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Why are flexible booking policies priced negatively?

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HIGHLIGHTS

- Prices negatively correlated with flexible cancellation policies or instant book availability.
- Bias arises from correlation between unobservable factors and a rational strategy.
- A solid algebraic framework is provided as well as empirical checks.
- Convergence in management between conventional and peer-to-peer markets.

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ABSTRACT

This work suggests a new direction to look at when explaining seemingly counterintuitive findings. Using data from 497,509 Airbnb listings in 44 cities of the world, we confirm a negative relationship in the peer-to-peer tourist accommodation market between flexible cancellation policies and nightly price, as well as between the possibility of instant booking and price. This phenomenon had been hypothesized to be caused by emotional factors that would go in the opposite direction to the monetary incentives. However, the economic analysis presented in this paper reinforces the idea that the functioning of these types of markets and, in particular, the vectors that determine supply are not very different from those that govern traditional markets.

1. Introduction

Despite growing activity in peer-to-peer renting research amongst economists in the field of industrial organization, the literature on peer-to-peer short-term accommodations is still scarce, perhaps due to the late emergence of this market. These so called peer-to-peer markets differ from traditional markets in that they do not necessitate of a firm. Instead, the individual has the means of production and the rights over the finished product, which may be sold directly to another individual. Because peer-to-peer sellers tend to be small in terms of capital, their means of advertising differ from those of the large hotel chains: although nowadays both types of accommodations are as readily searchable on online websites, those that are owned by "peers" can potentially be much more numerous and difficult to tell apart. Besides, they lack the reputational prestige of large firms. Thus, peer-to-peer accommodations tend to be listed in websites such as Airbnb, where owners must fill several fields of information so that ads are presented in a comparable and easy-to-search manner.

Each host has the capability to establish not only the price but, at least to a large extent, the terms and conditions under which they supply lodging. In the area of booking and cancellation policies, there are instances in which booking is automatically confirmed and can be cancelled without additional charge. The aim of this paper is to analyze how the enablement of flexible cancellation (FC) and of instant book (IB) may affect price, volume and profits. Although one would expect consumers to find more attractive, *ceteris paribus*, the accommodations that provides instant booking or total refund upon cancellation, data seems to contradict it: prices are negatively related to these characteristics. Are these flexible booking policies, then, really priced negatively -or is it an issue of estimation bias? This is a question that, to our knowledge, has not been specifically analyzed in the literature, and the econometric angle has been underemphasized. Rigorous analysis is required, which we intent to contribute in the sections that proceed.

The paper is organized as follows. First, we survey the relevant research literature. Afterwards, we describe the data. After that, we provide evidence on the effects of booking policies on prices in the peer-to-peer market for tourist accommodation. On that basis, we

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present two models that apply economic logic to understand the behavior of hosts and consumers, first regarding the choice of instant book, and then, for the choice of cancellation policy. Finally, we conclude.

2. Related literature

Peer-to-peer market research has to this day often focused on legal, social and psychological aspects rather than on economics (Brochado, Troilo, & Shah, 2017; Guttentag, 2015; Ikkala & Lampinen, 2015; Karlsson, Kemperman, & Dolnicar, 2017; Möhlmann, 2015; Tussyadiah & Pesonen, 2016). Among the strictly economic contributions, some refer to valuing the impact of the emergence of platforms like Airbnb in the hotel industry or in the tourism industry in general (Fang, Ye, & Law, 2016; Zervas, Proserpio, & Byers, 2017). Nonetheless, in this section we refer to studies on price determinants for accommodations supplied in the peer-to-peer market, and, besides that, those that analyze the effects of the chosen cancellation policy and instant booking.

2.1. Price determinants

For a hotel, its staff may be diverse and its property diluted. But for peers, the ownership and management of a property are usually attributed to a single figure, that of the host. The very peer-to-peer nature of the product may be the reason why, unlike for hotel chains, host characteristics have a crucial role in peer-to-peer exchanges. Those may be found out *ex ante* through hosts' public profile, which may display their name, a photograph and, sometimes, an additional text entry that may be filled with a brief self-description. Something similar exists for guests' accounts. This information can be potentially used by agents to discriminate. For instance, some studies argue that racial discrimination prevails in the market as certain ethnic groups (particularly Black, Asian and Hispanic) seem to be accepting remunerations for renting accommodations that would be higher if they were Caucasian, all else equal (Edelman, Luca, & Svirsky, 2017; Franco, Kakar, Voelz, & Wu, 2016; Gilheany, Wang, & Xi, 2015) and that guests with African-American sounding names had lower chances of being accepted than those with white sounding ones (Edelman & Luca, 2014). Moreover, the emotions and sentiments (e.g. trust, kindness) conveyed through the host's profile photograph also reportedly have an impact on the probability of booking their accommodation (Fagerstrøm, Pawar, Sigurdsson, Foxall, & Yani-de-Soriano, 2017; Karlsson & Dolnicar, 2016).

Another aspect, that is exclusive of the peer-to-peer platform of Airbnb, is the publicly visible, virtual, distinctive “Superhost badge” that is awarded to hosts who (i) register at least 10 bookings per year; (ii) answer promptly to guests' messages; (iii) maintain a response rate of no less than 90%; (iv) obtain no less than 80% of maximum star ratings; and (v) respect the confirmed bookings, canceling only in special occasions. Nevertheless, empirical evidence on the badge's effect on occupancy rates is limited. One exception is Liang, Schuckert, Law, and Chen (2017), who reports, based on Hong Kong data from 2015, that the negative association of price and review volume can be positively moderated by the Superhost badge, and that the host's effort to obtain the Superhost qualification may be rewarded by the ability to set higher prices, through an increased willingness to pay of guests for Superhosts' accommodations.

Although we emphasize the peer-to-peer aspect of this market (through the differential host-guest relationship) and its usual mechanisms (demand, price), the truth is that some hosts act closer to business intermediaries than we would expect. Li, Moreno, and Zang (2016), who refer as “professionals” to hosts offering more than one property, found out that they tended to fix prices more efficiently than nonprofessionals, as the former would adjust them in response to demand spikes from which they could profit.

Other published studies based on hedonic pricing attempt to quantify the influence of other attributes (room characteristics, location, amenities and services, rental rules, and online review rating) (Benítez-Aurioles, 2017a; Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2017; Wang & Nicolau, 2017), and generally agree on that price is positively related to more autonomous types of accommodation (i.e. entire homes being more priced with respect to private rooms, which in turn are more priced than shared rooms) and to the number of useful rooms (bedrooms and bathrooms), as well as to that of beds or accommodate capacity.

However, we have not been able to find a substantial treatment of the effect on prices and visits of hosts' booking mechanics of choice. Those are mainly (i) whether bookings can be made without host intervention, and (ii) the choice of cancellation policy. The first is determined in Airbnb by whether hosts choose to enable the so-called “instant book” feature in their listings, which is publicly marked by an orange ray-like symbol next to the listed price and indicates that the room can be immediately booked without previous approval from the host. The second booking mechanism is cancellation policy.

2.2. Cancellation policies

Deciding a cancellation policy implies choosing the terms and conditions under which a booking can be rescinded, and the form and amount, if any, of penalization to the clients who cancel a booking or do not show up at the agreed date. Such penalizations are not uncommon in the travel industry (Chen, 2016) and are known to have a non-negligible role in revenue management of airlines and hotel chains. The majority of academic contributions deal with models of the effect of booking cancellations on firms' income, with the aim of contributing rigor to the demand-managing process (Talluri, Ryzin, Karaesmen, & Vulcano, 2008). Emphasis has been placed on the airlines context. Studies for the lodging industry are scarcer, although they have sparked an ongoing debate over the possibility of accurately predicting hotel demand based on estimating bookings that may be cancelled (Antonio, Almeida, & Nunes, 2017; Morales & Wang, 2010).

In principle, hotels that set increasing sanctions for cancellation as it gets closer to the planned arrival date aim to minimize revenue losses. For instance, it has become a widespread practice to require bookings to be backed by credit card, so that, if the client does not show up, they are at least charged an overnight. On the basis of a survey conducted in 20 hotels between 2002 and 2003, DeKay, Yates, and Toh (2004) verified that the percentage of no-shows fell as much as 5%; meanwhile, in the rental car industry, where reservations are not backed by credit card, no-shows could reach up to 70%; and, in the cruise industry, where full payment upfront is needed, the percentage was below 1%.

Conversely, the choice of cancellation policy may have a non-trivial impact on consumer decisions, especially on those who are aware that they face uncertainty. In this regard, Schwartz (2000) proposed a model with search costs that addresses three different consumer strategies: book, book & search, search and book alternative. Results confirm that willingness-to-pay is greater as the date of the stay is closer. Chen, Schwartz, and Vargas (2011) investigated on the effects of cancellation policy on consumer's booking and search decision. Their experiment shows that the effect of cancellation deadlines on booking decisions was significant, but that of the magnitude of the sanction was not. That is, the “lenient” (24 h) cancellation policy did not seem to affect clients differently than allowing them to cancel whenever at no cost. Also on the basis on an experiment, Smith, Parsa, Bujisic, & Rest (2015) did not find significant differences either between the willingness-to-pay of clients in front of a non-penalizing cancellation policy and a costless cancellation policy up to 48 h before the arrival date, which lead them to suggest that the hotel industry may as well remove the open cancellation policy without incurring appreciable losses. Nevertheless, they found that a strict policy of no-refund affected negatively consumer's patronage.

Some work also exists regarding the quantification of the impact of different cancellation policies on prices. One example is Masiero, Heo, and Pan (2015). Based on a discrete-choice model, the authors conducted a survey on over 800 hotel guests staying in Hong Kong to quantify their willingness-to-pay for different room attributes. Cancellation policy was one of the aspects that weighted least in the total willingness-to-pay, in contrast to other elements such as exterior views, hotel club access, or free beverages in the mini-bar. In particular, the option to cancel up to 24 h prior with full refund vis-à-vis the alternative of a non-refundable booking was valued in HK$122 (approximately, US$16), while staying in one of the rooms with best street views increased the willingness-to-pay in HK$771 (approximately, US$100).

The last two paragraphs confirm that available evidence for the case of hotels supports that policies that do not penalize cancellation make little of a difference to consumers compared to those that penalize lightly, and yet, stricter policies do seem to impact the probability of room booking. Moreover, a positive willingness-to-pay for the possibility of flexible cancellation is to be expected. Actually, as noted by Quan (2002), booking a hotel room can be seen as a financial option: the hotel bears the risk of anticipated cancellation, for which it has to be compensated in some form.

Airbnb offers three main cancellation policies. The flexible policy allows a full refund to the guest if he cancels his reservation earlier than one day before the date of arrival, and only if he cancels with less than 24 h of advance, the amount corresponding to the first night is not refunded. In the case of a moderate one, the full amount will be refunded if it is canceled up to five days before the date of arrival and, if later, the first night is non-refundable but 50% of the accommodation fees for the remaining nights will be refunded. Finally, the strict policy requires at least a week of advance, and afterwards, there is no possibility of refund. Nonetheless it should be noted that cleaning fees, for a guest that did not arrive to the accommodation, are always refunded, unlike the service fee of Airbnb (3% of hosts and 6–12% to guests, depending on the total amount), that will be charged no matter what.

Regarding the influence of such variables over the price of accommodations in the peer-to-peer market, there is some evidence of a negative relationship between the price and the flexible cancellation policy. In other words, prices seem to be lower for accommodations that fully refund the booker who cancels with more than 24 h in advance of the planned arrival date, as compared to those with identical characteristics that do not. For instance, Benítez-Aurioles (2017a), with data from Airbnb listings in Barcelona, encountered that accommodations offering a flexible cancellation policy have prices that are, on average, 5.21% lower than accommodations of equivalent characteristics but stricter cancellation policies. For their part, Wang and Nicolau (2017), using data from over 33 cities around the world, found that a non-flexible cancellation policy is associated with prices that are 4.58% higher. These authors attributed that result to emotional considerations (as opposed to rational ones) that would be responsible for the offering of both “fair” prices and of flexibility to cancel, in spite of lower and more uncertain revenue.

One major issue with cancellation policies has to do with the effect that they could have on the emergence of third party companies offering listings and booking for an Airbnb accommodation through them. In fact, Airbnb itself devised the figure of the co-host, and its development was promoted by means of a platform that offers the owner the option to assign certain tasks, or even the integral management of their property, to an “experienced host”. On this basis, hosts and co-hosts decide on the split of tasks; of revenue per booking; and on the manner in which expenses related to their activity will be reimbursed (Airbnb, 2018a). This tendency towards the professionalization of the activity can have a non-negligible impact on the market's functioning. As mentioned, there is evidence that professional hosts (those that offer more than one property) manage their prices more efficiently (Li et al., 2016). On the other hand, from the hotels' perspective, Gibbs, Guttentag, Gretzel, Yao, and Morton (2017), citing previous work by O'Connor (2003), suggest that dynamic pricing increases with levels of professionalization. That is, professionalization in both the peer-to-peer and conventional hotel markets shares similar strategies. On this basis, it can be argued that regarding cancellation policies, the extension of professionalization to accommodations offered through platforms such as Airbnb may favor convergence to the price management policies that hotels have been applying for a long time.

2.3. Instant booking

The literature on the effects of the IB is, naturally, much smaller in comparison to that available for cancellation policies. After all, all the traditional tourist offer is, in principle, IB. Clients do not send a reservation request to hotels for them to examine it and decide whether they accept it or not. On the other hand, for peer-to-peer tourist accommodation, many hosts want to know the characteristics of the guests before accepting them on their property, as a consequence of the peculiar characteristics of that market. In fact, as we will see later, three out of four Airbnb hosts in our data will require a reservation request from potential guests.

The possibility of hosts selecting their clients may make room for discrimination. In fact, as previously mentioned, there is empirical evidence on the existence of discrimination (Edelman & Luca, 2014; Franco et al., 2016; Gilheany et al., 2015). In this sense, strategies have been proposed to eliminate discrimination. For example, Edelman et al. (2017) suggested expanding the IB option in addition to concealing guest photos and names before booking.

In any case, as Fradkin (2017) pointed out, clients do not like to be rejected. And, when that occurs, a negative externality is generated in the platform, which would justify the interest in extending the IB option. In fact, Airbnb (2018b) promotes the IB function by stressing the benefits that it could have on the hosts' side: convenience (possibility of obtaining reservations without having to respond to requests); higher guest interest (users may prefer ads that allow them to confirm their travel plans instantly); search placement (improving the response ratio will also improve the position of the ad in the search results); Superhost status (raising the response rate contributes to meeting one of the requirements to attain this distinction).

Some evidence exists regarding the relationship between the IB option and the reviews left by guests. On the one hand, Ke (2017), using a crawled data set containing 2.3 million listings, 1.3 million hosts, states that a listing that can be instantly booked will have, on average, 0.272 reviews more than those without the IB feature. On the other hand, Proserpio, Xu, and Zervas (2016) elaborate an analytical framework under the assumption that hosts who use this option are less sensitive to reciprocity, defined as the tendency to respond to good conduct with good conduct and meanness with meanness (Sobel, 2005), than those who do not. One of its hypotheses is that hosts with IB have fewer incentives to provide a good experience to their guests, so their accommodations should receive lower ratings than the guest who does not use that option. Based on a weekly panel of US Airbnb listings spanning to 17-month period from the beginning of July 2014 to the end of November 2015, they observed that, for both private and shared properties, the average ratings are higher for those listings that do not use the IB feature. In short, in accordance to the above, IB would imply more reviews but, at the same time, worse ratings.

Accordingly, if we take the number of reviews as proxy for demand, we could conclude that there is evidence of a positive relation between the option IB and demand. In fact, in the case of Airbnb, it is only possible to evaluate a room once the check-out has been made. For that reason, the number of reviews at a point in time can be interpreted as a lower bound on the demand reached to date for a given accommodation.

If we attempted to learn about the effective level of demand, we would face, at least, two obstacles. The first is that the real average number of overnight stays for each tourist is unknown. In this sense, Airbnb (2018c) published some figures on the economic impact of its activity in some cities. For some, it did provide information on the average length of stay in the accommodations offered through the platform. But, naturally, this information is punctual and partial. InsideAirbnb also provided some calculations which are, however, based on assumptions about the average stay of tourists. Consequently, these calculations on the real number of overnight stays are approximate and, to a certain extent, speculative.

The second issue concerns the possible bias underestimating the number of reviews received by the accommodations. For example, Fradkin, Grewal, Holtz, and Pearson (2015), through two field experiments, provide evidence to support the claim that a system such as that of Airbnb, which does not compensate for leaving a review, can cause a bias—to the extent that some experiences (which are not the best) may be underrepresented.

In spite of these shortcomings, the number of reviews may still be used as an indicator of the level of demand, to the extent that a strong relationship with room sales has been detected (D. Lee et al., 2015). On that basis, we would be able to confirm that, when hosts activate the IB option, they can expect greater demand for their accommodations.

3. Data

The model will be validated with information compiled from www.insideairbnb.com. This project developed by Murray Cox describes itself as an "independent, noncommercial set of tools and data" that allows any interested entity to "explore how Airbnb is really being used in cities around the world". This data is periodically scrapped from Airbnb listings in numerous cities of the world. For our estimation, we used the latest set available in each city (Table 1).

The price of the listings is, originally, expressed in dollars and, therefore, it has not been necessary to make any type of conversion. As mentioned, the data comes from scraping from the USA. Airbnb detects the location and automatically converts the different currencies. According to Airbnb itself, the base exchange rate uses data from one or more third parties, such as the financial services company Oanda. In any case, it is interesting to note that a good part of the sample that we have used is made up of cities that share the same currency (16 in the USA and 14 in the European Monetary Union).

Overall, we have information in 44 cities (497,509 listings in total). One average, one third of the listings have a flexible cancellation policy. Yet, this percentage varies across cities, ranging from 17.2% in Venice to as much as 42.2% in Copenhagen. On another note, 1 in 4 hosts in our sample choose to offer instant book; although, for this variable as well, variation is considerable between the extremes of only 9.8% in Santa Cruz County and over 50% in Venice and Athens.

Table 1
Characteristics of the data set by city and percent shares of the usage of flexible cancellation (FC) and instant book (IB) policies.

City	Compiled	Listings	FC%	IB%
Amsterdam, NL	Feb. 4, 2017	15,181	24.5	15.6
Antwerp, BE	May 12, 2017	1227	42.6	26.3
Asheville, US	Apr. 18, 2016	864	26.2	19.4
Athens, GR	May 9, 2017	5127	33.0	50.8
Austin, US	Mar. 7, 2017	9663	37.7	23.3
Barcelona, ES	Apr. 8, 2017	17,653	26.6	46.9
Berlin, GE	May 8, 2017	20,576	42.6	16.8
Boston, US	Sep. 7, 2016	3585	27.9	16.6
Brussels, BE	May 9, 2017	6192	42.4	25.2
Chicago, US	May 10, 2017	5207	26.3	28.9
Copenhagen, DK	Jun. 15, 2017	20,545	43.8	15.0
Denver, US	May 16, 2016	2505	36.8	15.8
Dublin, IE	Feb. 18, 2017	6729	36.2	25.8
Edinburgh, UK	Jul. 9, 2016	6272	31.4	19.1
Geneva, CH	Aug. 8, 2016	2408	41.2	12.7
Hong Kong, CN	Aug. 7, 2016	6474	29.8	24.9
London, UK	Mar. 4, 2017	53,904	36.1	22.5
Los Angeles, US	May 2, 2017	31,253	30.7	27.3
Madrid, ES	Apr. 8, 2017	13,335	32.5	27.4
Mallorca, ES	Mar. 15, 2017	14,858	17.3	36.4
Manchester, UK	Apr. 10, 2016	865	37.5	17.2
Melbourne, AU	Apr. 3, 2017	14,305	35.2	29.2
Montreal, CA	May 4, 2016	10,619	42.9	14.0
Nashville, US	Sep. 6, 2016	3277	27.7	23.6
New Orleans, US	Jun. 2, 2017	5307	18.9	37.6
New York City, US	May 2, 2017	40,753	32.4	19.6
Northern Rivers, AU	Apr. 2, 2016	2350	32.5	13.0
Oakland, US	May 4, 2016	1718	35.6	11.0
Paris, FR	Apr. 4, 2017	56,535	36.5	21.5
Portland, US	Apr. 7, 2017	3548	28.5	26.4
Quebec City, CA	May 6, 2017	1913	40.7	36.1
Rome, IT	May 8, 2017	25,275	33.1	44.7
San Diego, US	Jul. 7, 2016	6608	28.9	18.4
San Francisco, US	Apr. 2, 2017	8707	32.4	20.9
S.C. County, US	Oct. 15, 2015	814	23.7	9.8
Seattle, US	Jan. 4, 2016	3818	30.1	15.5
Sydney, AU	Apr. 3, 2017	24,038	34.6	19.5
Toronto, CA	Jun. 3, 2017	12,714	32.3	21.2
Trentino, IT	Oct. 12, 2015	1847	35.3	12.8
Vancouver, CA	Apr. 7, 2017	5541	27.9	21.2
Venice, IT	May 9, 2017	6027	17.2	50.3
Victoria, CA	Aug. 1, 2016	1691	29.0	20.7
Vienna, AT	May 9, 2017	7893	34.9	29.9
Washington, US	May 10, 2017	7788	36.2	30.0
Total		497,509	33.5	24.7

4. Estimations

Table 2 provides textual descriptions of the variables utilized. Price is taken at the accommodation level and does not include cleaning fees or additional charges for guests that are not included in the overall price. The room attributes are summarized on the one hand by the type of room (entire room, private room, or shared room, which will be used as the base room type category in our regression), and, on the other, by its number of bathrooms, bedrooms and accommodates that are included in the price. As for host attributes, we utilize an indicator for whether the host possesses the Superhost badge, which itself comprises multiple host attributes. From the consumer side, we include both the number of reviews of each accommodation and the mean valuation (score) of guests who have visited it. Naturally, those are imperfect demand measures as not all visitors may have left a review. However, all

Table 2
Description of the variables.

Name	Abbr.	Description
Price	*P*	Price per night in dollars
Entire home	*EH*	1 if accommodation is entire home, 0 if shared room
Private room	*PR*	1 if accommodation is private room, 0 if shared room
Bedrooms	*Bedr*	Number of bedrooms
Bathrooms	*Bath*	Number of bathrooms
Accommodates	*Acco*	Maximum beddable guests
Superhost	*SH*	1 if owner is Superhost, 0 if not
No. reviews	*NR*	Number of received reviews
Score	*Score*	Guests' mean ex post valuation, from 0[a] (least) to 100 (most)
Instant book	*IB*	1 if instant book is enabled, 0 if not
Flexible cancel.	*FC*	1 if cancellation policy is flexible, 0 if stricter

[a] In theory, the scale is 0–100, but the minimum value found in our database was 20.

those who have left a review must have been visitors due to Airbnb's regulations; hence, *no. reviews* constitutes a reliable lower bound for total visits. Finally, regarding booking rules, we have included indicators for instant booking availability and flexible cancellation.

The selected variables are those that showed greater explanatory power according to the previous studies mentioned in section 2, as well as in the different specifications that were tested. The objective was the choice of a set of variables that would allow us to get, in general terms, good fit with an acceptable explanatory

Table 3
OLS regression on log price. Results.

City	Room Type		Room attributes			Host	Reviews		Booking		cons	N	R2
	EH	PR	Bedr	Bath	Acco	SH	NR	Score	FC	IB			
Amsterdam	.521***	.150	.0985***	.0926***	.105***	.0929***	-.00002	.00440***	-.0759***	.0434***	3.371***	12840	.46
Antwerp	.780***	.314	.153***	.0670	.0496***	.0104	-.00061*	.00627***	-.0301	-.00835	2.565***	1005	.43
Asheville	1.533***	1.078***	.130***	.0597	.0614***	-.0352	-.00093***	.00865**	-.0586	.0125	2.027***	739	.61
Athens	1.282***	.761***	.0819***	.362***	.0578***	.139***	.00005	.00559***	-.0437**	-.0330*	1.241***	3880	.46
Austin	1.167***	.480***	.156***	.267***	.0461***	-.140***	-.00168***	.00285*	-.0644***	-.0195	2.982***	5924	.63
Barcelona	1.291***	.512***	.0426***	.131***	.0916***	.116***	-.00184***	.00676***	-.0301**	.0140	2.130***	13962	.65
Berlin	.913***	.396***	.116***	.121***	.0961***	.105***	.00029**	.00283***	-.0860***	.0332***	2.437***	15826	.52
Boston	.889***	.186**	.116***	.0956***	.0566***	.0467*	-.00077***	.00563***	-.100***	-.0815***	3.419***	2753	.61
Brussels	.779***	.345***	.0786***	.0105	.111***	.0621***	-.00025*	.00511***	-.0501***	.00655	2.490***	4807	.53
Chicago	1.195***	.602***	.0912***	.163***	.0533***	.00748	-.00113***	.00937***	-.0267	-.146***	2.299***	4462	.56
Copenhagen	1.002***	.544***	.113***	.0832***	.0798***	.0896***	.00135***	.00441***	-.0577***	-.00446	4.644***	16189	.49
Denver	1.188***	.665***	.0957***	.173***	.0611***	.0843***	-.00027	.00096	-.0335	-.0613*	2.937***	1919	.65
Dublin	1.135***	.552***	.130***	.0276*	.0902***	.0422**	-.00068***	.00308***	-.0188	-.0656***	2.814***	5272	.66
Edinburgh	1.099***	.566***	.107***	.135***	.0722***	.0399**	-.00154***	.00431***	-.00729	.00842	2.416***	4456	.62
Geneva	.995***	.573***	.125***	.195***	.0849***	-.00974	.00012	.00298**	-.0658***	.0549*	2.905***	1716	.51
Hong Kong	1.508***	.993***	.168***	.0629**	.0407***	.218***	-.00145***	.00545***	-.0384*	-.0921***	4.247***	4506	.60
London	1.254***	.548***	.0980***	.0981***	.0883***	.0617***	.00038***	.00288***	-.0467***	-.00397	2.571***	36478	.66
Los Angeles	1.309***	.710***	.204***	.127***	.0532***	.0351***	-.00009	.00638***	-.0330***	-.0690***	2.441***	23630	.67
Madrid	1.272***	.493***	.105***	.145***	.0675***	.0891***	-.00076***	.00544***	-.00834	-.00496	1.950***	10374	.68
Mallorca	.927***	.391	.0920***	.177***	.0432***	.0622***	-.00359***	.00498***	-.0174	-.0921***	2.512***	8274	.59
Manchester	1.011***	.323**	-.00357	.0985***	.118***	.0122	-.00008	.00428*	.0413	-.0513	2.466***	665	.70
Melbourne	1.222***	.554***	.134***	.122***	.0553***	.0354***	-.00028**	.00354***	-.0459***	-.0236**	2.896***	11063	.67
Montreal	1.014***	.321***	.100***	.174***	.0505***	.112***	.00064**	.00521***	-.0858***	-.0462**	2.502***	6792	.56
Nashville	.908***	.477***	.111***	.202***	.0619***	.0345*	-.00061***	.00650***	-.0255	-.101***	2.731***	2765	.68
New Orleans	1.011***	.551***	.0757***	.236***	.0621***	.0179	-.00173***	.00938***	.0301	-.0476***	2.467***	4488	.57
N.Y. City	1.004***	.340***	.0906***	.134***	.0740***	.0443***	-.00011	.00449***	-.0430***	-.0633***	3.165***	30477	.55
Nort. Rivers	.671***	.209	.203***	.109***	.0188	.0225	-.00258***	.00390*	-.166***	-.0114	3.608***	1687	.59
Oakland	.796***	.362***	.168***	.105***	.0817***	.0543*	-.00019	.00645***	.0320	-.104***	2.789***	1294	.70
Paris	.821***	.435***	.190***	.180***	.118***	.172***	.00025***	.00516***	-.0937***	.0816***	2.350***	41323	.53
Portland	.874***	.409***	.0998***	.185***	.0693***	.000785	-.00009	.00575***	-.000578	−0.0473***	2.703***	3200	.61
Quebec City	1.000***	.515***	.0918***	.0141	.0818***	.0223	-.00082*	.00386*	-.0607*	-.0711**	2.804***	1467	.48
Rome	1.095***	.729***	.0556***	.145***	.0647***	.0583***	-.00091***	.00134**	-.0752***	.0573***	2.665***	18482	.42
S. Diego	1.274***	.698***	.160***	.126***	.0593***	.0197	-.00145***	.00373***	-.0528***	-.0116	2.814***	4469	.72
S. Francisco	1.146***	.636***	.157***	.0621***	.0747***	.0881***	-.00090***	.00827***	-.00220	-.0305*	2.870***	6613	.59
S.C. County	.883***	.432***	.168***	.116***	.0530***	.0936**	-.00124***	.00325	-.0845**	.00858	3.442***	695	.73
Seattle	.974***	.471***	.149***	.111***	.0557***	.0656***	-.00077***	.00349***	-.0198	-.0571***	3.046***	3153	.64
Sydney	1.375***	.719***	.185***	.101***	.0707***	.0480***	-.00052***	.00442***	-.0688***	-.0349***	2.778***	16329	.68
Toronto	1.011***	.378***	.116***	.144***	.0768***	.0433***	-.00023*	.00387***	-.00029	-.0694***	2.867***	9744	.58
Trentino	1.054***	.932***	.0607*	.0663*	.0393***	-.00145	-.00678***	.00042	-.0467	-.00210	2.787***	903	.20
Vancouver	.981***	.367***	.186***	.112***	.0439***	.0711***	-.00043*	.00424***	-.0136	-.0697***	2.975***	4418	.56
Venice	.925***	.566***	.121***	.153***	.0363***	.0364*	-.00087***	.00251***	-.00995	-.00405	3.123***	5200	.41
Victoria	.891***	.527***	.107***	.112***	.0804***	-.0155	-.00144***	.00831***	-.0951***	-.000783	2.591***	1420	.56
Vienna	.771***	.181**	.116***	.110***	.0767***	.0712***	-.00031**	.00521***	-.0859***	.00791	2.426***	6299	.55
Washington	1.206***	.701***	.185***	.126***	.0407***	-.0247	-.00076***	.00628***	-.0316*	-.00578	2.670***	5558	.53
TOTAL	.997***	.407***	.188***	.0517***	.0612***	.0513***	-.00084***	.00702***	-.0478***	-.117***	2.678***	367516	.35

*p < .05; **p < .01, ***p < .001.

power. Naturally, the higher the number of regressors, the better the fit is. However, we sought to formulate a parsimonious model to present the regularities of a general nature. For example, distance is a variable that has substantial importance at the city level but loses its explanatory power at an aggregate level. In fact, in monocentric cities the distance to the city center has been revealed as a very significant variable in the explanation of the price of tourist accommodation (Benítez-Aurioles, 2017b). However, the inequality in the size (by number of listings) of the cities that made up the sample, and the peculiar urban design of each of them, made it difficult to compare the estimators associated with this variable. It introduced distortions in the rest of the estimators, and posed serious difficulties in aggregation for the calculation of the total estimators. Consequently, we excluded it. In accordance with the above, and after different tests, the variables in Table 2 were selected.

The reference framework for the estimations consists of hedonic pricing models, whose basic premise is that the price of a good can be reduced to a function of its constituent parts (characteristics or attributes). Tourist accommodation prices would be determined, consequently, by the characteristics of the destination and those of the services provided by the tourist establishments. In this line are the pioneering works of Carvell and Herrin (1990), Clewer, Pack, and Sinclair (1992), and Sinclair, Clewer, and Pack (1990), based on the seminal contribution of Rosen (1974). The idea is based on the fact that the set of attributes or characteristics of a good Z_k is reflected on its market price; therefore, the hedonic function of the price can be represented as the function of attributes of the good:

$$p(z) = f(Z_1, Z_2, \ldots, Z_k)$$

Thus, once we have observed the prices of the good and their respective attributes, and collected them in a data set $p_i(z), z_{ik}; i = 1, \ldots n; k = 1, \ldots, K$, the implicit prices of each attribute $[P(z_k)]$ can be obtained.

Numerous contributions can be found in that context on the determinants of hotel prices (Chen & Rothschild, 2010; Espinet, Saez, Coenders, & Fluvià, 2003; Hung, Shang, & Wang, 2010; Lee & Jang, 2011; Pawlicz & Napierala, 2017; Rigall-i-Torrent & Fluvià, 2007; Schamel, 2012; Thrane, 2007; White & Mulligan, 2002; Zhang, Zhang, Lu, Cheng, & Zhang, 2011). Less numerous have been the ones referred to other types of accommodation, such as motels (Bull, 1994; Wu, 1999), bed and breakfasts (Monty & Skidmore, 2003), rural accommodations (Fleischer & Tchetchik, 2005; Rambonilaza, 2006), apartments (Juaneda, Raya, & Sastre, 2011), or hostels (Santos, 2016). And, only recently, some evidence has been put forward regarding peer-to-peer housing (Chen & Xie, 2017; Gibbs et al., 2017; Wang & Nicolau, 2017).

We have L locations and R_l room IDs (listed on the first and third column of Table 1) for each $l \in 1, \ldots, L$. We estimate by ordinary least squares (OLS) Ltimes, one for each location $l \in 1, \ldots, L$., the equation

$$\log P_{r,l} = \beta_{1l}EH_{r,l} + \beta_{2l}PR_{r,l} + \beta_{3l}Bedr_{r,l} + \beta_{4l}Bath_{r,l} + \beta_{5l}Acco_{r,l} + \beta_{6l}SH_{r,l} + \beta_{7l}NR_{r,l} + \beta_{8l}Score_{r,l} + \beta_{9l}IB_{r,l} + \beta_{10,l}FC_{r,l} + \beta_0 \quad (1)$$

where r, l means "the listing r of city l" and variables are the ones referred to in Table 1. The aggregate or total regression corresponds to the equation

$$\log P_r = \beta_1 EH_r + \beta_2 PR_r + \beta_3 Bedr_r + \beta_4 Bath_r + \beta_5 Acco_r + \beta_6 SH_r + \beta_7 NR_r + \beta_8 Score_r + \beta_9 IB_r + \beta_{10} FC_r + \beta_0 \quad (2)$$

The total estimate has been made by adding the data of the complete sample without including dummies to control the effects of cities on prices. This option is justified because, rather than the goodness of the fit, we were interested in highlighting, at an aggregate level, the sign and statistical significance of the estimators. In this sense, all parameters were statistically significant at the 0.1% level. Results are presented in Table 3. As expected, the two types of accommodation included (entire home and private room) are associated with price premia over the base category (shared room): on average, an entire home and a private room have a price 2.71 times and 50% compared to a shared room, respectively.[1] Moreover, countable room attributes such as the number of bathrooms, bedrooms and accommodate capacity are also positively and appreciably related to price: each additional bedroom, bathroom or accommodate implies a raise in accommodation price by 18.8%, 5.17% and 6.12%, respectively. The Superhost label and total score are related to price in the same direction: accommodations owned by Superhosts have on average prices 5.13% superior, and each point in the 100 scale of ratings implies an average increase of .7% in prices. On the other hand, the number of reviews is negatively associated to price, which is likely a product of the conventional inverse relationship between demand and the price, by which a cheaper apartment *ceteris paribus* attracts more clients. Regardless, the associated drop in price for each additional review is only slight (less than 0.1%).

For their part, variables describing the booking process (IB and FC) are negatively associated to price. First, is there a premium on price from enabling the instantaneous feature that could offset its disutility to hosts, besides the increased number of bookings? Our results suggest that there is not: prices are 11.7% lower when instant book is enabled. In an analogous manner, the flexible cancellation policy is negatively related to price, such that, on average, they are 5% inferior for equal accommodation characteristics. Together with the previous result, we can suspect the existence of a strategy that combines low prices, instant booking and flexible cancellation. Other hypotheses have been made, as previously commented, ascribing this triple association to emotional factors. Nevertheless, our model will be starred by economic and econometric logic.

At a disaggregate level, there is a clear pattern: in almost every city, room types and attributes are significant price determinants. The evidence is less general for other variables, but whenever they result in significant parameters, they are almost invariably of the same sign as at the aggregate level: albeit with variable intensity, in most cities we encounter a positive relationship between the Superhost badge and price, while the number of reviews is negatively associated with the price of the accommodation.

[1] At this point it is convenient to be aware of a frequent error in the interpretation of dummy variables in semilogarithmic hedonic pricing equations. As noted by Halvorsen and Palmquist (1980), a frequent but incorrect assumption is to equate the coefficient of a dummy variable (times 100) to the percentage effect of that regressor on the dependent variable. That statement is valid as an approximation, as long as the percentage values are small; but, as they grow in absolute value, the approximation is increasingly inaccurate. The exact relationship is as follows:

$$g = e^{\beta} - 1$$

where β is the coefficient associated to the dummy variable and g is the relative change in the dependent variable.

Table 4
OLS regression on the number of reviews. Results.

City	Log Price	Room Type		Room attributes			Host	Reviews	Booking		Constant	N	R2
		EH	PR	Bedr	Bath	Acco	SH	Score	FC	IB			
Amsterdam	-.166	−5.813	18.55***	−3.697***	−4.110***	2.869***	21.80***	-.0220	−7.954***	7.703***	23.36***	12840	.144
Antwerp	−6.388*	33.79**	39.62**	−7.826***	−3.217	4.892***	8.045*	.155	−13.06***	6.822*	4.100	1005	.068
Asheville	−14.98***	8.960	-.0115	2.438	−2.949	-.844	18.10***	.229	−14.62***	8.503*	76.21**	739	.089
Athens	.525	13.59**	15.11**	−5.240***	−5.475**	1.622**	16.31***	-.381***	−14.47***	7.224***	54.84***	3880	.071
Austin	−7.825***	18.00***	5.320**	−1.747*	−2.980***	.693*	26.19***	-.110*	−9.766***	8.317***	55.79***	5924	.159
Barcelona	−13.46***	27.87***	15.70***	−2.552***	.318	2.558***	27.21***	.296***	−13.32***	9.445***	29.73***	13962	.084
Berlin	1.456**	-.421	.224	−2.566***	−1.509*	1.755***	23.62***	-.130***	−9.654***	8.302***	23.23***	15826	.109
Boston	−6.583***	8.708*	11.99***	−4.189**	−1.709	2.464***	25.15***	-.0290	−9.385***	19.55***	44.68***	2753	.118
Brussels	−2.539*	-.638	.0240	−4.252***	−2.541	2.330***	23.28***	.0865*	−14.02***	15.29***	25.59***	4807	.105
Chicago	−8.124***	9.994***	10.40***	−1.956*	−2.007	1.578***	19.12***	-.350***	−12.48***	1.912	86.37***	4462	.082
Copenhagen	4.428***	−9.478***	.567	−2.352***	-.811	.547**	18.80***	-.165***	−5.138***	4.758***	10.38**	16189	.115
Denver	−2.634	15.56***	20.14***	−2.549	−2.135	.179	17.43***	-.290**	−9.781***	12.05***	48.90***	1919	.092
Dublin	−6.008***	18.09***	16.50***	−9.326***	−2.497**	5.014***	14.93***	.0289	−13.25***	8.369***	33.25***	5272	.104
Edinburgh	−11.81***	12.94**	3.489	−4.647***	−2.012*	1.746***	24.73***	.0533	−12.50***	13.22***	59.37***	4456	.147
Geneva	.466	−11.79	−1.947	−2.523**	−1.554	1.642*	6.094*	-.0623	−5.696***	3.964*	27.89**	1716	.044
Hong Kong	−5.780***	5.821**	.874	−1.896**	−3.278***	2.804***	17.31***	.117***	−10.13***	5.403***	37.11***	4506	.107
London	1.971***	−4.725**	2.692	−5.318***	−1.999***	2.529***	16.85***	.0498***	−9.907***	6.992***	7.508***	36478	.085
Los Angeles	-.774	13.81***	12.00***	−7.564***	.295	1.482***	22.09***	-.0936***	−11.04***	7.905***	26.30***	23630	.101
Madrid	−8.739***	24.35***	15.32***	−4.353***	−1.437	2.371***	17.77***	.161***	−11.58***	12.02***	23.64***	10374	.089
Mallorca	−6.132***	9.248**	11.55***	−1.547***	.266	.0438	9.711***	.0840***	−4.797***	2.252***	24.96***	8274	.132
Manchester	-.555	4.075	4.739	1.030	−4.044*	-.575	14.85***	.294**	−12.37***	5.773	.0856	665	.070
Melbourne	−1.457**	10.14***	5.522***	−7.952***	−1.948***	3.071***	20.98***	-.0238	−1.01***	6.605***	22.60***	11063	.170
Montreal	1.697**	.785	1.826	−3.944***	−1.664**	1.927***	13.59***	.0351	−6.889***	6.527***	2.935	6792	.100
Nashville	−6.364***	12.22*	8.551	−4.547***	−2.302	.00986	23.72***	-.0237	−8.259***	9.410***	56.13***	2765	.128
New Orleans	−16.85***	18.89***	18.01***	1.340	−1.221	.397	24.43***	-.237**	−16.87***	1.985	112.5***	4488	.123
N.Y. City	-.535	.856	4.689***	−2.330***	−4.207***	2.521***	19.37***	-.153***	−13.01***	6.658***	35.04***	30477	.098
Nort. Rivers	−5.606***	10.61**	6.503	−3.027***	1.036	.431	13.89***	-.0158	−6.925***	2.380	36.26***	1687	.120
Oakland	−1.548	7.785*	4.974	−3.570*	−1.116	.288	28.50***	-.0634	−9.621***	10.56**	28.14**	1294	.178
Paris	1.687***	−5.294**	-.986	−2.620***	−1.509**	.569***	19.61***	-.106***	−11.46***	12.58***	28.96***	41323	.087
Portland	−2.470	3.473	4.183	−5.757***	−6.662***	.516	38.65***	-.519**	−14.17***	11.81***	102.2***	3200	.152
Quebec City	−4.488*	6.245	7.467	−2.815*	−6.114***	2.422***	14.64***	-.0724	−12.71***	8.540***	45.81***	1467	.087
Rome	−7.412***	18.01***	8.915**	−2.759***	−1.702**	.320	18.82***	.0597*	−9.421***	14.23***	38.80***	18482	.093
S. Diego	−9.479***	15.76***	11.68***	−2.119**	-.192	.692*	23.34***	-.0247	−9.775***	8.149***	51.68***	4469	.138
S. Francisco	−11.16***	6.021	7.222	−2.968***	−4.437***	2.140***	33.67***	-.0651	−15.49***	10.64***	85.06***	6613	.139
S.C. County	−26.81***	36.04***	17.66**	−4.265	−1.346	1.755	22.29***	.121	−7.874*	1.129	124.0***	695	.112
Seattle	−9.679***	12.68***	15.51***	−1.792	−2.697**	.681	2.31***	-.0336	−11.61***	8.052***	61.96***	3153	.100
Sydney	−1.639***	8.045***	7.596***	−5.475***	−1.207**	2.195***	2.97***	.00984	−6.447***	4.871***	14.28***	16329	.125
Toronto	−1.178*	3.337	1.720	−4.710***	−3.706***	2.664***	19.05***	-.0250	−7.926***	6.858***	24.79***	9744	.109
Trentino	−2.370***	4.822**	5.447***	-.190	.712*	-.306	7.442***	.0411**	−1.086	-.132	7.766***	903	.108
Vancouver	−2.543*	8.026**	6.361*	−5.454***	-.402	1.635***	24.40***	-.0498	−11.46***	4.521***	31.52***	4418	.126
Venice	−14.06***	11.15	14.01*	−2.235	−4.297**	1.234*	27.25***	.219***	−17.64***	5.485***	74.28***	5200	.082
Victoria	−9.045***	11.24*	6.165	−6.938***	−2.656	3.653***	24.12***	-.0451	−6.037***	2.379	53.87***	1420	.171
Vienna	−2.842**	-.133	−3.952	-.984	−1.433	.604	19.81***	-.265***	−10.60***	14.27***	57.72***	6299	.092
Washington	−5.745***	9.031***	11.00***	−7.450***	-.826	3.209***	29.02***	-.216***	−10.26***	6.085***	59.49***	5558	.132
TOTAL	−2.108***	4.666***	6.052***	−4.149***	−2.738***	1.902***	22.56***	-.0275***	−10.85***	9.980***	29.30***	367516	.103

*p < .05; **p < .01, ***p < .001.

To value the aggregate-level influence of booking conditions on accommodation prices, Table 5 classifies parameters accompanying IB and FC according to their statistical significance (p-value<.001) and their sign.

At first glance, we can observe that both IB and FC produce a vast majority of negative parameters. Restricting ourselves to the significant ones, the proportion of negatives is overwhelming (4/5 of the cities for IB,[2] all for FC).

Another model, equivalent to (1) and (2) but where log *P* and *NR* have their places interchanged, is estimated in Table 4 to see the effects of the rest of the variables on the number of reviews.

We conclude that IB and FC are different strategies, whose mechanics are summarized in Table 5. The price-for-volume tradeoff is clear for IB. Yet, it is less obvious why FC would even be an option. In the following section we will propose a model of the role of both booking parameters, why would they be chosen by hosts and why we obtain the correlation observed in the data.

5. Understanding booking parameters as a profit-maximizing strategy

5.1. Instant book

A hypothesis could be that, by "doing the favor" of enabling IB, hosts may expect higher scores. However, in light of the results of Table 6, these would not be rational expectations because the relationship between scores and IB seems to be generally the

Table 5
Observed signs of the correlation of IB and FC with price (P) and visits/reviews (Q).

	IB	FC
P	−	−
Q	+	−

[2] In some exceptional cases, corresponding to the European metropolises of Amsterdam, Berlin, Paris and Rome, the parameter for IB is significantly positive.

Table 6
OLS regression on the review score. Results.

City	Log Price	Room Type		Room attributes			Host	Reviews	Booking		Constant	N	R2
		ER	PR	Bedr	Bath	Acco	SH	NR	FC	IB			
Amsterdam	1.667***	.833	-.0565	.597***	-.234	-.725***	3.877***	-.000851	.272	−2.213***	86.63***	12840	.071
Antwerp	2.315***	5.846	7.545*	.767	.0378	-.549**	4.596***	.00544	.000896	-.571	76.64***	1005	.080
Asheville	2.161**	−3.721*	−3.197*	.475	.279	-.678***	3.610***	.00357	-.224	-.627	88.75***	739	.124
Athens	1.468***	7.684*	6.906*	-.136	.144	-.348**	4.244***	-.0103***	.120	-.123	81.76***	3880	.097
Austin	.405*	1.125	1.148	.492**	.589**	-.436***	2.653***	-.00334*	-.222	-.474*	92.46***	5924	.041
Barcelona	2.810***	−1.211	1.409	.800***	.404*	−1.060***	5.919***	.0168***	-.188	−1.040***	79.75***	13962	.068
Berlin	1.149***	1.064	1.607*	.509***	-.0904	-.550***	4.078***	-.0107***	-.179	−1.332***	88.73***	15826	.034
Boston	3.118***	-.647	.206	.602	-.837	-.454**	5.968***	-.00188	.353	-.207	77.71***	2753	.070
Brussels	2.956***	-.562	.812	.679**	.210	-.841***	5.519***	.00498*	.0364	-.639*	80.78***	4807	.054
Chicago	1.550***	.254	.785	.200	.170	-.368***	3.522***	-.00808***	.483*	−1.149***	87.81***	4462	.102
Copenhagen	1.619***	4.335***	4.025**	.0597	.709**	-.379***	3.327***	-.0185***	-.370**	−1.062***	80.28***	16189	.039
Denver	.238	1.474	1.782	.311	.716	-.197	2.596***	-.00741***	.229	-.598	91.98***	1919	.045
Dublin	1.471***	3.863***	4.454***	1.548***	.607*	-.934***	5.896***	.00156	.473	-.0409	80.31***	5272	.097
Edinburgh	1.946***	2.094	1.962	.178	.347	-.767***	4.367***	.00314	4.367***	-.609	84.35***	4456	.061
Geneva	1.610**	−2.300	-.818	.105	.552	-.272	5.217***	-.00840	.470	-.426	85.89***	1716	.031
Hong Kong	3.950***	−6.438***	−8.281***	.160	.283	-.857***	6.934***	.0214***	1.941***	−1.675***	72.11***	4506	.092
London	1.755***	2.189**	2.444***	1.824***	-.104	−1.128***	5.633***	.00585***	.739***	−2.371***	82.70***	36478	.067
Los Angeles	2.162***	.573	1.520***	.163	-.105	-.475***	4.144***	-.00359***	.401**	−1.048***	84.02***	23630	.083
Madrid	3.024***	.402	2.210	.612***	-.0138	-.822***	5.765***	.00774***	1.185***	-.128	79.26***	10374	.089
Mallorca	1.988***	.346	1.103	.593**	.602***	-.594***	5.374***	.0196***	-.0877	-.0827	82.21***	8274	.059
Manchester	2.413*	−1.482	−1.316	2.422**	−1.137	−1.088***	6.290***	.0238**	1.466	-.615	82.90***	665	.096
Melbourne	1.570***	6.257***	6.852***	.0932	.215	-.424***	3.791***	-.00199	.221	-.332*	80.68***	11063	.062
Montreal	2.224***	-.862	.670	.182	-.0203	-.398***	4.938***	.00564	-.560*	−2.124***	84.38***	6792	.056
Nashville	1.245***	−1.956**	−1.175	.130	.289	-.0748	2.869***	-.000436	.184	-.144	90.40***	2765	.072
New Orleans	1.602***	.480	.0893	.376**	-.228	-.307***	3.179***	-.00418**	.551	-.246	87.42***	4488	.087
N.Y. City	1.642***	.430	-.000475	.0439	.514***	-.572***	4.825***	-.0111***	.0239	−1.293***	85.96***	30477	.055
Nort. Rivers	1.335*	4.907	4.344	-.550	1.176**	-.347	3.600***	-.00250	1.169**	-.313	82.46***	1687	.038
Oakland	3.776***	−2.762	−1.566	-.250	.316	-.509**	4.009***	-.00443	-.759	-.514	79.88***	1294	.067
Paris	2.285***	.918	1.335**	.648***	-.00162	-.755***	4.937***	-.00707***	-.373***	−1.638***	82.84***	41323	.055
Portland	1.123***	-.175	-.402	-.110	.0722	-.171*	2.574***	-.00369***	.587**	-.215	91.13***	3200	.073
Quebec City	1.299*	.865	.444	2.075***	−2.591***	-.814***	5.412***	-.00446	-.426	.630	88.46***	1467	.119
Rome	.482**	3.964***	2.984**	.584***	.458**	-.496***	5.834***	.00263*	.193	-.174	85.76***	18482	.075
S. Diego	1.507***	-.280	1.126	-.164	.228	-.362***	3.601***	-.00152	-.115	-.653	87.77***	4469	.048
S. Francisco	2.579***	−2.263***	−2.254***	.419*	-.623*	-.385***	3.646***	-.00163	.207	−1.616***	84.65***	6613	.086
S.C. County	1.152	−1.336	−1.583	-.204	.669	-.225	3.383***	.00199	-.0636	-.140	89.81***	695	.058
Seattle	1.250***	.161	.678	.353	.516*	-.384***	3.737***	-.000962	.719*	.0922	87.53***	3153	.068
Sydney	2.199***	3.942***	5.076***	.808***	.351*	-.890***	4.148***	.00156	.204	-.836***	78.85***	16329	.045
Toronto	1.469***	-.910	−1.249*	.131	.310	-.328***	4.100***	-.00182	.0998	−1.126***	88.19***	9744	.056
Trentino	.239	.270	2.371	.435	2.125***	-.598*	5.678***	.0665**	-.204	.569	87.94***	903	.054
Vancouver	1.192***	-.561	−1.403	.216	.112	-.372***	3.759***	-.00238	.0814	-.279	89.56***	4418	.060
Venice	1.077***	4.005*	2.380	1.392***	.774**	−1.083***	6.560***	.00582***	.951**	-.235	82.19***	5200	.119
Victoria	2.836***	4.692	4.498	-.585	-.0768	-.352*	3.384***	-.00244	.111	−1.205**	78.27***	1420	.085
Vienna	1.593***	-.372	.327	.328	.0919	-.551***	4.610***	-.00882***	-.215	-.474*	88.47***	6299	.076
Washington	1.587***	3.088***	3.376***	.0512	.279	-.281***	3.997***	-.00725***	.583*	-.361	83.76***	5558	.070
TOTAL	1.047***	1.823***	1.611***	.584***	.367***	-.539***	5.075***	-.00165***	.230***	−1.114***	86.47***	367516	.063

*p < .05; **p < .01, ***p < .001.

opposite: only two cities (Quebec and Seattle) have positive coefficients on IB and are not even statistically distinguishable from zero; the remaining 42 are negative; and, in the aggregate, the coefficient is strongly negative (−1.114 at 0.1% significance). Therefore, evidence makes this hypothesis seem unrealistic.

IB guarantees a higher number of visits and, thus, of reviews. In fact, most of the checks in our cities verify a strong significance of enabled IB in relation to the number of reviews, which did not happen for FC. Thus, the tradeoffs in this case are different and need a different model. The ones of this case are schemed in the diagram of Fig. 1. The advantages of IB are easy and fast booking and higher rank of the listing upon search on the website, which will lead to a higher number of visits and, thus, of reviews, consequently increasing the chances of becoming Superhost and of future visits ((a)). The drawbacks are that arrangements with the bookers will only be made after confirmation, which may lead to overbooking and cancellations amongst the increased number of visits ((b)). (a) and (b) imply opposing forces on the total number of visits, but, since (c) is a drawback, if the combination of (a) and (b) was not overall positive then there would be no reason for IB to be an option and to be chosen by people. Moreover, in the controlled regression of Table 4, the coefficient associated to IB is positive for 43 of the 44 cities; and, in the aggregate dataset without city fixed effects, it is 9.98 with a p-value of less than .001. So, we assume overall (a) dominates (b), thus the net effect of instant booking on visits (accounting for cancellations and overbooking) is an increase. This increase is captured by a parameter $B > 1$ that factors nightly revenues.

Finally, (c) means that the host losses the power to discriminate guests, because automatic confirmation of booking requests means that the host cannot look at the guest's profile and decide whether to accept or decline them. This is relevant when there is a fraction $\eta \in (0, 1)$ of consumers that the host considers undesirable because they occasion damage on top of the usual costs. Therefore, for a given level of unobservable[3] room quality x, costs are $c((1+\delta)x)$

[3] To the econometrician, but not to the market participants.

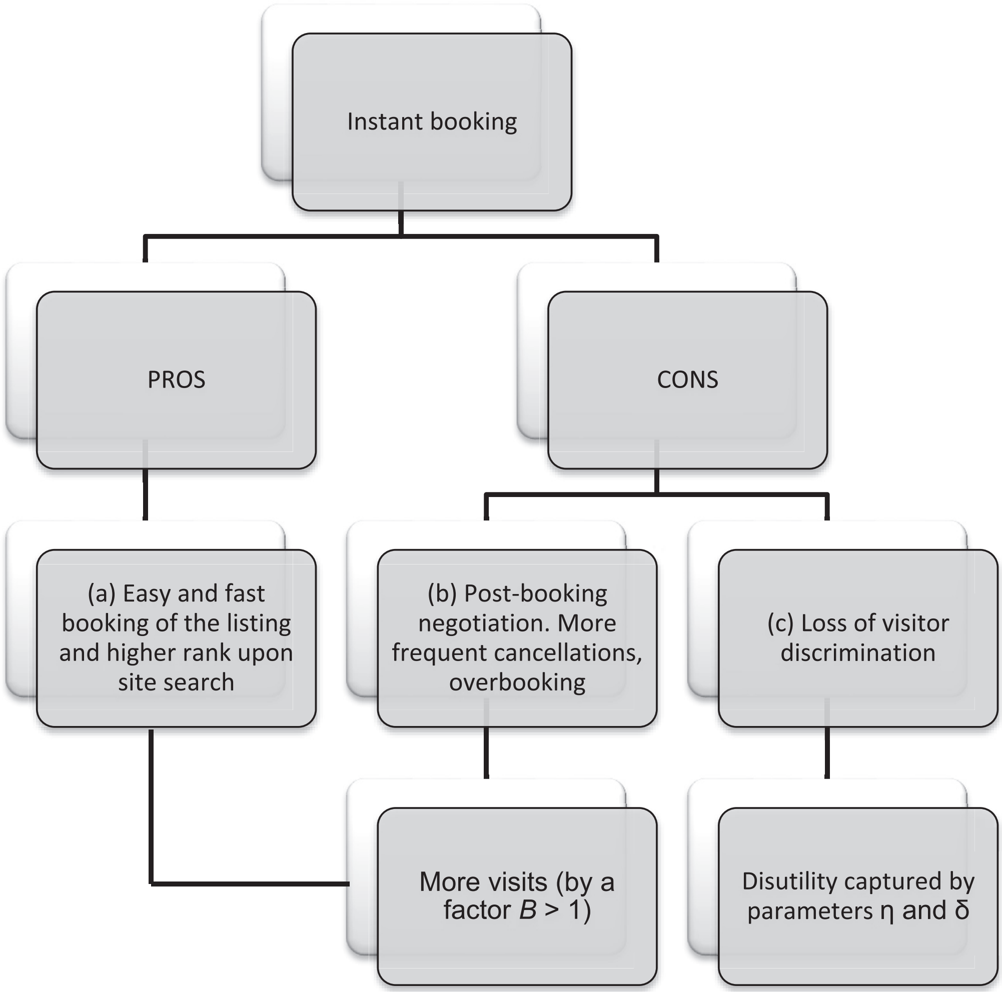

Fig. 1. Diagram of the advantages and disadvantages of instant booking for hosts.

with $\delta > 0$ instead of $c(x)$, which would be the case without IB. These damages may be destroyed equipment or structure, as well as disturbances to neighbors; therefore, it is represented as an amount proportional to x included in the input of the cost function.

If the host enables IB, they obtain per night profits $\pi(x|IB = 1)$

$$\begin{cases} p(x) - c(x) & \text{with Pr.} 1 - \eta \\ p(x) - c((1+\delta)x) & \text{with Pr.} \eta \end{cases} \tag{3}$$

and, on expected value,

$$E\pi(x|IB = 1) = p(x) - [\eta c((1+\delta)x) + (1-\eta)c(x)] \tag{4}$$

However, demand is B times larger for an accommodation with IB compared to another with the same $p(x)$ that does not have IB. Assuming risk-neutrality of the host, the comparison is between

$$E\pi(x|IB = 1) = B[p(x) - [\eta c((1+\delta)x) + (1-\eta)c(x)]] \tag{5}$$

and

$$E\pi(x|IB = 0) = \pi(x|IB = 0) = p(x) - c(x) \tag{6}$$

The host prefers setting $IB = 1$ when (5) is greater than (6); that is, when

$$(B-1)p(x) > B[\eta c((1+\delta)x) + (1-\eta)c(x)]] - c(x) \tag{7}$$

Both sides of (7) are positive. With perfect competition, the price for the attribute x is a positive constant, so that the left hand-side is an affine function $p(x) = \beta x$ with $\beta > 0$.

The first derivative of the right hand-side of (7) with respect to x is

$$B(1+\delta)\eta c'((1+\delta)x) + [(1-\eta)B - 1]c'(x) > 0 \quad \text{for all} \quad B > 0, \ \eta \in (0,1), \ \delta > 0 \tag{8}$$

While the second, assuming $c(x)$ convex ($c''(x) > 0$), is

$$B(1+\delta)^2 \eta c''((1+\delta)x) + [(1-\eta)B - 1]c''(x) > 0 \text{ for all } B > 0, \ \eta \in (0,1), \ \delta > 0 \text{ such that } (1-\eta)B > 1 \tag{9}$$

Thus, we have two possible situations that are depicted in Fig. 2. Case (B) is unlikely, since a right hand-side (RHS) always greater than the left hand-side (LHS) would imply that no host chooses $IB = 1$, which is in contradiction with the data. Therefore, the more likely case is one where an indifference threshold $\bar{x}$ exists, so that all hosts with $x < \bar{x}$ prefer to set $IB = 1$ and all hosts with $x > \bar{x}$ prefer to set $IB = 0$. Thus, even in absence of an actual negative price premium for IB, we can obtain a negative selection bias in the regression coefficient in front of the IB dummy. If B were a function of p, such that $B(p)$ were decreasing with price and

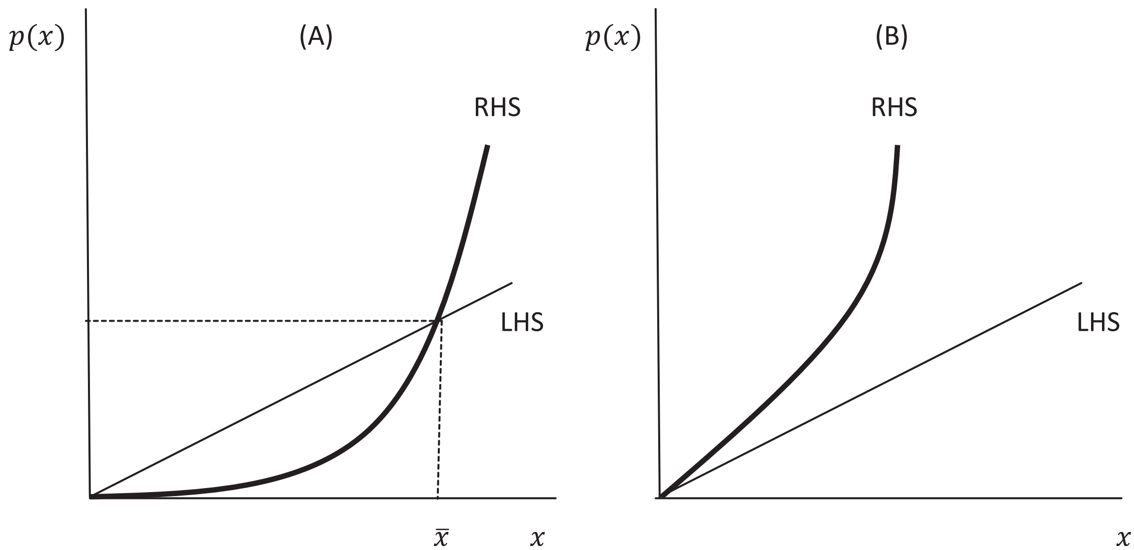

Fig. 2. Diagram of the advantages and disadvantages of instant booking for hosts.
The intercept of $c(x)$ is drawn to coincide with $p(0) = \beta \cdot 0 = 0$. It could also be possible that the RHS curve is shifted upwards in (A) or downwards in (B), if we were to account for fixed costs (and thus the minimum x in the range for which hosting is profitable would be greater than zero).

$\lim_{x \to +\infty} B(p(x)) > 1$ (in other words, if the multiplicative effect on visits of the instant bookability were most effective with lower prices and less useful for high end prices), the conclusions of this analysis would be reinforced.

5.2. Cancellation policy

Finding fewer visits (here, proxied by reviews) on flexible cancellation (FC) accommodations may be natural as it may induce some people to cancel even though they would not have done it under a strict policy. Indeed, that is what we find in our regressions where the dependent variable is the number of reviews: all coefficients on FC are negative; out of 44, 43 are significant at the 5% level; and 42 are at the .1%. In the aggregate regression without fixed effects, this coefficient is −10.85 with a p-value below .001.

If we ran a regression on price, we would expect FC to influence it in the opposite direction —namely, positively. The logic goes as follows: a flexible cancellation policy puts (most of) the risk of the loss of consumption of the accommodation on the host's hands. On the other hand, under a strict cancellation policy, it is the consumer who bears the loss. Once trip details and requirements are decided, accommodation choice logic would indicate that guests should be willing to pay more for the first product, unless they were absolutely certain that they would not miss the trip —in which case they would be willing to pay the same price for both. With this logic in mind, the results of the price regressions are counterintuitive: 41 out of 44 cities display a negative effect of FC on price, of which 19 are nonsignificant, 3 are significant between the 5% and 1% levels, 3 more between 1% and .1%, and 19 at less than .1%. In the aggregate, the coefficient is −.0478 with a p-value below .001.

Wang and Nicolau (2017) found the same striking sign for the effect of FC on price for 33 cities. To explain it, they resorted to a psychological rather than purely monetary hypothesis: it was argued that the choice of FC was emotional as opposed to rational, as they trade off a secure income for the establishment of a fair deal to the customer. We propose an alternative explanation within our framework that is consistent with the existence of both a positive premium for flexible cancellation and a negative selection bias on the estimated coefficient.

Just as in the previous model, we conserve the assumption that hosts are risk-neutral. To simplify, we will model the cancellation policy decision as a binary choice: whether the policy is flexible ($FC = 1$) or strict ($FC = 0$). Although we will ignore partial refund situations, these two definitions will be based on Airbnb's: $FC = 1$ hosts refund guests fully if they cancel within more than 24 h before the date of arrival, while $FC = 0$ hosts only refund guests completely if they cancel within more than one week before the date of arrival.

There are, thus, four relevant dates: $t_0,\ t_1, t_2,\ t_3$ .The timeline is depicted in Fig. 3. In t_0, hosts make their choice of cancellation policy. In t_1, guests make their choice of booking an accommodation for their future trip in t_3. In t_2, a variable $T_i \sim Bern(\tau)$ realizes. From the point of view of t_1, T_i is a random variable, and guests and hosts only know that $E[T_i] = \tau$ where τ is a constant within the interval $(0,\ 1)$ and, for simplicity, the same for all i. If $T_i = 0$, the guest's trip occurs as planned. But if $T_i = 1$, the guest aborts their travel plans and does not arrive to the accommodation. t_1 and t_3 are separated by no more than a week and no less than a day, so that $FC = 1$ is activated but $FC = 0$ is not.

The realization of $T_i = 0$, which happens with probability $1 - \tau$, implies

$$u(x,\ I - p(x, FC)) \quad FC = 0, 1 \tag{10}$$

where I is exogenous income, $I - p(x, FC)$ is money spent on other goods and comes from replacing the budget constraint in the objective function of the consumer utility-maximization problem, where y is the numeraire

$$\max_{x,y}\,(x, y) \quad s.t.\ p(x, FC) + y = I \tag{11}$$

We assume that (10) meets the participation constraint -that is, $u(x,\ I - p(x, FC)) > u(0, I)$ because users prefer diversity as they have a quasi-concave utility function (which is also known as convex preferences). When $T_i = 1$, which happens with probability τ, it implies that the amount paid for the accommodation can be recovered when $FC = 1$, but not when $FC = 0$. Therefore

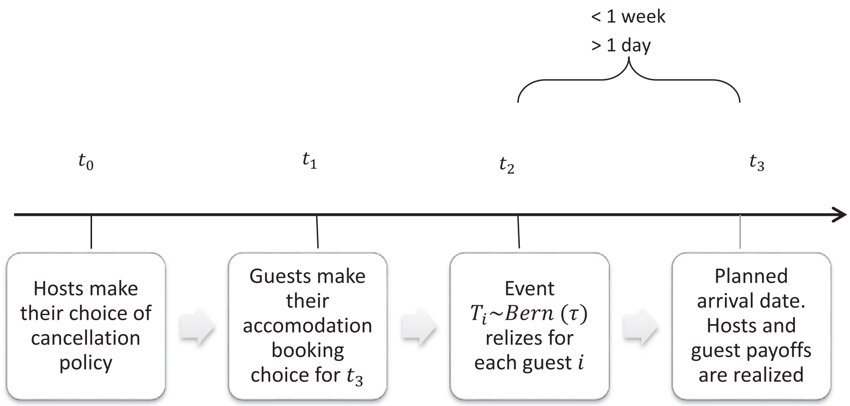

Fig. 3. Timeline of hosts' and guests' decisions that are relevant to cancellation policy.

$$\begin{cases} u(0,I) & \text{when } FC = 1 \\ u(0, I - p(x, FC = 0)) & \text{when } FC = 0 \end{cases} \tag{12}$$

Thus, the expected utility $E[u|FC]$ at t_1 is

$$\begin{cases} (1-\tau)u(x, I - p(x, FC = 1)) + \tau u(0, I) & \text{when } FC = 1 \\ (1-\tau)u(x, I - p(x, FC = 0)) + \tau u(0, I - p(x, FC = 0))) & \text{when} FC = 0 \end{cases} \tag{13}$$

For both $FC = 1$ and $FC = 0$ to coexist, it must be that $E[u|FC = 1] = E[u|FC = 0]$ which is equivalent to

$$\tau[u(0, I) - u(0,\ I - p(x, FC = 0))] \\ = (1-\tau)[u(x,\ I - p(x, FC = 0)) -\ u(x,\ I - p(x, FC = 1))] \tag{14}$$

On the left hand-side product in (14), the second factor $u(0, I) - u(0,\ I - p(x, FC = 0))$ is positive because of the monotonicity of consumer preferences: the bundle $(0,\ I)$ is preferred to the bundle with equal x but less money to spend on other goods, namely $(0, I - p(x, FC))$. Therefore, it must be that $FC = 0$ "leaves more money in the pocket of the consumer" than $FC = 1$, to enjoy on other goods:

$$u(x,\ I - p(x, FC = 0)) -\ u(x,\ I - p(x, FC = 1)) > 0 \tag{15}$$

or, in other words, that there must be a price premium for $FC = 1$ (or a price discount for $FC = 0$).

$$p(x, FC = 1) >\ p(x, FC = 0) \tag{16}$$

Back into t_0, and from the supply side, hosts anticipate that (14) has to hold, and choose $FC = 1$ iff

$$\pi(x, FC = 0) <\ (1-\tau)\pi(x, FC = 1) \tag{17}$$

This easily holds when τ is small, i.e. when unforeseen circumstances are unlikely to happen. But how does the ratio vary with x? As we assumed in the previous section, $p(x)\ = \beta x$ from perfect competition on the attribute, and $c(x)$ is convex. Then, the profit function is positive in a bounded range (x_m, x_M) and reaches a maximum at some point $x^* \in (x_m, x_M)$.

Let us assume that utility is additively separable on x and other goods y, so that

$$u(x, y) = v(x) + w(y) \tag{18}$$

can be written, where $v(.)$ and $w(.)$ are increasing functions. Therefore, condition (14) can be restated as

$$(1-\tau)[v(x) + w(I - p(x, FC = 1))] + \tau(0 + w(I)) \\ = (1-\tau)[v(x) + w(I - p(x, FC = 0))] -\ \tau(0 + w((I \\ - p(x,\ FC = 0))) \tag{19}$$

and rearranging it,

$$\tau w(I) = w(I - p(x, FC = 0)) -\ (1-\tau)w(\ I - p(x, FC = 1)) \tag{20}$$

Even though we cannot isolate the *FC* premium without imposing a form of $w(.)$, it is evident that the premium will be dependent on income, which also determines the price that the guest is willing to pay and, ultimately, the attribute that they consume.

Suppose the *FC* premium is a function $v(x)$ increasing on x and on top of profits $\beta x - c(x)$. Let us rewrite (17) as

$$\beta x - c(x) < (1-\tau)(\beta x + v(x) - c(x)) \tag{21}$$

so the condition for the host to choose $FC = 1$ becomes

$$\frac{\tau}{1-\tau}(\beta x - c(x)) < v(x) \tag{22}$$

i.e. that the odds ratio of the event of $T_i = 1$ to that of $T_i = 0$ (that is, how much more likely it is to need cancellation in relation to not needing it), multiplied by the basic unitary profits without the *FC* premium, are smaller than the *FC* premium. Condition (22) can be visualized graphically in Fig. 4. All hosts with $x \in [x_0,\ x_1]$ will choose $FC = 0$. If $c(x)$ is sufficiently convex, the segment $[x_m,\ x_0]$ will be longer than $[x_1,\ x_m]$, and thus, the accommodations with low $x$will dominate in a price regression where FC is included as a dummy. Because we do not have a direct way to weight by profits, and interacting price with FC will result in positive correlation with the dependent variable by construction, the coefficient for FC will be estimated negative despite the likely existence of a positive premium for FC for these econometric reasons.

6. Conclusions, limitations and lines for future research

The effect of booking policies on prices in the peer-to-peer market for tourist accommodation seems empirically unequivocal. Those that allow for immediate booking without confirmation (instant book, IB), or for cancellation in a lenient way (flexible cancellation, FC), have, on average, prices that are inferior to those who do not. This finding seems counterintuitive, as we would expect higher willingness-to-pay from potential guests in front of

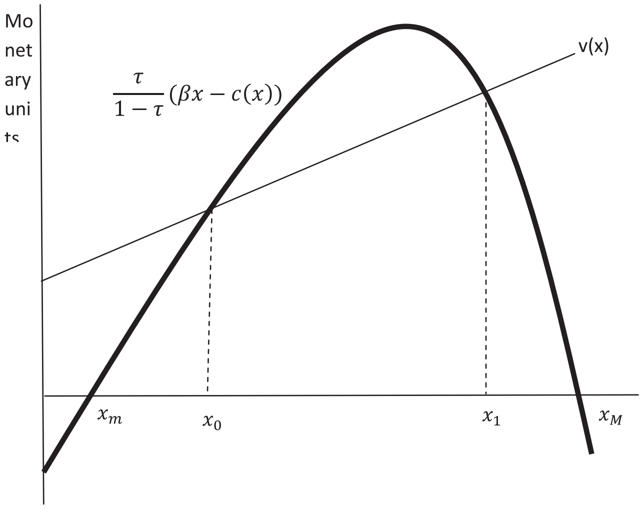

Fig. 4. Thresholds for setting or not the flexible cancellation policy.
The line ν(x) must cross [τ/(1−τ)](βx−c(x)) so that hosts who choose FC = 0 exist.

these amenities. An explanation could be found in the differential host-guest relationship of this market, in which both the supply-side and demand-side are affected by emotional factors aside from monetary incentives. But such a justification in an industrial organization framework may result vague or, at least, sketchy. An economic and econometrical analysis provides us with rigorous instruments that help understand the objective reasons why IB and FC appear negatively correlated to price in the peer-to-peer market for tourist accommodation, taking into account unobservable factors that lead hosts to choose these policies, and, at the same time, lower prices. Models that have been presented in this paper are sustained by the elementary principle of economics that individuals respond to incentives, and thus, consumers and firms respectively aim to maximize their utility and profit functions. This principle, being able to explain the workings of traditional markets, is still valid for peer-to-peer exchanges, and may coexist with social or psychological motives that, notwithstanding, do not nullify basic market forces. So, what at first sight may appear an anomalous behavior regarding booking policies in the peer-to-peer market for tourist accommodation could as well result from the application of economic logic. Consequently, our results support the notion that the functioning of this type of markets and, in particular, the vectors that determine supply are not very different from those that prevail in traditional markets. However, this does not mean that the weight of non-economic (emotional) factors is negligible. Instead, it implies that the rather strictly economic motivations are still sufficiently important to explain, by themselves and in general terms, how tourist establishments on platforms such as Airbnb are managed. At a more general level, it could be said that the construction of economic models, based on agents that maximize their utility or profit functions, is relevant for the explanation of the functioning of the peer-to-peer markets for tourist accommodation.

From a practical point of view, the fact that economic factors, as opposed to purely emotional factors, seem sufficient to understand the functioning of the peer to peer markets for tourist accommodation would explain the tendency to incorporate management guidelines that have traditionally been mostly used in conventional markets, where the pursuit of profit is the principal objective. Thus, for example, the price management skills acquired by the hotel industry over time to adapt to the different willingnesses to pay of customers (Kalnins, 2006) are being incorporated into the peer-to-peer market—in which some hosts go as far as to use complex algorithms to set the price of their supplied accommodation (Hill, 2015). Likewise, it is possible that, in terms of the booking management and cancellation policy, both markets are converging. In this line, the way Airbnb promotes the option of *Instant book* (IB)—the default in the traditional industry—can be understood not only as a tool to prevent discriminatory behavior, but as a strategy for raise turnover. Similarly, hosts have room for maneuver to build on the experience of hotels concerning the management of cancellations, since, although the academic contributions in this area are relatively scarce (mentioned in section 2.2), there is evidence that, for instance, customers' willingness to pay is not very different when they are allowed to costlessly cancel a reservation at any time (open cancellation) than when they are required to do it 24 h in advance in order to do it for free (flexible cancellation). In this context, it is a very significant result that, among the cancellation policies that Airbnb offers to the hosts, open cancellation is not an option.

However, it is also necessary to make some qualifications to the results that, to a certain extent, can be understood as limitations of the research. In this sense, some robust evidence has been found that, in principle, could be generalizable: the number of reviews (visitors) is positively related to the IB option and negatively to the FC; and the reviews score are negatively related to the IB option. Consequently, these relationships are a solid basis for building behavioral models applicable to any destination. More specifically, the data confirm the validity of the model that negatively correlates the price with the flexible cancellation policy (FC). On the other hand, the model that negatively relates the IB option to the price requires some qualifications insofar as, in some relevant cases, the relationship is reversed. These cases refer, if we look at those with statistically significant parameters, to cities belonging to continental Europe (Amsterdam, Berlin, Geneva, Paris, Rome) and that, except in the case of Geneva (whose parameter is significant at 5% and not 0.1% like the rest), these are large cities with a high capacity for tourist attraction. The fact that some cities deviate from the predictions of the model suggests the presence of idiosyncratic factors that would require a particular analysis that would include, among other factors, the difference in housing supply elasticities in the face of changes in demand. In this sense, within the logical framework of the models, these results could be explained by a violation of the assumption that increases in the number of visits are more intense when prices are low. In any case, we do not believe that exceptions to the rule should force us to throw the baby out with the bathwater. On the one hand, we have evidence that, in the vast majority of cases, the results are as expected. On the other, the conclusions of the models are still valid; and the exceptions or singularities detected are, to some extent, logical—insofar as the existence of econometrically unobservable variables in the models prevents their full implementation.

Another limitation, which is shared by studies with similar characteristics, is that the parameters' estimators are not BLUE (Best Linear Unbiased Estimator) in the presence of omitted variables, or of variables that considered independent but, in fact, are determined by a joint process. At a general level, the solution to these problems of endogeneity requires information that is not always available. However, the fact that we acknowledge the possible existence of endogeneity does not mean that this problem is as grave as to question the validity of the results and conclusions. We note that, in order to assess the importance of the aforementioned problem, alternative estimates have been made to circumvent the endogeneity problem and results obtained were very similar to those that have been presented in the manuscript since, in the vast majority of cases, not only the sign and statistical significance of the parameters were maintained; but also, their punctual value underwent relatively small alterations. On this basis, we can affirm that the presence of endogeneity is not as serious as to affect the results and conclusions.

On the other hand, the argument that we have exposed is based on an empirical estimation; and, later, an analytical model that justifies the results is constructed. However, the relationship between both approaches (empirical and theoretical) is weak insofar as the theoretical models include parameters and variables that cannot be observed econometrically—or, at least, with the existing data. This limitation of our work is, at the same, time an opportunity for new research aiming towards the construction and calibration of fully verifiable theoretical models.

This work suggests a new direction to look at when trying to explain seemingly counterintuitive findings. As such, it is meant to stimulate further research. Laboratory experiments may be rich complements to explain the behavior of hosts and consumers regarding those policies. From the theoretical point of view, our models are dependent on properties of functions whose form is difficult to observe or test, as they concern utility or profit functions of individuals. Secondly, we reduced the dimensionality of our variable set for the sake of tractability, but in a more realistic treatment there might be more than one attribute, potentially different ones, that affect the choices of IB and FC, and their potential interaction is important when uniting the two models.

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