On the determinants of Airbnb location and its spatial distribution

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Abstract

This article explores Airbnb accommodation spatial distribution and it estimates the main determinants of its location choice. It employs spatial bivariate correlations and spatial econometrics to understand the heterogeneous spatial relationship between established hotels and Airbnb for three kinds of local tourism destinations: sun and beach, nature-based, and city. The case study concerns the Canary Islands where a good mixture of these attractions can be found. The main conclusion drawn is that Airbnb regulation needs to distinguish the kind of tourism. More precisely, Airbnb supply overlaps established hotels in city tourism, but it does not so clearly in sun and beach nor nature-based destinations. Airbnb supply matches tourist visits spatial distribution better than established hotels in city and nature-based destinations, but not in sun and beach destinations, where the incumbent hotels are closer to the tourism resources. Finally, the results from the spatial econometrics model shows that population size and the number of tourist visits matters as determinants of Airbnb location. However, the main determinant is price, which has got a much larger elasticity.

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Introduction

The advent of Internet is still reshaping the market structure of the economy in many ways. Tourism and air transport sectors are among the most affected ones. Traditionally, long-haul holiday takers were used to buy bundled services comprised of charter flight, accommodation, catering, excursions, and/or local transport. Economies of scale from the provider side and lack of information and safety seeking from the consumer side were the main reasons for this success. Tourists were conformed to paying for services targeting a broad market niche. Established hotels were also conformed to negotiating with tour operators, who kept most of the market power. However, Internet boosted the provision of information and shrunk the "distance" between demand and supply. Together with the air traffic liberalization, it allowed the entrance of low-cost carriers which popularized direct bookings with travelers, breaking out with the tour operator and travel agency intermediation. Established hotels also allowed for direct bookings either through booking portals or by own websites. It provided the tourists with the opportunity to unbundle the tourism package and customize it.

Internet also provided the opportunity for the creation of communicating and sharing dedicated websites, where some tourists could announce their willing for exchanging their homes or even their cars. Such peer-to-peer (P2P) relationship was the origin of the so-called sharing economy for the tourism case. Its size was pretty small compared with the relevance of the established market. At the same time, real state Internet portals also got much popularity for buying or renting properties. The creation of a similar Internet portal for private tourism renting was a matter of time. In 2005, HomeAway started offering such opportunity, followed up by many other websites, such as Airbnb, which was opened in 2008. Their popularity has grown exponentially since then (Guttentag, 2015). Airbnb states that nowadays they are accommodating more than two million people every night, with a property listing comprising more than four million properties.

Such a disruptive entrance poses many research enquiries. The tourism literature has focused on them in the last 2 years, but there are still many issues to be understood. P2P accommodation may offer advantages over the established hotels for certain tourist profiles (Guttentag et al., 2018; So et al., 2018; Yang et al., 2019). It may increase the number of arrivals, but at the same time, it may crowd out established hotels, decreasing their sales (Blal et al., 2018) or decreasing their average daily rates (Zervas et al., 2017). Some incumbent hotels claim that P2P accommodation needs to be regulated or forbidden and they have lobbied Government institutions to pursue that way. However, Heo et al. (2019) have found that such impact is not so relevant in Paris, and they argue that they may not be in direct competition.

Nevertheless, P2P accommodation represents a new opportunity for a large number of different owners who can obtain capital rents from tourism. Thus, it can provide a more balanced tourism capital rent distribution as well as a more widespread spatial distribution. It may result on a more balanced income and spatial equity. This article addresses a further understanding of the Airbnb location decisions. It explores its spatial distribution over the territory with respect to current incumbent location as well as the tourist visits spatial distribution. Such analysis is carried out employing measures of the degree of spatial bivariate correlation between P2P and established hotels, as well as P2P and tourist visits. It distinguishes city, sun and beach, and nature-based tourism destinations. They can be useful indicators of tourism competition for policymaking and regulation of the P2P phenomenon, especially by distinguishing the kind of tourism. Such correlation analysis is very informative but it cannot conclude any causal relationship among the variables. Thus, the main determinants of Airbnb location are estimated with a spatial

econometrics model. More precisely, a generalized two-stage least squares method is applied to a spatial autoregressive model with an endogenous variable that is instrumentalized. The methods are applied to the Canary Islands where a good mixture of tourism destinations can be found.

Literature review

The entrance of P2P in the tourism accommodation market may imply an increase in market competition. However, the location of P2P accommodation is usually more heterogeneous and scattered over the territory, rather than geographically grouped as in the case of most hotels in tourism destinations. P2P location certainly depends on the preexistence of residential areas near tourism destinations (e.g. cities, see Gutiérrez et al., 2017) or the presence of second homes in tourism destinations (e.g. sun and beach). Nevertheless, the new market structure depends on the location of the new entrant P2P accommodation (see Adamiak, 2018). Theoretically, its understanding suits well under the spatial competition framework. According to Biscaia and Mota (2013), "spatial competition is mainly concerned with the locational interdependence among economic agents under imperfect competition."

Spatial competition in tourism

Chamberlin's (1933) theory of monopolistic competition was much influential on the development of spatial economics and the location theory in regional economics. In our case, it certainly suits well to think of two different kinds of accommodation, say hotels and P2P accommodation, with different characteristics, costs, and prices. Indeed, tourists make their accommodation decisions based on price (Önder et al., 2019), characteristics, and travel distance to the tourism resources (Benítez-Aurioles, 2018; Gunter and Önder, 2018; Rigall-I-Torrent et al., 2011). All this may fit well in characteristics-based models of Lancaster (1966), where distance to the tourism resource may be interpreted as an additional characteristic of a bundled commodity.

Another key concept suggested by Chamberlin (1933) is chain-linked markets. A market is said to be chain-linked if any firm that changes its price affects more strongly its proximate rivals, leaving relatively unaffected those further away (see Rothschild, 1982, for further development). Tourism destinations work pretty much this way. There is an unknown distance threshold that identifies accommodation belonging to the same chain-linked market. Such threshold should depend on the location of the tourist's origin(s), the preferences on the kind of tourism, and how far the tourist is willing or able to travel.

Hay (1976) addresses two weak assumptions of previous models that are required in tourism development. He considers sequential entry and immobility, so that "firms locates as to secure a market area for itself in the longer term." His conclusion is very appealing in tourism:

> firms in a differentiated industry do not respond to the threat of new entry by lowering price, but rather seek to proliferate products to fill up those parts of quality space where there could be sufficient consumer demand to attract new entry.

Finally, it should be noted that the hotel market structure is complex. It is composed by independent hotels, franchisees, and franchisors (see Kalnins, 2006, for further details). Thus, hotel chains may pursue strategic behavior beyond the local market perspective (Becerra et al., 2013). Such competition implies the existence of multimarkets where hotel chains compete with

multiproducts (Fernández and Marín, 1998). In tourism, the idea of multimarkets is reinforced due to destination competition, especially in the holiday segment. The approach of the industrial economics literature is mainly concerned with firm location decision that depends on customers' spatial distribution (Biscaia and Mota, 2013), whereas in tourism, the matter is the accommodation location which depends on the location of the tourism resources.

Hence, tourism accommodation market can be summarized as one with imperfect competition, where each firm provides a differentiated product based on its own characteristics, so that price differentiation takes place. In this setting, location or distance to the tourism resources belongs to the characteristics of the accommodation as part of a bundled commodity. The accommodation firms are immobile and they are subjected to a spatial chain-linked market, where multiproducts and multimarkets are usually in place. The literature has not developed a theoretical tourism model that suits this case, but its nature is so complex that an empirical approach seems to be the way forward.

Hotels spatial competition

This article focuses on the location of P2P new entrance and it pursues an empirical approach to the understanding of the presence of chain-linked markets in tourism. Their location will show a space of influence between incumbent firms and new entrants. Policymakers are concerned with such competition, especially for market and product regulation. Gan and Hernández (2013) analyzed Texas hotels and showed the presence of tacit collusion in hotels that are close to each other when they are agglomerated, but a more independent behavior when they are scattered. However, the size of such spatial chain-linked markets is not homogeneous and it varies with the characteristics of the different kinds of tourism. For instance, it is expected to find higher agglomeration in cities or sun and beach destinations rather than in nature-based destinations. Balaguer and Pernías (2013) studied hotel location in Madrid and showed that higher spatial agglomeration implied lower average hotel prices and less price variance. Thus, such agglomeration results seem to be a good indicator of spatial competition. This article works on this indicator. However, it should be noted that it is not a comprehensive one since prices and occupation rates are left aside.

P2P spatial competition

We have leaned on the article written by Gutiérrez et al. (2017). This article works with spatial correlations. They had been employed previously in a tourism context (see for instance, Luo and Yang, 2013). However, this is the only article that has analyzed P2P spatial correlation so far. They analyze Barcelona, which is a good case of city tourism. They employ local Moran's I statistics to test the presence of spatial clusters in hotels, Airbnb, and photographs (as a proxy for tourist visits) running independent tests and their pairs with bivariate local Moran's I statistics to test the presence of spatial cluster between each pair. The article shows a useful and clear picture of the spatial location of both kinds of supply and the degree of correlation between them and tourism demand. However, by definition, Moran's I statistics decreases its value with the size of the region and it is not bounded. Thus, it has got serious limitations to work as an indicator. In addition to Moran's I statistic, we suggest using spatial bivariate Pearson's r modified statistic because its value lies between -1 and 1, so that it can be compared across regions and for different kinds of tourism. Additionally, we extend the analysis to sun and beach and nature-based tourism destinations. It is relevant because the spatial correlation does not need to be as high as in the city case.

Their measure is relevant to understand how different the spatial correlation is and how different (if necessary) their regulation may/should be.

The degree of competition between established hotels and new P2P accommodation has been studied by Guttentag and Smith (2017). They employed a survey and found that only 2.3% of respondents would not have taken the trip if Airbnb did not exist. Thus, substitution of accommodation was the most likely strategy, where midrange hotels were the most affected ones (43.1%), followed by budget hotels/motels (17.5%), hostels (16.6%), and bed and breakfast (9.9%). Zervas et al. (2017) also found a negative hotel revenue impact of Airbnb for midprice, economy, and budget hotels, whereas the luxury hotels and business travel segment were not affected.

From the tourism economics perspective, there are many other issues to tackle. It is interesting to understand if such new market structure has increased the number of arrivals or travel frequency (Tussyadiah and Pesonen, 2016), Airbnb pricing (Önder et al., 2019), Airbnb efficiency (Zekan et al., 2019), or if such new arrivals correspond to a new market niche in terms of party composition, length of stay (Tussyadiah and Pesonen, 2016), or tourist expenditure per night. Any significant change in this sense will have an impact on aggregate expenditure, gross domestic product, and employment.

Hence, it should be noted that this article provides new insights to the literature in different ways. It provides (i) indicators of spatial competition with bivariate spatial correlation measures that are bounded and comparable across time and space; (ii) the analysis of city destinations, but also sun and beach and nature-based destinations, which have hardly been analyzed so far in the context of P2P spatial distribution; and (iii) the estimation of the determinants of Airbnb location and their elasticities.

Data set

The data set collected for this study concerns the Canary Islands in Spain. Spain is one of the most visited countries in the world and the Canary Islands is one of the most visited regions of Spain. It usually hosts around 13 million tourists every year. The islands are well known in Northern Europe, where they are very popular for German, British, and Scandinavian tourists. They are popular as a sun and beach destination, especially in Gran Canaria, Tenerife, Fuerteventura, and Lanzarote. However, nature-based destinations are popular in other islands, especially in La Palma, La Gomera, Lanzarote, and Tenerife where each of them has got a National Park. Actually, they represent 26% of Spanish National Parks. Additionally, the city of San Cristóbal de La Laguna in Tenerife or Las Palmas de Gran Canaria in Gran Canaria are also popular cities to visit. The former city has been declared UNESCO World Heritage site in 1999, and the latter city has got colonial architecture from 18th and 19th centuries as well as a linked with Cristobal Colombus presence in the island. In other words, the islands have got a good mixture of sun and beach, nature-based, and city tourism destinations.

Most of the literature has focused on city destinations and P2P impact on the established hotels. This article considers three different kinds of tourism destinations on the same region. The data set comprises all hotels and apartments registered and georeferenced according to Instituto Canario de Estadística (ISTAC), as provided by Sitcan open spatial data repository. In 2018, they are 1792 hotels and apartments with 370,750 available beds. For simplicity, all of them will be referred as hotels. It also considers the whole listing of Airbnb properties, according to Airdna data set. They are 25,987 georeferenced properties available in May 2017, which sum up to 105,230 available

beds. Local tourist visits are measured with georeferenced photos taken by tourists and uploaded to Flickr. 819,039 photos were taken and uploaded between 2005 and March 2018. However, some photos were taken by residents (13.5%) who were identified by registered location and ruled out of the data set. Some locations were the same and they were weighted accordingly. Thus, 194,777 unique tourism locations were identified by the tourists' photographs. They will be used as a proxy for the number and the spatial distribution of tourist visits.

Sun and beach destinations are defined by the Official Canary Islands Statistics Institute (ISTAC). They are known as microdestinations. There are marked differences among micro-destinations, but the hotels and apartments are pretty similar within each microdestination in terms of quality and architecture. They are found in sun and beach islands, such as Tenerife, Gran Canaria, Lanzarote, and Fuerteventura. Cities are defined cell by cell in the grid, and they cor-respond to San Cristobal de La Laguna and Santa Cruz de Tenerife in Tenerife; and Las Palmas de Gran Canaria in Gran Canaria. Nature-based destinations are interior areas of green islands such as La Palma, La Gomera, El Hierro, Tenerife, and Gran Canaria.

Methodology

The article provides results on bivariate spatial correlation and spatial econometrics. The meth-odological details are explained below.

Spatial correlation

Univariate Moran's I statistic shows how relevant spatially lagged variables are. The statistic was first introduced by Moran (1948) for serial correlation and later extended for spatial correlation (Moran, 1950). The current version of the statistic is due to Cliff and Ord (1969, 1981) who introduced, for this purpose, the concept of spatial weight matrix. The rationale behind the matrix departs from traditional serial correlation because space had to be treated differently since the ordering was not as obvious as in time dimension and its relationship had to be established a priori. More precisely, Moran's I can be defined as

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2} \tag{1}$$

where w_{ij} denotes the spatial weight for each pair ij.

Spatial weight matrix

The building of the spatial weight matrix W is critical for the results, so that careful thinking is required for its construction. W is a square matrix that relates all pairs of origin-destinations ij in space. Generally speaking, three kinds of formal expressions of connectivity in space can be constructed (Anselin, 1988: 16–21):

  (a) Contiguity-based. For this case, surrounding areas are relevant. They can take value 1 in the matrix, whereas the rest of the areas take null values. The order of contiguity can be larger than one, so that further areas can also be considered. The direction of the contiguity can be based on the queen as in the chess game or as the rook. Distance thresholds can also

be used to define the surrounding areas. It should be noted that the matrix is row standardized in order to obtain a balanced weighting.

(b) *K*-nearest neighbors. For coastal polygons, contiguity may fail when defining proximity. For instance, it can happen in queen contiguity when choosing nearest areas according to all queen directions. In the case of islands, it can be a problem because it can consider contiguity with close islands. Nearest neighbors can overcome this problem because it is based on Euclidean distance between centroids.

(c) Distance-based. In this case, it is usually expected that close areas have higher relevance than further areas. Inverse-related distance metrics can be used for this purpose in a linear or nonlinear way. They can also be extended to travel time or travel cost. It is convenient when road networks matter or when the territory has got marked height differences.

In tourism, distance-based spatial weight matrices make sense. Their use is constrained to points, so that point-to-point measures are considered. However, in our case, some sort of spatial aggregation is necessary, so that aggregated supply can be understood in space. Thus, two spatial aggregation criteria may be considered: On the one hand, a nonlattice case is defined by a political map with 2301 polygons, with a coordinate system defined by WGS 1984 UTM Zone 28 N. On the other hand, a lattice case based is built on a grid of squares of 1-km long, comprising 8222 squares in total. The advantage of the political map is that it counts with population information, which is missing for the grid. However, the grid has the advantage of considering homogeneous areas to work with. Hence, the grid will be employed for the bivariate spatial correlation, whereas the polygons will be used for the spatial econometric analysis.

The grid is spatially joined with georeferenced hotels, Airbnb, and photographs. The number of beds within each cell is summed up for hotels and Airbnb properties. Similarly, the number of photographs taken by tourists is summed up for each cell. The former data represent the two kinds of spatial tourism supply, whereas the latter represents the spatial tourist visits. Each cell has got a centroid with coordinates that will be useful for measuring the bivariate spatial correlation later on.

Thus, taking into account the need for spatial aggregation, in our case, k nearest neighbors is the preferred method for spatial weight matrix building. The choice of the number k of neighbors is critical. Indeed, the choice of the spatial weights needs to be in accordance with the actual data generating process. Our strategy is to run multiple Moran's I with increasing distance. However, Moran's I statistic is not directly interpretable, and it cannot be comparable since its expected value depends on n size. Thus, an adjustment is required (Bivand et al., 2008: 260–261). We use z-score Moran's I test values for this purpose, so that we choose the distance with the largest z-score.

Bivariate spatial correlation

For the purpose of this article, bivariate spatial correlation is the key to understand the spatial relationship between established hotels and P2P accommodation. A natural extension of the Moran's I statistic is the bivariate Moran's I statistic. It should be noted that the relationship contemplates variable x together with spatially lagged variable y. Thus, it does not represent a neat spatial bivariate correlation, since it is based on the spatially lagged variable of one of them. Moreover, Anselin (2018) states that the bivariate Moran's I statistic represents the slope of a regression of Wy on x.

Instead of extending the univariate Moran's I statistic, another alternative is to extend the Pearson's r correlation coefficient. Such extension was developed by Clifford et al. (1989), and

furtherly discussed by Dutilleul et al. (1993). The advantage with respect to the bivariate Moran's I statistic is that it deals with the proper bivariate correlation between x and y and its result always lies in the interval $(-1, 1)$. The method makes use of the coordinates of the locations or the centroids of the areas of interest to define the nearest neighbors.

More precisely, let Ω denotes the whole set of locations. Each location has got two variables of interest denoted by X_α and Y_α, where location $\alpha \in \Omega$. The correlation coefficient is given by Pearson's modified r

$$r = \frac{S_{XY}}{S_X S_Y} \tag{2}$$

where $S_{XY} = N^{-1}\sum_\Omega (X_\alpha - \bar{X})(Y_\alpha - \bar{Y})$ is the sample covariance, $S_X^2 = N^{-1}\sum_\Omega (X_\alpha - \bar{X})^2$, $S_Y^2 = N^{-1}\sum_\Omega (Y_\alpha - \bar{Y})^2$, and where $\bar{X} = N^{-1}\sum_\Omega X_\alpha$ and $\bar{Y} = N^{-1}\sum_\Omega Y_\alpha$.

Additionally, it is assumed that all ordered pairs of elements of Ω can be divided into k strata $S_0, S_1, S_2, \ldots, S_k$, so that the covariances within strata are constant, that is, $\text{cov}(X_\alpha, X_\beta) = C_X(k)$. The number of strata k is defined within the method, see Dutilleul et al. (1993) for details. Under this approach, a sample correlation can be calculated and a modified t-test can be performed to test the spatial bivariate correlation between two spatial processes.

A global statistic, such as Moran's I or Pearson's modified r, assumes that the global mean is an adequate representation of the variable of interest. It may be true for continuously distributed variables in space. However, in tourism, the spatial distribution is scattered with spatial clusters and many areas with null values. Global statistics ignore the instability of the spatial association (Anselin, 1995). Since such instability is usually present in tourism supply and demand spatial distribution, then it may be relevant to be taken into account. A solution is provided by Getis and Ord (1992) considering local statistics known as G_i and G_i^*, or local indicators of spatial association (LISA) as suggested by Anselin (1995), where the purpose is to distinguish the spatial association by spatial clusters. Local Moran's I is defined as

$$I_i = \frac{(y_i - \bar{y})\sum_{j=1}^n w_{ij}(y_i - \bar{y})}{\dfrac{\sum_{i=1}^n (y_i - \bar{y})^2}{n}} \tag{3}$$

The results can be plotted distinguishing quadrants at the mean values of the variable and its lagged values, so that it results in four quadrants: high-high, high-low, low-high, and low-low. In a similar fashion, it can be extended to get bivariate local Moran's I statistics (BiLISA) as developed by Anselin (1995) or as recently extended to multivariate local Geary's c statistic (Anselin, 2017).

Spatial econometrics modeling

A positive Airbnb spatial autocorrelation suggests that its location depends on the location of other Airbnb properties nearby. Such positive value is an indicator of the presence of agglomeration effects. It can be tested with spatial econometrics analysis. The literature distinguishes between spatial lag models and spatial error models. The former model is appropriate when the focus of interest is the assessment of the existence and the strength of spatial interaction, whereas the spatial error model is appropriate when the concern is with correcting for the potentially biasing influence of the spatial autocorrelation (Anselin, 2001). For our purpose, the spatial lag models are more suitable. They can be expressed as

$$y = \rho W y + x\beta + \varepsilon \tag{4}$$

where ρ denotes the parameter associated with the spatial autocorrelation. Generalized spatial two stages least squares (GS2SLS) method is suggested for estimating such endogenous models (Keleijan and Prucha, 1998).

Our model specification can be expressed as

$$s_{ai} = f\left(p_{ai}(p_{hi}), \mathrm{pop}_i, v_i, v_{j\neq i}, s_{aj\neq i} | v_p\right) \tag{5}$$

where s_{ai} denotes the number of beds of Airbnb in polygon i; p_{ai} denotes Airbnb price in polygon i, which depends on hotel prices in polygon i (p_{hi}); pop_i denotes population size in polygon i, as a proxy for the number of properties; v_i denotes the number of tourist visits to polygon i; $v_{j\neq i}$ denotes the number of tourist visits to surrounding polygons j; and $s_{aj\neq i}$ denotes the number of Airbnb beds in surrounding polygons j. All these determinants make sense as long as the territory represented by the polygon is not protected. The protected areas are conceived for conservation and recreation and once the protection is in place, s_{ai} cannot be enlarged anymore. Thus, it is necessary to control for such areas. International Union for Conservation of Nature level I and II categories of protection are considered. For the model specification, a binary dummy is not sufficient because some protected areas are more relevant than others in terms of visits. Hence, a multiplicative dummy of protected areas times the number of visits is more appropriate for controlling purposes. It is denoted by v_p.

The model specification requires of an additional treatment of the endogeneity between s_{ai} and p_{ai}. It is sorted out employing a GS2SLS model with instrumental variables, as developed by Drukker et al. (2013a). The key instrument is p_{hi}, which is correlated with p_{ai}, and its value is not a direct determinant for Airbnb entry, but indirectly through p_{ai}.

The way that surrounding tourist visits and surrounding Airbnb enter the model requires of different spatial weight matrices. Airbnb supply in a polygon makes sense depending on the number of tourist visits that receives but also on the number of visits to nearby polygons. The relevance of such "nearby polygons" is assumed to decrease with distance. Thus, an inverse distance spatial weight matrix is built for that purpose. It should be noted that the whole analysis comprises seven islands and traveling among the islands is unlikely to happen, so that most traveling happens within each island. For this reason, the resulting weight matrix has set zero weights to pairs of polygons located in different islands, with the usual inverse related distance working on the same island.

Airbnb supply spatial weight matrix was built differently. Inverse related distance assumes a continuous relationship that does not suit for the supply case, where closer distance makes sense. An incremental Moran's I test was performed and it was found that the maximum z-score is reached within 7-km radius. Given the average polygons size, it is similar to setting up the spatial weight matrix according with the 8 nearest neighbors (8NN). The nearest neighbors approach is preferred to a distance-based (with threshold) since the nearest neighbors are based on the same distance principle but it also keeps the number of neighbors homogeneous across polygons.

Finally, elasticities provide a homogeneous indicator of the strength of the determinant and it can be compared across space and time. Its estimation requires of the marginal effect of each explicative variable. However, such calculation is not straightforward. First, it should be noted that the reduced form of equation (4) is: $y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon$. Thus, dy/dx depends on W structure and direct and indirect effects can be disentangled (Drukker et al., 2013b). Our interest

lies on calculating the elasticities, so that both effects are added up to understand their total effect on Airbnb supply.

Results

Spatial distribution

The spatial distribution of demand and supply in Canary Islands is shown in Figure 1. Tourist visits are proxied by georeferenced photos taken by tourists. They are represented by tiny red circles at the bottom layer of the map. On top of this layer, we can find Airbnb supply represented by green circles. Finally, on top of all layers, hotels and apartments are represented by larger yellow circles.

The spatial distribution depends on the attractiveness of each island. Sun and beach islands such as Tenerife, Gran Canaria, Lanzarote, and Fuerteventura show established hotels located mainly on the coast, whereas Airbnb properties are more scattered but also close to the hotels. Many photos are taken in National Parks or protected areas, so that they are isolated of supply. It can be identified in most islands. For instance, the center of Tenerife has got Cañadas del Teide National Park and in the North-East of Lanzarote is located Timanfaya National Park. In both of them, tourist visits are clearly isolated of supply. Nature-based tourism is located in green islands such as El Hierro, La Palma, La Gomera, and the north and center of Tenerife and Gran Canaria. They are well covered by Airbnb supply with some hotels nearby, but more agglomerated. City tourism is located in the North-West of Tenerife and Gran Canaria where a good concentration of hotels and Airbnb supply can be found.

Figure 2 shows an example of a sun and beach destination in the south of Gran Canaria. The darker areas represent a higher concentration of the supply of hotels and apartments. Each area represents a different microdestination. On the left-hand side of the map, we can find luxury tourism Meloneras with some five-star hotels along the coast and very few Airbnb properties. Next to Meloneras, we can see Maspalomas dunes, a protected area with hundreds of photos. Next to the dunes, we can find Playa del Inglés, a mass tourism microdestination with a mixture of three-star and four-star hotels and apartments. Airbnb property owners have got a higher presence here because they have detached their apartments of the general management of the complexes. In the north of the map, far from the sea, there are some residential areas where a higher proportion of Airbnb supply is provided.
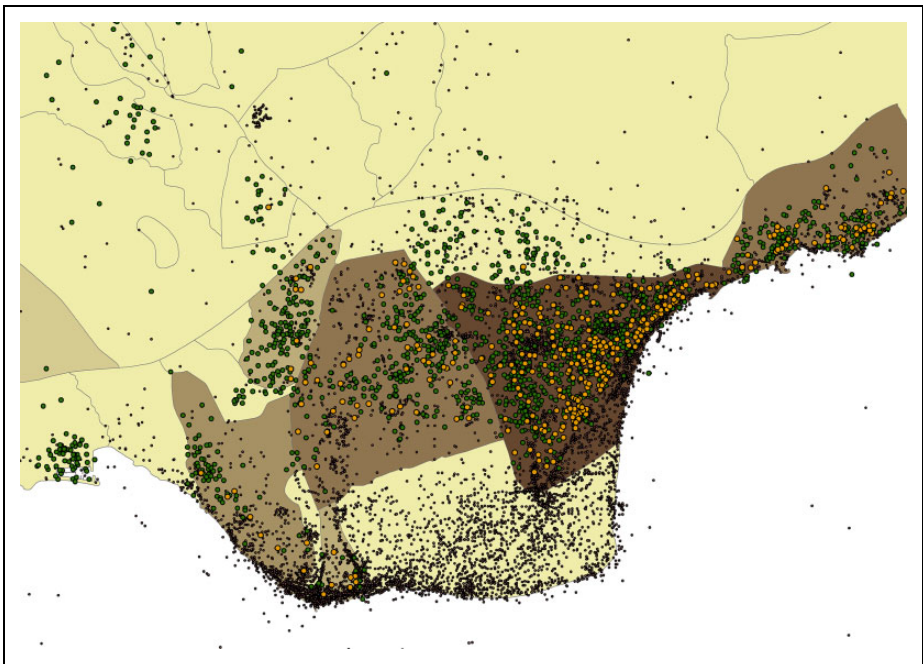
Global tests of bivariate spatial correlation

The article moves beyond the abovementioned intuition providing measures of the degree of spatial correlation between hotels and Airbnb supply and the degree of matching between tourist visits and supply. It employs Pearson's r modified correlation, as stated in equation (2). The problem of a Global test such as Pearson's r is that we need to assume that $\bar{y}$ is a good representation of the data. However, in this case, tourism supply and visits are concentrated around spatial clusters with many null cells in between. Null cells decrease the value of $\bar{y}$, and it may have an impact on the spatial correlation measurement. A solution is to disentangle spatial units, so that they can be more homogeneous. We consider three spatial sets, that is, sun and beach destinations, city destinations, and nature-based destinations. The results are shown in Table 1.

Table 1 presents marked differences among the different kinds of tourism. It should be noted that a high and positive bivariate spatial correlation means that both variables have a similar spatial pattern with their dots located close to each other. A very low value suggests an unrelated
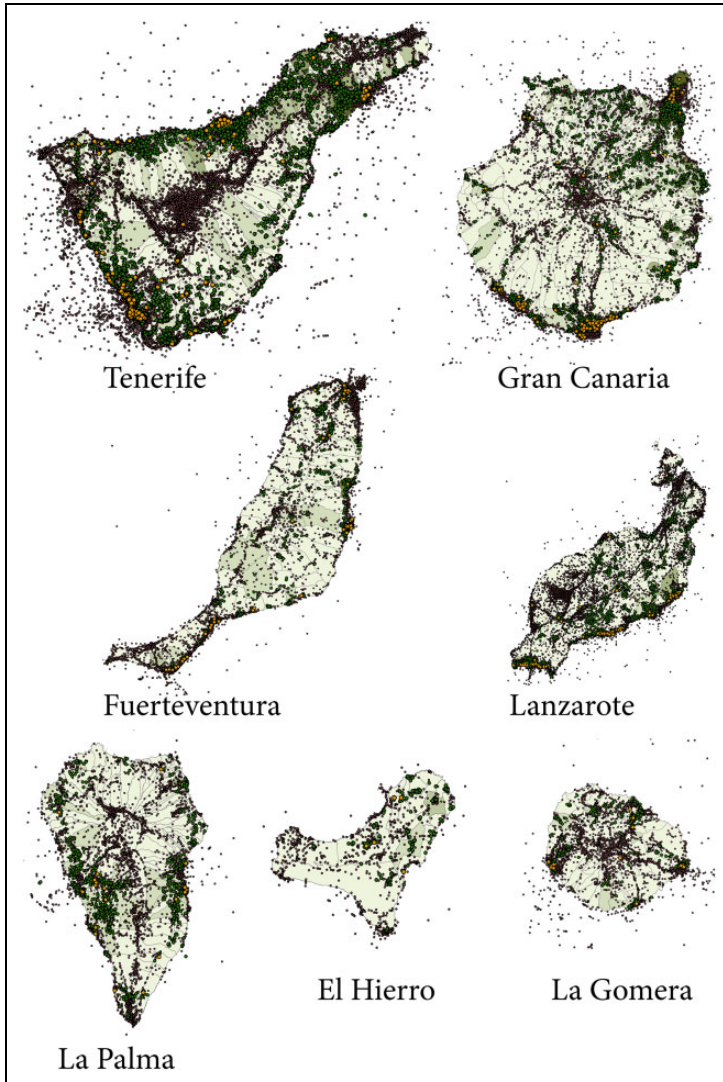
Figure 1. Canary Islands detailed tourism demand and supply spatial distribution.

relationship, whereas a negative value suggests the presence of two spatial clusters far from each other. The degree of bivariate spatial correlation between hotels and Airbnb supply is very high for city tourism destinations. Pearson's modified *r* shows a spatial correlation of about 0.910 for Gran Canaria and 0.809 for Tenerife. It shows that, on average, both kinds of supply are located very close to each other. However, the degree of spatial correlation in sun and beach destinations is much lower. It makes sense because private ownership in sun and beach destinations is limited with a majority of established hotels located in best coastal areas. That is the case of Fuerteventura, where the correlation is low (0.284). In some microdestinations of other islands, it is more common that private owners may use the property for their own pleasure, although some of them are forced

Figure 2. Maspalomas coast: a case of sun and beach destination.

Table 1. Pearson's modified *r* bivariate spatial correlation between established hotels and peer-to-peer accommodation by kind of tourism.

	Bivariate spatial correlation
City tourism	
Gran Canaria	0.9103
Tenerife	0.8089
Sun and beach tourism	
Gran Canaria	0.4771
Tenerife	0.6683
Lanzarote	0.5877
Fuerteventura	0.2842
Nature-based tourism	
Gran Canaria	0.4877
Tenerife	0.2106
La Gomera	0.7205
El Hierro	0.4433
La Palma	0.4873

to lease their property to the general management of the complex. It also varies with seasons. Such mixture is shown in Gran Canaria (0.477), Tenerife (0.668), and Lanzarote (0.588). Nevertheless, all these spatial correlation figures depart from the city tourism spatial correlation very clearly.

Finally, nature-based tourism spatial correlation figures also show a marked difference with respect to city tourism ones. The main difference relies between the largest island Tenerife (0.211) and one of the smallest islands La Gomera (0.720). The latter island is specialized mainly on nature, with astonishing Garajonay National Park in the center of the island. In this case, the degree of correlation between established hotels and Airbnb supply is very high. The other three islands show a similar spatial correlation: Gran Canaria (0.488), El Hierro (0.443), and La Palma (0.487). Again, all these figures are clearly far from the city tourism degree of spatial correlation.

The article is also concerned with how good is the matching of Airbnb supply as compared with hotels for different kinds of tourism destinations. In other words, can Airbnb supply outperform the location of hotels in terms of closeness to the tourism attractions? Hotels require a certain size to be profitable; otherwise, other kind of accommodation with less services and lower size is more convenient. That is the key for success of bed and breakfast network in the countryside of many countries. Airbnb plays a similar role or even of smaller scale. If hotels cannot be profitable at certain locations, Airbnb supply will not be competing but complementing the tourism supply.

Table 2 should be read horizontally. It shows that, overall, Airbnb supply outperforms hotel supply for city tourism and nature-based tourism. However, hotel supply outperforms Airbnb supply for the sun and beach tourism. It makes sense because Airbnb supply is very flexible in terms of location for city and nature-based tourism. Private houses are well spread over the territory to match most of the spots demanded by tourists, whereas hotels need to remain within the main areas. It should be reminded that the demand has been weighted by the number of photographs per cell. Popular nature-based tourism destinations such as La Palma (it hosts Caldera de Taburiente National Park) and La Gomera show a high matching for both Airbnb and hotels supply. However, larger islands such as Tenerife or Gran Canaria with much more widespread demand are not so easily covered by Airbnb supply and even less by hotels. Overall, nature-based tourism demand is the worst matched demand. One of the main reasons behind this result is the existence of National Parks or protected areas where the demand is concentrated and the supply cannot be located close to them. The sun and beach matching result is very interesting. It shows that incumbent hotels are much closer to the key coastal resources than Airbnb supply, which represents a clear competitive advantage.

Local tests of bivariate spatial correlation

The empirical strategy to obtain the local tests of bivariate spatial correlation is based on a series of steps. The first step requires incremental Moran's I tests to find out the distance that maximizes the z-score value of the test. The results show that all have got positive univariate spatial correlation with a varying optimal distance depending on the spatial process. Hotels reach its z-score peak at 3.7 km, whereas Airbnb supply reaches its peak at 4.7 km. It shows that Airbnb is a little bit more widespread than hotels. Finally, the demand has got a closer spatial radius of 2.8 km. The second step requires the spatial weight matrix building. As stated in the "Methodology" section, it is convenient to build one based on the k nearest neighbors. Since we are working on a rectangular grid with cells of 1-km long, it is straightforward to define the number of necessary nearest neighbors for each distance. In the following, the rationale for choosing the number of nearest neighbors is stated depending on each distance

Table 2. Pearson's modified *r* bivariate spatial correlation of matching between tourism supply and tourist visits by kind of tourism.

	Airbnb beds	Hotel beds
City tourism		
Gran Canaria	0.5230	0.4624
Tenerife	0.8356	0.6826
Sun and beach tourism		
Gran Canaria	0.5911	0.6765
Tenerife	0.2577	0.5215
Lanzarote	0.4113	0.6329
Fuerteventura	0.5808	0.6277
Nature-based tourism		
Gran Canaria	0.1362	0.0555
Tenerife	0.1474	0.1285
La Gomera	0.4367	0.4080
El Hierro	0.2772	0.2224
La Palma	0.4432	0.5137

$$1 \text{ km} : (1 + 2 \times 1) \times (1 + 2 \times 1) - 1 = 8$$
$$2 \text{ km} : (1 + 2 \times 2) \times (1 + 2 \times 2) - 1 = 24$$
$$3 \text{ km} : (1 + 2 \times 3) \times (1 + 2 \times 3) - 1 = 48$$
$$4 \text{ km} : (1 + 2 \times 4) \times (1 + 2 \times 4) - 1 = 80$$

Since Airbnb and hotels peaks are closer to 4 km, then the number of nearest neighbors chosen is 80. Thus, binary spatial weight matrices are built so that they take value 1 if the cell is among the closest 80 neighbors, and 0 otherwise. The matrix will be known as 80 nearest neighbors (80NN) spatial weight matrix. If the demand is closer to the 3-km radius, then the number of neighbors should be 48 (48NN).

Once the spatial weight matrices are built, the final step pursues the calculation and plotting of the local bivariate LISA. For the record, univariate and bivariate Moran's *I* statistics are shown in Table 3 for 48NN and 80NN spatial weight matrices.

The global univariate and bivariate Moran's *I* statistics are positive and significant for all cases. Table 3 provides their values. However, it should be reminded that the *I* statistic has not a direct interpretation and its expectation decreases with *n*. For that reason, for the 80NN spatial weight matrix, the *I* statistic values are lower than for the 48NN matrix. Nevertheless, since *n* is the same for each case and provided heterogeneity over space is not very asymmetric among the three kinds of tourism destinations, so that each $\bar{y}$ is similarly reliable, then they can be compared. Table 3 shows that Airbnb supply has got higher spatial autocorrelation than hotels. It also shows that the matching between Airbnb and spatially lagged tourist visits is better than the one between hotels and spatially lagged tourist visits. These results are in line with Tables 1 and 2.

As commented earlier, global tests rely on stable spatial patterns, which it is not the case for tourism. For that reason, Tables 1 and 2 distinguish different kinds of tourism, so that $\bar{y}$ can be more reliable. Additionally, local tests may provide richer information to distinguish correlation among different local areas. Figure 3 shows bivariate LISA plotting for the hotels and Airbnb supply pair. This result shows the local degree of spatial correlation and it is very clarifying.

Table 3. Tourist visitors and supply univariate and bivariate Moran's *I* statistics.

|	NN48	NN80
Univariate Moran's *I*		
Airbnb supply	0.1110	0.0726
Hotels supply	0.0963	0.0526
Tourist visitors	0.0681	0.0384
Bivariate Moran's *I*		
Airbnb-hotel	0.0865	0.0539
Airbnb-visitors	0.0685	0.0408
Hotel-visitors	0.0577	0.0294
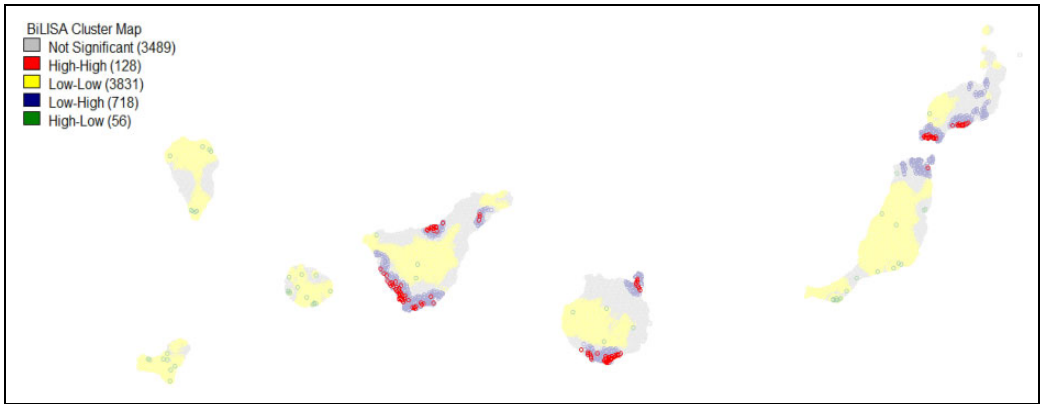
Figure 3. Bivariate LISA clustering of established hotels and Airbnb spatial correlation (80NN spatial weight matrix). LISA: local indicators of spatial association; 80NN: 80 nearest neighbors.

High-high quadrant comprises 128 cells. They represent cells where Airbnb accommodation overlaps hotels in a statistically significant way. They can be found in sun and beach coastal areas of Tenerife, sun and beach south coast of Gran Canaria, sun and beach south coast of Lanzarote, city tourism in Tenerife, and city tourism in Gran Canaria. Nature-based tourism islands do not show a marked pattern of bivariate spatial correlation. Fuerteventura—a sun and beach tourism destination—does not show bivariate spatial correlation neither (as also anticipated in Table 1). The low-high quadrant has got 718 cells. They represent cells where there is low presence of hotels and high presence of Airbnb accommodation. They are located at the outskirts of the high-high cells, and it clearly shows the higher widespread of Airbnb supply with respect to hotels. The high-low quadrant has got only 54 cells. They correspond to cells where hotels' presence is very high and Airbnb has got entry difficulties. Most cases are located in the south of Fuerteventura, where the incumbent hotels dominate the space.

The matching between Airbnb supply and tourist visits is shown in Figure 4. It shows that 212 cells belong to the high-high quadrant and are located in coastal sun and beach areas of Tenerife, Gran Canaria, and Lanzarote, as well as in city tourism in Tenerife and Gran Canaria. The low-high quadrant is related with protected areas, where tourists are attracted to visit but supply cannot exist.
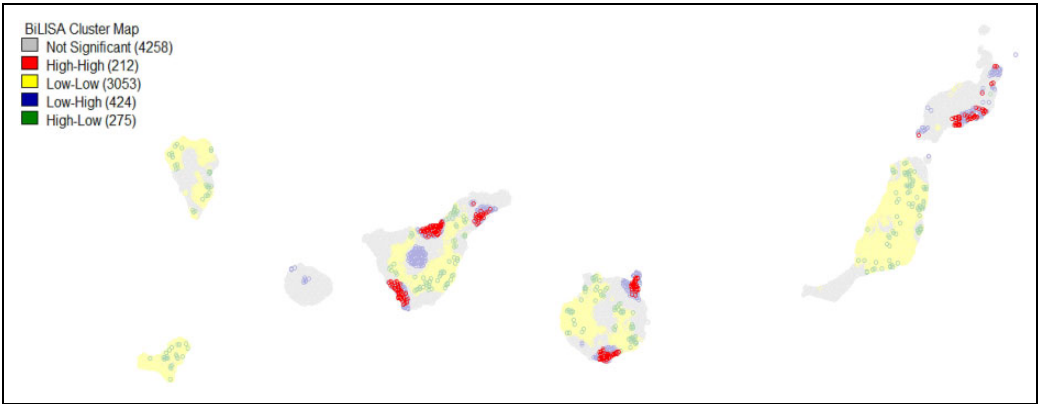
Figure 4. Bivariate LISA clustering between Airbnb supply and tourist visits spatial correlation (80NN spatial weight matrix). LISA: local indicators of spatial association; 80NN: 80 nearest neighbors.
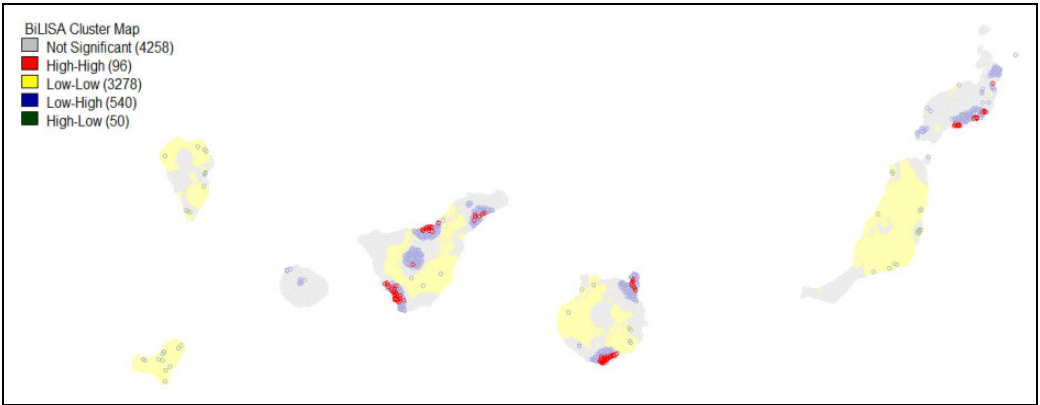
Figure 5. Bivariate LISA clustering between established hotels and tourist visits spatial correlation (80NN spatial weight matrix). LISA: local indicators of spatial association; 80NN: 80 nearest neighbors.

It comprises 424 cells and they are mostly located in National Parks or protected areas, especially in the center of Tenerife. The high-low quadrant has got 275 cells which are spread over the islands. They show the location of Airbnb supply which is far from located visits.

Figure 5 shows the relationship between established hotels and current tourist visits. It shows a more restricted pattern than Figure 4. The number of cells with a good high-high match is much lower (96 cells), with a much higher number of cells (540) belonging to the low-high quadrant. It shows more difficulties for established hotels to cover the spatial demand than what Airbnb supply does. However, hotels manage to remain at the middle of the cloud of points with higher demand, as expected. It misses out most of the demand at the outskirts of the heart of the destination.

Spatial econometrics analysis

The estimates of the determinants of Airbnb entry location are shown in Table 4. They show that the spatial autoregressive coefficient is significant, so that the spatial approach makes sense. It is

Table 4. GS2SLS spatial autoregressive model with an endogenous variable.

Variables	Estimates	Elasticities
Airbnb price	3.401*** (0.401)	4.456***
Population	0.010*** (0.000)	0.214***
Tourist visits	0.0723*** (0.007)	0.388***
Spatially lagged tourist visits	2.084*** (0.731)	0.575***
Tourist visits to protected areas	−0.228*** (0.033)	
Constant	−176.004*** (23.347)	
Spatial autoregressive coefficient	0.334** (0.168)	
Pseudo R^2	0.286	
No. of places	2301	

Note: GS2SLS: generalized spatial two stages least squares; $*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

positive, so that it proves the presence of agglomeration effects as shown in Figure 1. All other determinants are highly significant with the expected signs. Airbnb price is positive, so that higher Airbnb prices moves supply along the supply curve. Population is positive, so that higher population shifts supply curves to the right. Tourist visits are positive, so that higher tourist visits shift Airbnb demand curves to the right resulting on a new equilibrium with higher prices and higher Airbnb supply. Tourist visits in the surroundings contribute to a similar shift of Airbnb demand and its effect on higher Airbnb supply. The multiplicative dummy of tourist visits to protected areas plays its controlling role with the expected sign as well. In terms of elasticities, Airbnb price is very elastic (4.456) showing that it is the main driver of Airbnb supply. Tourist visits and spatially lagged tourist visits are positive but inelastic. It should be noted that the role of the spatially lagged tourist visits variable depends on the polygons size. Thus, the smaller (larger) the polygons are, the higher (lower) the relevance of the spatial lagged tourist visits variable is. Population is also positive but low.

It is interesting to disentangle the analysis between nature-based and sun and beach based tourism destinations. The procedure consists of adding multiplicative dummies to the variables so that it can be tested how different they are. The results are shown in Table 5. It shows that the pseudo R^2 has improved, but more interestingly, it shows that the tourist visits play a different role. In nature-based tourism destinations, the number of tourist visits do not determine the Airbnb entry, but in sun and beach destinations. It makes sense with the previous results of scattered tourist visits in nature-based destinations as compared with agglomerated tourist visits in sun and beach destinations. It is a key result for spatial equity policymaking. Sun and beach Airbnb supply must be located near coastal resources, whereas nature-based Airbnb supply does not require to be close to key resources for their entry. Moreover, in nature-based destinations, the number of visits in the surroundings makes a difference for Airbnb location, whereas for sun and beach destinations, it does not matter, but its own location. It proves that, overall, sun and beach tourists are more interested in the destination itself, whereas nature-based tourists are keen on traveling around the island.

Conclusions

The article has proved that Airbnb spatial correlation with incumbent hotels depends on the kind of tourism. Thus, any regulation of P2P accommodation market should not be homogeneous but

Table 5. GS2SLS spatial autoregressive model with an endogenous variable and disentangling nature-based and sun and beach tourism destinations.

Variables	Estimates	Elasticities (total effect)
Nature-based destinations		
Airbnb price	2.625*** (0.450)	3.871***
Population	0.011*** (0.001)	0.248***
Tourist visits	−0.004 (0.006)	−0.026
Spatially lagged tourist visits	1.044* (0.630)	0.324
Sun and beach destinations (multiplicative dummies)		
Airbnb price	−0.514 (0.384)	3.112
Population	−0.000 (0.006)	0.240
Tourist visits	0.103*** (0.009)	0.596***
Spatially lagged tourist visits	4.443 (3.186)	1.703
Constant	−123.632*** (24.978)	
Spatial autoregressive coefficient	0.558*** (0.119)	
Pseudo R^2	0.389	
No. of places	2301	

Note: GS2SLS: generalized spatial two stages least squares; *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

adapted to the kind of tourism supply. Global tests of bivariate spatial correlation have proved that the degree of spatial correlation between Airbnb supply and established hotels varies with the kind of tourism destination. City tourism shows the highest degree of spatial correlation, followed by far by sun and beach and nature-based tourism. Such high degree of spatial correlation is due to the flexibility of Airbnb supply to locate themselves close to the city attractions and/or established hotels. It is not the case of sun and beach destinations where the incumbent hotels have positioned earlier under a proper tourism development plan. Private owners are more limited in this case and they usually own properties in the outskirts of the main tourist areas and mainly linked with residential areas. In the case of nature-based tourism, the degree of spatial correlation is also much lower than in the city case. Two problems are faced by the nature-based tourism spatial competition. On the one hand, the territory is much larger than cities or coasts, so that the spatial overlapping is less likely to happen. On the other hand, economies of scale are constraining hotels to a limited number of locations, whereas the spatial distribution of Airbnb supply can be more scattered.

In terms of matching between tourist visitors and supply, overall, Airbnb supply is matching the visitors better than established hotels in city tourism and nature-based tourism. For the reason stated above, sun and beach visits are matched better by established hotels than Airbnb supply. Local tests of bivariate spatial correlation provide a further look at the relationship. It has shown that the most relevant cases of bivariate spatial correlation are happening in the cities and some relevant coastal areas, but not in all of them. Nature-based tourism areas have not shown any sign of marked spatial correlation. For this purpose, the bivariate LISA methodology has proved to be capable of distinguishing the areas more affected by spatial correlation. It is very relevant for policymaking.

Modified Pearson's *r* bivariate global spatial correlation and bivariate local spatial correlation LISA have proved to be useful and sensible tools for this task. Nevertheless, it is well known that correlation does not imply causality. A spatial econometric model can provide such causal tests as

long as it is based on a sensible economic model. The spatial econometric model developed in the article has proved the presence of agglomeration effects of Airbnb supply. It has shown that Airbnb price is the most relevant determinant for Airbnb entry, whereas population and tourist visits are also important, but at a much lower degree. The determinants of Airbnb entry also vary by the kind of destination. Airbnb entry in nature-based destinations depends on Airbnb prices and population, but not on tourist visits, on average. It is a key finding for policymaking, especially for spatial equity concerns. On the contrary, all sun and beach Airbnb accommodation must be located where tourist visits are taking place around coastal resources.

Hence, the main lessons learnt for policymaking are (i) Airbnb regulation needs to distinguish the kind of tourism; (ii) Airbnb located in sun and beach destinations may contribute to a more balanced income equity, but not toward spatial equity, whereas nature-based tourism destinations also contribute to a more balanced spatial equity; and (iii) population size and the number of tourist visits matters as determinants of Airbnb location. However, the main determinant is price, which has got a much larger elasticity; (iv) Airbnb supply matches tourist visits spatial distribution better than established hotels in city and nature-based destinations, but not in sun and beach destinations.

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