Airbnb, Hotels, and Localized Competition

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Abstract

Using data from Paris in 2017, we estimate demand for short-term accommodations, explicitly accounting for localized variation in demand across the city. Our counterfactual simulations show that Airbnb increases total consumer surplus by 924 million euros, affords Airbnb hosts a surplus of 21 million euros, while reducing total hotel profits by 778 million euros, resulting in an overall welfare gain of 167 million euros. Airbnb's value to consumers is highest when demand is high and hotels operate close to capacity constraints. The impact of Airbnb on consumers and hotels is heterogeneous across the city: Hotels in outer districts would gain most from a ban of Airbnb. Conversely, consumer surplus would be reduced the most from a ban of Airbnb in these outer districts.

Keywords: hotel industry, short-term rentals, localized competition, consumer welfare, sharing economy, peer-to-peer markets, Airbnb

JEL codes: D4, D6, L1, Z38

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1 Introduction

The rapid expansion of Airbnb and other peer-to-peer accommodation platforms has fundamentally reshaped the hospitality sector.[1] However, the potential welfare impacts of these short-term rental platforms go beyond just the hospitality sector and affect local economies more widely. While consumers enjoy greater choice and lower prices due to higher competitive pressures on hotels, hotels face lower demand, mark-ups, and profits. At the same time, Airbnb hosts enjoy an additional source of income, while residents face potential decreases in the supply of long-term rentals and housing, increases in rents and house prices, as well as other negative externalities such as noise or overcrowding. In this context, it is important to accurately quantify the benefits and costs associated with peer-to-peer rental platforms. In particular, the localized nature of their potential welfare impacts requires a careful analysis that sufficiently accounts for how the welfare implications can vary across different areas of the same city.

In this paper, we combine data on hotels and Airbnb listings in Paris for 2017 to estimate a structural model of demand and supply, allowing us to quantify how Airbnb affects consumer welfare, hotel profits, and host surplus. Our geographically granular data enable us to capture demand variation across different neighborhoods and to model consumer heterogeneity in location preferences. This approach allows us to identify the price-dampening effect of Airbnb on hotels within specific areas, thereby more accurately characterizing the welfare implications of Airbnb and the spatial heterogeneity of its impact on hotel profits. These insights can help policymakers better assess Airbnb's effects on the hotel sector across different locations.

The principal contribution of our paper is its ability to account for intra-city variation in demand. Our primary dataset comprises daily information on hotel and Airbnb bookings in

[1] As of May 2026, Airbnb featured over nine million active listings worldwide, significantly surpassing the total room count of Marriott International, the largest global hotel chain, which reported approximately 1.8 million rooms in 2025. See page 4 of Marriott International's 2025 Form 10-K, available at https://marriott.gcs-web.com/annual, and Airbnb, "Fast Facts," https://news.airbnb.com/about-us/ (both last accessed: June 2, 2026).

Paris, supplemented with data on events (such as fairs, concerts, and sporting events) that influence local accommodation demand. By leveraging the detailed geographic distribution of both hotels and Airbnb listings within the city, we model localized competition and incorporate a spatial dimension that, as our descriptive analysis reveals, plays a significant role in the functioning of the accommodation market. This geographic dimension complements prior research, which has relied predominantly on cross-city and temporal variation when assessing the welfare impact of Airbnb (Zervas et al., 2017; Farronato and Fradkin, 2022).

Based on insights from our descriptive analysis, which are consistent with location-specific demand patterns within the city, we estimate a structural demand model that incorporates localized demand shifters as well as consumer heterogeneity in both location preferences and price sensitivity. On the supply side, we follow Farronato and Fradkin (2022) in modeling hotels as strategic price setters and Airbnb hosts as passive price takers. A key extension relative to Farronato and Fradkin (2022) is our introduction of location-specific hotel supply functions, which allows us to capture hotels' responses to geographically differentiated demand shocks in our counterfactual simulations.

Using our model, we simulate a counterfactual city-wide Airbnb ban and find that consumer welfare, hotel profits, and host surplus are affected heterogeneously across time and space. In periods of low demand, Airbnb raises expected individual consumer surplus by around 10 euros per night. However, these consumer surplus gains can reach more than 80 euros per night when demand for short-term accommodation in Paris is high. This large fluctuation over time comes almost exclusively from the fact that Airbnb acts as a competitive constraint especially in periods of high demand. Absent Airbnb, hotels would be able to charge much higher mark-ups in these periods. We document geographic heterogeneity in how Airbnb affects price setting as well: hotels in peripheral areas could increase their prices most absent Airbnb while hotels in central districts are relatively less affected. Furthermore, we find that removing Airbnb in the outer districts of Paris would reduce consumer surplus by more than if Airbnb was removed from the city center. For policy-makers, these results suggest that restricting Airbnb in more central districts may allow alleviating pressures from central rental and housing markets while still harnessing many of the welfare benefits that Airbnb brings with it.

For our empirical analysis, we assemble a dataset from three principal sources. First, information on Airbnb listings—specifically, daily prices and bookings—is obtained from AirDNA.[2] Second, we measure hotel demand using a monthly survey conducted by the French National Institute of Statistics and Economic Studies (INSEE),[3] which contains information about daily occupancy rates of hotels. Because these survey data do not include transaction prices, we augment them with web-scraped hotel price information from Booking.com, Expedia, and Kayak.[4]

Combining these sources allows us to estimate a joint demand system for hotels and Airbnb listings. To explicitly account for local demand shocks, we construct an event-level database documenting the location and attendance of major fairs, sports competitions, and cultural events in Paris that plausibly shift local short-term accommodation demand. From these data, we derive a continuous measure of event exposure, which is inversely weighted by the distance between an accommodation and the event. This measure introduces both temporal and spatial variation, thereby facilitating the identification of substitution patterns across different districts of the city.

In the estimation, each product is defined by its accommodation type (hotel or Airbnb listing), quality, and geographical location (district of Paris). We estimate demand using a random-coefficient logit model featuring two sources of consumer heterogeneity: a random price coefficient and a random coefficient on the (dis)utility of distance from the city center. Combined with district fixed effects and our event-based demand shifters, this framework yields a flexible representation of spatial substitution and competition in the Paris accommodation market.

[2] See https://www.airdna.co/ (last accessed: June 1, 2026).

[3] See https://insee.fr/en/accueil (last accessed: June 1, 2026).

[4] The original data collection was undertaken as part of Hunold et al. (2020). We thank the authors for generously sharing the data.

On the demand side, our results reveal nuanced substitution patterns between hotels and Airbnb listings. While cross-price elasticities among hotels are higher than those between hotels and Airbnb listings, cross-price elasticities among Airbnb listings are smaller than those between Airbnb listings and hotels. The elasticities suggest asymmetric segmentation in the market: Airbnb demand is responsive to hotel price changes while hotel demand responds only much less to Airbnb price changes. The estimated substitution patterns are also consistent with localized competition: cross-price elasticities for nearby accommodations are systematically higher than for accommodations located farther apart. At the same time, the relationship between distance and substitutability is not uniform across the city. For centrally located accommodations, cross-price elasticities tend to decline more rapidly with distance than they do for locations farther from the city center. This is consistent with more centrally located units also enjoying a higher degree of market power due to some consumers' strong locational preferences.

Using the estimated parameters, we simulate consumer welfare, hotel profits, and host surplus under counterfactual scenarios in which we remove Airbnb from the market. We find that Airbnb increases the expected individual consumer surplus by 29 euros per night on average. This improvement reflects both the expanded choice set afforded by Airbnb and the reduction in hotel prices prompted by the added competitive pressure. When we abstract from this price effect, the average consumer surplus gain amounts to approximately 5 euros per night.

Therefore, our simulations imply that over 80% of the consumer surplus generated by Airbnb is attributable to its price-dampening effect on hotels. This differs from results in Farronato and Fradkin (2022) who find that this price channel contributes 52% of the consumer surplus impact of Airbnb. We attribute this difference to our geographically granular approach, which allows us to model location-specific demand shocks and preferences. As such, this larger importance of the pricing channel is not inconsistent with the results shown by Farronato and Fradkin (2022). They find that this price channel is most relevant in periods of high demand, when city-wide hotel occupancy is close to the city-wide hotel capacity. We also find this pattern. On nights when hotels operate near capacity city-wide, consumer surplus gains from Airbnb reach more than 80 euros per night. However, because we also account for localized demand, this price channel can become relevant also in periods in which some local hotel capacity constraints become binding. This happens much more frequently locally than it does on the city level. Ignoring localized demand could therefore lead to an underestimation of Airbnb's impact on consumer welfare in a city like Paris.

Regarding geographic heterogeneity with respect to hotel profits, we find that Airbnb's relative impact on hotel prices is most pronounced for hotels in less central locations. Furthermore, we find that removing Airbnb only from less central districts of Paris would decrease consumer surplus by more than removing Airbnb only from central districts of Paris. Airbnb in less central districts exerts more competitive pressure on hotels in these outer districts, especially in periods when hotel occupancies approach capacity constraints. These nuanced geographical patterns suggest that restricting Airbnb only in more central districts may offer a path to balance protecting local rental and housing markets while still capturing most of the welfare gains from Airbnb.

Our work is most closely related to the work by Zervas et al. (2017) and Farronato and Fradkin (2022). Using data from Texas, Zervas et al. (2017) find that an overall increase in Airbnb supply reduces hotel revenues by approximately ten percentage points in their sample, with lower-priced and non-business hotels being disproportionately strongly affected. They show that the revenue impact is mainly driven by a reduction in prices as opposed to a reduction in the number of rooms booked.[5]

Closest to our work, Farronato and Fradkin (2022) employ a random coefficient discrete choice model and estimate the demand and supply parameters using data for several US cities. Consistent with our results, they find that consumers profit most from Airbnb in locations and at times when hotels are capacity constrained. Because they use data on

[5] In a similar exercise, Neeser (2015) uses data from three Nordic European countries. Unlike Zervas et al. (2017), the author does not find a statistically significant impact of Airbnb on hotel performance.

the city level, they identify capacity constraints when demand for the entire city increases (e.g. for New Year's Eve in New York City). In our granular data, we show that capacity constraints in individual districts in the city are actually binding a lot more frequently than those for the entire city. Thus, if demand for short-term accommodation is localized within a city, ignoring within-city variation in demand and hotel capacities would likely underestimate the welfare impact of Airbnb.

Furthermore, our research is related to a growing body of literature studying competition between peer-to-peer platforms and incumbent firms. Seamans and Zhu (2014) and Kroft and Pope (2014) analyze the impact of Craigslist on incumbent industries. Aguiar and Waldfogel (2018) assert that streaming affects music sales using Spotify data. Cohen et al. (2016) and Lam et al. (2021) study consumer surplus from Uber, while Hall et al. (2018) address the question of Uber's complementary to public transport systems. Cramer and Krueger (2016) assess the relative efficiency of Uber drivers compared to taxi drivers. Relatedly, Fréchette et al. (2019) and Buchholz (2022) study matching frictions and the spatial equilibrium of supply and demand in the taxi industry. The emphasis of Buchholz (2022) on the geographic allocation of capacity is related to our focus on the spatial dimension of competition in the accommodation market.

More broadly, our paper is also related to the literature studying externalities related to the platform economy. One research strand studies how Airbnb affects housing markets (Horn and Merante, 2017; Koster et al., 2021; Garcia-López et al., 2020; Barron et al., 2021; Valentin, 2021; Duso et al., 2024; Jin et al., 2024; Almagro and Domínguez-Iino, 2025). Importantly, this literature already documents that the impact of Airbnb on housing markets can differ across different areas of the same city. For example, Garcia-López et al. (2020) find that Airbnb affects rents and house prices most in more central areas of Barcelona. Relatedly, Almagro and Domínguez-Iino (2025) show for Amsterdam that tourism and home-sharing reshape neighborhood amenities and thereby the spatial distribution of welfare within the city. We find that Airbnb affects travelers and hotels most in less central areas of Paris.

Combined, these insights suggest that policy-makers may be able to balance protecting local housing markets and harnessing welfare gains from Airbnb by focusing regulation on more central areas. Our paper is also broadly related to the emerging literature on online platforms and surge pricing (Cachon et al., 2017; Castillo, 2025; Guda and Subramanian, 2019) as we show that Airbnb is particularly valuable for consumers when hotels charge higher prices.

The remainder of the article is organized as follows. In Section 2, we describe some institutional details of the Parisian accommodation market and introduce the various data sources that we use in more detail. In Section 3, we present our empirical strategy by showing selective descriptives, introducing our model, providing some estimation details, and finally discussing identification of the key model parameters. In Section 4, we report the estimated parameters as well as demand elasticities. In Section 5, we outline our simulation procedure and present the results of the counterfactual analysis. Section 6 concludes.

2 Institutional Details and Data

In this section, we begin by briefly outlining key facts about the accommodation industry in Paris and the regulatory environment surrounding Airbnb at the time our data were collected. We then provide a detailed description of our datasets. Finally, we explain our product definitions for the analysis.

2.1 The Short-Term Accommodation Market in Paris

According to Mastercard's Global Destination Cities Index, Paris was the city with the third largest number of international visitors worldwide in 2017, surpassed only by Bangkok and London.[6] In the 2019 edition of the same report, Paris overtook London to become

[6]See https://www.mastercard.com/news/europe/en-uk/newsroom/press-releases/en-gb/2018/september/london-tops-europe-in-mastercard-s-2018-global-destination-cities-index/ (last accessed: June 2, 2026).

the second most visited city globally.[7] Paris was also the second most popular Airbnb destination in Europe in 2017, closely following London.[8] Thus, analyzing the competition between Airbnb and hotels in Paris provides insights into one of the most significant short-term accommodation markets, both in Europe and globally.

Paris has implemented regulations to limit the number of days an apartment can be rented out annually. Since October 2017, the City of Paris has required hosts of entire apartments on Airbnb to obtain and display a registration number. In 2018, lawmakers even proposed an outright ban on Airbnb rentals in the city center. As of January 2020, hosts of entire homes are prohibited from renting out their apartments for more than 120 days per year.

2.2 Data

To obtain information on equilibrium quantities and prices for Airbnb and hotels, we combine three datasets: one containing hotel bookings, one containing hotel prices, and one containing Airbnb bookings and prices. In the following, we describe these three datasets in more detail. Additionally, we outline the auxiliary datasets used for the analysis.

Hotel Demand Data Data on hotel bookings were provided by National Institute of Statistics and Economic Studies (INSEE). Each month, INSEE surveys a stratified random sample of French hotels and collects self-reported information on occupancy and the origin of guests.[9] Our primary variable of interest is the number of rooms booked for each day of the survey month. For each hotel, the data also include star rating, number of available rooms,

[7] See https://www.mastercard.com/news/insights/2019/global-destination-cities-index-2019-1/ (last accessed: June 2, 2026).

[8] See https://www.statista.com/statistics/957312/airbnb-leading-european-destinations/ (last accessed: June 2, 2026).

[9] The hotel population is stratified by region, star rating, and type (chain or independent). According to INSEE approximately 12,000 out of 18,000 hotels are contacted in the national sample. See https://insee.fr/en/metadonnees/source/operation/s1480/processus-statistique (last accessed: June 1, 2026).

and district.[10] Based on hotel responses, INSEE imputes occupancy for non-respondents as well as non-sampled hotels. Consequently, the data contain (imputed) quantity information for the entire population of hotels.

Hotel Price Data The INSEE data do not contain information on hotel prices. To address this, we use web-scraped hotel price data from the booking platform Booking.com. For each night in 2017, the dataset includes prices for each hotel available on Booking.com, recorded two weeks, one week, and one night prior to the date of interest. The reported prices correspond to a search for a one-night stay for two persons; if multiple room categories are available, the price for the cheapest category is used.[11]

We match this price information to the hotel quantity data using hotel names, which is possible for 983 of the 1,597 hotels in the quantity dataset.[12] Due to occasional web scraper instability, the number of hotels with price information varies across dates. Consequently, we exclude dates for which price data are available for less than 35% of the total number of rooms. This results in a final sample of 252 dates for our analysis. We address the issue of missing hotel prices in our definition of products discussed in the next section.

Airbnb Data We utilize web-scraped Airbnb data from AirDNA.[13] The dataset comprises all listings available for booking in Paris in 2017. A key advantage of the AirDNA data is the inclusion of information on whether a listing was available, blocked, or booked on each date. This status is imputed by AirDNA, which previously collected data from Airbnb when the platform indicated whether an unavailable listing was booked or blocked. AirDNA leverages this historical information to predict the current status of unavailable listings. Although this measure is imperfect, it represents the most reliable proxy for Airbnb demand available, aside from proprietary Airbnb data. In addition to the imputed booking status, the dataset

[10] The exact addresses of the hotels are also available; however, as the data are classified as sensitive, we are prohibited from geocoding the addresses.

[11] See Hunold et al. (2020) for more details on the data collection procedure.

[12] A comparison of matched and non-matched hotels is provided in Appendix A.

[13] See `https://www.airdna.co/` (last accessed: June 1, 2026).

contains information on price, location, and other listing-specific characteristics observable on the Airbnb website.

Auxiliary Datasets The main data on hotel and Airbnb quantities and prices are complemented by three additional data sources: (i) Google Trends data to construct a measure of market size, (ii) open-source car traffic data to capture exogenous Airbnb supply, and (iii) a self-compiled dataset containing information about events in and around Paris that influence accommodation demand. These datasets and the variables derived from them will be described in greater detail when discussing their specific roles in the estimation.

2.3 Product Definition and Sample

For our analysis, we define a product as the combination of accommodation type (Airbnb or hotel), quality, and city district. Aggregating geographical information to the city-district level helps address limitations associated with missing hotel price data.

Imperfect matching between hotel price and quantity data, due to reliance on hotel names for matching and scraper instability, results in missing prices both across hotels and over time for individual hotels. To address this, we aggregate booking information at the quality-district level and use the observed average room price for each quality-district combination as a proxy for the average price of all hotel rooms in that group. This approach assumes that errors from scraping and matching are random within each quality-district combination, so that the average observed price is representative of the average unobserved price. Aggregation at the district-quality level enables us to avoid imputing individual hotel prices while preserving geographical heterogeneity. Days are excluded from the analysis if price data is available for less than 35% of the total number of rooms at the city level.

Following this aggregation, we only use those observations which consist of at least three hotels. This restriction is to comply with INSEE's data privacy rules which prevent individual hotels from being identified from the data. In Subsection 3.1 we show that we obtain plausible patterns between occupancy and prices at the quality-district level, consistent with those found at the aggregate city-wide level in Farronato and Fradkin (2022).

An additional benefit of aggregation at the district-quality level is the mitigation of computational challenges associated with extremely low market shares or intractable choice sets involving tens of thousands of potential options.

For quality categories, we use official star ratings for hotels and a fixed effects approach inspired by Farronato and Fradkin (2022) for Airbnb listings. Specifically, we regress Airbnb prices on time and listing fixed effects, then divide the estimated listing fixed effects into quartiles, assigning each listing to one of four quality categories. This procedure yields four distinct Airbnb quality categories. For Airbnb prices, we use the average transaction price for each product on a given date of stay. With this aggregation, our analysis is based on a maximum of 180 possible products per market, corresponding to the combination of 20 districts and nine type-quality categories (four Airbnb quality categories and five hotel star ratings).

3 Empirical Strategy

This section outlines our empirical strategy. We first present descriptive statistics that underscore key features of the Parisian short-term accommodation market relevant for identification and estimation. We then describe the model and estimation procedure, and conclude with a discussion about identification.

3.1 Descriptives

In this section we focus on differences in the supply-side behavior between hotels and Airbnb and provide suggestive evidence for the importance of localized competition. Figure 1a presents the number of rooms available in Paris for each date in 2017, differentiating between hotels and Airbnbs. On average, Airbnb listings constitute approximately 40% of the total room capacity. While hotel room supply remains largely constant over time, Airbnb supply displays substantial fluctuations. These longer-term trends and seasonal patterns are likely driven by factors exogenous to short-term demand. For example, Airbnb supply peaks during holiday periods – such as Easter and summer – when residents are more likely to list their homes. Likewise, the decline after October 2017 coincides with the introduction of a mandatory registration number for Airbnb hosts. Our identification strategy exploits these holiday periods and supply trends to isolate the component of Airbnb supply plausibly exogenous to short-term demand variations.

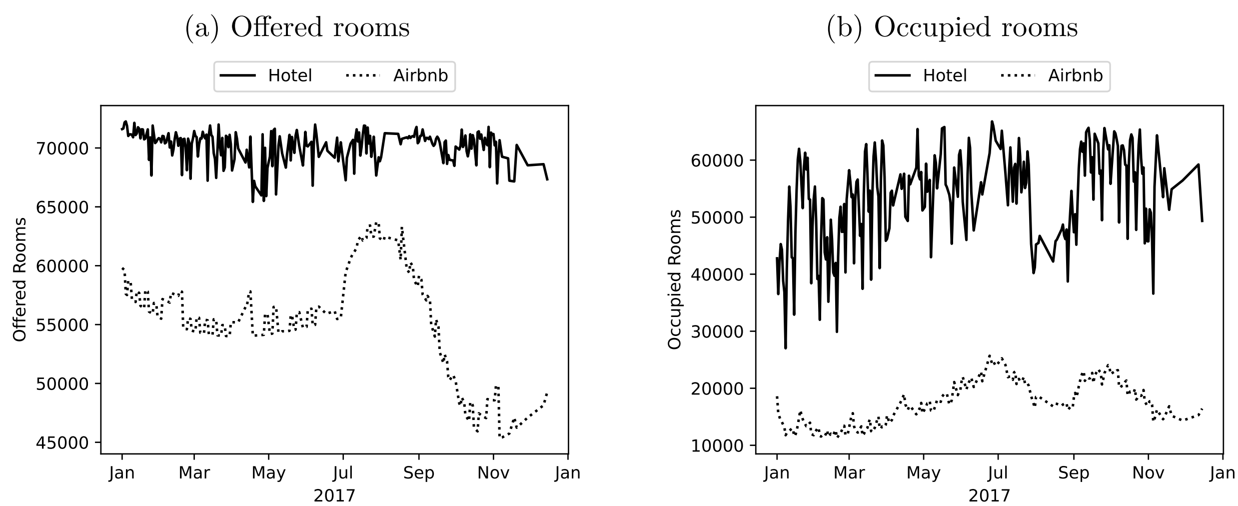


Figure 1: Offered and occupied rooms over time, split by hotels and Airbnb listings

Turning to bookings, Figure 1b shows the number of booked rooms for hotels and Airbnb listings. In contrast to the number of offered hotel rooms, hotel demand exhibits greater short-run variation, typically peaking on weekdays. Airbnb demand shows lower variability over time. Despite these differences, demands for both accommodation types generally move in tandem, suggesting that common trends drive the overall demand for short-term accommodation in the city.

Figure 2 displays the average daily prices for both accommodation types.[14] Average hotel prices exhibit greater variation and closely track the demand patterns shown in Figure 1b.

[14]For hotels, only days with sufficient price data are included.

In contrast, Airbnb prices show much less fluctuation. These patterns suggest fundamental differences in the price-setting behavior of hotels and Airbnb hosts. Therefore, and similarly to Farronato and Fradkin (2022), we model hotels as oligopolistic price-setters, whereas we think of Airbnb hosts as price-takers. Figure 3 shows the relationship between average daily hotel prices and the average daily hotel occupancy ratio at the city level. Average hotel prices are higher in periods of high demand when hotels are closer to their capacity constraints. This pattern closely matches the aggregate city-level results of Farronato and Fradkin (2022). With this relationship between hotel occupancy ratios and prices in mind, we model hotels' marginal cost functions as quadratic functions of the occupancy ratio whenever the occupancy ratio is above 50%.

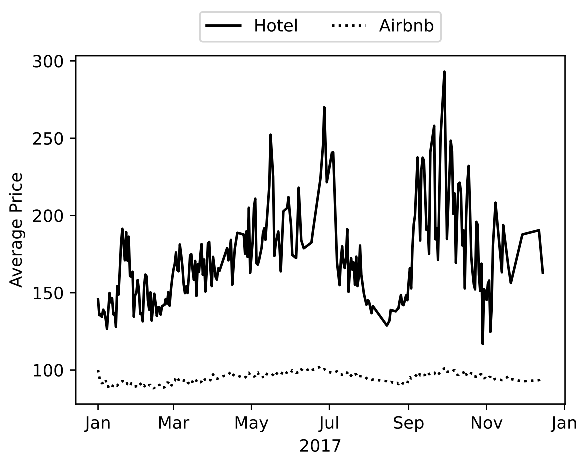


Figure 2: Average hotel and Airbnb prices over time

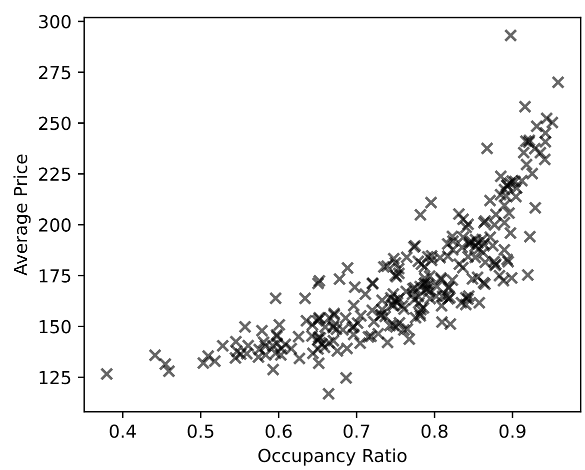


Figure 3: Average hotel prices and occupancy ratios by market

Figure 4 shows the city-wide and district-level hotel occupancy ratios. The solid black line shows the city-level daily hotel occupancy ratio over time. The horizontal dashed line marks an occupancy ratio of 85%. The figure shows that there are a few periods during the year in which hotels across the city are close to being capacity-constrained, in particular during the summer (outside of August) and fall. Adding some nuance to this, the dotted line shows the number of districts with a daily hotel occupancy ratio above 85% over time. Mechanically, in periods when the city-wide hotel occupancy ratio is high, many districts are capacity-constrained as well. However, there are also several instances where one or more districts experience high occupancy while the city-wide occupancy ratio is not high. This is consistent with significant geographic demand heterogeneity over time, which an analysis at the city-wide level cannot capture. A key advantage of our data, compared to prior research, is that it allows us to exploit this local variation. If demand is localized and if the impact of Airbnb on welfare is highest when hotel occupancy ratios are high (as the results in Farronato and Fradkin (2022) suggest), ignoring local capacity constraints might understate the welfare impact of Airbnb.

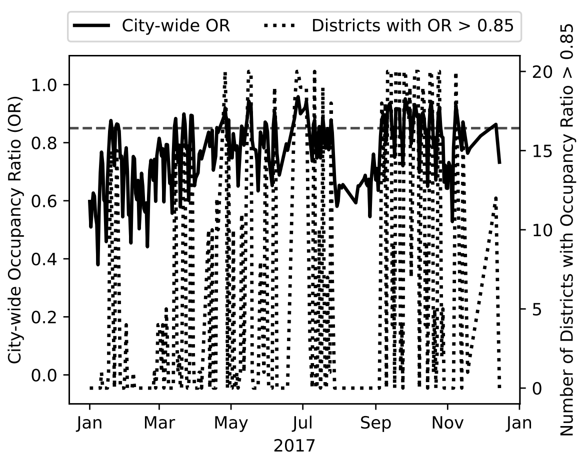


Figure 4: City-wide hotel occupancy ratio (OR) and number of districts in which hotel occupancy ratio is above 85 percent. The horizontal dashed line marks an occupancy ratio of 85 percent.

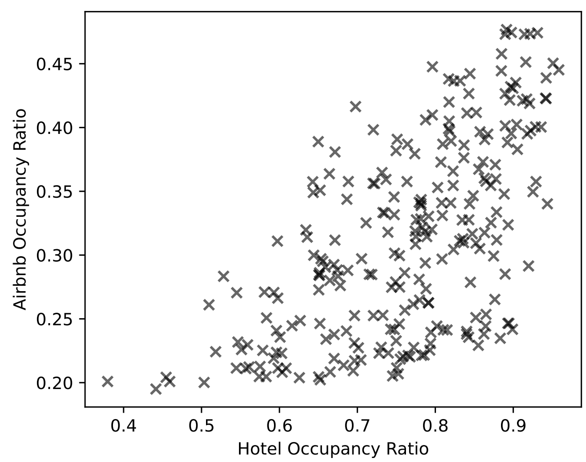


Figure 5: Occupancy ratios of hotels and Airbnb listings by market

Figure 5 illustrates the relationship between the daily occupancy ratios of hotels and Airbnb listings. Overall, occupancy ratios between hotels and Airbnb listings seem positively correlated. In particular when hotels are nearing their capacity constraints, Airbnb occupancy is higher, too. Farronato and Fradkin (2022) demonstrate that Airbnb becomes an especially valuable alternative for consumers when hotels approach their capacity limits. Figure 5 provides supporting preliminary evidence consistent with this result: as hotel occupancy nears its capacity threshold, Airbnb occupancy increases disproportionately. While common demand shocks drive up occupancy for both accommodation types simultaneously, the concentration of points in the upper right corner illustrates the key mechanism we explore: as these overall demand shocks push hotels toward their capacity constraints, the resulting scarcity induces stronger substitution toward Airbnb.

In summary, the descriptive analysis yields the following insights for our modelling assumptions and empirical strategy: (i) hotel supply is exogenous in the short-run, (ii) hotels set oligopolistic prices under exogenous capacity constraints (iii) Airbnb hosts are price-takers and adjust supplied quantity in response to demand changes (iv) localized demand shocks–where demand is concentrated in specific areas of a city–are an important driver of demand for short-term accommodation in Paris; and (v) Airbnb bookings increase especially when hotels are close to their capacity constraints. Insights (i) to (iii) are similar to patterns found at the city level by Farronato and Fradkin (2022). Insights (iv) and (v) are novel insights enabled by the geographically granular nature of our data and analysis.

3.2 Model

3.2.1 Consumer Demand

We specify the utility of individual i from choosing accommodation j in market (night) t as

$$U_{ijt} = \delta_{jt} + \mu_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where δ_{jt} denotes mean utility (common across individuals), μ_{ijt} captures individual-specific utility components for price and location, and ε_{ijt} is a Type I extreme value error term, assumed independent across individuals, accommodations, and markets. We decompose the mean utility as

$$\delta_{jt} = \gamma_{d(j)} + \lambda_t + \phi_{\tau(j)\cdot\varrho(j)} + \beta_{\text{abb}}\, ls_{jt} + \beta_{\text{h}}\, ls_{jt} \cdot \mathbb{1}\{\tau(j) = \text{hotel}\} + \mathcal{E}_{jt}. \tag{2}$$

$\gamma_{d(j)}$ is a district fixed effect and λ_t is a market (night) fixed effect. $\phi_{\tau(j)\cdot\varrho(j)}$ is a fixed effect for the interaction of accommodation type $\tau(j) \in \{\text{hotel}, \text{abb}\}$ and quality tier $\varrho(j)$, where $\varrho(j) \in \{1, \dots, 5\}$ for hotels and $\varrho(j) \in \{1, \dots, 4\}$ for Airbnb. $\mathcal{E}_{jt}$ denotes unobserved demand shocks that may be correlated with price.

The term ls_{jt} denotes a capacity-weighted, location-specific demand shifter. For now, let LSD_{dt} be an observable, district-level demand shifter. We discuss this demand shifter in more detail below. Let $\tilde{k}_j$ denote the median capacity of accommodation j over time. Define the capacity weight

$$w_j \equiv \frac{\tilde{k}_j}{\sum_{k:\, \tau(k)=\tau(j),\, d(k)=d(j)} \tilde{k}_k} .$$

w_j is the median capacity of accommodation j relative to the total median capacity of accommodations of the same type (hotels or Airbnb) in the same district. By construction, w_j is unrelated to short-run demand fluctuations. Using this weight, define ls_{jt} as

$$ls_{jt} \equiv w_j \cdot LSD_{d(j)t} . \tag{3}$$

The coefficient β_{abb} captures the baseline impact of the capacity-weighted, location-specific demand shifter on Airbnb demand. $\beta_{\text{h}} + \beta_{\text{abb}}$ captures the impact of the capacity-weighted, location-specific demand shifter on hotel demand.

For the individual-specific component of utility, we specify

$$\mu_{ijt} = -\alpha_i p_{jt} + \nu_i dist_{d(j),cc} , \tag{4}$$

where p_{jt} denotes price and $dist_{d(j),cc}$ is the distance between the centroid of district $d(j)$ and the city center of Paris. We assume α_i and ν_i are independent random coefficients with

$$\alpha_i \sim \log \mathcal{N}(\bar{\alpha}, \sigma_\alpha^2) \qquad \text{and} \qquad \nu_i \sim \mathcal{N}(\bar{\nu}, \sigma_\nu^2),$$

so that the individual price coefficient is strictly negative. Note that the mean distance coefficient $\bar{\nu}$ is perfectly collinear with the districts fixed effects $\gamma_{d(j)}$ included in δ_{jt}. Therefore, $\bar{\nu}$ is absorbed by the district fixed effects in the estimation.

Integrating over consumer heterogeneity yields market shares implied by the demand model:

$$s_{jt}(p_t) = \int\int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{j'} \exp(\delta_{j't} + \mu_{ij't})} \, dF(\alpha_i) \, dF(\nu_i), \tag{5}$$

where p_t denotes the full vector of prices in market t.

Construction of location-specific demand shocks

To construct location-specific demand shocks, we identify major events in Paris in 2017 and collect information on their daily attendance (a detailed description is provided in Appendix D). Using these data, we compute for each district d an inverse distance-weighted measure of event-related demand pressure:

$$LSD_{dt} = \sum_{e \in \mathcal{S}_t} \frac{\log_{10}(A_{et})}{max\{1, \Delta(l(e), d)\}}, \tag{6}$$

where A_{et} denotes attendance of event e on day t, $l(e)$ is the geographic location of event e, $\mathcal{S}_t$ is the set of events taking place on day t, and $\Delta(l(e), d)$ is the distance between event location $l(e)$ and the centroid of district d. This measure captures the size of observed events in Paris, inversely weighted by how far away from the event each product is located.

Heterogeneity in location-specific preferences

Because our products are aggregated on the district level, the mean (dis)utility of distance from the city center is absorbed by the district-specific fixed effects, $\gamma_{d(j)}$. Therefore, our modeling approach allows for a flexible mean utility from location preferences across districts, while capturing heterogeneity in location preferences across consumers through the variance on the random coefficient on distance from the city center.

3.2.2 Hotel supply

We assume that hotels engage in Bertrand–Nash competition. To account for capacity constraints, we follow Farronato and Fradkin (2022) and allow marginal costs to increase when occupancy ratios are high. Formally, hotel j in market t chooses p_{jt} to maximize

$$\pi_{jt} = p_{jt} q_{jt}(p_t) - C(q_{jt}(p_t)) \,, \tag{7}$$

where $q_{jt}(p_t) = M_t s_{jt}(p_t)$ is the demand implied by prices p_t and market size M_t. We assume the cost function takes the form

$$\begin{aligned} C(q_{jt}(p_t)) = {} & c_{jt} q_{jt}(p_t) \\ & + \mathbb{1}(q_{jt}(p_t) > 0.5\, k_{jt}) \, \frac{\theta_{d(j),\varrho(j)}}{3} \left(q_{jt}(p_t) - 0.5\, k_{jt}\right)^3 \\ & + \mathbb{1}(q_{jt}(p_t) > 0.99\, k_{jt}) \, \frac{\kappa}{3} \left(q_{jt}(p_t) - 0.99\, k_{jt}\right)^3 , \end{aligned} \tag{8}$$

where k_{jt} is capacity and c_{jt} and $\theta_{d(j),\varrho(j)}$ are cost parameters. The final term imposes a sharp increase in marginal costs near capacity to ensure capacity constraints are observed in simulations. We set $\kappa = 5$ and do not estimate it.

Equations (7) and (8) imply the first-order condition

$$\begin{aligned} & p_{jt} + \frac{s_{jt}(p_t)}{\frac{\partial s_{jt}(p_t)}{\partial p_{jt}}} - \mathbb{1}(q_{jt}(p_t) > 0.99\, k_{jt}) \, \kappa \left(q_{jt}(p_t) - 0.99\, k_{jt}\right)^2 \\ & = c_{jt} + \mathbb{1}(q_{jt}(p_t) > 0.5\, k_{jt}) \, \theta_{d(j),\varrho(j)} \left(q_{jt}(p_t) - 0.5\, k_{jt}\right)^2 . \end{aligned} \tag{9}$$

The left-hand side of (9) is computable given demand estimates and observable data, so we use it as the dependent variable to estimate marginal cost parameters. In our estimation, we allow $\theta_{d(j),\varrho(j)}$ to vary by district and quality tier. We allow c_{jt} to vary by product, month, and district-specific linear time trends.

3.2.3 Airbnb supply

We assume that Airbnb hosts are price-takers who decide whether to accept guests at a given price. Hosts face marginal costs and choose to host if the price exceeds their marginal costs. We assume marginal costs are normally distributed with mean μ_{jt} and standard deviation $\sigma_{\varrho(j)}$. For price p_{jt} and available capacity k_{jt} of Airbnb product j in market t, quantity supplied is

$$q_{jt}(p_{jt}) = k_{jt}\,\Phi\left(\frac{p_{jt} - \mu_{jt}}{\sigma_{\varrho(j)}}\right), \tag{10}$$

where $\Phi(\cdot)$ is the standard normal CDF. For estimation, we allow μ_{jt} to vary flexibly by product, day of week, month, and district-specific linear time trends while $\sigma_{\varrho(j)}$ varies only by quality tier.

Given estimates for μ_{jt} and $\sigma_{\varrho(j)}$, the expected profit per Airbnb host for a night booked at price p_{jt} is $\pi^{abb}_{jt}(p_{jt}) = \int_{-\infty}^{p_{jt}}(p_{jt} - c_{jt})dc_{jt}$ where $c_{jt} \sim N(\mu_{jt}, \sigma_{\varrho(j)})$. Because c_{jt} is normally distributed, there is a possibility of negative marginal costs. Therefore, we cap c_{jt} from below when calculating Airbnb host profits. Effectively, we calculate the expected profit per unit of available Airbnb capacity at price p_{jt} as

$$\pi^{abb}_{jt}(p_{jt}) = \int_{-\infty}^{p_{jt}}(p_{jt} - max(0; c_{jt}))dF(c_{jt})\,. \tag{11}$$

3.3 Estimation and Identification

We estimate demand, hotel supply, and Airbnb supply separately. First, we estimate demand parameters using the method of Berry et al. (1995), as implemented in PyBLP (Conlon and Gortmaker, 2020). After obtaining demand estimates, we estimate hotel supply cost parameters and the parameters of Airbnb host cost distributions. In this subsection, we discuss key details of our estimation procedure, including the construction of market shares, location-specific shocks, and instrumental variables.

3.3.1 Market shares

To determine market shares, we require an estimate of market size, i.e., the number of potential bookings for short-term accommodation in Paris on each day in 2017. We compute the market size using worldwide Google Trends data for the keywords "hotels Paris" and "Airbnb Paris." We aggregate the two trends to obtain a measure of total search interest for short-term accommodation. Google Trends data are normalized such that the peak takes the value of 100. Therefore, we scale the aggregate trend by setting its average value equal to the average combined number of offered hotel and Airbnb rooms in 2017 (see Figure 1a). As a result of this normalization, one unit of the combined Google Trends index corresponds to 1,100 searches.

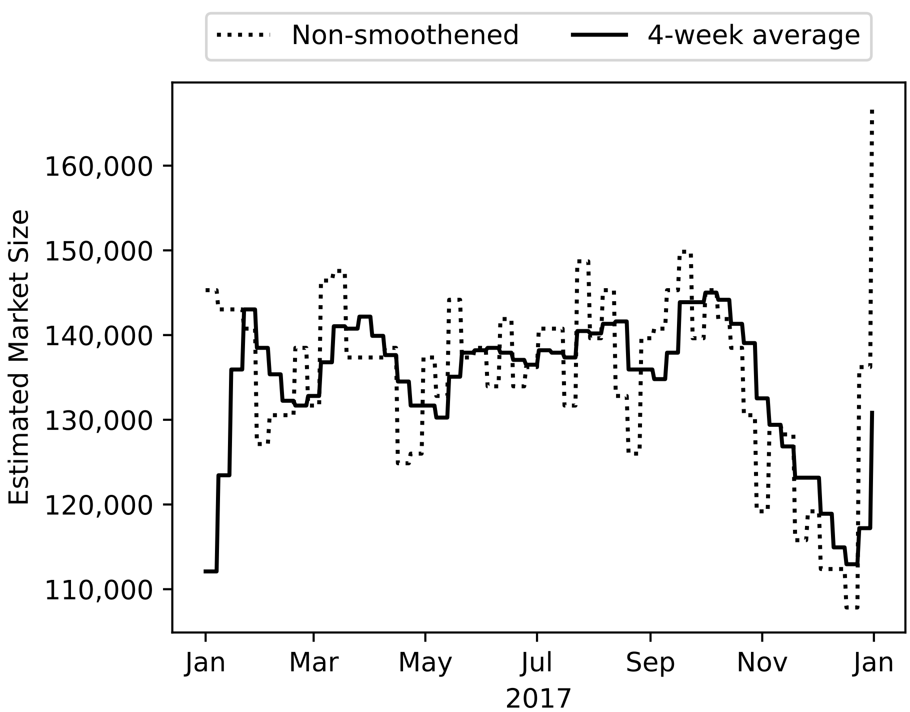


Figure 6: Market size (MS) measures

The dotted line in Figure 6 depicts our measure of search activity. According to this measure, average market size in 2017 corresponds to 134,000 potential bookings globally for either Airbnb listings or hotels, with values ranging from 107,000 to 165,000. To smoothen our market size measure, we average this measure of search activity over the preceding four weeks for each date and use this moving average as the market size . The solid line in Figure 6 presents this moving average. This averaging reflects the notion that travelers typically plan trips in advance.

3.3.2 Demand Identification and Instruments

Our demand instruments rely on capacities. The broad intuition is that own and rival capacities determine market power of firms in the short-run. However, because Airbnb capacity is likely correlated with demand, we first describe how we construct a plausibly exogenous measure of Airbnb capacity and then introduce the instruments.

Exogenous Airbnb Capacity For capacity to serve as the basis of a valid instrument, it must be uncorrelated with short-term demand variation. Figure 1a suggests this condition is satisfied for hotels, as hotel capacity does not appear to co-move with the number of observed bookings over time. By contrast, Figure 1a indicates that Airbnb capacity responds to demand shocks.

To construct a measure of Airbnb supply that is plausibly exogenous from unobserved short-term demand shocks, we predict Airbnb supply for each product using variables plausibly exogenous to short-term unobservable demand shocks: a quartic time trend and a measure of leisure-related outgoing car traffic from Paris. The quartic trend captures medium-term changes in Airbnb supply unlikely to be driven by short-run or localized demand. To measure leisure-related outgoing traffic, we use vehicle counts at major highway exits.[15] On the day before each weekend or holiday, we compute the difference between outgoing traffic on that day and average outgoing traffic during the preceding weekdays.[16] We assign this excess value to the respective weekend or holiday and set it to zero on weekdays, so weekday

[15] See https://opendata.paris.fr/explore/dataset/comptages-routiers-permanents/information/?disjunctive.libelle&disjunctive.etat_trafic&disjunctive.libelle_nd_amont&disjunctive.libelle_nd_aval (last accessed: June 1, 2026).

[16] To capture the summer holiday peak in Airbnb supply, we interact the quartic time trend with a dummy for the summer holiday period rather than using outgoing traffic.

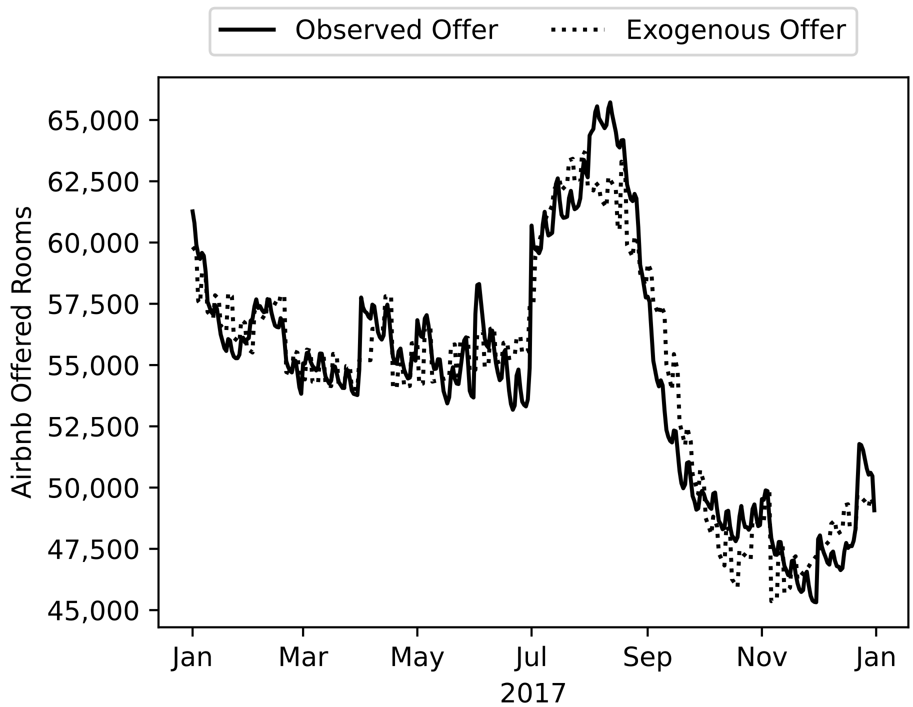


Figure 7: Observed and exogenous Airbnb offer over time

variation in predicted supply is driven by long-run trends. We estimate this relationship separately by product to allow for product-specific exogenous variation. Figure 7 illustrates observed and predicted Airbnb supply over time. We use these predicted Airbnb quantities to construct the exogenous Airbnb capacity measure used in our instrumental variable approach.

Demand Instruments Our instrumental variable strategy combines information on capacities with data from our event database. Specifically, the instrument for option j is defined as

$$Z_{jt} = \frac{\sum_{m \in R_j} k_{mt}}{1 + \sum_{m \in R_j} E_{mt}}, \tag{12}$$

where k_{mt} denotes the capacity of option m at time t, and R_j is a set of rivals associated with option j. We use different sets of rivals as described in more detail below. The term

E_{mt} captures the exposure of option m to events that are closer it than to option j:

$$E_{mt} = \sum_{e \in \mathcal{S}_t} \frac{\log_{10}(A_{et})}{\Delta(l(e), d(m))} \mathbf{1}\big\{\Delta\big(l(e), d(j)\big) > \Delta\big(l(e), d(m)\big)\big\} . \tag{13}$$

As before, A_{et} denotes attendance of event e on day t, $l(e)$ is the geographic location of event e, $\mathcal{S}_t$ is the set of events taking place on day t, and $\Delta(l(e), d(j))$ is the distance between event location $l(e)$ and the centroid of product j's district $d(j)$.

With different definitions of relevant competitors R_j, we can construct different instruments. Intuitively, the instrument captures how much of the rivals capacity remains effectively free after accounting for demand shocks for which the rivals are better positioned. Without demand shocks, the rivals capacities are free and hence equal to their total capacity. When the demand shock increases, the effectively free rival capacity tends to zero. We expect rivals to exert more competitive pressure when a lot of their capacity is free, and, conversely, less competitive pressure when their capacity is strongly exposed to demand shocks. In the latter case, because the rivals are less likely to have free available rooms, the focal listing is less constrained by the rivals' room capacity than compared to situations where more rival rooms are available.

We define neighboring districts as the four districts closest to the focal district, as measured by the distance between district centroids. Based on Equation (12), we construct six instruments by varying the definition of R_j. The first three instruments are defined as the set of rivals of the same type and (i) the same quality tier, (ii) the next-highest quality tier, and (iii) the quality tier two ranks above. The remaining three instruments are defined analogously, but using rivals of the other type. For products of different types, we match quality tiers based on the rank ordering of quality tiers within each category. For example, Airbnb listings of quality tier 2 are matched to two-star hotels.

Instrument Validity The validity of our instrumental variables requires that they are uncorrelated with unobserved demand shocks. This identifying assumption is made more plausible by the inclusion of district and market fixed effects as well as district-specific demand shifters in the demand specification. District fixed effects absorb differences in average demand for accommodations in different districts. Market fixed effects absorb city-level variation in demand for short-term accommodations. The district-specific demand shifters ls_{jt} described in Equations (3) and (6) account for variation in local demand due to large events in the city. Conditional on these observable demand shifters, the residual unobserved demand variation comes from unobserved variation in local demand. Examples of such local demand shocks are smaller events such as academic conferences that influence prices and market shares within the focal district $d(j)$.

To gain some intuition for the instruments, consider a stylized framework in which the districts of Paris, together with their respective room capacities, constitute segments along a Hotelling line, with a limited number of large conference venues situated at arbitrary points along this line. The entire line is subject to stochastic demand shocks: large shocks cluster at major conference venues, while smaller shocks materialize at arbitrary locations throughout.

For each district on the line, the instrument is constructed as the interaction between neighboring capacity and the large shocks closer to those neighbors. The aggregate effect of large demand shocks on demand at any point along the line is captured directly through the inclusion of ls_{jt} in Equation (1). Consequently, correlation between demand and instruments due to these large events is controlled for in the utility specification. This alleviates validity concerns related to correlation between our instrument and variation in mean utility due to large demand shocks.

Under this framework, the identifying assumption amounts to the requirement that the location and magnitude of shocks at large conference venues close to the focal district's neighbors are uncorrelated with the unobserved local demand shocks.

Note that it may well be that the degree to which small local demand shocks materialize in terms of actual bookings depends on the location of large events and the rival capacity occupied through these. For example, a small event in a given district might normally lead to an increase in demand for hotels in that district. However, if there is a large event taking place in that district at the same time, hotels would be at capacity and, as result, the small event would result in actual bookings materializing further away from this focal district. This kind of correlation between actual bookings (where the shock materializes) and our instrument that comes through equilibrium outcomes is not a violation of the identifying assumption. On the contrary, it is the mechanism by which our instruments are relevant. Instead, the identifying assumption only requires that our instruments should be uncorrelated with the timing and location of smaller events (where the shock originates). Given that different events are likely organized by different, independent teams and that small events use different types of venues than large events, these assumptions seem plausible.

Instrument Relevance From an economic perspective, rival capacity in neighboring districts determines the competitive constraint exerted on accommodations in the focal district. When demand shocks in neighboring districts exhaust rival capacity, local market power in the focal district should ceteris paribus increase. Similarly, this exhaustion of rival capacity in neighboring districts alters the relative attractiveness of the focal district $d(j)$ from the consumer's perspective. Jointly, these mechanisms provide an economic rationale for relevance of our instruments along both dimensions of interest: prices and market shares.

To develop intuition, consider two locations A and C subject to equally-sized demand shocks, with A shocked in every odd period and C shocked in every even period. Within our utility specification, the focal location B, situated exactly at the midpoint between A and C, experiences an identical shock ls_{jt} in each period. However, depending on the rival capacity located between A and B and between C and B, the competitive constraints induced by each shock through strategic pricing responses differ from one period to another, which in turn generates differential market shares. This stylized setting provides the argument for why our instruments produce variation in prices and market shares beyond that which is explained by the utility model.

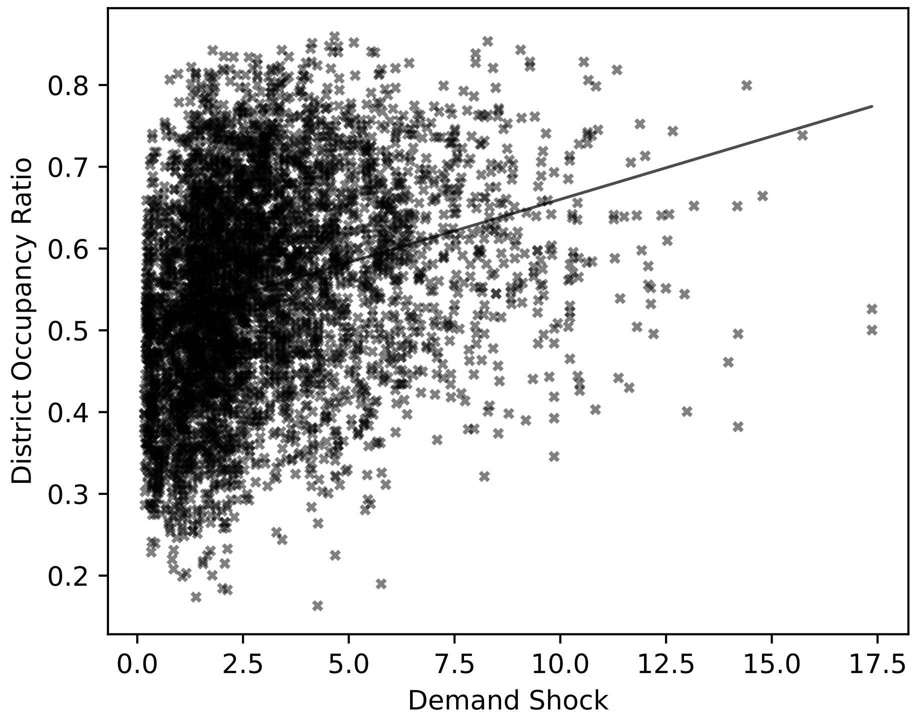


Figure 8: District-level occupancy ratio over demand shock variable

Figure 8 plots the district-wide occupancy ratio against the demand shock constructed from the event database. The solid line shows the corresponding linear fit which reveals a positive correlation. This provides reduced-form evidence that the demand shocks LSD_{jt} contain meaningful signal regarding demand. This correlation between the observable demand shock and district-level occupancy ratios is a prerequisite for our instrumental variable approach which exploits a sub-component of the signal captured by LSD_{jt} interacted with rival capacity.[17]

The F-statistic from a regression of price on the excluded instruments and the mean utility determinants is 140.11. We further assess the capacity of the instruments to predict prices and demand beyond the variation accounted for by the variables included in the mean utility specification, by regressing prices and the number of occupied rooms on each instrument, the demand shock ls_{jt}, and the controls included in the mean utility specification. The results,

[17] In Figure B.1 of Appendix B, we report the district-wise correlations between the demand shocks and occupancy ratios. For most districts the Pearson correlation coefficient lies between 0.3 and 0.47, thus achieving a medium correlation.

reported in Appendix B, document conditional correlations between each instrument and the dependent variable conditional on the location-specific demand shifter.

3.3.3 Cost estimation

As discussed in Sections 3.2.2 and 3.2.3, we assume that hotels set oligopolistic prices while Airbnb listings act as price-takers subject to their marginal costs. As a result, we estimate the underlying hotel cost functions and Airbnb cost distributions separately.

For hotels' marginal cost functions, we estimate the hotel first-order conditions shown in (9) as

$$\begin{aligned} & p_{jt} + \frac{s_{jt}(p_t)}{\frac{\partial s_{jt}(p_t)}{\partial p_{jt}}} - \mathbb{1}(q_{jt}(p_t) > 0.99\, k_{jt})\, \kappa\, (q_{jt}(p_t) - 0.99\, k_{jt})^2 \\ & = c_{jt} + \mathbb{1}(q_{jt}(p_t) > 0.5\, k_{jt})\, \theta_{d(j),\varrho(j)}\, (q_{jt}(p_t) - 0.5\, k_{jt})^2 + \varepsilon_{jt}\,. \end{aligned} \tag{14}$$

We impose $\kappa = 5$. We estimate (14) by regressing the left-hand side on product fixed effects, month fixed effects, district-specific linear trends, and, for observations with an occupancy ratio above 50%, squared excess demand $(q_{jt}(p_t) - 0.5\, k_{jt})^2$ interacted with district and quality fixed effects. The components not interacted with the squared excess demand represent c_{jt}, while the interacted components represent $\theta_{d(j),\varrho(j)}$.

The indicator for high-occupancy is correlated with demand by definition and may therefore be endogenous. We instrument for it using three demand shifters, each interacted with quality and district fixed effects: (i) log Google Trends search intensity for "airbnb paris," (ii) log Google Trends search intensity for "hotel paris," and (iii) the weighted local demand shock variable described in Section 3.2.1. We estimate parameters by two-stage least squares.

Differently from hotels, we model Airbnb hosts as price-takers. Given an achievable price p_{jt}, every Airbnb host decides whether to accept the price and host a guest or not. Every Airbnb host has an unobserved marginal cost that is drawn from a marginal costs distribution. If the price is above the marginal costs, they accept to host the traveler. If for a given price, we see a number of bookings on Airbnb, this means that these Airbnb hosts' marginal costs are below the price. Based on Equation (10), we estimate the marginal cost distribution parameters as

$$\Phi^{-1}\left(\frac{q_{jt}}{k_{jt}}\right) = \frac{p_{jt}}{\sigma_{\varrho(j)}} - \frac{\mu_{jt}}{\sigma_{\varrho(j)}}\,. \tag{15}$$

We estimate (15) by two-stage least squares, regressing the left-hand side on product fixed effects, district-by-day-of-the-week fixed effects, month fixed effects, district-specific linear time trends, and the price interacted with quality fixed effects. The price coefficients identify $1/\sigma_{\varrho(j)}$ (varying by quality tier), while the remaining components identify $-\mu_{jt}/\sigma_{\varrho(j)}$, allowing μ_{jt} to vary flexibly by product, day of week, and month. Because prices and quantities are jointly determined, we instrument for price using three demand shifters, each interacted with quality fixed effects: (i) log Google Trends search intensity for "airbnb paris," (ii) log Google Trends search intensity for "hotel paris," and (iii) the weighted local demand shock variable described in Section 3.2.1.

4 Estimation Results

In this section, we present the results of our demand- and supply-side estimations. We begin by presenting estimated demand parameters and elasticities. Next, we present the estimated hotel marginal cost functions. Finally, we present the estimated parameters of the Airbnb host cost distributions.

4.1 Demand Estimates

Table 1 reports the results of the demand estimation. The lowest-quality Airbnb category serves as the benchmark type–quality category. As expected, consumers tend to value higher-quality products more highly. Overall, consumers value hotels more highly than Airbnb listings. However, Airbnb listings in the highest quality tier are valued similarly to two- to three-star hotels.

The estimated mean and standard deviation of the normal distribution underlying the

Table 1: Estimated demand parameters

Parameter	Estimate	Std. error
Price (Mean)	-3.502	(0.160)
Airbnb cat. 2	2.125	(0.220)
Airbnb cat. 3	3.370	(0.377)
Airbnb cat. 4	5.476	(0.658)
Hotel cat. 1	2.793	(0.288)
Hotel cat. 2	4.415	(0.399)
Hotel cat. 3	6.209	(0.475)
Hotel cat. 4	7.502	(0.639)
Hotel cat. 5	11.658	(1.464)
Location Shock	0.547	(0.070)
Location Shock × Hotel	-0.170	(0.069)
Price (Std. dev.)	0.578	(0.115)
Distance City Center (Std. dev.)	10.639	(3.749)
Number of observations	33911	

Notes: Standard errors are heteroskedasticity robust. The specification includes market and district fixed effects whose estimates are reported in Appendix C. The baseline category for type–quality combinations are Airbnb listings in the lowest quality tier.

price coefficient are -3.5 and 0.6, respectively. These estimates translate into a log-normal price coefficient with a mean of -0.03 and a standard deviation of 0.02. The estimated coefficients on our measure of distance-weighted events in Paris (which we call location shock here) are 0.547 for Airbnb listings and 0.377 for hotels, respectively. This difference is consistent with location-specific demand shifters affecting demand for Airbnb accommodations more than that for hotels.

Finally, we find substantial heterogeneity in the (dis)utility associated with distance from the city center, with an estimated standard deviation of 10.639. The mean (dis)utility of distance to the city center is absorbed by the district fixed effects, since all products within a district are assumed to share the same distance to the city center.

4.2 Demand Elasticities

Table 2 reports the average estimated own- and cross-price elasticities of demand for all Airbnb and hotel quality categories, based on the estimates reported in Table 1. Demand is elastic for all type–quality combinations and is more elastic for higher-quality products. The columns for the cross-price elasticities report the average cross-price elasticities of a focal product group with respect to different comparison groups based on whether they are of the same type (hotels or Airbnb) or in the same district. For example, the demand for Airbnb listings of quality category 1 increases by an average of about 0.07 percent following a one-percent price increase of one of the other Airbnb products in the same district. The results reveal two main insights.

First, there is segmentation between Airbnb listings and hotels. Airbnb demand is more responsive to price changes of hotels than it is to price changes of other Airbnb products. This pattern can be seen by comparing the "Same type" to the "Different type" columns for the Airbnb categories, either for the same or across different districts. Going back to the example, if another Airbnb product in the same district increases their price by one percent, demand for category 1 Airbnb listings tends to increase by 0.07 percent. However, if a hotel in the same district increases their price by one percent, demand for category 1 Airbnb listings increases by 0.14 percent. This pattern holds both within as well as across districts. The cross-substitution patterns are different for hotels. Hotel demand is more responsive to price changes of other hotels than it is to price changes of Airbnb products. For example, if a hotel in the same district increases their price by one percent, the demand for 1-star hotels in that district increases by 0.14 percent. Instead, if an Airbnb product in the same district increases their price by one percent, demand for 1-star hotels in that district only increases by 0.03 percent. Again, this pattern holds both within as well as across districts. These patterns are consistent with consumers having a higher preference for hotels and switching to those whenever they become affordable.

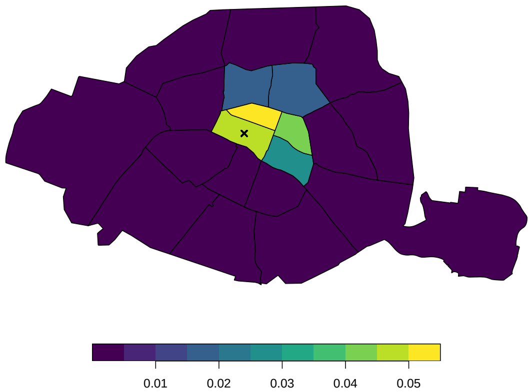
Second, consumers care about locations within the city. These locational preferences are reflected by substitution between competitors within the same district being stronger than substitution between competitors in different districts. This can be seen by comparing either the “Same district; Same type” column to the “Different district; Same type” column or the “Same district; Different type” column to the “Different district; Different type” column. Cross-price elasticities with respect to products in the same district are about three to four times as large as those with respect to similar products in other districts. Hotel demand is as responsive to price changes of Airbnb listings in the same district as they are to price changes of hotels in other districts even though hotel demand is much more responsive to hotel prices rather than Airbnb prices within the same district.

Table 2: Demand elasticities

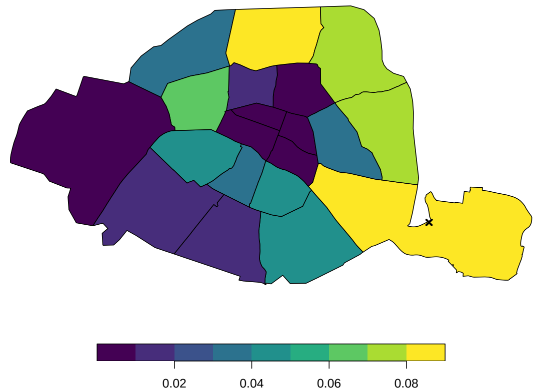
			Cross-price elasticities			
		Own-price	Same district		Different district	
Type	Category	elasticities	Same type	Different type	Same type	Different type
Airbnb	1	-2.145	0.067	0.136	0.019	0.032
	2	-2.673	0.048	0.154	0.013	0.036
	3	-3.179	0.036	0.165	0.009	0.038
	4	-4.019	0.014	0.175	0.005	0.039
Hotels	1	-2.839	0.142	0.033	0.033	0.009
	2	-3.320	0.207	0.036	0.041	0.009
	3	-3.464	0.157	0.029	0.040	0.006
	4	-3.891	0.152	0.023	0.038	0.005
	5	-4.652	0.119	0.012	0.025	0.002

Notes: The table reports average own- and cross-price elasticities across products and markets. Cross-price elasticities are computed conditional on product similarity (type) and geographic proximity (same versus different district).

To illustrate the geographical dimension of substitution more clearly, Figure 9 presents the average cross-price elasticities between products located in different districts with respect to products located in a focal district. These elasticities are averaged across all type–quality combinations and time periods. For products located in the central first arrondissement, substitution is largest with respect to products that are also located near the city center (see Figure 9a). The pattern suggests that if products in the first arrondissement increase their prices, demand for short-term accommodation in the other central districts increases



(a) 1st arrondissement



(b) 12th arrondissement

Figure 9: Average cross-price elasticities between products in different districts with respect to products in two example focal districts (marked with an x). These cross-price elasticities measure the average increase in demand of products in every district if a product in the focal district increases their price by 1%. We first calculate cross-price elasticities between each product in the focal district and all other products, including in the focal district itself. The reported elasticities are averaged across all type-quality combinations and over time. Appendix D shows the average cross-price elasticities for all district combinations.

by more than the demand in the outskirts.

However, the model generates substitution patterns that are more flexible than just being dependent on the distance between two products. Figure Figure 9b shows that for products in the 12th arrondissement, located at the South-Eastern edge of Paris, substitution to other districts generally decreases with distance, but this pattern is not uniform. In particular, cross-price elasticities are substantial for some more distant districts, including districts located in the city center. This pattern suggests that demand for products in the 12th arrondissement does not strongly care about its location per se. If products in the 12th arrondissement increase their prices, consumers substitute to some districts on the other side of the city in similar magnitude as they do to neighboring districts.

In summary, the model produces realistic and intuitive substitution patterns, reflecting stronger competition among geographically proximate units. At the same time, it accommodates geographically nuanced substitution, capturing substantial heterogeneity in preferences for location.

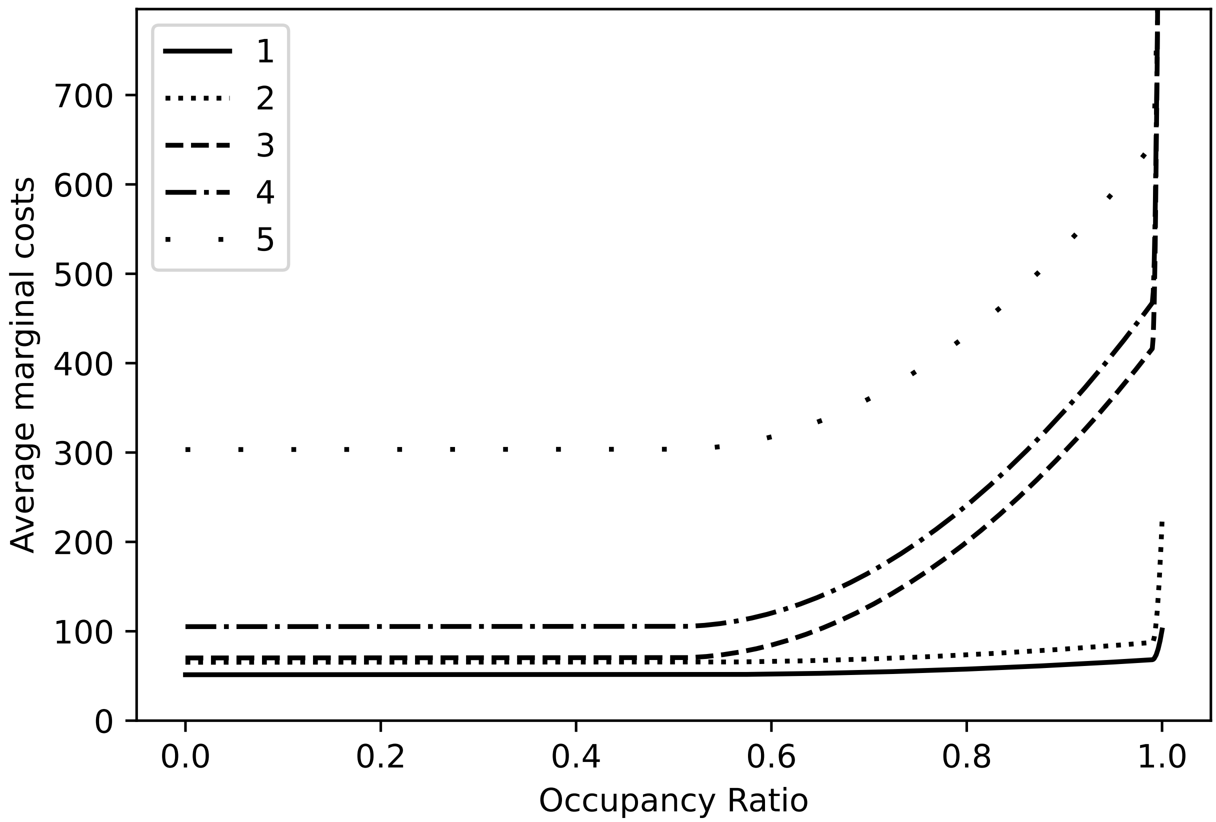


Figure 10: Average estimated marginal cost functions by hotel star category. The coefficients determining the constant marginal cost component as well as the squared component for occupancy ratios above 50% are estimated. A coefficient of 5 is imposed for occupancy ratios above 99% to create the capacity-enforcing steep part at capacity. The figure is constructed by computing average marginal cost functions by category and mapping them to occupancy ratios from 0 to 1.

4.3 Results of Hotel Cost Estimation

The two-stage least squares regression described in Section 3.3.3 yields estimates of hotel marginal cost functions that vary by product and market. To illustrate the shape of the estimated cost functions, Figure 10 presents average marginal cost functions for hotels of different quality tiers.

We compute these average cost functions by averaging the estimated marginal cost coefficients within each hotel star category across time and districts. For each category, this procedure yields an average constant marginal cost component and an average squared marginal cost component applicable at occupancy ratios above 50%. The capacity-enforcing steep increase in marginal costs at occupancy ratios of 99% and above is not estimated but imposed to ensure compliance with capacity constraints in the counterfactual simulations. Furthermore, we calculate the average capacity by hotel star category which we use as the 100% capacity point to create this plot.

With these different components, we obtain an average marginal cost function for each hotel star category. These functions are flat at occupancy ratios below 50%, squared in occupancy ratios for occupancy ratios above 50%, and feature a second, imposed squared component for occupancy ratios above 99%. For the figure, we normalize the x-axis to show occupancy ratios rather than occupancy numbers.

The average estimated marginal costs are higher for higher-quality hotels. At occupancy ratios of 50% and above, all hotel categories exhibit an increase in marginal costs as occupancy ratios increase. This increase is more pronounced for three-, four-, and five-star hotels. Note that this increase is not imposed during estimation. Therefore, marginal costs could also have been flat or even decreasing at high occupancy ratios.

4.4 Results of Airbnb Cost Estimation

Based on Equation (15), we estimate means and standard deviations for the marginal cost distributions that Airbnb hosts are facing. As discussed in Section 3.3.3, the mean of this marginal cost distribution (μ_{jt}) can vary across products, days-of-the-week, and months. We restrict heterogeneity in the underlying standard deviation of marginal costs to variation only by quality category. Figure 11 displays the average estimated mean of the Airbnb marginal cost distribution by quality category over time.

As in the hotel case, the estimated mean of the cost distribution is higher for higher-quality Airbnb listings and exhibits moderate seasonal variation over the year. By assumption, the estimated standard deviation does not vary over time and differs only by quality category. We estimate values of σ_j equal to 9.81, 11.30, 16.45, and 48.42 for Airbnb quality

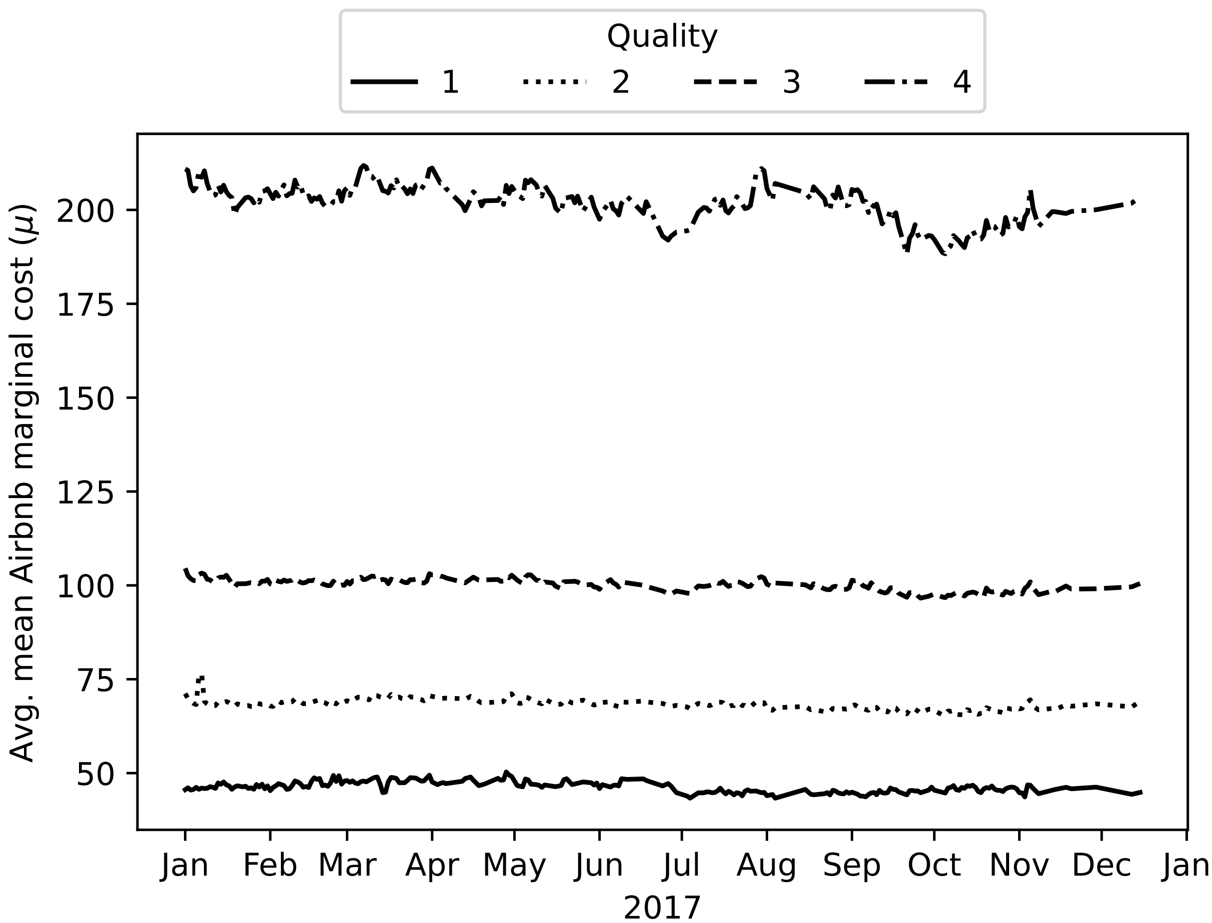


Figure 11: Average estimated mean of the marginal cost distribution by Airbnb quality category over time.

categories 1 to 4, respectively.

5 Model Fit and Counterfactual Simulations

In this section, we first evaluate the model's ability to fit the baseline outcomes observed in the data. Then, we employ the model for counterfactual simulations to shed light on the overall welfare impact of Airbnb, explicitly accounting for the geographic dimension of competition in the short-term accommodation market. Furthermore, our approach allows us to discuss geographical heterogeneity in how Airbnb impacts welfare. Finally, we simulate counterfactuals in which Airbnb is not removed from the entire city, but only from central or from outer districts, separately. These counterfactuals shed light on the importance of the localization of demand on Airbnb's welfare impact.

To quantify the welfare effects of Airbnb, we conduct counterfactual simulations in which Airbnb is removed from the market and compare the resulting outcomes to those observed in the data. In these counterfactuals, hotel prices are determined by re-solving their first-order conditions in the absence of Airbnb using the estimated hotel marginal cost functions. Given the counterfactual prices, we compute market shares, quantities, consumer surplus, and hotel and Airbnb profits using the estimated demand and cost functions and distributions.

Overall welfare is defined as the sum of consumer surplus, hotel profits, and Airbnb host profits. Comparing observed outcomes to those from the counterfactual scenario without Airbnb yields the welfare effects of Airbnb's presence in the short-term accommodation market. Theoretically, consumers and Airbnb hosts benefit from Airbnb, while hotel profits decrease. However, the overall welfare impact is not clear ex ante. Exploiting the geographic granularity of the data, we further examine how these effects vary across districts, which allows us to assess the potential implications of zoning regulations that restrict Airbnb activity in specific areas of the city.

Airbnb affects consumer welfare through two primary channels: increased product variety and enhanced price competition. To disentangle these channels, we consider two counterfactual scenarios corresponding to scenarios analyzed by Farronato and Fradkin (2022). In the first, Airbnb exits the market but hotel prices are held fixed at their observed levels. In the second, Airbnb exits the market and hotels optimally re-adjust prices. The difference in consumer surplus between the observed outcomes and the first counterfactual captures the welfare gains from expanded choice alone. The additional difference between the two counterfactuals reflects the consumer welfare gains arising from increased price competition induced by Airbnb.

5.1 Model Fit

To assess how well our model fits the data, we use it to simulate outcomes without changing the market structure. This simulation entails calculating optimal hotel prices based on their first-order conditions and finding Airbnb prices that rationalize the number of bookings that were accepted by Airbnb hosts, given the underlying marginal cost distributions. Given these prices, we calculate the corresponding quantities.

Focusing on prices first, Figure 12 compares the average observed prices to the average simulated prices for each type and quality combination. Note that we only define four quality categories for Airbnb listings which is why category 5 only exists for hotels. The figure shows that our model manages to fit average prices well across product types and quality categories. Adding to this result, Figure 13 compares the average observed and simulated prices over time. The figure shows that our model does not only cross-sectionally match prices well, but also manages to capture seasonal fluctuation in prices.

Turning to quantities, Figure 14 compares the observed average daily number of occupied rooms to that simulated by our model for each type and quality combination. The figure reveals that the model also matches average quantities well across product types and quality categories. Finally, Figure 15 shows that the model also simulates fluctuations in quantities over time well.

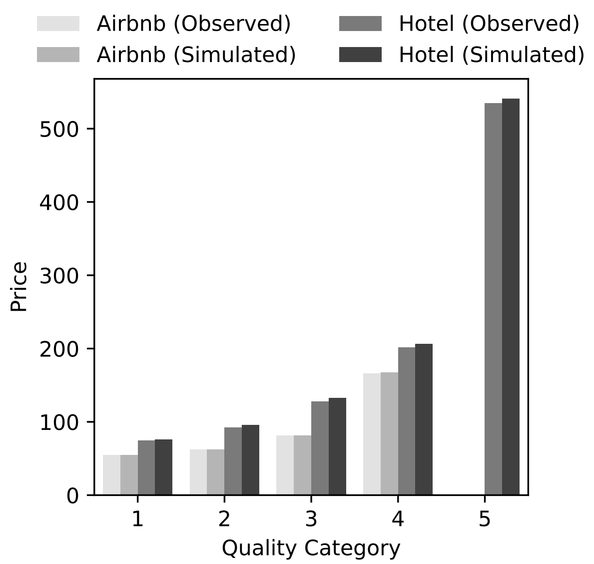


Figure 12: Sales-weighted average observed vs. simulated prices by type and quality

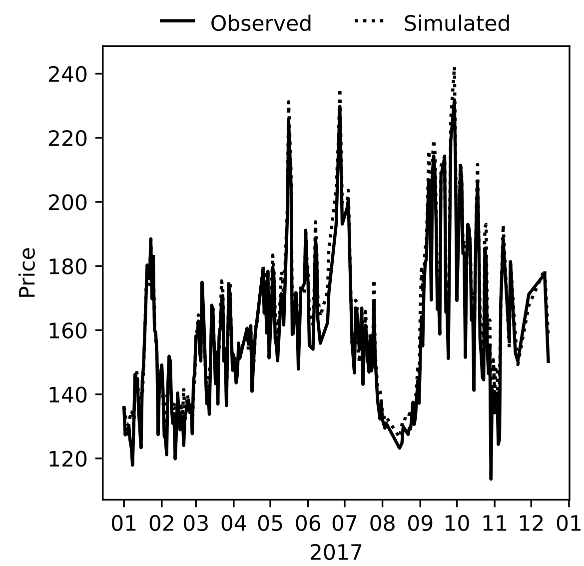


Figure 13: Sales-weighted average observed vs. simulated prices over time

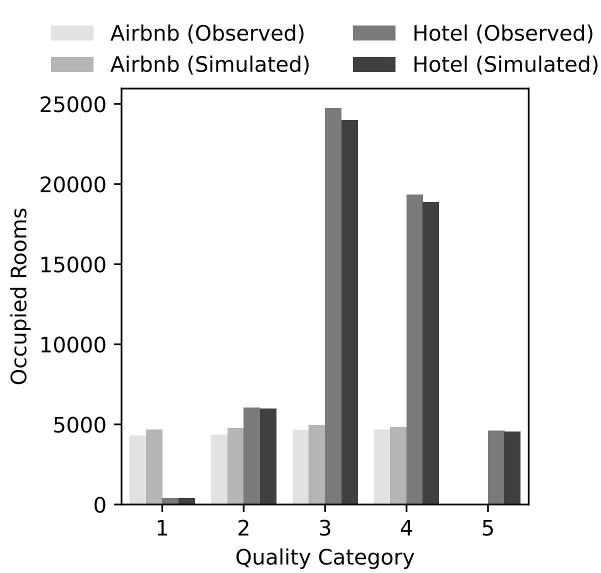


Figure 14: Sales-weighted average observed vs. simulated quantities by type and quality

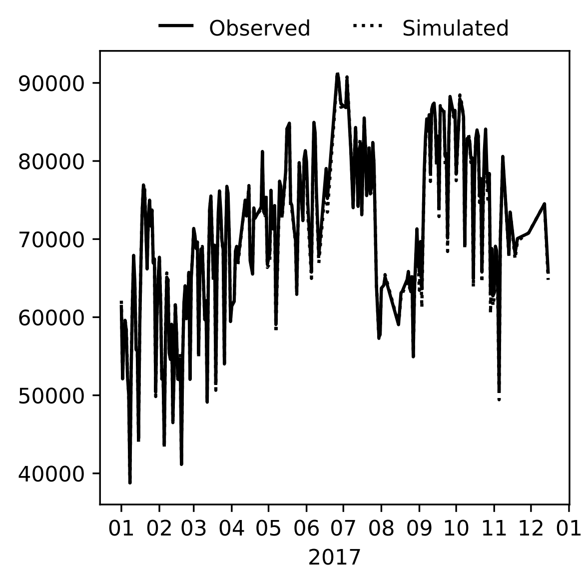


Figure 15: Sales-weighted average observed vs. simulated quantities over time

5.2 The Overall Welfare Impact of Airbnb

Following Farronato and Fradkin (2022), we consider two main counterfactual scenarios. In both scenarios, we remove Airbnb from the market entirely. In the first counterfactual, hotels do not re-adjust their prices and accommodate any additional demand resulting from Airbnb's exit, ignoring capacity constraints. In the second scenario, hotels re-adjust their prices optimally, taking into account the estimated marginal cost functions which implicitly enforce the capacity constraints.

Consumer Surplus Comparing these two counterfactual scenarios to the observed data allows decomposing the impact of Airbnb on consumer surplus. Comparing the first counterfactual to the observed data reveals the consumer surplus impact of Airbnb absent any hotel price changes. The impact of Airbnb in this comparison comes purely from consumers having fewer choices without Airbnb. Comparing the second counterfactual to the observed data reveals the full consumer welfare impact of Airbnb. This total welfare impact consists of both a change in consumer surplus due to changes in consumer choice sets as well as a change in consumer surplus due to increased competitive pressures for hotels when Airbnb is in the market. Finally, comparing the consumer surplus impacts of the two scenarios reveals the relative importance of the price channel and how its importance changes over time as well as cross-sectionally.

Table 3 reports the changes in consumer surplus under the two counterfactual scenarios without Airbnb. These changes reflect the benefits to consumers from Airbnb by showing how much worse consumers would be in the counterfactual scenarios compared to the observed data. We report results both as the change in average expected individual consumer surplus and as the change in total expected consumer surplus over the entire year. Total expected consumer surplus is computed by multiplying expected consumer surplus per consumer in each market by the estimated market size and summing across markets.

In the counterfactual scenario with fixed hotel prices, we estimate an average consumer

Table 3: Simulated consumer surplus changes

	(1) No price adjustment	(2) With price adjustment
$\Delta E(CS)$	-5.04	-29.39
Δ Total CS	-169,895,531.86	-923,845,383.65

Notes: Changes in consumer surplus from removing Airbnb. Expected consumers surplus ($E(CS)$) is calculated as sales-weighted average across markets. We calculate the total consumer surplus by calculating the expected consumer surplus in each market and multiplying it by the market size. Then, we sum over all markets. Column (1) shows the differences in consumer surplus between the scenario without Airbnb when hotel prices are fixed and the observed baseline. Column (2) shows the differences in consumer surplus between the scenario without Airbnb when hotels optimally readjust prices and the observed baseline.

surplus loss without Airbnb of 5 euros per night. When hotels are allowed to re-adjust prices, the estimated average loss increases to 29 euros per night. Thus, higher hotel prices in the absence of Airbnb account for over 80 percent of the total consumer surplus loss when Airbnb is removed. This share is substantially higher than the roughly 50 percent reported by Farronato and Fradkin (2022). We attribute this difference to the higher penetration of Airbnb in Paris relative to the average market in their sample, as well as to our explicit modeling of geographic competition. Aggregating across markets, we obtain a total consumer surplus reduction of 924 million euros, corresponding to approximately 3.67 million euros per night.[18]

Figure 16 shows that consumer surplus losses without Airbnb are unevenly distributed across markets. This variation over time comes almost entirely from variation in how changes in hotel pricing affect consumer surplus. The consumer surplus reductions from limited choice sets remain fairly stable around the average 5 euros per night shown in Table 3. However, the expected per-consumer surplus losses when allowing hotels to readjust prices absent Airbnb range from less than 10 euros to over 80 euros per night. Therefore, the relative importance

[18] Our sample includes 252 nights.

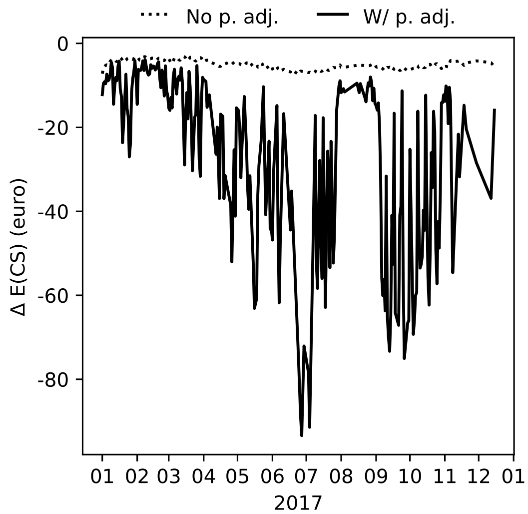


Figure 16: Changes in expected consumer surplus from removing Airbnb, without and with hotel price adjustment

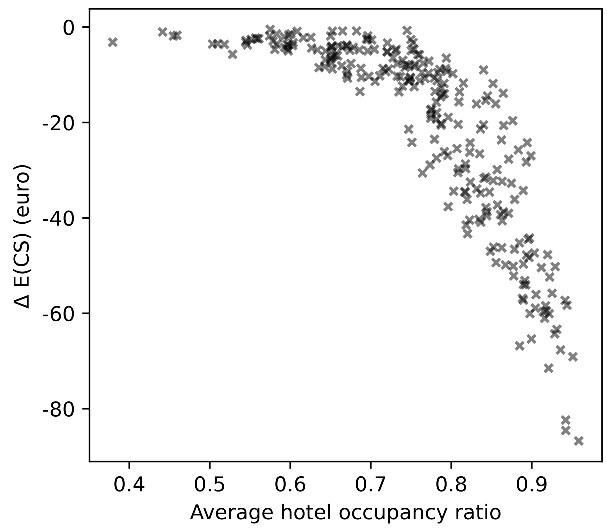


Figure 17: Changes in expected consumer surplus from removing Airbnb with hotel price adjustment, plotted against baseline hotel occupancy rates

of the price channel for consumer surplus from Airbnb varies over the year. In particular, the price channel affects consumer surplus most in periods in which overall demand for short-term accommodations in the city is high. This result is further illustrated in Figure 17 which relates the losses in expected consumer surplus in each market to the average observed hotel occupancy rate. These consumer surplus impacts are highest during periods of high demand. This result is intuitive and in line with results by Farronato and Fradkin (2022). When overall demand is high, hotels could charge substantially higher mark-ups if there was not the additional competitive constraint coming from Airbnb.

Producer Surplus Table 4 summarizes Airbnb's impact on supply-side welfare. The columns under the header "Baseline" report the observed number of bookings (Q), booked prices (P), and profits (π) for each type and quality combination. The bookings and profits are calculated by adding up all bookings and profits in each group over the entire sample, i.e. across districts and markets. The prices are calculated as sales-weighted average booked prices in each group. The columns reporting changes (Δ) show how these baseline quantities would differ in the absence of Airbnb. For this supply-side analysis, we focus on the counterfactual in which hotels readjust their prices in the absence of Airbnb.

To calculate hotel profits, we use the estimated cost parameters and calculate Equation (7). To calculate expected Airbnb host profits, we integrate over the estimated marginal cost distributions up to the observed price for each product as described in Equation (11). Since these marginal cost distributions are normally distributed, there is a possibility of negative marginal costs. Hence, we cap marginal costs from below at zero when calculating these expected Airbnb host profits.

Absent Airbnb, hotels increase their prices by an average of 37 to 47 euros per night. While these absolute price changes are relatively similar across quality tiers, they imply different relative adjustments, with higher-quality hotels increasing prices by a smaller percentage than lower-quality hotels. When Airbnb is absent, total hotel occupancy increases by approximately 2.1 million nights, with low- and mid-tier hotels absorbing most of these additional bookings. However, overall, the number of bookings would be 2.3 million nights lower without Airbnb. This result suggests that only about half of the observed 4.3 million booked Airbnb nights would substitute to hotels if Airbnb did not exist. Therefore, we estimate that about half of the demand for Airbnb is due to market expansion.

We estimate that total hotel profits increase by approximately 778 million euros (3.1 million euros per market) in the absence of Airbnb. Compared to the baseline profits, these are substantial profit increases. The low- to mid-scale hotels benefit most from an absence of Airbnb listings with two-star hotels' relative profit increase being the largest at approximate 190%. The other low- to mid-scale hotel categories also benefit substantially with one-star hotels' profits increasing by 166% and three-star hotels' profits increasing by 117%. For upscale hotels, the effects are more moderate but still sizeable: four-star hotels experience profit increases of approximately 75%, and five-star hotels of about 24%. These pronounced effects are consistent with Airbnb undermining hotels' local market power during peak-demand periods, when hotels operate close to their capacity constraints.

Table 4 also quantifies the foregone expected profits of Airbnb hosts if they were prevented from renting their properties on Airbnb. Summing profits across all markets, we find that Airbnb hosts would be approximately 21.6 million euros worse off, corresponding to an average loss of 0.09 million euros per market.[19]

Table 4: Simulated quantity, price, and profit changes

	Category	Baseline			Δ Q	Δ P	$\Delta\pi$
		Q	P	π			
Airbnb	1	1,035,592	55.04	2,421,468.94	-1,035,592		-2,421,468.94
	2	1,047,132	62.39	2,822,303.06	-1,047,132		-2,822,303.06
	3	1,115,059	81.34	4,442,905.07	-1,115,059		-4,442,905.07
	4	1,105,607	166.19	11,951,610.13	-1,105,607		-11,951,610.13
Hotel	1	34,580	74.40	1,114,209.54	+10,751	+37.07	+1,849,748.32
	2	1,472,505	92.73	47,387,629.94	+388,795	+46.36	+90,003,213.56
	3	6,094,471	128.07	299,662,439.29	+1,004,430	+46.83	+350,480,627.68
	4	4,766,550	201.90	359,890,967.63	+590,777	+47.24	+271,086,576.74
	5	1,112,676	534.63	271,565,430.01	+58,152	+47.29	+64,953,792.74
Total		17,784,172		1,001,258,963.61	-2,250,486		+756,735,671.85

Notes: Baseline columns show observed values. Baseline Q is the sum of booked nights. Baseline P is the sales-weighted average price per night. Baseline π shows the sum of baseline profits. The ΔQ column shows the total change in booked nights without Airbnb. ΔP shows the sales-weighted average difference in hotel prices when Airbnb is absent. The $\Delta\pi$ column shows the total change in profits without Airbnb. Hotels optimally readjust prices in the scenario without Airbnb.

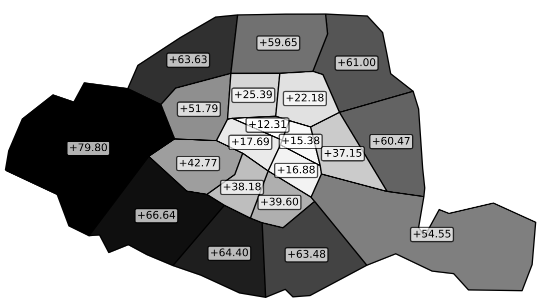
Combining hotel gains and Airbnb host losses, the results suggest an overall increase in producer surplus of about 757 million euros without Airbnb. Table 3 shows a consumer surplus reduction of approximately 924 million euros without Airbnb. Therefore, our counterfactual analysis yields an overall welfare gain of 167 million euros due to Airbnb. This overall welfare gain corresponds to a welfare gain of approximately 0.66 million euros per market. This welfare effect comprises a 924 million euros gain in consumer surplus, a 21 million euros gain in Airbnb host profits, and a 778 million euros loss in hotel profits.

[19]This figure reflects the estimated profits Airbnb hosts earn in the baseline scenario. It does not account for outside options available to hosts, such as renting on the long-term rental market. As a result, the true impact of Airbnb on host welfare is likely smaller.

5.3 Impact of Airbnb across Districts

The geographic granularity of our data allows us to further assess heterogeneity in Airbnb's impact on the hotel industry across geographical locations. Expected consumer welfare is calculated on the market level, which is why consumer welfare impacts cannot be clearly decomposed into localized impacts. However, changes in prices, quantities, and profits are calculated for each observation. Hence, we can analyze how Airbnb affects these outcomes differentially in different districts of Paris.

Figure 18 shows the average changes in hotel prices per night by district if Airbnb is removed from the entire city, both in absolute terms as well as relative to observed baseline prices. We observe considerable variation across districts, with price increases ranging from 12 to 80 euros per night, or from 6% to 69%. Price effects tend to be larger in outer districts than in more central areas, both in absolute and relative terms.

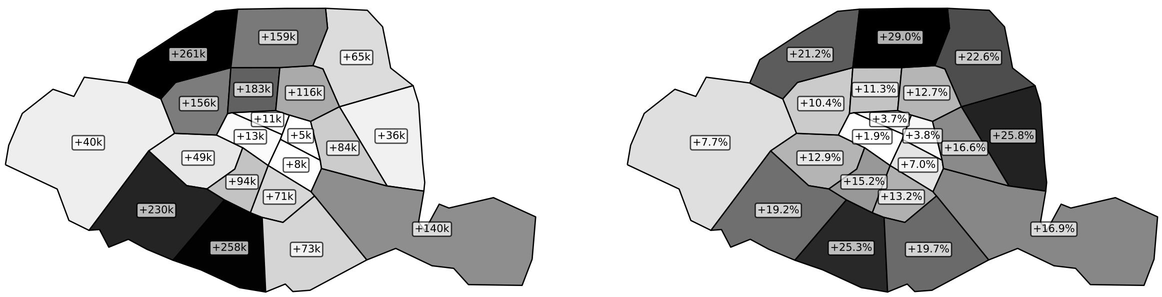


(a) Absolute (b) Relative

Figure 18: Average absolute and relative hotel price changes across districts. Absolute changes are shown in euro.

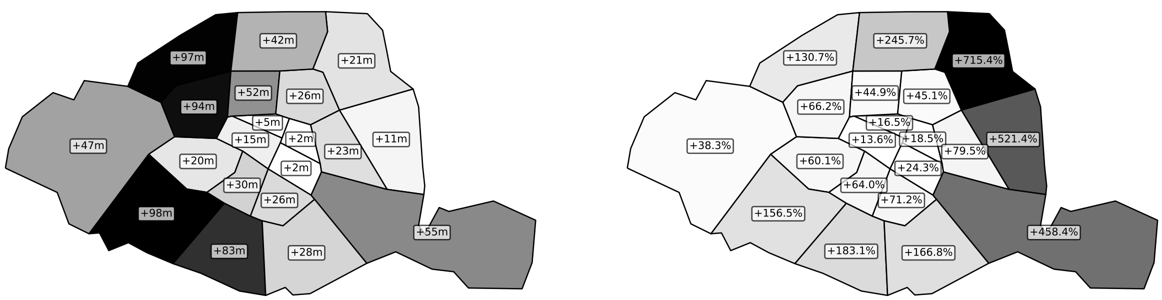
Turning to quantity changes in Figure 19, we observe a similar pattern. Focusing on the scenario in which hotels readjust prices without Airbnb, the total, district-level increase in booked hotel nights ranges from about 5,000 to an increase of up to 261,000 booking nights. Relative to the observed baseline quantities, these quantity increases range from 1.9% to 29%. Again, the quantity increase tends to be larger for hotels in less central areas of Paris.

Finally, we examine how Airbnb affects hotel profits across districts. Figure 20 shows



(a) Absolute (b) Relative

Figure 19: Absolute and relative hotel quantity changes across districts. Absolute changes are shown in thousands of booking nights.



(a) Absolute (b) Relative

Figure 20: Absolute and relative hotel profit changes across districts. Absolute changes are shown in millions of euro.

that in every district hotel profits increase in the absence of Airbnb but there is substantial heterogeneity across districts in the size of these profit increases. Absolute annual hotel profits increase by between 2 and 98 million euros across districts. Compared to baseline profits, these increases correspond to relative increases ranging from 14% to 715%. In line with the results on prices and quantities, the profit increases are largest for hotels in less central areas.

Understanding the geographically heterogeneous impacts of Airbnb on welfare is important, especially for a wider discussion of its impact on society. Many cities like Paris are concerned that Airbnb is removing supply from the long-term rental markets, adding tension to an already strained situation. Therefore, cities have introduced regulation to curb the ability of owners to rent out their homes on Airbnb. However, restricting owners' ability to rent their homes on Airbnb affects overall welfare in the short-term accommodation industry negatively, as first shown in the US by Farronato and Fradkin (2022) and confirmed in our results for Paris. Additionally, we document that this impact of Airbnb regulation can affect different areas in the same city differently. Presumably, the impact of Airbnb on rental and housing markets is also not homogenous across different areas of a city. Accounting for geographic heterogeneity in how Airbnb affects these two separate but related markets is therefore important to allow for informed policy decisions.

5.4 Removing Airbnb in the Center vs Outside

To further analyze the heterogeneity of Airbnb's welfare impact across districts of Paris, we next compare two additional counterfactual scenarios to the baseline: First, we remove all Airbnb listings from only the central districts of Paris. Second, we remove all Airbnb listings from only the outer districts of Paris. We define arrondissements 1 to 11 as the central districts. This definition yields two groups of districts that see similar numbers of Airbnb bookings: The central districts had about 2.3 million booked nights on Airbnb while the outer districts saw about 2 million booked nights. For both counterfactuals, we study how consumer welfare and hotel profits change compared to the observed status quo. Table 5 shows the resulting changes in consumer surplus. Column (1) shows the changes in consumer surplus between the status quo and a counterfactual without Airbnb in the central districts. Column (2) shows the changes in consumer surplus if Airbnb is removed from the outer districts. The table shows that consumers surplus decreases more if Airbnb is banned outside of the city center compared to a ban in the central districts. Comparing the results from Table 5 to those in Table 3, we can see that these consumer welfare losses are substantially smaller than those if Airbnb is removed across the entire city. This result suggests that a substantial part of the total gain in consumer surplus from Airbnb can be achieved even if

Airbnb was available only in either the city center or outside. Removing Airbnb in the entire city would decrease consumer surplus by about 924 million euros. Instead, removing Airbnb from only the center or only the outside would decrease consumer surplus by 271 or 385 million euros, respectively. These results suggests that even if Airbnb was banned from the city center, consumer surplus would still be 653 million euros higher compared to a market without Airbnb altogether.

Table 5: Simulated consumer surplus changes due to Airbnb in city center vs outside

	(1) Remove Airbnb from Center	(2) Remove Airbnb from Outside
$\Delta E(CS)$	-8.23	-12.23
Δ Total CS	-270,903,878.09	-384,896,805.02

Notes: Changes in consumer surplus from removing Airbnb in central vs outer districts. Expected consumers surplus ($E(CS)$) is calculated as sales-weighted average across markets. We calculate the total consumer surplus by calculating the expected consumer surplus in each market and multiplying it by the market size. Then, we sum over all markets. Column (1) shows the changes in consumer surplus when Airbnb is removed from central districts (arrondissements 1 to 11). Column (2) shows the changes in consumer surplus when Airbnb is removed from the outer districts. Hotels optimally readjust prices in these counterfactual scenarios.

We can further add the time dimension to these insights. Figure 21 shows the losses in expected consumer surplus over time from removing Airbnb from the city center (dark gray area) or from the outer districts (light gray area). The solid black line shows the change in consumer surplus when Airbnb is removed from the entire city (same as the solid line in Figure 16). The figure shows that the loss in consumer surplus from removing Airbnb from the city center is relatively constant over the entire year. In contrast, the reductions in consumer surplus from removing Airbnb from the outer districts fluctuate much more with overall demand. In periods of low demand, the consumer surplus losses from removing Airbnb in the outer districts is relatively low. However, even in periods of small demand spikes, removing Airbnb in these outer districts decreases consumer surplus by more than removing Airbnb in the center. This pattern is also true for the periods in which the city-

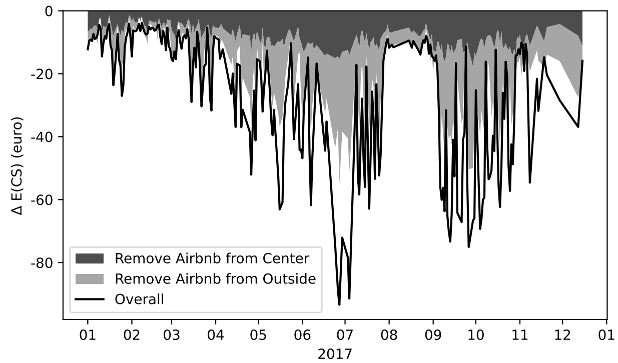


Figure 21: Consumer surplus impact of removing Airbnb in city center vs outside over time

wide level of demand is very high. The figure also shows that in periods in which overall city-level demand is not very high, the consumer surplus impacts of the two partial-removal scenarios approximately sum to the overall impact of Airbnb on consumer surplus. However, in periods of high city-wide demand, there is a large additional consumer surplus reduction from removing Airbnb in the entire city. This result is in line with local supply of Airbnb being sufficient to create sizeable gains in consumer welfare when hotel capacity constraints bind only locally. However, when hotel capacity constraints become binding city-wide, local availability of Airbnb is no longer sufficient to generate the same gains as city-wide availability of Airbnb can.

Turning to the supply side, Table 6 shows how removing Airbnb from only the city center would compare to removing it from districts outside the city center in terms of its impact on hotel profits and Airbnb host surplus. Removing Airbnb in the city center would lead to an overall decrease in booked nights of 1.4 million nights. This effect is substantially larger than the net reduction in booked nights if Airbnb was removed from the outer districts. This large difference in changes in quantities cannot be fully explained by differences in quantities in the baseline: We observe approximately 2.3 million booked nights on Airbnb in the city center compared to about 2 million booked nights on Airbnb in the outer districts. These results suggest that many Airbnb consumers in the city center prefer the outside option, instead of substituting to Airbnb listings in the outer districts or hotels. This pattern is in line with Airbnb consumers in the city center having strong preferences for being in the center, but not being willing to pay the higher prices that centrally-located hotels would charge if there were no Airbnb listings in the center.

Conversely, if Airbnb is removed in the outer districts, many consumers substitute to hotels as well as more central Airbnb listings. As a result, overall demand decreases much less while hotel prices increase much more. Consequently, hotel profits also increase more if Airbnb is removed in the outer districts compared to when it is removed in central districts. Remaining Airbnb hosts also profit in this scenario because they face higher prices in the market. This pattern reflects the patterns seen for consumer surplus well: Removing Airbnb in the outer districts reduces competitive constraints on hotels in the entire city because consumers who would have stayed in an Airbnb in less central locations are more likely to substitute to hotels or Airbnb listings anywhere else in the city.

The fact that overall demand decreases less when Airbnb is removed from outer districts while consumer surplus decreases more suggests that removing Airbnb from the outer districts mostly affects infra-marginal consumers who are worse off but still prefer some substitute over the outside option. Instead, many of the consumers affected by a removal of Airbnb from the city center seem to be marginal consumers who would not stay in Paris if Airbnb was not available in the center.

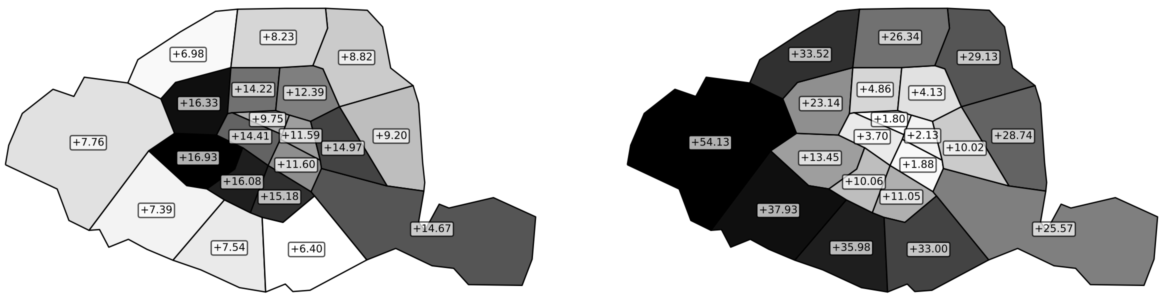
Further disaggregating the impact on hotels, Figure 22 shows the changes in average hotel prices by district if Airbnb is removed from the city center compared to when it is removed from outer districts. Figure 22a shows that removing Airbnb in the city center allows hotels in the city center to charge higher prices per night. Similarly, removing Airbnb in the outer districts allows hotels there to charge higher prices (Figure 22b). However, in both scenarios, the effects also spill over to the areas in which Airbnb is left in place. This result suggests that Airbnb offer acts as a competitive constraint for hotels all across the city, but that it does more so for hotels which are nearby.

The figure also reveals some differences between the two scenarios. Firstly, removing

Table 6: Simulated quantity, price, and profit changes due to Airbnb in city center vs outside

	Category	No Airbnb in center			No Airbnb outside		
		Δ Q	Δ P	$\Delta\pi$	Δ Q	Δ P	$\Delta\pi$
Airbnb	1	-522,521	+1.30	-982,071.65	-65,786	+0.45	+809,104.53
	2	-132,826	+1.94	+357,928.49	-638,977	+2.78	-579,125.18
	3	-424,236	+2.66	-1,670,103.77	-430,304	+3.19	+633,099.95
	4	-784,018	+4.80	-9,231,940.93	-204,827	+4.28	+948,272.15
Hotel	1	+4,098	+5.06	+385,072.05	+6,233	+20.15	+958,196.03
	2	+133,385	+8.34	+17,677,028.38	+253,896	+20.19	+40,838,112.92
	3	+137,135	+11.40	+75,355,798.26	+573,474	+20.85	+152,836,133.68
	4	+122,076	+11.79	+63,677,970.56	+269,334	+21.99	+118,024,857.92
	5	+23,218	+18.82	+29,192,717.16	+10,838	+20.03	+29,518,323.94
Total		-1,443,689		+174,762,398.55	-226,119		+343,986,975.95

Notes: Reported changes compare to the baseline values reported in Table 4. The ΔQ columns show the total change in booked nights in scenarios if Airbnb was removed in the center or outside the center, allowing for hotel price readjustment. ΔP shows the sales-weighted average difference in prices among remaining products if Airbnb is removed in the center or outside. The $\Delta\pi$ column shows the total change in profits without Airbnb in the center or outside.



(a) No Airbnb in center

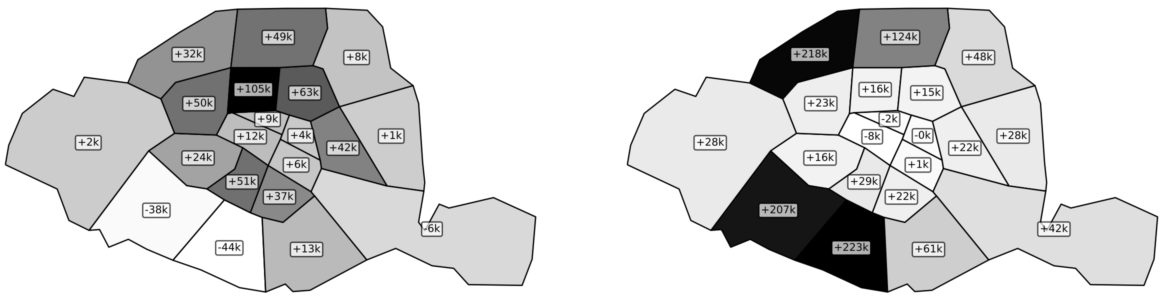
(b) No Airbnb outside

Figure 22: Changes in average hotel prices per night if Airbnb is removed from the city center vs outer districts

Airbnb listings in the outer districts has a stronger localized effect: Removing Airbnb from the outer districts raises relative hotel prices in outer districts more than removing Airbnb in inner districts does for hotels in inner districts. Secondly, removing Airbnb listings in the outer district has a smaller spill-over effect: Removing Airbnb listings from the outer district raises inner district hotel prices relatively less, than removing Airbnb in the inner district does for hotels in the outer district.

Finally, we can also analyze the distinct impacts on hotel quantities that the two scenarios have. Figure 23a shows that removing Airbnb in the city center results in quantity increases for hotels in almost all districts in the city with the exception of hotels in the 12th, 14th and 15th arrondissements. Instead, if Airbnb is removed in the outer districts, booked nights for hotels in the outer districts increase substantially (despite substantial price increases), but those of hotels in the city center do not change substantially or even slightly decrease (see Figure 23b).

Table 6 shows that removing Airbnb from the city center results in smaller overall quantity increases for hotels. However, Figure 23 suggests that these smaller overall quantity increases are spread more evenly across the city. Instead, if Airbnb is removed from the outer districts, overall hotel demand increases by more and this increase is concentrated mostly in hotels in the outer districts.



(a) No Airbnb in center (b) No Airbnb outside

Figure 23: Changes in hotel booked nights if Airbnb is removed from the city center vs outer districts

6 Conclusion

This paper analyzes localized, geographic competition between short-term accommodations to quantify the overall welfare impact of Airbnb on travelers, hotels, and Airbnb hosts. Complementing the study by Farronato and Fradkin (2022), we account for localized demand and competition within the city by including local demand shifters and allowing for heterogeneous consumer preferences across different locations within the city.

We specify and estimate a model in which consumers choose among short-term accommodations in Paris. Hotels set oligopolistic prices taking into account their marginal costs which reflect their capacity constraints. Airbnb hosts are price-takers with an underlying marginal cost distribution and accept to host guests whenever the market price is higher than their cost.

Our estimation reveals intricate yet plausible substitution patterns across accommodation types and geographies. We find that hotels substitute more strongly with other hotels, while Airbnb listings substitute more strongly with hotels than with other Airbnb listings. The effect of geographic proximity on competitive interactions depends on the centrality of accommodation locations within the city. Our counterfactual simulations reveal a strong impact of Airbnb on consumer surplus, which is primarily driven by its price-dampening effect rather than by increased variety. This contrasts with previous studies, which attribute about half of the consumer welfare gains to the latter channel.

Our counterfactual simulations reveal heterogeneous effects of Airbnb on consumers and hotels across different districts of Paris. Hotels in the outskirts of Paris experience a much larger decrease due to the presence of Airbnb than hotels in more central areas. At the same time, removing Airbnb from these outskirts would hurt consumers more than removing Airbnb from more central districts. Consumers gain from the availability of Airbnb listings in the outskirts especially in periods in which there are some local increases in demand. The presence of Airbnb in these periods restricts the degree to which hotels in the outskirts can charge excess markups in periods of local high demand.

These results highlight why it is important to take into account the geographic dimension of competition between short-term accommodation platforms when analyzing a city like Paris. This consideration is particularly relevant given the externalities Airbnb may exert on housing markets (Horn and Merante, 2017; Koster et al., 2021; Garcia-López et al., 2020; Barron et al., 2021; Duso et al., 2024) and on local neighborhoods (Basuroy et al., 2021). The general intuition in the literature and policy debate is that Airbnb benefits travelers and Airbnb hosts and hurts hotels and local rental and housing markets. Our results add some nuance to this intuition. We also find that Airbnb is beneficial for travelers and Airbnb hosts, but this is the case more so in districts outside of the city center. In contrast, prior research suggests that the impact of Airbnb on rental and housing markets may be largest in more central areas (e.g. Garcia-López et al., 2020; Duso et al., 2024). Jointly, these results suggest that regulating Airbnb only in more central areas may offer policymakers a pathway of balancing protecting local housing markets while still harnessing the majority of the welfare gains that platforms like Airbnb can offer.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Claude and Refine in order to check the draft for consistency and grammatical errors. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix

A Descriptives

Table A.1: Prices, occupancy, and offer

Quality	Price		Rooms Occupied		Rooms Offered	
	Hotels	Airbnb	Hotels	Airbnb	Hotels	Airbnb
1	85.43	41.23	226.01	4,109.49	345.17	12,721.34
	(30.83)	(15.81)	(194.80)	(882.47)	(278.17)	(1,100.57)
2	97.64	63.67	5,843.27	4,155.29	7,997.14	13,016.21
	(26.25)	(26.38)	(1,084.01)	(877.78)	(786.28)	(1,139.24)
3	128.96	92.12	24,184.41	4,424.84	31,156.13	14,330.40
	(34.21)	(29.02)	(3,619.24)	(979.54)	(399.57)	(1,124.36)
4	188.25	171.36	18,914.88	4,387.33	24,596.47	15,135.65
	(56.38)	(39.93)	(2,832.11)	(1,111.94)	(528.94)	(973.52)
5	482.51	-	4,415.38	-	6,228.55	-
	(231.67)	-	(915.67)	-	(499.80)	-

Notes: The statistics shown are averages calculated across markets (nights) and products. Standard deviations are shown in parentheses. For hotels, prices are calculated based on dates for which less than 65 percent of prices are missing.

Table A.2: Hotel-level comparison between matched and unmatched hotels

Star Rating		Rooms Occupied		Rooms Offered	
	Share	Matched	Non-matched	Matched	Non-matched
1	33.33	45.39	21.08	63.93	31.26
		(77.89)	(10.52)	(102.47)	(14.53)
2	26.75	28.69	31.39	38.77	41.73
		(33.86)	(33.31)	(43.36)	(41.80)
3	32.26	33.85	36.75	43.37	47.11
		(32.44)	(39.26)	(40.16)	(52.17)
4	45.13	59.91	51.63	78.10	65.75
		(96.16)	(68.56)	(125.52)	(83.51)
5	32.89	58.18	74.35	82.95	103.65
		(39.51)	(66.74)	(53.78)	(95.2)

Notes: The statistics shown are averages calculated across markets and individual hotels. Standard deviations are shown in parentheses. The second column shows the percentage of hotels that we could not match for each category.

Table A.3: Market-level comparison between matched and unmatched hotels

Star Rating		Rooms Occupied		Rooms Offered	
	Share	Matched	Non-matched	Matched	Non-matched
1	19.25	907.73	205.50	1278.78	304.71
		(153.63)	(34.94)	(8.94)	(9.13)
2	27.79	4753.02	1859.66	6423.65	2472.21
		(895.84)	(350.75)	(49.79)	(46.05)
3	35.84	15900.61	8877.17	20370.08	11378.27
		(2579.40)	(1397.01)	(58.68)	(131.76)
4	40.25	11686.96	8061.20	15236.77	10265.54
		(1881.30)	(1305.69)	(522.86)	(387.19)
5	35.48	2934.05	1650.19	4182.78	2300.53
		(488.89)	(321.76)	(60.70)	(171.71)

Notes: The statistics shown are averages calculated across markets. Standard deviations are shown in parentheses. The second column shows the percentage of hotel rooms that we could not match for each category.

B Location-specific demand shifters

Construction of event database

To approximate location-specific demand shifters for district d, we assemble a database of events held in Paris during the calendar year 2017. One primary source is the Global Association of the Exhibition Industry, which publishes the annual *Euro Fair Statistics* report.[20] This report provides, for each major European city, a list of fairs, their dates, and corresponding visitor attendance figures.

In addition, we compile a list of music and cultural events using information from `www.timeout.com/paris` (last accessed: June 1, 2026) as a primary source. For each event, we identify its timing and location(s) and estimate attendance figures. When available, official venue capacity is used; otherwise, attendance is approximated by extrapolating from the venue's physical size, assuming one visitor per square meter. Events for which neither reliable attendance data nor credible estimates of physical size are available are excluded from the database. The list of music and cultural events obtained from `www.timeout.com/paris` is complemented with a list of major concert events drawn from the website of the Stade de France (`www.stadefrance.com`, last accessed: June 3, 2026), the main arena in Paris, which hosts large sports and cultural events.

In addition, we include several major events that are commonly known to take place in Paris but could not be retrieved from the aforementioned sources. These events, together with their estimated attendance figures, are listed in Table B.1. We classify them as city-wide events and therefore assign their location to the city center of Paris.

Table B.1: Major City-Wide Events in Paris and Their Estimated Attendance in 2017

Event	Start Date	End Date	Estimated Attendance
Paris Fashion Week (Women's FW)	2017–02–28	2017–03–08	30,000
Paris Fashion Week (Men's FW)	2017–01–18	2017–01–22	5,000
Paris Fashion Week (Haute Couture SS)	2017–01–22	2017–01–26	5,000
Paris Fashion Week (Men's SS)	2017–06–21	2017–06–25	5,000
Paris Fashion Week (Haute Couture FW)	2017–07–02	2017–07–06	5,000
Paris Fashion Week (Women's SS)	2017–09–26	2017–10–03	30,000
Roland-Garros (French Open)	2017–05–28	2017–06–11	480,000
Tour de France (Paris Finish)	2017–07–23	2017–07–23	300,000
Bastille Day (Fête Nationale)	2017–07–14	2017–07–14	400,000
Paris Marathon	2017–04–09	2017–04–09	57,000
Journées Européennes du Patrimoine	2017–09–16	2017–09–17	500,000
Paris Jazz Festival	2017–06–17	2017–07–30	110,000
Nuit Blanche	2017–10–07	2017–10–08	1,000,000
Fête de la Musique (Music Day)	2017–06–21	2017–06–21	250,000

For sports events, we consider the home match schedule of Paris Saint-Germain, the local first-division football team, as well as the event calendar of the Stade de France, which hosts

[20] See https://www.ufi.org (last accessed: June 1, 2026).

matches of the national football and rugby teams. We use the total seating capacity of these venues as a first-order approximation of visitor numbers for such events.[21]

Location specific demand shifter is a useful predictor of aggregate room occupancy at the district level.

Figure B.1 shows the Pearson correlation coefficient between the location specific demand shifter and the total number of occupied rooms in a district for each district. The plot reveals that in most cases we have a medium correlation ranging from 0.3 to 0.47.

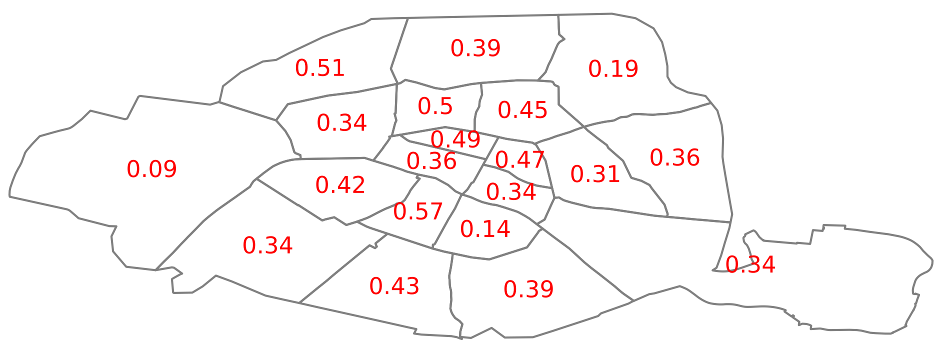

Figure B.1: Correlation between location specific demand shifters and total room occupancy by district

First stage regressions

Tables B.2–B.5 report regressions of prices and the number of occupied rooms on each of the instruments used in the demand specification, alongside the location-specific demand shifter ls_{jt}. Each column corresponds to a separate regression that includes one instrument at a time together with ls_{jt} and the fixed effects indicated at the bottom of the table. We report the analysis separately for hotels and Airbnb listings, both for prices (Tables B.2 and B.3) and for the number of occupied rooms (Tables B.4 and B.5).

[21]The Stade de France also hosts large concerts. When these are not already included in our music event database, we supplement our data accordingly.

For hotel and Airbnb prices (Table B.2 and Table B.3), we find that the instruments consistently predict prices above and beyond the factors included in the utility specification model. We refrain from interpreting these coefficients due to the complex nature of price interactions within and between the various accommodation types, which is further complicated by the different price-setting behaviors between hotels and Airbnb listings.

For the regressions with the number of occupied rooms as the dependent variable (Tables B.4 and B.5), we mostly obtain signs consistent with the notion that more slack rival capacity in nearby districts leads to fewer accommodations in the focal district being booked.

Table B.2: First-stage relevance regressions — dependent variable: hotel price; sample: hotels.

	(1)	(2)	(3)	(4)	(5)	(6)
ls_{jt}	13.567	13.715	13.930	13.802	13.608	13.588
	(0.738)	(0.743)	(0.752)	(0.745)	(0.735)	(0.753)
$Z_{\varrho}^{\text{same}}$	-1.342					
	(0.561)					
$Z_{\varrho+1}^{\text{same}}$		-0.062				
		(0.620)				
$Z_{\varrho+2}^{\text{same}}$			-1.534			
			(0.591)			
$Z_{\varrho^*}^{\text{other}}$				8.203		
				(1.604)		
$Z_{\varrho^*+1}^{\text{other}}$					6.674	
					(1.007)	
$Z_{\varrho^*+2}^{\text{other}}$						0.938
						(0.778)
Num. obs.	14,738	14,738	14,738	14,738	14,738	14,738
R^2 Within	0.016	0.016	0.016	0.019	0.018	0.016
RMSE	67.78	67.79	67.78	67.71	67.71	67.78
FE: district	X	X	X	X	X	X
FE: market (day)	X	X	X	X	X	X
FE: quality-by-type	X	X	X	X	X	X

Notes: The notes below apply to Tables B.2–B.5. Each column reports a separate OLS regression of the dependent variable stated in the caption on one instrument plus the location-weighted demand shifter ls_{jt} and the fixed effects indicated at the bottom of the table. ls_{jt} is the location-specific demand shifter that enters the demand specification (see Equation (2)). $Z_{\varrho+k}^{\text{same}}$ denotes the instrument constructed from rivals of the same accommodation type at quality tier $\varrho + k$ relative to the focal product's tier ϱ; $Z_{\varrho^*+k}^{\text{other}}$ uses rivals of the other accommodation type at the quality tier ϱ^* closest to ϱ. Heteroskedasticity-robust standard errors in parentheses.

Table B.3: First-stage relevance regressions — dependent variable: Airbnb price; sample: Airbnb listings.

	(1)	(2)	(3)	(4)	(5)	(6)
ls_{jt}	-1.217	-1.358	-1.268	-1.308	-1.386	-1.301
	(0.127)	(0.130)	(0.132)	(0.131)	(0.130)	(0.132)
$Z_{\varrho}^{\text{same}}$	5.970					
	(0.184)					
$Z_{\varrho+1}^{\text{same}}$		0.965				
		(0.191)				
$Z_{\varrho+2}^{\text{same}}$			-0.819			
			(0.168)			
$Z_{\varrho^*}^{\text{other}}$				1.176		
				(0.096)		
$Z_{\varrho^*+1}^{\text{other}}$					1.230	
					(0.091)	
$Z_{\varrho^*+2}^{\text{other}}$						-0.207
						(0.101)
Num. obs.	19,173	19,173	19,173	19,173	19,173	19,173
R^2 Within	0.072	0.011	0.011	0.017	0.017	0.009
RMSE	9.74	10.06	10.06	10.03	10.03	10.07
FE: district	X	X	X	X	X	X
FE: market (day)	X	X	X	X	X	X
FE: quality-by-type	X	X	X	X	X	X

Table B.4: First-stage relevance regressions — dependent variable: number of occupied rooms (hotels); sample: hotels.

	(1)	(2)	(3)	(4)	(5)	(6)
ls_{jt}	216.557	218.231	226.675	216.115	215.675	219.483
	(7.416)	(7.409)	(7.535)	(7.370)	(7.349)	(7.546)
$Z_{\varrho}^{\text{same}}$	8.629					
	(4.609)					
$Z_{\varrho+1}^{\text{same}}$		−26.131				
		(4.569)				
$Z_{\varrho+2}^{\text{same}}$			−76.608			
			(5.906)			
$Z_{\varrho^*}^{\text{other}}$				41.602		
				(8.617)		
$Z_{\varrho^*+1}^{\text{other}}$					−2.008	
					(7.192)	
$Z_{\varrho^*+2}^{\text{other}}$						−29.721
						(7.812)
Num. obs.	14,738	14,738	14,738	14,738	14,738	14,738
R^2 Within	0.104	0.106	0.117	0.106	0.104	0.105
RMSE	401.80	401.35	398.91	401.50	401.85	401.65
FE: district	X	X	X	X	X	X
FE: market (day)	X	X	X	X	X	X
FE: quality-by-type	X	X	X	X	X	X

Table B.5: First-stage relevance regressions — dependent variable: number of occupied rooms (Airbnb); sample: Airbnb listings.

	(1)	(2)	(3)	(4)	(5)	(6)
ls_{jt}	167.480	169.276	169.094	168.575	169.189	169.957
	(2.637)	(2.696)	(2.701)	(2.690)	(2.686)	(2.695)
$Z_{\varrho}^{\text{same}}$	−62.662					
	(2.940)					
$Z_{\varrho+1}^{\text{same}}$		−17.536				
		(2.487)				
$Z_{\varrho+2}^{\text{same}}$			−9.393			
			(3.207)			
$Z_{\varrho^*}^{\text{other}}$				5.294		
				(1.590)		
$Z_{\varrho^*+1}^{\text{other}}$					−11.694	
					(1.368)	
$Z_{\varrho^*+2}^{\text{other}}$						−18.526
						(1.592)
Num. obs.	19,173	19,173	19,173	19,173	19,173	19,173
R^2 Within	0.467	0.448	0.447	0.447	0.449	0.453
RMSE	135.62	138.00	138.15	138.15	137.95	137.47
FE: district	X	X	X	X	X	X
FE: market (day)	X	X	X	X	X	X
FE: quality-by-type	X	X	X	X	X	X

C District and market fixed-effects of demand specification

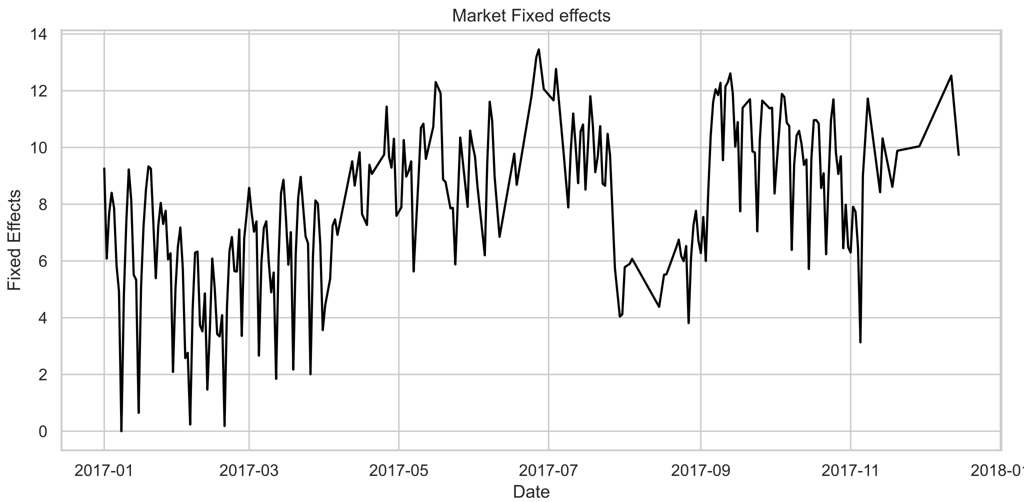

Figure C.1: Market fixed effects obtained from estimating Equation (1)

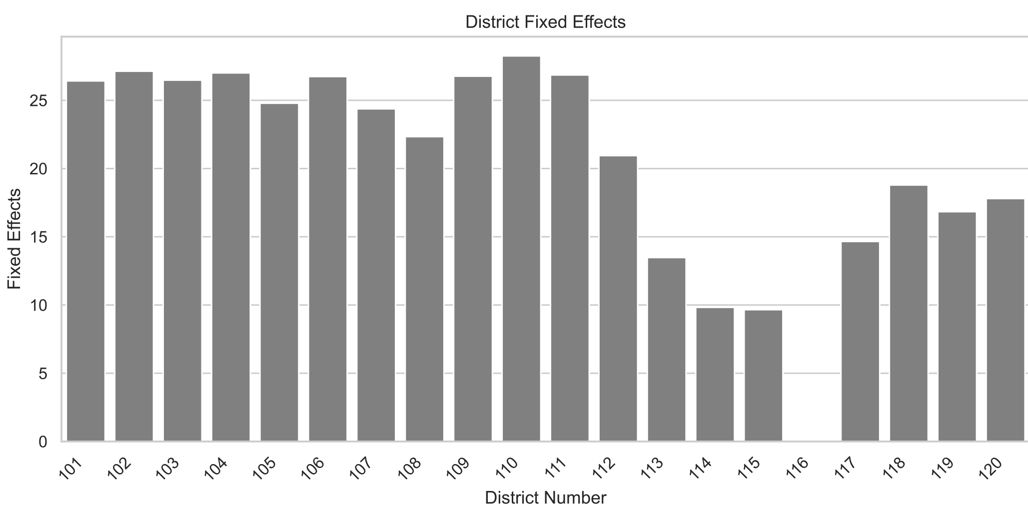

Figure C.2: District fixed effects obtained from estimating Equation (1)

D Average cross-price elasticities across districts

Demand response in arrondissement (columns); Price change in arrondissement (rows)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.048	0.051	0.041	0.029	0.002	0.005	0.002	0.000	0.015	0.017	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.021	0.021	0.019	0.015	0.001	0.002	0.001	0.000	0.008	0.009	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.015	0.015	0.014	0.014	0.002	0.003	0.002	0.000	0.009	0.011	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.014	0.015	0.018	0.018	0.006	0.008	0.005	0.001	0.016	0.019	0.008	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5	0.003	0.003	0.006	0.012	0.050	0.046	0.048	0.033	0.030	0.026	0.050	0.032	0.006	0.001	0.001	0.000	0.004	0.024	0.019	0.019
6	0.004	0.004	0.008	0.015	0.047	0.050	0.047	0.030	0.034	0.031	0.051	0.025	0.004	0.001	0.000	0.000	0.003	0.017	0.013	0.013
7	0.002	0.002	0.004	0.007	0.034	0.035	0.032	0.027	0.019	0.017	0.035	0.023	0.005	0.001	0.001	0.000	0.004	0.017	0.013	0.014
8	0.002	0.002	0.004	0.008	0.089	0.111	0.120	0.134	0.032	0.027	0.087	0.124	0.051	0.016	0.013	0.001	0.053	0.090	0.075	0.083
9	0.030	0.031	0.046	0.067	0.060	0.073	0.055	0.021	0.087	0.094	0.074	0.015	0.001	0.000	0.000	0.000	0.001	0.009	0.007	0.006
10	0.013	0.014	0.022	0.033	0.032	0.032	0.027	0.010	0.044	0.043	0.037	0.008	0.001	0.000	0.000	0.000	0.000	0.006	0.004	0.004
11	0.004	0.004	0.008	0.015	0.060	0.047	0.053	0.034	0.036	0.030	0.053	0.033	0.006	0.001	0.000	0.000	0.003	0.027	0.022	0.021
12	0.000	0.000	0.001	0.003	0.047	0.031	0.047	0.064	0.011	0.008	0.036	0.080	0.048	0.014	0.011	0.000	0.036	0.082	0.078	0.077
13	0.000	0.000	0.000	0.000	0.006	0.003	0.006	0.015	0.001	0.000	0.003	0.025	0.053	0.040	0.032	0.003	0.044	0.038	0.044	0.042
14	0.000	0.000	0.000	0.000	0.002	0.001	0.002	0.010	0.000	0.000	0.001	0.018	0.089	0.142	0.151	0.067	0.097	0.030	0.039	0.039
15	0.000	0.000	0.000	0.000	0.001	0.001	0.002	0.010	0.000	0.000	0.001	0.018	0.101	0.203	0.197	0.122	0.119	0.030	0.041	0.041
16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.052	0.069	0.349	0.012	0.000	0.001	0.001
17	0.000	0.000	0.000	0.000	0.009	0.006	0.011	0.037	0.001	0.001	0.006	0.057	0.133	0.124	0.114	0.018	0.126	0.077	0.091	0.091
18	0.000	0.000	0.001	0.001	0.039	0.016	0.036	0.055	0.007	0.004	0.022	0.077	0.071	0.024	0.017	0.000	0.045	0.096	0.102	0.095
19	0.000	0.000	0.000	0.001	0.022	0.008	0.020	0.034	0.004	0.002	0.011	0.049	0.060	0.024	0.016	0.000	0.036	0.071	0.072	0.070
20	0.000	0.000	0.000	0.000	0.014	0.005	0.012	0.021	0.002	0.001	0.007	0.030	0.040	0.016	0.010	0.000	0.022	0.046	0.049	0.040

Figure D.1: Average cross-price elasticities across districts. To calculate the numbers in this table, we first calculate the cross-price elasticities between all products. Then, for two districts i and j, we calculate the average of all cross-price elasticities that give us the percentage increase in demand in a product in district i, given that a product in district j increases their price by 1%. In the table above, the rows represent district j and columns represent district i. For example, Figure 9a shows the first row.