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ORIGINAL PAPER

The impact of Instagram on Airbnb's listing prices in the city of Barcelona

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Abstract

The purpose of our study is to analyse whether consumers' preferences—evaluated through social media—to different tourist sites have a significant impact on Airbnb's prices. With this purpose, we develop an empirical application in the city of Barcelona where we evaluate the impact of Instagram—identifying the main points of interest in this city—on listings' prices. We estimate a micro-territorial hedonic model on Airbnb's prices against different subsamples established according to listings' characteristics. Our results show a negative and significant effect for the representative variable of the geographic distance of Airbnb's listings to the tourist sites on Instagram. In particular, each additional 10% increase in the distance from Instagram tourist spots to Airbnb's listings resulted in a 2.7% decrease in Airbnb's listing price in Barcelona. This study provides additional evidence about the relevant role of social networks when accommodation offerings are examined, even when we consider accommodations included in the sharing economy.

JEL Classification G33 · Q14 · R10

1 Introduction

The development of the internet has revolutionised the concept of the sharing economy in the hospitality sector with Airbnb as a benchmark. This new business model is characterised by the peer-to-peer (P2P) economy, whereby providers and clients interact directly, without an intermediary. In contrast to traditional hotels, the accommodation sector in the sharing economy provides various advantages to users, such as cost savings, familiarity (Möhlmann 2015), the desire for closer

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contact with the local community (Tussyadiah and Pesonen 2016) and social interactions. This type of business model also provides extra income for hosts (Karlsson and Dolnicar 2016). These advantages have caused Airbnb's offering to undergo exponential growth over the 10 years this company has been in operation. Nowadays, Airbnb lists more than 6,000,000 accommodations around the world (Airbnb 2019). This phenomenon has attracted the attention of researchers, who are developing studies on the implications of Airbnb on the traditional economy and the strategic response in the hotel sector (Zervas et al. 2017; Li and Srinivasan 2019).

One of the most relevant research topics in this regard is the determination of Airbnb's listing prices. There have been reports that *Airbnb hosts lose about 50% of additional revenue due to inefficiency when pricing* (LearnAirbnb.com 2015). The main idea behind this result is that hosts are confused when setting their prices (Hill 2015). In order to overcome this situation, Airbnb has created tools for hosts to improve their pricing process (Airbnb 2019). Nevertheless, these approaches provide price approximations but do not identify the most relevant factors that condition Airbnb's accommodation offerings. To shed additional light on this topic, researchers have developed studies based on listing characteristics from Airbnb's webpage registers (see Gibbs et al. 2018 or Lorde et al. 2019, among others). We have found a few of them that consider not only internal accommodation conditions, such as price, number of beds or amenities, but also external characteristics (Eugenio-Martin et al. 2019;. Ki and Lee 2019; Lopez et al. 2019; Chica-Olmo et al. 2020). These studies examine the effects of the geographic proximity of Airbnb's listings to tourist sites on prices, finding significant results for these distances. Nevertheless, they define tourist sites without considering consumers' preferences. Given Airbnb's virtual characteristics and the relevance of social media as a marketing tool promoting tourist cities (Fantani and Suyadnya 2015), we hypothesize that consumers' preferences—evaluated through social media—to different tourist sites will have significant impact on Airbnb's listing prices in each examined territory. Thus, our hypothesis is that information from social media should be included as an additional factor in the determination of Airbnb's prices. The purpose of our study is to test this hypothesis showing an empirical application where we measure and quantify the impact of social media on Airbnb's prices. In particular, we chose Instagram as the representative social media platform. This social network provides relevant information about the main points of interest in the city, making it a marketing tool to attract visitors (Fantani and Suyadnya 2015). In addition, the information provided by Instagram allows us to include a specific weight (number of references) for each tourist site, quantifying consumers' preferences. In this paper, we show empirical evidence about the role consumer preference plays in pricing by studying the impact of the physical proximity of Airbnb's listings to the referenced tourist sites on Instagram. Our study explores the relationship between Airbnb's price offerings and information from social media about the city of Barcelona (Spain), estimating a micro-territorial hedonic model. The number of beds offered on Airbnb in Barcelona was 14,000 in 2019, which is equivalent to almost half the number of hotel rooms in that city (Sans and Quaglieri 2016). Furthermore, Barcelona ranks fourth in the Top 10 European Cities regarding the total number of beds and nights occupied by international tourists (Baudot 2015). Thus, given its relevance for the tourist sector, Barcelona is an excellent location to develop this empirical application.

We collected data from Airbnb to get a sample of 14,273 registers in Barcelona in 2019. In addition, we applied a web scraping process to obtain the tourist spots referenced in Instagram and the number of their references. Apart from these, we used other auxiliary datasets to build control variables (see Table 1). With this information, we quantify the extent to which the geographic proximity of Airbnb's listings to the tourist spots referenced in Instagram has an impact on Airbnb's prices. To identify the causal impact of the information from social media on Airbnb's prices, we apply spatial econometric techniques. In addition, we test the existence of nonlinearities on this model applying the nonparametric multivariate additive regression splines (MARS) technique. To perform our estimations, we regress against different subsamples established according to Airbnb's characteristics: the kind of listing (private room or full apartment) and the host's characteristics (professional or nonprofessional). In all our specifications, we include a set of control variables which take into account the particular listing and geographic characteristics of the surroundings of each evaluated accommodation. Our results show a negative and significant effect for the representative variable of the geographic distance of Airbnb's listings to the tourist sites on Instagram. Thus, a shorter physical distance from Airbnb's listings to Instagram referenced tourist sites increases prices. In particular for Barcelona, each additional 10% increase in the distance from Instagram tourist spots to Airbnb's listings resulted in a 2.7% decrease in Airbnb's listing price. In addition, this significant result is subjected to nonlinear behaviour, finding that each Instagram tourist point has, on average, a 120 m radius of influence. Thus, Airbnb's listings included in these areas of influence will have their prices affected as a consequence of their proximity to these tourist sites. In order to provide additional robustness to this causal relationship, we computed the Granger causality test with significant results.

Our results showed significant impact for the information on Instagram when it is included in a hedonic model to estimate Airbnb's listing prices. This study provides additional evidence about the relevant role of social networks when accommodation offerings are examined, even when we consider accommodations included in the sharing economy. This knowledge may have strong implications for managers in the hospitality sector even more nowadays when the particular social and economic characteristics are changing the market of tourist apartments in Spain—and especially in the city of Barcelona. In this sense, a high percentage of Airbnb apartments are moving to the long-term rental market due to the reduction of the number of tourists. Therefore, the fact of identifying additional factors in the Airbnb's pricing process is crucial for the players involved in the sharing hospitality market.

2 Do local factors of location impact Airbnb prices? The relevance of Instagram Hotspots

Despite the extensive literature examining the effects of location on hotel prices, the number of studies focussed on Airbnb's prices is scarce. We find some evidence in Van der Borg et al. (2017), who examine Airbnb's prices showing that listings near

Table 1 Variables and descriptive statistics

	Variable	Description	All	Private	Entire	Professional	Nonprofessional	Mean difference (entire—private)	Mean difference (professional—non-professional)
			Mean (std)					t-statistic (p value)	
Dependent variable	LPRICE	Price of offerings on Airbnb in logarithms	4,2484	3773	4,7803	4,7551	4,0695	99,1340	49,0620
			(0781)	(0539)	(0658)	(0738)	(0715)	(0000)	(0000)
Geographic variables	DHOTSPOT	Distance to the closest photograph spot	0,0142	0,6206	0,0137	0,4871	0,5894	− 13,5080	− 11,9810
			(0005)	(0648)	(0004)	(0377)	(0605)	(0000)	(0000)
	DMETRO	Distance to the closest underground entrance	0,4586	0,4410	0,4410	0,4366	0,4819	6,4899	− 8822
			(0031)	(0300)	(0300)	(0298)	(0314)	(0,000)	(0,000)
Listing characteristics	Bedrooms	No of bedrooms	1,6342	1091	2242	2,2065	1,4321	81,096	39,1240
			(0996)	(0470)	(1074)	(1,0880)	(0876)	(0000)	(0000)
	Guest included	Number of guests included in the offering	1,9855	1,1882	2,8775	3,0062	1,6251	67,5220	37,9480
			(1657)	(0684)	(1,945)	(2,0790)	(1300)	(0000)	(0000)
	Extra people	Price of one extra person	9,7426	8,6995	10,9097	8,6882	10,1148	8,8599	− 5,7879
			(14,899)	(14,851)	(14,859)	(11,6980)	(15,859)	(0,000)	(0,000)
	Minimum nights	Minimum nights of stay	5,9088	3,7519	8,3221	7,6589	5,2908	19,8720	8,7272
			(13,521)	(9,667)	(16,487)	(14,6040)	(13,063)	(0,000)	(0,000)
Reputational attributes	Total punctuation	No of reviews* rating of Airbnb customers	424,7231	383,0456	471,3568	281,7727	475,1946	8,3850	− 20,9690
			(623,213)	(571,733)	(673,174)	(391,2480)	(679,512)	(0,000)	(0,000)
	Superhost	1 if host has the level of "superhost", 0 otherwise	0,2314	0,2167	0,2446	0,1063	0,2756	− 3,9537	− 25,3600
			(0421)	(0412)	(0429)	(0,3083)	(0275)	(0000)	(0000)

Table 1 (continued)

	Variable	Description	All	Private	Entire	Professional	Nonprofessional	Mean difference (entire—private)	Mean difference (professional—non-professional)
Amenities	Air-conditioning	1 if Airbnb offering has air conditioning, 0 otherwise	0,5843	0,8809	0,3192	0,8754	0,4816	84,1800	54,0410
			(0492)	(0323)	(0466)	(0,3303)	(0499)	(0000)	(0000)
	Elevator	1 if Airbnb offering has elevator, 0 otherwise	0,6192	0,6581	0,5844	0,6848	0,1063	9,0819	9,8561
			(0485)	(0474)	(0492)	(0,4647)	(0446)	(0000)	(0000)
	Pool	1 if Airbnb offering has pool, 0 otherwise	0,0369	0,0369	0,0107	0,0414	0,0166	10,0900	7,0910
			(0188)	(0188)	(0103)	(0,1993)	(0127)	(0000)	(0000)
	Gym	1 if Airbnb offering has gym, 0 otherwise	0,0096	0,0065	0,0124	0,0062	0,0108	− 3,6149	− 2,8389
			(0097)	(0080)	(0110)	(0,0784)	(0103)	(0000)	(0000)
	24 h check in	1 if Airbnb offering has 24 h check in, 0 otherwise	0,1121	0,1639	0,0658	0,1720	0,0910	18,3360	11,9240
			(0315)	(0287)	(0248)	(0,3774)	(0287)	(0000)	(0000)

places of interest for tourists as well as those near lakes and mountains have higher occupancy rates. Perez-Sanchez et al. (2018) conclude that the location of properties in areas with a high concentration of food purchasing options and those closer to the beach have a positive impact on Airbnb's accommodation prices. Deboosere et al. (2019) determine that listings close to public transport have higher prices but only when this transport facilitates access to the city centre. In addition to these studies, we find other papers adding the spatial autocorrelation among Airbnb's prices as a possible determining element. Apart from physical proximity to tourist sites, the prices of other Airbnb accommodations in the surroundings also have significant impact on listing prices. In this regard, Zhang et al. (2018) consider the existence of spatial clusters of Airbnb offerings with similar prices in Tennessee. Gutiérrez et al. (2017) examine the spatial distribution of Airbnb's listings in Barcelona in comparison with hotels and sightseeing spots. They obtain a significant spatial autocorrelation pattern between Airbnb and hotels, with relevant centre-periphery behaviour. Lopez et al. (2019) propose a spatial hedonic model of Airbnb's prices, finding significant spatial autocorrelations for this variable. Finally, the published study by Chica-Olmo et al. (2020) include geographic proximities to external facilities and spatial autocorrelation effects in a spatial hedonic model of Airbnb tourist apartments in Malaga. Their results show that geographic proximity to the city centre, the beach or places of interest play a significant role in Airbnb's pricing.

Regarding previous studies, we conclude that geographic proximity to different points of interest are relevant in the Airbnb's pricing process. Nevertheless, previous studies include a wide range of interest points (beaches, city centres, and etcetera) which are subjectively selected and equally weighed, independent of consumers' preferences. In this context, social networks could play an important role in identifying the most relevant points of interest for tourists and the determination of Airbnb's prices in accordance with tourists' viewpoints. The value of social networks as a channel to transmit information about tourist destinations has greatly increased over the last five years (Fatanti and Suyadnya 2015). Travellers are conditioned by other travellers who share their experiences through pictures on the internet. This kind of tool is attractive and dynamic since users are able to update vast amounts of information about different tourist destinations. Therefore, in the tourism industry, not only should online platforms which connect clients and providers to share markets be considered but also social networks, which are an important engine to promote tourist destinations (Hanan and Putit 2013). Királová and Pavlíčeka (2015) show the potential opportunities of social networks to attract possible visitors to destinations with a personal, creative, and interactive approach. Social networks can help different destinations to present interesting contents, motivating visits to tourist attractions. Thus, social media is a powerful element addressing changes in the patterns of visitors which could even impact final market conditions.

Among the different social media platforms, Instagram currently has one billion active monthly users, and more than five hundred million of them are sharing online pictures daily[1]. Thus, this social media platform could be seen as a powerful tool

[1] https://instagram-press.com/our-story/

to advertise possible travel destinations (Stepchenkova and Zhan 2013). Through online pictures, users transmit information to other users, providing a viewpoint about a specific place. It could be expected that, in the accommodation selection process, users are influenced by Instagram information in terms of locations and preferences when choosing their accommodations. In this regard, we find studies identifying Instagram's effects on customers' behaviour in the tourist sector. Van der Zee and Bertocchi (2018) suggest that access to social network users' content has significant impact on the image of tourist destinations and on tourists' future behaviour. Shuqair and Cragg (2017) and Seeler et al. (2019) show that the publication of tourist spots on Instagram has impact on the behavioural intentions of visitors before travelling. Instagram motivates people to want to visit the places they have seen on the website and helps to create a favourable image for potential tourists. Chen and Chang (2018) find that information from Instagram publications about tourist spots has a positive and significant impact on consumer satisfaction, affecting their decisions on Airbnb. Thus, it is expected that the promotion of points of interest through Instagram will result in increased demand for those Airbnb listings close to those spots, which could even increase accommodation prices on the platform.

Hypothesis 1(H1) *The geographic proximity of Airbnb's listings to popular tourist spots on Instagram produces an increase in Airbnb prices.*

In addition, this effect could vary depending on the characteristics of the listings. Previous literature on Airbnb finds differences between types of accommodations when full apartments and private rooms are separately examined. In general, we find that prices are higher for full apartments than for private rooms (Gibbs et al. 2018; Deboosere et al. 2019; Maté-Sánchez-Val 2020). The number of nights and visitors is greater for full apartments. There are also differences when Airbnb's customers' characteristics are considered. Full apartments are sought by older clients and family travellers, whereas private rooms are requested by younger people travelling to visit the city (Wang and Nicolau 2017). Given these characteristics, we expect that geographic proximity to Instagram's hotspots has a greater effect on Airbnb's prices for private rooms because younger customers would be more influenced by Instagram. In most cases, the reason for their trip is to visit the city. Thus, they give more importance to the information from social networks that could influence their paying a higher price.

Hypothesis 1a (H1$_a$) *Instagram's impact on Airbnb's prices is greater in private rooms than in full apartments.*

Moreover, literature distinguishes between professional and nonprofessional listings. This classification is based on the number of offered listings by the accommodation's host. Professional listings are those accommodations offered by hosts with a large number of listings on Airbnb, while nonprofessional listings are those offered by hosts with a reduced number of listings on the platform (one or two listings on Airbnb). Previous research concludes that professional hosts earn a higher daily income on the properties they manage (Gibbs et al. 2018; Deboosere et al. 2019; Maté-Sánchez-Val 2020). In addition, these kinds of listings are more efficiently managed since controlling an extended offering requires better administration. Thus, we assume that these listings will be less influenced by references in social networks.

Hypothesis 1b (H1$_b$) *Instagram's impact on Airbnb's prices is greater in nonprofessional than in professional listings*

3 Methodology

3.1 The model: The Hedonic Price

We proposed a Hedonic Price model, disentangling the impact of various attributes on implicit prices, where positive characteristics are expected to boost the overall price, having a positive effect on individual utility levels (Papatheodorou 2012). In addition, we selected the log–log model since it is one of the best options for this type of research focussed on accommodation markets (Andersson et al. 2010). The use of log–log models reduces the difficulty of interpreting the coefficients when drawing conclusions from the model. This model was used to estimate the implicit marginal prices of different hosts and the environmental characteristics. Equation (1) shows the following specification

$$P = \alpha + X_{\mathrm{NG}}\beta_{\mathrm{NG}} + X_G\beta_G + \varepsilon \tag{1}$$

where $P_{N\times 1}$ represents a vector of logarithms of prices for the different listings i, with $i = 1, \dots, N$. X_{NG} represents the $(N \times K)$ matrix of non-geographical explicative variables in logarithm terms, $\beta_{\mathrm{NG}} = \left(\beta_{\mathrm{NG}_1}, \beta_{\mathrm{NG}_2}, \dots, \beta_{\mathrm{NG}_K}\right)$ the $(K \times 1)$ vector of non-geographical coefficients. X_G represents the $(N \times K')$ matrix of geographical explicative variables in the model, with $\beta_G = \left(\beta_{G_1}, \beta_{G_2}, \dots, \beta_{G_{K'}}\right)$ the $(K' \times 1)$ vector of geographical coefficients. α is the constant term and ε is the $(N \times 1)$ vector of random errors which are independently distributed with constant variance, $\varepsilon \sim iid\left(0, \sigma^2 I_N\right)$. Following this specification, the partial derivative of the hedonic function of each characteristic of the offering provides the implicit marginal price, which represents the maximum acceptable marginal price for buyers and the minimum acceptable marginal price for sellers for each attribute.

3.2 Multivariate additive regression splines (MARS) algorithm methodology

MARS is a nonparametric methodology which allows the automatic selection of the relevant variables in a regression analysis and captures potential nonlinearities when there is not additional understanding about the functional form between them (Friedman 1991). Unlike the more popular linear regression techniques, MARS does not assume that the coefficients are stable over the entire range of each variable but, instead, supposes the existence of particular slopes for different intervals through piecewise linear functions to model nonlinear relationships (López and Kholodilin 2020). The MARS methodology is applied in two steps. Firstly, the algorithm finds possible knots to improve the adjustment between variables. From this phase an overfit model is arrived at. Secondly, the procedure eliminates the least effective elements. The MARS code from R, developed by Milborrow (2019)—*earth*—was applied to identify nonlinear relationships in geographic variables. We found extensive previous evidence on the nonlinear character of the spatial dimension when the behaviour of firms is examined (see De Silva and McComb 2012 for further review).

Let us consider that the K' geographic variables of the model (1) present nonlinearities with respect to the dependent variable P then the specification (1) should be substituted by the following specification (2):

$$P = \alpha + X_{\mathrm{NG}}\beta_{\mathrm{NG}} + f(X_G)\beta_G^{'} + \varepsilon \tag{2}$$

where now the geographical variables are estimated through the MARS procedure. This methodology applies the known basic functions (BFs) with the form $\max\left\{0, X_G - c\right\}$ and $\max\left\{0, c - X_G\right\}$ where X_G represents the geographical variables in the model and c is a constant, known as knot. Applying the BFs the modelling procedure is like the classical stepwise regression. The function f represents the BFs for each geographical variable X_G and the coefficients $\beta_G^{'}$ are obtained applying MARS algorithm.

3.3 Spatial regression models

Spatial autocorrelation occurs when there is a significant relationship between what happens in one geographic point and what happens in another point (Anselin 1988). Given the significance of spatial autocorrelation in pricing literature (Basu and Thibodeau 1998), we assumed the existence of spatial structures in the model. In order to take this effect into account, spatial specifications were considered (Le Sage and Pace 2010). To identify the most adequate spatial structure, we followed a specific-to-general approach (Stge) based on the Lagrange multipliers (Florax and Folmer, 1992)[2]. In addition, we applied the MARS algorithm in the presence of spatial terms in the modelling process with the objective of selecting the correct model in the presence of nonlinearities in the geographical variables of the model. In this sense, López and Kholodilin (2020, pp.26) highlight "the ability of the MARS algorithm to select the correct specification" in the spatial modelling process. In particular, a specification with spatial autocorrelation in the dependent variable is known as the spatial lag model (SLM), and controlling for nonlinearities through MARS methodology presents the following structure (3):

$$P = \alpha + \rho WP + X_{\mathrm{NG}}\beta_{\mathrm{NG}} + f(X_G)\beta_G^{'} + \varepsilon \tag{3}$$

[2] See Mur and Angulo (2009) for a further discussion about selection strategies in spatial models.

where now we include the term ρWP to consider possible spatial autocorrelation in the model.W represents the $(N \times N)$ spatial weight matrix that defines the neighbourhood structure among Airbnb's listings. ρ is the spatial autoregressive parameter that collects the intensity of the interdependencies in the prices of Airbnb's offerings. If this coefficient is significant, the listing prices in Airbnb depend not only on the characteristics of the listings but also on the prices of surrounding listings. When there are significant spatial interactions in the explicative part of the model (WP), the spatial autocorrelation effect is caused by the structural spatial nature of the prices listed on Airbnb.

A specification with spatial autocorrelation in the error term is named as a Spatial Error Model (SEM), and controlling for nonlinearities in the geographical explicative variables through the MARS procedure is expressed as in (4):

$$\begin{aligned} P &= \alpha + X_{\mathrm{NG}}\beta_{\mathrm{NG}} + f(X_G)\beta_G^{'} + u \\ u &= \delta Wu + \varepsilon \end{aligned} \tag{4}$$

where now the error term $u_{N\times 1}$ evaluates the possible spatial structure in the model (Wu), with δ the spatial autocorrelation parameter. When the spatial error term (Wu) is significant, then the spatial structure in the model is explained by the omission of relevant variables. Selection strategy based on LM tests considers the raw LM tests: LM-LAG to contrast the existence of spatial autocorrelation in the dependent variable (3), whereas the LM-ERR test evaluates spatial autocorrelation in the error term (4). The null hypothesis is the absence of spatial effects in both cases. Raw LM tests are not robust to misspecifications in the alternative hypothesis of spatial structure. In order to overcome this limitation, Bera and Yoon (1993) proposed their robust version: LMLE (for LM-LAG test) and LMEL (for LMERR test). Selection strategy based on LM tests states that when both raw LM tests are significant, the best spatial specification is related to the more significant robust LM test. If both are significant and LMLE is larger than LMEL, the best specification is the SLM. If LMLE is lower than LMEL, we must estimate the SEM specification (Florax and Folmer 1992). If only LMLAG is significant, then the most adequate spatial structure is the SLM. If only LMERR is significant, then the adequate spatial structure is the Spatial Error Model (SEM). Finally, López et al. (2014) recommend to compute the marginal, or conditional, LM tests (LMM) to contrast for no correlation in one part of the model allowing for spatial correlation in the other. In particular, LMM(ρ/λ) tests for the existence of residual spatial effects in the error terms of the SLM [3] and LMM(λ/ρ) the existence of substantive spatial effects in SEM (4).

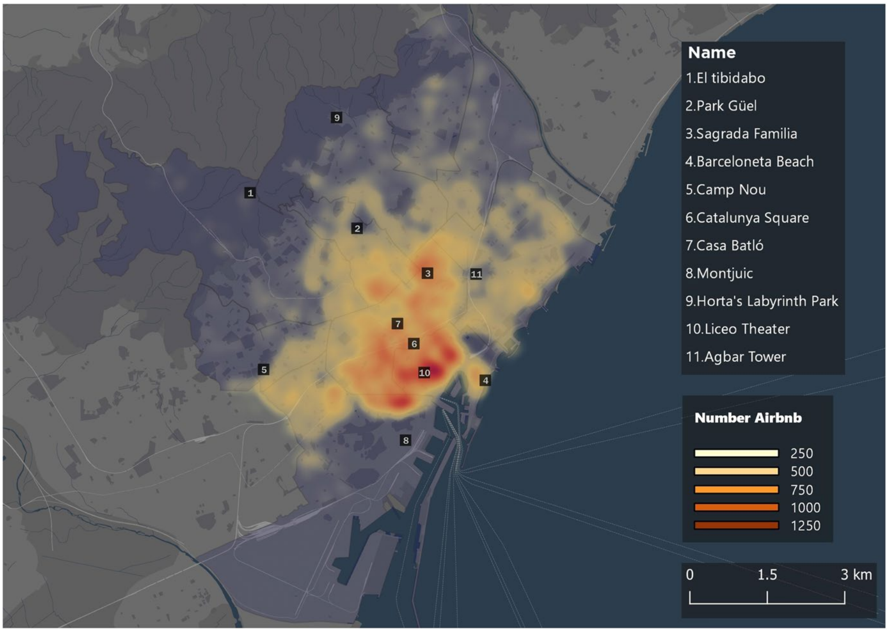

Fig. 1 Spatial distribution of Airbnb's listings in Barcelona. *Source* Own elaboration

4 Dataset and variables

4.1 Dataset

The information used to develop this study was obtained from the open-source database "Inside Airbnb"[3] which provides data about Airbnb listings located in different cities around the world. From this database, we found 19,532 offerings located in the city of Barcelona on July 14, 2019. From this initial data, we dropped Airbnb's offers that do not provide valid information as those with empty offers where the clients started the registration but never completed it. The final sample contained 14,273 accommodations. Figure 1 shows the spatial distribution of total offered listings by Airbnb in Barcelona. As can be seen, most Airbnb offerings are in the downtown area, arriving to the port of Barcelona, with a fairly marked spatial concentration in the city centre.

In order to show additional information about Airbnb's accommodations, we categorized listings according to some key characteristics. We considered full apartments and private rooms[4]. Full apartments account for 47.33%, while private rooms represent 52.67% of the total offerings. In addition, we distinguished listings by the types of hosts. To do this, following previous literature, we differentiated listings

[3] www.insideairbnb.com/get-the-data

[4] Shared rooms were eliminated because this category weighs 1.06% in the sample.

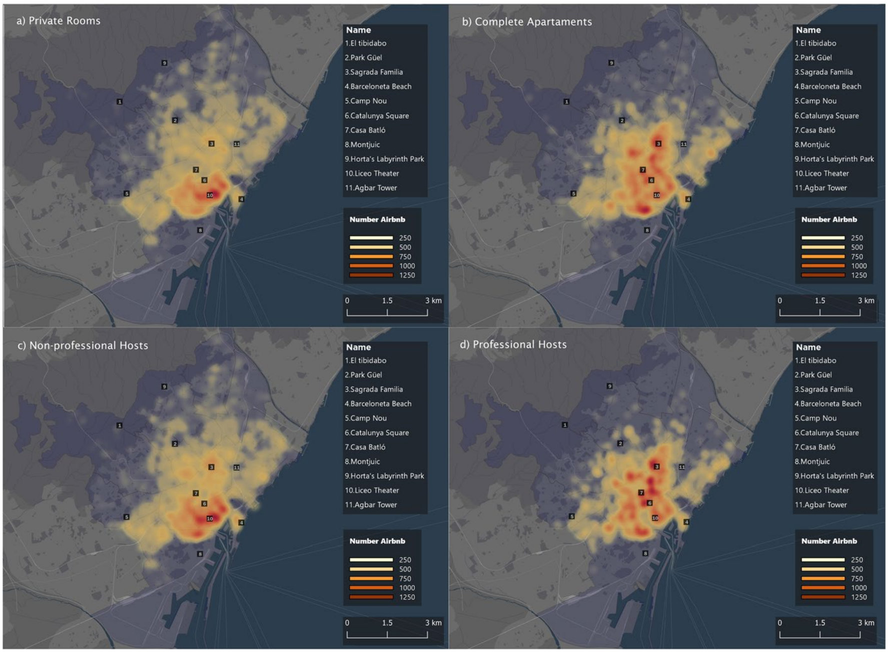

Fig. 2 Spatial distribution of Airbnb's listings in Barcelona (subsets). (As we have commented, professional hosts account for 26.10% of total offers, while non-professional 74.90%. Private rooms account for 52.81% of the total offers, while entire apartments account for 47.19%.) *Source* Own elaboration

whose hosts offered more than two Airbnb accommodations from those who offered fewer than two listings (Xie and Mao 2017; Zhao and Rahman 2019). We referred to the former as *professional hosts* since controlling a larger number of listings requires greater experience in the administration of the offerings and the objective is to maximise benefits[5]. Following this classification, we found that non-professionals have an average value of 1.3 offered listings while the average value for professional hosts is 36.3 offered listings. Figure 2 shows the spatial distribution of Airbnb listings, differentiating between kinds of apartments and hosts.

The spatial distribution of these subsets is different. Private rooms are more concentrated in the city centre than full apartments, which present wider dispersion throughout the city. Similarly, when we considered the kind of host, we found differing patterns. Offered listings by professional hosts show greater dispersion than nonprofessional hosts, who are more concentrated in the city centre (Gutierrez et al. 2017).

[5] This classification should not be confused with the term "superhost", which refers to the badge that Airbnb awards to hosts that meet certain objectives set by the company every three months.

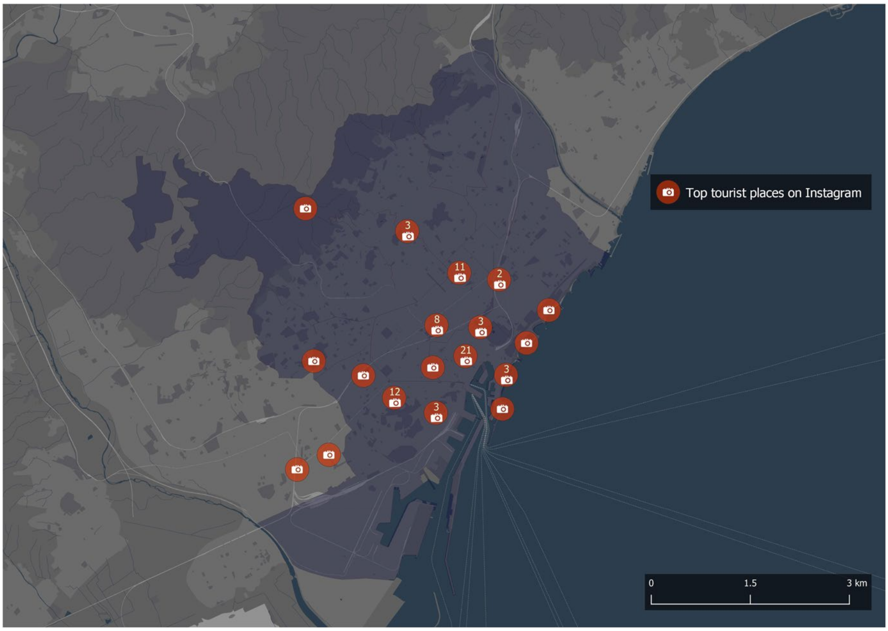

Fig. 3 Location of Instagram Hotspots. *Source* Own elaboration

In addition to Inside Airbnb's database, we obtained the environmental characteristics of the listings from the Open Data Service of Barcelona City Council, "Open data"[6]. This database has been established by the public administration of Barcelona to provide general data obtained from public entities, allowing free access for the purpose of analysis. Finally, we used information from the *Locationscout*[7] webpage and webscrapped it in order to obtain a list of the most frequently referenced places in Instagram for each city and the number of publications of each of them. *Locationscout* is a worldwide travellers' network that collects the most iconic tourist locations of different cities through social networks. Its objective is to inform future travellers about the most popular and most frequently photographed hotspots. This gives us reliable information about the places tourists visited most often in the city of Barcelona. Once these Instagram hotspots were identified, we web-scraped the Instagram webpage to find the number of publications of each of these spots in the city of Barcelona.

4.2 Variables

The dependent variable was the logarithm of Airbnb's listing prices (P). Table 1 shows some descriptive results for this variable. We found that the cheapest listings

6 https://opendata-ajuntament.barcelona.cat/en

7 https://www.locationscout.net/home

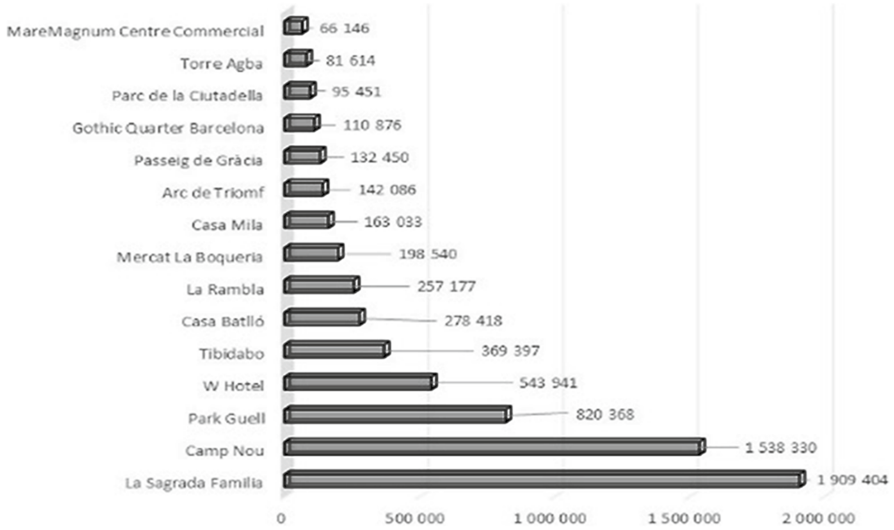

Fig. 4 Number of Instagram publications of most relevant hotspots in Barcelona. *Source* Own elaboration with Instagram information

are private rooms with an average value of 3.77 (52.26 euros). Full rooms have, on average, a higher price, with 4.78 (151.81 euros). We also obtained differences in prices between professional and nonprofessional hosts. While nonprofessional listings have an average value of 4.07 (79.85 euros), the value of professional host listings amounts to 4.75 (154.18 euros). This is consistent with the study by Li et al. (2015) that proves that professional hosts earn significantly more than nonprofessional hosts in New York City. Gibbs et al. (2018) also conclude that more experienced hosts with active offerings and a more professional pricing strategy can obtain higher prices.

In order to determine whether physical proximity to Instagram hotspots is significant to Airbnb's pricing, we defined a variable using information from the Locationscout webpage, from which we identified the most frequently referenced tourist spots on Instagram in the city of Barcelona. In this way, several museums, restaurants and relevant tourist sites were detected (see Fig. 3). These hotspots were geolocated in order to compute a representative variable for the Distance to the Photograph Hotspot on Instagram as the Euclidean distance from each Airbnb listing to its closest Instagram hotspot in Barcelona.

In addition, this variable was weighed by the number of publications of each hotspot in order to consider consumers' tourist preferences and distinguish the importance of each tourist spot (Fig. 4). Descriptive statistics for the resulting variable (DHOTSPOT) are shown in Table 1. As we can see, private apartments and professional listings are closer to Instagram hotspots, with significant differences in terms of distance when we compare them with the other categories. Thus, we could infer that private apartments and professional listings are better located in relation to points of interest in Barcelona.

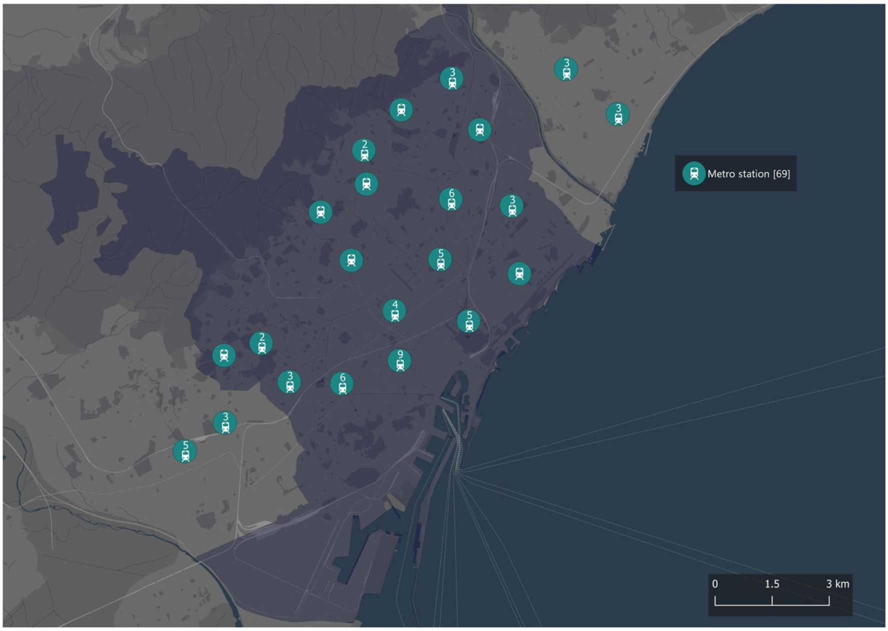

Fig. 5 Location of relevant underground entrances. *Source* Own elaboration

Apart from this geographic variable, we also considered the geographic proximity of Airbnb's accommodations to underground stations as an explanatory variable. Ki and Lee (2019) highlight the relevance of this factor because Airbnb's clients are mainly foreign travellers who may not have alternative transportation. In addition, this variable can be representative of the commercial activity in the surroundings of the accommodation. In this regard, we computed the correlation coefficient between the number of underground entrances and the income per capita in each district of Barcelona, finding a positive and significant relationship. In order to compute this variable, we geo-located relevant underground entrances from the open-source database of Barcelona (see Fig. 5). With this information, we calculated the variable Distance to Underground Entrances (DMETRO) as the Euclidean distance from each Airbnb listing to its closest underground entrance.

In accordance with previous literature, we also proposed additional control variables related to the characteristics and amenities of the listings, which were divided into three categories: listing characteristics, reputational attributes and amenities. Table 1 shows significant differences among the categories, with higher values for professional and entire rooms (Deboosere et al. 2019).

For reputational attributes, the TOTAL PUNCTUATION shows the total number of reviews received by the host multiplied by the score given by the guests. This variable has frequently been used in previous publications (Lorde et al. 2019; Gibbs et al. 2018; Wang and Nicolau 2017), with a negative coefficient indicating that a greater number of reviews implies slightly lower prices. Therefore, offerings with a lower price tend to have higher review values, as is the case for nonprofessional and

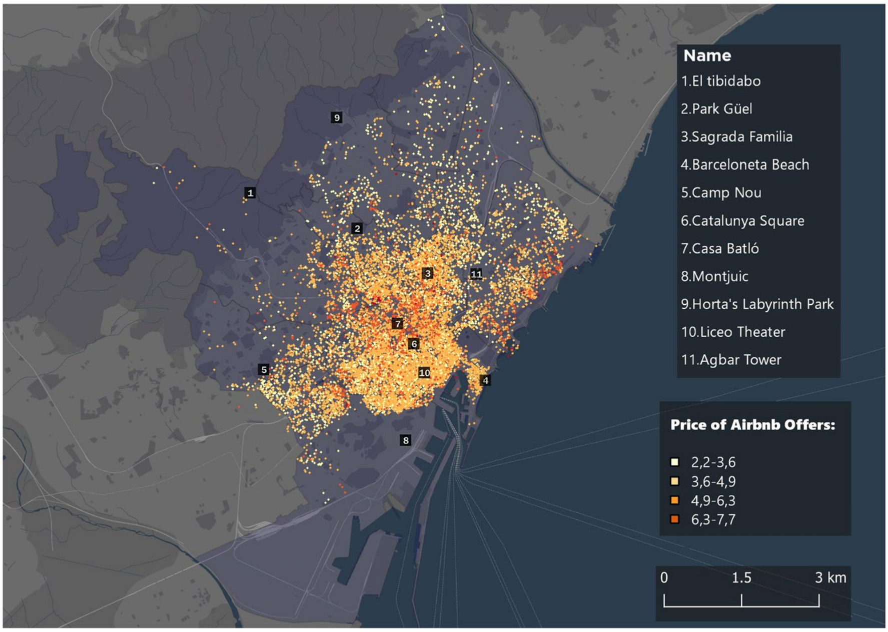

Fig. 6 Price of Airbnb listings in Barcelona. *Source* Own elaboration

private rooms. The variable SUPERHOST (with a value of one) evaluates whether the host has reached the *superhost* category by fulfilling a series of Airbnb requirements every three months. This category is also related to private and nonprofessional hosts, who make greater efforts to obtain a good reputation to attract potential visitors (Zhao and Rahman, 2019). The amenities of each accommodation (e.g. air conditioning, elevator, pool) were built as dichotomy variables. With more than 15 potential amenities to choose from in the Inside-Airbnb database, we computed the frequency of these variables, eliminating those variables where the amenities were verified in almost 100% of the listings, such as the availability of WI-FI (available in 98% of the accommodations). This selection process is supported by previous literature. In this regard, air conditioning, a pool and a gym are variables of special interest in hedonic hotel price models (Thrane 2008). These variables were log-transformed in order to be included in the modelling process.

5 Results

5.1 Exploratory spatial analysis of Airbnb's prices

This section shows an exploratory spatial analysis of the dependent variable representing Airbnb's listing prices to contrast whether it presents a spatial pattern, or whether it is randomly distributed throughout the territory. Figure 6 shows the

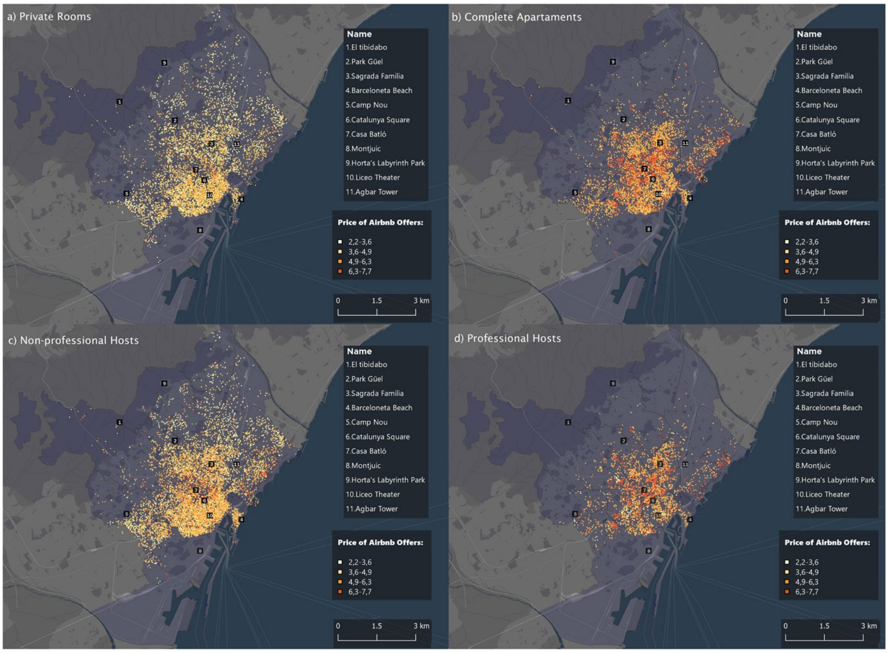

Fig. 7 Price of Airbnb listings in Barcelona (subsets). *Source* Own elaboration

geographic distribution of Airbnb's accommodation log prices according to a quartile map. We found spatial concentration of the highest prices in the centre of Barcelona and near the coast (Gutierrez et al. 2017).

In addition, we differentiated between the kinds of accommodations, examining the quartile maps in each case (Fig. 7). A greater concentration of higher prices is observed in full apartments than in the private rooms. We also observed a greater concentration of higher prices in apartments with professional hosts compared to nonprofessional ones.

Previous graphical results showed symptoms of spatial autocorrelation in Airbnb's prices with spatial clusters of listings with similar prices. This behaviour was tested computing Moran's *I* test. A positive and significant Moran's I test indicates the existence of a positive spatial autocorrelation in Airbnb's prices, whereas a negative and significant sign corroborates negative spatial correlation. In order to determine Moran's I test, a weight matrix *W* should be defined. This is a square and symmetric $N \times N$ binary matrix which identifies—*with values different to zero*—the interconnection between two different listings. In order to provide a neighbourhood criterion, we considered the geographic distance—*evaluated in metres*—between two listings. Based on this criterion, the elements of the W_d weight matrix values one ($w_{ij} = 1$ with $i \neq j$) if the distance between the accommodations i and j is shorter than a certain distance d and values zero ($w_{ij} = 0$) otherwise. Table 2 shows Moran's I test results for the prices of Airbnb's listings, taking into account different d values. As can be observed, Moran's I test increases as the distance (d)

Table 2 Moran's *I* test for Airbnb's listing prices

Spatial weight matrixes	Distance (km)	All	Room	Entire	Professional hosts	Nonprofessional hosts
	0.1	0.8231 (0.205)	0.1978 (0.424)	0.4209 (0.336)	0.3291 (0.225)	0.0255 (0.489)
	0.2	4.491*** (0.000)	0.7088 (0.239)	2.4314*** (0.007)	1.7575** (0.039)	0.1507 (0.559)
	0.3	9.969*** (0.000)	1.3427* (0.089)	5.9012*** (0.000)	4.1185*** (0.000)	0.4547 (0.326)
	0.4	15.196*** (0.000)	1.6736** (0.047)	8.9548*** (0.000)	7.2773*** (0.000)	1.4992** (0.006)
	0.5	19.541*** (0.000)	2.4189** (0.007)	11.6210*** (0.000)	9.8264*** (0.000)	2.9651*** (0.001)
	0.6	23.846*** (0.000)	3.4216*** (0.000)	14.9182*** (0.000)	12.512*** (0.000)	5.1881*** (0.000)
	0.7	27.608*** (0.000)	3.7090*** (0.000)	16.7822*** (0.000)	15.702*** (0.000)	7.3828*** (0.000)
	0.8	32.045*** (0.000)	4.8602*** (0.000)	19.1121*** (0.000)	18.896*** (0.000)	8.8391*** (0.000)
	0.9	36.121*** (0.000)	5.2451*** (0.000)	21.1711*** (0.000)	21.452*** (0.000)	11.512*** (0.000)
	1.0	39.901*** (0.000)	6.4323*** (0.000)	23.1898*** (0.000)	23.889*** (0.000)	12.646*** (0.000)
Hollow spatial weight matrixes	0.1–0.2	3.2404*** (0.000)	0.3989 (0.345)	1.7231** (0.042)	1.2794 (0.104)	-0.2106 (0.583)
	0.2–0.3	5.8352*** (0.000)	0.5524 (0.290)	3.2864*** (0.000)	2.3657*** (0.008)	0.4506 (0.326)
	0.3–0.4	8.2179*** (0.000)	0.4058 (0.342)	3.8497*** (0.000)	3.734*** (0.000)	0.8234 (0.205)
	0.4–0.5	9.7321*** (0.000)	1.4218* (0.077)	5.0175*** (0.000)	4.558*** (0.000)	2.0791* (0.018)
	0.5–0.6	10.984*** (0.000)	1.6637** (0.048)	6.8799*** (0.000)	5.9256*** (0.000)	2.8077* (0.018)
	0.6–0.7	12.608*** (0.000)	1.3596* (0.086)	6.4601*** (0.000)	7.1585*** (0.000)	2.7605*** (0.002)
	0.7–0.8	14.874*** (0.000)	1.7956** (0.036)	8.1005*** (0.000)	8.2018*** (0.000)	2.5409** (0.005)
	0.8–0.9	15.251*** (0.000)	1.0756 (0.141)	8.8441*** (0.000)	7.4625*** (0.000)	3.5655*** (0.000)
	0.9–1.0	15.676*** (0.000)	2.6121*** (0.004)	9.8609*** (0.000)	8.2487*** (0.000)	3.5892*** (0.000)
Additional information for W 0.5–0.6						
	Average of links	683.018	363.462	351.525	391.971	317.074
	Isolated regions	1.000	1.000	10.000	4.000	1.000

(***) significant at 1%. (**) significant at 5%. (*) significant at 10%. *P* values in brackets increases[8]. The lack of a limit for the Moran's I test could be explained by the high concentration of examined observations—Airbnb's accommodations—which could cause biased results in the Moran's I test because it is accumulating local spatial autocorrelation patterns. To control for this effect and determine the optimal order for the spatial weight matrix, W, we computed the Moran's I test with hollow spatial weight matrixes of different contiguity orders (Matilla-García and Ruiz 2011). In this way, we discounted the possible bias derived from the global spatial autocorrelation pattern.

Regarding Table 2, we concluded that W_d with $d = 0.6$ is the most adequate spatial weight matrix to evaluate the spatial structure in Airbnb's prices. In this regard, Moran's I test reaches a local maximum value when we considered the hollow spatial weight matrix ($W_{0.5-0.6}$), which takes into account the interconnection of each listing to the listings located at five hundred to six hundred metres' distance. Thus, additional metres from this distance should include spatial autocorrelation effects from other local structures. The average number of links and isolated regions of each of the samples when used the hollow spatial weight matrix $W_{0.5-0.6}$ are included in Table 2.

5.2 Regression results

5.2.1 OLS regression

In accordance with previous results, we proposed a hedonic model to determine Airbnb's accommodation prices. With this purpose, we start from the general OLS estimation model (1). Based on this specification, we determined possible nonlinearities in the model applying MARS methodology. From its application has determined the existence of nonlinearities in the geographic variables DPHOHOTS and DMETRO. When we considered the full sample (second column), we found that these geographic variables were significant at distances shorter than 120 (knot = −4.4208) and 81 (knot = −2.5107) metres, respectively. Thus, we redefined these variables to consider these nonlinearities. In this way, the new variable DHOTSPOTL was defined as the old variable DHOTSPOT for those points lower than −4.4208 and zero otherwise. DMETROL is equal to the variable DMETRO for those points lower than −2.5107 and 0 otherwise.

In addition, we computed LM tests to check for the existence of spatial structures in the model (see Table 3). We found that the LM tests were significant in all the cases, with higher values for LM-LAG proving the existence of spatial autocorrelation in the dependent variable specified through the structure spatial lag model (SLM). Nevertheless, we went one step further by testing for the existence of residual spatial effects in the error term of the SLM computing the LMM (ρ/λ) test (Table 3). This test was significant in all the cases, demonstrating the need to apply the following spatial lag specification with spatial errors (SARAR) model (5).

[8] This increase is continuous, even when we increased the distance d to values above 0.10 kms.

Table 3 Ordinary least square results for the hedonic model of Airbnb prices (log–log model)

Variables	All	Private room	Entire apartment	Professional hosts	Nonprofessional hosts
(Intercept)	3.4494*** (0.000)	3.5612*** (0.000)	3.9966*** (0.000)	3.3077*** (0.000)	3.4842*** (0.000)
DHOTSPOTL	−0.0231*** (0.000)	−0.0305*** (0.000)	−0.0148*** (0.000)	−0.0136*** (0.000)	−0.0238*** (0.000)
DMETROL	−0.0033* (0.069)	−0.0017 (0.8229)	−0.0262** (0.007)	−0.0223* (0.002)	−0.0092 (0.2800)
Beds	0.1686*** (0.000)	−0.0561*** (0.0259)	0.2074*** (0.000)	0.1161*** (0.000)	0.2407*** (0.000)
Guest included	0.1384*** (0.000)	0.3251*** (0.000)	0.0367** (0.002)	0.1226*** (0.000)	0.1458*** (0.000)
Extra people	−0.0270*** (0.000)	−0.0178*** (0.000)	−0.0210*** (0.000)	−0.0209*** (0.000)	−0.0183*** (0.000)
Minimum nights	−0.0918*** (0.000)	−0.0522*** (0.000)	−0.1711*** (0.000)	−0.0981*** (0.000)	−0.0737*** (0.000)
Total punctuation	−0.0368*** (0.000)	−0.0542*** (0.000)	−0.0318*** (0.000)	−0.0282*** (0.000)	−0.0405*** (0.000)
Superhost	0.1378*** (0.000)	0.1319*** (0.000)	0.1713*** (0.000)	0.2055*** (0.000)	0.1007*** (0.000)
Air_conditioning	0.2395*** (0.000)	0.1912*** (0.000)	0.0921*** (0.000)	0.2727*** (0.000)	0.2049*** (0.000)
Elevator	0.0672*** (0.000)	0.0097 (0.3696)	0.1535*** (0.000)	0.0969*** (0.000)	0.0263 (0.201)
Pool	0.2530*** (0.000)	0.2948*** (0.000)	0.2279*** (0.000)	0.1995*** (0.000)	0.3471*** (0.000)
Gym	0.1776*** (0.000)	0.1652*** (0.000)	0.2629*** (0.001)	0.3397*** (0.000)	−0.0547 (0.371)
24 h check in	0.1240*** (0.000)	0.0016 (0.999)	0.1701*** (0.000)	0.1671*** (0.000)	0.0386* (0.0530)
Additional information					
R-squared	0.5061	0.3744	0.3645	0.5471	0.5180
N	14,237	7518	6719	7308	6929
Knots in accordance with MARS for geographic variables					
DHOTSPOTL	−4.4208 (120 m)	−4.4635 (121 m)	−4.3676 (191 m)	−4.4175 (120 m)	−4.4473 (122 m)
DMETROL	−2.5107 (81 m)	−0.2765 (100 m)	−0.0691 (30 m)	–	−0.2127 (10 m)
LM tests for spatial dependence analysis					
Weight matrix	$W_d = 0.07$	$W_d = 0.06$	$W_d = 0.06$	$W_d = 0.06$	W = 0.06
LM-ERR	104.002*** (0.000)	54.763*** (0.000)	69.222*** (0.000)	82.611*** (0.000)	33.373*** (0.000)
LM_LAG	143.545*** (0.000)	27.911*** (0.000)	32.547*** (0.000)	98.145*** (0.000)	32.572*** (0.000)
LMEL	50.587*** (0.000)	37.813*** (0.000)	49.054*** (0.000)	42.284*** (0.000)	19.464*** (0.001)
LMLE	69.233*** (0.000)	40.112*** (0.000)	52.560*** (0.000)	57.562*** (0.000)	19.872*** (0.001)
LMM (ρ/λ)	14.408** (0.002)	2.439* (0.085)	3.235** (0.021)	12.254*** (0.006)	14.320*** (0.004)

Table 3 (continued)

P values in brackets. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

Table 4 Spatial autoregressive model with spatial autocorrelation in the error terms for the hedonic model of Airbnb prices (log–log model)

Variables	All	Private room	Entire apartment	Professional hosts	Nonprofessional hosts
(Intercept)	3.2801*** (0.000)	3.8460 *** (0.023)	4.4481*** (0.000)	3.8245 *** (0.000)	3.7752*** (0.000)
DHOTSPOTL	−0.0271*** (0.000)	−0.0387*** (0.000)	−0.0234*** (0.000)	−0.0207*** (0.000)	−0.03223*** (0.000)
DMETROL	−0.0171*** (0.001)	−0.0003 (0.968)	−0.0234** (0.022)	−0.0281*** (0.005)	−0.0069 (0.4651)
Beds	0.6048*** (0.000)	0.1640*** (0.000)	0.4511*** (0.000)	0.5483*** (0.000)	0.6576*** (0.000)
Guest included	0.3010*** (0.000)	0.4871 (0.000)***	0.0841*** (0.000)	0.2660*** (0.000)	0.3042*** (0.000)
Extra people	−0.0155*** (0.000)	0.0091 (0.000)***	−0.0236*** (0.000)	−0.0186*** (0.000)	−0.0118*** (0.000)
Minimum nights	−0.0984*** (0.000)	−0.0858 (0.000)***	−0.1928*** (0.000)	−0.1180*** (0.000)	−0.0701*** (0.000)
Total punctuation	−0.0353*** (0.000)	−0.0497 (0.000)***	−0.0336*** (0.000)	−0.0347*** (0.000)	−0.0305*** (0.000)
Superhost	0.0919*** (0.000)	0.1098 (0.000)***	0.1516*** (0.000)	0.1384*** (0.000)	0.0796*** (0.000)
Air_conditioning	0.3878*** (0.000)	0.2328 (0.000)***	0.1263*** (0.000)	0.4475*** (0.000)	0.2938*** (0.000)
Elevator	0.0489*** (0.000)	−0.0070 (0.542)	0.1548*** (0.000)	0.0867*** (0.000)	−0.0002 (0.9860)
Pool	0.3274*** (0.000)	0.2824*** (0.000)	0.2842*** (0.000)	0.2778*** (0.000)	0.4032*** (0.000)
Gym	0.0707 (0.139)	0.1197** (0.021)	0.2278*** (0.000)	0.2072*** (0.002)	−0.117** (0.0429)
24 h check in	0.1368*** (0.000)	0.0000 (0.999)	0.1671*** (0.000)	0.1807*** (0.000)	0.0403 (0.0630)
Rho	0.0440*** (0.000)	0.0138*** (0.001)	0.0199*** (0.000)	0.0376*** (0.000)	0.0177*** (0.000)
Lambda	0.0966*** (0.000)	0.0877*** (0.000)	0.0986*** (0.000)	0.0875*** (0.000)	0.0646*** (0.000)
Additional information					
LIK	−11,739.07	−5126.418	−5267.117	−6387.945	−4949.097
N	14,237	7518	6719	7308	6929

coefficient (standard error) ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$

$$\begin{aligned} P &= \alpha + \rho WP + X_{\mathrm{NG}}\beta_{\mathrm{NG}} + f(X_G)\beta_G' + u \\ u &= \delta Wu + \varepsilon \end{aligned} \tag{5}$$

5.2.2 SARAR estimation

In this section, we present maximum likelihood estimation results of the model (5) including previously detected nonlinearities with the MARS algorithm in the geographical explanatory variables X_G, and differentiating between subsamples (Table 4).

Regarding the spatial structure of the model, we find that the spatial coefficients, rho and lambda, are significant and positive. Thus, we confirm the existence of spatial autocorrelation caused by the spatial structure of the dependent variable. Therefore, the price of each Airbnb accommodation is also influenced by the prices of the Airbnb listings closest to it. In addition, the significance of the parameter Lambda indicates that there is a spatial structure in the error term of the model. This finding coincides with previous literature which examines the spatial autocorrelation structures in Airbnb's prices (Lopez et al. 2019; Chica-Olmo et al. 2020). In addition to previous studies, we compared subsamples according to the type of Airbnb listing. Regarding the spatial coefficients for the different subsamples, we found that the highest spatial autocorrelation Rho coefficient is for the subsample of professional hosts (0.0376). This could be explained by the fact that these accommodations are more efficiently and jointly managed. Thus, information about closer listings could play a relevant role in their pricing process (Deboosere et al. 2019; Maté-Sánchez-Val 2020).

Both geographic variables showed negative and significant signs, indicating that longer distances from Airbnb listings to these points of interest decrease listing prices, up to a certain value, from which point this effect becomes insignificant. These variables are also significant when we distinguished between subsamples, where we found that the representative variable of the distance to the closest hotspot on Instagram plays a significant role in all the cases, with a radius of influence of approximately one hundred and twenty metres from each listing. This finding confirms our Hypothesis 1 (H1) about the significant impact on accommodation price increases of geographic proximity of Airbnb's listings to popular tourist spots on Instagram. In addition, when we distinguished between subsamples, we found differences between coefficients for the variable DHOTSPOT. In this regard, the coefficient for entire apartments is lower than the coefficient for private rooms. This could be explained by the more static demand for entire apartments given that these offerings are associated with longer stays and older guests travelling with families (Gibbs et al. 2018; Deboosere et al. 2019). Thus, for these clients, environmental characteristics will be less relevant in their rental decision. This result corroborates our hypothesis $\mathrm{H1}_{\mathrm{a}}$. In addition, we found that the coefficients of DHOTSPOTSL are significantly lower for professional hosts than for nonprofessional hosts. This finding was expected given the characteristics of each subsample. Airbnb accommodations offered by professional hosts are more efficiently managed since these hosts are specialists in the service, aiming to maximise their benefits. More efficient management means that these kinds of Airbnb accommodations are less affected by factors having to do with location. Thus, these listings should be less influenced by promotion in social networks. This result corroborates hypothesis $H1_b$.

Regarding the control variables, we found the expected signs in accordance with previous literature. We got a positive and significant sign for the number of beds in each Airbnb listing (Gibbs et al. 2018, Wang and Nicolau 2017 and Lorde and Jacob 2019). In addition to previous studies, we also distinguished between types of Airbnb offerings for each subsample with significant and positive results. About the number of included guests, we also found a significant and positive sign (Gibbs et al. 2018). This increase is higher in private room listings than in entire apartments. The offerings of professional hosts present a lower increase per guest than those of nonprofessional hosts. About the minimum number of nights, an increase in the minimum number of nights required by the host has a negative effect on prices in all the cases. This effect is more accentuated in private rooms than in entire apartments. Our results also showed that the badge of superhost results in an increase in the price of the offerings. This is consistent with previous studies. On average, being a superhost causes an increase of 9.19% in the price of the offering. It should be noted that professional hosts that are awarded the superhost badge—this is more complicated since it is necessary to comply with all of Airbnb's requirements in all the listings—implies a price increase of 13.84%, compared to nonprofessional hosts (7.96%). This is in line with the study by Liang et al. (2017) concluding that guests are willing to spend more money on accommodations with a host who has more experience and a better reputation. For all the apartments, we found a relevant effect for the status of superhost, with an increase of 10.98%. We also studied the effect of offerings with higher scores, where a higher range of scores is related to cheaper price. This is due to the fact that apartments with affordable prices tend to have more scores and tend to receive more positive reviews. In contrast, offers with excessively high prices do not receive so many guests. This coincides with the studies conducted by Gibbs et al. (2018), Wang and Nicolau (2017) and Lorde and Jacob (2019).

On the amenities of the listings, we found that all of them result in an increase in price when they are present in the offering. In the regression with the full sample, a listing with a pool caused a 32.74% price increase, 38.78% for air conditioning and 4.89% for an elevator. Being able to check in 24 h represented a 13.68% increase. Focussing on the offerings of private rooms, the amenities that seem to be most influential for guests were gyms (11.97%), air conditioning (23.28%) and, especially, swimming pools (28.24%). The ability to check in 24 h or having an elevator did not affect price. On the other hand, in the full apartment listings, all amenities affected prices, especially pools (28.42%), 24 h check in (16.71%), air conditioning (23.28%) and elevator (15.48%). Focussing on nonprofessional host listings, we found significant effects for air conditioning (29.38%), 24 h check in (4.03%) and pools (40.32%). By professional hosts, the results were gyms (20.72%), air conditioning (44.75%), pools (27.78%) and 24 h check in (18.07%). Special attention should be paid to the importance of 24 h check in in entire apartments and professional host offerings. This was not relevant in private rooms.

Table 5 Granger's causality test

Subsamples	Test (*p* value)
All the sample	2.1439** (0.057)
Private room	2.3284** (0.040)
Entire apartment	1.2043 (0.304)
Professional hosts	2.0308* (0.071)
Nonprofessional hosts	2.8212*** (0.003)

(***) significant at 1% (**) significant at 5% (*) significant at 10%. In order to compute Granger's test for each subsample. We have considered a five-year temporal lag for the variable Airbnb's prices. This information was obtained from the Inside Airbnb dataset

5.2.3 Does information from social networks cause changes in Airbnb's prices?

In order to show additional evidence about the role of social networks in Airbnb's prices, we computed Granger's causality test for the representative variable of the physical distance from each Airbnb accommodation to its closest tourist spot on Instagram (DHOTSPOTS). Table 5 shows these results.

Granger's causality test was significant for the whole sample and when we distinguished between subsamples. The only case where it was not significant was for the subsample of entire apartments. This subsample is characterised by longer stays of older clients and family travellers, where physical distances to tourist attractions should be less relevant (Gibbs et al. 2018). Thus, though previous regression analysis provided significant coefficients for this variable, when we extended the relationship to generalise this effect with a greater number of periods for the Airbnb price variable, we found nonsignificant effects for this specific case.

6 Conclusion

This study investigated the pricing behaviour of hosts in Airbnb's listings in the city of Barcelona, with special relevance placed on the role played by social networks. A total of 14,273 offerings were jointly examined. A detailed study was carried out according to the type of listing (private rooms or complete apartments) and host profile (professional and nonprofessional), showing differences in the price determination process. The main objective of this study was to examine the relevance of information from social media—represented by Instagram—on Airbnb's prices. Our results confirm the popularity of certain spots in social networks condition other travellers' experiences. This is consistent with previous studies that state that social networks are an important engine to promote tourist destinations and increase tourist demand. According to our results, this increase in demand near tourist sites that are specifically popular on Instagram has effects on the accommodations offered on Airbnb, impacting listing prices. We found that each additional 10% increase in the distance from Instagram tourist sites to Airbnb listings resulted in a 2.7% decrease in Airbnb's listing price. This pricing effect is even more pronounced in private rooms and those with nonprofessional hosts. This is consistent with the studies that observe how Instagram posts about tourist spots have a positive and significant impact on the intention to rent Airbnb's accommodations in certain areas. Thus, our study confirms the proposed hypothesis about the significant impact of social networks, highlighting their role in accommodation pricing. In a further analysis, we examine the causal relationship between Instagram hotspots and Airbnb's prices, finding significant results in all the cases with the exception of entire apartments.

This research has direct implications for managers in the accommodation sector, who should consider social networks as important tools to examine market tendencies, allowing them to identify those relevant tourist destinations which cannot be observed through other information channels. The role of social networks and influencers in social networks is relevant in tourists' decision-making processes. Researchers in this area should consider additional sources of information to the ones usually included in these types of studies, such as that obtained in social networks. This information could provide relevant data to give greater robustness to the traditional market models in the accommodation sector. This study also has some limitations which could be considered for future research. One of the limitations is that it is focussed on the city of Barcelona. Thus, further analysis should consider other scenarios to corroborate our results. In future studies, information collected on other social networks about the popularity and number of visits to the city's tourist sites could be added. It is possible that the information from each social network may be biased due to the average age of the users. For example, Instagram is a social network normally used by younger people. Other platforms, such as Google Places or TripAdvisor, could give complementary information to that used in this study.

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