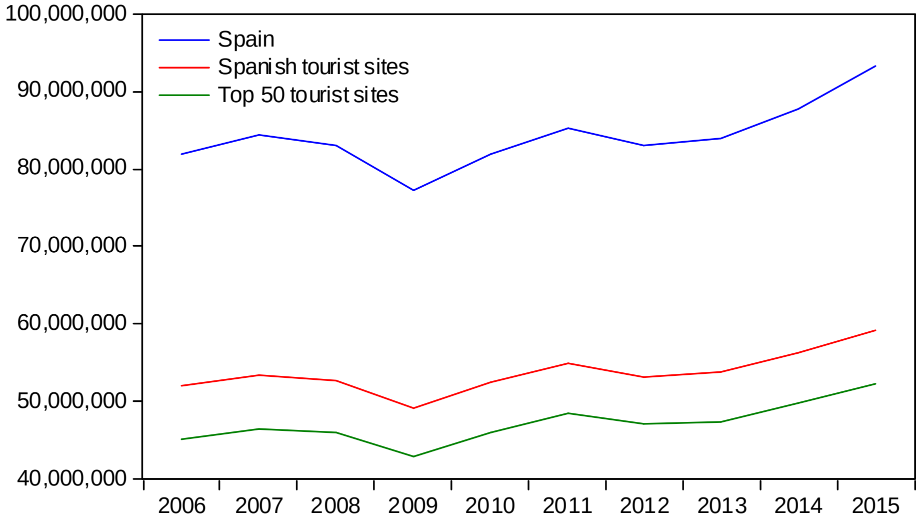

Figure 1: Tourists lodged at hotels

In order to analyze the main determinants of tourism demand in the most popular tourist cities in Spain, we estimate the model proposed in Section 2 (Eq. (2)) using data disaggregated by city of destination. We use a balanced panel data set consisting of 93 Spanish tourist sites for the period 2006-2015. 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 for this heterogeneity run the risk of obtaining biased results. Moreover, panel data usually give a large number of data points, so increasing the degrees of freedom, reducing the collinearity among explanatory variables and improving the efficiency of econometric estimates (Hsiao, 2003 and Baltagi, 2008).

Our model includes economic demand variables, such as income and prices, and a quadratic form to capture the effect of the past tourists. The quadratic relationship allows the effect of the previous tourists not to be constant, but depend on the ratio between previous tourists and carrying capacity of the destination. (Equation (3)). Additionally, we also include two dummy variables for controlling the effects of the economic crisis, and a dummy variable to capture the difference in terms of tourist flows between the top 50 tourist sites and the rest.

According to the model, the dependent variable is the number of tourists (T) who choose hotels and similar establishments as accommodation. Data are taken from the Encuesta de Ocupación Hotelera (EOH) of the INE. Two traditional economic factors are included among the explanatory variables: origin income and price. To measure origin income, we use the real per capita GDP of EU28 (GDP), since Europe is by far the main origin of the most of the international tourism flows to Spain. This variable was taken from OCDE. The price variable included in our model reflects the cost of living of tourists at the different destinations relative to the cost of living in the country of origin (IP):

$$IP_{destination} = \frac{CPI_{destination}}{CPI\_EU28 \cdot EX\_EU28}$$

where $CPI_{destination}$ is the consumer price index (CPI) for each of the 93 destinations considered. For each city we consider the IPC corresponding to the province where it is located. CPI_EU28 is the CPI for EU28, and EX_EU28 is the nominal effective exchange rate of Spain vs EU28. Data on exchange rates and CPI for EU28 were collected from Eurostat. Data on CPI for the provinces in Spain were collected from the INE.

A measure of carrying capacity (CC) of tourist sites has to be defined to build the quadratic form of our model. The measurement of the carrying capacity of a destination has been done using very different aspects and methods. It has been identified in terms of limits of environmental, social, economic or physical factors (Butler, 1980; Saveriades, 2000; Cole, 2009; Diedrich and García-Buades, 2009). In this paper we focus on physical factors and use as carrying capacity the square kilometers of each city. The bigger a city, the more possibilities to offer an extensive and diversified tourist supply, thus the higher the chance of accommodating visitors suitably. In addition, since the relationship between tourist flows of a destination and its geographic area is related to the congestion or overcrowding suffered by the destination, using square kilometers as a measure of carrying capacity allow testing the influence of tourism congestion over tourism demand.

Based on Figure 1, we consider two dummy variable ($Y2009$, and $Y2012$) to capture the influence on tourism of the financial and economic crisis in Spain. $Y2009$, takes the value 1 in 2009 and 0 in other years, and $Y2012$ takes the value 1 in 2012 and 0 in other years. 2009 and 2012 were the years of the Spanish recession when GDP growth rate decreased more extensively. Finally, our model also includes a dummy variable (TOP) that takes value 1 if the city is one of the top 50 tourist points and zero in another case.

4 Methodology and model specification

Following the model proposed in Section 2 and considering the variables defined above, the econometric model is represented as

$$T_{it} = \eta_i + \beta_1 T_{it-1} + \beta_2 \frac{T_{it-1}^2}{CC_i} + \beta_3 GDP_t + \beta_4 IP_{it} + \beta_5 Y2009_t + \beta_7 Y2012_t + \beta_8 TOP_i + \varepsilon_{it} \tag{4}$$

where the subscript i denotes the destination tourist site, and t indicates the time period ($t = 2006 - 2015$). η_i is the unobserved destination-specific variable (or fixed effects) that varies across cities but is invariable within a city over time, and ε_{it} is a disturbance term. A key assumption throughout this paper is that the disturbance ε_{it} is uncorrelated across cities, but heteroskedasticity across time and cities is allowed for. The number of tourists, real per capita GDP and the relative price are in logs, and therefore coefficients may be interpreted as elasticities.

As discussed in Section 2, the effect of the previous tourist ($T_{ij,t-1}$) depends on β_1, β_2, T_{it-1}, and CC_i (see equation (3)). Since a log-log model is used, this effect represents the elasticity of current tourism demand with respect to previous demand. A positive sign is expected for β_1, thus a negative β_2 would imply that this elasticity decreases with the ratio between previous tourists and squared kilometers ($\frac{T_{it-1}}{CC_i}$). If β_2 is zero, the elasticity is constant. We expect a positive sign for β_3 and β_8 and a negative sign for β_4, β_5, β_6 and β_7.

A generalized method of moments (GMM) panel data estimation (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) 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 the regressors. The lagged dependent variable is correlated with the unobserved effect (η_i) which gives rise to "dynamic panel bias" (Nickell, 1981). The within groups and random effects estimators do not eliminate the "dynamic panel bias" and 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 differenced lagged dependent variable is still potentially endogenous, it is instrumented with lagged levels of the endogenous variable to solve the problem of autocorrelation. If the ε_{it} are not serially correlated, we can use lags 2 and upwards of the endogenous variable as instruments. Blundell and Bond (1998) extended this estimator by building a system of equations formed by the equation in first differences and the equation in levels. The extended GMM estimator, called system GMM, uses lagged first-differences as instruments for equation in levels in addition to the usual lagged levels as instruments for equation in first-differences.

In this paper, we apply the system GMM (Blundell and Bond, 1998) procedure to estimate the model (4). We use the one-step robust to heteroskedasticity estimator and the two-step estimator for comparison.[2] Although the two-step estimator is theoretically preferred, it is appropriate to consider the one-step results when making inferences since the asymptotic standard errors of one-step GMM estimators are virtually unbiased (Arellano and Bond, 1991).

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[3], and the Arellano and Bond

[2] One-step GMM estimator is based on the assumption that the ε_{it} are i.i.d. In this paper, we use one-step robust estimators, where the resulting standard errors are consistent with panel-specific autocorrelation and heteroskedasticity.

[3] The Hansen statistics is a chi-squared test to determine if the residuals are correlated

(1991) test for autocorrelation in the disturbance term, ε_{it}.

5 Results

We show two different GMM estimates: one-step and two-step versions of the system GMM (GMM-SYS). In both estimates the lag of the dependent variable and the quadratic term are treated as endogenous. Since 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.

The empirical results from the estimation are shown in Table 3. The estimated coefficient of the lagged dependent variable is significant and positive, and the estimated coefficient of the quadratic term is significant and negative, revealing that the effect of the lagged dependent variable is negatively affected by the ratio $\frac{T_{it-1}}{CC_i}$. Thus, there is a non-constant effect of the previous tourists over current tourists. 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 3: *Estimation results for international tourism demand model, 2001-2014*

Dependent variable: T_{it}	GMM-SYS	
Explanatory variables	one-step	two-step
T_{it-1}	0.7783***	0.7946***
$\frac{T^2_{it-1}}{CC_{t-1}}$	-0.0067**	-0.0058**
GDP_t	0.2552***	0.2372***
IP_{it}	-1.1887***	-1.3132***
$Y2009_t$	-0.0614***	-0.0609***
$Y2012_t$	-0.0526***	-0.0579***
$TOP50_i$	0.3769***	0.3342***
Hansen test (p-value)	0.104	0.104
AR(1) (p-value)	0.000	0.000
AR(2) (p-value)	0.205	0.234
Number of observations	770	770
Number of groups	77	77

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

with the instrument variables. If nonsphericity is suspected in the errors, the Hansen overidentification test is theoretically superior to the Sargan (1958) test.

Both estimates (one-step and two-step) yield similar results. All variables are statistically significant. Estimated β_1 (0.7783, 0.7946) is positive and estimated β_2 (-0.0067, -0.0058) is negative. Therefore, for current levels of tourists, the elasticity of tourism demand with respect to the previous tourists is positive and decreases slowly with the ratio between previous tourists and geographic area of the tourist site. Since a lower ratio indicates a lower congestion, this means that in the most popular tourists cities the lower tourist congestion, the more beneficial influence of previous tourists on the current demand. The estimated income elasticity (0.2552 and 0.2372) is positive and significant, showing that the arrival of tourists depends positively on the economic situation of the European Union, which is the main market of origin. As expected, a negative elasticity is estimated for price with values of -1.1887 and -1.3132, suggesting that tourist arrivals is also sensitive to price changes. The dummies variables representing the impact of the global crisis, $Y2009$ and $Y2012$, has the expected negative sign. Their estimated coefficients indicate a drop in tourist arrivals around 6% in 2009 and 5% in 2012. Finally, the estimated coefficient of the dummy variable TOP, indicates that, on average, tourist arrivals in the top 50 tourist sites are a 30% higher than in the rest of tourist sites.

One of the most important determinants of the tourism demand seems to be the lagged dependent variable, which controls both the effect of the word-of-mouth recommendations and the effect of habit persistence. The significant estimated β_2 indicates that the effect of this variable is not constant and prove the need of a quadratic specification in the model. The elasticity of tourism demand with respect to the previous tourists depends negatively on tourist congestion at the destination city. As a consequence, the elasticity varies across the destinations and through time. Given a particular tourist site, the positive effect of the past visitors decreases as tourist flows increases. It shows evidence of a S-shaped curve to define the evolution of tourists arrivals according to the TALC theory. In any given year, the effect of the previous tourists varies between the different tourist sites depending on the relationship between previous tourism demand (tourists) and the extension of the city (squared kilometers). Thus, the positive effect of past tourists is lower in the most crowded tourist sites, making evident that tourist congestion is negatively perceived by tourists.

6 Concluding remarks

This paper uses a nonlinear dynamic specification to model the tourism demand in the most popular Spanish tourist cities. These cities receive a high number of tourist arrivals which contribuye to the growth of Spanish economy, but the space requirements of tourists can bring out problems of congestion. In this context, it is important to know the determinants of demand of these popoular cities and especially how previous tourists affect tourism demand decisions.

Most empirical studies on tourism demand include previous tourists in a linear regression model to measure the effect of word-of-mouth recommendations and habit persistence. These specifications assume that the effect of previous tourist is constant over time, i.e. independent of variables like tourist congestion that could affect tourist arrivals.

Following the TALC theory, we propose a dynamic tourism model to analyze the effect of previous tourists in the demand for tourism in the Spanish tourist cities. The specification includes traditional economic factors and a quadratic form of the lagged demand allowing a non constant word-of-mouth and persistence effect. In our model, the effect of previous tourists can depend on the ratio between previous tourists and the carrying capacity of the destination city, defined as its geographic area. Considering this ratio as measure of the congestion, the effect of previous tourists is linked to the congestion of the destination.

The model is estimated using a panel data set consisting of the 93 Spanish cities chosen by the INE as tourist sites, for the period 2006-2015. We apply the system GMM procedure to estimate the econometric model. Our results show that previous tourists have played an active role in the growth of tourism in the most popular Spanish tourist cities. Furthermore, the relationship between current demand and previous tourist follows a quadratic form.

According to the TALC theory, the influence of previous visitors is positive and decreasing with the ratio between previous tourists and square kilometers of the destination. Then, the impact of previous tourists in a specific destination is not constant over time, it decreases when tourist arrival increase. Additionally, the effect of previous tourists varies across the cities depending on the tourist congestion. Consequently, the congestion affects the destinations reputation.

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