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Understanding Peer-to-Peer, Two-Sided Digital Marketplaces: Pricing Lessons from Airbnb in Barcelona

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Abstract: Peer-to-peer, two-sided digital marketplaces are reshaping the way in which consumers exchange products and interact with brand value propositions, particularly in the travel and tourism industry. Within the dynamics of these marketplaces, pricing approaches are of the utmost importance; yet, in contrast to conventional digital marketplaces, prices are set by non-professional vendors who are also consumers. We contribute to research on the topic by examining pricing within a single peer-to-peer, two-sided marketing platform: Airbnb. We use a large dataset covering accommodation listed by non-professional hosts in Barcelona, Spain. We identify a range of intrinsic and extrinsic attributes of the value propositions of Airbnb peer-to-peer accommodation, which enables us to explain differences in price levels. The paper offers evidence that higher accommodation prices are best explained by guests' preference for the intrinsic functional qualities of the value proposition; and that the systematic interaction of valence and volume of online reviews can produce a crucial impact on pricing.

Keywords: peer-to-peer; digital marketplace; pricing; Airbnb; consumer

1. Introduction

A transformation is underway in peer-to-peer, two-sided digital marketplaces. Not only do consumers now interact with brand value propositions and participate in exchange relationships, but the definition of vendors has also been transformed, in that vendors are now regular consumers as well as traders. With the understanding that vendors cannot deliver value but can offer value propositions and facilitate value co-creation [1,2], peer-to-peer vendors give information about their value proposition, socialize around the brand, and engage in monetary exchange relationships in the same way as professional vendors in regular digital marketplaces. In addition to this, vendors set prices and share responsibility with their peer consumers to utilize their value propositions more efficiently [3].

Perhaps the most significant peer-to-peer, two-sided digital marketplace in the accommodation industry is that of Airbnb. This company has grown at an incredible rate and has built a thriving marketplace that is clearly ahead of home-sharing platforms run by direct competitors (including Booking, HomeAway, and TripAdvisor) [4,5]. Airbnb's platform offers a wide and diverse selection of listings (from single rooms to entire houses, even including houseboats and castles), which covers more than 100,000 cities in over 220 countries worldwide, and it generates an average of 2 million people staying in Airbnb rentals on a given night [5].

Unlike traditional hotel chains, Airbnb neither owns nor manages accommodation. Instead, it enables its consumers to share their homes with travelers, offering an informal and less expensive

service than hotels [6]. In contrast to traditional consumption processes, whereby a product is mostly used by a single consumer, Airbnb properties can be used by many travelers for a short time. Idle resources are paired with the needs of consumers, reducing an economy's overall costs [7]. There are benefits for travelers, too: by having access to private accommodation, they have more opportunities to mingle with locals and experience local life [3]. For their part, homeowners are able to earn income by renting their properties when they are not using them. For the arrangement to work, both homeowners and travelers have to socially interact and collaborate in the co-creation of value [8]. This does not necessarily mean that homeowners try to please travelers, but that they interactively work together with travelers to jointly create value by having active dialogues and co-constructing customized service experiences that better suit their context [9,10]. These two-sided networks of consumers are interconnected via information technologies and social media applications provided by the company that owns the digital platform (in this case, Airbnb) [11]. Hence, consumer co-creation activities can take place both at the individual level (the homeowner and the traveler themselves jointly create value for the traveler) and at the network level—in which multiple consumers' involvement as co-creators benefits other consumers (either homeowners or travelers) [12,13].

It can be argued that pricing is one of the most critical components of a value proposition in two-sided digital marketplaces. For consumers who provide or share assets, price is the only element of their value proposition that generates revenue. Price also has a direct and immediate effect on prospective customers' decisions, and is the easiest marketing component to communicate [14]. In the travel and tourism industry, the price-based competition generated by two-sided intermediaries such as Airbnb can also impact transportation network structures, real estate price dynamics, and consequently urban spatial structures [15,16].

Pricing is a hot topic of emerging research on peer-to-peer digital marketplaces, with empirical studies often conducted with large datasets extracted from Airbnb (see, e.g., [17]). Airbnb hosts are free to set their own prices, so these studies typically use hedonic regression models in an effort to explain how the attributes of the value propositions influence price (e.g., [18–20]). However, these datasets include properties managed by business operators who run Airbnb listings on a fully professional basis, and are therefore not a good fit with the peer-to-peer marketing model. Even more importantly, a handful of studies on the quality of Airbnb hosts as decision makers have found that, compared to professional hosts, regular (consumer) hosts set different, less dynamic pricing strategies [21,22]. We aim to overcome the limited generalizability of existing studies on Airbnb price determinants to the specific context of pure peer-to-peer relationships. To fill this research gap, we focus specifically on the mechanisms involved in price formation for regular consumers on Airbnb, who offer their homes to peer counterparts in a casual fashion.

Previous research has typically suggested that the intrinsic qualities of Airbnb value propositions (such as size, location, and amenities of the accommodation) account for a significant proportion of the variance in Airbnb prices [18,20,23–25]. Airbnb guests, however, are highly interconnected with each other throughout their consumption journeys, as well as with the consumers who offer their houses [20,26]. Guests' accounts of their experiences and their opinions about value propositions may influence a prospective guest's purchase decision [20]. To date, however, evidence has been limited to the prominent role of guest reviews and ratings in price setting [27,28]. This brings us to the second goal of this study: to examine how the reputational capital of value propositions, collectively built by guests, could impact on regular consumers' pricing decisions for their houses.

In addition, we aim to offer insights into the effect on pricing strategy of the possible interplay among Airbnb hosts. Unlike the traditional hotel industry and professional operators with businesses on Airbnb (who are likely to focus primarily on persuading prospective guests and run competitive analyses about hotels [19,26]), regular consumers who offer their houses on Airbnb are likely to depend more on their peers who, like them, market their homes on Airbnb. Yet, to the best of our knowledge, this potential price driver has been overlooked in the literature to date.

The paper is structured as follows. In Sections 2 and 3, we review relevant studies and derive our theoretical framework and hypotheses. Section 4 describes the dataset used and presents the methodology and principal results obtained. In Section 5, we discuss the findings, theoretical implications, and limitations of the study, and suggest areas for further research. Section 6 summarizes and concludes the paper.

2. Pricing and Peer-to-Peer Accommodation on Airbnb

Airbnb is a prominent intermediary platform that supports a peer-to-peer, two-sided digital marketplace [12], in which pricing is a crucial lever. On Airbnb, prices match accommodation offered by consumers to potential guests according to guests' demands. Consumers are initially attracted to Airbnb and subsequently provide accommodation largely because the price level generates revenues that can substantially increase the financial return on their real estate assets [23,29,30]. This is due to cost savings derived from the management structure Airbnb provides [11], and also because Airbnb affords consumers who host accommodation greater opportunities to justify their price levels according to the experiential aspects of their value propositions, since private houses and services offer greater flexibility and more authentic tourism experiences, and infuse a stronger sense of engagement and community [31]. In addition, the extent of the digital marketplace, as well as Airbnb's brand awareness and reputation, makes it highly appealing to potential accommodation guests. Even more importantly, prices on Airbnb are low enough to satisfy guests, who are usually able to obtain a better price than those offered by the traditional accommodation industry [23,29,30].

Understanding specific behavioral patterns for pricing strategies among peers—whereby prices should be high enough to entice consumers to offer accommodation, but low enough to draw potential guests—is crucial to understanding the co-creation of value on Airbnb [32]. Airbnb's popularity relies not on the provision of the cheapest accommodation [31], but rather on prices that justify the value proposition because they are in line with the attributes and functionalities of the accommodation and offer greater value than competing options. However, despite the growing body of literature on the topic yielding some significant evidence, research to date is still inconclusive, tending to merge results for consumers who share and host accommodation on Airbnb with findings related to business operators who run their Airbnb listings in a fully professional capacity and are not a good fit with the peer-to-peer marketing model.

An earlier line of research explored the effects on Airbnb pricing of a wide range of attributes largely related to the intrinsic qualities of the value proposition of the accommodation. One group of studies found a positive connection between the price level and the size of the dwelling, whether the accommodation was rented as an entire house (or apartment) [18–20,26,27,33–36], and the provision of certain amenities, such as free parking [26,33]. A number of studies reported a negative connection between the price and the distance from the property to the city center or main tourist attractions [18,20,26,27,33]; others observed lower prices among listings which offer instant booking [20,26,33,35] or a flexible cancellation policy [18,19,26,27,33].

Another group of studies examined the role of trust-building mechanisms in pricing strategies on Airbnb, though their results are inconclusive and contradictory. On the one hand, many of these studies detected a dual yet contradictory effect of the reputation system on prices: while positive guest ratings contributed to higher prices [18,20,24,26,33,35], the higher the number of reviews received by a dwelling, the lower its prices [20,26,27,33,35,37]. On the other hand, the impact of the rating score was observed to be negative by Zhang et al. [37], and insignificant by Chen and Xie [19] and Ert et al. [36]. Similarly, the empirical testing of host attributes as a price driver has yielded mixed results: despite the fact that earning a “superhost” badge has been associated with premium prices in a few studies [26,33], this association has not been shown to be significant in others [19,27]; nor have host experience [26] and host verification [19,33] been reported as decisive in rising listing prices, according to two other studies [27,37]. Findings in relation to these price drivers appear to be subject to sample selection. For example, the effect of amenities, instant bookability policies, and reputation systems has been

found to differ among large metropolitan areas in Canada [20]. Rental policies and superhost status have both been shown to have a heterogeneous impact when a broad sample of cities around the world is considered [35], and the influence of amenities has been reported to vary across heterogeneous cities in the US [24].

A further group of studies has examined the extent to which Airbnb hosts have adopted revenue management practices and adjusted prices strategically. Once again, however, findings are mixed. Magno et al. [38] found that hosts in Verona, Italy, increased their prices in response to a surge in demand. However, Aznar et al. [25], who examined Airbnb listings and hotels for Barcelona (Spain), observed that, though Airbnb hosts did vary prices by season, unlike hotels, they did not fine-tune prices by day of the week. Similarly, Gibbs et al. [39] reported that dynamic pricing strategies are not uniformly adopted on Airbnb Canada listings; hosts who manage multiple listings vary their prices more frequently than hosts who manage only one. This suggests that hosts who offer their houses on Airbnb may differ from their professionalized counterparts when it comes to defining and adjusting their pricing strategies.

Perhaps the most important shortcoming of prior research is that it has failed to fully capture the pricing phenomenon in the particular context of pure peer-to-peer relationships [40]. Because the listings of amateur vendors (who happen to be consumers) and business operators (e.g., realtors and tourism intermediaries) coexist and compete with each other on the Airbnb platform, many studies neglect to consider the differences between them [18,19,24,35–37]. Moreover, the proportion of Airbnb hosts that manage their listings as part of their room-renting business is growing substantially [22]. This shortage in research is even more compelling when we consider that regular consumers on the one hand, and businesses or professional players on the other, operate on Airbnb with quite different goals, resources, and capabilities, and that pricing decisions can be particularly complex for regular consumers. Because Airbnb allows hosts substantial leeway in price setting [41]—despite providing them with an algorithm-based pricing tool—regular consumers face the challenging task of trying to optimize their income while pleasing guests and competing with the ever-increasing number of properties offered on the platform [20]. As a result, the pricing behavior of regular consumers may be more affected by overconfidence, loss aversion, or lack of expertise compared to professional players [32].

3. Theoretical Framework and Hypotheses

Hedonic demand theory (HDT) offers a framework for understanding pricing strategies in a peer-to-peer digital marketplace such as Airbnb [42]. According to this theoretical framework, each attribute of a particular good or service can be priced to show consumers' valuation of this value-adding element and their willingness to pay a premium for it [43]. Since tourism and hospitality are heterogeneous products, HDT has been liberally used in previous research in the field [19,20,26,27]. However, low transaction costs, many-to-many interactions among consumers, high frequency of bookings, and the hedonic component of guests' experiences all bring Airbnb accommodation consumption closer to the assumptions of hedonic demand modeling [44].

Cue utilization studies offer additional insight for identifying and examining potential drivers of consumers' valuation of Airbnb's attributes. According to this theory, the broad and diverse range of evaluative cues used by consumers as indicators of a focal good's or service's value can be classified as intrinsic or extrinsic to its value proposition [45,46]. Intrinsic cues are the core value proposition's qualities that determine its functional performance [47,48], such as reliable statistics related to the product's performance and descriptions about the product's physical parts [49,50]. Conversely, extrinsic cues are mediated by market relationships and often refer to brand positioning—such as the seller's image and reputation [47] and the consumers' electronic word-of-mouth, or eWOM, about the value proposition [51]. In contrast to the value proposition's intrinsic attributes, extrinsic qualities are more easily generalizable across the product's category and are intangible and abstract [52], and although they are related to the product, they are not inherent parts of it [46].

In sync with this, the array of pricing drivers on Airbnb can be mainly categorized as intrinsic and extrinsic, as shown in Figure 1. The former refers to the Airbnb value proposition's functional and objective qualities, which consumers often use to make inferences about a listing's performance and worth and which are inherent to the accommodation service itself (e.g., physical dimensions of the property and availability of free parking) [14,28]. The latter are used heuristically by prospective travelers to subjectively predict the accommodation's perceived value and are essentially defined by relationships and interplays within the accommodation market. They are related to many-to-many interactions between hosts and travelers [19], through which they take part in co-production networks to co-create value [53], and they are a sign of the accommodation's unique strategic positioning.

3.1. Intrinsic Qualities of the Value Proposition

Intrinsic attributes allow customers to objectively assess the performance of the value proposition, and thus co-create value based on the belief that the product is functionally effective [27]. The size, physical location, and amenities of the accommodation; whether it is a self-contained unit (i.e., an entire house or apartment); and whether a cancellation policy is offered are clearly intrinsic attributes of Airbnb accommodation [33].

The first intrinsic attributes considered (i.e., size and amenities of the accommodation and whether it is an entire house or apartment) allow customers to assess the functional or utilitarian values of the value proposition, including whether the accommodation is spacious, how well it can accommodate an entire family or large group of guests, the level of privacy it provides, and to what extent the stay is likely to be comfortable [19,26,33]. We expect that these features will drive price levels and therefore state our first hypotheses as follows:

Hypothesis 1a (H1a). *Accommodation size is related to higher prices.*

Hypothesis 1b (H1b). *Entire-home accommodation is related to higher prices.*

Hypothesis 1c (H1c). *The accommodation's amenities are related to higher prices.*

Rental policy heterogeneity could also account for price differences, though the rationale behind this connection might appear somewhat counterintuitive [20,35]. At first glance, a less flexible cancellation policy could be perceived as an inflexibility, even a nuisance for guests, which could cause the accommodation to appear less convenient and less attractive, and thus lower prices [54]. But because on Airbnb there are less indulgent cancellation policies—which include requirements such as minimum number of nights per stay, payment of a cleaning fee, and verification of guests' phone numbers and personal photos by Airbnb [35]—potential guests may perceive such policies as a sign of a host's concern to find trustworthy customers and their commitment to building collaborative, reliable relationships with their customers [18,19,26,27,33]. We therefore hypothesize that:

Hypothesis 2 (H2). *Less indulgent rental policies are related to higher prices.*

The connection between housing location and price level has been extensively studied in urban economics and research into hospitality services. In terms of housing or accommodation, mainstream urban economics considers access to certain places a crucial price lever (see, e.g., [55,56]). For hospitality services, it has been revealed that when the distance is greater between two accommodation options, the influence of location becomes a more significant aspect of the consumer's journey [57]. In this respect, a number of HDT studies on Airbnb [18,20,21,33,37] have established a connection between the physical location of an accommodation and its attractiveness and perceived value [58]. Hence, we propose that:

Hypothesis 3 (H3). *Proximity to tourist attractions is related to higher prices.*

3.2. Extrinsic Attributes of the Value Proposition

Extrinsic qualities of the value proposition result from peer-to-peer interplay and many-to-many interactive collaborations among hosts and guests. These extrinsic attributes are not a physical part of the accommodation, nor do they imbue the accommodation with functionality properties [19]. However, they are strongly related to the value proposition: they help prospects to assess the accommodation's performance subjectively, based on its image or reputation and other relevant differentiation-based competitive advantages.

Economic theory literature has long established the existence of a positive relationship between reputation and pricing, insofar as reputation discloses quality attributes that are unobservable to consumers prior to the transaction [59,60]. The role of reputation can be even more important for experience products in digital marketplaces such as Airbnb, since potential guests can only accurately assess the performance of the value proposition during actual consumption [61]. In the traditional hospitality industry, information asymmetries between sellers and potential buyers, and buyers' uncertainty about quality [62], have traditionally been overcome with five-star ratings [63] assigned by independent agencies, as well as with professional branding and marketing communication practices [64]. Individual accommodation services on Airbnb lack these quality signals, but the digital marketplace platform enables alternative reputation and value creation indicators which mainly show: (1) the level of customer service provided by the host; and (2) the degree to which the host's accommodation creates compelling or satisfactory customer experiences [65].

First, potential Airbnb guests can gauge a host's ability to deliver excellent customer service from indicators that rate the host's efforts to meet the needs of guests: verification of the host's identity by Airbnb [36], award of an Airbnb superhost label for customer service [19], and the host's experience in accommodating Airbnb guests [18,27]. Bearing in mind the above economic rationale for quality signals, we hypothesize that these indicators are meaningful for potential guests [27,33,66] and therefore drive prices:

Hypothesis 4a (H4a). *Accommodation listed by verified hosts is related to higher prices.*

Hypothesis 4b (H4b). *Accommodation listed with superhost status is related to higher prices.*

Hypothesis 4c (H4c). *Accommodation listed by hosts with greater experience is related to higher prices.*

Second, an accommodation can build a good reputation through ratings and reviews, which display previous guests' consumption stories and how well the host met their expectations. For many potential guests, this user-generated information helps them to make better decisions [67] and diminishes choice risk [68,69], filling a role traditionally assigned to brands [70] and marketing communications [71]. Consumers are particularly trusting of this information in their decision processes, as it comes directly from their peers [68,72]. Accordingly, we hypothesize that the price of an accommodation is driven by the overall valence of the reviews received by the accommodation [73,74], as reflected by the average rating scores:

Hypothesis 5a (H5a). *Accommodation with high review valence is related to higher prices.*

Volume, defined as the number of reviews received by a product, might be important for potential Airbnb guests because it helps to determine the potential value they could derive from an accommodation. However, review volume can also pose a problem for potential guests, who are faced with the task of processing numerous reviews, which potentially interact with their beliefs about the value proposition [75], formed by means of the review valence [76]. When it comes to the effect of review volume on pricing, findings have not been consistent across products and markets: while a number of studies for electronic products [68], books [71], and traditional accommodation [77] have

observed a positive volume–price connection, recent inquiries have observed an inverse relationship on Airbnb [20,26,27,33,78]. This downward volume–price effect has been justified by the high turnover that cheaper listings tend to generate [27,78], which translates into greater numbers of reviews [20,33]; and also by the fact that a large number of heterogeneous reviews are not necessarily helpful for potential guests, due to the cognitive effort entailed in processing them [76].

On the one hand, reviews accurately represent peer consumption experiences and provide a rich source of information. On the other, a high review volume poses a significant challenge for the prospect whose task is to process the information. The coexistence of helpful yet heterogenous reviews and the problem of information processing can be understood as a tradeoff [79]. Thus, we propose that the way in which Airbnb guests interpret review volume depends on the overall valence of the accommodation [73,75]. Put differently, for a certain positive valence, a higher review volume implies that more guests have had a positive experience of the accommodation. Hence, we hypothesize the following:

Hypothesis 5b (H5b). *Accommodation with greater review volume is related to lower prices.*

Hypothesis 5c (H5c). *The interaction of review valence with review volume is related to higher prices.*

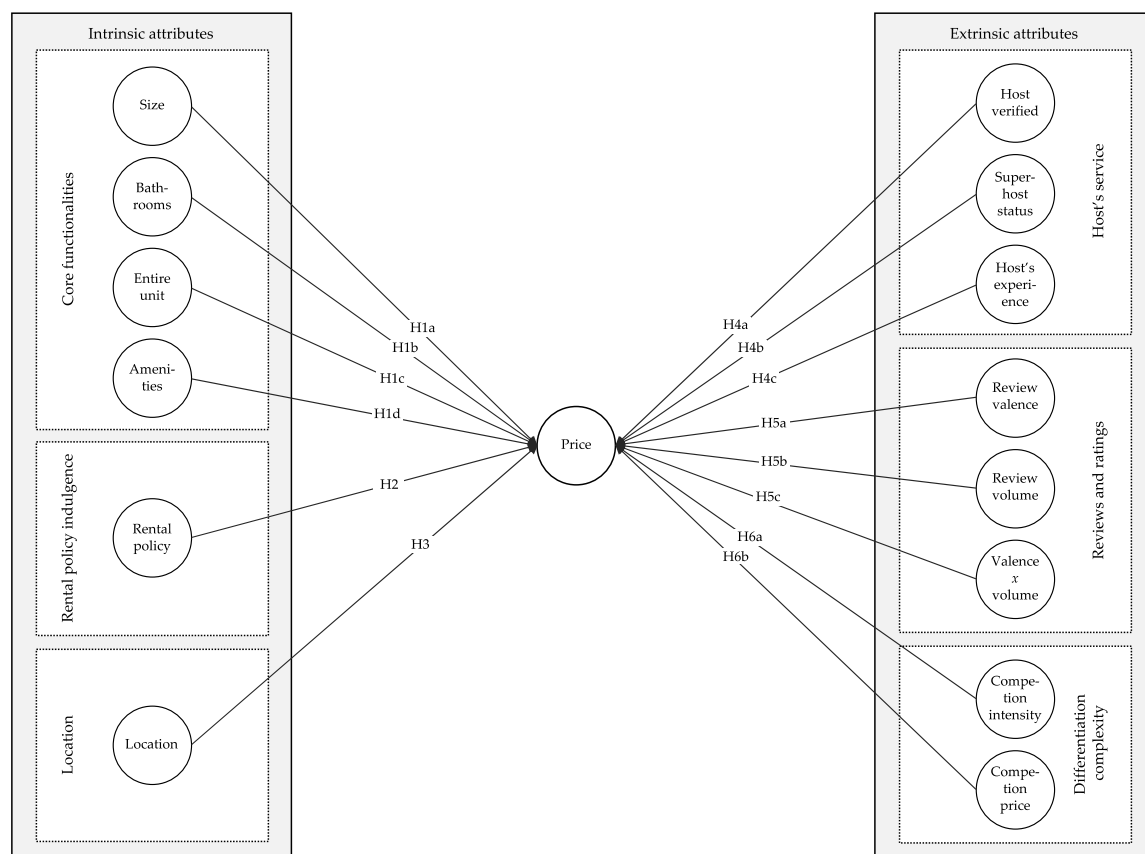


Figure 1. Conceptual model.

The complexity of competitive dynamics in the vicinity of the accommodation, in terms of intensity (i.e., number of competitors) and price, may also be fundamental to price formation [19,26,80]. While previous studies have noted the negative effect on price formation of a high number of hotels in the same district as the Airbnb accommodation [19], the influence of the most direct competitors (i.e., nonprofessional Airbnb hosts) has not so far been explored. However, it seems reasonable to expect that the more intense and price-based the competition, the more likely it is that the consumer

offering the accommodation will find it difficult to differentiate their value proposition and display significant differentiation-based competitive advantages in order to justify higher prices; and also that a spatial dependence of rates will emerge from nonprofessional Airbnb hosts in the same vicinity. Therefore, we suggest the following hypotheses:

Hypothesis 6a (H6a). *A higher density of direct competitors in the vicinity is related to lower prices.*

Hypothesis 6b (H6b). *Lower prices fixed by direct competitors in the vicinity are related to lower prices.*

4. Data and Methods

We collected a dataset of 20,423 Airbnb listings in Barcelona, one of the most visited cities in the world [81]. Data were retrieved on November 9, 2019, from Airbnb [82], which makes data referring to accommodation listings publicly available. These data include listing identification, location, listing creation date, number of bedrooms, number of bathrooms, property type, maximum number of guests, guest ratings, and average price per night.

We removed all accommodations managed by professional hosts from the dataset, since our focus was on understanding the pricing decisions made by regular consumers using Airbnb to offer accommodation, despite the noncommercial object of the exchange. In doing so, we assumed nonprofessional hosts to be those who offered only one listing on Airbnb's bilateral marketplace and did not list their dwellings as "hotel rooms", nor tag their properties as "aparthotels", "boutique hotels", "hostels", or "hotels".

To carefully clean the dataset, we dropped accommodations where the number of guests was greater than two times the number of bed places reported, and used the interquartile range rule on the variable price per guest (so as to avoid outliers). We also eliminated all cases with missing values.

The final dataset contained 6184 observations (30.28% of the total Airbnb listings in Barcelona on the data-gathering date), and therefore enabled extensive modeling.

4.1. Hedonic Pricing Modeling

We built a hedonic pricing model (HPM) to test our working hypotheses. Since HPMs are based on the underlying idea that a product's price depends on its particular value-adding components [83–85], hedonic functions break down the price of the product into its attributes or qualities, which in turn can be organized into groups according to their characteristics [86].

The literature does not suggest specific functional forms for the hedonic functions [87], and there is no particular pronouncement on the best functional form [83,88]. Different specifications can be applied to link prices to their potential explanatory variables. Studies on hedonic prices usually consider simple functional forms (i.e., linear, log-linear, double log-linear, and semi-log forms), which are then analyzed as ordinary least square (OLS) regression models [89]. Since the prices of Airbnb listings tend to exhibit a high level of heterogeneity, we adopt the following linear additive model:

$$Price = c + \beta X + \varepsilon \quad (1)$$

where Price is the vector of Airbnb listed prices, c is the constant vector, β is the vector of coefficients, X is the matrix of all attributes, and ε is the error term.

4.2. Variables

Our model contained 15 variables, which are described in Table 1. Some of these variables were directly extracted from the final version of the original dataset (e.g., *Size*, *Bathrooms*, *HostExperience*) while others were built using one or more variables of the original dataset. The dependent variable was the price of the accommodation (expressed in US dollars), and the independent variables were grouped into six blocks.

The first block of independent variables, *Core functionalities*, captured data about the maximum guest capacity of the accommodation (*Size*), number of bathrooms (*Bathrooms*), level of privacy offered (*EntireUnit*), and an amenities indicator (*AmenitiesIndex*). This last variable was built as an additive index to take into account up to nine different amenities offered by the accommodation (family friendly, breakfast, parking, Wi-Fi, cable television, pool, elevator, gym, and doorkeeper).

The second block, *Rental policy indulgence*, consists of a single additive index made up of five dichotomic variables: *CancellationFlexibility* (the cancellation policy is strict/very strict or flexible/moderate), *MinimumNights* (minimum number of nights greater/not greater than 1), *CleaningFee* (cleaning fee greater/not greater than 0), *GuestPhoto* (guest photo required/not required), and *GuestPhone* (guest phone number required/not required).

The third block, *Listing location*, included a single variable to reflect the accommodation's location. This variable (*Location*) measured the mean of the Haversine distance between each lodging and seven main tourist amenities in Barcelona (Park Güell, Casa Milà, Sagrada Família, Casa Batlló, Museu Picasso, Museu del F. C. Barcelona, and Born Centre de Cultura). We calculated the Haversine distance using the Earth radius for the latitude of Barcelona ($R = 6368.833$ km).

The third block of independent variables referred to the host's attributes and took into consideration whether the host had been verified by Airbnb (*HostVerified*), whether they had been awarded superhost status (*Superhost*), as well as the extent of their experience on Airbnb (*HostExperience*), measured according to the number of months elapsed since the first time the host's listing was published on Airbnb.

The fifth block, *Listing reputation and customer reviews*, consisted of three variables: (1) *ReviewValence_PCA*, which captured previous guests' average ratings of the accommodation, obtained through the first component scores of a principal component analysis (PCA) performed on six underlying factors (accuracy, cleanliness, check-in, communication, location, and value); (2) *ReviewVolume*, which measured the total number of guest reviews received by the accommodation; and (3) *Valence_x_Volume*, which referred to the interaction between the variables *ReviewValence_PCA* and *ReviewVolume* and was built by multiplying their corresponding values.

Table 1. Groups of variables and variable descriptions.

Group	Variable	Description
Dependent variable	Price	Listed price of the accommodation (\$)
Core functionalities	Size	Number of guests
	Bathrooms	Number of bathrooms
	EntireUnit	Dichotomic variable: 1 = entire home/apt., 0 = not entire home/apt.
	AmenitiesIndex	Additive index: Family Friendly + Breakfast + Parking + Wi-Fi + CableTV + Pool + Elevator + Gym + Doorman
Rental policy indulgence	RentalPolicy	Additive index: CancellationFlexibility (strict/very strict) + MinimumNights (>1) + CleaningFee (>0) + GuestPhoto + GuestPhone
Location	Location	Mean (Haversine) distance to: Güell Park (41.413525, 2.153077); Milà House (41.395183, 2.161801); Sagrada Família Church (41.404065, 2.174648); Batlló House (41.391737, 2.164962); Picasso Museum (41.385167, 2.180831); FCB Museum (41.380218, 2.120824); Born Cultural Center (41.385661, 2.183570)
Host's service	HostVerified	Dichotomic variable: 1 = host verified by Airbnb, 0 = not verified
	Superhost HostExperience	Dichotomic variable: 1 = host is a superhost, 0 = not a superhost Number of months since host's appearance in the Airbnb listing
Reviews and ratings	ReviewValence_PCA	First component scores from the PCA with variables: review_scores_accuracy; review_scores_cleanliness; review_scores_check-in; review_scores_communication; review_scores_location; review_scores_value
	ReviewsVolume Valence_x_Volume	Number of reviews Number of reviews multiplied by ReviewValence_PCA
Differentiation complexity	CompetitionIntensity	Number of competitors with same room type in the neighborhood
	CompetitionPrice	Nearby competitors' price per guest mean value

The sixth and last block, *Differentiation complexity*, included the number of competitors of the same accommodation type within the neighborhood (*CompetitionIntensity*), and the nearby competitors' mean value of the price per guest (*CompetitionPrice*). For the purposes of this study, a competitor was deemed to be in the same neighborhood where the distance between the accommodation and the competitor accommodation was less than 0.5 km.

5. Results

5.1. Measurement Model

To assess the measurement model, we first checked for internal consistency reliability and individual item reliability of the multi-item construct in the model (i.e., *ReviewValence_PCA*). Internal reliability is satisfactory, given that the Cronbach's α value is 0.89 (greater than the requested 0.70 level) and that all item-to-total correlations for each of the six items surpass the minimum recommended value of 0.60. Additionally, the PCA on these six items showed just one component with an eigenvalue greater than 1 (3.89). We also have individual item reliability, since all factor loadings associated with this component (Table 2) exceed the recommended level of 0.70. Hence, from the internal point of view, the measurement of *ReviewValence_PCA* was deemed adequate.

Table 2. Item mean values and loadings of the construct *ReviewValence_PCA*.

Item	Mean	Loading
review_scores_accuracy	9.577	0.874
review_scores_cleanliness	9.334	0.776
review_scores_checkin	9.750	0.823
review_scores_communication	9.727	0.843
review_scores_location	9.659	0.765
review_scores_value	9.275	0.833

Next, we studied the discriminant validity of all the explanatory variables. Following Anderson and Gerbing [90], we analyzed the correlations between the independent variables (Table 3) and found that none of the 95% confidence intervals of the correlations contained either 1 or -1 . Consequently, no paired factors were perfectly correlated, and the discriminant validity of the measurement model is also satisfied [91].

Table 3. Correlations between the explanatory variables.

[illegible]

5.2. Model Estimation

The main regression issues associated with HPM estimation are usually related to autocorrelation and heteroscedasticity in the error terms and multicollinearity within the independent variables [87,92]. In the autocorrelation analysis, we found that the Durbin–Watson statistic in the initial regression was very close to two (1.99), and thus no evidence of first-order autocorrelation AR(1) errors was found. In the White test, however, the p -value of the statistic $N \cdot R^2 = 2223.06$ was 0.00, suggesting that the model estimation had heteroscedasticity issues. To solve these, and thus obtain reliable coefficient standard errors and t -statistics, we adjusted the standard errors in the regression estimation using White’s consistent coefficient covariance matrix [87].

The results of the hedonic pricing model’s OLS-adjusted estimation are shown in Table 4. Individual variance inflation factors (VIFs) are below the critical value of 10, which indicates an absence of multicollinearity problems [93]. Overall, the fit of the hedonic pricing model is good. Measured by the R -squared, the explanatory power of the regression equation is high: 59.65% of the variation of the Airbnb listing prices is explained by the independent variables included in the model. The HPM is globally significant (F -statistic = 651.28, p -value = 0.00), and most of the explanatory variables are significant (with coefficients statistically different from zero). All p -values are lower than 0.05 except for the variables *HostVerified*, *HostExperience*, and *ReviewValence_PCA*. The variables *Size*, *Bathrooms*, *EntireUnit*, *AmenitiesIndex*, *Superhost*, *RentalPolicy*, *Valence_x_Volume*, *CompetitionIntensity*, and *CompetitionPrice* show positive effects on price, while *Location* and *ReviewVolume* have negative relationships with the dependent variable (see also Figure 2).

Table 4. Regression results of the hedonic pricing model (HPM).

Variable	Coefficient	Standardized Coefficient	Std. Error	t -Statistic	p -Value	VIF
(Constant)	−7.537	—	3.862	−1.952	0.051	—
Size	16.288	0.563	0.761	21.413	0.000	3.183
Bathrooms	14.242	0.130	1.806	7.885	0.000	1.052
EntireUnit	14.957	0.143	1.692	8.839	0.000	2.840
AmenitiesIndex	2.401	0.058	0.434	5.529	0.000	1.308
RentalPolicy	0.925	0.020	0.416	2.223	0.026	1.199
Location	−3.097	−0.059	0.516	−5.998	0.000	1.550
HostVerified	0.038	0.001	0.843	0.045	0.964	1.058
Superhost	5.308	0.047	1.129	4.701	0.000	1.471
HostExperience	−0.002	−0.002	0.005	−0.338	0.736	1.024
ReviewValence_PCA	0.165	0.003	0.495	0.334	0.739	1.181
ReviewVolume	−0.047	−0.068	0.008	−5.815	0.000	1.799
Valence_x_Volume	0.043	0.038	0.013	3.390	0.001	1.715
CompetitionIntensity	0.004	0.023	0.002	2.617	0.009	1.433
CompetitionPrice	0.108	0.032	0.050	2.177	0.030	1.494
R -squared	0.596					
Adjusted R -squared	0.596					
F -statistic	651.277					
Prob(F -statistic)	0.000					

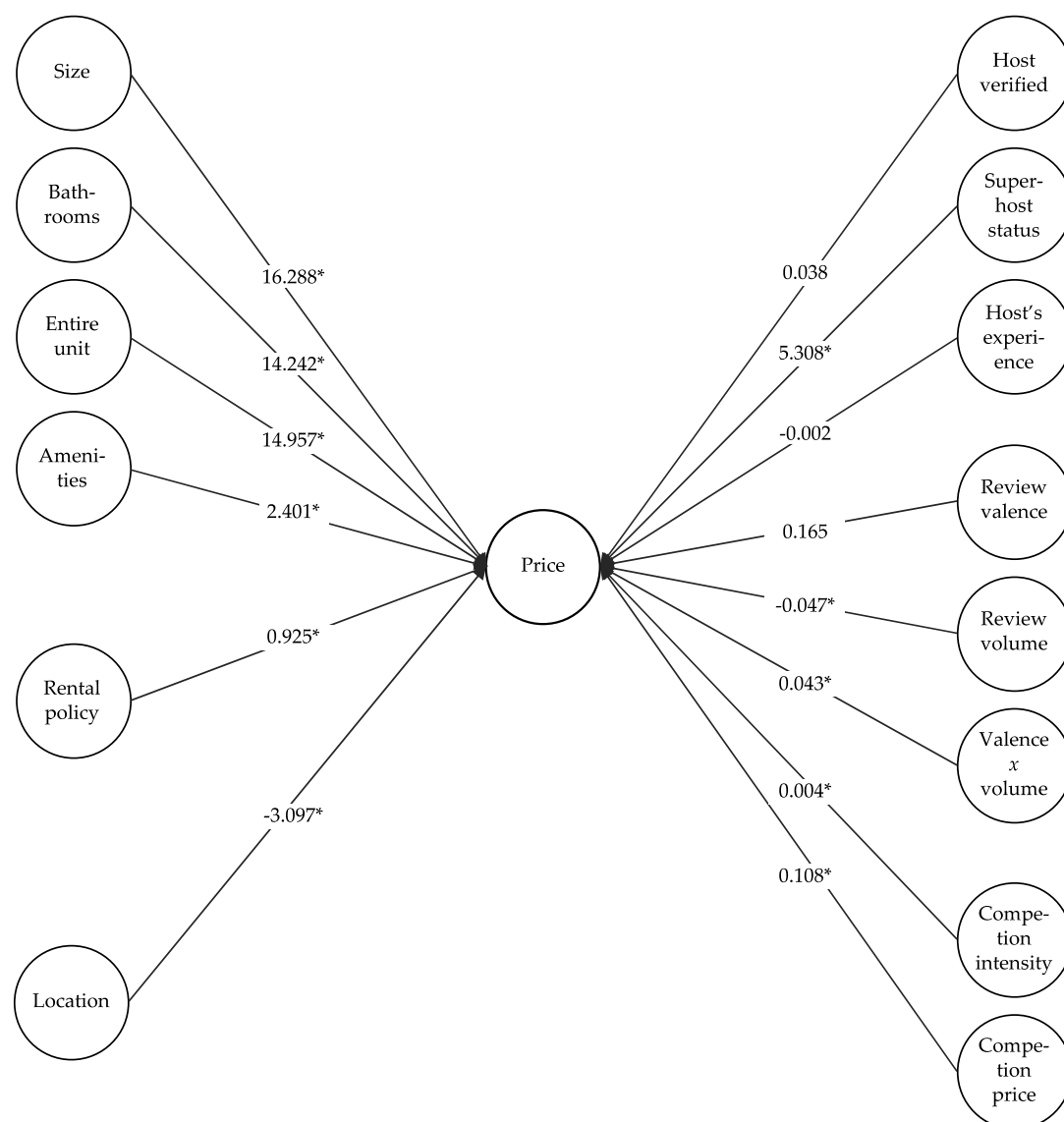


Figure 2. Coefficient values of variables in the HPM model. * p -value < 0.05.

6. Discussion

From the analysis of the HPM, we deduce that pricing on Airbnb's peer-to-peer, two-sided digital marketplace is influenced by both intrinsic (functional) and extrinsic (interplay-related) attributes of the value proposition. Together, these attributes significantly account for differences in the prices listed by regular consumers who offer or share their houses on Airbnb (59.65% of variance explained). Although both types of attributes have a significant effect on pricing, it is the intrinsic qualities of the value proposition that most influence prospective guests in their booking decisions. In fact, three of the four variables related to an accommodation's core functionalities have the highest standardized coefficients, as seen in Table 4.

The size, number of bathrooms, and "entire place" accommodation type generate utilitarian value for Airbnb guests (room to move around freely, storage room, opportunities for families and large groups to stay together in one place, privacy, etc.). All of these attributes contribute to higher prices, as stated in H1a, H1b, and H1c. The pricing of Airbnb accommodation is also positively influenced by the provision of a wide range of amenities designed to offer more convenient, comfortable, friendly, and pleasant stays (H1d).

The strictness of the accommodation's rental policy—including non-refundable cancellation fees, minimum stay restrictions, cleaning fees, and requiring guest identities to be verified by the platform—is another contributory factor in price formation (H2). Stricter rental policies not only make hosts feel that their furniture, appliances, and building elements are better protected, but they also offer value to guests, who see them as an indication of better-equipped accommodation and greater host involvement in the accommodation service.

Likewise, our analysis confirms that the accommodation's location significantly influences price levels (H3). The highest prices are found in listings with downtown locations, or those close to tourist attractions, which confirms previous findings [18,20,26,27,33].

As expected, accommodation with superhost status is perceived to be of superior value, and hence is associated with premium prices (H4b). Like five-star systems and brands in the hotel industry, superhost status acts as a risk reliever in decision-making by providing reliable and useful information about the host's efforts to satisfy their guests' needs.

Echoing Teubner et al.'s findings for the 86 largest cities in Germany [27], the fact that a host is verified by Airbnb is not perceived as an indication of quality and offers no significant value to potential guests in Barcelona. This non-significant effect (p -value = 0.964) could be explained by the wide adoption of the Airbnb verification procedure among regular hosts. Accordingly, hypothesis H4a has been rejected.

Another unexpected finding is that price levels are not affected by the host's degree of experience (H4c). Although host experience may contribute to the host's reputation and positively enable trust in the accommodation's value proposition, it does not lead to premium prices. Because Airbnb guests are aware of the casual collaboration of many hosts (i.e., consumers who offer accommodation at their houses in an informal and collaborative fashion), the accumulated experience of a host on Airbnb appears to be of little interest to them.

Interestingly, the effect on pricing of a high overall review valence is negligible (p -value = 0.739), hence H5a is also rejected. This could be due to the low variance of reviews on Airbnb and the vast preponderance of high ratings (on a 2–10 scale, the mean values of the items of the construct *ReviewValence_PCA* range from 9.28 to 9.75, as seen in Table 2), which gives amateur Airbnb hosts very little leverage in terms of pricing. At the same time, potential guests are unable to form expectations about their bookings.

However, the findings strongly confirm prior evidence reporting a negative association between price and review volume (H5b) (see, e.g., [26]). This suggests that the amount of reviews received by an accommodation is more of an indication of demand (since cheaper listings tend to receive more bookings and more reviews) than a sign of quality [33].

Similarly, we bring new evidence that supports the idea that review volume interacts with review valence (H5c), complementing the findings of Teubner et al., who observed that the negative impact of review volume was stronger for accommodations with lower average rating scores [27]. We show that, for a given valence, an increase in review volume boosts its positive impact on prices (p -value = 0.001). This reveals that Airbnb prospective guests effectively employ user-generated information in the form of ratings and reviews, by first gaining perception of an accommodation through review valence, then confirming their beliefs through review volume. The way in which prospective guests interpret review volume depends on the overall valence of the accommodation, and their expectation of the value of an accommodation has a higher impact when the accommodation has received a high number of reviews. To be effective in terms of pricing strategies, then, a host's reputation and equity effort need to translate into large numbers of excellent reviews.

Direct competition and competitor pricing strategies in the same vicinity also affect price levels, though the direction of the relationship between competitor density and prices is opposite to that hypothesized (H6a). This means that, in districts with a greater choice, the proximity of alternative Airbnb accommodations does not push prices down. This counterintuitive result mirrors that of Önder et al. [94], who examined the effect of hotels and Airbnb accommodation in the Estonian capital

city of Tallinn, and may be a consequence of the distribution of tourist services in Barcelona, which are disproportionately concentrated in the downtown and surrounding tourist attraction areas. Thus, Airbnb accommodation in those districts (51.25% of the total listings) has a greater chance of attracting guests, despite the higher density of direct competitors.

Finally, positive price dependencies with respect to same-type properties located within a 500-m radius prove significant (H6b). This indicates that consumers who offer or share accommodation serve as role models for their peers in terms of pricing decisions. Intense, price-based competition and relatively lower business experience and skills [32] give rise to these spatial price dependencies.

7. Conclusions

This paper has been motivated by the very limited and inconclusive empirical findings on pricing strategies deployed by regular hosts on Airbnb, with specific reference to Airbnb consumers that offer the entire or shared use of their homes to peer counterparts in an informal, amateurish, and collaborative way. Most previous studies on price formation on Airbnb have included professional hosts in their samples. Airbnb has rapidly scaled up, however, attracting interest among firms and professional agents, who use the platform to expand their business opportunities and optimize the returns and profitability of their property portfolio. As a result, Airbnb is increasingly hosting marketing networking activities that do not necessarily fit with the collaborative consumption model for which it is best known [40]. This study provides evidence on how regular hosts (consumer hosts), in direct competition with their peers and professional operators, make complex pricing decisions.

This is one of the first studies to tackle pricing at peer-to-peer consumer level in the two-sided digital marketplace created by Airbnb, and to examine the joint effect of the intrinsic and extrinsic attributes of the value proposition. Our research contributes to a more comprehensive understanding of consumer decisions in peer-to-peer markets in three different ways. First, it overcomes the limited generalizability of existing studies in the specific context of pure peer-to-peer marketing relationships by providing a specific analysis of the mechanisms that intervene in price formation. Second, it delivers robust support for our hedonic price model—absent from the literature to date—which explains pricing decisions based on the intrinsic and extrinsic attributes of the value proposition. More specifically, it provides evidence that, though collaborative consumption decisions are guided by both utilitarian and reputational components of the value proposition, the quest for functionality dominates consumer valuation of accommodation when only regular hosts are considered. Third, our study complements research into online reviews, which has devoted a great deal of effort to understanding the role of valence and volume of online reviews. Indeed, we show that, in a pure peer-to-peer market, the influence of the reputational capital of the value proposition, collectively built by guests, is affected by a demand-pull effect, yet plays a critical role when review valence and volume interact.

The valuation of Airbnb listings according to intrinsic and extrinsic attributes has profound implications for regular hosts formulating pricing strategies. The evidence from this study suggests that, before listing their properties in the digital marketplace, casual hosts need to correctly understand the attributes that generate more value for consumers. Given the wide diversity of accommodation traded and the intense competition on the digital platform, an appropriate assessment of the different utility-bearing attributes seems to be crucial to pricing strategy and sustainability in a highly competitive, two-sided digital market.

Our analysis assists policymakers by offering new knowledge about the spatial price dependencies that exist among peers operating in the same physical area, and by predicting the impact of Airbnb on the local rental market. More specifically, it reveals the difficulties for regular hosts of differentiating their value proposition in a highly competitive, peer-to-peer digital market, as well the significant spatial price dependencies that appear in the territory (since pricing positively depends on both density of listings and pricing strategies employed by nearby Airbnb hosts).

We acknowledge two important limitations in our study, which in turn offer windows of opportunity for future research. First, future studies could consider price formation from the demand

perspective. In fact, research is needed to build bridges between consumers' motivational orientations toward entering a pure peer-to-peer digital marketplace and the hedonic drivers of price levels. Second, despite the robustness of our model for pure peer-to-peer relationships, we are cautious as to whether these findings can be generalized for other cities. A further study could assess and corroborate these results in other locations.

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