MASTER PROJECT

Implications of market rating-based segmentation on intra-platform competition: An application to Airbnb's market in Barcelona

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Abstract

In recent years, large platforms have raised concerns that they may engage in anti-competitive practices that affect market competition. Therefore, analyzing the competition structure inside platforms is a relevant issue that has not been treated in many empirical research. This study analyzes how a platform's owner could affect the degree of competition among members of one group in the platform through biasing search results using rating classifications. In this paper, we perform an application to Airbnb's market in Barcelona given the particularity of rating is an unavailable searching filter to guests. We found evidence that listing's rating classification represents an important market segmentation in the Airbnb's market in Barcelona that could imply a possible practice of biasing search results. Moreover, we found that the intensity of competition is differentiated by the rating-related segments, which means that this segments are concentrating competition.

Keywords: platform competition, digital market, economics of sharing.

JEL Clasification:C13; C55; L15; L20; L40

Contents

1 Introduction

Digitalization has encouraged platforms' presence in diverse services such as hospitality, transportation and entertainment, hence these platforms are playing a more important role in worldwide economy. In particular, digital platforms such as Amazon. Airbnb, Facebook and Google have increased their market share and expanded their operations.

These large platforms, in combination with their privileged ecosystem position, have raised concerns that they may engage in anti-competitive practices that reduce innovation and consumer welfare such as excessive prices, algorithmic pricing collusion and data use to establish non-price discrimination (Parker et al. (2020)). Consequently, many empirical research have assessed the competition between and within platforms (see Belleflamme and Peitz (2018b), Cennamo and Santalo (2009), Jullien and Sand-Zantman (2021), and Kim et al. (2017)).

Regarding Airbnb, many empirical literature have focused on its effects on different markets so, for instance, on hotels (Schäfer and Tran (2020)), rents (Duso et al. (2020)) and housing (Garcia-López et al. (2020)). Nonetheless, analyze the competition structure inside platforms is still a relevant issue that has not been treated in many empirical research.

Since platforms themselves are ecosystems of users, they can shape the competition among sellers through quality. For example, platforms can choose how ratings influence the probability of being seen by a buyer. This can generate concentration of competition among high-rated sellers. (Charlson (2021)). This decision is one of the drivers of platforms' profits, since platforms will try to encourage visibility of high-rated sellers given the higher demand faced by them (Belleflamme and Peitz (2018b)), but, simultaneously, the increase in competition would lower the prices and, ultimately, platforms' revenues.

We will address whether rating classification represents a segmentation within a platform. Airbnb is an ideal platform to explore it, since its filters do not allow users to discriminate listing under this feature and, therefore, a rating segmentation could imply a possible practice of biasing search results.

Additionally, Airbnb is a relevant[1] case since it is the first and largest two-sided online platform in the short-term rental market and they could have a greater impact in the future. Moreover, its presence in Barcelona is important[2] and it has been growing through time [3]. Also, the city itself is relevant for tourism, since, according to the Statistical Institute of Catalonia, from 2010 to 2019,

[1]According to 'See Transparent' web page, it reaches nearly 5 millions listings with an exclusivity ratio higher than 50% in most of the relevant cities in the world.

[2]According to Datahippo website, Airbnb accounts for the majority of short-term rentals in Barcelona with respect with its main competitors.

[3]Airbnb's listings in the city has been growing from 2015 to 2021, with an average increasing rate of 17.6%.

the number of visitors increased in 12.2% and Barcelona was the 6th most visited destination city in Europe and 17th worldwide in 2018[4].

We use monthly-level data of Airbnb's listings in Barcelona to analyze how competition is shaped by rating classification of rentals. Since we have information on location, type of listing and rating, we can allow for segmentation of the demand according with these variables.

Our main contribution is that we provide insight about competition within Airbnb's hosts (sellers), highlighting the importance of rating as a market segmentation within platform. We found evidence that listing's rating classification represents an important market segmentation in the Airbnb's market in Barcelona even though guests (buyers) can not filter their search results using this feature. Moreover, we found that the intensity of competition is differentiated by the rating-related segments, in other words, the segments are able to concentrate intra-platform competition.

The study is organized as follows. In Section 2, we describe Airbnb's market in Barcelona. In Section 3, we present literature related with rating effects, intra-platform competition and Airbnb's empirical studies. In Section 4, we describe the econometric models we used and the link between those models and intra-platform competition. In Section 5, we discuss the variables needed for model specifications. In Section 6, we explain the results and elasticities obtained. Finally in Section 7, we discuss our conclusions and limitations.

2 Airbnb's Market in Barcelona

Airbnb is the first and largest two-sided online platform in the short-term rental market worldwide. Its business is focused in short-term rental services with some recent experience's services. Particularly, its revenue model consists in charging a service fee depending on total booking price from each host and guest that use the service. Additionally, Airbnb has an algorithm focused on search results and a pricing algorithm that recommends 'optimal' prices to hosts.

Airbnb is highly demanded in Barcelona, in 2017, the city was the fourth most preferred destination in Europe for Airbnb users[5]. Additionally, Barcelona is the sixth biggest city in the world for Airbnb's rentals[6]. Moreover, from the end of 2016 to the middle of 2020, it has shown an important increase in the number of listings offered in the city (see Figure 1 of Annex).

This supply is not proportional between listing types given majority of rentals are entire apartments and private rooms, while shared and hotel rooms represent the smallest amount of list-

[4]According to Mastercard's Global Destinations Cities Index

[5]According to information of Statista

[6]According to *Forbes*

ings in the city, this structure has been the rule, regardless of the time considered (see Figure 2 of Annex). Similarly, the presence of Airbnb in neighborhoods has not been homogeneous, given that majority of listings are gathered in Eixample and Ciutat Vella, meanwhile, Nou Barris and Sant Andreu are neighborhoods with the least amount of rentals (see Figure 3 of Annex).

The incremental of listings has risen concerns in the city[7] which has introduced regulations that seek to limit the quantity of short-term rentals. Since 2011, Barcelona has required entire apartments offered for short stays to have a license[8], in 2014, new licenses were frozen in central Barcelona[9] Two years later, Airbnb was fined with 60,000 euros for advertise apartments that did not have license[10]. While in 2018, the city introduced a host identification system to verify whether apartments offered online were done so legally. And, in 2020, a temporary rule to ban listing rentals for less than 30 days was imposed[11].

3 Literature Review

In this Section, we discuss relevant literature grouped in three categories: (i) studies who explore ratings as a tool to improve platforms' network effects; (ii) studies who analyze intra-platform competition, its effects on platform's owner incentives and, ratings' capability to affect this type of competition; and (iii) empirical studies who use Airbnb's scraped data.

3.1 Platform's network effects and ratings

In the literature, platforms are defined as services that create value from trade while coordinates and facilitates economic or social exchange between distinct groups of consumers (Rochet and Tirole (2003), Evans (2003), Belleflamme and Peitz (2018a), and Parker et al. (2020)). Regarding value creation and business model, we can define roughly a two-sided platform as an economic agent that enable interactions between end-users, and try to get the two sides "on board" by appropriately charging each side; that is, a platform courts each side while attempting to make, or at least not lose, money overall (Rochet and Tirole (2006)).

Network externalities (effects) arise when the utility that a user derives from consumption of the good increases with the number of other agents consuming the good, likewise, there are several possible sources of these externalities such as the presence of post purchase services and developing of complementary services (Katz and Shapiro (1985))[12]. Particularly, most markets

[7] Nieuwland and Melik (2018), provides a relevant policy and research review related to the presence of Airbnb in Barcelona.

[8] According to *Bloomberg*

[9] According to *The Wall Street Journal*

[10] According to *The Guardian*

[11] According to *Bloomberg*

[12] According to Franck and Peitz (2019) network effects can be divided in two groups: (i) direct network effects

with network effects are characterized for the presence of two sides who benefit from interacting through a common platform (Rochet and Tirole (2003)). Also, in this markets, the benefit of one group depends on the size of the other group that joins the platform (Armstrong (2006)).

From the above, platforms provide a number of services that generate so-called "network effects," insofar as the attractiveness of a particular platform increases with the volume of interactions that the platform manages (Belleflamme and Peitz (2018a)). This volume of interactions will depend on the size of platform's users and the platform's capability to incentive its use through commercial strategies and changes in the platform's design.

Following this, Belleflamme and Peitz (2018a) analyze how reviews, ratings, and recommendations systems generate network effects on platforms. They argued the ratings and reviews can be an important source of network effect since the more users that are active the better informed other users are[13]. Consequently, the authors establish that rating and review systems fuel self-reinforcing mechanisms that make successful platforms even more successful since they generate platform-specific network effects.

To sum up, the literature is certain about that the key for a successful platform is its capability to generate positive network effects. Also, the literature shows that the rating and review systems are able to increase the presence of network effects in platforms.

3.2 Intra-platform competition and ratings

Most of the relevant literature is focused on: (i) platform competition; (ii) cross group external effects and platform's attractiveness; and (iii) asymmetric pricing between platforms' sides. Regarding platform competition, in the last 20 years, the literature is focused on analyzing how platforms compete either within the market or for the market and the possibility that platform competition will derive in a monopoly situation (Jullien and Sand-Zantman (2021)).

However, there are some literature that analyze the impacts of the degree of competition among members of one group in the platform -which, for the purpose of this study, we called as 'intra-platform competition'- on the platform outcomes[14]. For instance, Belleflamme and Peitz (2018b) study how a change in the degree of competition among sellers may affect platform's pricing

which occur when the utility of a user depends on the decisions of other users and all of these users belong to a group and, they can be negative or positive; and (ii) indirect network effects which occur when the benefit of a user depends from increased participation of other users only because of the interaction with the participation (or usage) decisions of another group of users.

[13] As Belleflamme and Peitz (2018a) said product rating systems have the potential to solve asymmetric information problems. Therefore, the quantity and quality of reviews and ratings increases with the numbers of users in the platform.

[14] Belleflamme and Peitz (2018b) relates this type of competition with the concept of negative within-group effects which arise when the presence of additional sellers, given a fixed number of buyers, could affect the expected profits of the sellers established in the platform

strategy finding that the platform will maximize its profit when the total value of the transactions between buyers and seller decreases with the intensity of seller competition.

Similarly, Galeotti and Moraga-González (2009) study how differentiated product sellers compete for consumers within the platform, and how the platform's owner should price its services to maximize its profits (pricing strategy). Likewise, the effects of intra-platform competition could affect user's benefits. For instance, Belleflamme and Toulemonde (2016) shows that sellers may be better off, and buyers worse off, in markets with more sellers (higher competition); and, also, sellers and buyers may prefer full product differentiation while platforms may prefer no differentiation which could affect product variety strategy by the platform owner.

Nonetheless, pricing and product variety strategies are not the only available tools by platforms' owners to respond to changes on intra-platform competition. In particular, there are non-pricing strategies such as product visibility and quality control[15] that platforms' owners can exploit to influence the degree of intra-platform competition and, consequently, its outcomes (Belleflamme and Peitz (2018b)).

With respect to product visibility, as we mentioned, platforms' owners are interested in attracting more users to platforms to increase network effects. Thus, they can use search engines to guide consumers to products they like and generate more attractiveness to the platform (Belleflamme and Toulemonde (2016)). Therefore, platforms' owners have the incentive to bias its search results to obtain more profits either through generating more attractiveness or softer the competition among sellers.

Regarding the latter, we would expect that the value of each seller will be reduced due to competition which could affect the profits of the platforms' owners (reduction of total transaction). Therefore, platforms' owners have the incentive to softer the competition which it is possible through biasing search results.

In particular, biasing search results could imply that a buyer do not observe closer substitutes sellers which would led to sellers do not face a high competition within the market. In the literature, Chen and He (2011) and Eliaz and Spiegler (2011) show that search engines have an incentive to decrease the relevance of their search results and, thus, discourages buyers from searching extensively and softening the competition among sellers.

In this context, naturally, we wonder if platforms' owners can bias search results using ratings. Regarding this, Charlson (2021) states that since demand is higher for high quality products,

[15]With respect to quality control, as Belleflamme and Peitz (2018b) states platforms may control the quality of sellers and remove underperforming sellers from the platform. In the presence of seller competition this may come at the cost of reducing competitive pressure.

there is an incentive to increase the probability that highly-rated sellers are observed by biasing search results towards them. However, biasing search results in this way results in competition being more concentrated, reducing prices.

In conclusion, the degree intra-platform competition is able to affect platforms' profits and the well being of platforms' users. In that sense, platforms' owners have the incentive to influence intra-platform competition through price and non-price strategies and, particularly, they could use rating to bias product visibility and softer intra-platform competition. However, this decision will depend on the characteristics of the platform as Charlson (2021) states[16].

3.3 Airbnb's scraped data in empirical studies

Recent studies have used Airbnb's data with an exploratory objective, for instance, Sutherland and Kiatkawsin (2020) use Airbnb's reviews data from New York with a text processing technique to analyze topics of interests that drive customer experience. Also, Gyódi (2017) explore Airbnb's characteristics in Warsaw, finding that number of listings is higher in more attractive parts of the city, which makes more difficult for locals to find a long-term rental in these areas.

Regarding demand analysis, the studies have focused on the elasticities of Airbnb's short-term rental, for example, Jiang and Yin (2020) use this data to estimate the demand in China, while Gunter and Önder (2018) finds a price-inelastic demand for for Airbnb's listings in Vienna.

Similarly, some research have relied on hedonic modelling techniques to estimate the determinants of prices and revenues of Airbnb's listings. For instance, Deboosere et al. (2019) account for large neighbourhood effects on the prediction of both average price per night and revenue generated by each listing in New York. Whereas for Spain, Lladós-Masllorens et al. (2020) find that prices are best explained by guests' preference for characteristics of the rental and for the systematic interaction of valence and volume of online reviews.

Instead, several studies have used this kind of data to explore the impacts of platforms on rental housing. Zou (2019) analyzes the implications in Washington, D.C.; and the results suggest that having Airbnb establishments in the neighborhood can significantly inflate property prices, which inequitably affect low income home buyers, since there is a uneven penetration of the platform on neighborhoods. In parallel, Garcia-López et al. (2020) explore the effects of Airbnb on housing rents finding that its activity has increased the latter. Similarly, Duso et al. (2020) exploit policy changes in short-term rental regulation in Berlin finding that Airbnb's presence increases average monthly rents by at least seven cents per square meter. In Barcelona, Agustí et al. (2020) have found that the platform has increased the rent prices, although, they do not

[16] In Subsection 4.3, we explain in more detail the possible rating-based segmentation for Airbnb according to Charlson (2021).

obtain indication that Airbnb affects transaction prices.

Conversely, some research is centred in the effects of Airbnb on hotels, such as Schäfer and Tran (2020), who use data for Paris to estimate a segmented demand of Airbnb listings. They conclude that Airbnb increases average consumer surplus due to the increase number of choices and lower prices, although, the platform reduces average hotel revenues. While, Zervas et al. (2017) analyzes the impact of Airbnb in the Texas hotel industry, showing an heterogeneous negative effect of the platform on hotel revenues depending on hotel type, the impact is attributed to a higher level of competition faced by hotel owners.

In contrast, Li and Srinivasan (2019) use Airbnb data from the United States and obtain that Airbnb's flexible supply helps recover the lost underlying demand due to hotel seasonal pricing and even stimulates more demand in some cities. While, Maté-Sánchez-Val (2021) finds mixed results for Barcelona, where, on the one hand, Airbnb plays a substitutive role for traditional hotels, specially when the platform's offer is composed by private rooms and multi-listing hosts But, on the other hand, in locations where traditional hotels do not have sufficient numbers of rooms available to meet demand, Airbnb plays a complementary role.

In this context, our work is closer to the literature that addresses intra-platform competition. In particular, this paper contributes to the discussion of how the intra-platform competition is shaped due to factors that may be controlled by the platform itself, biasing seller's probability of being seen based on rating classification.

4 Model Specification

We assume that listings are differentiated products where prices are endogenously determined by price-setting hosts (Berry (1994)). This insight allows different substitution patterns across listings which permits us to estimate demand determinants based on discrete choice models.

This kind of models consider products as a bundle of characteristics. Berry (1994) proposed a framework to estimate discrete choice models when there is unobserved consumer heterogeneity. This framework allows for estimation using traditional instrumental variables techniques and, among others, includes the Logit and Nested logit model.

These models can be transformed into a simple linear regression of market shares on product characteristics, by "inverting" the market share equation as proposed by Berry (1994). This feature makes the use of these models extended in the literature (Grigolon and Verboven (2014)). The assumption of the logit model relies on that consumer's preferences are uncorrelated across products. While the nested logit model allows preferences to be correlated across products within the same "nest" (Grigolon and Verboven (2014)). This, "allows for more reasonable substitution patterns as compared with the simple logit model" (Berry (1994)).

4.1 Logit model

In this model, the main assumption relies on the independence of the ratio of probabilities of choosing two products from other alternatives different than those two products (Train (2009)). This is usually called independence of irrelevant alternatives (IIA).

In this type of setting the utility of consumer i for good j is given by equation 1, where x_j is a vector of observed characteristics of product j, p_j is the price, ξ_j is an unobserved characteristic for product j, while ϵ_{ij} is a consumer-specific component of utility, which provides the variation on consumer taste. This last component is unobserved and it is assumed to be identically and independently distributed across consumers and choices.

$$u_{ij} = x_j\beta - \alpha p_j + \xi_j + \epsilon_{ij} \tag{1}$$

One can denote $\delta_j = x_j\beta - \alpha p_j + \xi_j$, where δ_j represents the mean utility common to all consumers for j. In models where individual tastes across consumers and choices are i.i.d, the elasticities are determined solely by the mean utility levels, δ_j (Berry (1994)). The mean utility for the outside good is normalized to 0 ($\delta_0 = 0$). In our case, the outside good represents the hotels (see explanation in subsection 5.1). After rearrange the market share equations (see details in Annex), we have the following linear equation:

$$\ln\left(\frac{s_j}{s_0}\right) = x_j\beta - \alpha p_j + \xi_j \tag{2}$$

The market share of each product j is given by $s_j = q_j/L$, which is the observed market share Björnerstedt and Verboven (2016). L denotes the total potential market. Therefore, we can rewrite equation 2 as,

$$\ln\left(\frac{q_j}{L - \sum_{k=1}^{J} q_k}\right) = x_j\beta - \alpha p_j + \xi_j \tag{3}$$

Likewise, the own-price elasticity of product j and the cross-price elasticity of product j with respect to k can be recover from this model as shown by equation 4 and equation 5, respectively.

$$\epsilon_{jj} = \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = -\alpha(1 - s_j)p_j \tag{4}$$

$$\epsilon_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \alpha s_j p_j \tag{5}$$

4.2 Nested logit model

The nested logit model is usually applied when the set of choices available for a consumer can be divided into subsets or "nests". In these kind of models, IIA property should be satisfied within each nest, which means that the ratio of the probabilities of choosing two products in the same segment is independent of the attributes or existences of all other alternatives within the same segment attributed by the "nest", while the property does not need two hold for products in different segments (Train (2009)).

The nested logit model divides the products into $G+1$ exhaustive and mutually exclusive sets, $g = 0, .., G$. The utility of consumer i for product j that belongs in a particular group g can be written as,

$$u_{ij} = x_j\beta - \alpha p_j + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}$$

Where ζ "is common to all products in group g and has a distribution function that depends on σ, with $0 \leq \sigma < 1$" (Berry (1994)). We can rearrange terms (see details in Annex) and following Berry (1994), the solution can be written as,

$$\ln\left(\frac{s_j}{s_0}\right) = x_j\beta - \alpha p_j + \sigma \ln(s_{j|g}) + \xi_j \tag{6}$$

Following Björnerstedt and Verboven (2016), equation 6 can be rewritten as,

$$\ln\left(\frac{q_j}{L - \sum_{j=1}^{J} q_j}\right) = x_j\beta - \alpha p_j + \sigma \ln\left(\frac{q_j}{\sum_{j\in g} q_j}\right) + \xi_j \tag{7}$$

Likewise, the own-price elasticity of product j and the cross-price elasticity of product j with respect to k can be recover from this model as shown by equation 8 and equation 9, respectively.

$$\epsilon_{jj} = \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = -\alpha\left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma}s_{j|g} - s_j\right)p_j \tag{8}$$

$$\epsilon_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \alpha\left(\frac{\sigma}{1-\sigma}s_{j|g} + s_j\right)p_j \tag{9}$$

4.3 Rating-based segmentation and biased search results

Charlson (2021) provides a model where platform's decision to bias seller's visibility is explored. This choice is shaped by a trade-off between more concentration of competition, which results in lower expected prices across the network, and rents induced by the higher willingness to pay of consumers due to the matching with high quality products. Moreover, it states that an increase of substitutability between products as well as reduction in sensitivity to quality by consumers would reduce the extent to which search process is biased towards highly-rated products.

In the host industry, such as Airbnb, consumers differentiate services due to the heterogeneity of listing's characteristics and, therefore, according to Charlson (2021) it is profitable for these business to bias users search process.

We estimated the logit model as a reference, however, our main interest relies on the estimation of market segmentation, in particular, in rating-based market segmentation. Hence, we are focusing mainly on the results of the nested logit model, and, specifically, in the estimation of σ related with rating-based nest. A large and significant rating-based nest coefficient will indicate that listings inside each rating group will be seen as substitutes for consumers, since the decisions that users face are separated by this particular "nest" (Donnelly et al. (2019)). This means that competition will be concentrated since an existing nest will indicate a process of decision by the consumer Davis et al. (2014).

Considering that rating-based filters are not available in the Airbnb search page, the results will indicate that such nest will be given by an external factor, for instance, Airbnb. This will be consistent with the view that some platforms, like Airbnb will bias their search results based on rating Charlson (2021). Therefore, we evaluate the following main hypothesis: there is degree of substitution within segments determined by quality differences established by rating level of Airbnb listings.

5 Data and Estimation

5.1 Data treatment

We used Airbnb web-scraping data collected by *Inside Airbnb*, which is an independent, non-commercial set of tools and data about Airbnb's listings in several cities. Usually, this scraping data is gathered in a monthly basis and it is composed by two main databases which contain information about calendar availability and price for each listing from the scraping day until next measure; and the characteristics of each listing. For this study, we used both databases from listings in Barcelona scraped during November 2016 to February 2021[17]. In total, we gathered nearly 30 millions of daily observations and we aggregated them to monthly data resulting in 970,222 observations.

Our demand and price variables have been constructed using the calendar availability database. Particularly, we consider as demand variable, the number of booked days; however, the dataset does not contain information whether a listing is booked or not, so we build a proxy variable using the number of unavailable nights until next scraping date, we implicitly assume that there

[17] The data was retrieved on the 22 April 2021 and it has a gap between February and April 2018.

is no difference between blocked and booked days[18]. Even though, the latter could be a strong assumption, we reduce its effect excluding listing with zero booked days (see subsection 5.2). Additionally, we perform an estimation with a sub-sample excluding hotel and shared rooms, which are more likely to be blocked, and we verify the robustness of our results. Regarding the price variable, we consider it as the average of available daily prices until next scraping date.

Likewise, control variables have been obtained using the listing characteristics database, while the potential market size was build using the hotels' overnight in Barcelona retrieved from the Statistics Institute of Catalonia (see subsection 5.2). Moreover, after excluding missing values related with the relevant variables, we obtained 761,489 observations. In Table 2, we show the descriptive statistics for those observations.

From the descriptive statistics, we conclude that average prices are higher for entire apartments and hotel rooms than private and share rooms, although the result is mixed with booked days. We identify Eixample as the most expensive neighborhood on average, while, there seems to be no substantial difference in the average booked days across neighborhoods. On the other hand, being super host represents a small advantage in price with respect to those hosts without this condition, nonetheless, there is no significant difference on booked days among them. Finally, those who do not have reviews, charges the highest price on average compared with listings with ratings. Whilst there seems to be a slightly increase in the booked days when rating increases, the price seems to marginally decrease, with the exception of listings with rating higher than 97.

5.2 Estimation

The final models based on equations 3 and 7 to estimate are given by:

$$\ln\left(\frac{s_{jt}}{s_{0t}}\right) = x_{jt}\beta - \alpha p_{jt} + \gamma_r + time_t + \xi_{jt} \tag{10}$$

$$\ln\left(\frac{s_{jt}}{s_{0t}}\right) = x_{jt}\beta - \alpha p_{jt} + \sigma \ln(s_{j|gt}) + \gamma_r + time_t + \xi_{jt} \tag{11}$$

The main variables required to estimate demand models described in equations 10 and 11 are the following: market shares, prices and listing characteristics. To calculate the market shares we need to define an outside good or a potential market size.

According to Berry (1994), the outside good is the one that might be purchased by consumers instead of one of the 'inside' goods, also, the distinction between these goods is that the price of the outside good is not set in response to the prices of the inside goods. However, given that our data is aggregated, the size of the outside good will be unobservable. Therefore, we must follow

[18] This database does not allow us to identify if a day is not available because it is booked or the host has blocked the day for other purposes.

the customary procedure of assuming a 'potential market size' and, then, calculating the outside good as the total size of the potential market minus the shares of the inside goods (Huang and Rojas (2010), and Nevo (2000)).

As Nevo (2000) states the potential market size is assumed according to the context. In that sense, there are many approaches to estimate the potential market size. So, for instance, Berry et al. (1995) and Verboven (1996) assume the potential market size of car markets to be the total number of households in the economy. Also, Björnerstedt and Verboven (2016) estimate the potential market size of analgesics, for a constant expenditures logit model, as twice the average amount spent over the entire period; in other words, it estimates the potential market as a proportion the analyzed market.

Additionally, since the outside option represents either an aggregate of other alternatives that are considered as further substitutes, or non-purchasing behavior (Bonnet and Richards (2016)), we could build a potential market using information about further substitutes. So, for example, Bonnet and Réquillart (2013) estimate a potential market size using purchases of fruit juices as the outside option in a random coefficient logit model for a focal soft drink demand estimation.

In this study, we restrict our model to Airbnb listings' data and build the potential market using information about total hotels' overnight in Barcelona city. We calculate the potential market size as the sum of the total nights per month both for hotels and for Airbnb listings. This assumption could raise some concerns as to whether it is appropriate to use the data from a 'substitute' product to build the potential market size. Regarding this, we consider that Airbnb is a niche product and hotels would not be a close substitute (Guttentag (2015)), and, also, hotel's revenues would not be affected by Airbnb's demand (Zervas et al. (2017)).

Furthermore, the estimation procedure for demand models (equations 10 and 11 cannot be performed in presence of market shares equivalent to zero since the dependent variable is in logarithm. The presence of zero demand or zero sales is a common problem in 'big data' applications given the more granular views of consumers, products, and markets (Gandhi et al. (2019)). We face this problem given the large number of listings and observations in our data.

To solve it, we follow a straightforward approach which consists in dropping all zero market shares (nearly 10% of observations). Although, this approach could imply that observed zeros are treated as true zeros, which would assume that there is no demand for these products and, consequently, it could create a potential selection bias in demand estimations (Quan and Williams (2018) and Gandhi et al. (2019)); we consider that a potential selection bias is mitigated in our estimation since our estimation is based on aggregated data. Thus, it is reasonable to assume that a listing with zero market share during a month is inactive as it is considered in Gunter and Önder (2018); then, there is a high probability that, our observed zeros are true zeros.

Moreover, to control for listing's characteristics, we include the following variables: number of bathrooms, beds, bedrooms, amenities, maximum of accommodates; and dummies on whether the listing is instant bookable, on whether it has a license to be rented for less than 30 days, and on whether it is an entire apartment, private, shared or hotel room. Additionally, we include data about host characteristics such as whether the host is a 'super host' and whether the host's identity is verified.

Finally, we include time binary variables ($time_t$) to control for common time-related shocks, and, to control for unobservable time-invariant neighborhood characteristics, such as place reputation and touristic attractiveness, that can derive in constant differences in the booked days (see figure 8 in Annex). Also, we include fixed effects by neighborhood (γ_r); even though, the inclusion of fixed effects alleviate the endogeneity problem, it does not necessarily eliminate it, then the inclusion of instrumental variables becomes relevant.

5.3 Identification

The main identification assumption is that products' characteristics other than price are uncorrelated with the error term, ϵ. Nonetheless, as the usual demand specifications, logit and nested logit models (equations 3 and 7) suffer from endogeneity in price and, in the nested logit model, segment market share. The problem comes from the fact that demand shocks that enter in ϵ_{jt} will affect, not only market shares; but also prices and segment market shares, resulting in simultaneity between the variables. This problem, if it is ignored, will result in biased and inconsistent estimators of α and σ coefficients.

To address endogeneity of the relevant variables, we need to use at least one instrumental variable (IV) for the logit model and at least two instrumental variables for the nested logit model. This selected variables need to be correlated with price and in-group market share and they have to be exogenous to the willingness to pay of guests. Considering this, we use a dummy variable indicative whether the listing has license to be rented for less than 30 days and the usual BLP instruments (Berry et al. (1995)).

The rationale behind the validity of $license$ as an instrument rests on that the price setting will depend on costs associated with possession of a license. On the other hand, in principle, the possession of a license should not affect the willingness to pay of guests, since it comes from the regulatory side. Also, this variable will vary over time[19] with different associated costs related to regulatory decisions.

The BLP instruments are constructed as the sum of the characteristics of other listings owned by

[19] According with *El Pais*, Airbnb has been fined for hosts that break this rules, which means that there is history of listings without license that have been rented for less than 30 days.

the same host and the sum of characteristics of each listing's competitor. Let H be the set of all hosts, therefore, for a given host h, the BLP instruments can be calculated as $\sum_{k\neq j, k\in H_h} x_k$ and $\sum_{k\notin H_h} x_k$, with x_k being the specific characteristic x of listing k. We can use these instruments since there is variation in the quantity of listings owned by hosts across time (see figure 8 in Annex), which guarantee the relevance of these instruments.

The logic behind the relevance and exogeneity of these instruments relies on the fact that it is likely that characteristics of other listings (owned by the same or other hosts) shape the price setting of each host and, at the same time these characteristics should not affect the willingness to pay of guests for that specific listing. These constructed variables are the standard instruments used in logit demand applications (Gandhi and Houde (2019)).

6 Results

We now present the results from our logit model (equation 10) and nested logit model (equation 11). Then, we complement the results by describing the estimation from an alternative version of the nested logit which includes the interaction of the main nest considered, with in-group market shares. Finally, we present the elasticities derived from the main specifications.

6.1 Logit Models

In Table 3, we show the results for the logit model under different specifications. Column 1 and 2 refer to the logit model excluding rating, while column 3 and 4 incorporate rating in its continuous version as a control variable. All estimations in Table 3 are computed with fixed effects by region and time effects, although, column 2 and 4 are computed using IV described in section 5.3 while, column 1 and 3 are estimated without any IV.

For all specifications, most parameters have the expected sign and all of them are estimated significantly different from zero. In all settings, the coefficient of interest, α, is negative and significant, although its magnitude is small. Including instruments increase the size of α in the specification that excludes rating, and decrease its magnitude when controlling for it.

For the relevant estimation, in column 4, demand grows when there is an increase in the number of bedrooms, the host is categorized as super host or has the identity verified; the same occurs when the listing has kitchen, heating, as well as when there is an increase in the rating. The opposite happens with hotel, private and share rooms, in comparison with entire apartments, surprisingly, the demand tends to decrease when the number of bathrooms, beds and amenities increase or whether the listing has air conditioner or TV.

6.2 Nested Logit Models

Table 1 shows the results for the nested logit model under different nests. All the estimations were computed including time effects, fixed effects by region[20] and using the IVs described in section 5.3. Column 1, 2 and 3 shows the output when super host, room type and neighborhood are used as a nest. While, column 4 describes the results when the nest is determined by rating classification[21].

In column 1, the α has the expected sign and it is statistically significant, while σ has the opposite sign, although it is not significantly different from zero, which means that 'super host' does not perform well as a market segmentation, even though it is part of the filters in the Airbnb search web site. Most of the control variables have the expected sign except for number of beds, quantity of accommodates and whether the listing has AC or TV.

When we include room type as a nest, σ becomes relatively high and significant, the estimated α, as before, is statistically different from zero and negative. With the exception of number of bathrooms, beds, amenities and whether the listing has AC, the other control variables have the expected sign.

The estimated σ increases when we use neighborhood as a nest, which highlight the importance of this variable for the user, it seems that listings within neighborhood are seen as close substitutes. Under this specification, the α has the expected sign and it is statistically different from zero. The majority of the control variables have the expected sign excluding the number of beds, bedrooms, and whether the listing has TV.

From all nests tested, rating classification is the most important, with a statically significant and high σ. This means that the listings within each rating classification are seen as close substitutes by consumers, even though, the filter is not available in Airbnb's search page, therefore, as discussed in section 4, this means that competition is concentrated in these segments created by this variable.

Under this specification, α has the expected sign and; as the other specifications, is statistically different from zero, although is small in magnitude. There is expected increase in demand when listings have more bedrooms, amenities or allow more accommodates; while there is an expected decreased in demand when there is an increase of number of bathrooms, beds or whether the listing has kitchen, air conditioner or TV, these results could be due to the possibility that these variables are capturing some other effects not included in the models.

[20] Except when we used neighborhood as a nest

[21] Categorical representation of the rating (≤ 80, > 87 and ≤ 93, > 93 and ≤ 97 and > 97)

Table 1: Nested Logit model

	$ln(s_j/s_0)$			
	Super host	Room type	Neighborhood	Rating class.
Price	-0.0017^{***}	-0.0003^{***}	-0.0005^{***}	-0.0001^{***}
	(0.0001)	(0.00004)	(0.0001)	(0.00002)
$ln(s_{j\|g})$	-0.0140	0.5355^{***}	0.8776^{***}	0.9766^{***}
	(0.0173)	(0.0093)	(0.0338)	(0.0044)
Bathrooms	0.0205^{***}	-0.0413^{***}	0.0883^{***}	-0.0021^{***}
	(0.0025)	(0.0012)	(0.0034)	(0.0005)
Bedrooms	0.0460^{***}	0.0739^{***}	-0.0408^{***}	0.0017^{***}
	(0.0023)	(0.0012)	(0.0036)	(0.0005)
Beds	-0.0058^{***}	-0.0399^{***}	-0.0271^{***}	-0.0003
	(0.0011)	(0.0008)	(0.0012)	(0.0002)
Hotel room	-0.1647^{***}	-	0.1734^{***}	0.0107^{***}
	(0.0117)		(0.0164)	(0.0026)
Private room	-0.1927^{***}	-	-0.0814^{***}	-0.0041^{***}
	(0.0045)		(0.0058)	(0.0012)
Shared room	-0.5477^{***}	-	-0.3148^{***}	-0.0159^{***}
	(0.0160)		(0.0144)	(0.0035)
Superhost	-	0.0416^{***}	0.0594^{***}	-0.0155^{***}
		(0.0018)	(0.0028)	(0.0008)
Identity verified	0.0508^{***}	0.0270^{***}	0.0336^{***}	0.0284^{***}
	(0.0034)	(0.0013)	(0.0019)	(0.0005)
Instant Bookable	0.1150^{***}	0.0286^{***}	0.0663^{***}	0.0033^{***}
	(0.0022)	(0.0018)	(0.0028)	(0.0007)
Amenities	0.0003	-0.0004^{***}	-0.0035^{***}	0.0008^{***}
	(0.0003)	(0.0001)	(0.0001)	(0.00003)
Kitchen	0.0956^{***}	0.1121^{***}	0.0381^{***}	-0.0012
	(0.0035)	(0.0020)	(0.0040)	(0.0009)
Heating	0.0243^{***}	0.0335^{***}	0.0300^{***}	0.0101^{***}
	(0.0030)	(0.0015)	(0.0023)	(0.0006)
AC	-0.0226^{***}	-0.0217^{***}	0.1014^{***}	-0.0131^{***}
	(0.0028)	(0.0016)	(0.0053)	(0.0006)
TV	-0.0115^{***}	0.0074^{***}	-0.0641^{***}	-0.0024^{***}
	(0.0027)	(0.0015)	(0.0029)	(0.0005)
Accommodates	-0.0122^{***}	0.0132^{***}	0.0522^{***}	0.0030^{***}
	(0.0017)	(0.0010)	(0.0028)	(0.0003)
Region fixed effects	Yes	Yes	No	Yes
Time effects	Yes	Yes	Yes	Yes
BLP & License instruments	Yes	Yes	Yes	Yes
Observations	768,428	768,428	768,428	761,489
Adjusted R^2	0.0034	0.7622	0.5122	0.9563

Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

6.3 Evaluating differences in level of competition

As we explain above, we estimated a complementary model only for the nested logit model using rating classification as potential market segmentation. This model consists in the inclusion of interactions between the classifications given by rating and the in-group market shares. This approach allows us to differentiate the intensity of competition among segments. The results in Table 4 are computed using control variables, fixed and time effects, and IVs considered above interacted with the stratification added by rating.

This output indicates that the intensity of competition increases when the listings have a rating above 87 and below 97. Although, the reverse occurs with listings without rating or when they are rated above 97. Given these results, we infer that, even though, there is an important segmentation in this market that makes a difference on the intensity of competition faced by listings, this distinction does not seem to follow a defined pattern.

6.4 Elasticities

In Table 5 we show the estimated own-price demand elasticities from the logit model after controlling by rating and from the nested logit model using rating classification as a nest. Finally, in Table 6 we show the cross-price elasticity under the last specification. The estimation were made using equations 4 and 6 respectively, described in section 4.

The elasticities computed under the logit model indicate that the demand for Airbnb listings is highly inelastic, this regardless of the sub-sample considered. As noted by Nevo (2000), the problem related with almost homogeneous elasticities is that for almost all the listings the market shares are small, therefore, the equation 4 is nearly constant, depending only on α and price.

Whilst for both models we find an inelastic demand, the inclusion of rating classification as a nest, not only increase (in absolute value) the elasticities in all sub-samples made, but also, adds heterogeneity to them. This can be explained by the importance of rating classification as market segmentation provided by the large σ estimated, as well as the heterogeneity in the in-group market shares.

On the other hand, the estimated cross-price elasticities (Table 6) highlight the implications described in subsection 6.2, and they allow us to consider how much listings in different segments compete with each other (Hausman et al. (1994)). Since the estimation is larger for listings that belong to the same segment than those who belong to different segments, the competition intensity faced by those listings is different.

7 Discussion

7.1 Conclusion

In this paper, we study how different variables, and in particular, rating; shape segmentation in the context of Airbnb's market in Barcelona from November 2014 to February 2021. Specifically, using a nested logit model, we found an inelastic demand of Airbnb's listings in Barcelona in a market that is divided by rating classification. Our empirical results show the following two points.

First, the majority of hosts face an inelastic demand. These results are consistent under the two main models we used. From the nested logit model under rating segmentation, we found that when there is a 10% increase in price of available nights, there is an expected decrease in booked nights of 4.5%. These results imply that there is room to increase the price without reducing the revenues of the hosts.

Second, even though, the rating is not available as a filter in the Airbnb web page, it creates an important market segmentation. This means that the competition between two listings that belong to the same segment is different from the competition faced by two listings that belongs to different rating classifications. Moreover, we found differences in intensity of competition faced by listings that belong to different segments.

These results are consistent, partially, with the model provided by Charlson (2021), since the existence of segmentation suggest that Airbnb is performing a rating-based market division. Yet the rating segmentation does not show a clear pattern of competition intensity in each group.

7.2 Limitations

The analysis we made faces some limitations associated to data, model specification and estimation procedure. The data is restricted to Airbnb's market in Barcelona and it is limited to Airbnb's scraping data solely. Likewise, we have taken some assumptions in our models and estimation methods which could be challenged. As follows, we explain the nature of these limitations and the robustness tests performed to evaluate their implications in our results.

Our results cannot be generalized since Barcelona has a large number of listings (nearly 17,000) and it is one of the Top10 most visited cities in Europe, therefore, Airbnb's market in Barcelona is more dynamic and competitive than others. This implies that a rating-based segmentation may not have the same effects (or even exists) on another Airbnb's markets. Thereby, there is room for further research to contrast our suggested results in other cities.

The scraping data used does not include booked days as a variable. This data restriction led us to build a proxy with a strong assumption (all unavailable days are booked days). In this context, as a robustness test, we perform estimations with a sub-sample excluding hotel and shared rooms[22] obtaining results consistent with our main outputs (see Table 10 of Annex). Nonetheless, future research can explore our approach using booked days data available in some alternative non-publicly sources.

With respect to discrete choice models, an important assumption is that consumers have the entire selection set available (Bonnet and Richards (2016), Nevo (2001)). However, this assumption could be not reasonable in our study given that, we consider that nearly 17,000 listings are available. Therefore, our results could be biased since the choice set may be heterogeneous across consumers, and endogenously determined (Bonnet and Richards (2016)). To address this issue, we follow a straightforward robustness check through limiting the size of choice set. Specifically, we perform estimations limiting the number of listings available to consumers obtaining mixed results compare to our main outputs (see Table 11 and 12 of Annex).

Regarding to the estimation, we are aware that the potential market size (using hotel's data) assumption, could raise concerns about not including hotels as Airbnb's subtitutes. In that sense, we test an scenario where the outside option is not included and the model is limited to predict results about consumers who already chose a group of alternatives (Bonnet and Richards (2016)); with this purpose, we followed the procedure mentioned in Nakanishi and Cooper (1982) and Morais et al. (2016). We consider a potential market size composed only by listing's booked nights in our database, then we use a log-centering transformation to calculate the relevant market, obtaining results consistent with our main estimations (see Table 13 of Annex).

Likewise, we perform an alternative scenario where the potential market size depends on a proportion (Nevo (2000)). We build a potential market size equivalent to three times the total booked nights of the listings obtaining consistent results as well (see Table 14 of Annex).

Finally. there could be some concerns about the presence of zero market shares in our data and the approach we followed given that as Quan and Williams (2018) states this scenario could led to create a selection bias in demand estimates. Regarding it, even thought we consider our approach is reasonable, we hope that further research explore some alternative methods as mentioned by Gandhi et al. (2019) and Nurski and Verboven (2016).

[22] We consider that in these type of listings there is a higher probability that an unavailable day is, in fact, a blocked day instead of a booked day.

8 Annex

A1: Evolution of total listings

Figure 1: Total listings over time

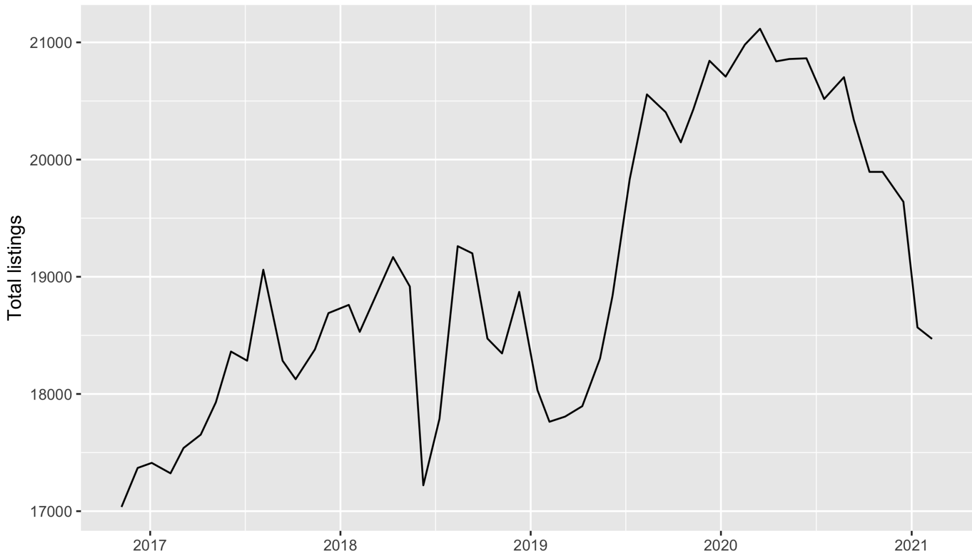


Figure 2: Total listings by room type over time

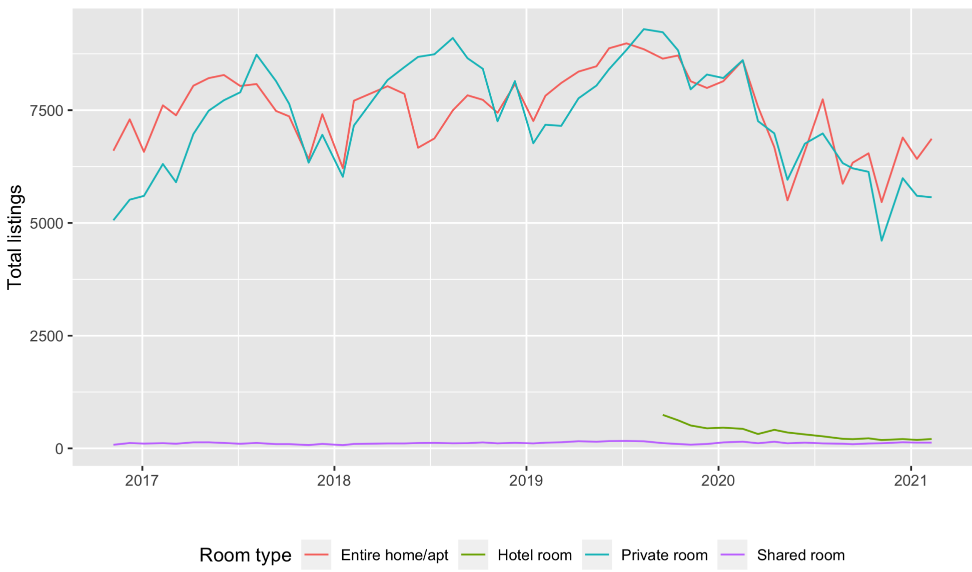
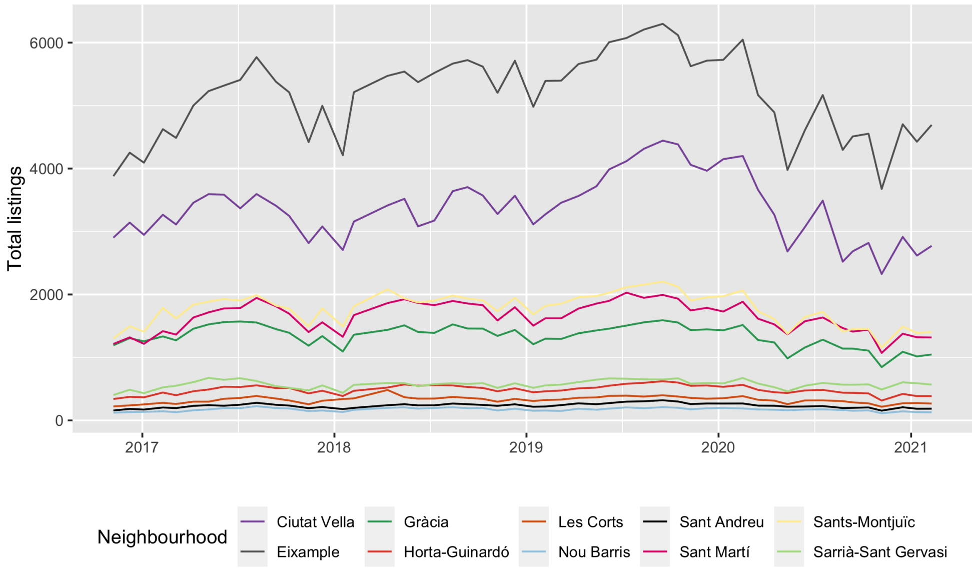


Figure 3: Total listings by neighborhood over time



A2: Methodology for logit and nested logi model

A2.1: Logit model

In the logit model ϵ_{ij} is modeled as an i.i.d. random variable with an extreme value distribution,

$$F(\delta_0, ..., \delta_J) = exp(-exp(-I)) \tag{12}$$

Where I is an inclusive value defined as:

$$I = \ln \sum_{k=0}^{J} exp(\delta_k)$$

The individuals choose the product out of the $J+1$ products that maximizes utility. The probability that consumer i chooses product j takes the following standard logit form (McFadden (1977)):

$$s_j = \frac{exp(x_j\beta - \alpha p_j + \xi_j)}{1 + \sum_{k=1}^{J} exp(x_k\beta - \alpha p_k + \xi_k)} \tag{13}$$

Notice that the probability that consumer i chooses the outside good is given by:

$$s_0 = \frac{1}{1 + \sum_{k=1}^{J} exp(x_k\beta - \alpha p_k + \xi_k)} \tag{14}$$

Taking the logarithm of the ratio of equations 13 and 14 we can derive equation 2.

A2.2: Nested Logit model

In the Nested Logit model, the individual-specific error follows the same distribution given by equation 12, although, now the inclusive value I can be written as,

$$I = \ln \sum_{g=1}^{G} exp(I_g)$$

Where I_g is given by

$$I_g = (1 - \sigma_g) \ln \sum_{j=1}^{j_g} exp\left(\frac{\delta_j}{1 - \sigma_g}\right)$$

Under this specification, the probability that individual i chooses product j is provided by,

$$s_j = s_{j|g}s_g = \frac{exp(\delta_j/(1 - \sigma_g))exp(I_g)}{exp(I_g/(1 - \sigma_g))exp(I)}$$

And, the probability to choose the outside good is given by:

$$s_0 = \frac{1}{exp(I)}$$

Following Berry (1994) and Björnerstedt and Verboven (2016) we can find equation 7.

A3: Price and booked days

Figure 4: Price by neighborhood over time

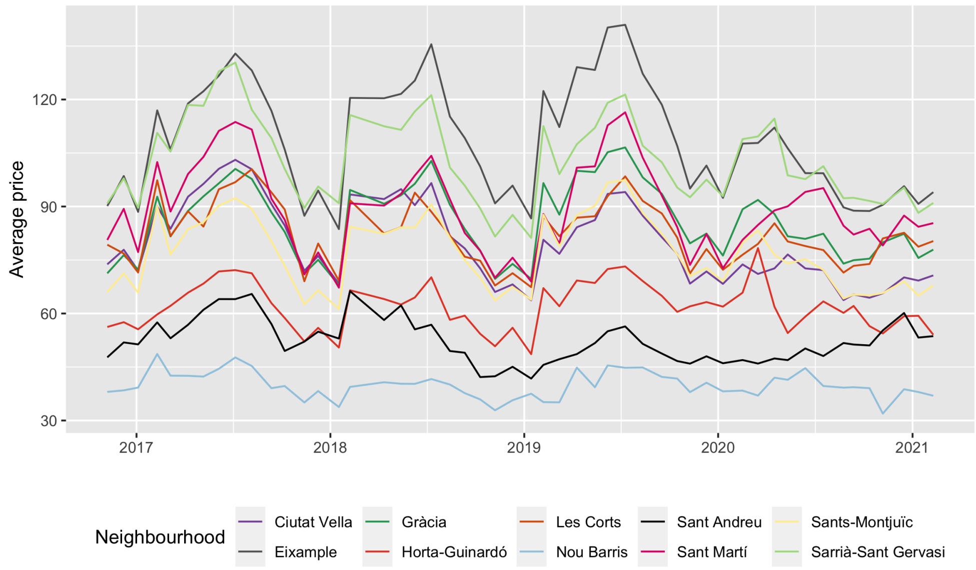


Figure 5: Price by room type over time

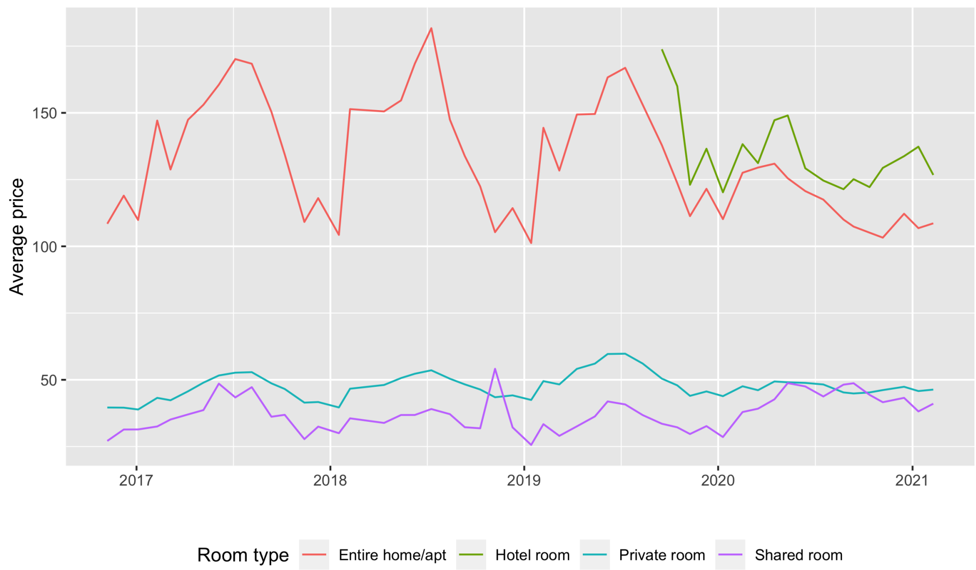


Figure 6: Distribution of price by room type

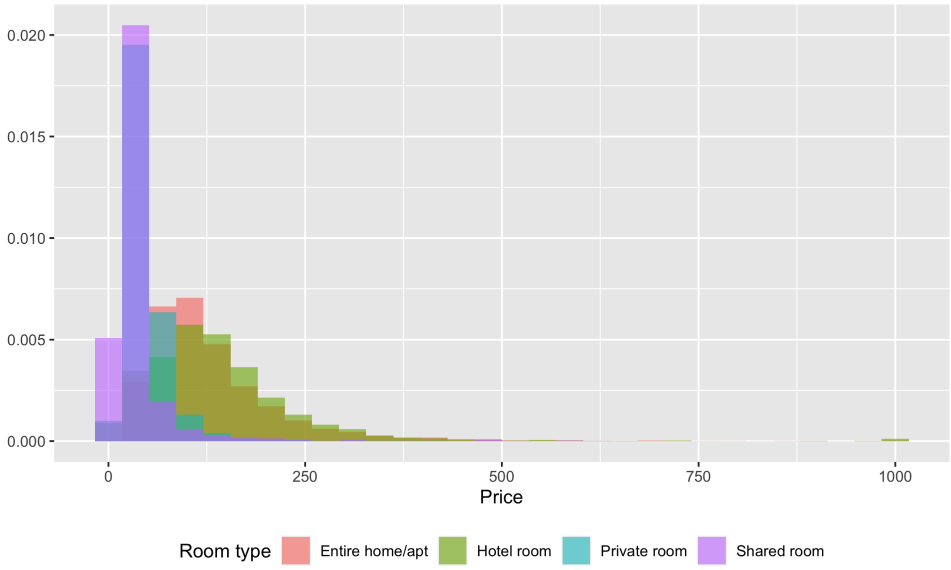


Figure 7: Total booked days by neighborhood over time

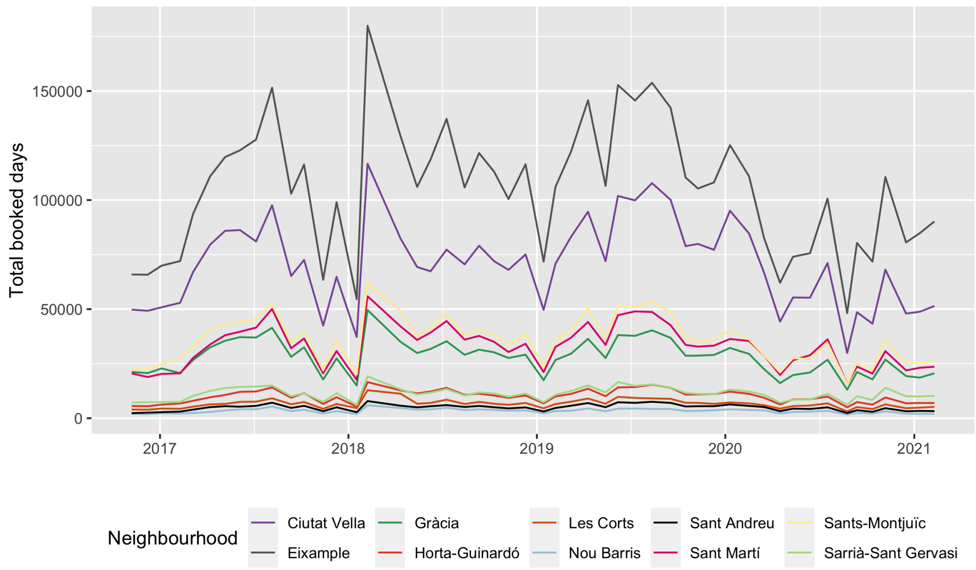
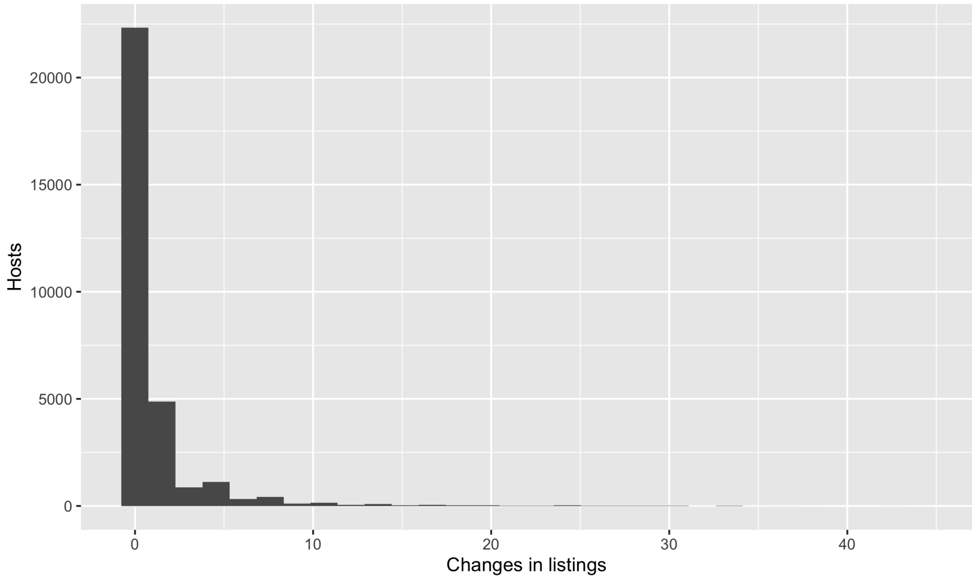


Table 2: Descriptive statistics

		Price		Booked days	
	Total listings	Mean	s.d.	Mean	s.d.
All	761,489	91.16	85.64	20.39	10.82
Room type					
Entire home/apt	379,389	133.21	97.16	20.45	10.25
Hotel room	6,273	139.43	107.75	16.13	10.30
Private room	369,986	48.07	37.76	20.46	11.35
Shared room	5,841	36.99	48.65	16.51	11.98
Neighborhood					
Ciutat Vella	170,536	80.09	69.84	20.87	10.72
Eixample	261,107	109.64	97.16	20.28	10.57
Gràcia	67,495	86.66	75.60	20.90	10.79
Horta-Guinardó	24,417	62.74	78.98	20.56	11.20
Les Corts	16,456	82.62	78.06	20.23	11.30
Nou Barris	8,529	39.92	34.89	19.35	11.96
Sant Andreu	11,672	52.08	64.63	20.87	11.50
Sant Martí	82,989	90.01	96.33	19.87	11.10
Sants-Montjuïc	89,274	78.02	65.84	20.22	10.96
Sarrià-Sant Gervasi	29,014	103.53	91.32	19.57	11.13
Super host					
No	640,462	90.82	85.39	20.32	10.87
Yes	121,027	92.94	86.93	20.81	10.55
Rating class.					
$\leq$87	152,329	91.84	80.09	19.85	10.57
$>$87 and $\leq$93	185,868	90.16	79.68	20.40	10.39
$>$93 and $\leq$97	147,433	88.76	77.52	20.84	10.39
$>$97	140,349	90.32	93.11	21.12	11.05
No reviews	135,510	95.23	98.77	19.75	11.81

A4: Identification

Figure 8: Changes in listings owned by hosts over time for non-single observation hosts



A5: Estimations

Table 3: Logit model

	$ln(s_j/s_0)$			
	(1)	(2)	(3)	(4)
Price	-0.0011^{***}	-0.0016^{***}	-0.0010^{***}	-0.0002^{***}
	(0.00002)	(0.0001)	(0.00002)	(0.0001)
Bathrooms	0.0113^{***}	0.0202^{***}	0.0056^{***}	-0.0100^{***}
	(0.0019)	(0.0024)	(0.0021)	(0.0027)
Bedrooms	0.0388^{***}	0.0442^{***}	0.0375^{***}	0.0283^{***}
	(0.0018)	(0.0020)	(0.0020)	(0.0022)
Beds	-0.0046^{***}	-0.0054^{***}	-0.0053^{***}	-0.0041^{***}
	(0.0011)	(0.0011)	(0.0012)	(0.0012)
Hotel room	-0.1847^{***}	-0.1710^{***}	-0.2145^{***}	-0.2306^{***}
	(0.0112)	(0.0114)	(0.0120)	(0.0121)
Private room	-0.1768^{***}	-0.1922^{***}	-0.1736^{***}	-0.1463^{***}
	(0.0030)	(0.0039)	(0.0033)	(0.0044)
Shared room	-0.5031^{***}	-0.5333^{***}	-0.5177^{***}	-0.4666^{***}
	(0.0116)	(0.0126)	(0.0130)	(0.0142)
Super host	0.0880^{***}	0.0910^{***}	0.0497^{***}	0.0464^{***}
	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Identity verified	0.0460^{***}	0.0433^{***}	0.0295^{***}	0.0334^{***}
	(0.0021)	(0.0022)	(0.0022)	(0.0022)
Instant bookable	0.1156^{***}	0.1179^{***}	0.0918^{***}	0.0884^{***}
	(0.0020)	(0.0021)	(0.0022)	(0.0022)
Amenities	-0.0009^{***}	-0.0008^{***}	-0.0023^{***}	-0.0025^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Kitchen	0.1085^{***}	0.1032^{***}	0.1137^{***}	0.1179^{***}
	(0.0034)	(0.0035)	(0.0035)	(0.0036)
Heating	0.0206^{***}	0.0199^{***}	0.0174^{***}	0.0191^{***}
	(0.0026)	(0.0026)	(0.0028)	(0.0028)
AC	-0.0305^{***}	-0.0240^{***}	-0.0315^{***}	-0.0398^{***}
	(0.0026)	(0.0028)	(0.0027)	(0.0029)
TV	-0.0111^{***}	-0.0101^{***}	-0.0142^{***}	-0.0150^{***}
	(0.0026)	(0.0026)	(0.0027)	(0.0027)
Accommodates	-0.0180^{***}	-0.0113^{***}	-0.0170^{***}	-0.0267^{***}
	(0.0011)	(0.0015)	(0.0012)	(0.0016)
Rating	-	-	0.0042^{***}	0.0038^{***}
			(0.0001)	(0.0001)
Time & Region fixed effects	Yes	Yes	Yes	Yes
BLP & License instruments	No	Yes	No	Yes
Observations	768,428	768,428	625,980	625,980
Adjusted R^2	0.0220	0.0212	0.0205	0.0175

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4: Measure of intensity of competition

	$ln(s_j/s_0)$
Price	-0.0016^{***}
	(0.00005)
$ln(s_{j\|g})$	0.3220^{***}
	(0.0138)
$ln(s_{j\|g})$*(Rating class.:87 $>$ and $\leq$ 93)	0.0263
	(0.0205)
$ln(s_{j\|g})$*(Rating class.:93 $>$ and $\leq$ 97)	0.0901^{***}
	(0.0204)
$ln(s_{j\|g})$*(Rating class.:97 $>$)	-0.2649^{***}
	(0.0179)
$ln(s_{j\|g})$*(Rating class.: No reviews)	-0.1243^{***}
	(0.0156)
Rating class.:87 $>$ and $\leq$ 93	0.3380^{**}
	(0.1714)
Rating class.:93 $>$ and $\leq$ 97	0.8135^{***}
	(0.1676)
Rating class.:97 $>$	-2.0957^{***}
	(0.1473)
Rating class.: No reviews	-1.0824^{***}
	(0.1288)
Control variables	Yes
Time & Region fixed effects	Yes
BLP*Rating class. instruments	Yes
Licence*Rating class. instrument	Yes
Observations	761,489
Adjusted R^2	0.6634

Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

A6: Elasticities

Table 5: Estimated own-price elasticities

	Logit				Nested Logit: Rating class.			
	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
All	-0.02	0.02	-0.23	-0.00	-0.45	0.42	-4.93	-0.00
Room type								
Entire home/apt	-0.03	0.02	-0.23	-0.00	-0.66	0.48	-4.93	-0.04
Hotel room	-0.03	0.02	-0.23	-0.00	-0.69	0.53	-4.92	-0.05
Private room	-0.01	0.01	-0.23	-0.00	-0.24	0.19	-4.93	-0.00
Shared room	-0.01	0.01	-0.14	-0.00	-0.18	0.24	-3.44	-0.04
Neighborhood								
Ciutat Vella	-0.02	0.02	-0.23	-0.00	-0.39	0.34	-4.93	-0.04
Eixample	-0.03	0.02	-0.23	-0.00	-0.54	0.48	-4.93	-0.00
Gràcia	-0.02	0.02	-0.23	-0.00	-0.43	0.37	-4.93	-0.04
Horta-Guinardó	-0.01	0.02	-0.23	-0.00	-0.31	0.39	-4.93	-0.04
Les Corts	-0.02	0.02	-0.23	-0.00	-0.41	0.38	-4.93	-0.04
Nou Barris	-0.01	0.01	-0.23	-0.00	-0.20	0.17	-4.93	-0.04
Sant Andreu	-0.01	0.02	-0.23	-0.00	-0.26	0.32	-4.88	-0.04
Sant Martí	-0.02	0.02	-0.23	-0.00	-0.44	0.47	-4.93	-0.04
Sants-Montjuïc	-0.02	0.01	-0.23	-0.00	-0.38	0.32	-4.93	-0.04
Sarrià-Sant Gervasi	-0.02	0.02	-0.23	-0.00	-0.51	0.45	-4.93	-0.04
Rating class.								
≤ 87	-0.02	0.02	-0.23	-0.00	-0.45	0.39	-4.93	-0.02
>87 and ≤ 93	-0.02	0.02	-0.23	-0.00	-0.44	0.39	-4.93	-0.04
>93 and ≤ 97	-0.02	0.02	-0.23	-0.00	-0.44	0.38	-4.93	-0.04
>97	-0.02	0.02	-0.23	-0.00	-0.44	0.46	-4.93	-0.04
No reviews	-	-	-	-	-0.47	0.49	-4.93	-0.00

Table 6: Nested logit model: rating class. Cross-price elasticities

	Mean	s.d.	Min	Max
Whithin same segment	1.41e-04	1.70e-04	4.80e-07	6.39e-03
Different segments	1.64e-07	3.14e-07	3.54e-10	1.40e-05

Table 7: Elasticities: Logit model

	Mean	s.d.	Min.	Max.
All	-0.15	0.14	-1.61	-0.00
Room type				
Entire home/apt	-0.22	0.16	-1.61	-0.01
Hotel room	-0.23	0.17	-1.61	-0.02
Private room	-0.08	0.06	-1.61	-0.00
Shared room	-0.06	0.08	-1.13	-0.01
Neighborhood				
Ciutat Vella	-0.13	0.11	-1.61	-0.01
Eixample	-0.18	0.16	-1.61	-0.00
Gràcia	-0.14	0.12	-1.61	-0.01
Horta-Guinardó	-0.10	0.13	-1.61	-0.01
Les Corts	-0.13	0.13	-1.61	-0.01
Nou Barris	-0.06	0.06	-1.61	-0.01
Sant Andreu	-0.08	0.10	-1.60	-0.01
Sant Martí	-0.15	0.16	-1.61	-0.01
Sants-Montjuïc	-0.13	0.11	-1.61	-0.01
Sarrià-Sant Gervasi	-0.17	0.15	-1.61	-0.01

Table 8: Elasticities nest: Room type

	Mean	s.d.	Min.	Max.
All	-0.07	0.06	-0.73	-0.00
Room type				
Entire home/apt	-0.10	0.07	-0.73	-0.01
Hotel room	-0.10	0.08	-0.73	-0.01
Private room	-0.03	0.03	-0.73	-0.00
Shared room	-0.03	0.04	-0.51	-0.01
Neighborhood				
Ciutat Vella	-0.06	0.05	-0.73	-0.01
Eixample	-0.08	0.07	-0.73	-0.00
Gràcia	-0.06	0.05	-0.73	-0.01
Horta-Guinardó	-0.05	0.06	-0.73	-0.01
Les Corts	-0.06	0.06	-0.73	-0.01
Nou Barris	-0.03	0.03	-0.73	-0.01
Sant Andreu	-0.04	0.05	-0.72	-0.01
Sant Martí	-0.07	0.07	-0.73	-0.01
Sants-Montjuïc	-0.06	0.05	-0.73	-0.01
Sarrià-Sant Gervasi	-0.08	0.07	-0.73	-0.01

Table 9: Elasticities nest: Neighborhood

	Mean	s.d.	Min.	Max.
All	-0.40	0.38	-4.41	-0.00
Room type				
Entire home/apt	-0.59	0.43	-4.41	-0.04
Hotel room	-0.61	0.47	-4.40	-0.04
Private room	-0.21	0.17	-4.41	-0.00
Shared room	-0.17	0.22	-3.08	-0.04
Neighborhood				
Ciutat Vella	-0.35	0.31	-4.41	-0.04
Eixample	-0.48	0.43	-4.41	-0.00
Gràcia	-0.38	0.33	-4.41	-0.04
Horta-Guinardó	-0.27	0.35	-4.41	-0.04
Les Corts	-0.36	0.34	-4.41	-0.04
Nou Barris	-0.18	0.15	-4.39	-0.04
Sant Andreu	-0.23	0.28	-4.36	-0.04
Sant Martí	-0.40	0.42	-4.41	-0.04
Sants-Montjuïc	-0.34	0.29	-4.41	-0.04
Sarrià-Sant Gervasi	-0.46	0.40	-4.41	-0.04

A7: Robustness tests

Table 10: Excluding potential bias (No shared rooms / No hotels)

	$ln(s_j/s_0)$	
	(1)	(2)
Price	-0.0010^{***}	-0.0001^{***}
	(0.0001)	(0.00002)
$ln(s_{j\|g})$ (Rating class.)		0.9808^{***}
		(0.0047)
Bathrooms	0.0051^{*}	-0.0021^{***}
	(0.0030)	(0.0006)
Bedrooms	0.0357^{***}	0.0018^{***}
	(0.0022)	(0.0005)
Beds	-0.0032^{***}	-0.0008^{***}
	(0.0012)	(0.0002)
Private room	-0.1717^{***}	-0.0025^{*}
	(0.0045)	(0.0013)
Superhost	0.0482^{***}	-0.0156^{***}
	(0.0029)	(0.0008)
Identity verified	0.0303^{***}	0.0291^{***}
	(0.0022)	(0.0005)
Instant bookable	0.0909^{***}	0.0027^{***}
	(0.0022)	(0.0007)
Amenities	-0.0023^{***}	0.0009^{***}
	(0.0001)	(0.00003)
Kitchen	0.1171^{***}	-0.0007
	(0.0036)	(0.0009)
Heating	0.0178^{***}	0.0105^{***}
	(0.0028)	(0.0006)
AC	-0.0305^{***}	-0.0137^{***}
	(0.0029)	(0.0006)
TV	-0.0148^{***}	-0.0029^{***}
	(0.0027)	(0.0006)
Accommodates	-0.0189^{***}	0.0033^{***}
	(0.0017)	(0.0004)
Rating	0.0042^{***}	
	(0.0001)	
Time & Region fixed effects	Yes	Yes
BLP & License instruments	Yes	Yes
Observations	616,931	749,375
Adjusted R^2	0.0191	0.9558

Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 11: Reducing sample in time (year=2019)

	$ln(s_j/s_0)$	
	(1)	(2)
Price	-0.0002^{**}	0.0004^{***}
	(0.0001)	(0.00001)
$ln(s_{j\|g})$ (Rating class.)		0.9369^{***}
		(0.0035)
Bathrooms	-0.0098^{***}	-0.0122^{***}
	(0.0035)	(0.0004)
Bedrooms	0.0307^{***}	0.0009^{**}
	(0.0030)	(0.0004)
Beds	-0.0109^{***}	-0.0019^{***}
	(0.0017)	(0.0002)
Hotel room	-0.3285^{***}	-0.0309^{***}
	(0.0153)	(0.0023)
Private room	-0.1299^{***}	0.0146^{***}
	(0.0057)	(0.0010)
Shared room	-0.7592^{***}	-0.0081^{**}
	(0.0202)	(0.0037)
Superhost	0.0627^{***}	-0.0080^{***}
	(0.0041)	(0.0007)
Identity verified	0.0264^{***}	0.0168^{***}
	(0.0034)	(0.0005)
Instant bookable	0.0227^{***}	0.0027^{***}
	(0.0034)	(0.0005)
Amenities	-0.0009^{***}	0.0010^{***}
	(0.0002)	(0.00002)
Kitchen	0.1086^{***}	0.0062^{***}
	(0.0052)	(0.0008)
Heating	0.0268^{***}	0.0068^{***}
	(0.0043)	(0.0006)
AC	-0.0374^{***}	-0.0117^{***}
	(0.0043)	(0.0006)
TV	0.0102^{**}	-0.0046^{***}
	(0.0042)	(0.0006)
Accommodates	-0.0241^{***}	-0.0053^{***}
	(0.0022)	(0.0003)
Rating	0.0035^{***}	
	(0.0002)	
Time & Region fixed effects	Yes	Yes
BLP & License instruments	Yes	Yes
Observations	162,341	200,039
Adjusted R^2	0.0343	0.9835

Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 12: Reducing choice sets (Only Eixample & Only entire apartments)

	$ln(s_j/s_0)$	
	(1)	(2)
Price	-0.0013^{***}	0.0020^{***}
	(0.0002)	(0.0001)
$ln(s_{j\|g})$ (Rating class.)		0.8697^{***}
		(0.0214)
Bathrooms	0.0566^{***}	-0.1328^{***}
	(0.0114)	(0.0060)
Bedrooms	0.0245^{***}	0.0001
	(0.0035)	(0.0016)
Beds	0.0043^{**}	0.0011
	(0.0018)	(0.0007)
Superhost	0.0568^{***}	-0.0892^{***}
	(0.0059)	(0.0046)
Identity verified	-0.0142^{***}	0.0523^{***}
	(0.0046)	(0.0022)
Instant bookable	0.0593^{***}	0.0039
	(0.0045)	(0.0026)
Amenities	-0.0002	0.0001
	(0.0002)	(0.0001)
Kitchen	0.0560^{***}	0.0711^{***}
	(0.0155)	(0.0054)
Heating	0.0473^{***}	0.0297^{***}
	(0.0074)	(0.0027)
AC	-0.0191^{**}	-0.0456^{***}
	(0.0077)	(0.0030)
TV	-0.0281^{***}	0.0060
	(0.0100)	(0.0037)
Accommodates	-0.0188^{***}	-0.0160^{***}
	(0.0026)	(0.0010)
Rating	0.0024^{***}	
	(0.0003)	
Region fixed effects	Yes	Yes
Time effects	Yes	Yes
BLP & License instruments	Yes	Yes
Observations	123,163	146,230
Adjusted R^2	0.0204	0.8537

Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 13: Excluding outside good (L=$\sum q$)

	$ln(s_j/s_0)$	
	(1)	(2)
Price	-0.0002^{***}	-0.0001^{***}
	(0.0001)	(0.00002)
$ln(s_{j\|g})$ (Rating class.)		0.9766^{***}
		(0.0044)
Bathrooms	-0.0100^{***}	-0.0021^{***}
	(0.0027)	(0.0005)
Bedrooms	0.0283^{***}	0.0017^{***}
	(0.0022)	(0.0005)
Beds	-0.0041^{***}	-0.0003
	(0.0012)	(0.0002)
Hotel room	-0.2306^{***}	0.0107^{***}
	(0.0121)	(0.0026)
Private room	-0.1463^{***}	-0.0041^{***}
	(0.0044)	(0.0012)
Shared room	-0.4666^{***}	-0.0159^{***}
	(0.0142)	(0.0035)
Superhost	0.0464^{***}	-0.0155^{***}
	(0.0029)	(0.0008)
Identity verified	0.0334^{***}	0.0284^{***}
	(0.0022)	(0.0005)
Instant bookable	0.0884^{***}	0.0033^{***}
	(0.0022)	(0.0007)
Amenities	-0.0025^{***}	0.0008^{***}
	(0.0001)	(0.00003)
Kitchen	0.1179^{***}	-0.0012
	(0.0036)	(0.0009)
Heating	0.0191^{***}	0.0101^{***}
	(0.0028)	(0.0006)
AC	-0.0398^{***}	-0.0131^{***}
	(0.0029)	(0.0006)
TV	-0.0150^{***}	-0.0024^{***}
	(0.0027)	(0.0005)
Accommodates	-0.0267^{***}	0.0030^{***}
	(0.0016)	(0.0003)
Rating	0.0038^{***}	
	(0.0001)	
Region fixed effects	Yes	Yes
Time effects	Yes	Yes
BLP & License instruments	Yes	Yes
Observations	625,980	761,489
Adjusted R^2	0.0175	0.9563

Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 14: $L = 3\sum q$

	$ln(s_j/s_0)$	
	(1)	(2)
Price	-0.0002^{***}	-0.0001^{***}
	(0.0001)	(0.00002)
$ln(s_{j\|g})$ (Rating class.)		0.9766^{***}
		(0.0044)
Bathrooms	-0.0100^{***}	-0.0021^{***}
	(0.0027)	(0.0005)
Bedrooms	0.0283^{***}	0.0017^{***}
	(0.0022)	(0.0005)
Beds	-0.0041^{***}	-0.0003
	(0.0012)	(0.0002)
Hotel room	-0.2306^{***}	0.0107^{***}
	(0.0121)	(0.0026)
Private room	-0.1463^{***}	-0.0041^{***}
	(0.0044)	(0.0012)
Shared room	-0.4666^{***}	-0.0159^{***}
	(0.0142)	(0.0035)
Superhost	0.0464^{***}	-0.0155^{***}
	(0.0029)	(0.0008)
Identity verified	0.0334^{***}	0.0284^{***}
	(0.0022)	(0.0005)
Instant Bookable	0.0884^{***}	0.0033^{***}
	(0.0022)	(0.0007)
Amenities	-0.0025^{***}	0.0008^{***}
	(0.0001)	(0.00003)
Kitchen	0.1179^{***}	-0.0012
	(0.0036)	(0.0009)
Heating	0.0191^{***}	0.0101^{***}
	(0.0028)	(0.0006)
AC	-0.0398^{***}	-0.0131^{***}
	(0.0029)	(0.0006)
TV	-0.0150^{***}	-0.0024^{***}
	(0.0027)	(0.0005)
Accommodates	-0.0267^{***}	0.0030^{***}
	(0.0016)	(0.0003)
Rating	0.0038^{***}	
	(0.0001)	
Region fixed effects	Yes	Yes
Time effects	Yes	Yes
BLP & License instruments	Yes	Yes
Observations	625,980	761,489
Adjusted R^2	0.0175	0.9563

Standard errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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