Accounting for spatial dependence in tourist expenditure functions

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Abstract

The level of development of the tourism industry is remarkable at the edge of the 21st century. In this way, the analysis of factors driving tourism receipts and expenditures has boomed in the last years. Micro-economic analysis has become an important branch of this literature, however this approach lacks a more grounded methodology bringing the role of destination characteristics at the forefront of the tourist behaviour analysis. In this paper we introduce the geographical dimension in the study of tourist expenditures. By relying on spatial statistics and spatial econometrics framework, we account for spatial dependence patterns arising in the modelling of factors driving spendings of tourists at destinations. In doing so we made three main contributions. In first place, we rigorously account for the spatial dimension of the process under analysis, controlling for spatial autocorrelation effects in the estimation procedure and improving robustness of previous results in the literature. In second place, we extend the scope of the micro-level focus in the analysis of tourist expenditure behaviour, by adding destination spatial features to the traditional visitor´s related covariates. In third place, we are able to compute indirect effects arising in the spatial model, adding in this way quantitative measures of the forces conforming tourism clusters in the neighbourhood of major destinations. After stating the theoretical framework informing the research, we obtain evidence on the performance of the spatial modelling approach by using a data set of more than 102,000 questionnaires made to international visitors reaching 1872 destinations in Spain in year 2014. Results confirm the relevance of the proposed methodology in the study of tourist expenditure behaviour in space.

Keywords: tourist expenditure, spatial dependence, micro-economic modelling, spill over effects, spatial clustering, tourism policy.

JEL codes: D01, C31, R12, Z32, Z38.

1. Introduction

The expansion of the tourism industry at the beginning of the 21st century is shown to be remarkable. More than 1.18 billion people travelled internationally in 2015, this number expected to reach 1.8 billion in 2030 according to UNWTO forecasts. Related receipts accounted for €1136 billion, resulting in significant growth of employment and income levels at destinations (UNWTO, 2016). Despite that tourism presents some negative impacts (Archer, Cooper, & Ruhanen, 2005), its capacity to foster development is undeniable at the national and local level (Paci & Marrocu, 2014; Figini & Vici, 2010).

Given the importance of the economic dimension of tourism, the study of factors surrounding expenditure of visitors occupies a central place. Macroeconomic approaches to tourism demand represent an important branch of this literature, including times-series forecasting of arrivals and receipts (Song, Li, Witt & Fei, 2010; Song & Witt, 2000). However, most recent approaches to tourist expenditure build on micro-economic modeling, with researchers employing survey data in order to identify the factors driving the spending behaviour of visitors. Recent reviews of this literature include those of Brida & Scuderi (2013), Sainaghi (2012), and Wang & Davidson (2010). Research exercises concentrate in understanding the two main choices involved in the tourist spending action, namely, the choice of spending or not in tourism services and how much spend. In dealing with the first type of decisions the literature employs the "categorical response" models, applying discrete choice models to ascertain how to allocate disposable income between several alternatives. In the second case researchers build on the "metric response" models, where the level of expenditure is thought to be a function of individual characteristics (Brida & Scuderi, 2013). In the metric type of analysis, the dependent variable is usually defined as the total or daily expenditure per traveling group, household or individual tourist, while explanatory factors include information on economic constrains and socio-demographic attributes of the visitors, as well as on their trip and psycho-graphic characteristics (Marrocu, Paci & Zara, 2015). Some researchers also highlight the need of jointly modelling these two choices, employing econometric techniques such as the double-hurdle models or the Heckman equation in order to improve the robustness of results (see i.e., Weagley & Huh, 2004, and Jang & Ham, 2009, respectively).

Given that the micro-economic tourist expenditure literature puts the individual in the centre of the analysis, research models focus in explaining why people consume tourist services and what factors lead the volume of individual spending. Correspondingly, slight attention has been paid to the geographical dimension influencing the tourist experience and related expenditures at a micro-level. Territorial characteristics, geography in a wider sense, has usually entered in these models in a tangential way, either by including dummy variables controlling for destination characteristics in aggregate, or through trip characteristics linked to the specialization of the destination that could be influencing the size of spendings (Brida & Scuderi, 2013; Sainaghi, 2012). An example of the latter can be found in variables reflecting trip purposes (business, leisure, studies), accommodation supply (hotels, second-home residences), or tourism activities (gambling, hunting, culture) that majorly define the tourist experience at particular destinations.

In this context, the present paper aims to introduce the geographical or spatial dimension as a central variable in the analysis of tourist expenditure at a micro-level. Several reasons underlie this focus. Tourism follows an unbalanced pattern of development across space, with important differences in the number of arrivals received for example by seaside and inland destinations (Aguiló & Juaneda, 2000; Andriotis, 2006). Accordingly, total tourist expenditure is unevenly distributed in space, following a clustering pattern similar to that governing other socio-economic variables such as the GDP or population (Le Gallo & Ertur, 2003). Seaside regions specialize in the sun and sand product, becoming mass tourism places able to attract a significant number of visitors annually. In these regions, tourism demand and supply co-locate around well-known destinations, conforming tourism clusters. This feature of data brings the issue of spatial dependence, traditionally arising when studying the locational pattern of socio-economic processes in the territory, as shown by the spatial statistics literature (Haining, 2003). In this case, the level of expenditure at one particular destination is conformed by the level of expenditure at surrounding destinations, showing the presence of spatial autocorrelation in data. Failure to incorporate such spatial dependence effects when modeling expenditure would result in potentially misleading econometric results (Le Sage & Pace, 2009).

The general objective of the present paper is then to account for spatial dependence when modelling tourist expenditure at destinations. It would help to provide some robustness checks for findings of the preceding literature, both regarding the role of covariates in the model and stability of estimated coefficients. In this setting, the subject of analysis changes from individual tourists to destinations. However, and taking advantage of geo-referenced survey data, we will be able to retain some features of the preceding framework of analysis, namely, the tourist profile and trip & psychographic characteristics. The modelling strategy would be then mixing geographical and tourist related characteristics when modelling tourist expenditures. In this way, we extend the scope of the previous micro-level studies of tourist expenditure, as another contribution of the paper. Spatial econometric techniques allow to identify the spatial features of data for a given territory. Building on these, we scrutinize the main spatial features of tourist expenditures for our case of study, the municipalities of Spain. Employing Exploratory Data Analysis will help to identify how tourist expenditure spreads across the country geography, and how this variable clusters in the territory. Further, spatial econometric modelling provides two main effects from covariates in the model, that is, direct and indirect effects. Direct effects account for the usual relationships between dependent and independent variables in the model, circumscribed to the spatial limits of each municipality in the sample. Indirect effects show how covariates in a given municipality influence the level of expenditure at neighbouring destinations, in a so-called spillover effect. Building on the spatial modelling framework, we will identify the main covariates driving both direct and indirect effects, and the nature of spillover effects shaping expenditure at Spanish destinations. All these research findings will help to provide important guidelines for tourism policy at the level of destinations and, more generally, will help to inform regional planning in the tourism sector.

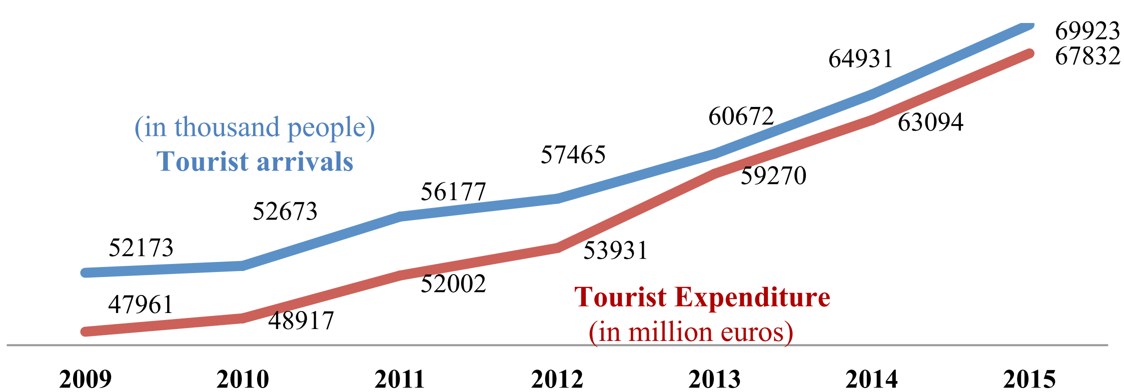
The rest of the paper is structured as follows. After this introduction, section 2 describes the data set, and develops the exploratory analysis of spatial dependence in tourist expenditure. Section 3 presents the econometric model and results of the estimation procedure. Section 4 focuses on main results regarding spillover effects in the spatial model. Section 5 discusses main findings of the investigation and future extensions. Finally, section 6 concludes and presents some policy recommendations emerging from the investigation.

2. Tourist expenditure in Spain: Data issues and exploratory spatial analysis

2.1 Trends in tourist expenditure in Spain

The present paper introduces the spatial dimension in the analysis of tourist expenditure at a micro-level. Spain is a leading destination in the world's tourism market. In 2015 the country received around 70 million of international tourists that spent 68000 € millions, positioning the country in the third place of the world's tourism ranking for these two demand indicators (UNWTO, 2016). Figure 1 shows the trend followed by international tourism in Spain in recent years. Departing from 52 million of arrivals in 2009 and despite the evident impact of the global crisis, flows grew at an average rate of 5% per year in 2009- 2015, and tourist expenditure did it at a 6.5% rate.

Figure 1: International tourist arrivals and expenditure in Spain 2009-2015



Source: IET, Ministry of Tourism, Spain.

A detailed review of tourist expenditures in Spain is shown in table 1, with the predominance in total spendings of British, German, French and Nordic visitors, accounting for 55% of total expenditure in 2014. Average expenditure was around €971 per trip, with nine nights of stay, and €110 per day. Nordic, US and Swiss tourists spent the most per day and per trip, with higher mean stays, while French, Italian, and Portuguese made shorter stays and spent less per day and per trip.

Table 1: Expenditure of international visitors in Spain by country of residence

COUNTRY	Total		Average by visitor	Daily average by visitor	Length of Stay
	Million Euros	%	Euros	Euros	nights
Total Spain	**63094**	**100%**	**971**	**110**	**9**
UK	12746	20.2%	849	96	9
Germany	10024	15.9%	962	101	10
France	6555	10.4%	617	82	8
Nordic Countries	5811	9.2%	1152	120	10
USA	2849	4.5%	2338	182	13
Italy	2734	4.3%	739	105	7
The Netherlands	2424	3.8%	876	90	10
Belgium	1875	3.0%	860	89	10
Switzerland	1720	2.7%	1054	122	9
Ireland	1181	1.9%	915	101	9
Portugal	807	1.3%	430	94	5
Rest of Europe	5240	8.3%	1152	120	10
Rest of America	4279	6.8%	2233	178	13
Rest of the World	4849	7.7%	1747	210	8

Source: Own elaboration from Survey EGATUR, IET, Ministry of Tourism, Spain.

Table 2: Expenditure of international visitors in Spain by region of destination in 2014

COUNTRY	Total		Average by visitor	Daily average by visitor	Average length of stay
	Million Euros	%	Euros	Euros	nights
Total Spain	**63094**		**971**	**110**	**9**
Catalonia	15132	24.0%	900	120	7
Canary Islands	12444	19.7%	1084	110	10
Balearic Islands	10380	16.5%	913	110	8
Andalusia	9349	14.8%	1100	102	11
Madrid	5478	8.7%	1205	168	7
Valencian Region	5388	8.5%	864	78	11
Basque Country	927	1.5%	590	124	5
Rest of Spain	3996	6.3%	926	97	9

Source: Own elaboration from Survey EGATUR, IET, Ministry of Tourism, Spain.

By destination, table 2 shows the prominent role of the region of Catalonia (24%) for total expenditure of visitors, followed by Canary Islands (20%), Balearic Islands (16%), Andalusia (15%), Madrid and Valencia with 8%-9% of total expenditure. By visitor, trip expenditure is higher in Madrid, Andalusia and Canary Islands, while daily expenditure appears to be higher in Madrid and Catalonia, this being the two main urban centres in the country. Longer stays arise in Valencia, Andalusia and Canary Islands.

Table 3: Expenditure of international visitors in Spain by length of stay in 2014

	Total		Average by visitor	Daily average by visitor	Average length of stay
	Million Euros	**%**	**Euros**	**Euros**	**nights**
Total Spain	**63094**	**100%**	**971**	**110**	**9**
1 night	1162	1.8%	363	363	1
2-3 nights	5928	9.4%	622	239	3
4-7 nights	25856	41.0%	846	141	6
8-15 nights	18837	29.9%	1159	101	12
16-30 nights	5790	9.2%	1505	66	23
31-60 nights	4005	6.3%	2956	61	48
More than 60 nights	1516	2.4%	6581	64	102

Source: Own elaboration from Survey EGATUR, IET, Ministry of Tourism, Spain.

In terms of duration of stay, table 3 shows that the main group of expenditure corresponds to the visitors staying for 4-7 nights, followed by those staying for 8-15 nights. These two groups accumulated 70% of total spendings. As shown in the table, daily spending decreased with stay duration, while average spending increases with stay.

Table 4: Expenditure of international visitors in Spain by accommodation

	Total		Average by visitor	Daily average by visitor	Average length of stay
	Million Euros	**%**	**Euros**	**Euros**	**nights**
Total Spain	**63094**	**100%**	**971**	**110**	**9**
Hotel	40208	63.7%	979	144	7
Rent house	9451	15.0%	1277	90	14
Friends house	5530	8.8%	688	69	10
Second-home	4580	7.3%	1019	60	17
Other	3324	5.3%	833	95	9

Source: Own elaboration from Survey EGATUR, IET, Ministry of Tourism, Spain.

Table 4 for expenditure by type of accommodation shows that tourists in hotels account for the bulk of spending (63%), followed by those at rented houses and in houses of friends and relatives, and second-homes. Daily spending appears to be higher for tourists in hotels, although they show shorter stays. As a result, tourists in rented houses and second-homes show higher full-trip average expenditure.

2.2 Accounting for spatial dependence in tourist expenditure: global and local indicators of spatial association

As we have seen, tourist expenditure is unevenly distributed along the Spanish geography. In this section we get deeper understanding of the spatial pattern of this variable by relying on spatial statistic techniques. As a first step, we build on the Exploratory Spatial Data Analysis (ESDA). Anselin (1988) defines ESDA as a collection of techniques to describe and visualize spatial distributions, identify atypical locations or spatial outliers, discover patterns of spatial association, clusters or hot spots, and suggest spatial regimes in data. Spatial statistics literature points to two main types of spatial effects of interest for researchers, namely, spatial autocorrelation and spatial heterogeneity. A variable exhibits spatial autocorrelation if the value shown by the variable in a particular spatial unit is significantly associated with the value shown by neighbouring spatial units. Spatial association can be both positive and negative, and the relevant issue here is the statistical significance of these linkages. Positive association exists when similar values in magnitude for the variable of interest cluster together in space, either for high or low levels of the variable. Negative association arises when high values are surrounded by low values of the variable and viceversa, describing patterns of high-low and low-high values for neighbouring spatial units. Random patterns exhibit non-spatial autocorrelation or association. The second spatial effect, heterogeneity, refers to the uneven distribution of a variable or event across a spatial unit of reference (Anselin, 1988).

In the present paper we will concentrate in the analysis of spatial association or autocorrelation features in data, given the cluster nature of tourist expenditure in space. Expenditure data in the study comes from the Tourist Expenditure Survey

(Egatur), carried out by the Institute of Tourism Studies of the Ministry of Tourism until September 2015, then moved to the Spanish Statistics Institute (INE, www.ine.es). The survey builds on questionnaires collecting data from international tourists reaching Spain, including questions about their level of total expenditure, personal and trip characteristics, and other features of their vacational experience such as the overall level of trip satisfaction.[1] The year of reference for data in the study is 2014, and we get access to more than 102,000 questionnaires. Egatur provides information at the level of the individual tourist and the municipality visited. The focus of this study is geographical, as we are interested in highlighting the spatial nature of tourist expenditure. Accordingly, the dependent variable is the average total expenditure by tourist per destination. As explanatory factors, we focus on two main information data sets. The first set of information includes local destination features able to influence the level of expenditure of tourists, proxied by variables reflecting the development of the tourism sector. Covariates in this set include a tourism development index, and the level of local population. In the second set we want to take advantage of the trip and visitor´s characteristics at destinations provided by Egatur survey, but keeping the spatial scope of the analysis. In this way, we compute territorialized measures of these characteristics for the distribution of each variable at the level of destination. Further details on the data set will be given in the econometric procedure section.

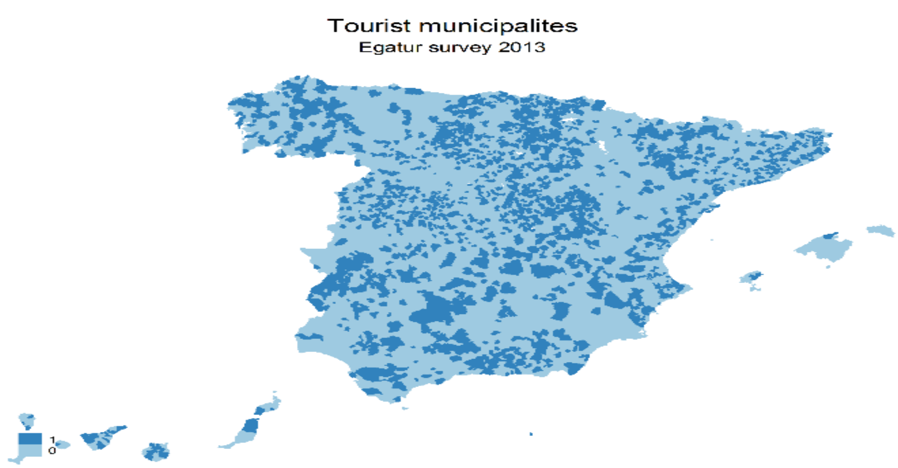
Map 1 shows the municipalities in the data set, including a number of 1872 municipalities with information in Egatur from the total 8100 municipalities in Spain. The sample includes the main tourist areas in the country, with the rest of municipalities not showing a significant tourism development level. In modelling spatial association, a key issue is the definition of the relationship between spatial units in the data set. In dealing with spatial dependence effects, it is necessary to formulate a definition of neighbourhood or spatial association pattern in data, usually captured by the spatial weights matrix W. For a set of N spatial entities, it is usual to define the contiguity relation in terms of sets $N(i)$ of neighbours of the spatial unit i.

[1] For further details consult: http://estadisticas.tourspain.es/es-ES/turismobase/Paginas/default.aspx

These are coded in the form of a weights matrix W, with a zero diagonal, and the off-diagonal nonzero elements showing association measures between spatial units in the sample, usually row-standardized to unity, with typical element $w_{ij}= w_{ij}/\Sigma w_{ij}$.

Most usual definitions of the W matrix account for the binary matrix, where $w_{ij}=1$ if spatial unit i is a neighbour of j and $w_{ij}=0$ otherwise, or other standard definitions based in ensuring k-nearest neighbours in the analysis, or some type of geographical distance function. In this paper, in order to deal with a necessary continuous space, we define a W matrix where all municipalities account for at least one neighbour, resulting in a maximum threshold distance between spatial units of 32 km. The proximity definition in the paper is set for first-order contiguity linkages and a standardized W matrix. Map 1 shows in light blue the tourist municipalities in the sample according to the Egatur survey for the 2014 edition.

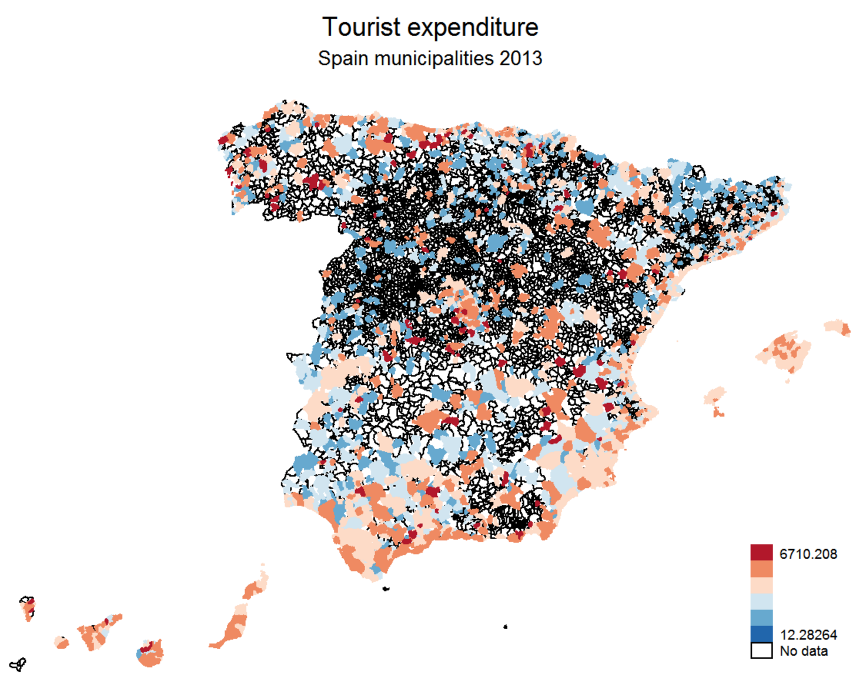
Map 1: Tourist Municipalities in Egatur Survey, Spain 2014



Source: Own elaboration

Map 2 plots data on the level of expenditure of tourists from Egatur 2014. The spatial distribution of tourist expenditure in Spain shows the concentration of total expenditure in the seaside areas, including the Eastern Mediterranean coast, with Catalonia, Valencia, Murcia, and Andalusia. Other regions with important levels of total expenditures are Balearic and Canary Islands, and the capital Madrid in the centre of the map. The north of the country, Basque Country region, also shows some tourist expenditure, although with lower levels than the major regions. Map 2 reflects the spatial pattern previously shown in table 2. From a descriptive point of view it seems to emerge some sort of spatial autocorrelation in tourist expenditure, with destinations with the highest level of spending agglomerated in particular areas of the country, and low spending areas surrounded by other low level neighbours.

Map 2: Total tourist expenditure by Spanish municipalities in 2014



Source: Own elaboration

To provide a deeper analysis of the spatial pattern of association for the tourist expenditure in Spain, we continue applying ESDA tools taken from spatial statistics. The global Moran´s I (MI) statistic is the usual measure to test for spatial autocorrelation at the level of the whole sample (Le Sage and Pace, 2009). By definition, given n spatial units, a variable of interest x, and a weights matrix W, Moran´s I statistic is defined as:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})2} \qquad (1)$$

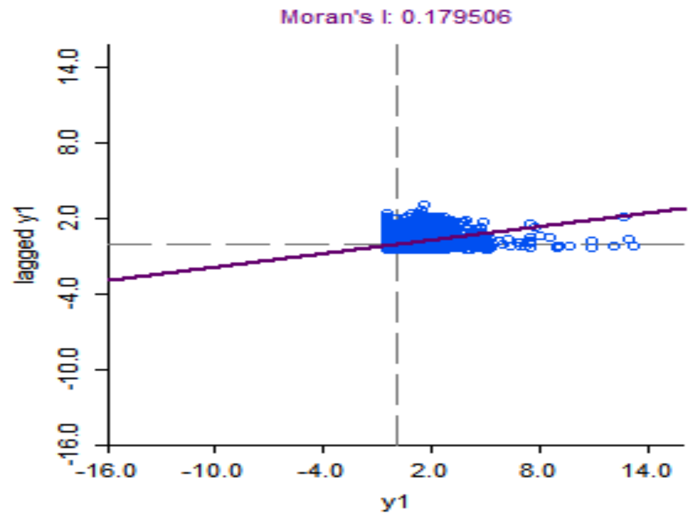
with x being measured at the $i=1, 2, \ldots, n$ locations in the sample, and w_{ij} being the element in row i and column j of a spatial weights matrix. Under the randomness assumption, the asymptotic distribution of the normalized MI statistic is N (0, 1), with the statistic ranging in the interval [−1 and +1]. A positive value of the MI statistic denotes positive spatial autocorrelation, while a negative stands for negative spatial autocorrelation. A value of 1 (-1) indicates perfect positive (negative) autocorrelation, and 0 value indicates a random spatial autocorrelation pattern.

Figure 2 shows the value of the MI Scatterplot for the total tourist expenditure in Spain in 2014 (Anselin, Syabri & Kho, 2006). The figure plots the correlation value for each municipality (X-axis) in the data set against their geographical neighbours (Y-axis, or spatial lag of y variable) according to the contiguity definition in the W matrix. Moran Scatter plot shows four quadrants (I, II, III, and IV), corresponding to four different types of regional disparities:

1. I quadrant (HH): high values surrounded by high values
2. II quadrant (LH): low values surrounded by high values.
3. III quadrant (LL): low values surrounded by low values.
4. IV quadrant (HL): high values surrounded by low values.

Quadrants I and III are for positive autocorrelation values, both high and low respectively, and II and IV for negative autocorrelation values. As shown by figure 2 total tourist expenditure for municipalities in Spain mainly locate at quadrant I (HH) and to a lower extent at quadrant III (low-low). The value of the global MI statistics shown upward in the figure is of around 0.18 with 99% level of significance, showing the presence of spatial autocorrelation in tourist expenditure at the level of destinations in Spain.

Figure 2: Moran´s I Scatterplot for total tourist expenditure in Spain in 2014



Source: Own elaboration

The global spatial autocorrelation analysis yields only one statistic for the whole area of study, hence assuming homogeneous behaviour of the variable of interest along the space. If this assumption doesn´t hold, such a single statistic loses informative capacity, as the MI statistic could be expected to change across the geographical space. Even if we found no global autocorrelation treats, there can still be found clustering behaviour at a local level by using local spatial autocorrelation indicators Given that global MI index is a summation of cross-products by individual locations, Local Indicators of Spatial Association (LISA) can exploit this feature for calculating local MI indexes, also evaluating the statistical significance for each local cluster found. As shown by Anselin (1995), local MI indicators can provide, in this way, more detailed insights into the locational-specific nature of spatial dependence, allowing to detect places with unusual concentrations of high or low values of the variable of interest.

The local Moran statistic (I_i) is defined as:

$$I_i = \frac{z_i}{\sum_i z_i^2} * z_i^0 \qquad (2)$$

where z_i expresses the value for region i of a given variable, as a deviation from the mean, and z_i^0 is the spatial lag for location i, obtained as:

$$z_i^0 = \sum_{j=1}^{n} w_{ij} z_j \qquad (3)$$

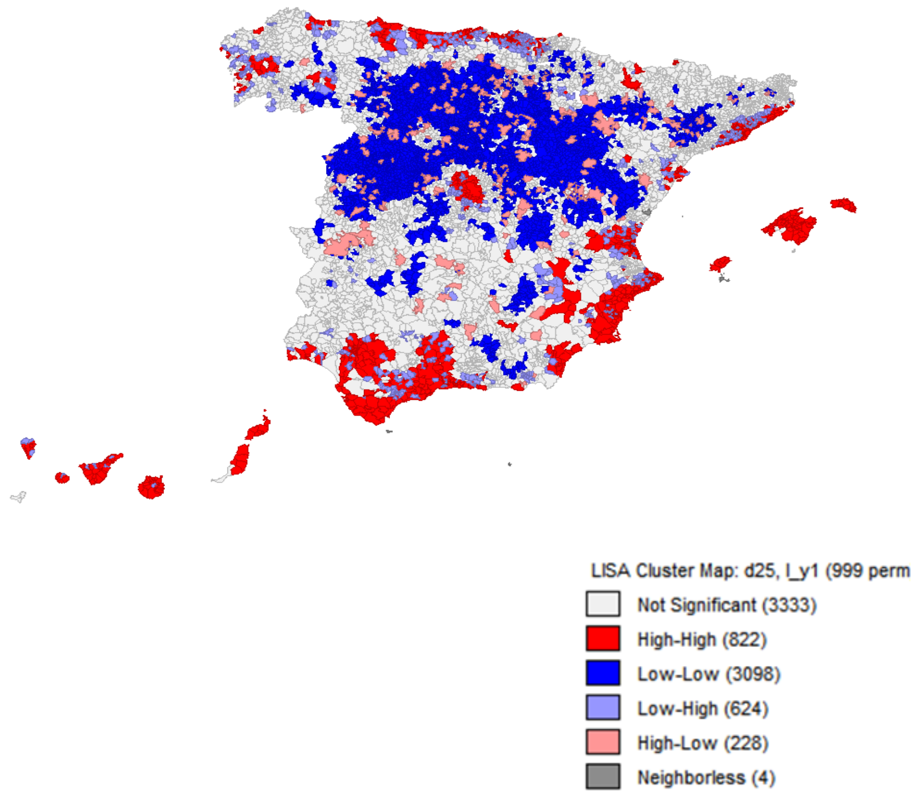
The LISA statistics serve two purposes. On the one hand, they may be interpreted as indicators of local pockets of non-spatial stationarity, or hot spots, similar to the Gi and Gi* statistics of Getis and Ord (1992). On the other hand, they may be used to assess the influence of individual locations on the magnitude of the global MI statistic and to identify outliers, as in the Moran scatterplot from Anselin (1993).

Following the same notation, local Geary statistic (Gi), is defined as (Anselin, 1995; Getis & Ord, 1992):

$$G_i = \sum_j w_{ij} (z_i - z_j)^2 \qquad (4)$$

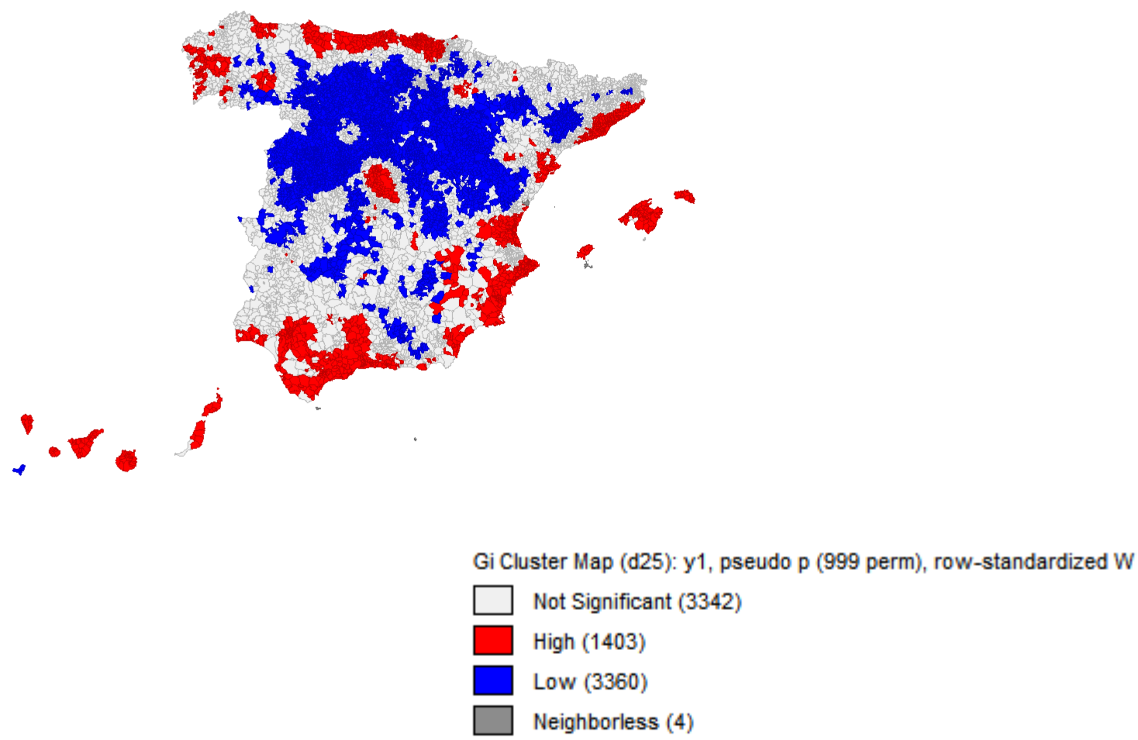
Map 3 presents the LISA indicators for tourist expenditure in Spain, showing local significant HH (high-high) clusters in the Mediterranean coast, including Valencia, Murcia, Andalusia, Catalonia, the two Islands, and Madrid. The north of Spain, i.e. the Basque Country, shows some HH clusters too. LH (low-high) local clusters arise in the same seaside regions, but for single destinations located in the inland of the region. HL (high-low) clusters are more present in the centre of the country, away from the seaside destinations that accumulate the highest total average expenditure of tourists. LL (low-low) clusters follow the same pattern as HL ones, located in the middle of Spain where rural tourism is present, a product with lower levels of average expenditure by visitor, given the lower stay duration.

Map 3: LISA map for tourist expenditure in Spain 2014



Local indicators in Gi Cluster Map point as well to the presence of HH spatial clusters in total tourist expenditure at the main tourist destinations in Spain, such as Malaga, Las Palmas, Santa Cruz de Tenerife, Cadiz, Mallorca, Ibiza, and Alicante in the coastal area and the Islands, and Sevilla and Granada in the south of Andalusia (map 4). In this case the local Geary statistic shows significant high and low local clusters where average expenditure per tourist differ from the global mean value, well below (low clusters) or above that (high clusters). In general, we see important spatial dependence patterns in data for tourist expenditure in Spain, both from a global and local focus. In this way, the next section deals with the econometric analysis, extending the modeling approach to account for those important spatial association patterns found in data.

Map 4: Gi Cluster Map of Geary



3. Econometric analysis

In this section we run the econometric model, starting by the OLS procedure and then moving to the spatially extended specifications with spatial econometrics. Our model of tourist expenditure includes as dependent variable the average expenditure by tourist at destination (in logs), given the spatial nature of the analysis. Data in the model comes from Egatur survey, including around 102,000 questionnaires made to international tourists reaching Spain in 2014. Explanatory factors include the following covariates:

<u>Profile of the tourist per destination:</u>

This group of variables reflects the profile of tourists at destination. It is computed as the share of visitors, over total, with a particular profile arriving at each single destination in year 2014. Information regarding these variables includes:

- Origin of the tourist: Grouped for visitors coming from the European Union (EU), USA + Canada, North of Europe (Sweden, Finland, Denmark), Rest of Europe and Rest of the World.

- Level of studies: Primary, secondary and tertiary schooling (according to UNESCO ISEC 2011 classification; see UNESCO, 2011).

- Level of income: High (more than €80,000 per year), medium (between €20,000 and €80,000 per year), low (less than €20,000 per year).

Trip characteristics of tourists per destination:

This group of variables accounts for the trip characteristics of tourists per destination, computed as the share of tourists over total with particular trip characteristics arriving to each single destination in year 2014. Information in the model regarding the trip characteristics of tourists per destination includes:

- Size of the party: number of people coming in the tourist group (in logs).

- Purpose of the visit: including leisure, studies, personal, business, and other purpose.

- Type of accommodation: hotel, rent apartment, second-home, and other accommodations.

- Length of stay: in average days for all visitors at destination (in logs).

Destination specific attributes:

As destination specific attributes we include:

- Tourist index: This variable reflects the degree of specialization in tourism activities of the municipality, as a weighted average of the existing supply of tourist accommodation establishments, food and restaurants establishments, and leisure and tourist activities available (in logs) (source: Caixabank Annual Report, Spain, http://www.caixabankresearch.com).

- Total population: As a variable capturing the destination size and tourist consumption opportunities (in logs) (source: INE, Statistics Institute of Spain, www.ine.es).

The basic specification of the tourist expenditure model is then as follows:

$$EXP_i = \alpha_i + PROF_i + TRIP_i + \ TOURIND_i + \ POP_i + u_i \qquad (5)$$

where:

EXP$_i$: Total average expenditure by tourists at destination *I* (in logs)

PROF$_i$: Variables conforming the profile of the tourists visiting destination i

TRIP$_i$: Variables conforming the trip characteristics of tourists visiting destination i

TOURIND$_i$: Tourist Index of destination *I* (in logs)

POPi : Resident population at destination *I* (in logs)

u_i : Residual of the model (error term).

Descriptives on the data set for the econometric model are presented in table 5, showing an average spending per visitor of around 952 euros at destination, with a mean stay of 12 days, tourists coming in couple majorly, for leisure, personal and business purposes, accommodated in hotels and second-homes, coming from Europe mostly, with middle and high income levels, and with secondary and tertiary studies.

Table 5: Descriptives of the covariates in the econometric model

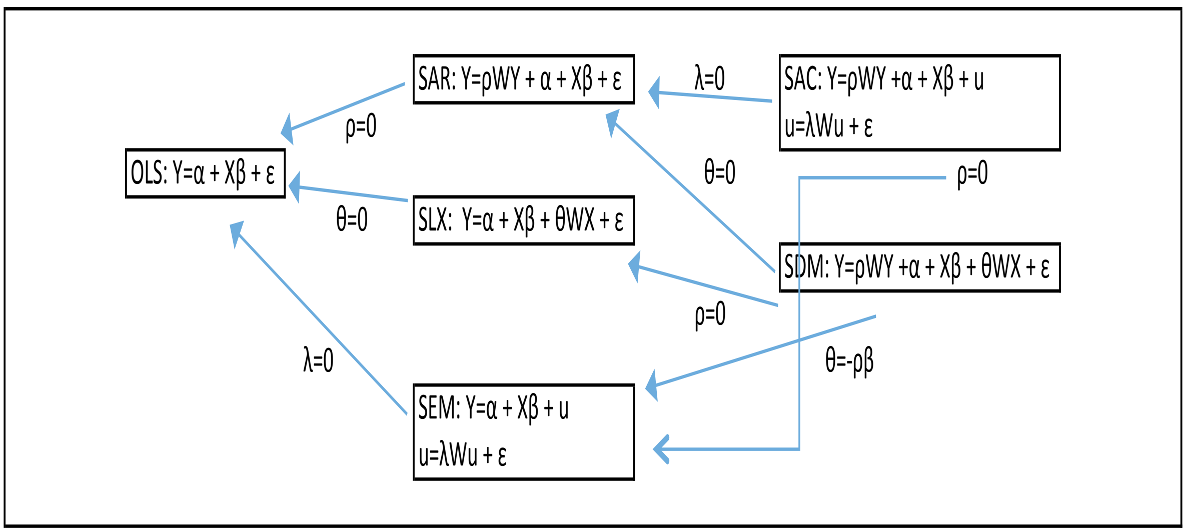
Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Total av. expenditure per tourist (in euros)	952	118	12	3710
Length of stay (average days)	12	10	1	50
Size of the party (av. number of people)	2.17	1.75	1	12
Leisure (percentage)	0.57	0.40	0	1
Studies (percentage)	0.02	0.09	0	1
Personal (percentage)	0.26	0.35	0	1
Business (percentage)	0.11	0.24	0	1
Other purpose (percentage)	0.04	0.02	0	1
Accommodation-second home (percentage)	0.27	0.34	0	1
Accommodation-hotel (percentage)	0.54	0.40	0	1
Accommodation-rent apartment (percentage)	0.08	0.19	0	1
Other accommodation (percentage)	0.09	0.03	0	1
European Union (percentage)	0.64	0.21	0	1
USA + Canada (percentage)	0.04	0.01	0	1
North of Europe (percentage)	0.05	0.01	0	1
Rest of Europe (percentage)	0.13	0.05	0	1
Rest of the World (percentage)	0.14	0.03	0	1
High income (percentage)	0.20	0.14	0	1

Medium income (percentage)	0.75	0.22	0	1
Low income (percentage)	0.05	0.02	0	1
Tertiary studies (percentage)	0.23	0.12	0	1
Secondary studies (percentage)	0.59	0.27	0	1
Primary studies (percentage)	0.18	0.08	0	1
Tourist index	81	431	1	940
Population (in people)	20961	95705	5	3198645

Source: Own elaboration based on Egatur 2014, INE and CaixaBank data.

Modelling strategy includes the basic estimation by OLS procedure, followed by spatially extended models to account for spatial dependence. The approach to spatial modeling followed in this paper is shown in figure 3:

Figure 3: Interrelationships in spatially extended models



Source: Adapted from Vega & Elhorst (2015).

Note: OLS=Ordinary Least Squared model, SAR=Spatial Autoregressive Model, SLX=Spatial Lag of X model, SEM= Spatial Error Model, SAC= Spatial Autoregressive Combined model, SDM=Spatial Durbin Model.

As shown by literature, OLS estimates result in biased and inefficient coefficients in the presence of spatial dependence in data. Accounting for such issues requires to impose some spatial structure in the model. Usual approach employs the SAR

(Spatial Autoregressive) and SEM (Spatial Error) specifications of the linear model, introducing the spatial dimension either in the dependent variable or in the error term respectively, depending on the nature of data (Anselin, 1988).

SAR model extends the simple linear model by introducing the spatial lag term Wy, accounting for spatial autocorrelation effects in the dependent variable. In this way, estimates of the coefficients in the model are now unbiased, while error term shows the expected behaviour. Such an specification of the model deals with previous estimation problems in the OLS estimator. Additionally, the SEM specification imposes the spatial structure in the error term of the model, as shown in figure 3. These two models are estimated by Maximum Likelihood procedure (Anselin & Bera 1998). Further, some scholars suggested the necessity of introducing other specifications and modelling strategies, proposing the SAC model (Spatial Autoregressive Combined Model), with spatial effects in the dependent and error terms, or the SDM model (Spatial Durbin Model) with effects in the dependent and explanatory variables (Le Sage and Pace 2009; Elhorst 2010). More recently, some authors have claimed for the possibility of using the SLX model as a benchmark point of departure, when there is not clear underlying theory or coherent economic argument for a different initial approach (Vega and Elhorst, 2015).

Following these recommendations, we estimate six models for tourist expenditure in table 6, with log-log specification. The first one is the OLS specification showing quite important goodness-of-fit in this type of models, where values of R-sq up to 0.5 are considered reliable (Thrane, 2014). In order to test for the existence of spatial dependence in data we confront the OLS, SAR and SEM specifications. The usual way of testing for the best specification starts by noting the significance of the spatial parameters in the SAR (ρ) and SEM (λ) models. In this case, both specifications show significant spatial parameters with values, 0.14 and 0.12 respectively, in an expected range according to this type of models (Arbia & Baltagi, 2009). Data seems not to violate the normality and homoskedasticity assumptions as shown by Jarque-Bera and Breusch-Pagan tests in table 6 (Le Sage & Pace, 2009). Next step includes testing the OLS vs SAR and OLS vs SEM specifications of the spatial models by means of the classical Anselin and Burridge Lagrange Multiplier (LM) tests. Rule of thumb states that if the LM lag test and the LM error test are both significant for the classic version of the tests, then we have to apply the robust versions in order to discern the best model specification fitting the data (Anselin et al., 1996; Anselin & Florax, 1995).

[Insert Table 6 here]

In this regard, it appears that the OLS model is not appropriate, given the presence of spatial structure in data, while the model that better fits data appears to be the SAR model. The significance of robust LM Lag test and the non-significance of the LM Error robust test confirm that extent. Results of the SAR model show how relevant covariates in the previous literature of tourist expenditure maintain momentum in the spatially extended framework (Sainaghi, 2012; Wang & Davidson, 2010). For example, the most important explanatory factor in order to influence the (log of) average tourist expenditure at destination is the length of stay, followed by type of accommodation (hotel and rent apartment), and origin of the tourist for more distant visitors (those from North American, and the Rest of the World). The following variables increasing expenditure in the model are those of being a business tourist, with high-income level, and tertiary education. In this way, trip characteristics and profile of the visitor at destination continue to be important determinants in the spatial tourist expenditure model, as in the previous micro-economic exercises focused on survey data for individual tourists (Marrocu, Paci & Zara, 2015; Brida & Scuderi, 2013). Fixed regional effects in the model do not appear to be significant, perhaps because we are yet controlling for spatial structure in the model. Other spatial specifications in table 6, such as the SAC, SDM and SLX models, also show interesting results in the analysis of tourist expenditure. For example, SAC model shows the significance of the two spatial parameters conforming this specification (ρ and λ), despite the second one shows negative sign in this case. SDM model including both spatial lags for the dependent (Y) and explanatory variables (X´s), shows the ρ parameter to be significant, but WX covariates appear non-significant in nearly all cases. Finally, the SLX model, able to act as non-spatial benchmark as the traditional OLS model, seems to perform well too, despite many WX covariates appear to be non-significant again, as in the Spatial Durbin Model (SDM).

The use of R-sq measures is shown not to be appropriate in the spatial econometrics framework (Anselin, 1988). Instead, when measuring goodness-of-fit of models, we rely on additional information criteria such as the Log-Likelihood or Akaike-AIC. Log-likelihood criterion appears to favour SDM and SLX models, while AIC points to the superior performance of SAR and SAC models. Given the previous results on LM lag and LM error robust tests, our preferred specification would be that of the SAR model. We discard to use the SDM and SLX specifications given the non-significant nature of WX covariates in both models, not providing in this way additional information to the investigation. LR test for SDM model also shows evidence on the non-significance of the ρ parameter in this model, while SLX does not overcome the OLS specification if we employ the usual parsimony approach, given that WX appear to be non-significant (Vega & Elhorst, 2015).

4. Direct and indirect effects in the spatial model

As posed by Le Sage and Pace (2009), in spatial models the interpretation of estimated coefficients is not direct as in the case of OLS. Coefficients in the spatial regression models jointly account for direct and indirect effects of covariates. Direct effects can be though as the effect of covariates on the dependent variable within the spatial limits of the *ith* destination. Indirect effects would be capturing the effects of covariates from *ith* destination spilling over the neighbouring area. More technically, in a SAR model (see, i.e., Vega & Elhorst, 2015):

$$y = \rho WY + \alpha \iota_N + X\beta + \varepsilon,$$
$$y = (I - \rho W)^{-1}\alpha \iota_N + (I - \rho W)^{-1} X\beta + (I + \rho W)^{-1}\varepsilon \tag{6}$$

the direct effects would be computed as the own derivative of y on x for the ith region:

$$\frac{\delta y_i}{\delta x_i} = (I - \rho W)^{-1}\beta_i \text{ (for diagonal elements of W)} \tag{7}$$

while indirect effects are shown by the derivative of y *on* x for $r \neq i$ (off-diagonal elements of).

$$\frac{\delta y_i}{\delta x_{ir}} = (I - \rho W)^{-1}\beta_i \text{ (for off-diagonal elements of W)} \tag{8}$$

Spatial spillovers arise as a result of impacts extending through neighbouring regions or even coming back to the origin region itself in a chain of spatial connection of indirect effects. The magnitude of the indirect effects will then depend on: (1) the position of the region in space (or in general in the contiguity structure), (2) the degree of connectivity among regions as expressed by the weight matrix W of the model, (3) the value of the parameter ρ measuring the strength of the spatial dependence in data, and (4) the level of the β coefficients (Le Sage and Pace, 2009).

Table 7 shows the direct and indirect effects arising in the model for the preferred SAR specification of the tourist expenditure equation. Results in the table show that variables with major direct impact on tourist expenditure are the length of stay of the visitor, type of accommodation chosen, long-distance visitors (USA + Canada, Rest of the World), level of income and educational endowment. In the case of indirect or spillover effects in the model, size of the coefficients appear to be of less magnitude than those of direct effects as expected, with some covariates appearing more important than others in influencing the level of expenditure at neighboring municipalities. In particular, we observe the relevance of length of stay, accommodation type and long-distance visitors in pushing average expenditure at closer destinations. In this way, these variables would be helping to conform high-high and low-low clusters of tourist expenditure along the Spanish geography. Regional dummies now appear to gain significance when we decompose direct and indirect effects in the model, an interesting result in table 7.

[Insert Table 7 here]

Moreover, in search of a deeper understanding of the role of covariates in explaining tourist expenditure at Spanish municipalities, we group information for spillover effects by characteristics of the destinations relevant for the country tourism sector. Table 8 computes spillover effects for different grouping factors, clearly showing that spillover effects vary depending on the particular characteristics of destinations and type of tourism specialization. For example, “tourist areas”, defined by Spanish Institute of Statistics as “municipalities where the concentration of tourist amenities is significant” (http://www.ine.es/en/daco/daco42/ocuphotel/notaeoh_en.htm), show indirect mean effects in table 8 above the average country value, or even above those of “non-tourist areas”. Such findings reflect how the most visited tourist destinations in the country contribute to increase the level of expenditures at neighbouring destinations, in a clear clustering process reinforced by significant positive externalities at the geographical level. Other type of destinations where positive indirect effects reach higher levels above the mean are those of coastal destinations, sun and sand destinations, and Med coast and Islands in the country. As shown by table 8 and results of previous sections, main tourist destinations in terms of average expenditure are those located in the seaside areas of the Mediterranean coast, in the two Islands, Canary and Balearic, or in Madrid, the capital of the country. Seaside, coastal, Mediterranean, or Islands tourist agglomerations appear to reinforce the capacity of attracting tourists and expenditure through spillover effects. In particular, for the case of Spain, higher indirect effects are shown to arise at the “tourist areas” and Mediterranean destinations, followed by Islands, coastal areas and sun & sand places. Non-coastal areas, urban areas and “non-tourist areas”, by contrary, show positive but well below-the-mean spillover effects for tourist expenditure, reflecting the specialization of Spain in seaside tourist products and the leading role of sun and sand destinations.

[Insert Table 8 here]

5. Discussion of results and future research extensions

According to the main results of the investigation, spatial dependence appears to be an issue for tourist expenditure studies. Previous research focusing on micro-economic models, based on survey data, has contributed quite significantly to improve our knowledge on what are the major determinants of the expenditure of tourists. However, a more grounded approach seems to be appealing when disentangling the factors diving the behaviour of tourists at the level of destinations. Formation of clusters of high and low level of tourist expenditure seems to be the pattern in Spain, as well as in many other tourist countries and regions in the world. In this way, our modeling exercise could be generalized to the analysis of other world tourism regions, or even to other tourism topics characterized by spatial dependence patterns. Regarding the main results of the econometric modeling section, length of stay appears to be the most important determinant of tourist expenditure, as shown extensively by previous contributions (Thrane & Farstad, 2011). Trip characteristics as the type of accommodation chosen, and the purpose of the visit also influence the level of expenditure majorly. Profile of the visitor, particularly according to the origin of the tourist, and the level of income and studies appear as relevant factors in explaining tourist expenditure at destinations in Spain too (Marrocu, Paci & Zara, 2015; Brida & Scuderi, 2013).

All these results open important avenues of research for the future, in order to introduce the spatial approach in the tourism literature. As shown in this investigation, characteristics of destinations should be progressively added as important factors explaining the behaviour of tourists, at least as important as those related to the profile of the tourist and the particular features of the trip. Moreover, as we have seen in the analysis of indirect effects, all these factors explaining tourist behaviour could in fact conform one single framework of analysis, where the specialization features of a destination determine, endogenously, the profile of visitors arriving and the trip experience themselves. In this setting, highlighting the own characteristics of the destination and surrounding geographical areas could provide pivotal information in order to understand how tourist clusters arise and develop.

Additionally, from a methodological view, future improvements of the research account for employing new methods of estimation able to deal, for example, with potential endogeneity issues in the estimation of expenditure equations. Relying on 2SLS or GMM procedures by introducing IV-based controls helping to deal with the stay/expenditure linkage in the spatial modeling framework would be a necessary step, as shown by previous authors for the non-spatial setting. Accounting for a wider set of variables enriching the picture of destination characteristics in the model would be also desirable. The authors of the paper are yet dealing with both issues.

In sum, the aim of this paper has been to highlight how space is an issue in tourism studies, introducing spatial statistics and econometrics methods in the analysis of spatial association patterns arising at the tourism discipline. These methods have proven to be helpful in extending the scope of the micro-economic literature for tourism research. In this way, introducing the geographical and spatial approach in tourism analysis would progressively confer a richer focus to this literature, historically characterised by its great degree of interdisciplinary nature.

6. Conclusions and policy recommendations

The present paper has focused on extending the scope of tourist expenditure analysis with a micro-level approach. Spatial dependence is an important issue for many socio-economic processes and corresponding academic disciplines. Human behaviour is highly determined by characteristics of the place where people born and live. Introducing a geographical focus in tourism studies is an appealing issue for its development, particularly for the specific area of research where tourist destinations and places become the subject of analysis. With this aim, the present investigation has focused on the introduction of spatial modelling in the study of factors explaining the level of tourist expenditure at destinations.

Building on a data set for more than 102,000 international visitors reaching 1872 relevant tourist municipalities in Spain in year 2014, we have identified in first place the spatial clustering process conforming the tourist expenditure pattern in the country. Spatial autocorrelation pattern has been identified at the level of the data distribution of our variable of interest, tourism spendings. Global and local indicators of spatial association have shown the presence of spatial dependence processes for this variable, both for the whole country geography, and for particular tourist places in Spain. In terms of the econometric framework, OLS and five spatially extended models have been applied in estimating the tourist expenditure equation in the paper. The research approach in this section has allowed to specify a novel framework of analysis, by mixing territorially related variables with other traditional variables of the micro-economic approach. However, and in order to follow the spatial or geographical spirit of the paper, the latter set of variables has changed its nature from an individual related focus to a destination related one. In this way, the modelling exercise has been able to keep the key variables of the previous literature on tourist expenditure, as the tourist profile and characteristics of the tourist experience themselves, but in what regards to the tourist destination instead to the visitor.

Main findings of the investigation have shown that spatial dependence is an important issue in tourist expenditure modelling, ands should be accounted for in order to improve the robustness of coefficient estimates in the model. Clustering behaviour characterises the level of tourist expenditure at destinations in Spain, with seaside and Islands destinations showing the higher levels of expenditure in the country. In contrast, inland destinations and territories in the centre of the geography, away from sun and sand product specialization show lower levels of tourist average expenditure per destination. Spillover or indirect effects arising in the spatial econometric framework have also shown how the clustering process for tourist expenditure becomes reinforced at the neighbourhood of major tourist destinations in Spain, all located in the seaside part of the country, as well as around the capital, Madrid.

Policy recommendations would be mixing traditional recipes taken from the local and regional policies with those belonging to the tourism policy corpus. Regarding the first set of guidelines emerging from results of the investigation, we can see a traditional centre-periphery development model, but in this case with the centre located in the coastal areas, and the periphery in the core of the country geography. Typical recipes of funding transferring schemes from the centre to the periphery would result in a desirable tourist and regional policy where highly crowded destinations could redistribute arrivals and corresponding expenditure to neighbourhood places and in a wider extent to less crowded more distant territories.

This more balanced pattern of tourism development would require however a global strategy at the country level, including the launching of new tourism products for less developed destinations, and some repositioning policies for highly crowded destinations. In particular terms, policies focused on increasing tourism expenditure at destinations should be more prone to deal with the major determinants identified by the model, namely, the length of stay of visitors, the accommodation pattern characterizing the destination, the capacity of attracting long distance visitors with higher purchasing power, and those with high and mid income levels and upper secondary and tertiary studies. Once more, specific targets in the tourism sector in Spain require the usage of specific policies, for example to increase the level of average tourist expenditure.

Finally, clustering and spillover effects in tourist expenditure found by the modelling exercise raise important questions in policy terms. In this regard, big destinations are shown to exert important indirect effects of surrounding areas in terms of expenditure levels of visitors, while most popular areas in the country, such as the seaside and sun and sand destinations show bigger spillover effects on their surrounding areas. In this way, taking advantage of such spilling over effects for the development of new tourism destinations brings again the issue of an existing trade-off between the capacity of top tourist destinations in the country top conform future clusters in tourism, versus the carrying capacity and sustainability levels of these currently crowded destinations. The impact of crowded destinations on quality of life of the resident population, and on the natural resources where the destination builds on, are no doubt two salient topics of the present literature in tourism research. In any case, the study of all these issues transcends the scope of the present research, although many of them share the geographical component as a key dimension of the analysis. At this extent, this becomes another fruitful field of research where employing the spatial modelling techniques that we have been introducing in the present investigation for the tourism literature.

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Table 6: Results of the expenditure equaition for the OLS and Spatial models

	Ref category	Variables	OLS				SAR				SEM				SAC				SDM				SLX			
			coeff	std error	t	p>t	coeff	std error	z	p>z	coeff	std error	z	p>z	coeff	std error	t	p>t	coeff	std error	z	p>z	coeff	std error	z	p>z
Trip		lnsize_party	-0.1082	0.0194	-5.570	0.0000	-0.1101	0.0192	-5.750	0.0000	-0.1089	0.0193	-5.650	0.0000	-0.1086	0.0191	-5.680	0.0000	-0.1137	0.0191	-5.950	0.0000	-0.1083	0.0195	-5.561	0.0000
		ln_length of stay	0.6240	0.0151	41.390	0.0000	0.6174	0.0150	41.240	0.0000	0.6214	0.0150	41.390	0.0000	0.6161	0.0150	41.070	0.0000	0.6135	0.0150	40.940	0.0000	0.6104	0.0152	40.026	0.0000
	other purpose	perc_leisure	0.0862	0.0710	1.210	0.2250	0.0751	0.0701	1.070	0.2840	0.0743	0.0707	1.050	0.2930	0.0730	0.0698	1.050	0.2960	0.0596	0.0704	0.850	0.3970	0.0448	0.0720	0.622	0.5340
		perc_studies	0.1891	0.1317	1.440	0.1510	0.1695	0.1300	1.300	0.1920	0.1699	0.1308	1.300	0.1940	0.1756	0.1296	1.360	0.1750	0.1786	0.1294	1.380	0.1680	0.1524	0.1323	1.152	0.2500
		perc_personal	-0.0795	0.0759	-1.050	0.2950	-0.0847	0.0749	-1.130	0.2580	-0.0892	0.0754	-1.180	0.2370	-0.0865	0.0746	-1.160	0.2460	-0.0894	0.0750	-1.190	0.2330	-0.1083	0.0766	-1.413	0.1580
		perc_business	0.2956	0.0813	3.630	0.0000	0.3039	0.0802	3.790	0.0000	0.2958	0.0805	3.670	0.0000	0.2997	0.0800	3.750	0.0000	0.2941	0.0803	3.660	0.0000	0.2796	0.0816	3.427	0.0010
		perc_hotel	0.5796	0.0522	11.110	0.0000	0.5780	0.0515	11.230	0.0000	0.5807	0.0516	11.250	0.0000	0.5792	0.0514	11.280	0.0000	0.5873	0.0515	11.410	0.0000	0.5772	0.0523	11.046	0.0000
		perc_second-home	0.1076	0.4904	2.190	0.0280	0.1148	0.0484	2.370	0.0180	0.1091	0.0485	2.250	0.0240	0.1157	0.0484	2.390	0.0170	0.1118	0.0482	2.320	0.0200	0.1098	0.0491	2.236	0.0250
characteristics	other accomm	perc_rent apartment	0.5387	0.0724	7.440	0.0000	0.5408	0.0714	7.580	0.0000	0.5388	0.0716	7.520	0.0000	0.5347	0.0713	7.500	0.0000	0.5429	0.0710	7.650	0.0000	0.5430	0.0725	7.493	0.0000
	rest of Europe	perc_EU	-0.1567	0.0378	-4.150	0.0000	-0.1565	0.0372	-4.200	0.0000	-0.1541	0.0374	-4.120	0.0000	-0.1593	0.0372	-4.280	0.0000	-0.1571	0.0374	-4.200	0.0000	-0.1587	0.0379	-4.185	0.0000
		perc_US+Canada	0.3985	0.1023	3.900	0.0000	0.3872	0.1009	3.840	0.0000	0.3928	0.1012	3.880	0.0000	0.3873	0.1007	3.840	0.0000	0.3913	0.1003	3.900	0.0000	0.3559	0.1029	0.000	0.0010
		perc_North_Europe	0.0907	0.0934	0.970	0.3320	0.0848	0.0921	0.920	0.3570	0.0886	0.0924	0.960	0.3380	0.0848	0.0920	0.920	0.3570	0.0768	0.0923	0.830	0.4050	0.0987	0.0936	1.055	0.2920
Tourist profile		perc_Rest_of_World	0.3554	0.1124	3.160	0.0020	0.3548	0.1108	3.200	0.0010	0.3484	0.1113	3.130	0.0020	0.3451	0.1108	3.110	0.0020	0.3446	0.1101	3.130	0.0020	0.3413	0.1126	3.032	0.0020
	low income	perc_high income	0.2577	0.0687	3.750	0.0000	0.2622	0.0677	3.870	0.0000	0.2547	0.0679	3.750	0.0000	0.2596	0.0675	3.850	0.0000	0.2360	0.0676	3.490	0.0000	0.2520	0.0693	3.639	0.0000
		perc_middle income	0.1363	0.0653	2.090	0.0370	0.1405	0.0644	2.180	0.0290	0.1339	0.0646	2.070	0.0380	0.1420	0.0642	2.210	0.0270	0.1204	0.0644	1.870	0.0620	0.1353	0.0657	2.059	0.0400
	secondary educ	perc_tertiary	0.1429	0.0320	4.470	0.0000	0.1368	0.0316	4.330	0.0000	0.1402	0.0317	4.430	0.0000	0.1372	0.0315	4.360	0.0000	0.1384	0.0312	4.430	0.0000	0.1386	0.0322	4.304	0.0000
		perc_primary	-0.2033	0.0744	2.730	0.0060	-0.2002	0.0734	-2.730	0.0060	-0.1962	0.0738	-2.660	0.0080	-0.1977	0.0732	-2.700	0.0070	-0.2052	0.0730	-2.810	0.0050	-0.1933	0.0753	-2.566	0.0100
Destination		ln_turist index	0.0190	0.0085	2.230	0.0260	0.0182	0.0084	2.160	0.0310	0.0177	0.0085	2.100	0.0360	0.0171	0.0084	2.050	0.0400	0.0141	0.0084	1.670	0.0940	0.0152	0.0856	0.000	0.0750
		ln_total_population	0.0098	0.0089	1.100	0.2710	0.0082	0.0088	0.930	0.3510	0.0096	0.0088	1.080	0.2800	0.0083	0.0087	0.950	0.3430	0.0095	0.0088	1.070	0.2830	0.0105	0.0091	1.155	0.2480
	ccaa17	ccaa1	-0.0813	0.1061	-0.770	0.4430	-0.0678	0.1047	-0.650	0.5170	-0.0750	0.1049	-0.720	0.4740	-0.0660	0.1041	-0.630	0.5260	-0.0729	0.1040	-0.700	0.4840	-0.0707	0.1067	-0.662	0.5080
		ccaa2	0.0260	0.1162	0.220	0.8230	0.0401	0.1146	0.350	0.7270	0.0365	0.1150	0.320	0.7510	0.0411	0.1141	0.360	0.7190	0.0513	0.1141	0.450	0.6530	0.0375	0.1167	0.321	0.7480
		ccaa3	0.0508	0.1274	0.400	0.6900	0.0563	0.1256	0.450	0.6540	0.0677	0.1263	0.540	0.5920	0.0515	0.1251	0.410	0.6810	0.0465	0.1253	0.370	0.7100	0.0604	0.1285	0.470	0.6380
		ccaa4	0.0477	0.1179	0.400	0.6860	0.0543	0.1163	0.470	0.6400	0.0585	0.1166	0.500	0.6160	0.0549	0.1157	0.470	0.6350	0.0632	0.1157	0.550	0.5850	0.0559	0.1182	0.473	0.6360
		ccaa5	-0.0358	0.1168	-0.310	0.7590	-0.0157	0.1153	-0.140	0.8920	-0.0239	0.1158	-0.210	0.8360	-0.0169	0.1148	-0.150	0.8830	-0.0145	0.1144	-0.130	0.8990	-0.0208	0.1178	-0.177	0.8600
		ccaa6	-0.0235	0.1211	-0.190	0.8460	-0.0225	0.1195	-0.190	0.8510	-0.0221	0.1195	-0.190	0.8530	-0.0176	0.1190	-0.150	0.8830	-0.0087	0.1186	-0.070	0.9410	-0.0075	0.1222	-0.061	0.9510
		ccaa7	0.1604	0.1169	1.370	0.1700	0.1690	0.1153	1.470	0.1430	0.1651	0.1156	1.430	0.1530	0.1707	0.1147	1.490	0.1370	0.1667	0.1150	1.450	0.1470	0.1863	0.1175	1.586	1.1300
		ccaa8	-0.1435	0.1079	-1.330	0.1830	-0.1278	0.1064	-1.200	0.2300	-0.1343	0.1067	-1.260	0.2080	-0.1248	0.1059	-1.180	0.2390	-0.1287	0.1058	-1.220	0.2240	-0.1216	0.1085	-1.121	0.2630
		ccaa9	-0.2299	0.1059	-2.170	0.0300	-0.2197	0.1044	-2.100	0.0350	-0.2234	0.1046	-2.130	0.0330	-0.2166	0.1038	9.000	0.0370	-0.2057	0.1039	-1.980	0.0480	-0.2086	0.1066	-1.957	0.0510
		ccaa10	-0.1018	0.1075	-0.950	0.3440	-0.0928	0.1061	-0.870	0.3820	-0.0934	0.1064	-0.880	0.3800	-0.0914	0.1055	-0.870	0.3860	-0.0940	0.1057	-0.890	0.3740	-0.0880	0.1084	-0.812	0.4170
		ccaa11	-0.1396	0.1153	-1.210	0.2260	-0.1122	0.1140	-0.980	0.3250	-0.1300	0.1140	-1.140	0.2540	-0.1183	0.1135	-1.040	0.2970	-0.1111	0.1134	-0.980	0.3270	-0.1097	0.1159	-0.946	0.3440
		ccaa12	-0.0859	0.1138	-0.760	0.4500	-0.0762	0.1123	-0.680	0.4970	-0.0754	0.1124	-0.670	0.5020	-0.0657	0.1118	-0.590	0.5570	-0.0705	0.1118	-0.630	0.5290	-0.0739	0.1143	-0.647	0.5180
		ccaa13	-0.0597	0.1182	-0.510	0.6140	-0.0569	0.1166	-0.490	0.6250	-0.0591	0.1168	-0.510	0.6130	-0.0528	0.1159	-0.460	0.6490	-0.0660	0.1163	-0.570	0.5700	-0.0590	0.1192	-0.495	0.6210
		ccaa14	-0.0449	0.1305	-0.340	0.7310	-0.0346	0.1287	-0.270	0.7880	-0.0407	0.1288	-0.320	0.7520	-0.0394	0.1279	-0.310	0.7580	-0.0315	0.1287	-0.240	0.8070	-0.0507	0.1320	-0.384	0.7000
		ccaa15	-0.0215	0.1186	-0.180	0.8560	-0.0101	0.1170	-0.090	0.9310	-0.0168	0.1172	-0.140	0.8860	-0.0077	0.1163	-0.070	0.9470	-0.0170	0.1163	-0.150	0.8840	-0.0155	0.1200	-0.129	0.8980
characteristics		ccaa16	-0.1154	0.1111	-1.040	0.2990	-0.1071	0.1096	-0.980	0.3280	-0.1088	0.1098	-0.990	0.3220	-0.1041	0.1089	-0.960	0.3390	-0.0965	0.1090	-0.890	0.3760	-0.0987	0.1122	-0.880	0.3790
Trip		w1x_lnsize_party																	-0.0361	0.0975	-0.370	0.7110	-0.0092	0.0898	-0.103	0.9180
		w1x_ln_length of stay																	0.0480	0.0836	0.570	0.5660	0.0059	0.0655	0.090	0.9290
	other purpose	w1x_perc_leisure																	-0.3832	0.3385	-1.130	0.2580	0.3742	0.3556	1.052	0.2930
		w1x_perc_studies																	0.8259	0.6686	1.240	0.2170	0.8901	0.6710	1.327	0.1850
		w1x_perc_personal																	-0.6048	0.3503	-1.730	0.0840	0.0914	0.3701	0.247	0.8050
		w1x_perc_business																	-0.3901	0.3970	-0.980	0.3260	0.0172	0.4054	0.042	0.9660
		w1x_perc_hotel																	-0.3713	0.2367	-1.570	0.1170	0.0243	0.2393	0.102	0.9190
		w1x_perc_second-home																	-0.2192	0.2188	-1.000	0.3160	0.0481	0.2201	0.219	0.8270
characteristics	other accomm	w1x_perc_rent apartment																	0.1660	0.3427	0.480	0.6280	0.2761	0.3290	0.839	0.4010
	rest of Europe	w1x_perc_EU																	0.1437	0.1659	0.870	0.3860	-0.3077	0.1847	-1.665	0.0960
		w1x_perc_US + Canada																	0.2074	0.4963	0.420	0.6760	-0.0554	0.4546	-0.122	0.9030
		w1x_perc_North Europe																	-0.6093	0.4307	-1.410	0.1570	0.2382	0.4774	0.499	0.6180
		w1x_perc_ Rest of World																	-0.0745	0.4997	-0.150	0.8820	-0.2880	0.4774	-0.603	0.5460
Tourist profile	low income	w1x_perc_high income																	0.0772	0.3038	0.250	0.7990	0.2539	0.3356	0.757	0.4490
		w1x_perc_middle income																	0.0789	0.2952	0.270	0.7890	0.4680	0.3255	1.438	0.1510
	secondary educ	w1x_perc_tertiary																	-0.1672	0.1535	-1.090	0.2760	0.1112	0.1380	0.806	0.4210
		w1x_perc_primary																	-0.6166	0.3281	-1.880	0.0600	-0.0320	0.3394	-0.094	0.9250
Destination		w1x_ltourist index																	0.0239	0.0328	0.730	0.4650	-0.0197	0.0341	-0.579	0.5630
		w1x_lntotal population																	0.0094	0.0343	0.270	0.7850	0.0486	0.0345	1.409	0.1590
	ccaa17	w1x_ccaa1																	-0.4327	0.4323	-1.000	0.3170	-0.9824	0.5394	-1.821	0.0690
		w1x_ccaa2																	-0.8674	0.4834	-1.790	0.0730	-0.9482	0.5714	-1.659	0.0970
		w1x_ccaa3																	-1.0204	0.5462	-1.870	0.0620	-0.7185	0.6327	-1.136	0.2560
		w1x_ccaa4																	-0.6306	0.4769	-1.320	0.1860	-1.1096	0.5701	-1.946	0.0520
		w1x_ccaa5																	-0.3341	0.4675	-0.710	0.4750	-0.7461	0.5529	-1.349	0.1770
		w1x_ccaa6																	-0.6788	0.4874	-1.390	0.1640	-0.5111	0.5979	-0.855	0.3930
		w1x_ccaa7																	-0.7348	0.4723	-1.560	0.1200	-0.5765	0.5837	-0.988	0.3230
		w1x_ccaa8																	-0.7884	0.4575	-1.720	0.0850	-0.8762	0.5470	-1.602	0.1090
		w1x_ccaa9																	-0.6882	0.4330	-1.590	0.1120	-0.9149	0.5229	-1.750	0.0800
		w1x_ccaa10																	-0.4978	0.4389	-1.130	0.2570	-0.7610	0.5450	-1.396	0.1630
		w1x_ccaa11																	-0.9868	0.4858	-2.030	0.0420	-1.2576	0.5501	-2.286	0.0220
		w1x_ccaa12																	-0.5296	0.4852	-1.090	0.2750	-0.9866	0.5374	-1.836	0.0670
		w1x_ccaa13																	-0.6395	0.4913	-1.300	0.1930	-0.8945	0.5783	-1.547	0.1220
		w1x_ccaa14																	-0.1850	0.5212	-0.350	0.7230	-0.5204	0.6299	-0.826	0.4090
		w1x_ccaa15																	-0.4966	0.5134	-0.970	0.3330	-1.0456	0.5828	-1.794	0.0730
characteristics		w1x_ccaa16																	-0.9504	0.4539	-2.090	0.0360	-0.7235	0.5879	-1.231	0.2190
		constant	4.7557	0.1550	30.6800	0.0000	3.8480	0.2882	13.3500	0.0000	4.7683	0.1536	31.0400	0.0000	3.5293	0.3118	11.3200	0.0000	5.4687	0.7984	6.800	0.0000	4.8107	0.7638	6.298	0.0000
		Rho					0.1422	0.0383	3.7200	0.0000					0.1916	0.0429	4.4700	0.0000	0.0535	0.0691	0.7700	0.4390				
		Lambda									0.1211	0.0663	1.8300	0.0680	-0.1627	0.0919	1.7700	0.0770								
		N	1872				1872				1872				1872				1872				1872			
		R^2	0.6348				0.6377				0.6348				0.6381				0.6475				0.6458			
		Log-Likelihood	-1161.29				-1154.49				-1159.68				-1152.94				-1127.77				-1132.70			
		AIC	0.2104				0.2088				0.2104				0.2085				0.2108				0.2119			
		JB Normality	6.3520			0.3615	7.6040			0.3862	7.2581			0.5436	7.5526			0.4968	7.2256			0.4281	6.6620			0.5539
		BP Heteroskedasticity	9.3250			0.0829	8.2657			0.0045	8.6627			0.0066	8.3365			0.0063	8.6625			0.0051	8.8826			0.0082
		Moran MI Error Test	4.3860			0.0000	0.9168			0.3592	2.0731			0.0382	0.7081			0.4789	2.3988			0.0164	4.4940			0.0000
		LM Error (Burridge)	0.1690			0.0020	0.6576			0.4174	3.7506			0.0528	0.3689			0.5436	0.7695			0.3804	10.1840			0.0010
		LM Error (Robust)	0.1430			0.6810	0.9313			0.3345	1.8221			0.1771	0.0304			0.8616	2.9424			0.0863	0.0880			0.7670
		LM Lag (Anselin)	18.2180			0.0000	5.8415			0.0157	22.8864			0.0000	0.5428			0.4613	0.3218			0.5705	20.7490			0.0000
		LM Lag (Robust)	8.7890			0.0030	6.1152			0.0134	20.9579			0.0000	0.2043			0.6513	2.4946			0.1142	10.6520			0.0010
		LR Test SAC vs. OLS (H0: Rho+Lambda=0)													20.8644			0.0000								
		LR Test SDM vs. OLS (H0: Rho=0)																	0.5994			0.4823				
		LR Test (H0: WX=0)																	44.9496			0.1210				

Table 7: Estimated direct and indirect effects in the SAR model of tourist expenditure

		Direct effects				Indirect effects			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Trip characteristics	lsize_party	-0.0938	0.0135	-0.1320	-0.0534	-0.0159	0.0130	-0.0573	0.0274
	ln_length of stay	0.5309	0.0190	0.4779	0.5945	0.0851	0.0188	0.0208	0.1472
	perc_leisure	0.0622	0.0090	0.0342	0.0962	0.0096	0.0092	-0.0183	0.0379
	perc_studies	0.1444	0.0022	0.1349	0.1520	0.0232	0.0022	0.0168	0.0292
	perc_personal	-0.0770	0.0078	-0.1053	-0.0551	-0.0120	0.0079	-0.0415	0.0124
	perc_business	0.2603	0.0053	0.2422	0.2758	0.0419	0.0056	0.0241	0.0589
	perc_hotel	0.4978	0.0078	0.4707	0.5223	0.0796	0.0081	0.0468	0.1039
	perc_second-home	0.0972	0.0088	0.0683	0.1248	0.0161	0.0089	-0.0132	0.0457
	perc_rent apartment	0.4637	0.0043	0.4503	0.4805	0.0743	0.0044	0.0597	0.0901
Tourist profile	perc_EU	-0.1350	0.0076	-0.1568	-0.1086	-0.0214	0.0076	-0.0460	0.0023
	perc_US+Canada	0.3314	0.0025	0.3239	0.3387	0.0530	0.0025	0.0447	0.0609
	perc_North_Europe	0.0744	0.0028	0.0665	0.0825	0.0118	0.0028	0.0027	0.0206
	perc_Rest_of_World	0.3065	0.0023	0.2998	0.3149	0.0491	0.0023	0.0413	0.0559
	perc_high income	0.2196	0.0079	0.1940	0.2432	0.0353	0.0077	0.0083	0.0626
	perc_middle income	0.1151	0.0083	0.0908	0.1447	0.0188	0.0082	-0.0072	0.0500
	perc_superior	0.1182	0.0082	0.0889	0.1446	0.0187	0.0086	-0.0053	0.0506
	perc_primary	-0.1746	0.0035	-0.1860	-0.1631	-0.0281	0.0034	-0.0388	-0.0163
Destination characteristics	ln_turist index	0.0134	0.0407	-0.1043	0.1295	0.0034	0.0398	-0.1201	0.1309
	ln_tot_population	0.0059	0.0410	-0.1203	0.1490	0.0031	0.0405	-0.1120	0.1239
	ccaa1	-0.0655	0.0086	-0.0934	-0.0394	-0.0109	0.0092	-0.0427	0.0160
	ccaa2	0.0265	0.0045	0.0117	0.0391	0.0044	0.0044	-0.0097	0.0196
	ccaa3	0.0478	0.0033	0.0378	0.0603	0.0077	0.0032	-0.0019	0.0207
	ccaa4	0.0472	0.0043	0.0353	0.0628	0.0075	0.0042	-0.0067	0.0209
	ccaa5	-0.0230	0.0045	-0.0379	-0.0077	-0.0040	0.0044	-0.0182	0.0089
	ccaa6	-0.0264	0.0037	-0.0368	-0.0158	-0.0046	0.0038	-0.0181	0.0071
	ccaa7	0.1445	0.0043	0.1307	0.1579	0.0233	0.0041	0.0083	0.0357
	ccaa8	-0.1111	0.0067	-0.1295	-0.0907	-0.0178	0.0067	-0.0388	0.0021
	ccaa9	-0.1929	0.0089	-0.2192	-0.1630	-0.0310	0.0088	-0.0625	-0.0042
	ccaa10	-0.0862	0.0077	-0.1056	-0.0561	-0.0136	0.0075	-0.0367	0.0118
	ccaa11	-0.1107	0.0045	-0.1251	-0.0949	-0.0178	0.0044	-0.0324	-0.0018
	ccaa12	-0.0650	0.0051	-0.0829	-0.0486	-0.0103	0.0049	-0.0282	0.0103
	ccaa13	-0.0505	0.0042	-0.0627	-0.0371	-0.0081	0.0043	-0.0210	0.0058
	ccaa14	-0.0433	0.0032	-0.0547	-0.0335	-0.0068	0.0032	-0.0166	0.0030
	ccaa15	-0.0166	0.0041	-0.0302	-0.0044	-0.0026	0.0041	-0.0147	0.0106
	ccaa16	-0.0970	0.0057	-0.1140	-0.0767	-0.0153	0.0057	-0.0327	-0.0004

Table 8: Indirect or Spillover effects of the tourists expenditure model by type of destinations

	length stay	hotel	Rent apartmt	USA + Canada	Rest of World	business	high income	studies	North EU	primary	**mean**
tourist areas	0.1020	0.0955	0.0894	0.0640	0.0586	0.0502	0.0433	0.0280	0.0140	-0.0331	**0.0512**
non-tourist areas	0.0967	0.0906	0.0847	0.0607	0.0556	0.0476	0.0411	0.0266	0.0133	-0.0314	**0.0485**
coast	0.1011	0.0947	0.0886	0.0634	0.0581	0.0498	0.0429	0.0278	0.0139	-0.0328	**0.0508**
non coast	0.0979	0.0916	0.0857	0.0614	0.0563	0.0482	0.0416	0.0269	0.0135	-0.0317	**0.0491**
urban tourism	0.0978	0.0915	0.0856	0.0613	0.0562	0.0481	0.0415	0.0268	0.0134	-0.0317	**0.0491**
sund and sand	0.1006	0.0942	0.0882	0.0631	0.0578	0.0495	0.0427	0.0276	0.0138	-0.0326	**0.0505**
MED coast	0.1018	0.0953	0.0892	0.0639	0.0585	0.0501	0.0432	0.0280	0.0140	-0.0330	**0.0511**
Islands	0.1012	0.0948	0.0887	0.0635	0.0582	0.0498	0.0430	0.0278	0.0139	-0.0328	**0.0508**
Spain	**0.0988**	**0.0925**	**0.0866**	**0.0620**	**0.0568**	**0.0487**	**0.0420**	**0.0271**	**0.0136**	**-0.0321**	0.0496