Universitat de les Illes Balears

The hedonic value of coastal amenities in peer-to-peer markets.

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Abstract:

Coastal amenities are public goods that represent an important attraction for tourism activities. This paper studies consumers' willingness to pay for beach characteristics using hedonic pricing methods. We examine the implicit economic value of several beach characteristics like sand type, width, longitude, accessibility, or frontage in the Airbnb rental market. Using data for 16,663 Airbnb listings located in 67 municipalities of the Balearic Islands (Spain) during the summer of 2016, together with detailed information about the attributes of 263 beaches, our modelling approach considers interaction terms between the beach amenities and distance to the closest beach within a hedonic framework. Controlling for a set of listings' characteristics, host features and municipality fixed effects, we find that Airbnb guests attach economic value to beach length, the presence of vegetation, the type of coastal frontage and beach accessibility and exclusivity. However, there is no evidence of price premiums depending on the beach width or the type of sand.

Keywords: *hedonic pricing, coastal amenities; capitalization effects; peer-to-peer markets; distance decay*

Universitat de les Illes Balears

1. Introduction

Coastal amenities are important attraction factors for coastal areas, especially for those regions specialized in tourism activities. As shown by Onofri and Nunes (2013), tourists choose coastal destinations because they have strong preferences for beach characteristics. The marine ecosystem quality of coastal areas is therefore a significant predictor of tourism flows and revenues (Otrachshenko and Bosello, 2017; Spalding et al., 2017), which in turn causes large and significant long-run local economic gains in terms of employment and GDP (Faber and Gaubert, 2019). Due to the expected sea level rise caused by climate change, many coastal areas and beaches are at a high risk of erosion. According to the sixth report by the Intergovernmental Panel on Climate Change (IPCC, 2021), sea level is expected to rise up to 81 cm along the Spanish coastline in the next 80 years. The identification of the welfare effects of coastal amenities is therefore economically relevant for the appropriate development of policy interventions (Gopalakrishnan et al., 2016a; Parsons et al., 2013), especially in tourism-led economies.

Hedonic pricing functions have been widely used to study consumers' willingness to pay for a variety of local environmental amenities in many different settings (e.g., Chay and Greenstone, 2005; Franco and Macdonald, 2018). Typically, residential property transaction prices are used to measure the 'capitalization effects' of proximity to environmental amenities, which inform about the economic value of non-marketed goods. Previous research has shown that the quality of nearby coastal areas generates substantial price premiums on residential housing values because consumers value aspects like water quality (Walsh et al., 2017), water view (Lansford and Jones, 1995), beach quality (Landry and Hindsley, 2011) or beach width (Landry et al., 2021). However, for tourism development, a proper understanding of tourists' preferences over coastal amenities seems even more relevant because coastal attractiveness is a key driver of inbound tourists' destination choices and beach visitation (Pascoe, 2019). In this sense, whereas residents' preferences for coastal attributes are widely documented, less is known yet about tourists' willingness to pay for beach characteristics.

This paper studies tourists' marginal willingness to pay for a large set of coastal amenities. We apply the hedonic pricing method to estimate the implicit prices of several beach characteristics like sand type, width, longitude, accessibility or coastal frontage in the Airbnb rental market. Some studies in the tourism literature have analysed the economic value of sea view or beach attributes using hotel prices (Fleischer, 2002; Rigall-i-Torrent and Fluvià, 2011; Rigall-i-Torrent et al., 2011). However, to the best of our knowledge, there are no studies on how beach amenities capitalize into the prices of peer-to-peer accommodation markets[1]. Airbnb stands nowadays as the leading online marketplace for peer-to-peer accommodation. It has been shown to be a relevant competitor for traditional accommodations (e.g., Zervas et al., 2017) because

[1] The peer-to-peer economy (also known as collaborative consumption or sharing economy) has disrupted traditional business practices in the accommodation sector (Guttentag, 2015). It consists of the use of under-utilized inventory through fee-based sharing that has been framed as a more sustainable form of consumption that could foster innovation (Martin, 2016).

of offering different services and experiences to tourists, being also generally cheaper (Tussyadiah and Pesonen, 2016). Despite the vast literature on Airbnb hedonic pricing (e.g., Voltes-Dorta and Sánchez-Medina, 2020; Moreno-Izquierdo et al., 2020; Casamatta et al., 2022), the economic value of coastal amenities has been overlooked to date in this market segment.

We use data for 16,663 Airbnb listings located in 67 municipalities in the Balearic Islands (Spain) in the summer of 2016. The Balearic Islands is a relevant case study because of being a well-known tourist destination specialized in sun and beach (mass) tourism for whom the tourism sector is an important economic driver (Ginard-Bosch and Ramos-Martín, 2016).[2] These islands are of additional interest because of the concomitant presence of high recreation values, poor protection status and high erosion risk, as documented in Ghermandi (2015). We combine data on Airbnb transaction (equilibrium) daily rates, host attributes (e.g., number of listings on property, experience as a host, etc.) and listing structural characteristics (e.g., size, type of property, etc.) with detailed information about the attributes of 263 beaches in the islands. We match each Airbnb listing with the closest beach based on Euclidean distance to the shoreline, so each property is vis-à-vis matched with a beach in our data. Since listings are sparsely located throughout the territory, some listings are very close to the beach whereas others are quite distant. In this respect, the hedonic pricing literature has documented a distance decay effect in the contribution of environmental amenities to property values (Lansford and Jones, 1995; Gibbons et a., 2014; Landry and Hindsley, 2011; Athukorala et al., 2019; Landry et al., 2021). We exploit listings' closeness to the beach as an indicator of exposure to different beach amenities. Therefore, our modelling approach incorporates interaction terms between the beach attributes and the distance to the closest beach in the hedonic equation to properly estimate the price premiums of coastal amenities. This allows us to uncover edge and proximity effects.

Conditional on an array of structural characteristics, host features and municipality fixed effects, we document that Airbnb guests value the length of the beach, the presence of vegetation, the type of coastal frontage and whether the beach is in an urban environment. However, there is no evidence of price premiums associated with beach width, the type of sand of the presence of protected natural spaces in the beach. Interestingly, beaches with a difficult access on foot convey a price premium of 16.2%, which is interpreted in terms of exclusivity and lower beach occupancy. These results are specially convincing because they remain consistent under a battery of robustness checks.

The contribution of the paper is twofold. First, unlike previous research on the implicit value of coastal amenities that mainly focus on beach width (Landry and Hindley, 2011; Landry et al., 2021) or a single environmental attribute (Leggett and Bockstael, 2000; Lutzenhiser and Netusil, 2001), we estimate the marginal willingness to pay for a wide set of beach attributes, separately. From this perspective, the paper follows the lines of Gibbons et al. (2014), although

[2] An important advantage of using this data is that nourishment projects have not been undertaken in the beaches belonging to the Balearic Islands. As such, we avoid potential problems of reverse causality in beach width (Gopalakrishnan et al., 2011; Landry et al., 2021).

in a different context. Importantly, to capture potential distance-decay effects, the marginal willingness to pay for such attributes are allowed to be moderated by the distance to the shoreline. Second, we provide the first empirical characterization of the impact of coastal amenities on daily rates in Airbnb accommodations. The analysis of capitalization effects in the peer-to-peer rental market is convenient for at least two reasons. Firstly, hotels generally concentrate around the coast (Marco-Lajara et al., 2016), so the separate identification of the capitalization effects of coastal amenities from other hedonic attributes is, to some extent, cumbersome due to reduced variability. On the contrary, Airbnb listings are more scattered across the islands (Eugenio-Martín et al., 2019), which offers the advantage of a better *ceteris paribus* comparison between properties that are close to the beach and others located further away. In this vein, unlike other studies that restrict the sample to properties within *ad hoc* distance thresholds (Landry and Hindsley, 2011; Walsch et al., 2017; Catma, 2020), we consider the universe of Airbnb properties in the islands that have been rented at least once during the study period. This further creates spatial variability for identification. Second, compared to the analysis of capitalization effects on the residential real-estate market, studying short term accommodation rentals entails an additional advantage. Housing selling prices typically conflate the current value of coastal amenities with expectations on the future evolution of beach quality (Bishop and Murphy, 2019). By contrast, Airbnb accommodation prices merely reflect consumer preferences for current levels of environmental amenities.

The remainder of the paper is structured as follows. The following section reviews the related literature. In Section 3, we present a theoretical characterization based on Rosen's framework (Rosen, 1974) but extended to consider potential hosts' market power. Section 4 presents and describes the data and the variables used in the analysis. Section 5 outlines the econometric modelling and some empirical aspects to bear in mind. The results are presented and discussed in Section 6. Finally, Section 7 concludes with a summary of the findings and some implications.

2. Literature review

2.1. The hedonic value of environmental amenities

A large body of literature has studied how residential property values capitalize the value of environmental amenities. To this end, scholars have estimated hedonic pricing functions that regress transaction prices to a set of local environmental amenities and appropriate controls. This literature has documented relevant price premiums from water quality (Leggett and Bockstael, 2000; Walsh et al., 2011; 2017; Calderón-Arrieta et al., 2019), water clarity (Michael et al., 2000), waterfront view (Brown and Pollakowski, 1977; Lansford and Jones, 1995), open spaces (Lutzenhiser and Netusil, 2001), air quality (Chay and Greenstone, 2005) or cultural heritage (Franco and Macdonald, 2018). Similarly, other scholars have studied the price discounts from disamenities in the form of bushfires exposure (Athukorala et al., 2019), road noise (Andersson et al., 2010), hurricane occurrence risks (Cohen et al., 2021), closeness to hazardous waste sites (Greenstone and Gallagher, 2008) or to power plants (Davis, 2011).

Universitat de les Illes Balears

Rather than focusing on the hedonic value of a specific amenity, other scholars have estimated the separate shadow prices of several environmental attributes. Gibbons et al. (2014) estimate the amenity value associated with proximity to habitats, designated areas, domestic gardens, rivers and other natural amenities in England. They document considerable positive price premiums for gardens, freshwater, food plain locations and green spaces within the census ward. These authors warn about the importance of considering all potentially relevant environmental amenities to avoid biased results. Liu et al. (2020) analyse the spillover effects on housing prices of ecological lands considering forest, grassland, wetland and cultivated land in China. Using a multilevel hedonic model, they find that forest size, wetland size and a moderate grassland area exert positive and linear effects on house prices.

Climate change is producing a gradual increase in sea level, worsening beach erosion and increasing the frequency of coastal flooding. Since beach width is an important attribute for both shore protection and beach quality, beach nourishment projects have been developed to fill the beaches with sand. Given the large costs associated with these projects, another stream of research has focused on estimating the economic value of beach width using residential property prices. Landry and Hindsley (2011) study the influence of beach quality on coastal property values. They show that beach and dune widths increase house values but within a 300-meter radius from the shore, over which their effects become non-significant. Similarly, Landry et al. (2021) examine how coastal beach width affects residential property values, taking into account the role played by shoreline proximity and potential measurement error problems. They find positive price premiums for beach width and no problems of errors-in-variables. Catma (2020) estimates spatial hedonic regressions and documents that beach width positively influences values of properties located within 193 meters of the shoreline. Gopalakrishnan et al. (2016b) revisit the impact of beach width on house property values studying the potential attenuation bias when the beaches under study have implemented beach replenishment projects that produce measurement error. Using IV methods, they find that the capitalization effect of beach width is larger than previously estimated.

Overall, a common finding of these studies is that the contribution of coastal amenities to property values vanishes as we move away from the shoreline. That is, consumers' willingness to pay for coastal amenities is subject to a distance decay pattern (Brown and Pollakowski, 1977; Lansford and Jones, 1995; Landry and Hindsley, 2011; Gibbons et al., 2014; Athukorala et al., 2019; Landry et al., 2021). The rationale is that, for residential property, the hedonic value of coastal amenities stems from aesthetic view, which becomes negligible as distance to the shoreline increases. That is why empirical applications typically restrict the samples to those properties that lie within certain *ad hoc* distance boundaries.

2.2. The economic value of beach quality

In the tourism economics literature, several scholars have applied the hedonic method to uncover the implicit prices of accommodation attributes for hotels (e.g., Rigall-i-Torrent and Fluviá, 2011), second homes (e.g., Saló and Garriga, 2011) and Airbnb listings (e.g., Casamatta et al., 2022). Most of this literature focuses on the hedonic value of intrinsic characteristics and typically control for location factors through neighbourhood fixed effects. However, although the economic value of the sociodemographic composition of the neighbourhood has started to be recognized (Rigall-i-Torrent et al., 2011; Saló and Garriga, 2011; Saló et al., 2014; Moreno-Izquierdo et al., 2020), studies that estimate the economic value of beach amenities are scarce. We briefly discuss the existing evidence.

One of the first studies that analyzes the economic value of coastal amenities for tourist accommodation properties is Hamilton (2007), who investigates the influence of landscape attributes on the average prices of hotels, bed and breakfast and private rooms in 92 districts in Germany. This author finds that districts with open coast charge higher prices, whereas an increase in the length of dikes is associated with lower prices. Beyond this work, most existing studies have focused on the aesthetic value of sea view. Conditional on other hedonic characteristics, Rigall-i-Torrent and Fluviá (2011) and Espinet et al. (2003) document that hotel rates are significantly higher when the hotel locates in front of the beach. Fleischer (2002) goes a step further showing that more important than hotel location is whether the room has a sea view. His estimates point to a 10% price differential between rooms with and without sea view. Similarly, using data for both hotels and second homes, Saló et al. (2014) find a price premium of around 15.7% from beachfront view. They also report a smoothly price decrease as the distance between the accommodation and the closest beach increases. The moderating effect of distance on amenities' capitalization is also reported in Saló and Garriga (2011). In a study on the relationship between second-home prices and neighbourhood amenities, they report that prices decrease linearly as the dwelling locates further away from the shoreline.

Overall, the price premium of being close to the beach is widely recognized. However, beaches are highly heterogeneous and less is known yet about the separate capitalization effects of their distinct features. For example, how much are tourists willing to pay for lodging close to a beach with gold sand? Do they attach value to beach accessibility? Does the type of beach frontage affect accommodation prices? What are tourists' economic valuation of a marginal change in beach width? To the authors' knowledge, Rigall-i-Torrent et al. (2011) is the only study that examines the impact of beach characteristics on hotel prices using data for Catalonia. They consider beach width, length, degree of urbanization, type of sand, and the availability of services like WC facilities or umbrellas for rent, among others. They show that beachfront location translates into a price premium of around 17% and that prices decrease as distance to the beach increases. Additionally, prices are negatively correlated with beach width but unrelated to beach length. Interestingly, hotels next to beaches with fine or very fine sand are highly priced. In the current study, we expand their work by focusing on the beach capitalization effects in the Airbnb peer-to-peer rental market, paying attention to the moderating role of distance on amenities' capitalization.

Universitat de les Illes Balears

3. Theoretical framework

3.1.Hedonic prices under perfect competition

Listings offered on Airbnb can be understood as a bundle of characteristics in the sense of Lancaster (1966) that embed a combination of private and public attributes. Conditional on having decided to stay at an Airbnb accommodation, consumers derive utility from the private characteristics of the listing (e.g., size or the type of building) as well as from its geographic location. In this regard, the public characteristics of the area where the accommodation is placed (such as safety, cleanliness or accessibility to natural amenities) are additional sources of utility for a tourist stay. Therefore, consumers' utility per night stay is expressed as follows:

$$U(x, C, Z) \tag{1}$$

where C are Airbnb private attributes c_k (for $k = 1, \ldots K$), Z is a vector of public goods z_m (for $m = 1, \ldots M$) that characterize the environment where the listing is located (e.g., coastal amenities), and x is a composite good to be consumed during the tourist stay. The utility function is assumed to be monotonically increasing in its three arguments so that $\frac{\partial U}{\partial x} > 0$, $\frac{\partial U}{\partial C} > 0$ and that $\frac{\partial U}{\partial Z} > 0$.

Since in equilibrium $MRS_{z_m,X} = p_{z_k}/p_x$ and $p_x = 1$, it holds that consumers' decision regarding the quantity of public attribute z_m embedded into the Airbnb property is optimal when the marginal willingness to pay for such attribute equals the marginal increase in price per change in the attribute m. Therefore, consumers' willingness to pay for the bundle of private and public characteristics embedded in Airbnb listing i (for $i = 1, \ldots, N$) taking utility and income as given is expressed as:

$$WTP_i = \theta\ (c_1, c_2 \ldots, c_k;\ z_1, z_2 \ldots, z_m)_i \tag{2}$$

with $\frac{\partial \theta}{\partial c_k}$ and $\frac{\partial \theta}{z_m}$ being the marginal willingness to pay for private attribute c_k and public attribute z_m, respectively.

Airbnb listings located in areas with a greater supply of public attributes are expected to be highly priced conditional on the same private characteristics. This greater WTP stems from quasi-rents from product differentiation derived from consumers' preferences over site-specific public attributes (Taylor and Smith, 2000).

Let us for the moment assume Airbnb hosts operate in a competitive market. The price at which a host is willing to supply an additional private characteristic (willingness to accept) equals the marginal cost (including opportunity ones). The total price per night is therefore the sum of the shadow prices of each listing attribute. In equilibrium, consumers' willingness to pay for listing i equals its market price ($WTP_i = P_i$) and the marginal willingness to pay for attribute c_k equals its corresponding shadow price ($\frac{\partial \theta}{\partial c_k} = \frac{\partial P}{\partial c_k}$). As a result, the market price of Airbnb listings can be expressed as a function of implicit prices of the private and public characteristics as follows:

$$P_i = f(C_i, Z_i) \tag{3}$$

A regression of observed market prices on private and public attributes will therefore provide estimates of the marginal valuation for the different attributes if consumer preferences are homogeneous (Rosen, 1974). The error term would capture unobserved variability in prices stemming from unobserved characteristics that are assumed to be uncorrelated with the regressors. In case of preference heterogeneity for the attributes, the recovered estimates would be an average WTP across subpopulations.

3.2.Hedonic prices with market power

The hedonic price model presented before assumes perfect competition so that the shadow price of each characteristic is given by the intersection between consumers' willingness to pay and hosts' willingness to accept. This assumption is based on the fact that Airbnb originally emerged as an online platform in which non-professional hosts rented their underutilized space (rooms) to peers, generally at lower prices than the ones charged by traditional market-based accommodations. However, several studies have documented a radical change in Airbnb use, with a substantial share of listings currently managed by a reduced number of hosts, who operate close to business firms. These hosts have been shown to charge higher rates (Gibbs et al., 2018), to be more proficient in dynamic pricing (Kwok and Xie, 2019) and therefore to earn greater revenues (Xie et al., 2021; Casamatta et al., 2022). Since they manage several listings, usually concentred geographically, they are better able to exploit economies of scale (Li and Srinivasan, 2019). This has led to a *professionalization* of Airbnb (Gil and Sequera, 2020; Dogru et al., 2020).

Therefore, Airbnb can be understood as a monopolistic competition market as defined by Chamberlin (1933), where hosts face a downward sloping demand curve. Since professional hosts are motivated by profit maximization, they are expected to keep prices close to the perfect competitive equilibrium under a highly elastic demand and to exert market power under an inelastic demand. Since the demand curve is unobserved from the host viewpoint, they must form a belief. Those managing several properties in the same market and with longer experience (professionals) are predicted to have better knowledge about the market conditions, *ceteris paribus*, and therefore better able to assess market demand. Evidence presented in Gunter et al. (2020) and Bibler et al. (2021) show that Airbnb demand is quite inelastic, which allows professionals to increase revenues via price hiking. In this vein, Casamatta et al. (2022) documents that professionals indeed charge larger prices, particularly during the peak season when demand elasticity is lower.

Similar to Harding et al. (2003) and Cotteleer et al. (2008), we assume a set of host characteristics (including the number of properties as a professionalism indicator) are a valid proxy of the parallel shift in the hedonic price function caused by market power. Therefore, the expanded hedonic pricing function in the presence of market power is given by:

$$P_i = f(C_i, Z_i, H_i) + \epsilon_i \tag{4}$$

where H_i is a set of host characteristics and ϵ_i is the error term[3].

4. Data

4.1. Case study

The Balearic archipelago is a well-known tourism-led economy. According to local statistics (IMPACTUR, 2014), the tourism industry contributes to 45% of regional GDP and 32% of local employment. With more than 13.6 million of international tourist arrivals in 2019 (FRONTUR, 2020), the Balearic Islands are one of the most popular 'sun and beach' tourist destinations worldwide. Domestic tourism accounts for about 17% of arrivals, while most international tourists come from Germany, United Kingdom, Italy and France. Its tourism demand is strongly seasonal, with more than 60% of tourist arrivals concentrated during the summer period.

Beaches are among the main attractions for tourism activities in the Balearic Islands which, paradoxically, have contributed to the degradation of the archipelago's natural resources. As documented in Ghermandi (2015), these islands are characterized by a poor protection status and high erosion risk. Roig-Munar et al. (2019) indicate that the geomorphological and environmental peculiarities of the islands' coastal ecosystems have not been properly considered by local authorities, which has led to suboptimal conservation policies. Coastal management has basically consisted in making beaches functional to satisfy tourists' needs, without paying the needed attention to conservation requirements. This has resulted in a strong exposure to coastal erosion, loss of beach surface and volume, elimination of dune formation and loss of biodiversity, among others (Roig-Munar, et al., 2019).

4.2. Data description

Our analysis uses two types of information: (i) Airbnb listings' prices, their structural characteristics and host features, and (ii) detailed beach amenities. The following paragraphs are devoted to the description of the data sources and variable definition.

[3] As in Feenstra (1995) and Cotteleer et al. (2008), we assume host characteristics (as a proxy of market power) do not interact with the private or public characteristics.

Universitat de les Illes Balears

Airbnb data

Data on Airbnb listings has been obtained from AirDNA and cover the entire Balearic archipelago (Mallorca, Menorca, Ibiza and Formentera). For the month of August 2016, we have information on daily prices and status (*booked*, *blocked, available*) for all the properties listed on Airbnb platform in the islands (N=30,204). Those properties that have not been booked (n=13,541) are excluded from the analysis since their corresponding prices do not reflect equilibrium prices (i.e., inactive accommodations). For the retained sample (n=16,663), we compute the average daily rate (ADR) as the mean price for booked days during August 2016. This variable will act as our dependent variable.

The dataset also provides detailed information about (i) the most relevant structural characteristics of the accommodations (type of property, entire versus shared/private room, minimum required stay, number of bedrooms), (ii) reputation and quality indicators like the number of photos and the rating score from previous guests, which have been shown to explain Airbnb prices (Ert et al., 2016), (iii) rental cancellation policies (Benítez-Aurioles, 2018), and (iv) some other host-specific variables like the experience gained as a host, whether the host holds the *Superhost* badge or the number of listings managed. The latter is considered as a proxy of market power (Casamatta et al., 2022).

Table 1 presents the definition of these variables together with summary statistics. The average daily rate is €257. There is great price dispersion in the dataset, ranging from a minimum of €11 to a maximum of €3,558 per night. Figure A1 in Supplementary Material presents a histogram of the ADR. Its distribution is heavily right skewed.

About 83% of the sample is represented by entire properties. Most of the listings are (or located within) apartments (45%) or houses (34%), with an average of 2.4 bedrooms. The minimum stay demanded by the host is 3.86 nights on average, with each property having around 23 photos. Concerning reputation indicators, approximately 28% of the properties have no visible rating. This might happen because the listing has received less than 3 reviews or because it has never been rented before. For those with a positive number of reviews, more than 40% have received high ratings. This is in line with the existing literature on user-generated content showing that online reviews are left-skewed (Fradkin et al., 2021). Whereas 17% of the host adopt a flexible cancellation policy (no cancellation fees), the vast majority (70%) enforce a strict cancellation policy (no cancellation fees only during the first 48 hours since the booking). The share of properties allowing for an immediate booking is only 26%. This low figure could imply a certain type of screening of guests' profiles and is consistent with potential discrimination as documented in some studies (Edelman et al., 2017; Ahuja and Lyons, 2019). Importantly, only 7% of hosts attain the *Superhost* status. This is a quality badge conceded by the platform to those hosts that satisfy several requirements and represent a relevant quality signal for potential guests.[4]

[4] To become a *Superhost*, the host needs to meet the following criteria: (i) completed a minimum of 10 stays that sum up to 100 nights; (ii) maintained a response rate of 90% or higher; (iii) maintained a cancellation rate of 1% or less; and (v) maintained a general rate of 4.8/5 in the last 365 days (Airbnb, 2021).

Universitat de les Illes Balears

Label	Description	Mean (%)	SD	Min	Max
ADR	Average daily rate	257.94	275.08	11	3,558
Num. days booked	Number of days in August 2016 the listing was booked	16.49	9.43	1	31
Apartment	=1 if apartment	45.21			
House	=1 if house	34.43			
Villa	=1 if villa	10.35			
Chalet	=1 if chalet	2.37			
Other	=1 if bed &breakfast, bungalow, castle, condominium, guesthouse, dorm, loft or townhouse, among others	7.64			
Entire	=1 if entire property	83.34			
Shared/private	=1 if the listing is shared with others/private room	16.66			
Min. Stay	Minimum number of nights required per booking	3.86	2.29	1	90
Bedrooms	Number of bedrooms	2.38	1.45	0	10
Num. Photos	Number of photographs available	22.71	15.70	1	780
Never rated	The listing has never been rated	27.69			
High rate	=1 if 4,5<score rating≤5	41.10			
Medium rate	=1 if 4<score rating≤4,5	19.79			
Low rate	=1 if 0≤score rating≤4	11.40			
Flexible Canc.	Flexible cancellation policy	17.23			
Moderate Canc.	Moderate cancellation policy	11.87			
Strict. Canc.	Strict cancellation policy	69.92			
Instant Booking	Bookings are instantly accepted with no screening needed	25.92			
Superhost	=1 if host attains the 'Superhost' badge	7.38			
Host Experience	Number of days since the account creation	444.47	408.17	5	2,524
Num. listings	Number of listings owned by the host	35.58	118.58	1	624

Table 1.- Definition and descriptive statistics of the property and host characteristics (N=16,663)

On average, hosts' experience in the Airbnb platform is 444 days. However, the large standard deviation (SD=401) indicates the market is composed of both highly experienced and unexperienced hosts. Interestingly, hosts manage on average 35 listings. This high mean value is the result of the process of professionalisation of Airbnb markets that makes it nowadays to be far from the original peer-to-peer sharing paradigm (Gil and Sequera, 2020; Dogru et al., 2020). Indeed, only 36% of listings belong to single unit hosts.

Apart from the above-mentioned property and host characteristics, listings are georeferenced with longitude and latitude coordinates. Most of the listings are located in Mallorca (69%), followed by Ibiza (28%). The remaining 3% is evenly distributed in Formentera and Menorca.

Beach characteristics

The Spanish *Ministerio para la Transición Ecológica y Cambio Demográfico* (MITECO) has made publicly available a cartographic tool that includes detailed geo-referenced information for all the beaches in the country.[5] The dataset is updated annually and includes physical and environmental aspects, geographic extension data and facilities. We retrieved the corresponding dataset for the Balearic Islands in the year 2015. This contains information for a total of 263 beaches: 52% are located in Mallorca, 25% in Ibiza, and the remaining 23% in Menorca and Formentera. From the array of beach characteristics available, we select the following variables for the analysis:

- Length: beach extension (in kilometers)
- Width: width of the beach (in meters). This variable is the average of beach width during low tide and high tide.
- Sand type: dummy variables for the predominant type of sand: white (*Clear Sand*), gold (*Gold Sand*) or dark (*Dark Sand*).
- Type of coastal frontage: dummy variables capturing the type of environment behind the beach. There are five types of coastal frontage in the dataset: urban (*Urban front*), semi-urban (*Semiurban front*), cliff-type (*Cliff front*), mountain-type (*Mountain front*) and dune-type (*Dune front*).
- Vegetation: a dummy for the presence of vegetation in the beach (*Vegetation*).
- Protected area: a dummy indicator for whether the beach contains any protected space (*Protect. Area*), either in the form of *parque natural*, *paisaje protegido*, LIC (*Lugares de Importancia Comunitaria*) or ZEPA (*Zonas de Especial Protección para las Aves*).
- Tide: a dummy for predominant average calm tide (*Calm tide*) as opposed to heavy swell.
- Accessibility: dummy indicators for whether the beach is easily accessible on foot (*Easy Acc*), it has a difficult access (*Diff. Acc*) or it can only be accessed by boat (*Only by boat*).
- Degree of urbanization: this refers to the area in which the beach is located. Three types are distinguished depending on the number of buildings in the surroundings: isolated (*Isolated*), semi-urban (*Semi-Urban*) and urban (*Urban*).[6]

The definition of the beach characteristics presented before is based on objective environmental criteria set by experts at MITECO.[7] The dataset offers other valuable information concerning the presence of different services (toilets, showers, public telephones, bins, cleaning services, tourist office, etc.), the tenure of a promenade or the availability of designed spaces in the beach

[5] The latest version of the dataset can be downloaded at https://www.miteco.gob.es/es/cartografia-y-sig/ide/descargas/costas-medio-marino/guia-playas-descargas.aspx

[6] Although some related studies have paid attention to the economic value of water quality in the real estate market (Leggett and Bockstael, 2000; Walsh et al., 2011; 2017; Calderón-Arrieta et al., 2019), this dimension is not considered. On the one hand, all the beaches in the islands are highly homogeneous in this dimension at the period of analysis, exhibiting high levels of water quality (Consejería de Salud y Consumo, 2016). Therefore, there is not enough water quality variability for the identification of their hedonic value (Leggett and Bockstael, 2000). On the other hand, unlike it happens with other beach amenities, the level of water quality is likely to be an unobserved attribute to potential tourists. Therefore, we assume the impact of this dimension on the willingness to pay is negligible in our context.

[7] While a single annual snapshot of beach characteristics is not ideal, it is the best available information and the common way to proceed in related studies (Landry et al., 2021).

for nudism, scuba diving, surf or children. However, preliminary analyses indicate all these variables are strongly correlated with the length and width of the beach. As such, their inclusion in the analysis will produce serious multicollinearity problems. The beach characteristics presented above and used for the analysis present by contrast low correlation levels so that their joint inclusion in a regression framework does not produce collinearity concerns (see the correlation matrix presented in Table A1 in Supplementary Material).[8]

Table 2 reports descriptive statistics of the beach variables introduced above. The average length is 360 m, with a mean width of 39 m. Nonetheless, there is notable variability in these two dimensions across beaches. Most beaches mainly have white sand (50%) or gold sand (43%). Concerning the type of coastal frontage, 25% and 32% of the beaches present an urban and semi-urban frontage, respectively. Around 16% have a cliff-type frontage while another 16% exhibits a mountain-type frontage. The remaining 8% has a dune-type frontage. Approximately 67% have coastal vegetation in the beach and 57% present calm tide. The share of beaches with protected areas inside them is 35%. The majority are easily accessible on foot (86%), although 2% can only be reached by boat and 9.5% have a difficult access. Finally, 38% are placed in isolated areas, 35% in semi-urban locations and 26% in urban zones.

To study the role of the above-presented beach characteristics on Airbnb property prices, we need a vis-à-vis matching between properties and beaches. Since each property is georeferenced with latitude and longitude coordinates, this was done by computing the Euclidean distance between each property and the shoreline of each beach. Subsequently, each property was only matched with the closest beach. As a result, each of the 16,663 listings in the dataset were linked to one of the 263 beaches in the islands. The average distance to the shoreline is 3.92 km. Due to its greater size, properties in Mallorca islands are on average far more distant (4.92 km on average), than in the other islands (1.95, 1.68 and 1.66 km for the case of Menorca, Ibiza and Formentera, respectively). Nevertheless, about 17% of properties are located within 500 meters from the shoreline while about 33% lie within 1 km.

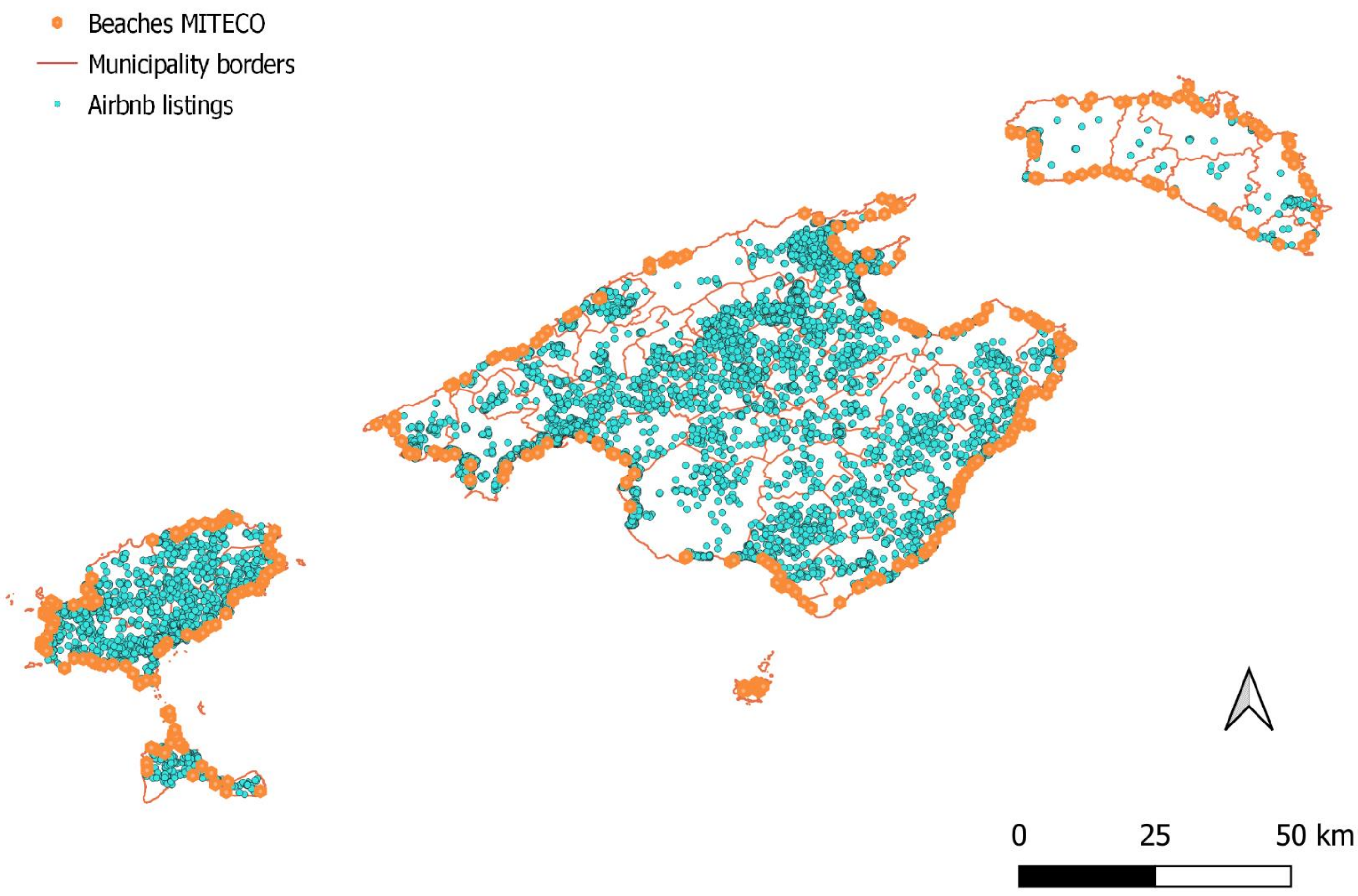
[8] The only exceptions are the categories *Urban* (degree of urbanization) and *Urban front.* (type of coastal frontage), whose correlation amounts to 0.72. For this reason, they are both left as the reference category in each case.

Label	Definition	Mean (%)	SD	Min	Max
Length	Beach length (in kilometers)	0.36	0.685	0.01	4.60
Width	Beach width (in meters)	39.21	36.70	3	250
Clear Sand	=1 if the beach has white sand	50.57			
Gold Sand	=1 if the beach has golden sand	43.34			
Dark Sand	=1 if the beach has dark sand	6.08			
Urban front	=1 if the beach has urban frontage	25.85			
Semiurban front	=1 if the beach has semi-urban frontage	32.69			
Cliff front	=1 if cliffside beach	15.96			
Mountain front	=1 if the beach has a mountain-type frontage	16.73			
Dune front	=1 if the beach has dune-type frontage	8.74			
Calm tide	=1 if the beach presents calm tide	57.03			
Vegetation	=1 if the beach has coastal vegetation	67.30			
Protect. Area	=1 if the beach contains any protected space	35.36			
Easy Acc	=1 if the beach is easily accessible on foot	86.69			
Diff. Acc	=1 if the beach has a difficult access on foot	9.50			
Only by boat	=1 if the beach is only accessible boat	2.28			
Isolated	=1 if the beach is isolated	38.02			
Semi-Urban	=1 if the beach is located in a semi-urban area	35.36			
Urban	=1 if the beach is located in an urban area	26.61			

Table 2.- Definition and descriptive statistics for beach characteristics (N=263)

Figure 1 plots the location of the listings and the beaches in the four islands. Maps were created using QGIS 3.16. Light-blue points represent Airbnb listings, orange points represent beaches while pink lines delimit municipality borders.[9] As can be seen, most of the listings are in Mallorca (69%), followed by Ibiza (28%), Formentera (1.5%) and Menorca (1.5%). However, Ibiza is the island with highest concentration (8.16 listings per km^2), followed by Mallorca (3.15 listings per km^2), Formentera (3.00 listings per km^2) and Menorca (0.36 listings per km^2). In Figure 2, we distinguish between entire properties (yellow dots) and shared properties (light blue dots). Ibiza has the highest proportion of shared properties (25.6%), followed by Menorca (19.4%), Formentera (16.2%) and Mallorca (13.1%).

[9] The municipality raster was downloaded from the website of the Spanish *Centro de Descargas*. https://centrodedescargas.cnig.es/CentroDescargas/linkUnMD. Accessed on December 10th, 2021.


Beaches MITECO
Municipality borders
Airbnb listings
0
25
50 km

Universitat de les Illes Balears

Figure 1.- Geographical distribution of Airbnb listings and MITECO beaches across the Balearic Islands.

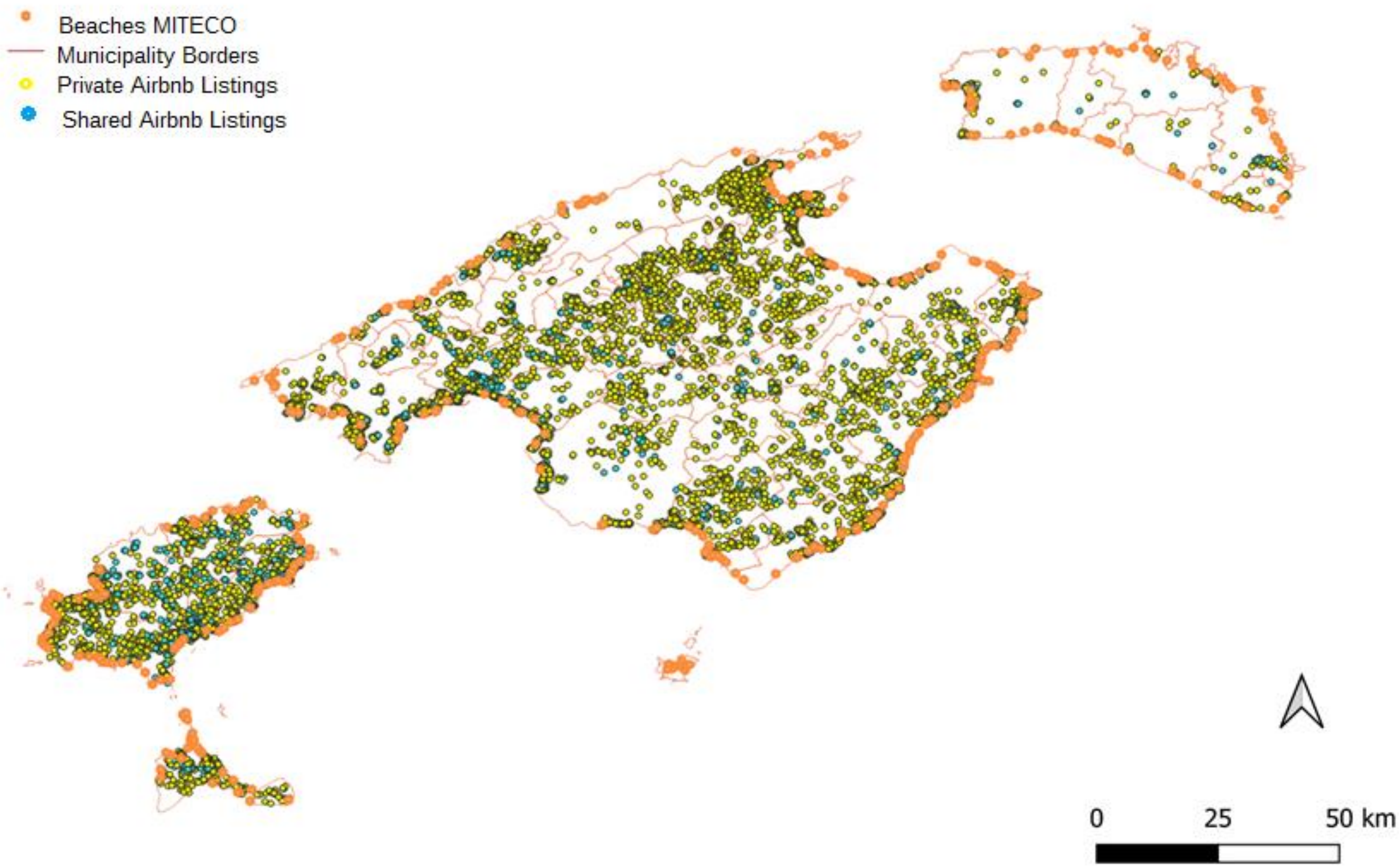


Figure 2.- Geographical distribution of Airbnb listings and MITECO beaches across the Balearic Islands, by property type.

5. Econometric Modelling

Consistent with the theoretical framework presented in Section 3, the baseline empirical model to be estimated is the following:

$$Ln\ ADR_i = \alpha + \beta Beach\ Atrib_i + \theta \ln Distance + \gamma C_i + \delta H_i + Mun\ FE_i + \varepsilon_i \tag{5}$$

where $Ln\ ADR_i$ is the (log of) average daily rate, $Beach\ Atrib_i$ gathers the beach characteristics of interest, $\ln Distance$ measures the Euclidean distance between each listing and the shoreline (in logs), C_i reflects listing structural characteristics, H_i refers to host features, $Mun\ FE_i$ is a set of municipality fixed effects and ε_i is a normally distributed error term.

One unresolved issue when estimating hedonic price models is the appropriate functional form (see on this Cropper et al., 1988). Whereas some use linear specifications, the semi-log specification is by far the most widely used (Gibbons et al., 2014). In the hospitality accommodation context, Faye (2021) advocates for formally testing the appropriate functional form through a Box-Cox regression. Auxiliary Box-Cox regressions (Table A2 in Supplementary Material) provide support for the proposed functional form of the hedonic price function. Log transforming the dependent variable also helps it to resemble the normal distribution (Figure A2 in Supplementary Material).

The inclusion of municipality fixed effects intends to capture any omitted factor at the municipality level that impacts prices, like accessibility to transportation hubs, provision of public services or the sociodemographic composition of the area (Rigall-i-Torrent et al., 2011; Saló et al., 2014). Omitted municipality confounders are a common concern in related works (Leggett and Bockstael, 2000; Landry et al., 2021). Furthermore, the distribution of unobserved characteristics of the listings, tourists' demand for accommodation and competitive rivalry also vary across administrative units. Therefore, these fixed effects capture price shifts across submarkets (Straszheim, 1974), gathering the effect of all public amenities Z_i other than beach characteristics.

As shown in Figures 1 and 2, listings are sparsely distributed throughout the islands. This results in some listings being close to the shoreline while others locating far away. Even though we control for it in the regression, the model in (5) assumes an equal impact of beach characteristics on daily rates for all the sample, regardless of listings' proximity to the coast. Consistent with related studies (Landry and Hindsley, 2011; Saló et al., 2014; Rigall-i-Torrent et all., 2011; Landry et al., 2021), we expect the capitalization effect of coastal amenities to decrease as distance to the beach increases. To capture this *distance-decay* effect, we expand the specification in (5) with interaction terms between the log of distance and beach amenities as follows:

$$\begin{aligned} Ln\ ADR_i = \alpha + \beta Beach\ Atrib_i + \theta \ln Distance + \tau\ Beach\ Atrib_i \times \ln Distance + \gamma C_i \\ + \delta H_i + Mun\ FE_i + \varepsilon_i \end{aligned}$$

(6)

The expanded specification with interactions allows us to test for edge and proximity effects in the sense of Walsh et al. (2011); that is, distinct capitalization effects in listings that are close to the shoreline and listings located further away. As such, the exposure to a specific environmental amenity is moderated by the distance to the shoreline in a non-linear way through the log transformation.

Some aspects concerning our empirical strategy deserve mention. First, unlike other studies in the real estate market, we do not restrict the sample to those units that fall within a certain distance threshold, at least in our main analysis. Related works typically define a distance boundary (usually *ad hoc*) within which environmental amenities would capitalize into property prices (Landry and Hindsley, 2011; Walsch et al., 2017; Catma, 2020). We, instead, assume a continuous distance decay effect. This assumes that capitalization effects expand beyond the immediate vicinity. To inspect potential spatial discontinuities in the relationship between prices and distance to the beach, prior to the analysis we conducted *binscatter* regression (Cattaneo et al., 2021)[10]. We do not detect any clear discontinuity, so we opted for considering the whole sample in the main analysis. Nonetheless, spatial discontinuities are examined later in robustness checks.

Second, we work with a cross-sectional database for the summer peak period rather than longitudinal data for two reasons. On the one hand, it is widely known that panel datasets in a hedonic framework allows the research to control for unobserved quality in the form of fixed effects and lead to unbiased estimates. However, in our case study, the beach amenities are time invariant so their implicit values cannot be separately identified from listing fixed effects.[11] On the other hand, vacation rental markets exhibit high seasonality (particularly coastal ones) so that consumers change the mix of hedonic characteristics selected at different periods, as shown in Smith and Palmquist (1994). As such, using panel data in this context would lead to implicit prices that conflate consumers' WTP for the amenity with intertemporal substitution effects. Therefore, we prefer to estimate the hedonic price function at a given point in time (August 2016).[12]

Third, a key aspect for the parameter identification of beach characteristics and distance to the shoreline conditional on the municipality fixed effects is the existence of sufficient variability

[10] This consists of first computing the residuals from auxiliary regressions of ln ADR and Ln Distance on the control variables and then *binscatter* the means within 20 equal-sized bins. See Figure A3 in Supplementary Material.

[11] If the individual effects are treated as 'random', that imposes the restrictive assumption that unobserved quality is uncorrelated with the structural characteristics. Mundlak correlated random effects modelling requires the regressors to be time variant.

[12] Another reason for the use of panel datasets in hedonic studies using residential property values is that when buying a house consumers consider the future levels of local amenities (they are forward looking), thereby potentially requiring dynamic models for appropriate inference (Bishop and Murphy, 2019). However, the static cross-sectional version of the hedonic price function seems to be appropriate in our setting because consumers demand Airbnb listings for reduced stays, so that they do not care about prospects in the future evolution of environmental amenities.

in the number of beaches (and the associated distance to them) within municipalities. Table A3 in Supplementary Material presents the number of beaches and properties per municipality and the mean distance to the shoreline of all the listings located in each municipality. As shown there, properties are matched to several beaches within municipalities so that beach amenities and municipality fixed effects are separately identified.[13]

Notwithstanding this, the identification of the hedonic price function using cross-sectional data relies on some important assumptions and has some limitations (Gibbons et al., 2014; Landry et al., 2021). Conditional on the large set of controls for intrinsic attributes, host characteristics and municipality fixed effects, we assume independence between unobserved listing attributes and beach amenities. In such case, the estimates for the beach characteristics are consistent. Fourth, standard errors are clustered at the beach level to correct for potential Moulton bias (Moulton, 1990) when specifying aggregate level variables. This is because each Airbnb that is assigned to a specific beach shares a common component of the variance that is not entirely attributable either to their private attributes or to the rest of controls. If not accounted for, this produces the error terms of listings close to the same beach to be positively correlated, leading to a downward bias in the standard errors (see on this Abadie et al., 2017). The clustering adjustment also alleviates potential omitted variable bias from unmeasured beach characteristics.[14]

Finally, to reflect market equilibrium prices, our dataset is restricted to those properties that have been rented at least one night during August 2016. However, as presented in Table 2, there is nonnegligible variation in the number of days each of the retained listings has been occupied. Since there is a clear negative relationship between the number of days booked and the ADR as predicted by microeconomic theory (Figure A4 in Supplementary Material), it seems necessary to weight observations by the number of days the property has been booked during the month (*Num. days booked*). In this way, the estimation of consumers' willingness to pay as a welfare measure for non-marketed goods considers quantity effects in the hedonic framework.[15] Consequently, equations (8) and (9) are estimated by Weighted Ordinary Least Squares (WOLS) using *Num. days booked* as the weighting variable.

6. Results

6.1. Main analysis

[13] The reader might notice that the sum of beaches in each municipality in Table A3 is over 263 (the total number of beaches in the sample). This is because depending on their geographic location, properties within municipalities are matched with the closest beach, which in some cases could be a beach that is physically located in another municipality. In other words, beaches are in some cases matched with properties located in different municipalities.
[14] Note that even if we have information of all beach characteristics that are relevant to consumers it would be unfeasible to include all of them in the regressions. We consider our model specification does a good job in capturing all relevant environmental attributes while minimizing collinearity problems.
[15] This adjustment is similar to the one implemented by Brown and Pollakowski (1977), who weight observations by the inverse of the property size.

Table 3 presents the results for the hedonic regressions. Model 1 reports the estimates from the specification in (5) with no interaction effects; Model 2 shows the results from the full specification in (6). We only report the estimates for the coastal amenities to save space, but the parameter estimates for the rest of controls are presented in Supplementary Material, Table A4.

The distance to the shoreline is not significant for explaining the ADR (neither the partial derivative, see column 2). This is contrary to our expectations, since one would expect daily rates to decrease as we move away from the beach. As shown in Figure A3, Panel D in Supplementary Material, this result is due to the inclusion of municipality fixed effects, which capture common level differences associated with closeness to the beach.

Beach length is positively associated with listings' daily rates. This is consistent with previous studies showing that tourists attach value to longer coastlines (Hamilton, 2007; Onofri and Nunes, 2013). Surprisingly, beach width is not found to exert significant effects on prices. This is contrary to prior works focusing on housing prices (Catma, 2020; Gopalakrishnan, 2016b; Landry and Hindsley, 2011; Landry et al., 2021). Nonetheless, the positive effects of beach width documented in related studies are typically detected only for properties in close proximity to the beach. For instance, Landry and Hindsley (2011) indicate beach width exerts a negative effect on prices in regressions that consider properties threshold points of up to 500 or 600 meters from the shoreline. Moreover, Rigall-i-Torrent et al. (2011) document that beach width is negatively associated with hotel prices in Costa Brava, possibly through a crowding mechanism. Overall, the non-significant effect of beach width could reflect that the hedonic value of size is offset by the disutility of crowded beaches. Additionally, no price differences are detected based on the sand colour.

Concerning the type of beach frontage, tourists are willing to pay more when listings locate close to beaches with semi-urban, cliff-type and mountain-type frontages, respectively (relative to an urban frontage). Plausibly, this finding is explained by an aesthetic motive based on subjective evaluations. In this regard, people have been shown to attach value to open green spaces and scenic amenities (Gibbons et al., 2014; Athukorala et al., 2019). Aesthetics and visual quality have been also revealed as key factors driving tourism demand (Onofri and Nunes, 2013) and residential properties (Lansford and Jones, 1995). For instance, dunes have been found to capitalized into property values (Landry and Hindley, 2011). The degree of urbanization of the area where the beach is located also matters for explaining listings' price: Airbnb guests seem to value more beaches in highly urbanized areas. This likely reflects the fact that beaches with a large number of buildings in its surroundings might convey greater accessibility to ancillary facilities like shops, restaurants or bars and public services like transportation hubs, in line with Rigall-i-Torrent and Fluvià (2011) and Saló et al. (2014).

Universitat de les Illes Balears

Dependent variable: Ln ADR Explanatory variables	(1) Coeff. (SE)	(2) Coeff. (SE)
Ln Distance	0.001	0.029
	(0.007)	(0.039)
Ln Length	0.027***	0.028***
	(0.010)	(0.009)
Ln Length x Ln distance		-0.007
		(0.006)
Ln Width	-0.016	-0.008
	(0.013)	(0.013)
Ln Width x Ln distance		-0.015
		(0.009)
Gold sand	0.014	0.010
	(0.025)	(0.025)
Gold sand x Ln Distance		0.019
		(0.017)
Dark sand	-0.040	-0.052
	(0.043)	(0.038)
Dark sand x Ln Distance		0.021
		(0.023)
Cliff front.	0.094***	0.092***
	(0.033)	(0.034)
Cliff front. x Ln Distance		-0.014
		(0.027)
Semi-urban front.	0.116***	0.119***
	(0.038)	(0.036)
Semi-urban front. x Ln Distance		0.008
		(0.017)
Mountain front.	0.090*	0.129***
	(0.046)	(0.046)
Mountain front. x Ln Distance		-0.059*
		(0.030)
Dune front.	0.112**	0.103**
	(0.044)	(0.046)
Dune front. x Ln Distance		0.017
		(0.031)
Calm tide	-0.022	-0.019
	(0.022)	(0.023)
Calm tide x Ln Distance		-0.006
		(0.013)
Vegetation	0.051**	0.045**
	(0.022)	(0.020)
Vegetation x Ln Distance		0.026*
		(0.014)
Protec. area	-0.007	0.030
	(0.026)	(0.027)
Protect. area x Ln Distance		-0.037**
		(0.017)
Diff. access	0.113***	0.206***
	(0.043)	(0.041)
Diff. access x Ln Distance		-0.106***
		(0.027)
Only by boat	0.094*	0.054
	(0.055)	(0.057)
Only by boat x Ln Distance		0.020
		(0.043)
Isolated envir.	-0.069*	-0.100***
	(0.039)	(0.037)
Isolated envir. x Ln Distance		0.026

		(0.026)
Semi-urban envir.	-0.075**	-0.078**
	(0.033)	(0.031)
Semi-urban envir. x Ln Distance		0.019
		(0.018)
Structural characteristics	YES	YES
Host characteristics	YES	YES
Municipality fixed effects	YES	YES
Constant	3.592***	3.569***
	(0.073)	(0.073)
VIF	4.09	5.69
Observations	16,663	16,663
R-squared	0.746	0.747

Table 3.- WOLS hedonic price regression estimates under different model specifications. Clustered standard errors at the beach level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Acc* and *Urban envir.*

Interestingly, ADRs do not vary depending on whether the beach exhibits an average calm tide. Similarly, the presence of protected natural spaces does not convey any price premium neither. However, vegetation in the beach is found to be associated with higher ADRs. This suggests the green spaces are key attributes for coastal quality, mainly though their aesthetic value. Regarding the role of accessibility, listings close to beaches with a difficult access on foot exhibit higher prices relative to comparable listings close to beaches with an easy access (reference category). This finding falls in line with Rigall-i-Torrent and Fluvià (2011) and might be interpreted in terms of strong preferences for exclusivity. Beaches with a difficult access might be less crowded, thereby offering users more privacy and space for recreation. In this case, the interaction term with the log of distance is negative and significant, implying that the price premium of exclusivity decreases as we move away from the shoreline. Specifically, the positive effect turns zero for listings located 7 km away from the shoreline of difficult-access beaches.

Overall, we find little evidence for distance decay capitalization when considering properties located in the vicinity of the shoreline and properties in inland areas. Most of the interaction terms are not significant. Although this could be partially due to the inclusion of municipality fixed effects in the regression and the clustered standard errors, we believe this might also reflect that capitalization effects in tourism markets operate differently from the housing market, being potentially wider and less concentrated around the shoreline.

Concerning the effect of the rest of control variables, the estimates are consistent with Airbnb hedonic price studies in the tourism literature. Entire properties are more expensive, with daily rates being positively correlated with the number of bedrooms and the minimum stay (Ert et al., 2016; Gibbs et al., 2018). Chalets and villas convey significant price premiums. Properties with strict cancellation policies are more expensive (Faye, 2021; Moreno-Izquierdo et al., 2020), whereas enabling the instant booking option is associated with lower prices (Gibbs et al., 2018; Casamatta et al., 2022). Daily rates increase with host experience and the number of photos (Moreno-Izquierdo et al., 2020; Casamatta et al., 2022). However, holding the *Superhost* badge is not found to be significant. Finally, rates positively increase with the number of listings the host has on property, as also found in Faye (2021), Moreno-Izquierdo et al. (2020) and Gibbs et al. (2018). This result is consistent with our theoretical arguments about the potential exercise of market power. Multi-property host are more likely to better assess the price elasticity of demand and therefore to exercise market power, particularly during the peak season (Casamatta et al., 2022).

6.2.Price premiums and Willingness-to-pay

The marginal WTP for each beach characteristic, *ceteris paribus*, are obtained by partially differentiating the hedonic price function. Table 4 presents the average marginal effects (AME) for each beach amenity (i.e., $\sum_{i=1}^{N}\frac{1}{n}\frac{\partial \ln ADR}{\partial X}$), the corresponding price premiums in percentage terms and the WTP expressed in euros.[16] For the non-significant variables, price premiums and WTP estimates are not computed since they are taken as zero.

Variable	AME	Price premium (%)	WTP (€)
Ln Length	0.024***	2.42	6.24
Ln Width	-0.015		
Gold sand	0.019		
Dark sand	-0.040		
Cliff. front.	0.084***	8.76	22.60
Semi-urban front.	0.123***	13.08	33.74
Mountain front.	0.098**	10.29	26.54
Dune front.	0.111***	11.73	30.26
Calm tide	-0.021		
Vegetation	0.058***	5.97	15.40
Protec. area	0.011		
Diff. access	0.151***	16.20	41.79
Only by boat	0.064		
Isolated envir.	-0.086**	-8.24	-21.25
Semi-urban envir.	-0.068**	-6.57	-16.95

Table 4.- Average marginal effects, price premiums and willingness to pay for beach characteristics.
*** p<0.01, ** p<0.05, * p<0.1

The elasticity of ADRs with respect to beach length is 2.4, which implies that, on average, tourists are willing to pay €6.24 more for a one percent increase in the beach length. Compared to beaches with an urban frontage, beaches with cliff-type, semi-urban type, mountain-type and dune-type frontage register price premiums between 8% and 13%. This implies tourists are willing to pay between €22-€30 to locate in beaches with non-urban frontages. The presence of vegetation is associated with a price premium of around 6%, which corresponds to a WTP of €15.4. Properties close to beaches with difficult access exhibit a 16.2% price premium, which represents around €42 relative to easily accessible beaches. Finally, properties in semi-urban

[16] Consistent with Halvorsen and Palmquist (1980), the price premiums for the dummy variables are calculated as PP=(exp(AME)-1)*100. The WTP is computed by multiplying the price premium by the average daily rate in the sample (€258).

areas are less valued, with tourists' willingness to pay being €17 lower than for properties in urbanized areas. The disamenity value is slightly larger for isolated environments, for whom tourists are willing to pay €21 less per day.

6.3. Distance thresholds

As mentioned before, the related literature has documented that beach capitalization effects vanish from a certain distance threshold onwards. However, conditional on the municipality fixed effects, our regressions do not detect distance decay effects except for the case of the binary indicator for difficult access. To inspect whether our findings could be affected by the spatial extent from the shoreline considered, we repeated our model estimation considering different subsamples. Specifically, we consider subsamples of listings that are located up to 500, 750, 1000, 2000, 3000, 4000 and 5000 meters away from the shoreline. The corresponding estimates are shown in Supplementary Material, Table A5.

Overall, the results of these regressions are in line with those presented in Table 3, both in sign direction and statistical significance. Beach length is positively and significantly associated with ADR, but the magnitude of the effect decreases as we move to subsamples that consider listings located more distant from the beach. Non-urban frontage types are associated with higher prices, with their capitalization effects decreasing as inland listings are added to the sample. Difficult accessibility is consistently found to translate into price premiums, especially when considering subsamples based on small distance thresholds to the shoreline. Surprisingly, the degree of urbanization becomes significant only when listings located up to 3km are included in the analysis.

6.4.Robustness checks

We performed a battery of robustness checks to our main analysis. First, we conducted a stepwise estimation in which the blocks of explanatory variables were sequentially included in the regression. The regression output is shown in Supplementary Material, Table A6. Results prove the importance of controlling for listing structural characteristics and host variables to get finer estimates of the WTP for coastal amenities. The inclusion of municipality fixed effects appears to be particularly relevant as it produces notable changes in magnitude and significance in the coefficient estimates. Second, we re-estimated the model considering different standard error clustering structures. Specifically, we clustered standard errors at the host, postal code and municipality level, respectively. The results from these regressions are presented in Supplementary Material, Table A7. Furthermore, we implemented the arbitrary cluster correlation proposal originally developed by Conley (1999) and recently reformulated by Colella et al. (2019) considering different distance thresholds. The results are shown in Supplementary Material, Table A8. Consistent with the econometric literature on the topic (e.g., Abadie et al., 2017), these results highlight the relevance of allowing for cross-sectional dependence in the residuals, as illustrated in Moulton (1990).

Third, we re-estimated the model using listings' closeness to the beach (inverse of distance) rather than Euclidean distance. This follows Leggett and Bockstael (2000) and Landry et al. (2021). Results are presented in Supplementary Material, Table A9 and are about the same as in the main analysis. Finally, we re-estimated the model in (9) replacing the municipality fixed effects by the following municipality characteristics: population (*Pop*), average age (*Av. Age*), percentage of foreign residents *(% Foreign*), percentage of low educated residents *(% Low educ*), average household size (*Av. House size*), percentage of large dwellings *(% Large dwellings*), gross income (*Gross Income*) and Gini inequality index (*Gini*). In addition, we also control for the degree of market competition in the municipality by including the number of Airbnb listings and the number of hotel beds. A short description of the variables, data sources, descriptive statistics and their construction is available in the Supplementary Material, Table A10. The estimation results are shown in Table A11 in Supplementary Material. We find Airbnb daily rates increase with the number of competitors in the same postal code and the Gini index but decrease with the average age of the neighbourhood. The rest of variables are not significant. In any case, a comparison with the results in Table 3 shows there are notable differences in the point estimates between the two model specifications. This indicates that including the full set of municipality fixed effects better captures all geographic-level confounders.

7. Conclusions

The current study has investigated how peer-to-peer tourist accommodations, traded through Airbnb platform, capitalize the amenity and recreational value of several beach amenities. For the analysis, we have used a large dataset involving 16,663 Airbnb listings in the Balearic Islands that were booked at least one night during August 2016. This case study offers the advantage that no replenishment activities have been undertaken prior to the study period, thereby preventing problems associated with reverse causation (Landry et al., 2021). Using latitude and longitude coordinates, each property has been matched with the closest beach. The environmental characteristics of the 263 beaches in the islands have been retrieved from a dataset provided by MITECO. Using hedonic price modelling, we have estimated the nonmarket implicit prices of several coastal attributes like beach length and width, sand type, presence of vegetation, coastal frontage or accessibility. Our model specification has explicitly allowed for the potential moderating effect of distance documented in previous studies through interaction terms.

According to our results, tourists are willing to pay around €6.24 more per day for a percentage increase in beach length, everything else being equal. Tourists are found to attach value to the presence of vegetation (+€15.4) and prefer beaches with a difficult access over easily accessible ones (+€41.8), which is interpreted in terms of demand for exclusivity and lower occupancy. Interestingly, we find notable price premiums depending on the coastal frontage. In particular, tourists are willing to pay €30.2 and €26.5 per night if the beach has a dune-type of mountain-type frontage over an urban one, *ceteris paribus*. Concerning the degree of urbanization, Airbnb guests prefer urbanized areas (-€17 and -€21.2 per day in the case of beaches in semi-urban or isolated environments, respectively). This likely captures preferences for amenities that

Universitat de les Illes Balears

correlate with the number of buildings in the surroundings of the beach. On the contrary, no significant amenity values are detected for the type of sand, calm tide, beach width or the presence of protected natural spaces. Furthermore, we do not detect prices to decrease as distance to the shoreline increases conditional on municipality fixed effects. Overall, the hedonic estimates suggest Airbnb users attach economic value for non-marketed aspects like beach exclusivity, the presence of aesthetic natural environments and beach length.

The work has relevant implications for coastal management policies. Climate change has increased the frequency of extreme climatic events, which is damaging coastal quality through sea level rise and increasing beach erosion. Beaches represent ecological habitat, aesthetic amenities and serve as a natural protective barrier against storm surge. Beyond that, they represent major attraction factors for tourism activities. Therefore, in areas with strong dependence on the tourism sector, the design and implementation of conservation policies must consider the economic value assigned by tourists to beach characteristics. As discussed in several works (Ghermandi, 2015; Roig-Munar et al., 2019), the Balearic Islands stand as a region with high recreation values but with poor protection status and high erosion risk. Therefore, uncovering tourists' value for coastal amenities offers relevant insights for public authorities to be considered when developing benefit-cost analysis of potential beach nourishment projects. Maintaining high levels of beach quality in the Balearic Islands adds significant value to peer-to-peer rental markets. Although this type of tourist accommodations is associated with some negative externalities, on the positive side they stimulate local economies, represent additional income for residents, satisfy the needs of new consumer segments and provide potential revenues through tourist tax rates.

The paper contributes to the existing literature on the hedonic value of coastal amenities in different ways. First, whereas most studies on the economic value of coastal landscape examine capitalization effects in the real estate market, our study adopts a different perspective and focuses on the economic value of beach amenities from a tourism viewpoint, which has been to some extent neglected to date. Moreover, to our knowledge, this paper is among the first that investigates capitalization effects in the peer-to-peer accommodation market. Apart from their increasing relevance as an accommodation alternative to hotels, Airbnb listings offer some methodological advantages over hotels or the real estate market. On the one hand, since they tend to be more sparsely located across the territory than hotels, we can exploit the variability in geographical location to better identify the influence of beach characteristics on their prices. On the other hand, in contrast to residential markets, Airbnb prices do not conflate the current hedonic value of the property with the expectation on the future evolution of environmental amenities. Second, unlike most studies that focus on a single factor, we have considered the separate hedonic value of different coastal amenities exploiting variability in beach attributes across the 263 beaches in the islands. In doing so, we have examined the economic value of some amenities that have been neglected so far like the type of coastal frontage and beach accessibility. This is relevant, since previous works on the nonmarket value of beach width have not paid much attention to the role of other beach amenities. Finally, unlike other studies that restrict the sample to properties within certain distance thresholds, we have expanded the recipients of beach amenity value to properties both in the surroundings of the shoreline and in inland locations within the islands.

Our analysis has some limitations that we consider as avenues for future research. First, we cannot completely rule out potential biases stemming from omitted variables. This is a common risk in related studies using cross-sectional data. As discussed before, because of the reduced time variability in beach characteristics, the use of longitudinal data makes little sense in the context. In any case, since we control for a wide array of observable characteristics, we consider omitted variable biases are minimized. Second, we do not consider potential spatial dependences in price formation. Although this is partially controlled for through the municipality fixed effects and the standard error clustering structure at the beach level, future studies could expand our analysis using spatial econometrics methods. Finally, for the reasons discussed in the paper, we have used data for the high season (August 2016). Future research should deepen into potential seasonal differences in the capitalization of environmental amenities between low and high seasons.

Universitat de les Illes Balears

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Universitat de les Illes Balears

SUPPLEMENTARY MATERIAL FOR

The hedonic value of coastal amenities in peer-to-peer markets

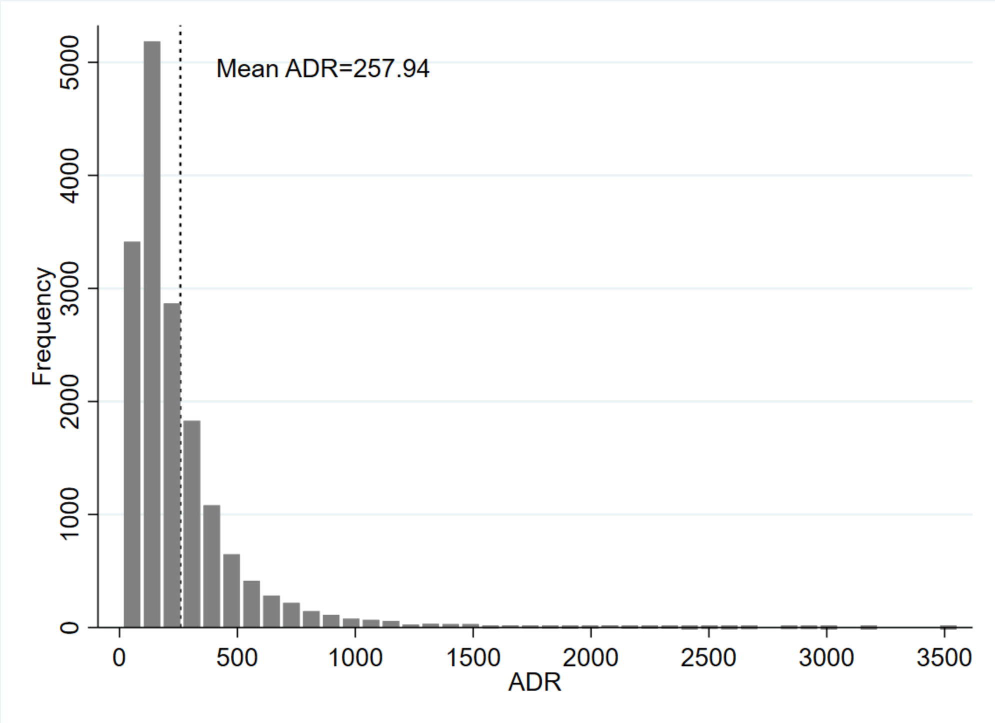

Figure A1.- Histogram of ADR

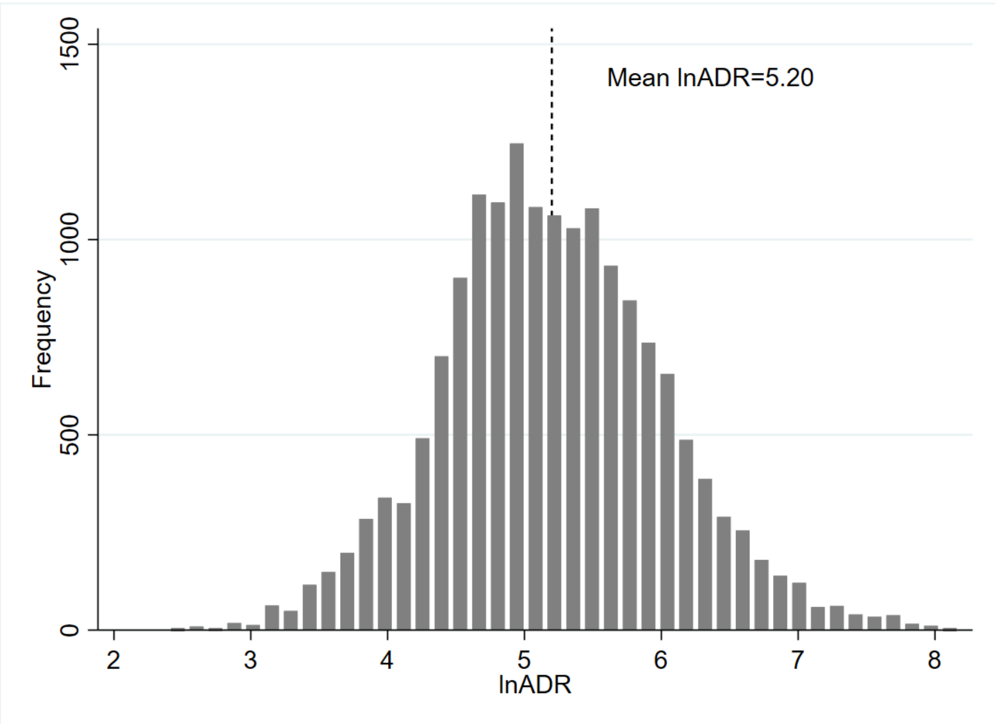

Figure A2.- Histogram of ln ADR

	Length	Width	Isolated	Semi-urban	*Urban*	Gold sand	Dark sand	*White sand*	*Urban front.*	Semi-urban front.	Cliff front.	Mount. front.	Dune front.	Calm tide	Veget.	Protec. area	*Easy access*	Diff. access	Only by boat
Length	1.000																		
Width	0.020	1.000																	
Isolated	-0.035	-0.143	1.000																
Semi-urban	-0.074	0.164	-0.582	1.000															
Urban	0.121	-0.020	-0.469	-0.443	1.000														
Gold sand	-0.111	-0.313	0.204	-0.162	-0.048	1.000													
Dark sand	0.002	-0.119	0.062	0.044	-0.116	-0.222	1.000												
White sand	0.108	0.367	-0.232	0.140	0.103	-0.884	-0.259	1.000											
Urban front.	0.138	0.005	-0.460	-0.197	0.722	-0.033	-0.113	0.087	1.000										
Semi-urban front.	-0.019	0.163	-0.331	0.483	-0.159	-0.198	0.059	0.168	-0.409	1.000									
Cliff front.	-0.132	-0.157	0.299	0.085	-0.237	0.060	0.105	-0.110	-0.256	-0.305	1.000								
Mount. front.	-0.168	0.122	0.487	-0.248	-0.268	0.206	-0.029	-0.190	-0.263	-0.314	-0.196	1.000							
Dune front.	0.214	0.085	0.228	-0.061	0.185	0.029	-0.022	-0.018	-0.181	-0.216	-0.135	-0.139	1.000						
Calm tide	0.049	0.078	-0.093	0.034	0.065	-0.159	-0.132	0.221	0.051	0.034	-0.102	-0.041	0.052	1.000					
Veget.	0.074	0.181	0.057	0.156	-0.233	-0.153	0.040	0.133	-0.191	0.137	-0.230	0.203	0.097	-0.109	1.000				
Protec. area	0.168	0.034	0.418	-0.150	0.298	0.078	0.077	-0.115	-0.306	-0.161	0.132	0.179	0.333	-0.175	0.207	1.000			
Easy access	0.169	0.130	-0.361	0.150	0.234	-0.179	0.053	0.152	0.230	0.250	-0.317	-0.363	0.121	0.201	-0.008	-0.248	1.000		
Diff. access	-0.144	-0.081	0.306	-0.132	-0.194	0.137	-0.028	-0.122	-0.190	-0.227	0.247	0.340	-0.100	-0.137	0.086	0.220	-0.827	1.000	
Only by boat	0.060	-0.125	0.195	-0.113	-0.091	0.124	-0.039	-0.104	-0.089	-0.107	0.211	0.067	-0.047	-0.124	-0.166	0.099	-0.389	-0.049	1.000

Universitat de les Illes Balears

Table A1.- Correlation matrix for beach characteristics (N=262)

Note: The variables in italics are the excluded category for the regressions

Universitat de les Illes Balears

Dependent variable: ADR	(1)	(2)	(3)	(4)
Lambda	-0.027***	-0.028***	-0.027***	-0.027***
	(0.005)	(0.005)	(0.005)	(0.005)
Beach variables	YES	YES	YES	YES
Structural characteristics	YES	YES	YES	YES
Host characteristics	YES	YES	YES	YES
Municipality fixed effects	YES	YES	YES	YES
Observations	16,663	16,663	16,663	16,663

Table A2.- Box Cox regressions assuming a common lambda parameter. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note: Column 1 reports the results from a common transformation for ADR, Length, Width and Distance. Column 2 only computes the required transformation for ADR and Length; Column 3 only for ADR and Width; Column 4 only for ADR and Distance.

The estimated value of lambda is in all cases statistically significant. Because the point estimate is closer to zero than to one, the Box Cox regression provides greater support for a log-log model (Cameron and Trivedi, 2009, p.94).

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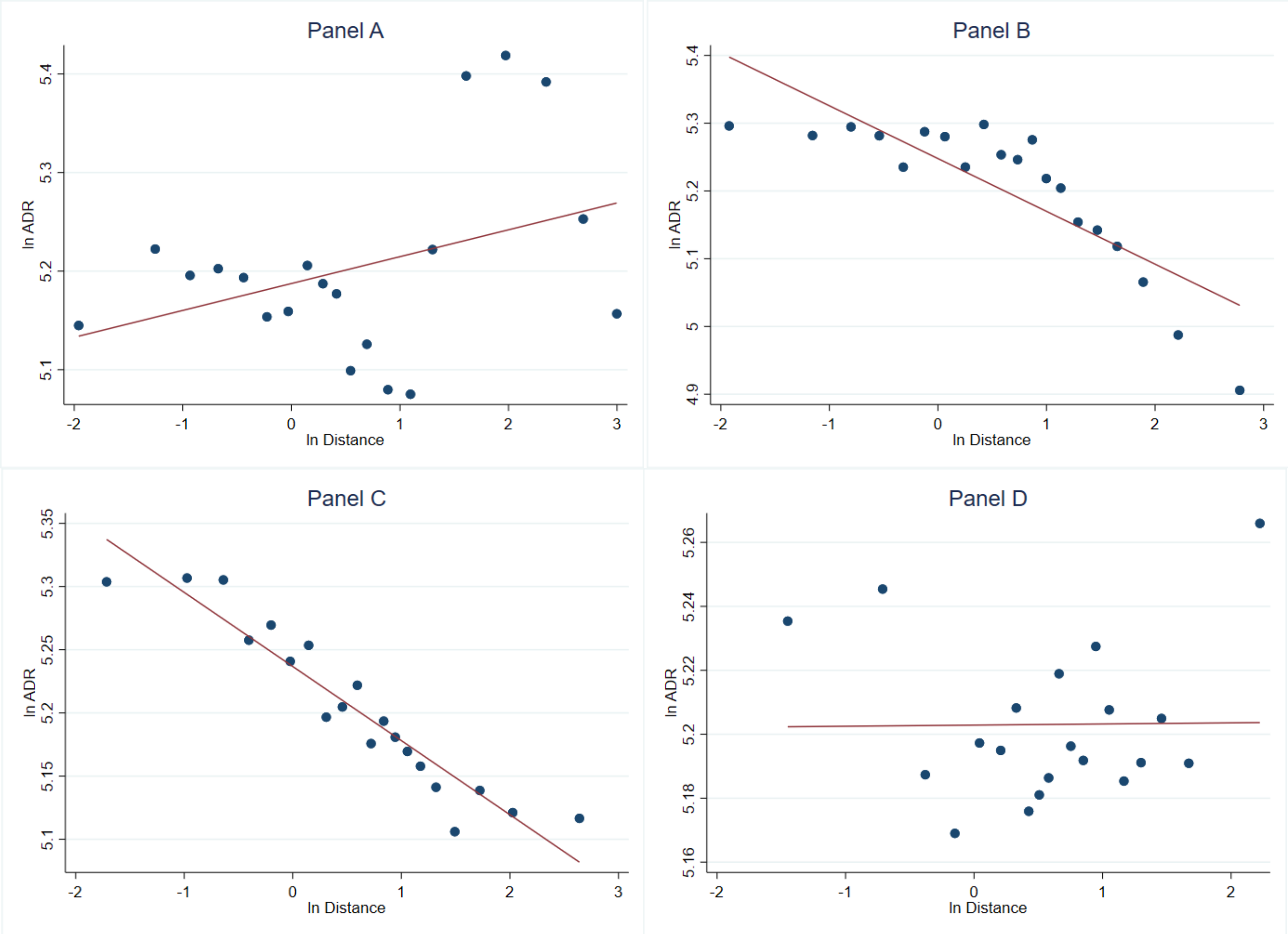

Figure A3.- Binscatter regression plot of ln ADR on ln Distance.

Note: Panel A presents the unconditional relationship between ln ADR and ln Distance to the shoreline. Panel B controls for listing and host characteristics. Panel C adds beach characteristics as an additional control. Panel D further adds municipality fixed effects. The inclusion of municipality fixed effects reverts the negative relationship between ln ADR and ln Distance to the shoreline as they capture level differences in listings' closeness to the shoreline across municipalities (see Table A3 below).

Universitat de les Illes Balears

Municipality	#distinct beaches	#Airbnb properties	Mean distance to the shoreline (km)
Alaró	2	68	14.712
Alcudia	6	809	1.632
Algaida	3	108	17.362
Andrach	13	173	1.969
Ariany	3	28	13.254
Artá	10	218	3.819
Bañalbufar	1	28	0.715
Binisalem	4	76	18.893
Búger	3	81	16.757
Buñola	8	76	10.242
Calviá	13	661	1.047
Campanet	3	82	15.942
Campos	12	516	4.588
Capdepera	12	251	1.029
Consell	2	19	18.270
Costitx	5	52	24.392
Deyá	3	82	1.386
Escorca	4	19	4.249
Esporlas	3	88	4.811
Estellenchs	1	17	1.100
Felanich	8	240	7.216
Fornalutx	2	57	5.133
Inca	3	135	18.945
Lloret de Vista Alegre	2	25	25.495
Lloseta	2	51	16.172
Llubí	1	91	16.515
Lluchmayor	7	319	4.866
Manacor	19	481	4.830
Mancor del Valle	1	30	12.910
María de la Salud	2	37	13.800
Marrachí	4	98	9.482
Montuiri	1	50	23.568
Muro	1	69	10.358
Palma de Mallorca	12	2,933	1.951
Petra	3	34	18.248
Pollensa	8	879	3.330
Porreras	4	55	17.604
La Puebla	3	173	11.633
Puigpuñent	3	43	6.700
Las Salinas	8	177	1.765
San Juan	4	35	23.591
San Lorenzo de Cardessar	9	83	8.728

Universitat de les Illes Balears

Sancellas	3	75	21.967
Santa Eugenia	1	36	15.773
Santa Margarita	7	530	2.974
Santa María del Camino	4	51	14.556
Santañy	14	437	1.895
Selva	2	157	14.341
Sineu	2	53	20.137
Sóller	3	250	2.592
Son Servera	9	223	1.186
Valldemosa	4	95	3.091
Villafranca de Bonany	3	42	22.180
Eivissa	5	1,59	1.034
Santa Eulalia del Río	26	1,054	2.051
Sant Joan de Labritja	16	262	3.133
Sant Jusep de sa Talaia	33	1,303	1.304
Sant Antoni de Portmany	11	406	3.501
Ciutadella	12	99	0.953
Ferreries	3	11	2.272
Es Mercadal	4	25	1.948
Es Migjorn Gran	2	6	1.300
Alaior	3	15	3.864
Maó	5	43	3.876
Es Castell	2	12	2.386
Sant Lluis	4	26	1.309
Formentera	12	315	1.660

Table A3.- List of municipalities in the sample, number of beaches and properties per municipality, and mean distance to the shoreline per municipality.

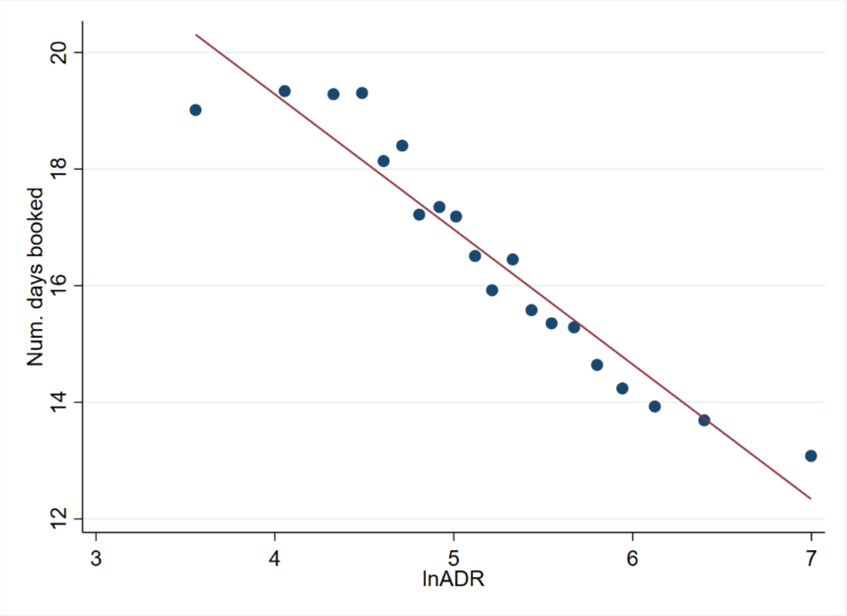

Figure A4.- Binscatter relationship between the number of days the property is booked and the (log of) ADR

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Dependent variable: Ln ADR Explanatory variables	(1) Coeff. (SE)	(2) Coeff. (SE)
Ln Distance	0.001 (0.007)	0.029 (0.039)
Ln Length	0.027*** (0.010)	0.028*** (0.009)
Ln Length x Ln distance		-0.007 (0.006)
Ln Width	-0.016 (0.013)	-0.008 (0.013)
Ln Width x Ln distance		-0.015 (0.009)
Gold sand	0.014 (0.025)	0.010 (0.025)
Gold sand x Ln Distance		0.019 (0.017)
Dark sand	-0.040 (0.043)	-0.052 (0.038)
Dark sand x Ln Distance		0.021 (0.023)
Cliff front.	0.094*** (0.033)	0.092*** (0.034)
Cliff front. x Ln Distance		-0.014 (0.027)
Semi-urban front.	0.116*** (0.038)	0.119*** (0.036)
Semi-urban front. x Ln Distance		0.008 (0.017)
Mountain front.	0.090* (0.046)	0.129*** (0.046)
Mountain front. x Ln Distance		-0.059* (0.030)
Dune front.	0.112** (0.044)	0.103** (0.046)
Dune front. x Ln Distance		0.017 (0.031)
Calm tide	-0.022 (0.022)	-0.019 (0.023)
Calm tide x Ln Distance		-0.006 (0.013)
Vegetation	0.051** (0.022)	0.045** (0.020)
Vegetation x Ln Distance		0.026* (0.014)
Protec. area	-0.007 (0.026)	0.030 (0.027)
Protect. area x Ln Distance		-0.037** (0.017)
Diff. access	0.113*** (0.043)	0.206*** (0.041)
Diff. access x Ln Distance		-0.106*** (0.027)
Only by boat	0.094* (0.055)	0.054 (0.057)
Only by boat x Ln Distance		0.020 (0.043)
Isolated envir.	-0.069* (0.039)	-0.100*** (0.037)
Isolated envir. x Ln Distance		0.026

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de les Illes Balears

		(0.026)
Semi-urban envir.	-0.075**	-0.078**
	(0.033)	(0.031)
Semi-urban envir. x Ln Distance		0.019
		(0.018)
Apartment	-0.107***	-0.108***
	(0.023)	(0.023)
House	0.037	0.033
	(0.023)	(0.024)
Villa	0.283***	0.278***
	(0.026)	(0.026)
Chalet	0.100***	0.094***
	(0.026)	(0.026)
Entire	0.652***	0.651***
	(0.036)	(0.037)
Minimum stay	0.008***	0.008***
	(0.003)	(0.003)
Bedrooms	0.265***	0.265***
	(0.009)	(0.009)
Number of photos	0.003***	0.003***
	(0.001)	(0.001)
Never rated	0.274***	0.274***
	(0.019)	(0.019)
High rated	0.088***	0.088***
	(0.009)	(0.009)
Low rated	0.060***	0.061***
	(0.014)	(0.014)
Canc. policy: Moderate	-0.025	-0.024
	(0.017)	(0.017)
Canc. Policy: Strict	0.115***	0.114***
	(0.012)	(0.012)
Instant booking	-0.038***	-0.037***
	(0.012)	(0.012)
Superhost	0.002	0.004
	(0.018)	(0.018)
Host experience	5.2e-05***	-5.2e-05***
	(1.5e-05)	(1.5e-05)
Host number of listings	8.5e-05**	8.8e-05**
	(3.9e-05)	(3.9e-05)
Municipality fixed effects	YES	YES
Constant	3.592***	3.569***
	(0.073)	(0.073)
Observations	16,663	16,663
R-squared	0.746	0.747

Table A4.- WOLS hedonic price regression estimates (full) under different model specifications. Clustered standard errors at the beach level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac*, *Urban envir.*, *Other*, *Shared/private*, *Medium rate* and *Flexible Canc.*

Universitat
de les Illes Balears

Dependent variable: Ln ADR	(1) Less than 500 m.	(2) Less than 750 m.	(3) Less than 1,000 m	(4) Less than 2,000 m.	(5) Less than 3,000 m.	(6) Less than 4,000 m	(7) Less than 5,000 m
Explanatory variables	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)
Ln Distance	-0.000	0.106	0.006	0.102	0.122**	0.090*	0.085*
	(0.113)	(0.083)	(0.073)	(0.067)	(0.054)	(0.053)	(0.049)
Ln Length	-0.005	0.041**	0.040***	0.038***	0.038***	0.037***	0.034***
	(0.025)	(0.020)	(0.015)	(0.012)	(0.011)	(0.010)	(0.010)
Ln Length x Ln distance	-0.015	0.012	0.011	0.008	0.009	0.006	0.004
	(0.014)	(0.012)	(0.011)	(0.011)	(0.008)	(0.008)	(0.007)
Ln Width	0.019	-0.037	-0.013	-0.028*	-0.023	-0.019	-0.014
	(0.043)	(0.029)	(0.024)	(0.016)	(0.014)	(0.013)	(0.013)
Ln Width x Ln distance	-0.012	-0.047**	-0.029	-0.042**	-0.040***	-0.033***	-0.029**
	(0.026)	(0.019)	(0.018)	(0.017)	(0.013)	(0.013)	(0.011)
Gold sand	-0.008	-0.027	0.005	-0.002	-0.009	-0.002	-0.004
	(0.082)	(0.058)	(0.048)	(0.025)	(0.024)	(0.024)	(0.024)
Gold sand x Ln Distance	0.003	-0.009	0.011	-0.004	-0.020	-0.010	-0.011
	(0.049)	(0.034)	(0.028)	(0.029)	(0.024)	(0.022)	(0.021)
Dark sand	-0.152	-0.022	-0.042	-0.067	-0.074**	-0.073**	-0.078**
	(0.165)	(0.110)	(0.069)	(0.041)	(0.034)	(0.034)	(0.035)
Dark sand x Ln Distance	-0.034	0.068	0.048	0.010	-0.023	-0.002	-0.008
	(0.102)	(0.079)	(0.051)	(0.039)	(0.038)	(0.038)	(0.038)
Cliff front.	0.074	0.033	0.111**	0.104**	0.109***	0.121***	0.114***
	(0.082)	(0.054)	(0.054)	(0.045)	(0.040)	(0.037)	(0.036)
Cliff front. x Ln Distance	-0.001	-0.025	0.046	0.040	0.047	0.054*	0.039
	(0.055)	(0.041)	(0.038)	(0.034)	(0.032)	(0.029)	(0.027)
Semi-urban front.	-0.130*	-0.021	0.041	0.148***	0.135***	0.135***	0.138***
	(0.072)	(0.042)	(0.041)	(0.046)	(0.040)	(0.035)	(0.033)
Semi-urban front. x Ln Distance	-0.088*	-0.027	0.009	0.076*	0.057*	0.055**	0.052**
	(0.048)	(0.034)	(0.039)	(0.046)	(0.033)	(0.027)	(0.023)
Mountain front.	-0.030	0.227**	0.240***	0.181***	0.161***	0.145***	0.146***
	(0.182)	(0.105)	(0.091)	(0.063)	(0.055)	(0.048)	(0.047)
Mountain front. x Ln Distance	-0.071	0.067	0.089	0.027	0.016	-0.024	-0.025
	(0.095)	(0.076)	(0.074)	(0.057)	(0.046)	(0.041)	(0.040)
Dune front.	0.177	-0.127	0.084	0.148**	0.127**	0.123**	0.132**
	(0.282)	(0.198)	(0.126)	(0.058)	(0.059)	(0.056)	(0.051)

Dune front. x Ln Distance	0.075	-0.213	-0.031	0.018	-0.054	-0.012	-0.001
	(0.247)	(0.230)	(0.167)	(0.085)	(0.065)	(0.063)	(0.055)
Calm tide	-0.125**	-0.038	0.007	-0.018	-0.017	-0.022	-0.030
	(0.062)	(0.051)	(0.037)	(0.027)	(0.026)	(0.024)	(0.023)
Calm tide x Ln Distance	0.001	0.039	0.060**	0.017	0.007	0.003	-0.010
	(0.036)	(0.031)	(0.027)	(0.025)	(0.018)	(0.017)	(0.016)
Vegetation	0.067	0.042	0.067	0.037	0.028	0.036	0.036
	(0.064)	(0.050)	(0.043)	(0.029)	(0.025)	(0.022)	(0.022)
Vegetation x Ln Distance	-0.014	-0.019	0.006	-0.003	-0.011	0.008	0.010
	(0.037)	(0.028)	(0.024)	(0.022)	(0.019)	(0.018)	(0.017)
Protec. area	0.055	-0.019	-0.040	-0.018	0.004	0.015	0.013
	(0.125)	(0.080)	(0.056)	(0.039)	(0.034)	(0.031)	(0.029)
Protect. area x Ln Distance	0.130	0.073	0.037	0.006	0.002	-0.014	-0.025
	(0.083)	(0.057)	(0.042)	(0.030)	(0.026)	(0.027)	(0.025)
Diff. access	0.625***	0.238*	0.196*	0.233***	0.218***	0.220***	0.211***
	(0.178)	(0.144)	(0.115)	(0.064)	(0.052)	(0.043)	(0.043)
Diff. access x Ln Distance	0.218**	-0.012	-0.055	-0.046	-0.088*	-0.096*	-0.109**
	(0.099)	(0.109)	(0.102)	(0.062)	(0.047)	(0.054)	(0.044)
Only by boat	-5.116***	-0.065	-0.114	0.017	0.052	0.066	0.070
	(0.793)	(0.281)	(0.117)	(0.087)	(0.078)	(0.070)	(0.069)
Only by boat x Ln Distance	-5.583***	-0.493	-0.723***	-0.305***	-0.250***	-0.158*	-0.117
	(0.859)	(0.468)	(0.099)	(0.095)	(0.092)	(0.094)	(0.083)
Isolated envir.	-0.067	-0.012	-0.084	-0.071	-0.067	-0.069*	-0.076*
	(0.104)	(0.083)	(0.068)	(0.052)	(0.046)	(0.041)	(0.040)
Isolated envir. x Ln Distance	-0.061	-0.013	-0.069	-0.026	0.011	0.032	0.028
	(0.077)	(0.074)	(0.067)	(0.047)	(0.038)	(0.037)	(0.035)
Semi-urban envir.	-0.065	0.016	-0.020	-0.079*	-0.084**	-0.081**	-0.078**
	(0.072)	(0.047)	(0.043)	(0.046)	(0.039)	(0.034)	(0.033)
Semi-urban envir. x Ln Distance	0.013	0.064**	0.030	-0.018	-0.008	-0.001	0.001
	(0.045)	(0.029)	(0.027)	(0.036)	(0.028)	(0.024)	(0.022)
Municipality fixed effects	YES	YES	YES				
Constant	3.448***	3.683***	3.517***	3.572***	3.562***	3.537***	3.522***
	(0.201)	(0.153)	(0.122)	(0.078)	(0.071)	(0.068)	(0.067)
Observations	2,859	4,329	5,544	9,592	11,263	12,376	12,931
R-squared	0.733	0.727	0.733	0.749	0.760	0.765	0.767

Table A5.- WOLS hedonic price regression estimates considering different distance thresholds. Clustered standard errors at the beach level in parentheses. *** p<0.01, **p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac* and *Urban envir.*

Universitat de les Illes Balears

Dependent variable: Ln ADR Explanatory variables	(1) Coeff. (SE)	(2) Coeff. (SE)	(3) Coeff. (SE)	(4) Coeff. (SE)	(5) Coeff. (SE)
Ln Distance	0.002	-0.068***	-0.063***	0.001	0.029
	(0.018)	(0.017)	(0.016)	(0.007)	(0.039)
Ln Length	0.017	0.032	0.030	0.027***	0.028***
	(0.031)	(0.027)	(0.025)	(0.010)	(0.009)
Ln Length x Ln distance	0.000				-0.007
					(0.006)
Ln Width	-0.055	-0.085**	-0.080**	-0.016	-0.008
	(0.044)	(0.037)	(0.034)	(0.013)	(0.013)
Ln Width x Ln distance					-0.015
					(0.009)
Gold sand	0.106	0.259***	0.247***	0.014	0.010
	(0.089)	(0.070)	(0.065)	(0.025)	(0.025)
Gold sand x Ln Distance					0.019
					(0.017)
Dark sand	-0.058	0.056	0.050	-0.040	-0.052
	(0.098)	(0.102)	(0.093)	(0.043)	(0.038)
Dark sand x Ln Distance					0.021
					(0.023)
Cliff front.	0.006	0.095	0.083	0.094***	0.092***
	(0.176)	(0.112)	(0.105)	(0.033)	(0.034)
Cliff front. x Ln Distance					-0.014
					(0.027)
Semi-urban front.	0.328**	0.175	0.164	0.116***	0.119***
	(0.149)	(0.117)	(0.110)	(0.038)	(0.036)
Semi-urban front. x Ln Distance					0.008
					(0.017)
Mountain front.	0.110	0.225*	0.205*	0.090*	0.129***
	(0.172)	(0.124)	(0.116)	(0.046)	(0.046)
Mountain front. x Ln Distance					-0.059*
					(0.030)
Dune front.	0.154	0.136	0.122	0.112**	0.103**
	(0.188)	(0.153)	(0.143)	(0.044)	(0.046)
Dune front. x Ln Distance					0.017
					(0.031)
Calm tide	0.233*	0.265***	0.247***	-0.022	-0.019
	(0.122)	(0.085)	(0.079)	(0.022)	(0.023)
Calm tide x Ln Distance					-0.006
					(0.013)
Vegetation	0.134	-0.001	-0.004	0.051**	0.045**
	(0.091)	(0.073)	(0.068)	(0.022)	(0.020)
Vegetation x Ln Distance					0.026*
					(0.014)
Protec. area	-0.145	-0.112	-0.103	-0.007	0.030
	(0.089)	(0.077)	(0.071)	(0.026)	(0.027)
Protect. area x Ln Distance					-0.037**
					(0.017)
Diff. access	0.119	0.051	0.063	0.113***	0.206***
	(0.134)	(0.097)	(0.090)	(0.043)	(0.041)
Diff. access x Ln Distance					-0.106***
					(0.027)
Only by boat	0.139	-0.155	-0.144	0.094*	0.054
	(0.155)	(0.117)	(0.108)	(0.055)	(0.057)
Only by boat x Ln Distance					0.020
					(0.043)
Isolated envir.	0.266*	-0.019	-0.013	-0.069*	-0.100***
	(0.148)	(0.104)	(0.097)	(0.039)	(0.037)

Isolated envir. x Ln Distance					0.026
					(0.026)
Semi-urban envir.	0.065	-0.003	0.006	-0.075**	-0.078**
	(0.120)	(0.092)	(0.086)	(0.033)	(0.031)
Semi-urban envir. x Ln Distance					0.019
					(0.018)
Structural characteristics	NO	YES	YES	YES	YES
Host characteristics	NO	NO	YES	YES	YES
Municipality fixed effects	NO	NO	NO	YES	YES
Constant	4.924***	3.867***	3.844***	3.592***	3.569***
	(0.245)	(0.195)	(0.185)	(0.073)	(0.073)
Observations	16,663	16,663	16,663	16,663	16,663
R-squared	0.075	0.643	0.658	0.746	0.747

Table A6.- WOLS hedonic price regression estimates under stepwise estimation. Clustered standard errors at the beach level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac* and *Urban envir*.

Universitat de les Illes Balears

Dependent variable: Ln ADR	(1) Default	(2) Clustered at host level	(3) Clustered at postal code level	(4) Clustered at municipality level
Explanatory variables	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	
Ln Distance	0.029	0.029	0.029	0.029
	(0.022)	(0.026)	(0.034)	(0.035)
Ln Length	0.028***	0.028***	0.028**	0.028**
	(0.005)	(0.006)	(0.011)	(0.013)
Ln Length x Ln distance	-0.007*	-0.007	-0.007	-0.007
	(0.004)	(0.004)	(0.005)	(0.006)
Ln Width	-0.008	-0.008	-0.008	-0.008
	(0.007)	(0.009)	(0.014)	(0.015)
Ln Width x Ln distance	-0.015***	-0.015**	-0.015*	-0.015*
	(0.006)	(0.007)	(0.008)	(0.008)
Gold sand	0.010	0.010	0.010	0.010
	(0.013)	(0.015)	(0.026)	(0.029)
Gold sand x Ln Distance	0.019**	0.019	0.019	0.019
	(0.010)	(0.011)	(0.016)	(0.016)
Dark sand	-0.052*	-0.052	-0.052*	-0.052*
	(0.030)	(0.033)	(0.030)	(0.031)
Dark sand x Ln Distance	0.021	0.021	0.021	0.021
	(0.020)	(0.023)	(0.023)	(0.023)
Cliff front.	0.092***	0.092***	0.092**	0.092**
	(0.021)	(0.024)	(0.037)	(0.041)
Cliff front. x Ln Distance	-0.014	-0.014	-0.014	-0.014
	(0.016)	(0.019)	(0.028)	(0.038)
Semi-urban front.	0.119***	0.119***	0.119***	0.119***
	(0.013)	(0.016)	(0.034)	(0.034)
Semi-urban front. x Ln Distance	0.008	0.008	0.008	0.008
	(0.011)	(0.013)	(0.022)	(0.027)
Mountain front.	0.129***	0.129***	0.129**	0.129***
	(0.032)	(0.036)	(0.053)	(0.044)
Mountain front. x Ln Distance	-0.059**	-0.059**	-0.059*	-0.059
	(0.023)	(0.027)	(0.032)	(0.036)
Dune front.	0.103***	0.103**	0.103**	0.103**
	(0.033)	(0.041)	(0.046)	(0.046)
Dune front. x Ln Distance	0.017	0.017	0.017	0.017
	(0.025)	(0.032)	(0.030)	(0.032)
Calm tide	-0.019	-0.019	-0.019	-0.019
	(0.012)	(0.015)	(0.029)	(0.029)
Calm tide x Ln Distance	-0.006	-0.006	-0.006	-0.006
	(0.008)	(0.010)	(0.011)	(0.009)
Vegetation	0.045***	0.045***	0.045**	0.045**
	(0.012)	(0.014)	(0.019)	(0.020)
Vegetation x Ln Distance	0.026***	0.026**	0.026	0.026
	(0.009)	(0.011)	(0.017)	(0.021)
Protec. area	0.030	0.030	0.030	0.030
	(0.021)	(0.023)	(0.027)	(0.027)
Protect. area x Ln Distance	-0.037***	-0.037***	-0.037**	-0.037
	(0.013)	(0.014)	(0.018)	(0.023)
Diff. access	0.206***	0.206***	0.206***	0.206***
	(0.034)	(0.039)	(0.047)	(0.053)
Diff. access x Ln Distance	-0.106***	-0.106***	-0.106***	-0.106***
	(0.024)	(0.029)	(0.031)	(0.039)
Only by boat	0.054	0.054	0.054	0.054
	(0.069)	(0.077)	(0.064)	(0.068)
Only by boat x Ln Distance	0.020	0.020	0.020	0.020

Universitat de les Illes Balears

	(0.041)	(0.050)	(0.056)	(0.063)
Isolated envir.	-0.100***	-0.100***	-0.100**	-0.100**
	(0.023)	(0.027)	(0.043)	(0.041)
Isolated envir. x Ln Distance	0.026	0.026	0.026	0.026
	(0.018)	(0.020)	(0.026)	(0.031)
Semi-urban envir.	-0.078***	-0.078***	-0.078**	-0.078**
	(0.016)	(0.018)	(0.031)	(0.032)
Semi-urban envir. x Ln Distance	0.019	0.019	0.019	0.019
	(0.012)	(0.014)	(0.018)	(0.022)
Structural characteristics	YES	YES	YES	YES
Host characteristics	YES	YES	YES	YES
Municipality fixed effects	YES	YES	YES	YES
Constant	3.569***	3.569***	3.569***	3.569***
	(0.076)	(0.087)	(0.073)	(0.080)
Observations	16,663	16,663	16,663	16,663
R-squared	0.747	0.747	0.747	0.747

Table A7.- WOLS hedonic price regression estimates under different standard error clustering structures (in parentheses). *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac* and *Urban envir.*

Universitat de les Illes Balears

Dependent variable: Ln ADR	(1) Dist. Cutoff=250 m	(2) Dist. Cutoff=500 m	(3) Dist. Cutoff=750 m	(4) Dist. Cutoff=1000 m
Explanatory variables	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)
Ln Distance	0.029	0.029	0.029	0.029
	(0.032)	(0.031)	(0.029)	(0.026)
Ln Length	0.028***	0.028***	0.028***	0.028***
	(0.009)	(0.009)	(0.008)	(0.007)
Ln Length x Ln distance	-0.007	-0.007	-0.007	-0.007
	(0.006)	(0.006)	(0.005)	(0.005)
Ln Width	-0.008	-0.008	-0.008	-0.008
	(0.012)	(0.011)	(0.010)	(0.009)
Ln Width x Ln distance	-0.015*	-0.015**	-0.015**	-0.015**
	(0.008)	(0.007)	(0.007)	(0.006)
Gold sand	0.010	0.010	0.010	0.010
	(0.021)	(0.020)	(0.019)	(0.016)
Gold sand x Ln Distance	0.019	0.019	0.019	0.019*
	(0.014)	(0.013)	(0.013)	(0.011)
Dark sand	-0.052	-0.052	-0.052	-0.052*
	(0.032)	(0.032)	(0.032)	(0.031)
Dark sand x Ln Distance	0.021	0.021	0.021	0.021
	(0.026)	(0.025)	(0.024)	(0.022)
Cliff front.	0.092**	0.092***	0.092***	0.092***
	(0.036)	(0.034)	(0.031)	(0.026)
Cliff front. x Ln Distance	-0.014	-0.014	-0.014	-0.014
	(0.025)	(0.024)	(0.022)	(0.019)
Semi-urban front.	0.119***	0.119***	0.119***	0.119***
	(0.031)	(0.030)	(0.027)	(0.021)
Semi-urban front. x Ln Distance	0.008	0.008	0.008	0.008
	(0.016)	(0.016)	(0.015)	(0.013)
Mountain front.	0.129***	0.129***	0.129***	0.129***
	(0.045)	(0.043)	(0.040)	(0.036)
Mountain front. x Ln Distance	-0.059**	-0.059**	-0.059**	-0.059**
	(0.030)	(0.029)	(0.028)	(0.026)
Dune front.	0.103*	0.103**	0.103**	0.103**
	(0.053)	(0.051)	(0.048)	(0.041)
Dune front. x Ln Distance	0.017	0.017	0.017	0.017
	(0.037)	(0.037)	(0.035)	(0.031)
Calm tide	-0.019	-0.019	-0.019	-0.019
	(0.023)	(0.022)	(0.020)	(0.016)
Calm tide x Ln Distance	-0.006	-0.006	-0.006	-0.006
	(0.012)	(0.012)	(0.011)	(0.010)
Vegetation	0.045**	0.045**	0.045***	0.045***
	(0.019)	(0.019)	(0.017)	(0.015)
Vegetation x Ln Distance	0.026*	0.026**	0.026**	0.026**
	(0.013)	(0.013)	(0.012)	(0.011)
Protec. area	0.030	0.030	0.030	0.030
	(0.027)	(0.026)	(0.025)	(0.023)
Protect. area x Ln Distance	-0.037**	-0.037**	-0.037**	-0.037**
	(0.016)	(0.016)	(0.016)	(0.014)
Diff. access	0.206***	0.206***	0.206***	0.206***
	(0.044)	(0.043)	(0.042)	(0.039)
Diff. access x Ln Distance	-0.106***	-0.106***	-0.106***	-0.106***
	(0.031)	(0.030)	(0.029)	(0.027)
Only by boat	0.054	0.054	0.054	0.054
	(0.082)	(0.082)	(0.080)	(0.076)
Only by boat x Ln Distance	0.020	0.020	0.020	0.020
	(0.053)	(0.052)	(0.050)	(0.046)

Isolated envir.	-0.100***	-0.100***	-0.100***	-0.100***
	(0.035)	(0.034)	(0.031)	(0.027)
Isolated envir. x Ln Distance	0.026	0.026	0.026	0.026
	(0.025)	(0.024)	(0.022)	(0.020)
Semi-urban envir.	-0.078***	-0.078***	-0.078***	-0.078***
	(0.025)	(0.023)	(0.022)	(0.019)
Semi-urban envir. x Ln Distance	0.019	0.019	0.019	0.019
	(0.016)	(0.015)	(0.014)	(0.013)
Structural characteristics	YES	YES	YES	YES
Host characteristics	YES	YES	YES	YES
Municipality fixed effects	YES	YES	YES	YES
Constant	3.569***	3.569***	3.569***	3.569***
	(0.084)	(0.083)	(0.085)	(0.083)
Observations	16,663	16,663	16,663	16,663
R-squared	0.747	0.747	0.747	0.747

Table A8.- WOLS hedonic price regression estimates under arbitrary standard error clustering (Conley, 1999) with different distance cutoffs. *** p<0.01, ** p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac* and *Urban envir*.

Dependent variable: Ln ADR Explanatory variables	(1) Coeff. (SE)	(3) Coeff. (SE)
Ln Closeness	-0.001 (0.007)	-0.048 (0.046)
Ln Length	0.027*** (0.010)	0.028*** (0.009)
Ln Length x Ln Closeness		0.007 (0.006)
Ln Width	-0.016 (0.013)	-0.008 (0.013)
Ln Width x Ln Closeness		0.015 (0.009)
Gold sand	0.014 (0.025)	0.010 (0.025)
Gold sand x Ln Closeness		-0.019 (0.017)
Dark sand	-0.040 (0.043)	-0.052 (0.038)
Dark sand x Ln Closeness		-0.021 (0.023)
Cliff front.	0.094*** (0.033)	0.092*** (0.034)
Cliff front. x Ln Closeness		0.014 (0.027)
Semi-urban front.	0.116*** (0.038)	0.119*** (0.036)
Semi-urban front. x Ln Closeness		-0.008 (0.017)
Mountain front.	0.090* (0.046)	0.129*** (0.046)
Mountain front. x Ln Closeness		0.059* (0.030)
Dune front.	0.112** (0.044)	0.103** (0.046)
Dune front. x Ln Closeness		-0.017 (0.031)
Calm tide	-0.022 (0.022)	-0.019 (0.023)
Calm tide x Ln Closeness		0.006 (0.013)
Vegetation	0.051** (0.022)	0.045** (0.020)
Vegetation x Ln Closeness		-0.026* (0.014)
Protec. area	-0.007 (0.026)	0.030 (0.027)
Protect. area x Ln Closeness		0.037** (0.017)
Diff. access	0.113*** (0.043)	0.206*** (0.041)
Diff. access x Ln Closeness		0.106*** (0.027)
Only by boat	0.094* (0.055)	0.054 (0.057)
Only by boat x Ln Closeness		-0.020 (0.043)
Isolated envir.	-0.069* (0.039)	-0.100*** (0.037)
Isolated envir. x Ln Closeness		-0.007

		(0.021)
Semi-urban envir.	-0.075**	-0.078**
	(0.033)	(0.031)
Semi-urban envir. x Ln Closeness		0.019
		(0.018)
Structural characteristics	YES	YES
Host characteristics	YES	YES
Municipality fixed effects	YES	YES
Constant	3.592***	3.569***
	(0.073)	(0.073)
Observations	16,663	16,663
R-squared	0.746	0.747

Table A9.- WOLS hedonic price regression estimates using closeness (i.e., 1/distance) instead of distance. Clustered standard errors at the beach level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac* and *Urban envir*.

Universitat de les Illes Balears

Municipality socioeconomic characteristics and competitors

We collected a wide set of population socio-economic characteristics for the 67 municipalities where Airbnb listings are located. This information is drawn from the 2011 Balearic Census and the Household Income Distribution Atlas for the year 2016 (INE, 2021). For each municipality, the dataset includes the following information: population size, average age, percentage of foreign citizens, percentage of population with low education, average household size (number of people), share of large dwellings, average gross income and Gini inequality index.

Moreover, to control for the degree of market competition in each municipality, we include the number of Airbnb listings (other than self-listing) and the number of hotel beds. The former is calculated from AirDNA data. The latter is drawn from the Balearic Islands Statistics Office for the year 2016.

Table A10 presents summary statistics of these variables.

Variable	**Description**	**Mean**	**SD**	**Min**	**Max**
Socioeconomic indicators					
Pop	Population (Census 2011)	88,863.46	144,653.10	260.00	400,370
Av. Age	Average age (2016)	40.44	1.58	38.40	51.40
% Foreign	Percentage of foreign citizens (Census 2011)	0.23	0.06	0.00	0.35
% Low educ	Percentage of population with low education (Census 2011)	0.07	0.03	0.03	0.19
Av. House size	Average household size (Census 2011)	0.27	0.13	2.03	3.03
% Large dwellings	Percentage big dwelling (Census 2011)	16.83	36.50	0.59	610.91
Gross Income	Average gross Income (2016)	14,053.44	1,384.10	11,570.14	23,158
Gini	Gini Index (2016)	32.93	1.94	23.92	44.60
Competition					
Airbnb listings	Number of Airbnb listings in the neighbourhood (postal code)	358.57	438.75	0.00	1,589
Hotel beds	Number of Hotels beds in the neighbourhood	11,885.65	12,740.75	0.00	35,455

Table A10.- Summary statistics of municipality socioeconomic indicators and competitors

Universitat de les Illes Balears

Dependent variable: Ln ADR Explanatory variables	(1) Coeff. (SE)	(2) Coeff. (SE)
Ln Distance	-0.025** (0.012)	0.005 (0.054)
Ln Length	0.009 (0.021)	0.022 (0.023)
Ln Length x Ln distance		-0.021*** (0.008)
Ln Width	-0.066*** (0.024)	-0.064** (0.025)
Ln Width x Ln distance		-0.013 (0.014)
Gold sand	0.096** (0.037)	0.096** (0.038)
Gold sand x Ln Distance		0.007 (0.026)
Dark sand	-0.042 (0.062)	-0.076 (0.076)
Dark sand x Ln Distance		0.014 (0.034)
Cliff front.	0.135*** (0.050)	0.139*** (0.050)
Cliff front. x Ln Distance		-0.001 (0.032)
Semi-urban front.	0.119** (0.057)	0.141*** (0.050)
Semi-urban front. x Ln Distance		0.014 (0.023)
Mountain front.	0.184*** (0.068)	0.198*** (0.071)
Mountain front. x Ln Distance		-0.052 (0.043)
Dune front.	0.220** (0.087)	0.203** (0.095)
Dune front. x Ln Distance		0.028 (0.046)
Calm tide	0.056* (0.030)	0.072** (0.033)
Calm tide x Ln Distance		-0.016 (0.020)
Vegetation	-0.014 (0.046)	-0.019 (0.045)
Vegetation x Ln Distance		0.021 (0.023)
Protec. area	-0.110** (0.046)	-0.069 (0.046)
Protect. area x Ln Distance		-0.037 (0.024)
Diff. access	-0.010 (0.072)	0.138** (0.068)
Diff. access x Ln Distance		-0.133*** (0.034)
Only by boat	-0.156** (0.079)	-0.021 (0.110)
Only by boat x Ln Distance		-0.100* (0.060)
Isolated envir.	-0.081 (0.057)	-0.114* (0.058)
Isolated envir. x Ln Distance		0.007

		(0.037)
Semi-urban envir.	-0.023	-0.012
	(0.052)	(0.044)
Semi-urban envir. x Ln Distance		-0.015
		(0.024)
Pop	-4.7e-07*	-5.0e-07*
	(2.75e-07)	(2.9e-07)
Av. Age	-0.078***	-0.078***
	(0.029)	(0.029)
% Foreign	-0.175	-0.407
	(0.429)	(0.443)
% Low educ	0.291	0.353
	(1.224)	(1.310)
Av. House size	0.277	0.285
	(0.174)	(0.174)
% Large dwellings	4.8e-04	0.001
	(0.001)	(4.7e-04)
Gross Income	1.9e-05	1.2e-05
	(1.9e-05)	(2.0e-05)
Gini	0.053***	0.056***
	(0.010)	(0.009)
Airbnb listings	1.7e-04***	1.7e-04***
	(5.2e-05)	(5.2e-05)
Hotel beds	-2.9e-06	-2.48e-06
	(3.5e-06)	(3.7e-06)
Structural characteristics	YES	YES
Host characteristics	YES	YES
Constant	4.371***	4.411***
	(1.445)	(1.444)
VIF	2.60	5.02
Observations	16,663	16,663
R-squared	0.708	0.712

Table A11.- WOLS hedonic price regression estimates including municipality controls instead of municipality fixed effects. Clustered standard errors at the beach level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: The reference categories are *Clear sand*, *Urban front*, *Easy Ac* and *Urban envir*.