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PROFESSIONALIZATION OF AIRBNB HOSTS IN MEXICO CITY: A STRUCTURAL MODELING APPROACH

PROFESIONALIZACIÓN DE LOS ANFITRIONES EN AIRBNB, CIUDAD DE MÉXICO: UN ENFOQUE DE MODELADO ESTRUCTURAL

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Abstract:

We offer a first approach to the demand and supply structure of Airbnb in Mexico City using a unique panel dataset of daily listings and rentals on the platform. We find descriptive evidence of a large sector of professional hosts. We estimate various models of demand accommodating price endogeneity and taste heterogeneity, as well as a supply model under the assumption of Bertrand-Nash's competition. We consistently find that professional hosts have lower marginal costs than non-professional hosts. We also find that overall price-cost margins are high regardless of hosts' professionalization status, and slightly higher in the case of professional ones. Finally, motivated by a worldwide regulatory trend, we investigate counterfactually the effect of producer and consumer ad valorem taxes that discriminate between types of hosts.

Resumen:

Realizamos una primera aproximación a la estructura de la demanda y la oferta de Airbnb en la Ciudad de México usando datos panel que siguen diariamente todas las propiedades ofertadas y rentadas. Encontramos evidencia descriptiva de la existencia de un sector importante de anfitriones profesionales. Nuestras estimaciones de múltiples modelos de demanda (que acomodan endogeneidad del precio y heterogeneidad en las preferencias) y un modelo de oferta bajo el supuesto de competencia de Bertrand-Nash muestra que los anfitriones profesionales tienen menores costos marginales. También se encuentran altos márgenes precio-costo en la industria en general, y ligeramente mayores para los anfitriones profesionales. Finalmente, siguiendo una tendencia regulatoria a nivel mundial, investigamos de manera contrafactual el efecto de impuestos ad valorem al consumidor y productor que discriminan entre tipos de anfitriones.

Clasificación JEL/JEL Classification: C59, L11, L83, L86, Z31.

Palabras clave/keywords: sharing economy, structural econometrics, peer-to-peer markets, market structure, professionalization.

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1. Introduction

A controversial worldwide characteristic of the evolution of Airbnb in the last decade is the gradual professionalization of hosts within the platform, which has been interpreted as a shift from a disruptive peer-to-peer market towards a more traditional business-to-consumer market (Popper, 2015). A flourishing multi-disciplinary literature has documented such pattern in Europe (Demir and Emekli, 2021; Gyódi, 2019), the United States (Dogru *et al.*, 2020), Canada (Gibbs *et al.*, 2018b), and South Korea (Ki and Lee, 2019), among others. Some authors argue that this professionalization (a.k.a. hotelization) of Airbnb escalated its negative externalities on the urban landscape (Gil and Sequera, 2022; Lee, 2016). Increasingly, regulations in major touristic destinations make a clear distinction between professional and nonprofessional individual hosts, subjecting the former to a stricter set of rules or blankly banning such professional activity (Lee, 2016; Briel and Dolnicar, 2020; Iacovone, 2023).[1]

In this paper, we offer a first approach to the so far unknown structure of demand and supply in the Airbnb market in Mexico City, leveraging a rich panel dataset obtained from a short-term rental intelligence firm and a structural model, which we describe below. In the first step, a descriptive analysis of the daily posted properties reveals that there is heterogeneity in the type and number of properties a host manages in the platform, varying from 1 to 77 per host, as well as in the number of days a property is available to be rented in the platform during a year, ranging from 1 day to 365 days (actually rented days vary from 1 to 352 days per property). Moreover, the market share of multi-unit hosts amounts to 65.6% of the annual market, despite them being only 27.93% of the total number of hosts on the platform. These facts suggest that, like some other major touristic hubs, the Mexico City market for short-term peer-to-peer rentals is a mixture of professional and nonprofessional hosts.

Motivated by these descriptive findings, we further investigate the professionalization of Airbnb's hosts in Mexico City, estimating a stylized structural model of daily demand and supply for short-term rentals in the spirit of Berry *et al.* (1995). In our model, guests choose among classes of accommodations (which differ in quality, location, and accommodation type) managed by professional or nonprofessional hosts.[2] Our stylized framework still captures four crucial

[1] At the time of finishing this writing, Mexico City government had just publicly announced that it was preparing regulations in this spirit. See EFE (2023).

[2] We distinguish between professional and nonprofessional hosts by the num-

features of interest in the market for short rentals: daily demand and price fluctuations, accommodations and portfolio heterogeneity across professional and nonprofessional hosts, and rich substitution patterns.

The estimation delivers marginal costs, markups, and price-cost margins, which help to understand the differences between professional and nonprofessional hosts. Moreover, being structural, the model allows us to investigate the equilibrium effects of a differential tax targeting professional hosts, a policy in line with worldwide regulatory trends that might be of interest to local authorities.

Estimated marginal costs are in line with intuition. As expected, professionals face smaller marginal costs than nonprofessionals, consistent with economies of scale, scope, and superior management practices. Entire homes/apartments have higher associated marginal costs than private rooms. Properties in wealthier *alcaldías* have higher marginal costs. Regardless of host type, price-cost margins are high, consistent with differentiated products and high fixed costs like mortgage and rent payments. Professionals have slightly higher markups and price-cost margins, which can be partially explained by their lower marginal costs and multi-product portfolio. Finally, we evaluate two counterfactual scenarios focused on differential tax targeting professional hosts. An additional consumption tax of 5% on properties owned by professionals naturally increases the total amount to be paid by the consumer, decreases the market share of professionals by 5.52%, improves the market share of nonprofessionals only marginally by 0.57%, and increases the market share of the traditional accommodation sector. On the other hand, a producer tax of 5% increases prices, decreases the market share of professionals by 5.96%, marginally improves the market share of nonprofessionals by 0.61%, and increases the market share of the traditional accommodation sector. The main difference between scenarios is that the consumer pays less in the consumer tax scenario. These results are robust overall to different estimation methodologies, which we will describe later.

To the best of our knowledge, we have made two original contributions. Firstly, we are the first to provide systematic empirical evidence on the professionalization of Airbnb in a Latin American city. Despite the increasing regulatory focus on this issue, particularly in Mexico, there is no systematic empirical investigation on this

ber of properties they manage. We discuss this definition and the implications and limitations of our modeling choices in sections 2 and 3. We perform a robustness test for the leading definition of professional hosts in Appendix A.4.

subject matter in Latin America, which sharply contrasts with other regions. This lack of knowledge is particularly troublesome because, as stated by the United Nations, in developing countries, the sharing economy can help improve households' welfare through additional income (UNCTAD, 2020). We contribute to filling this gap.

Secondly, we are the first to take a structural approach to the professionalization of Airbnb hosts worldwide. Our structural perspective on the Airbnb supply and demand in Mexico City offers an original framework that, in the tradition of the new empirical industrial organization literature, allows us to obtain estimates of economic fundamentals like marginal costs and price-cost margins. While challenging to estimate otherwise, these economic fundamentals are crucial to understanding the nature of competition within a given market and the potential responses of market participants to policy interventions (see, for instance, Gandhi and Nevo, 2021). Interestingly, our results suggest a more complex picture than the stark contrast between professional and nonprofessional hosts usually made in the literature on Airbnb.

1.1 *Related literature*

Only recently has the literature started to use structural models of demand and supply for differentiated products to study different aspects of Airbnb (Farronato and Fradkin, 2022; Farhoodi, 2021; Calder-Wang, 2021). However, these are about Airbnb in the U.S., and the differences between professionals and nonprofessional hosts have yet to be studied. The closest to us is Farhoodi (2021), who studied the distribution of benefits among neighborhoods in the Chicago Airbnb market, finding that higher-income neighborhoods benefit the most from access to the platform and that a tax on platform users has redistributive effects. Our research contributes to this growing literature using structural methods to study markets for short-term rentals by offering a stylized structural framework to study the differences between professional and nonprofessional hosts, and doing so in a Latin American city.

Chen and Xie (2023) is the only other paper previous to us investigating the roles of professional and nonprofessional hosts in the Airbnb market using econometric techniques. They used a quasi-experimental design, exploiting a policy change in San Francisco and New York that caps the number of properties a host can manage. This provides indirect empirical evidence of substitution between properties managed by professional and nonprofessional hosts. On the other hand, there is a large number of papers providing descriptive evidence on the professionalization of Airbnb hosts; in addition to those cited in the Introduction, Abrate *et al.* (2022) and Ki and Lee (2019) documented the complex pricing strategies followed by professional hosts as compared to nonprofessional ones. By implementing structural econometric techniques, we offer an alternative approach to studying the relevant economic differences between professional and nonprofessional Airbnb hosts, some of which (such as costs and margins) are difficult to recover otherwise.

Regarding Airbnb in Mexico City, only a few studies have been conducted so far. López Tamayo and Ramírez Álvarez (2021) conducted a hedonic price analysis for Airbnb in Mexico City, finding positive determinants of price such as the maximum number of guests allowed, number of bedrooms, number of bathrooms, number of amenities, and professional host, as well as negative determinants such as crime in the accommodation area. Ruiz-Correa *et al.* (2019) and Madrigal Montes de Oca *et al.* (2018) approached the issue of Airbnb in Mexico City from an Urban Studies perspective. Banco de México (2021) examined the evolution of the Airbnb market in Mexico City. We provide a state-of-the-art framework to estimate unobservable economic primitives in the industry, and a first set of estimates speaking to the differences between Airbnb hosts in Mexico City. Moreover, the proposed structural framework can be further refined to provide insights into the effect of different public policies.

We follow the literature on estimating models of product differentiation initiated by Berry *et al.* (1995) to address several methodological challenges. We estimate several logit and random coefficients (RC) demand models using the standard nonlinear IV technique with modern differentiation instruments of Gandhi and Houde (2019) to account for price endogeneity. To deal with the significant heterogeneity in Airbnb listings in a computationally tractable way, we adopt an aggregation method developed by Farronato and Fradkin (2022). Finally, many listed properties are not rented on a given day, which translates into the well-known zero market share problem (Dubé *et al.*, 2021). Our results are robust to the two most common ways of handling products with zero market share in these types of models, excluding observations with zero market share and imputing to them a positive market share value close to zero (Gandhi *et al.*, 2023).

2. Background, data, and preliminary analysis

Airbnb was introduced in Mexico City in 2009. In 2017, the Mexico City government introduced a state tax for Airbnb guests, ranging between 3% to 5% (Airbnb, 2019). In 2019, the platform collected approximately 202.8 million Mexican pesos in taxes (Airbnb, 2020).

For hosts, listing an accommodation on Airbnb is free, and there is complete flexibility in setting the available rental days as desired. Airbnb provides hosts with complimentary protection called Aircover, which covers potential damages, unexpected cleaning (Airbnb-Help Center, 2024b), and also extends to guests in case they suffer injuries during their stay (Airbnb-Help Center, 2024a). Hosts can set their prices manually, using a dynamic pricing tool offered by the platform (Airbnb-Help Center, 2024c) or using third-party algorithms.

Potential guests register for free on the Airbnb platform and search for accommodation options through the application. They can indicate their desired dates and length of stay and further refine their search using filtering tools.

Airbnb earns revenue by charging a fee to hosts and guests through two fee structures: the shared fee and the host-only fee. In the shared fee model, the fee is split between the host and the guest. Most hosts pay a 3% fee of the subtotal before taxes. The guest fee is typically less than 14.2% of the reservation's subtotal before taxes, varying based on several factors. In the host-only fee model (mandatory for hotels and hosts using an external property management system), the entire fee is deducted from the host's earnings, generally ranging from 14% to 16% of the subtotal before taxes.

2.1 *Data*

We use a private microdata set provided by AirDNA, a short-term rental intelligence firm, containing data for the 16 *alcaldías* in Mexico City during 2019, scraped from the Airbnb portal.[3] It records the final status (not booked, booked, unavailable) and corresponding rental price (in US dollars) for each posted accommodation and date. Additionally, it offers detailed information about each accommodation, including exact location (latitude and longitude), number of bedrooms,

[3] Because Airbnb data is not public, most of the time, researchers have to rely on data scraped by third parties. The AirDNA dataset has been extensively used in academic research, for instance: Chen and Xie (2023), Calder-Wang (2021), Farhoodi (2021), Abrate et al. (2022), Banco de México (2021), Dogru et al. (2020), Gibbs et al. (2018b), Iacovone (2023), Ding et al. (2023), Xie et al. (2021), Sainaghi, et al. (2021), and Tong and Gunter (2022). Based on official Airbnb quarterly earnings reports, AirDNA claims their dataset has 95% accuracy. See https://www.airdna.co/airdna-accuracy (retrieved on May 2nd, 2024).

bathrooms, number of photos posted, internet access, and whether the accommodation is an entire home/apartment or a shared/private room, whether it is offered by a "superhost", and amenities offered, among others. A major drawback of this data is that it does not contain any demographic or other guests' characteristics, which makes it difficult to identify taste variation.

Our initial microdata set consisted of 6,471,668 observations corresponding to daily accommodations offered in Airbnb in Mexico City for the year 2019 (for the economy of language hereafter, we refer to one of these accommodation-date observations as a listing). We conducted the following data cleaning process: First, we removed 2,682 listings with a zero price. Subsequently, we eliminated 1,228,841 listings from 7,448 available accommodations that were never rented during 2019. Of the remaining 5,240,145 listings, shared rooms and hotel rooms represent small percentages (1.83% and 1.57% respectively, see Table 1), so we focus our analysis on private rooms and entire homes/apartments exclusively.

Table 1

Number of booked and available listings by accommodation type during the year 2019

Listing type	*Frequency*	*Percentage*	*Cumulative percentage*
Hotel room	82,109	1.57	1.57
Shared room	96,050	1.83	3.40
Entire home/apt.	2,500,380	47.72	51.12
Private room	2,561,606	48.88	100.00
Total	5,240,145	100.00	

Source: Authors' elaboration.

Additionally, to prevent biases and enhance the accuracy of our estimates, for each accommodation type and *alcaldía*, we filtered out all listings with prices above 99% or below 1% of the prices of booked listings during 2019.

Our final sample contains 4,844,410 listings, of which 40.72% correspond to booked ones. This information pertains to 24,956 unique accommodations scattered across the 16 *alcaldías* of Mexico City. The *alcaldías* with the most significant number of total listings, as well as booked and non-booked listings, are Cuauhtémoc, Miguel Hidalgo, and Benito Juárez (see Table A.1).

Table 2

Average daily accommodations in Mexico City, 2019

Month	*Hotel rooms available*	*Hotel rooms occupied*	*Airbnb listings available*	*Airbnb listings occupied*
January	51,284	27,770	10,765	4,585
February	51,234	33,738	10,749	5,043
March	51,204	34,071	11,529	5,261
April	51,208	32,886	12,634	5,134
May	51,207	33,822	12,926	4,792
June	51,239	33,003	13,733	5,212
July	51,239	34,658	14,174	5,733
August	51,324	32,852	14,202	5,163
September	51,324	33,515	14,353	5,571
October	51,316	35,639	13,528	5,529
November	51,333	37,771	14,539	6,540
December	51,385	31,155	15,962	6,280

Source: Hotel room occupancy data was obtained from DataTur, a public monitoring system of Mexico's Secretary of Tourism. The Airbnb averages shown were calculated using our final sample of AirDNA data.

Finally, in our demand models, we assume guests' outside option is booking a room in the traditional lodging sector.[4] We obtain data on monthly average daily hotel room occupancy from DataTur, a tool implemented by the Mexican Secretary of Tourism to monitor hotel occupancy. Table 2 compares these averages with Airbnb's average daily occupancy calculated by us from our final sample described in the previous paragraphs. It shows that in terms of the monthly average of daily occupancy (resp. available accommodations), Airbnb rentals represent between 16% and 20% (resp. 20% and 31%) of the occupancy (resp. availability) in Mexico City's traditional sector.

[4] We discuss the choice set in detail in section 3.1.

2.2 *Preliminary analysis*

The 24,956 accommodations belong to 14,788 hosts. We classify these hosts as professional or not according to the number of accommodations they manage on the platform. In the body of the paper, we adopt the single-unit/multi-unit definition of nonprofessional and professional hosts, largely adopted in the literature.[5] In Appendix A.4, we review the robustness of our results to more nuanced definitions of what it means to be a professional host, also based on the number and type of properties.

Table 3

Number of booked and non-booked listings by type of host

Host	*Status*		*Total*
	Non-Booked	*Booked*	
Non-professional	1,325,680	698,290	2,023,970
Professional	1,546,157	1,274,283	2,820,440
Total	2,871,837	1,972,573	4,844,410

Note: Listings corresponding exclusively to Entire home/apartment and Private room accommodations.

Source: Author's elaboration.

Of the 14,788 hosts, 26.93% were classified as professional hosts who can manage between 2 and 77 accommodations, amounting to 56.70% of the accommodations posted on Airbnb in Mexico City during 2019. More specifically, 55.22% of professional hosts offer exactly two accommodations, and 20.02% offer exactly three accommodations. On the other hand, Table 3 presents the annual number of listings by type of host. Professional hosts offered 58.22% of the listings and 64.60% of the booked listings.

[5] For instance, Chen and Xie (2023), Abrate et al. (2022), Gil and Sequera (2022), Li et al. (2016), López Tamayo and Ramírez Álvarez (2021), Gibbs et al. (2018a), Magno et al. (2018), and Tong and Gunter (2022) explicitly define professionals as those managing more than one accommodation. The distinction between single-unit and multi-unit as a source of heterogeneity in managerial practices is also present in Koh et al. (2020), Kwok and Xie (2019), and Lorde et al. (2019).

Table 4

Regression of listing prices with respect to fixed effects of alcaldía, reservation status

	Listing prices	
	Coefficient	*p-value*
Intercept	52.16	0.00
Alcaldia (0 = Azcapotzalco)		
Miguel Hidalgo	33.28	0.00
Cuauhtémoc	20.19	0.00
Cuajimalpa de Morelos	20.06	0.00
Coyoacán	9.84	0.00
Álvaro Obregón	9.67	0.00
Benito Juárez	4.94	0.00
Milpa Alta	4.60	0.04
Tlalpan	3.62	0.00
La Magdalena Contreras	2.66	0.00
Gustavo A. Madero	-1.70	0.00
Xochimilco	-3.25	0.00
Iztapalapa	-3.41	0.00
Venustiano Carranza	-4.36	0.00
Iztacalco	-6.33	0.00
Tláhuac	-6.41	0.00
Status (0 = Non-Booked)		
Booked	-6.70	0.00
Host type (0 = nonprofessional)		
Professional	6.24	0.00
Accommodation type (0 = Entire home/apartment)		
Private room	-42.28	0.00
Date FE	Yes	
Observations	4,844,410	

Notes: Prices are in January 2019 real dollars. Recall we define listing as an accommodation-date observation.

Source: Author's elaboration.

Finally, Table 4 shows descriptive evidence regarding price variation among accommodations posted on the platform. We regress prices at the listing level (i.e., accommodation-date) on reservation status, host type, accommodation type, *alcaldía*, and date fixed effects. The *alcaldías* with the highest prices are Miguel Hidalgo, Cuauhtémoc, and Cuajimalpa. Booked listings are \$6.70 less expensive than non-booked ones. Listings offered by professional hosts are \$6.24 costlier than those from nonprofessional hosts. Lastly, private rooms are \$42.28 cheaper than entire homes/apartments.

Motivated by these preliminary findings suggesting there might be differences between professional and nonprofessional hosts, the rest of the paper is dedicated to building and estimating models of demand and supply of differentiated products for the Airbnb market in Mexico City. As a preliminary step, the following section addresses an issue that arises due to the nature of Airbnb.

3. Creating categories and representative products

Airbnb is a market with highly heterogeneous products, which imposes nontrivial challenges in model estimation. In fact, to account for all this product heterogeneity, one would need a model of accommodation-specific demand for each date, which would imply endogenous choice sets for arriving guests and capacity constraints on the supply side, which are unsolved issues at the forefront of the literature on discrete choice estimation and identification (Agarwal and Somaini, 2022; Farhoodi, 2021). On top of that, such a model would have a large number of products, a well-known challenge in the estimation of discrete choice models of demand (see for instance Skrainka and Judd (2011), many of which would have zero market share (offered but not rented), which adds another layer of complexity to the estimation procedure (Dubé *et al.*, 2021).

To overcome these challenges, we classify the accommodations into disjoint categories and create representative products for each category.[6] We created 116 categories and an equal number of representative products. In this section, we give an overview of how we created these categories and representative products and their implications for modeling.[7]

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[6] Product aggregation is commonly used in discrete choice demand models. Dubé et al. (2021) already cited elaborates on this.

[7] Appendix A.3 contains a more detailed explanation of product categorization.

We follow a procedure similar to that described by Farronato and Fradkin (2022) for classifying accommodations and restricting attention to booked listings only (which is without loss since every accommodation in our final dataset was booked at least once). We start with a hedonic regression where the natural logarithm of the prices of booked listings depends on the fixed effects of accommodation and date.[8] The accommodation fixed effects are intended to capture the average utility a guest obtains from booking a particular accommodation.[9]

To create categories, we first group individual accommodations by accommodation type (entire home/apartment or private room) and *alcaldía*. Within each such group, we establish quality tiers using the accommodation fixed effects previously estimated; the number of quality tiers varies according to the group size. Each subgroup of individual accommodations of the same type, located in the same *alcaldía* and within the same quality tier, is further split between professional and nonprofessional hosts, which enables our analysis. The resulting subgroup in this way is a product category, of which we have 116.[10]

For each category, a representative product is created, whose characteristics are the average of the features of the unique accommodations that make it up throughout the year; these remain constant over time. On the other hand, the daily price for each representative product is calculated by averaging the prices of the accommodations within the category reserved for that date. Similarly, to calculate the quantity of the representative product sold for each date, we sum up the reservations of accommodation within the category for that date.

[8] Other fixed effects, such as *alcaldía*, accommodation type, and type of host, are omitted due to collinearity.

[9] Following Farronato and Fradkin (2022), we apply a Bayesian shrinkage procedure to the accommodation fixed effects to mitigate the impact of sampling error.

[10] Since our research question is different from that of Farronato and Fradkin (2022), our categorization is finer than the one implemented by them. They have 4 categories per city-date (10 cities), while we have 116 potential categories for each date. The actual number varies with date, as some categories might not always be offered.

3.1 *The stylized choice problem*

Within this stylized framework, the choice set faced by every consumer looking for accommodation on a given date is the subset of the 116 representative products offering accommodation on that date, plus an outside option of booking a hotel room outside the platform. The demand for a given representative product for a given date is the count of accommodations belonging to the corresponding category that were booked for that date. We estimate the size of the outside option with the corresponding monthly average of daily occupied hotel rooms (Table 2).

If no individual accommodation belonging to a specific category is offered on a given date, we drop that particular representative product from the corresponding date's choice set. Relatedly, there are dates when no accommodation belonging to a given category is rented despite having available accommodations, resulting in a zero market share, which might create some issues in the estimation of the demand models. We implement the two most widespread ways of dealing with this issue (see section 4.3 for a detailed discussion).

On the supply side, representative products offered by nonprofessionals are assumed to be provided by single-product hosts. In contrast, the representative products offered by professionals are assumed to be supplied by a multi-product host who maximizes joint profits.

Our framework, though highly stylized, still captures crucial features of the market for short-term rentals while keeping the estimation issues mentioned at the beginning of this section under control. Specifically, our model captures daily demand and price fluctuations; it still captures variation in quality, location, and type of accommodations offered by professional and nonprofessional hosts, and complex substitution patterns; as well as the multi-product nature of professional hosts' portfolio, which enables economies of scope and internalization of within portfolio substitution effects.

Naturally, this stylized aggregation abstracted some aspects of the Airbnb market for short rentals. The most critical elements lost by our modeling choices (on top of the choice set endogeneity) are the variation across professional hosts' portfolios and an even more extensive product heterogeneity, which we leave for future research.

4. Model and estimation

In this section, we present our theoretical models of demand and supply, as well as our estimation strategy. It is important to emphasize that we model and estimate daily demand and supply, resulting in 365 markets in total.

4.1 *Models of demand*

We model consumer demand using logit and mixed logit (a.k.a. random coefficients) models. On a given date, guests demand one out of a subset of the 116 categories offered by professional hosts (who offer more than one accommodation type) and nonprofessional hosts (who offer only one accommodation type) or the outside option of renting a hotel room in the traditional lodging sector.[11] Next, we formalize these ideas.

Logit: Guest n chooses an accommodation belonging to category $j \in \mathcal{J}_t$, where $\mathcal{J}_t$ is the set of categories available in day t on the platform. The utility guest n receive from an accommodation in category j, with observed features $\vec{x}_j$ and price p_{jt}, including the tax rate τ_j on day t is:

$$U_{njt} = \vec{\beta}' \vec{x}_j - \alpha \log\left(p_{jt}\left(1+\tau_j\right)\right) + \xi_{jt} + \varepsilon_{njt} \tag{1}$$

$\vec{\beta}$ and α characterize consumers' preferences for accommodations' observed attributes. ξ_{jt} captures preferences for unobserved features that do not vary among guests. ε_{njt} corresponds to preferences for unobserved aspects that do vary among guests. As usual, we assume that ε_{njt} are i.i.d. Gumbel. For simplicity, we denote $\delta_{jt} = \vec{\beta}' \vec{x}_j - \alpha \log\left(p_{jt}\left(1+\tau_j\right)\right) + \xi_{jt}$ to represent the average utility. There is an outside option (such as renting a hotel room outside the platform) whose utility we normalize to 0 in any day t. Thus, the probability of a guest choosing the accommodation in category j for day t is:

$$s_{jt}\left(\overrightarrow{\delta_t}\left(\vec{p}_t, \vec{x}_t, \vec{\beta}, \alpha\right)\right) = \frac{e^{\delta_{jt}}}{1+\sum_{i\in\mathcal{J}_t} e^{\delta_{it}}} \tag{2}$$

Mixed logit: Also known as the random coefficients model, it is the most popular extension of the logit model in demand estimation because of its flexibility to accommodate heterogeneity in tastes

[11] See section 3.1.

among consumers, which allows flexible substitution patterns (Berry and Haile, 2021; Einav and Levin, 2010; Gandhi and Nevo, 2021). In relation to the baseline model, the choice problem for guest n remains unchanged: to choose $j \in \mathcal{J}_t$. However, the random utility model in equation (1) becomes now:

$$U_{njt} = \vec{\beta}_n^{\prime} \vec{x}_{\mathrm{j}} - \alpha_n \log\left(p_{jt}\left(1+\tau_j\right)\right) + \xi_{jt} + \varepsilon_{njt} \tag{3}$$

with $\vec{\beta}_n$ a random vector and α_n a random variable such that $\beta_{nk}\left(\bar{\beta}_k, \sigma_k^2\right)$ for the kth characteristic, mutually independent, and $\alpha_n\left(\bar{\alpha}, \sigma_p^2\right)$, independent from each component of $\vec{\beta}_n$. As before, these coefficients characterize the guest n's preferences for accommodations' observed attributes. Also, as before, ξ_{jt} captures preferences for unobserved features that do not vary among guests, and ε_{njt} captures unobserved taste variation among guests, assumed to be distributed i.i.d. Gumbel.

It is useful to separate the average and individual taste shocks. Rewrite (3) as,

$$U_{njt} = \delta_{jt} + \mu_{njt} + \varepsilon_{njt} \tag{4}$$

where $\delta_{jt} = \sum_k \bar{\beta}_k x_{jk} - \bar{\alpha} \log p_{jt} + \xi_{jt}$ is the part of utility which varies across alternatives but not consumers. On the other hand, $\mu_{njt} = \sum_k \sigma_k \upsilon_{nk} x_{jk} - \nu_{np} \sigma_p \log p_{jt}$ is the part of utility varying across consumers, with ν_{nk}, $k = 1 \ldots, dim\left(\overrightarrow{x_j}\right)$ and ν_{np} mutually independent normal standard taste shocks. Thus, the unconditional probability of a guest choosing the accommodation in category j for day t is now:

$$s_{jt}\left(\vec{\delta}_{jt}, \vec{p}_t, \vec{x}_j, \{\sigma_k\}_k, \sigma_p\right) = \int \frac{e^{\delta_{jt}+\mu_{njt}}}{1+\sum_{i \in \mathcal{J}_t} e^{\delta_{it}+\mu_{nit}}} dF\left(\nu_{n1}, \ldots, \nu_{ndim(\vec{x}_j)}, \nu_p\right) \tag{5}$$

With F a multivariated standard normal distribution with dimension $dim\left(\vec{x}_j\right)+1$.

Table 5
Demand results

	(1) Logit				*(2) Logit with endogeneity*				*(3) Mixed logit with endogeneity*			
	Drop		*Imputation*		*Drop*		*Imputation*		*Drop*		*Imputation*	
	Coeff.	*SE*	*Coeff.*	*SE*	*Coeff.*	*SE*	*Coeff.*	*SE*	*Coeff.*	*SE*	*Coeff.*	*SE*
β												
ln(price(1+ τ))	-1.09	0.01	-1.57	0.05	-1.97	0.02	-2.60	0.05	-1.90	0.12	-1.45	0.68
amenities	1.87	0.03	2.96	0.11	2.31	0.04	3.52	0.10	-0.87	5.87	-0.45	1.63
bathrooms	-0.18	0.03	-0.04	0.11	-0.21	0.03	-1.01	0.08	-1.80	0.33	-15.06	3.05
bedrooms	1.15	0.04	2.61	0.20	0.74	0.05	2.36	0.17	0.24	0.16	-1.41	0.64
maxguests	-0.55	0.02	-1.34	0.07	-0.01	0.02	-0.30	0.06	-0.05	0.07	-3.65	1.16
professional (0 = nonprofessional)	0.28	0.01	0.71	0.03	0.05	0.01	0.13	0.03	-0.10	0.03	-0.69	0.19
private room (0 = entire home/apt.)	-0.84	0.02	-1.85	0.06	-0.45	0.02	-0.44	0.04	-0.71	0.10	-4.73	0.92
intercept absorbed	Yes		Yes		Yes		Yes		Yes		Yes	
Date FE	Yes		Yes		Yes		Yes		Yes		Yes	
Alcaldia FE	Yes		Yes		Yes		Yes		Yes		Yes	
σ												
ln(price(1+τ))									0.00	25.70	0.01	9.53
amenities									3.25	2.62	8.28	1.42
bathrooms									1.52	0.15	8.87	1.59
bedrooms									0.00	3.77	0.00	11.97
maxguests									0.00	2.26	2.62	0.76
intercept									3.19	4.93	5.63	1.13
N	39,715		40,493		39,715		40,493		39,715		40,493	

Notes: SE symbolizes robust standard errors. Prices are in dollars in January 2019 real values. The Drop method excludes observations with zero market share, while the Imputation method keeps these observations but imputes them with a market share value of 10^{-12}.

Source: Authors' elaboration.

4.2 *Supply model*

We assume Nash-Bertrand competition. Hosts choose prices to maximize daily profits. The crucial difference between professional and nonprofessional hosts is that the former offer accommodations in different categories and maximize the joint daily profit, while nonprofessionals only offer accommodations in a single category. Let $\mathcal{J}_t^{\Omega} \subset \mathcal{J}_t$ the set of categories belonging to professional hosts and $\mathcal{J}_t^{\omega} \subset \mathcal{J}_t$ the ones belonging to nonprofessional hosts. Let $\mathcal{M}_t$ the market size in day t. For the categories of products belonging to professional hosts, we set up a unique decision-maker who faces the following profit maximization problem:

$$\underset{\{p_{jt}\}_{j\in\mathcal{J}^{\Omega}}}{max} \sum_{j\in\mathcal{J}_t^{\Omega}} (p_{jt} - c_{jt}) \mathcal{M}_t s_{jt} \left(\vec{\delta}_t \left(\vec{p}_t, \vec{x}_j, \vec{\beta}, \alpha\right)\right) \tag{6}$$

On the other hand, for the representative products belonging to nonprofessional hosts, for each category $j \in \mathcal{J}_t^{\omega}$, we set up a decision maker who faces the following profit maximization problem:

$$\underset{p_{jt}}{max} \quad (p_{jt} - c_{jt}) \mathcal{M}_t s_{jt} \left(\vec{\delta}_t \left(\vec{p}_t, \vec{x}_j, \vec{\beta}, \alpha\right)\right) \tag{7}$$

The market equilibrium for the day t consists of the seller's prices and consumer's choices, such that both hosts and guests make the decision that maximizes their profits and utilities, respectively, and that their optimal decisions are consistent with those of others.

4.3 *Estimation*

We follow the standard procedure for estimating models of demand and supply for differentiated products with aggregate data (Berry *et al.*, 1995). Demand is estimated using the Generalized Method of Moments (GMM) with the moments obtained from the IV orthogonality conditions and the expected market shares. For mixed logit, we leverage state-of-the-art techniques implemented in PyBLP, a freely available Python library developed by leading researchers in empirical IO and increasingly used in the discipline to estimate BLP-type models (Conlon and Gortmaker, 2020). Demand estimates coupled with hosts' optimality conditions pin down their marginal costs, which are, in turn, used to perform counterfactuals.[12]

4.3.1 *Demand*

To estimate our logit model, we analytically invert the expressions for the choice probabilities (2) as in Berry (1994) to obtain an estimate of the δ_j's which are afterward regressed on our variables of interest to obtain the corresponding coefficients for the utility. Specifically, since the mean utility of the outside option is normalized to zero, the expression:

$$\delta_{jt} = \ln s_{jt} - \ln s_{0t} \tag{8}$$

resulting from inverting the logit probabilities pin downs analytically the δ_{jt} for each product j and market t (Berry, 1994: 250). These δ_{jt}'s are afterward regressed against product characteristics according to the following specification:

$$\delta_{jt} = \vec{\beta}' \vec{x}_j - \alpha \log\left(p_{jt}\left(1+\tau_j\right)\right) + \xi_{jt} \tag{9}$$

We report the results in the Table 5, column (1).

The previous specification assumes p_{jt} is exogenous. To correct for price endogeneity, we employ the methodology of Berry *et al.* (1995), using differentiation instruments in the spirit of Gandhi and Houde (2019).[13] Once the δ_{jt}'s are obtained from equation (8), moment conditions obtained from the instruments' orthogonality conditions are used to obtain estimates for β and α using GMM and PyBLP. We report the results in Table 5, column (2).

[12] The code to recover marginal costs and perform counterfactuals was written in Python, and it is available upon request.

[13] The differentiation instruments proposed by Gandhi and Houde (2019) are a variation of the broadly-known BLP instruments, which are functions of product characteristics and leverage the fact that the price of product j depends on characteristics of other products and that dependence differs if these are their products or competitors' products. The differentiation instruments are intended to improve empirical performance and avoid weak IV challenges that can arise in practice by leveraging distances among products in the characteristics space. In particular, their "local" version captures localized competition through the number of "close-by" products in the characteristics space. Specifically, these instruments are constructed as follows: Given the matrix of characteristics X, x_{jtk} is the characteristic k in X for product j in market t, which is produced by firm f, that is, $j \in J_{ft}$. The instruments are constructed using the function

Finally, for the estimation of the mixed logit, we employ the two-step GMM method as implemented in PyBLP and use differentiation instruments to correct for endogeneity. To estimate the value of the integral in (5), we employ 1000 Halton draws. From integral (5), for any given values of $(\{\sigma_k\}_k, \sigma_p)$, the $\vec{\delta}$ values such that the predicted share equals the observed market share are calculated, which implies solving a fixed point problem, which is solved using a SQUAREM routine. We report the results in Table 5, column (3).

Zero-valued market shares: It is important to emphasize that certain representative products have no bookings for some dates despite being offered in the market. Such products, therefore, exhibit a market share of zero in those dates, an issue that happens in 778 day-category pairs (out of 40,493 day-category pairs). This is a well-known issue in estimating discrete choice models because it rejects any multinomial choice probabilities (Dubé *et al.*, 2021; McFadden, 1974). In this research, we consider the two most common solutions to this problem, which are either to eliminate observations with a zero market share (hereafter "Drop") or to impute an extremely small value (hereafter "Imputation"); we use a value of 10^{-12} for "Imputation".

Remarks on data: Recall our final estimation dataset, which consists of market shares of the representative products and the outside option for every day in 2019 (section 3). The features of the representative products are the logarithm of the total amount paid by guests to rent an Airbnb accommodation ("$\ln(\text{price}\,(1+\tau))$") with τ the lodging tax (3% in 2019) and the price in US dollars of January 2019; the number of amenities in tens ("amenities");[14] the number of bathrooms ("bathrooms"); the number of bedrooms ("bedrooms"); the maximum number of guests allowed ("maxguests"); "professional", a

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$g_{jtk}(X) = \left[\sum_{j' \in J_{ft}} 1\left(|d_{jtkj'}| < SD_k\right), \sum_{j' \notin J_{ft}} 1\left(|d_{jtkj'}| < SD_k\right)\right]$, where $j \neq j', d_{jtkj'} = x_{jtk} - x_{j'tk}$, and SD_k is the standard deviation of these pairwise differences computed across all markets. We leverage the PyBLP implementation of these instruments, together with their own product characteristics, which are assumed to be exogenous and, therefore, instruments by themselves. On top of Gandhi and Houde (2019) see also Gandhi and Nevo (2021).

[14] The AirDNA dataset registers a large variety of amenities each accommodation offers. The variable "amenities" was constructed by counting the number of amenities recorded in the database for each accommodation.

dummy variable indicating whether the host type for a given category has multiple listings on the platform; and "private room", a dummy variable indicating whether the representative product is a private room or an entire home/apartment. Additionally, we employ fixed effects for the 16 *alcaldías* of Mexico City and for each day of the year 2019. To create the differentiation instruments, we use "amenities", "bathrooms", "bedrooms", and "maxguests". To measure the size of the outside option for each day, we used the corresponding monthly average of hotel bookings per day reported in DataTur (see Table 2).

4.3.2 *Supply*

For each day, to obtain marginal costs that are consistent with market equilibrium, the first-order conditions for professional hosts and for each category of nonprofessional hosts,

$$s_{jt} + (p_{jt} - c_{jt})\left(\frac{ds_{jt}}{dp_{jt}}\right) + \sum_{it \in \mathcal{J}_t^{\Omega} \setminus \{jt\}} \left[(p_{it} - c_{it})\,\frac{ds_{it}}{dp_{jt}}\right] = 0, \forall j \in \mathcal{J}_t^{\Omega} \tag{10}$$

$$s_{jt} + (p_{jt} - c_{jt})\left(\frac{ds_{jt}}{dp_{jt}}\right) = 0 \tag{11}$$

are inverted and evaluated using the demand estimates.

5. Results

In this section, we present our estimates for the models of demand and supply. These estimates are used to explore the equilibrium effects of a hypothetical policy taxing professional hosts within Airbnb.

5.1 *Demand*

Table 5 presents our estimations of the different demand specifications, i.e., the logit, logit corrected for endogeneity, and the mixed logit corrected for endogeneity, for both ways of addressing the zero market share problem.

Beginning with the logit model without addressing endogeneity (Table 5, column 1), most coefficients are statistically significant at

95%, and their signs are consistent between the "Drop" and "Imputation" methodologies of handling the zero market share problem (with the exception of "bathrooms" in the "Imputation" method).

Controlling for endogeneity in prices using the IV approach outlined in the previous section (Table 5, column 2), most of the estimates remain significant at 95% (with the exception of "maxguests" in the "Drop" method) and preserve the directions obtained in the simplest specification. Most coefficients increase in absolute value relative to the estimation, which does not correct the endogeneity issue, emphasizing the importance of correcting the endogeneity issue.

With the inclusion of heterogeneity in consumer preferences using the mixed logit, and correcting for endogeneity (Table 5, column 3), we find that the parameters corresponding to the variance of the random taste shocks are only significant for "bathrooms" in both methodologies and "amenities", "maxguests", and the intercept in the imputation methodology. This is not surprising given the lack of demographic or other information varying at the guest level.

In our analysis, the most relevant estimates are those associated with "$\ln(\text{price}\,(1+\tau))$" due to their implications on the price elasticity of demand, which is crucial for the supply model estimations. Values close to 0 would correspond to inelastic demands, which are incompatible with the profit maximization proposed in our supply model. Relative to these coefficients on "$\ln(\text{price}\,(1+\tau))$", we observe they are consistent across models and ways of handling the zero market share, that they have the expected sign, and the values for logit models for the "Drop" versions are more negative in magnitude compared to their "Imputation" counterparts. For the mixed logit specification, the variances for "$\ln(\text{price}\,(1+\tau))$" are insignificant. The fact that the coefficients on the taste shock parameters are not different from zero offers statistical evidence in favor of the simpler logit model (Train, 2009). Therefore, our preferred specification overall is the logit with endogeneity, which we use for subsequent analyses.

The discrepancy across models regarding the preferences for the physical characteristics of accommodations ("amenities", "bathrooms", "bedrooms", and "maxguests") or the insignificance of the estimates suggests that possibly their linear specification in consumer utility is not the most appropriate way to include them. However, since the analyses of the supply and counterfactual primarily depend on the price elasticities of demand, which are consistent across specifications and ways of handling the zero market share problem, we leave this subject matter for future research.

Table 6

Results of the supply model

	MC				*P-MC*				*(P-MC)/P*			
	Drop		*Imputation*		*Drop*		*Imputation*		*Drop*		*Imputation*	
	Coeff.	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*
Intercept	22.39	0.00	28.22	0.00	23.22	0.00	17.65	0.00	0.5100	0.0000	0.3854	0.0000
Host type (0 = nonprofessional)												
Professional	-1.76	0.00	-1.60	0.00	3.67	0.00	2.31	0.00	0.0921	0.0000	0.0702	0.0000
Accommodation type (0 = Entire home/apartment)												
Private room	-20.72	0.00	-25.56	0.00	-21.49	0.00	-15.98	0.00	0.0301	0.0000	0.0222	0.0000
Alcaldia (0 = Azcapotzalco)												
Álvaro Obregón	5.42	0.00	6.80	0.00	5.63	0.00	4.25	0.00	-0.0201	0.0000	-0.0152	0.0000
Benito Juárez	7.75	0.00	9.95	0.00	8.04	0.00	6.22	0.00	-0.0141	0.0000	-0.0108	0.0000
Coyoacán	17.60	0.00	23.40	0.00	18.23	0.00	14.62	0.00	-0.0209	0.0000	-0.0159	0.0000
Cuajimalpa de Morelos	12.20	0.00	15.29	0.00	12.65	0.00	9.56	0.00	-0.0302	0.0000	-0.0228	0.0000
Cuauhtémoc	29.29	0.00	36.92	0.00	30.39	0.00	23.10	0.00	-0.0269	0.0000	-0.0203	0.0000
Gustavo A. Madero	-0.30	0.74	-0.38	0.74	-0.31	0.74	-0.24	0.74	0.0002	0.9000	0.0001	0.9000
Iztacalco	-2.25	0.01	-2.82	0.01	-2.33	0.01	-1.76	0.01	0.0093	0.0000	0.0070	0.0000
Iztapalapa	-1.85	0.04	-2.34	0.04	-1.92	0.04	-1.46	0.04	0.0066	0.0000	0.0050	0.0000
La Magdalena Contreras	3.90	0.00	4.93	0.00	4.03	0.00	3.08	0.00	-0.0121	0.0000	-0.0093	0.0000
Miguel Hidalgo	28.87	0.00	36.71	0.00	29.93	0.00	22.95	0.00	-0.0293	0.0000	-0.0222	0.0000
Milpa Alta	3.62	0.04	4.34	0.05	3.59	0.05	2.61	0.06	-0.0175	0.0000	-0.0132	0.0000
Tlalpan	2.48	0.01	3.12	0.01	2.58	0.01	1.95	0.01	-0.0077	0.0000	-0.0058	0.0000
Tláhuac	0.29	0.80	0.33	0.80	0.27	0.82	0.19	0.81	0.0416	0.0000	0.0277	0.0000
Venustiano Carranza	0.41	0.66	0.51	0.65	0.43	0.65	0.32	0.65	-0.0076	0.0000	-0.0057	0.0000
Xochimilco	0.71	0.45	0.76	0.51	0.74	0.45	0.47	0.51	0.0056	0.0000	0.0035	0.0000
Date FE	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	39,715		40,493		39,715		40,493		39,715		40,493	

Notes: The Drop method excludes observations with zero market share, while the Imputation method keeps these observations but imputes them with a market share value of 10^{-12}. Prices and marginal costs are in dollars in January 2019 real values.

Source: Authors' elaboration.

5.2 *Supply*

For the estimation of the model of the supply, we use the coefficients of our preferred specification for the demand model: logit with endogeneity. Table 6 presents regressions of our estimates of daily marginal costs (c_{jt}), equilibrium markups ($p_{jt} - c_{jt}$), and price-cost margins $\left(\frac{p_{jt}-c_{jt}}{p_{jt}}\right)$ against host and accommodation type, alcaldia, and date. The full distributions by host and accommodation (Figure A.3 and Figure A.4).

It is meaningful to note that both methods of addressing the zero market share issue yield similar results, as shown in Table 6.[15] As a result, we will focus on the "Drop" method.

Regarding host type, compared to nonprofessional hosts, professional hosts' accommodations have a lower daily cost by \$1.76 ($p-value < 0.05$) and earn \$3.67 more ($p-value < 0.05$) per reserved accommodation, also have 9 percentage points ($p - value < 0.05$) higher price-cost margin. On the one hand, the lower marginal costs estimated for professional hosts are consistent with the intuition that they might take advantage of economies of scale, scope, and superior management practices, which in turn explains the higher markups professional hosts are able to capture. On the other, it is important to notice that price-cost margins are overall high regardless of host type (the baseline in the most conservative estimation is 38%), which is consistent with the existence of large fixed costs (rent, mortgage, certain amenities like internet or cable service) and differentiated products.

Compared to renting an entire home/apartment, renting a private room costs \$20.72 less ($p - value < 0.05$) and earns \$21.49 less ($p - value < 0.05$), but has a higher price-cost margin of 0.0301 ($p - value < 0.05$). Therefore, while more dollars are earned by renting an entire home/apartment, renting by room yields a higher price-cost margin.

Regarding the different alcaldías in Mexico City, Cuauhtémoc, Miguel Hidalgo, and Coyoacán have the highest daily costs but also the highest dollar gains. In contrast, Iztacalco, Iztapalapa, and Gustavo A. Madero have the lowest daily costs but also the lowest markups. Concerning price-cost margins, the highest are those of Tláhuac, Iztacalco, and Iztapalapa, and the lowest are those of Cuajimalpa, Miguel Hidalgo, and Cuauhtémoc.

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[15] There are some minor differences due to the differences in the magnitude of the coefficient associated with the price elasticity in the demand model.

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Table 7

Percentage comparison: Counterfactual vs. current equilibrium, consumption tax

	Professional				*Accommodation type*				*Total*	
	Yes		*No*		*Entire home/apt.*		*Private room*			
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Drop										
Δ%Price	-1.53	1.07	0.00	0.00	-0.51	0.72	-1.04	1.30	-0.77	1.08
Δ%Price(1+τ)	3.24	1.12	0.00	0.00	1.86	1.96	1.40	1.61	1.63	1.81
Δ%Share	-5.52	2.06	0.57	0.05	-2.91	3.64	-2.07	3.01	-2.49	3.37
Δ%(P-MC)	-2.40	1.40	0.00	0.00	-0.86	1.13	-1.57	1.83	-1.21	1.56
Δ%((P-MC)/P)	-0.88	0.39	0.00	0.00	-0.35	0.43	-0.54	0.58	-0.44	0.52
Imputation										
Δ%Price	-1.22	0.85	0.00	0.00	-0.41	0.58	-0.80	1.02	-0.60	0.85
Δ%Price(1+τ)	3.58	0.89	0.00	0.00	1.97	2.04	1.58	1.72	1.78	1.90
Δ%Share	-7.97	2.11	0.81	0.08	-4.00	4.97	-3.09	4.23	-3.54	4.64
Δ%(P-MC)	-2.51	1.47	0.00	0.00	-0.90	1.19	-1.59	1.91	-1.25	1.63
Δ%((P-MC)/P)	-1.32	0.66	0.00	0.00	-0.50	0.63	-0.81	0.92	-0.65	0.81

Notes: The Drop method excludes observations with zero market share, while the Imputation method keeps these observations but imputes them with a market share value of 10^{-12}. Prices and marginal costs are in dollars in January 2019 real values.

Source: Authors' elaboration.

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Table 8
Percentage comparison: Counterfactual vs. current equilibrium, tax on hosts

	Professional				*Accommodation type*				*Total*	
	Yes		*No*		*Entire home/apt.*		*Private room*			
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Drop										
Δ%Price	3.52	1.21	0.00	0.00	2.02	2.12	1.52	1.74	1.77	1.96
Δ%Price(1+τ)	3.52	1.21	0.00	0.00	2.02	2.12	1.52	1.74	1.77	1.96
Δ%Share	-5.96	2.22	0.61	0.05	-3.14	3.93	-2.24	3.26	-2.70	3.64
Δ%(P-MC)	-2.59	1.51	0.00	0.00	-0.93	1.22	-1.69	1.98	-1.30	1.68
Δ%((P-MC)/P)	-5.91	0.40	0.00	0.00	-2.83	2.87	-3.12	3.05	-2.97	2.97
Imputation										
Δ%Price	3.88	0.96	0.00	0.00	2.14	2.21	1.72	1.87	1.93	2.06
Δ%Price(1+τ)	3.88	0.96	0.00	0.00	2.14	2.21	1.72	1.87	1.93	2.06
Δ%Share	-8.60	2.27	0.88	0.09	-4.32	5.36	-3.34	4.57	-3.83	5.00
Δ%(P-MC)	-2.71	1.59	0.00	0.00	-0.97	1.28	-1.71	2.06	-1.34	1.76
Δ%((P-MC)/P)	-6.35	0.68	0.00	0.00	-2.98	3.04	-3.32	3.36	-3.15	3.21

Notes: The Drop method excludes observations with zero market share, while the Imputation method keeps these observations but imputes them with a market share value of 10^{-12}. Prices and marginal costs are in dollars in January 2019 real values.

Source: Authors' elaboration.

5.3 *Counterfactual exercises*

In 2019, guests making a reservation on Airbnb paid a 3% lodging *ad valorem* tax. As mentioned in the Introduction, governments around the world have implemented differential regulations for professional and nonprofessional hosts, with the former being subject to stricter rules. Consequently, we examine two counterfactual *ad valorem* tax policies that differentiate professional and nonprofessional hosts, one targeting guests and another targeting hosts.[16]

Importantly, the counterfactual exercises were performed for both methodologies addressing the zero market share issue, and similarly to the demand and supply analyses, no major differences were found between the two approaches, which is reassuring. Therefore, as in the case of the supply model, we will focus on the estimates using the "Drop" method.

The first counterfactual examines the effects of a consumption tax, τ, of 5% (additional to the existing 3%) on accommodations belonging to professional hosts only. Table 7 presents the average changes (in percentage) relative to the current equilibrium estimates in subsection 5.2. As expected, the additional tax for booking with professional hosts decreases the price charged by professional hosts (by 1.53%), increases the total amount paid by a guest for staying in a professional host's property (by 3.24%), and decreases professionals' market share (by 5.52%). Naturally, markups and price-cost margins for professionals decrease. The market share lost by professionals is only marginally captured by nonprofessional hosts within the platform (0.57%), the remaining being captured by the traditional lodging sector (outside option). Considering the accommodation type, the effects for the entire home/apartment and private rooms are identical in signs, but those for private rooms are larger in absolute magnitude.

The second counterfactual examines the effects of a producer tax, ρ, of 5% of the price of accommodations belonging to professional hosts only. Table 8 presents the average changes (in percentage) relative to the current equilibrium estimates in subsection 5.2. Not surprisingly, the tax on renting imposed on professional hosts increases the price charged by professional hosts (by 3.52%), increases the total amount paid by a guest for staying at a professional host's property

[16] While it has been shown that physical incidence of per unit taxes is irrelevant under very general conditions (Weyl and Fabinger, 2013), it is a matter of elementary algebra to corroborate that even in the textbook examples, physical incidence of *ad valorem* taxes is not irrelevant (Pauwels and Schroyen, 2024).

in the same proportion (3.52%), and decreases the market share of professionals (by 5.96%). As expected, markups and price-cost margins for professionals decrease. The market share lost by professionals is only marginally captured by nonprofessional hosts within the platform (0.61%), the remaining being captured by the traditional lodging sector (outside option). Considering accommodation type, the effects for entire homes/apartments and private rooms are identical in signs.

Comparing both counterfactual scenarios, from the consumer's perspective, there is an overall higher cost to rent a property belonging to a professional host when the tax is directed at the host; however, it is important to note that the difference is marginal (0.28%). From the producer's side, the market share of professional hosts experiences a greater percentage decrease when the tax is imposed on them for renting out an accommodation. However, the overall effect of either tax on a professional's price-cost margins is a reduction of only about three percentage points relative to the baseline scenario.

6. Conclusions

Using a unique, detailed panel dataset containing information on daily accommodations for Airbnb in Mexico City, we found descriptive evidence consistent with professional hosts playing a significant role in the platform, similar to what has been found elsewhere. Motivated by this fact, we estimated multiple demand and supply models to determine market structure indicators like marginal costs, markups, and price-cost margins.

Consistent with intuition, professional hosts' accommodations are found to be associated with lower marginal costs and larger markups, which indicates professional hosts have more ability to capture benefits, probably due to economies of scale, scope, and improved management practices. However, overall, price-cost margins are high and only slightly higher for professionals, which is consistent with the existence of large fixed costs (like mortgages, rents, furniture, and some utilities) and the differentiated products nature of the market.

Regarding the property type, the estimated marginal costs for entire homes/apartments are more significant than those for private rooms. This result is in line with the understanding that entire homes/apartments may require more resources for cleaning, utilities, and amenities. Even though entire homes/apartments have larger markups, private rooms have a slightly higher price-cost margin, which is statistically significant.

We examined two counterfactual tax policies that differentiate between professional and nonprofessional hosts: a tax of 5% over the price of accommodations belonging to professional hosts, levied on guests or hosts. Because neutrality of physical incidence of *ad valorem* taxes does not necessarily hold, not surprisingly, we found some differences in the point estimates for both scenarios; however, in both cases, prices paid by the consumer increase, the market share for professional hosts decreases, and the traditional lodging sector mostly captures it. Finally, the impact on hosts' margins was relatively small.

A remarkable and reassuring fact is that there are no substantial differences between the estimates obtained with the two most widespread methods of addressing the zero market share issue across all the exercises, i.e., imputing a small strictly positive value to those products with zero market shares ("Imputation") and dropping them ("Drop").

Overall, on top of the structural differences between professional and nonprofessional hosts in the Airbnb market in Mexico City, our findings highlight the usability of structural models for the counterfactual evaluation of policies for Airbnb. However, while an advantage of our modeling and estimation results lies in avoiding any time aggregation bias by estimating daily markets, the performed product aggregation leaves room for improvement in several dimensions that we discuss next.

To overcome econometric challenges that remain unresolved on the research frontier on discrete choice estimation and identification (endogenous choice sets, capacity constraints), we classified accommodations into categories and created representative products for each category. This product aggregation loses part of the Airbnb market's large product variety. Allowing for more heterogeneity and choice set endogeneity, while challenging, is crucial to enable variations in choice sets that can offer evidence of the diversity of consumers' tastes, allowing the estimation of substitution patterns that reflect this diversity (Goldberg, 1995; Petrin, 2002).

On the supply side, our stylized model permits variation in quality, location, and type of accommodations across professional and nonprofessional hosts, as well as some degree of economies of scope for the former ones. However, we have abstracted from entry and exit issues, and, more critically, we do not allow variation across professional hosts' portfolios.[17] There is a significant variation in portfolio

[17] Since our model is one of daily markets, entry is not a significant concern in a first approximation.

size among Airbnb professional hosts (and probably qualities as well), which suggests there might exist considerable variation in the type of own-product substitution patterns and the magnitude of economies of scope that the professional hosts can capture, which are not present in our model. Follow-up research on this issue is granted.

Lastly, while the dataset used is on par with the ones used in the literature, it does have its limitations. Being scraped data, it lacks essential information, such as guest-specific demographics, which is crucial to identifying taste variation. This, in turn, is vital to obtaining realistic substitution patterns, and it is an issue to be dealt with in the future.

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Appendix 1. Tables

Table A.1

Listings during the year 2019 by alcaldía

	Status		*Total*
	Non-Booked	*Booked*	
Alcaldía			
Cuauhtémoc	1,037,084	988,007	2,025,091
Miguel Hidalgo	450,836	324,680	775,516
Benito Juárez	472,477	270,237	742,714
Coyoacán	273,913	135,903	409,816
Álvaro Obregón	165,778	59,247	225,025
Tlalpan	139,861	49,241	189,102
Cuajimalpa de Morelos	65,499	26,115	91,614
Venustiano Carranza	55,282	34,284	89,566
Gustavo A. Madero	51,831	22,110	73,941
Iztacalco	40,873	22,697	63,570
Azcapotzalco	36,125	15,272	51,397
Iztapalapa	40,612	10,637	51,249
La Magdalena Contreras	21,746	8,132	29,878
Xochimilco	18,196	4,764	22,960
Tláhuac	1,698	985	2,683
Milpa Alta	26	262	288
Total	2,871,837	1,972,573	4,844,410

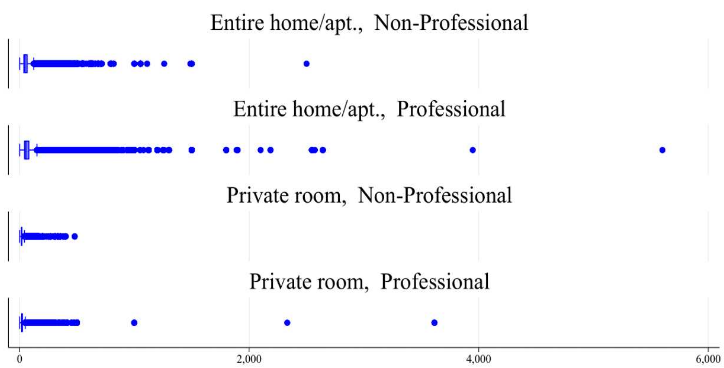
Notes: The listings correspond only to entire homes/apartments and private rooms. The number of listings corresponds to our final sample after cleaning the data.

Source: Authors' elaboration.

Appendix 2. Figures

Figure A.1

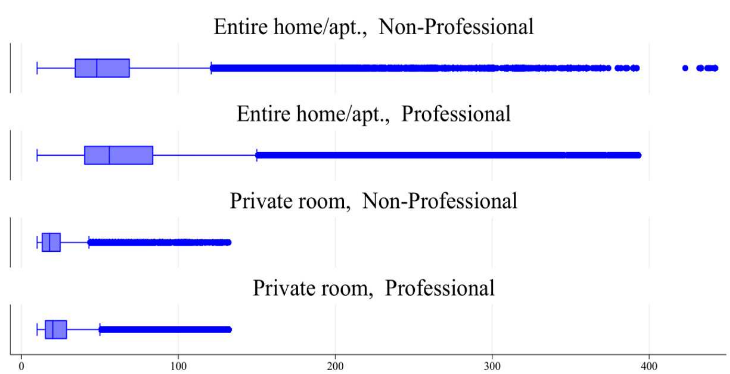
Listings price distribution before filtering by the interaction between the accommodation type and type of host



Source: Authors' elaboration.

Figure A.2

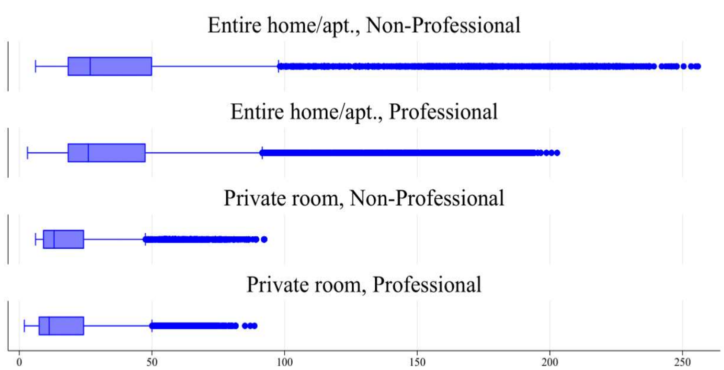
Listings price distribution after filtering by the interaction between the accommodation type and type of host



Source: Authors' elaboration.

Figure A.3

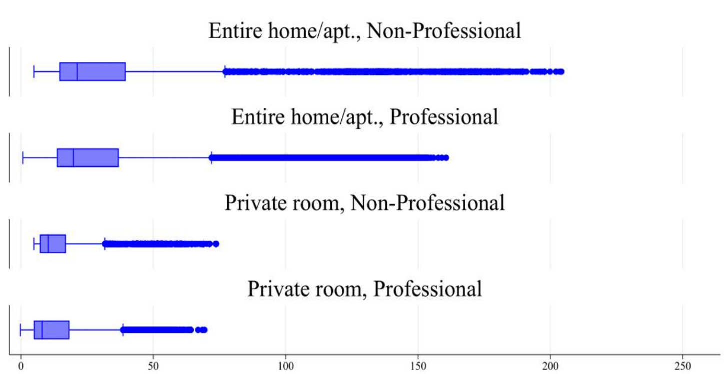
Distribution of the marginal costs by the interaction between the accommodation type and type of host, drop method



Source: Authors' elaboration.

Figure A.4

Distribution of the marginal costs by the interaction between the accommodation type and type of host, imputation method



Source: Authors' elaboration.

Appendix 3. Classification and aggregation

In section 3, we briefly described the procedure for generating product categories and corresponding representative products. In this subsection, we provide more details.

To classify accommodations, we follow a procedure similar to the one described by Farronato and Fradkin (2022),[18] and restrict our attention to reserved listings only (which is without loss since every accommodation in our final dataset was reserved at least once). Although the reason behind using only the information from reserved listings is not explicitly mentioned in Farronato and Fradkin (2022), this idea is supported by the hedonic prices literature (Rosen, 1974).

The process we follow to categorize accommodations comprises a sequence of five steps in the following order: First, we run a hedonic regression where the natural logarithm of the prices of reserved listings depends on the fixed effects of accommodation and date.[19] Second, we use Bayesian shrinkage to shrink the accommodation fixed effects towards the mean to mitigate the impact of sampling error.[20] Third, we group individual accommodations by type (entire home/apartment or private room) and *alcaldia*. Fourth, to establish quality tiers,[21] the range of shrunken accommodation fixed effects values of the accommodations for each group was evenly divided. Finally, each subgroup was split into two, distinguishing between accommodations belonging to professional hosts and those belonging to nonprofessional hosts. We refer to the product categories as the

[18] Since our research question is different from that of Farronato and Fradkin (2022), our categorization is finer than the one implemented by them. They had four categories per city-date, while we have 116 potential categories for each date. The actual number varies with date as some categories might not always be offered.

[19] The hedonic regression has the following form: $ln\,(price_{hd}) = \Gamma_h + \iota_d + \eta_{pd}$, where the $price$ corresponds to reserved listings, Γ represents the accommodation fixed effects of accommodation h, ι represents the date fixed effects of date d, and η is the error term. Other fixed effects, such as *alcaldía*, accommodation type, superhost, and host type (professional or nonprofessional), are omitted due to collinearity.

[20] We use the term "shrunken accommodation fixed effect", denoted as γ, to refer to the "accommodation fixed effects", Γ, that has undergone the Bayesian shrinkage procedure.

[21] Higher shrunken fixed effects of accommodation were used as a proxy for higher quality.

grouping of accommodations based on their *alcaldía*, accommodation type (entire home/apartment or private room), quality tier, and host type (professional or nonprofessional).

For each category, a representative product is created, whose characteristics are the average of the features of the unique accommodations that make it up throughout the year; these remain constant over time. On the other hand, the daily price for each category is calculated by averaging the prices of the accommodations within the category reserved for that day. Similarly, to calculate the quantity of the representative product sold for each date, we sum up the reservations of accommodations within the category for that date.[22]

Using the procedure mentioned earlier, we created 116 categories and representative products. It should be noted, however, that the number of categories per date tends to fluctuate throughout the year. Certain categories do not have any accommodations available on specific dates, and at times, even though certain categories have available accommodations, none may be rented, resulting in a market share of zero. On average, there are 108.81 categories with reserved accommodations per date. However, if we include categories with zero market share, the average daily number of categories increases to 110.94.

Quality tiers: Ideally, for creating quality tiers, we would use quantiles to divide the shrunken accommodation fixed effects (which we denoted as γ) to maintain tiers with an equal number of accommodations. However, firstly, as seen in Table A.2 and Table A.3, the number of accommodations, and thus shrunken accommodation fixed effects, by *alcaldía* and accommodation type is generally low. Secondly, as observed in Figure A.5 and Figure A.6, in most cases, the values are clustered around the mean. Therefore, if we used quantiles, we would have quality tiers with considerable dispersion of γ values, especially in the higher and lower quantiles, due to the general presence of outliers. For all of the above, we opted to divide the range of values into equal parts at the cost of having tiers with different numbers of accommodations, and this approach results in tiers with more homogeneous γ values. The number of qualities per *alcaldía* was chosen based on the number of accommodations offered. We established four tiers for Benito Juárez, Coyoacán, and Miguel Hidalgo; five tiers for Cuauhtémoc; for the remaining *alcaldías*, only one quality tier was designated.

[22] The average price of the available accommodations is used only for categories with zero market share on a specific date.

Table A.2

Statistics of shrunken fixed effects of accommodations corresponding to entire homes/apartments

Alcaldía	*Mean*	*SD*	*Median*	*Min*	*Max*	*N*
Álvaro Obregón	0.80	0.56	0.80	-0.72	2.46	491
Azcapotzalco	0.41	0.36	0.35	-0.22	1.44	102
Benito Juárez	0.64	0.45	0.63	-0.60	1.92	1698
Coyoacán	0.68	0.60	0.64	-0.70	2.68	715
Cuajimalpa de Morelos	1.12	0.50	1.13	-0.01	2.26	286
Cuauhtémoc	0.99	0.56	0.94	-0.36	2.96	6088
Gustavo A. Madero	0.32	0.51	0.30	-0.70	2.07	118
Iztacalco	0.11	0.44	0.06	-0.77	1.24	139
Iztapalapa	0.16	0.61	0.06	-0.78	1.73	92
La Magdalena Contreras	0.55	0.66	0.60	-0.63	1.85	59
Miguel Hidalgo	1.21	0.60	1.16	-0.20	3.02	2453
Milpa Alta	0.62	0.93	0.40	-0.79	1.96	9
Tlalpan	0.56	0.66	0.46	-0.65	2.21	327
Tláhuac	0.26	1.06	-0.04	-0.76	2.12	17
Venustiano Carranza	0.35	0.46	0.28	-0.55	1.80	225
Xochimilco	0.39	0.65	0.29	-0.78	2.98	64

Source: Authors' elaboration.

Table A.3

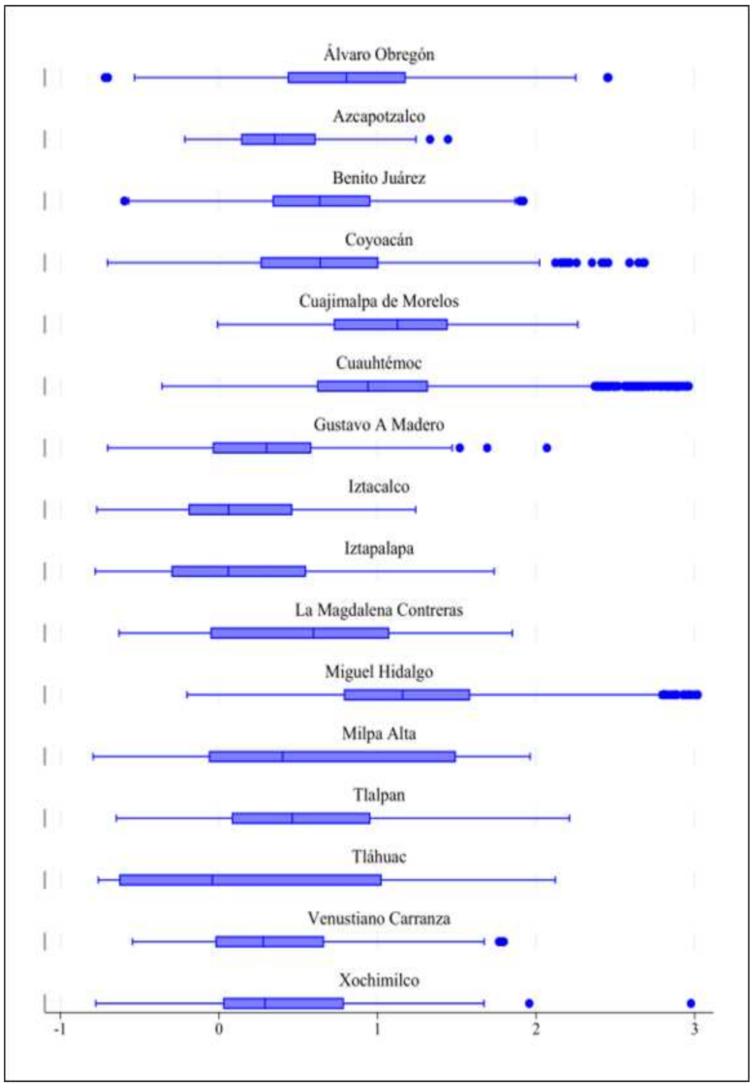
Statistics of shrunken fixed effects of accommodations corresponding to private rooms

Alcaldía	*Mean*	*SD*	*Median*	*Min*	*Max*	*N*
Álvaro Obregón	-0.02	0.57	-0.09	-0.86	1.74	672
Azcapotzalco	-0.30	0.44	-0.40	-0.83	1.79	184
Benito Juárez	-0.17	0.42	-0.21	-0.87	1.32	2251
Coyoacán	-0.12	0.56	-0.23	-0.89	1.75	1342
Cuajimalpa de Morelos	0.18	0.55	0.16	-0.80	1.73	218
Cuauhtémoc	0.06	0.51	-0.01	-0.89	1.92	3983
Gustavo A. Madero	-0.38	0.35	-0.43	-0.85	0.58	249
Iztacalco	-0.27	0.47	-0.38	-0.86	1.53	195
Iztapalapa	-0.41	0.41	-0.55	-0.89	0.83	207
La Magdalena Contreras	-0.11	0.50	-0.20	-0.80	1.53	96
Miguel Hidalgo	0.13	0.54	0.09	-0.82	1.86	1675
Milpa Alta	-0.14	0.39	-0.21	-0.58	0.54	8
Tlalpan	-0.26	0.53	-0.35	-0.89	2.01	643
Tláhuac	-0.65	0.19	-0.74	-0.90	-0.15	21
Venustiano Carranza	-0.23	0.46	-0.29	-0.89	1.14	230
Xochimilco	-0.32	0.43	-0.37	-0.82	1.24	99

Source: Authors' elaboration.

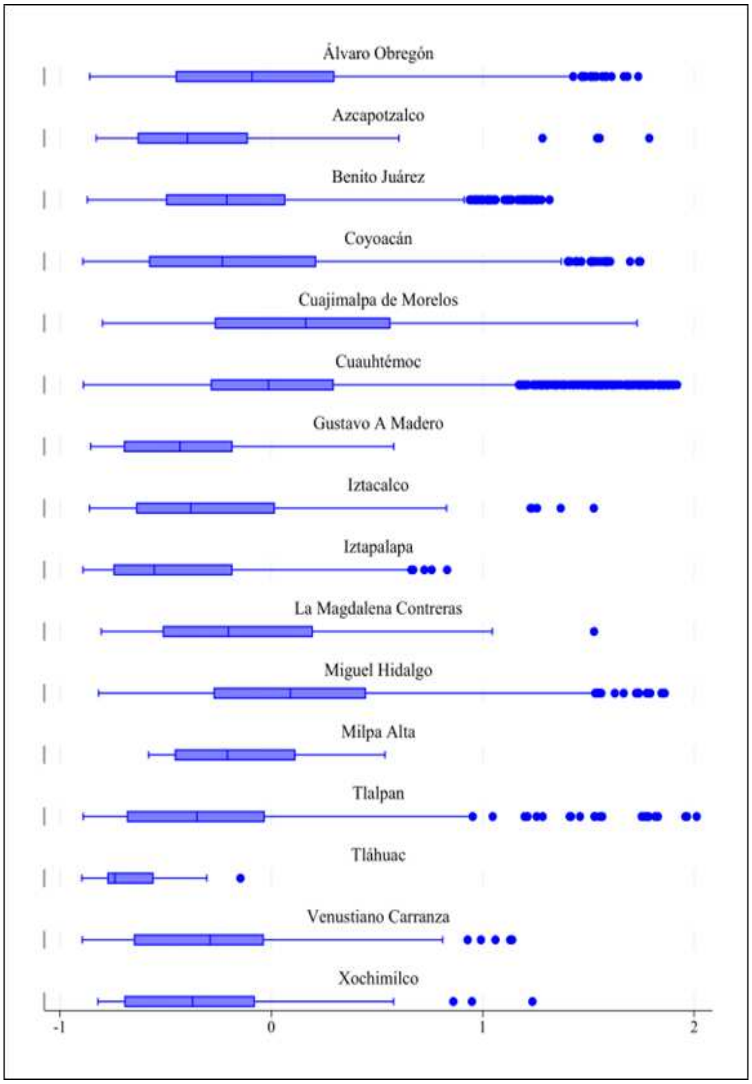
Figure A.5

Distribution of shrunken fixed effects corresponding to entire homes/apartments by alcaldía



Source: Authors' elaboration.

Figure A.6
Distribution of shrunken fixed effects corresponding to private rooms by alcaldía



Source: Authors' elaboration.

Appendix 4. Robustness

Our investigation compares nonprofessional hosts to professional hosts (which, following the literature, we define as multi-product hosts). We test the robustness of our results by modifying our definition of professional hosts. We divide multi-product hosts into six segments that are created from the interaction between the number of accommodations they offer (2 to 3, or at least 4) and the accommodation type they offer (only entire homes/apartments, only private rooms, or both). We use the same procedure for creating categories of products described in section 3 (and detailed in Appendix 3), with the difference that we use the division of products by the number of accommodations of the host (1, 2 to 3, at least 4) instead of dividing products by single-product hosts and multi-product hosts.

This creates 275 categories and representative products in this robustness test, more than double the number of products used in our leading estimation (section 5). This means that we have more observations for both the "Drop" and "Imputation" methods of handling market shares of 0. The "Drop" method has 89,619 observations, while the "Imputation" method has 96,574 observations. In contrast, the dataset from section 5 had only 39,715 and 40,493 observations for the "Drop" and "Imputation" methods, respectively.

Consistent with this new product categorization, we modify our representative hosts as follows: Instead of a unique representative host for all categories belonging to multi-product hosts, we set up six decision-makers that originate from the interaction between the number of accommodations they offer (2 to 3, or at least 4) and the accommodation type they offer (only entire homes/apartments, only private rooms, or both).[23] We keep a representative host for each category belonging to single-product hosts.

Demand results: Table A.4 shows the estimation results. As in section 5.1, the variances of the taste shocks in the mixed logit models are mostly statistically non-significant. Therefore, as in the body of the text, we prefer the logit corrected for endogeneity.

The coefficients of main interest are those related to variable "$\ln(\text{price}\,(1+\tau))$". These coefficients have a negative impact on consumer utility, which is as expected, and their magnitudes are similar to those reported in subsection 5.2. The coefficient for the "Drop"

[23] In a sense, this heterogeneity of multi-unit hosts can be regarded as more realistic than our baseline specification.

method is -1.53, while for the "Imputation" method, it is -2.87. In comparison, the coefficient for the "Drop" method in subsection 5.1 is -1.97, and for the "Imputation" method, it is -2.60.

Supply results: As in subsection 5.2, we use the logit coefficients corrected by endogeneity, and we will focus on the "Drop" method. The results are shown in Table A.5.

While subsection 5.2 estimates suggested that multi-product hosts generally have lower marginal costs by \$1.76 ($p - value < 0.05$), higher markups by \$3.67 ($p - value < 0.05$) and slightly higher price-cost margins by 0.0921 ($p - value < 0.05$) than single-product hosts, this is not always the case when we segment hosts by the number of accommodations. When comparing hosts who offer only one accommodation to those who offer 2 to 3 accommodations, the latter have lower costs by \$2.08 ($p - value < 0.05$), lower markups by \$2.98 ($p - value < 0.05$), and only slightly higher price-cost margin by 0.0101 ($p - value < 0.05$). Conversely, hosts with at least 4 accommodations have statistically equal costs than single-product hosts, but have higher markups by \$2.04 ($p - value < 0.05$) and higher price-cost margins by 0.0209 ($p - value < 0.05$).

For a host, when compared to renting out an entire home or apartment, renting out just a private room has a lower marginal cost of \$13.74 ($p - value < 0.05$), lower markups by \$26.75 ($p - value < 0.05$), and a lower price-cost margin of 0.0022 ($p - value < 0.05$). These estimates align in sign and magnitudes with those previously reported in subsection 5.2.

Table A.4

Robustness - Demand results

	(1)				(2)				(3)			
	Logit				Logit with endogeneity				Mixed logit with endogeneity			
	Drop		Imputation		Drop		Imputation		Drop		Imputation	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
β												
ln(price(1+ τ))	-0.74	0.01	-2.08	0.04	-1.53	0.03	-2.87	0.12	-1.51	0.04	-4.14	5.17
amenities	1.32	0.02	2.07	0.09	1.56	0.02	2.57	0.10	-0.38	0.15	3.06	0.40
bathrooms	0.01	0.02	-0.87	0.09	-0.10	0.02	-0.54	0.08	-0.71	0.13	-2.59	1.14
bedrooms	0.09	0.02	2.30	0.11	0.22	0.02	2.05	0.11	0.02	0.12	-6.69	4.95
maxguests	-0.18	0.01	-0.77	0.04	0.10	0.01	-0.65	0.05	0.17	0.02	-0.05	0.55
Host by number of accommodations												
(0 = 1 accommodation)												
2 to 3	-1.15	0.01	-2.55	0.04	-1.25	0.01	-2.39	0.04	-1.26	0.01	-2.95	0.14
at least 4	-1.04	0.01	-1.66	0.04	-1.22	0.01	-1.77	0.04	-1.24	0.02	-2.74	0.32
Private room (0 = entire home/apt.)	-0.62	0.01	-1.59	0.05	-0.42	0.01	-1.72	0.05	-0.45	0.02	-2.73	0.10
Intercept absorbed	Yes		Yes		Yes		Yes		Yes		Yes	
Date FE	Yes		Yes		Yes		Yes		Yes		Yes	
Alcaldia FE	Yes		Yes		Yes		Yes		Yes		Yes	
σ												
ln(price(1+ t))									0.00	18.20	1.45	2.53
amenities									1.55	0.09	0.00	30.00
bathrooms									0.61	0.10	0.84	1.87
bedrooms									0.19	0.23	4.31	1.19
maxguests									0.00	4.64	0.00	22.49
intercept									0.00	229.51	0.02	226.20
N	89,619		96,574		89,619		96,574		89,619		96,574	

Notes: SE symbolizes robust standard errors. Prices are in dollars in January 2019 real values. The Drop method excludes observations with zero market share, while the Imputation method keeps these observations but imputes them with a market share value of 10^{-12}.

Source: Authors' elaboration.

Table A.5
Robustness - Supply results

	MC				*P-MC*				*(P-MC)/P*			
	Drop		*Imputation*		*Drop*		*Imputation*		*Drop*		*Imputation*	
	Coeff.	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*
Intercept	15.99	0.00	30.22	0.00	30.63	0.00	16.32	0.00	0.6599	0.0000	0.3521	0.0000
Host by number of accommodations												
(0 = 1 accommodation)												
2 to 3	-2.08	0.00	-1.97	0.00	-2.98	0.00	-0.80	0.00	0.0101	0.0000	0.0052	0.0000
at least 4	0.03	0.84	0.32	0.25	2.04	0.00	0.74	0.00	0.0209	0.0000	0.0113	0.0000
Accommodation type												
(0 = Entire home/apartment)												
Private room	-13.74	0.00	-26.02	0.00	-26.75	0.00	-14.18	0.00	-0.0022	0.0000	-0.0012	0.0000
Alcaldia (0 = Azcapotzalco)												
Álvaro Obregón	4.14	0.00	7.35	0.00	7.72	0.00	3.93	0.00	-0.0079	0.0000	-0.0040	0.0000
Benito Juárez	5.13	0.00	10.41	0.00	9.60	0.00	5.57	0.00	-0.0043	0.0000	-0.0023	0.0000
Coyoacán	10.53	0.00	22.52	0.00	19.70	0.00	12.04	0.00	-0.0063	0.0000	-0.0034	0.0000
Cuajimalpa de Morelos	10.15	0.00	18.90	0.00	19.03	0.00	10.10	0.00	-0.0099	0.0000	-0.0052	0.0000
Cuauhtémoc	19.25	0.00	37.45	0.00	36.14	0.00	20.04	0.00	-0.0087	0.0000	-0.0045	0.0000
Gustavo A. Madero	-0.19	0.67	-1.04	0.19	-0.45	0.58	-0.57	0.18	0.0004	0.1900	0.0008	0.0000
Iztacalco	-1.04	0.02	-2.96	0.00	-2.09	0.01	-1.60	0.00	0.0007	0.0200	0.0018	0.0000
Iztapalapa	-0.75	0.10	-1.89	0.02	-1.48	0.08	-1.01	0.02	0.0013	0.0000	0.0008	0.0000
La Magdalena Contreras	4.33	0.00	7.52	0.00	8.04	0.00	4.01	0.00	-0.0064	0.0000	-0.0024	0.0000
Miguel Hidalgo	18.66	0.00	35.71	0.00	35.01	0.00	19.10	0.00	-0.0094	0.0000	-0.0049	0.0000
Milpa Alta	2.12	0.07	3.90	0.08	3.78	0.09	2.04	0.08	-0.0068	0.0000	-0.0035	0.0000

Table A.5
(Continued)

	MC				*P-MC*				*(P-MC)/P*			
	Drop		*Imputation*		*Drop*		*Imputation*		*Drop*		*Imputation*	
	Coeff.	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*	*Coeff.*	*p-value*
Tlalpan	2.38	0.00	4.06	0.00	4.41	0.00	2.17	0.00	-0.0035	0.0000	-0.0017	0.0000
Tláhuac	0.27	0.70	0.23	0.84	0.37	0.78	0.11	0.86	0.0030	0.0000	0.0017	0.0000
Venustiano Carranza	0.62	0.15	0.83	0.28	1.12	0.16	0.44	0.29	-0.0037	0.0000	-0.0018	0.0000
Xochimilco	1.06	0.03	0.88	0.29	1.81	0.06	0.46	0.31	-0.0049	0.0000	-0.0019	0.0000
Date FE	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	89,619		96,574		89,619		96,574		89,619		96,574	

Notes: The Drop method excludes observations with zero market share, while the Imputation method keeps these observations but imputes them with a market share value of 10^{-12}. Prices and marginal costs are in dollars in January 2019 real values.

Source: Authors' elaboration.