The Effect of Short-Term Rentals on Local Consumption Amenities: Evidence from Madrid*

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Abstract

This paper investigates the impact of the arrival of Airbnb on local consumption amenities in Madrid. We exploit the exogenous variation created by the timing and the unequal distribution of Airbnb listings across the urban geography to identify its effects on food and beverage establishments. Using an instrumental variable strategy, we find positive local effects on both the number of restaurants and their employees: an increase in ten Airbnb rooms in a given census tract translates into almost one more restaurant, and the same increase in a given neighborhood generates eight new tourist-related employees. The results are robust to specification and sample composition. This paper contributes to the literature on the economic impacts of the platform economy on urban areas by providing evidence of market expansion externalities from short-term rentals.

Keywords: consumption amenities, short-term rentals, tourism
JEL Classification: R10, R23, Z32

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1 Introduction

The economic landscape in urban areas is rapidly changing as peer-to-peer (P2P) accommodation platforms enter cities (Ferreri and Sanyal, 2018). In a short time, Airbnb, the leader in the sector, has grown from a few thousand properties in 2009 to over seven million in 2020 in more than 100,000 cities worldwide.[1] The explosive increase of short-term rentals in urban areas has spurred a vigorous debate about its economic impact. Several studies have pointed out its deleterious effects of increased housing prices and rents on the housing market (Garcia-López et al., 2020; Barron et al., 2021; Franco and Santos, 2021), the negative impact on hotel performance (Zervas et al., 2017; Schaefer and Tran, 2021), and the welfare impact on residents and tourists (Almagro and Domınguez-Iino, 2019; Calder-Wang, 2019; Farronato and Fradkin, 2022).

As short-term rental platforms spread, it is crucial to study their effect on the local economy, particularly their potentially uneven consequences across the urban geography of economic activity. Since tourists are consumers with different needs and tastes, their arrival may change the economic activities around the new establishments. As short-term residents substitute long-term residents, the Airbnb-induced demand increases, potentially impacting stores *locally*. If, as Airbnb claims, guests prefer to stay around and consume near their listings, the arrival of these new temporary residents may represent a market expansion externality, leading to an increase in the demand for local consumption amenities like restaurants, coffee shop and other retail services. This effect gains special relevance because of the unequal distribution of short-term rentals across the urban geography: unlike the traditional accommodation industry, short-term rentals spread across the city, therefore redistributing the economic impact of tourism across the urban geography. This new form of tourist accommodation might have the capacity to expand the benefits of tourist activities beyond the more traditionally touristic areas. Therefore, these effects could justify the policies undertaken recently by local authorities to restrain short-term rental activity in the city center but allow them to operate in peripheral areas (Valentin, 2021).

To analyze the impact of short-term rentals on tourism-related activities, we focus on how Airbnb's arrival has fostered Madrid's food and beverage establishments. Four conditions allow us to pinpoint the effect of short-term rentals on local consumption

[1] See https://news.airbnb.com/about-us/

amenities: (i) Short-term rentals are more dispersed than traditional accommodations, which are concentrated in the city center. Local planning ordinances restrict the location of traditional accommodations whereas short-term rentals can freely expand in already existing dwellings across the city. The possibility to bring visitors to non-touristic areas allows us to disentangle Airbnb's effect from other accommodations; (ii) The rapid diffusion of Airbnb. The flexibility and absence of regulation have led to a sudden increase in those accommodations, unthinkable for other regulated accommodation types; (iii) Food and beverage establishments quickly react to changes in the local demand due to low startup costs; (iv) As hotel customers, Airbnb users are likely to spend a large share of the time budget in the immediate vicinity of the accommodation (Shoval et al., 2011). Hence, Airbnb is expected to transform the surrounding area to better meet new customers' needs.

In this study, we introduce a novel methodological approach to exploit the exogenous variation created by the unequal entry of Airbnb across the Madrid geography. To measure the impact of Airbnb on local consumption amenities, we use a Bartik-like instrumental variable (IV) approach, exploiting the share of rental houses in 2011 (before the arrival of Airbnb in Madrid) and the number of worldwide Airbnb Google searches as an instrument for short-term rental activity. Our IV approach relies on the importance of the local supply of rental houses before Airbnb's entry to explain the increase in the number of short-term rentals afterward. We exploit the sharp geographic and temporal variation in the availability of short-term rentals using census tracts and neighborhoods as our main geographical units of analysis.

Our results show that the entry of Airbnb has positively impacted both employment and the number of food and beverage establishments: an increase in ten Airbnb rooms in a given census tract translates to almost one more food and beverage establishment. The same increase in a given neighborhood generates eight new employees in food and beverage activities. The new and displaced establishment equally drives the creation of local consumption amenities. Also, Airbnb employment effects are evenly explained by the intensive and extensive margin. Interestingly, Airbnb spillover effects on local consumption amenities are heterogeneous within food and beverage activities, with restaurants the main activity that benefited from Airbnb penetration. Across the urban geography, the impact of Airbnb is stronger in less touristic areas, which reinforces the idea that peer-to-peer accommodations help redistribute tourism consumption over the city. We find no evidence of pre-trends, and our results are robust to sample composition and functional specification.

Overall, we make four contributions. First, we identify positive *local* effects on the food and beverage sector from short-term rental activity. We have access to a yearly finer-grained data set for the universe of all economic activities in Madrid from 2014 to 2019. The richness of our data allows us to identify areas where Airbnb enters by using the smallest geographical unit of analysis available: census tracts. Using a narrow geographic unit of analysis helps overcome the problems of heterogeneity within larger spatial units such as ZIP codes and neighborhoods.

Second, we evaluate the heterogeneous effects of short-term rentals across food and beverage establishments typologies, identifying which types of food and beverage establishments cater to potential Airbnb users. Moreover, we show that the overall Airbnb-induced establishment effect is equally explained by displacement and net establishment creation. Finally, we decompose the overall Airbnb-induced employment effect between the intensive and the extensive margin, showing that the positive effects also extend to incumbents.

Third, we contribute a new Bartik-like instrument to solve the endogeneity in the Airbnb activity variable: the interaction between the share of rental houses for each census tract previous to the Airbnb arrival and worldwide Airbnb Google searches. Using a supply driver rather than a demand driver represents a novelty in the literature that may help overcome the inherent problem of using demand shares related to city center characteristics.

Fourth, this is the first study that analyzed the Airbnb economic spillover effect in a European city.[2] This is of particular interest since the distinction between commercial and residential areas is more nuanced in European urban areas than in the US, even though the difference is diminishing over time (Gordon and Cox, 2012). As such, the

[2]Not related to our research question, the only papers that analyze other Airbnb externalities in European contexts are Garcia-López et al. (2020), who address the effect of Airbnb on rental prices in Barcelona, Almagro and Domınguez-Iino (2019), who study the effect of Airbnb in changing neighborhood amenities in Amsterdam, and Fontana (2021) who examines the discontent of tourists that results from Airbnb-induced tourism flows in London.

arrival of short-term rentals to residential zones is expected to significantly impact the business configuration, fostering the opening of food and beverage establishments.

The rest of the paper is organized as follows. Section 2 provides a review of the extant literature on the effect of short-term rentals on local urban economic activities. Section 3 and Section 4 describe the data and methodology, respectively. Section 5 presents and discusses our main findings. We draw our conclusions and discuss future research directions in Section 6.

2 Related literature

The rise of the sharing economy and, in particular, the crucial role played by home-sharing platforms have spurred a burgeoning literature about their impact on local economies.[3] Most of the literature has been devoted to analyzing the effects of short-term rentals on the real estate sector, documenting the deleterious impacts of Airbnb on housing prices and rents (Garcia-López et al., 2020; Barron et al., 2021; Batalha et al., 2022). The reallocation of housing units away from long-term rentals to short-term rentals spurred by P2P accommodations has induced a rise in housing rental prices. Similarly, the increase in housing prices has been rationalized as an increase in the option value of owning a housing unit, thanks to the possibility of short-renting and the capitalization of higher rental prices. The disruption effect of home-sharing platforms goes beyond the housing sector, negatively affecting the performance of traditional accommodations (Zervas et al., 2017; Li and Srinivasan, 2019), but at the same time, contributing to a more diversified supply of accommodation offer and lowering prices because of hotels' capacity constraints during periods of peak demand (Farronato and Fradkin, 2022; Schaefer and Tran, 2021).

Although most of the literature so far has stressed the negative consequences of Airbnb on the local economy, the advent of short-term rentals has also brought positive externalities, stimulating neighborhood and residential investment (Xu and Xu, 2021; Bekkerman et al., 2022). In particular, Alyakoob and Rahman (2019) and Basuroy et al. (2020) analyze whether Airbnb has positively affected local food and beverage

[3] For a comprehensive list of the contributions on the economic impact of Airbnb, see Table A1 in the Appendix.

services. Alyakoob and Rahman (2019) consider neighborhood or ZIP code data for New York City whereas Basuroy et al. (2020) use aggregated information at the ZIP code level for the state of Texas. Both papers rely on a Difference-in-Differences (DiD) strategy that exploits the different timing and intensity in the entrance of Airbnb across geographical areas. In this way, they can identify the effect of Airbnb, measured through the number of reviews or the number of reviews per household, respectively, on restaurant performance by comparing high and low Airbnb intensity zones before and after Airbnb entry. Both studies find that Airbnb positively affects restaurant outcomes even though the intensity of the effect varies considerably: a 1% increase in the number of reviews per household leads to a 1.7% increase in restaurant employment in New York (Alyakoob and Rahman, 2019); a 1% increase in the number of Airbnb reviews is associated with a 0.011% increase in restaurant revenue in the state of Texas (Basuroy et al., 2020). Available studies focus on the US context, not considering the different effects across the geography of cities or between different types of establishments. Against this background, our paper provides evidence of the overall effect of Airbnb on local consumption amenities in an European context. Moreover, we rely on a different instrumental strategy and analyze Airbnb effects across the geography and within the food and beverage sector.

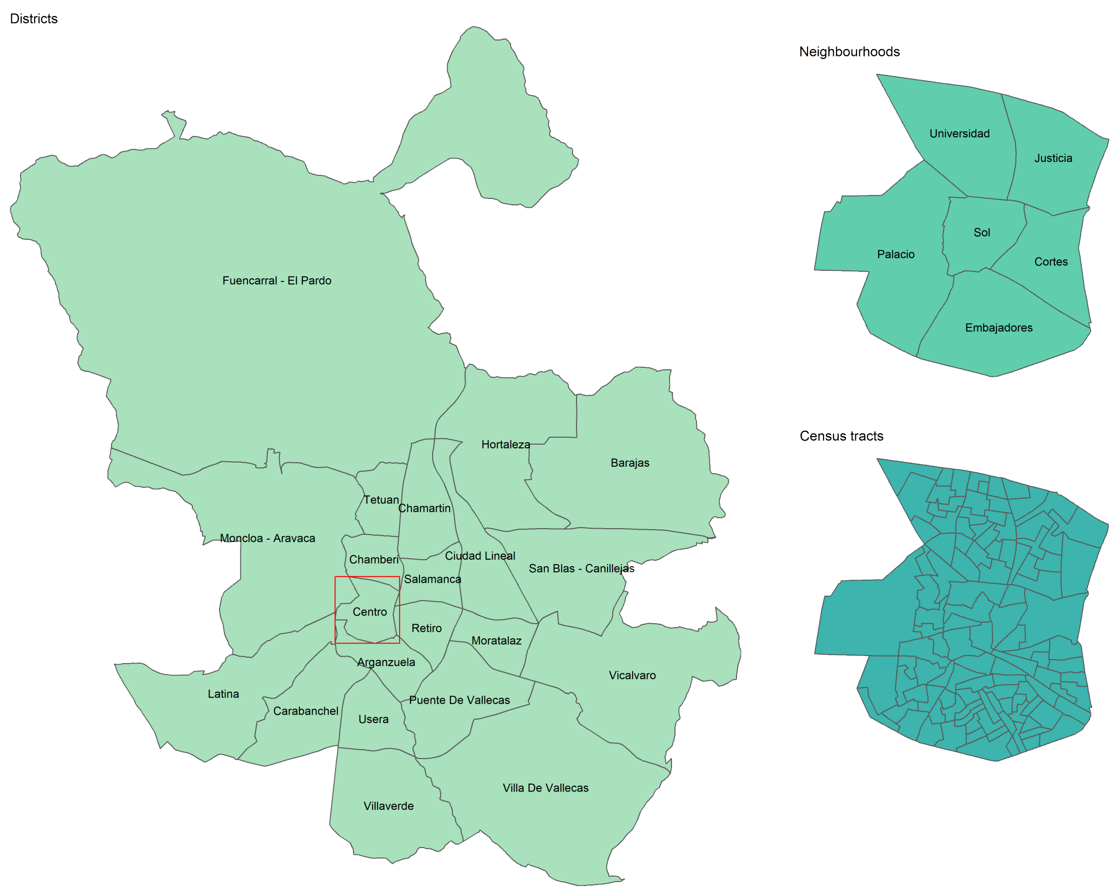
Our study also relates to the urban consumption literature (Glaeser et al., 2001). Several papers have shown how densely populated areas benefited from a great variety and provision of food-related establishments (Mazzolari and Neumark, 2012; Couture, 2013; Schiff, 2015; Couture and Handbury, 2020). Among the main channels that explain this trend are the overrepresentation of young people and the heterogeneity of ethnic origins citizens in urban areas. Both the number of local consumption amenities and their quality have proven to play a role (Kuang, 2017). Particularly relevant to our research question are the studies that show how spatial frictions explain the consumption, commuting, and prices patterns of cities. Many contributions highlight the role of *local consumption* (Davis et al., 2019; Eizenberg et al., 2021; Miyauchi et al., 2021; Su, 2022): consumers are much less likely to visit venues that are far from where they live. This is key in our study since we analyze the Airbnb-induced demand effect on *local* consumption amenities. Although most of the literature has analyzed the role of consumption amenities from the residents' lens, we instead focus on how tourists foster the performance and the creation of food-related establishments near their accommodations.

3 Data

Given the expected local effects of Airbnb-induced demand, it is advisable to use the most fine-grained level of analysis available. Therefore, our primary geographical units of analysis are Madrid's census tracts. Census tracts are the smallest statistical unit in Spain. In particular, the city of Madrid is organized in districts (21), neighborhoods (128), and census tracts (2,409), from the largest to the smallest administrative unit (see Figure I). As census tracts are built to represent a similar population (1,000-2,500 people) at a narrowly defined geographical resolution, they are suitable for analyzing local effects.[4]

[4]We create consistently-defined census tracts by fixing the boundaries at 2011 definition.

Figure I: Administrative units in Madrid.



3.1 Airbnb

We build the Airbnb activity variable by collecting yearly consumer-facing data from *Inside Airbnb* from 2014 to 2019.[5] As stated on its website, *Inside Airbnb* is an *"independent, non-commercial set of tools and data that allows you to explore how Airbnb is being used in cities around the world."* It offers listing information at different points in time from different cities around the world. For our purposes, we are interested mainly in the information regarding the geographical coordinates of the listing, the size, and

[5] *Inside Airbnb* provides annual snapshots of the evolution of the short-term rental sector in Madrid from 2015 onward. As Airbnb enters Madrid before 2015, we can recover the 2014 supply by looking at the date of the first review as a proxy of a listing's opening conditional on the listing's not have been deleted the platform. At the end of our sample period, the Madrid City Council approved a regulatory plan for short-term rentals (*Plan Especial de Hospedaje*). Under the new regulation, short-term rental activity was constrained to certain city areas. However, as the impact of such regulation was negligible (Urquiaga et al., 2019), we decided to incorporate the 2019 in our sample period.

insights about short-term rentals activity in Madrid. We must come up with a way to define when a listing is active or not. To do so, we use the date of the first and the last reviews as a proxy for the beginning and the end of the period that the listing has been active on the platform. On top of that, we consider the number of rooms in each accommodation unit as a proxy of its size. In this way, we are identifying Airbnb's potential impact on food and beverage establishment users.[6] Finally, we decided to remove shared and private rooms and instead of keep entire flats whenever we build our measure of Airbnb activity. The inclusion of shared and private rooms may confound the effect on local expenditure for Airbnb-induced tourists with the composition effect of owner-present and Airbnb users.

3.2 Local consumption amenities

We obtained yearly information from the Madrid City Council's census of business premises. The database created by the Madrid City Council Statistics Department (*Servicio de Estadística Municipal*) covers the universe of all business establishments in the Madrid municipality. The data set compresses establishment-level data under a four-digit NACE-based classification, location, and status (opening, closing, or under some reform). As the goal of the paper is to assess how Airbnb has affected local consumption amenities, we will focus on food and beverage establishments (NACE I.56), which account for the main expenditures made in-situ by tourists in Spain (INE, 2020). Previous research has shown for the case of Madrid that tourist expenditure is mainly concentrated in restaurants (Aparicio et al., 2021). For this reason, our main dependent variable will be the total number of food and beverage establishments at the census tract level.[7]

We have also accessed yearly food and beverage establishment employment from

[6] Previous contributions have trusted in different metrics of Airbnb activity such as the simple number of listings (Xu and Xu, 2021), the number of reviews (Garcia-López et al., 2020; Barron et al., 2021), or the proportion of listings over the number of dwellings (Franco and Santos, 2021). In our analysis, we consider alternative measures of Airbnb activity as robustness checks.

[7] Food and beverage establishments included the following activities: restaurant, fast food restaurant, self-service restaurant, bar restaurant, bar with kitchen, cafe, chocolate shop, tea room and ice cream parlor, bar without performance, bar with performance, tavern, bar without kitchen, cafe with performance. We disregard other consumption amenities highlighted in the literature as 1) the consumer pool is not local, e.g., museums, performance arts, and sports events and 2) they are not fully tourist-oriented, e.g., grocery, clothing, and gyms.

the Madrid City Council Statistics Department. However, because the employment data is confidential, we have access only to employment statistics at the neighborhood level from 2010 to 2019. Therefore, as a second dependent variable, we consider the number of employees of the food and beverage service sector at the neighborhood level.

3.3 Control variables

We complement our data set with a set of variables to control for other factors related to either the establishments or employment in the food and beverage business. Previous studies have shown these factors, such as population, proportion of foreign people, average household income, distance to the city center and number of rooms in hotels and hostels, to be important determinants (Mazzolari and Neumark, 2012; Schiff, 2015). Our goal is to control for local market demand, urban revival, tourism trends and business cycles, adding population, income, and traditional accommodation supply variables. Demographic variables were obtained from inhabitants' register statistics (*Padrón Municipal*) whereas traditional accommodations information comes from the Madrid City Council Statistics Department and Expedia. Average household income was collected through the Spanish Household Income Distribution Atlas and distance to the city center from the Spanish National Geographic Institute[8]. A final list with all the variables used can be found in Table A2 in the Appendix.

3.4 Descriptive statistics

Airbnb activity and the number of food and beverage establishments have increased in Madrid over the period analyzed. Meanwhile, the total hotel room supply has only marginally changed (see Table 1 and Figure II). That divergence is partially explained by local planning ordinances that restrict the location of traditional accommodations and the flexibility of short-term rental supply based on already existing dwellings. We can also observe how sociodemographic indicators like average household income or population improve over the period of study. This is the result of the recovery process taking place in Madrid in the years after the Great Recession and the burst of the Spanish housing bubble.

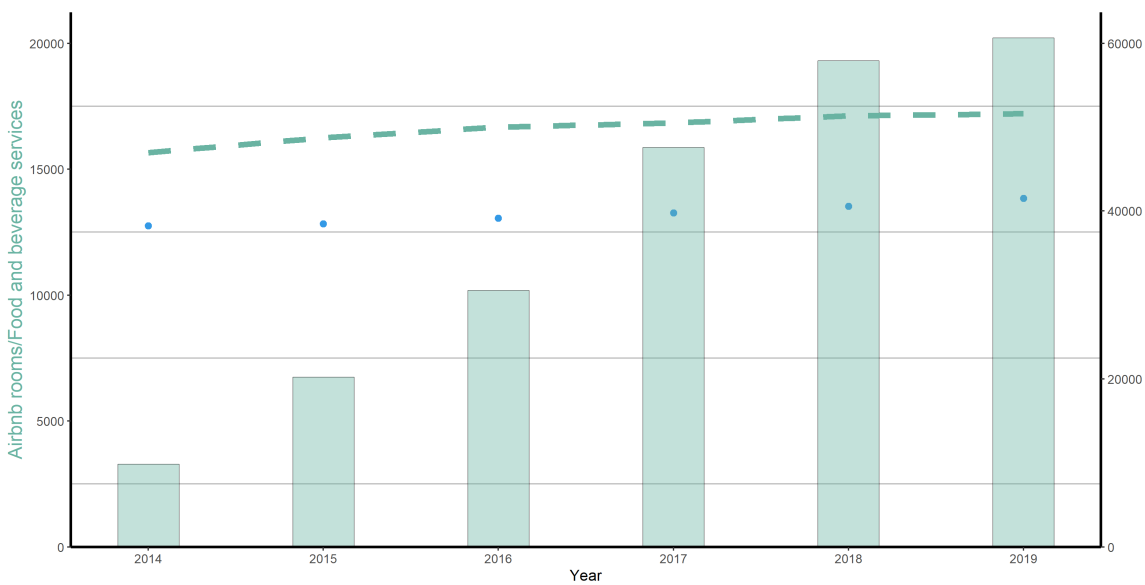
[8]We measure the distance to the center as the distance from *Puerta del Sol* (main square in Madrid city) to the centroid of each census tract.

Table 1: Descriptive statistics

	2014			2019		
	Sum	Mean	S.d.	Sum	Mean	S.d.
Food and beverage establishments	15,660	6.501	8.124	17,212	7.145	9.094
Airbnb listings	2,153	0.894	3.516	12,763	5.298	16.598
Airbnb rooms	3,288	1.365	5.337	20,215	8.391	25.855
Hotel rooms	38,255	15.88	83.099	41,534	17.241	87.894
% Foreign population	311.7	0.129	0.071	356.9	0.148	0.085
Population	3,166,465	1,314.431	508.245	3,278,988	1,361.141	668.755
Avg. household income	86,736,299	36,005.105	14876.846	99,176,288	41,169.069	17,359.439

Notes: N = 14454, census tracts = 2409. Descriptive statistics for census tract level observation.

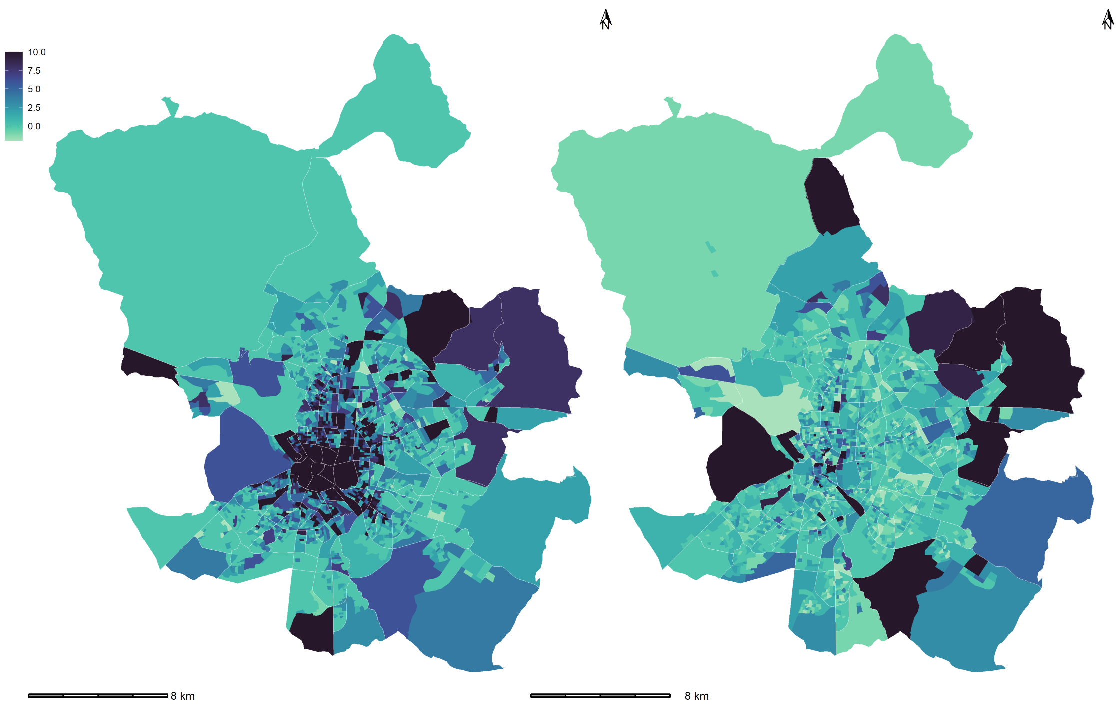
Figure II: Number of food and beverage establishments, Airbnb and hotel rooms from 2014 to 2019.



Notes: Left scale is for food and beverage establishments (dashed) and Airbnb rooms (bars). Right scale is for evolution of hotel rooms (dots).

The positive correlation between short-term rentals and food and beverage establishments also holds spatially, as we can see in Figure III. The uneven distribution of short-term rentals across the city allows us to infer that Airbnb spillover into local consumption occurs not only in city center areas (where the increase in the number of Airbnbs has been the highest) but also in more peripheral areas. As peer-to-peer accommodations are based on owners' dwellings, they can rapidly expand over the urban geography. In turn, Airbnb listings tend to localize not only near the tourist attractions that, in the case of Madrid, coincide with the city center and surrounding areas but also in other non-touristic neighborhoods.

Figure III: Spatial correlation in the change of the number of Airbnb rooms and consumption amenities during the period 2014-2019.



(a) Δ Airbnb rooms 2014-2019 (b) Δ Consumption amenities 2014-2019

Notes: Map (a) plots the change in the number of short-term rentals during the period 2019-2014 whereas map (b) depicts the change in food and beverage establishments for the same period.

4 Methodology

4.1 Model specification

The aim of this paper is to study the impact of Airbnb entry in Madrid on the local food and beverage sector. We claim that Airbnb entry might have a positive impact on local food and beverage activities, especially in non-touristic areas. To answer our research question, we start with our baseline specification, which takes the following form:

$$Y_{i,t} = \beta Airbnb\ rooms_{i,t} + \rho X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is the number of food and beverage establishments in a census tract i in year t, $Airbnb\ rooms_{i,t}$ is the number of rooms in Airbnb listings in each census tract, $X_{i,t}$ are time-varying variables, δ_t are year fixed effects, and γ_i are census tract fixed effects. Among the time-varying characteristics, we include the population, the proportion of foreign residents, the average household income and the number of traditional accommodation rooms. With this set of variables, we aim to control for time-varying census-specific trends correlated with the number of food and beverage establishments and Airbnb listings as a local process of urban revival, business cycle, and tourism trends other than short-term rentals. We also include the interaction between a time trend and the distance to the center to allow for different trends according to the geographical location of each census tract. To account for time-invariant characteristics, like the size area, we add census tract fixed effects. Finally we include year time fixed effects for cyclical changes.

Above all, we are interested in β of Eq. 1, which measures the average treatment effect of Airbnb on the number of food and beverage establishments. However, the number and type of Airbnb rooms are likely correlated with the disturbance term because of time-varying unobserved location characteristics (e.g., changing census tract amenities). Besides, we may have a problem of reverse causality as the number of food and beverage establishments might attract (agglomeration effect) or deter (inhibition effect) new Airbnb listings. Finally, we do not know precisely when they are active or not since we approximate the number of active Airbnb rooms with the number of listings with customer reviews. Therefore, our empirical setting calls for an instrumental variable (IV) strategy to deal with the endogeneity of our variable of interest.

Our IV strategy is based on a Bartik-like instrument, where we use the share of rental houses in each census tract in 2011 (before Airbnb's arrival to Madrid) as the initial shares, and the worldwide Airbnb Google searches as the shift.[9] The growth of Airbnb rentals in an area relies on the local supply of rental houses that can be let out for Airbnb. As Airbnb grows globally over time, there is different growth in the number of Airbnb listings across census tracts due to the availability of housing to be let out for Airbnb. Therefore, census tract housing supply, which is mainly historically determined, creates different tracts to experience different levels of Airbnb's penetration. We use this variation in short-term rentals census tract growth to measure the effects on food and beverage establishments.

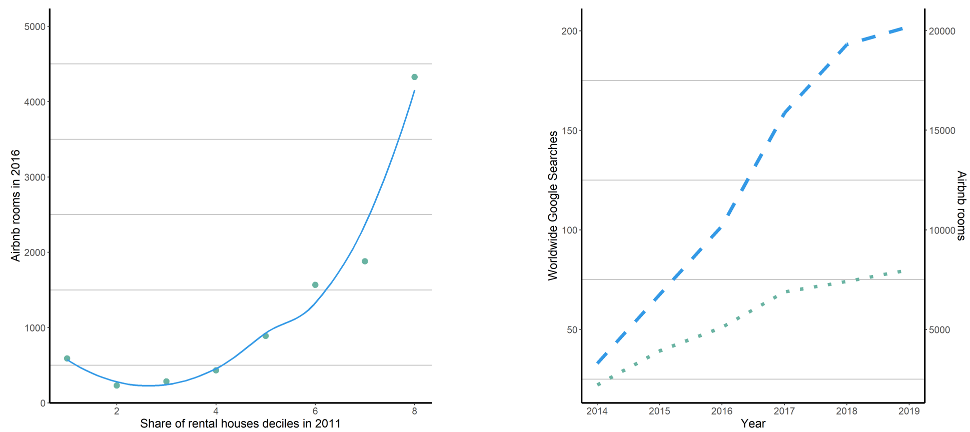
It can be easily seen that, whereas the shares explain either the extensive or the intensive margin of the treatment, the shift describes timing. More formally,

$$Shift\text{-}Share_{i,t} = Share\ Rental\ houses_{i,2011} \times Worldwide\ Airbnb\ Google\ Searches_t \quad (2)$$

where $Share\ Rental\ houses_{i,2011}$ are the share rental houses in census tract i in 2011, and $Worldwide\ Airbnb\ Google\ Searches_t$ are the normalized worldwide Airbnb Google searches. The relevance of our instrument rests on the fact that, as Horn and Merante (2017) have shown, the main mechanism by which Airbnb is expanding in the real estate sector is by the decrease of the stock of long-term rentals and the increase of the supply of short-term rentals. In fact, we can see that there is a positive and significant relationship between the share of rental houses in each census tracts and the posterior Airbnb activity (in Figure IV, panel a). Moreover, we can also observe that the evolution of worldwide Airbnb Google Searches mimics Airbnb growth (in Figure IV, panel b).

[9] We get tenancy type information from the Spanish Census 2011 and the number of worldwide searches of the word Airbnb from Google Trends. This variable is measured yearly and is normalized to 100 for the year with the highest number of searches.

Figure IV: Shift-share instrument relevance.



(a) Airbnb Madrid supply and rental houses.

(b) Worldwide Airbnb Google searches and Airbnb Madrid supply.

Notes: Subplot (a) depicts how Airbnb supply in 2016 is positively correlated with the share of rental houses divided by deciles. Subplot (b) shows the evolution of worldwide Airbnb Google searches (dashed dotted line) and the growth of Airbnb in Madrid (dashed line).

Differently from Garcia-López et al. (2020) and Barron et al. (2021), we rely on a supply share driver rather than a demand share for two reasons. First, the share of rental houses predicts prospective Airbnb activity outside the city center (see Figure A2). Short-term rentals are based on owners' idle property rather than construction. Therefore, between two census tracts located at the same distance to the city center, it is more likely that new Airbnb listings appear in the census tract with the higher share of rental houses as hosts may find it easier to switch from long-term rentals to short-term rentals rather than investing in new flats. Second, the number of tourist features used in Garcia-López et al. (2020) and Barron et al. (2021) may violate the exclusion restriction, as they are directly related to the distance to the city cente, where most of the tourist amenities are concentrated. Regarding our shift instrument, the number of worldwide Airbnb Google searches parallels the timing and expansion of Airbnb in Madrid, as Figure IV, panel (b) shows. The basic idea behind using this shift is that potential hosts in Madrid are more likely to rent their property in the short-term market in response to growing interest in Airbnb as a global platform (Barron et al., 2021).

Concerning the exclusion restriction, it is highly unlikely that worldwide Airbnb

Google searches are directly correlated with the increase in the aggregate attractiveness of Madrid. Airbnb is a global company with a presence in more than 100,000 cities in over 190 countries. Therefore, we can safely claim that our Bartik-like instrument's shift part is exogenous to Madrid's local conditions. To satisfy the exclusion restriction, our share instrument $Share\ Rental\ houses_{i,2011}$ must be correlated only with the *changes* in our dependent variable through the effect of Airbnb. In our setting, the main channel through which the stock of rental houses before Airbnb's arrival should affect the number of food and beverage establishments is through the switch from long-term rentals to short-term rentals driven by Airbnb disruption. We test for this requirement as follows.

First, we check whether our share instrument predicts the changes in the number of food and beverage establishments for census tracts that have never experienced any Airbnb activity. This exercise aims to prove whether the instrument is valid and correlated only with the dependent variable through its effects on Airbnb. We do not find any significant relation between our share instrument and the change in the number of food and beverage establishments in those census tracts (see the estimates of the reduced form of our baseline IV specification in Equation (1) and Equation (2) in Column 1 from Table A3 in the Appendix).

Second, a key concern with the instrument is that census tracts with high shares of rental houses may explain changes in local consumption amenities even before Airbnb's arrival (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). On the one hand, as can be seen in Figure A1, long-term residents' taste for tourism-related activities barely changed over the period of study, regardless of the tenancy regime. On the other hand, to show that the parallel trends hold in our setting, we regress the pre-period 2005-2010 change in the number of food and beverage establishments against the 2014-2019 change in Airbnb rooms predicted by the share of rental houses in 2011.[10] We control for population, proportion of the foreign population, distance to the city center and number of traditional accommodation rooms measured in 2005. We can notice that whereas the coefficient of interest is not statistically significant for the Airbnb pre-entry

[10] We obtained yearly information about local consumption amenities from the Madrid Region Census of business premises. This database compiles information for the universe of establishments in the Madrid region for the period 1998-2010. For our purpose, we restrict consumption amenities data to Madrid municipality.

period, it is significant for the period 2014-2019, where we replicate the same specification but using contemporaneous local consumption amenities data (see Column 2 in Table A3 and Column 3 in Table A3). All in all, our findings show that historical areas with a high share of rental houses are not in census tracts that were already undergoing different trends correlated with the evolution of local consumption amenities.

Having provided evidence about the validity of our proposed instrumental strategy, we now turn to analyzing the effect of Airbnb's arrival on the food and beverage establishments in Section 5.

5 Results

In this section, we summarize the main results of our analysis. First, we describe and discuss the estimates of the effect of Airbnb on the food and beverage sector for our baseline specification and then for our instrumental strategy specification. Then, we decompose the overall effect into displacement and net food and beverage establishment creation.

Table 2 presents the results of our baseline OLS and IV specifications. Our baseline sample includes 2409 census tracts for six years. Our dependent variables are the number of food and beverage establishments in Columns 1-5 and the number of new and existing establishments, using 2014 as the reference year, in Columns 6 and 7, respectively. In Column 1, we regress the number of food and beverage establishments on the number of Airbnb rooms, controlling for time-varying controls. Due to the potential existence of time-invariant census-specific characteristics related to the number of food and beverage establishments and the Airbnb activity or the existence of a common trend that equally affects all our geographical units, we add census tract and year fixed effects in Columns 2 to 7. Finally, we also include the interaction between a time trend and the distance to the center to allow for different trends according to the geographical location of each census tract in Columns 3 and 5-7.

Table 2: THE IMPACT OF AIRBNB ON THE NUMBER OF FOOD AND BEVERAGE ESTABLISHMENTS (OLS AND IV).

	OLS			IV			
	(1)	(2)	(3)	(4)	(5)	(6)[a]	(7)[b]
Airbnb rooms	0.197***	0.022***	0.021***	0.054***	0.071***	0.039***	0.032***
	(0.009)	(0.004)	(0.004)	(0.009)	(0.014)	(0.008)	(0.009)
Covariates	x	x	x	x	x	x	x
Census tract fixed effects		x	x	x	x	x	x
Year fixed effects		x	x	x	x	x	x
Distance × year			x		x	x	x
Adjusted R-squared	0.450	0.986	0.987				
F Stat, Excluded instrument				48.466	68.246	68.246	68.246

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. [a] new food and beverage business premises, [b] existing food and beverage business premises. Heteroskedasticity standard errors for Column 1 and cluster standard errors at the census tract level for Columns 2-7. The dependent variable is the number of food and beverage establishments in Columns 1-5, the number of new food and beverage establishments in Column 6[a], and the number of existing food and beverage establishments in column 7[b] using as reference existing establishments in 2014. We use the interaction between the share of rental houses in 2011 and the worldwide Airbnb Google searches as an instrument for *Airbnb rooms* variable.

At first glance, the results do not seem to depend on the selected model: in all models, we find a positive and significant effect of Airbnb activity on the number of food and beverage establishments. The inclusion of controls makes the coefficients for Airbnb activity somewhat reduced. However, they remain significant across all specifications. Although we control for an extensive range of factors, we cannot rule out unobserved time-varying characteristics related to Airbnb activity and the changes in the number of food and beverage establishments. Therefore, we use an instrumental variable strategy to overcome the potential endogeneity problem in the Airbnb activity variable. Our instrument, the interaction between the share of rental houses in 2011 and worldwide Airbnb Google searches, predicts Airbnb activity as can be seen in the Kleibergen-Paap Wald F-test value. In the second stage, we can see that the sign of the Airbnb effect remains positive and the magnitude has increased.[11]

[11] One potential criticism of our share instrument is that the proportion of rental houses may be affected by Airbnb arrival because of the anticipation behavior of future hosts. To rule out potential anticipated demand for short-term rentals in 2011, we modify our share component by computing the share of rental houses in 2001 using 2001 Spanish census information. Column 4 in Table A3 in the Appendix confirms our initial findings. Also, we show that our main results hold no matter the source of exogenous variation exploited in our identification strategy. We select a series of supply share drivers instruments related to the number of food and beverage establishments only from their effect on the posterior evolution of Airbnb. Columns 5-8 in Table A3 show that our main tenets hold

Indeed, the IV coefficient (Column 5) is more than twice as large as the OLS (Column 2). The downward bias in the OLS estimates may be explained by omitted factors positively correlated with the presence of Airbnb in a census tract but negatively related to the change in the number of food and beverage establishments. Also, measurement errors might play a role in biasing our OLS estimates toward zero since we do not know precisely whether an Airbnb is active or not. Lastly, the IV coefficients reflect the effect of converting the stock of rental houses into short-term rentals. In contrast, the OLS specification estimates only the effect of the number of short-term rentals. Consequently, in the presence of heterogeneity of the effect, IV-coefficients estimate the local average treatment effect (LATE) on compliers; that is, we estimate the effect in census tracts identified by our instrument as having a high number of home rentals before Airbnb's arrival and potentially a large number of short-term rental rooms afterward.

In economic terms, our estimates imply that for each increase in 10 Airbnb rooms, the number of food and beverage establishments increases on average to near the unity in each census tract. However, our coefficient may mask displacement effects from other non-local consumption amenities. To rule out that the entry of Airbnb is associated with pure displacement effects, we disaggregate our main dependent variable, the number of food and beverage establishments, into two groups: new establishments which provide food and beverage services and existing establishments which provide food and beverage services, too. New establishments represent the opening of new physical business premises, taking the number of establishments present in 2014 as the reference.[12] We can observe that the growth in local consumption amenities led by Airbnb is explained equally by new and existing establishments. The sums of each group approximately return our coefficient, 0.071 food and beverage establishments per census tract per year, as expected since we are estimating a linear additive specification.

with either an absolute measure as the total number of houses, total number of rental houses, and total number of empty houses or a relative measure such as the proportion of rental and empty houses. However, our share instrument lost relevance in some cases as can be seen in the lower values of the Kleibergen-Paap Wald F-test.

[12] As an example, a business premise which offered hairdresser services in 2014 and starts to offer restaurant services in the following years would be in our group of existing establishments. The building of business premises that offer food and beverage services would be in the new establishment group.

5.1 Robustness checks

We tackle the threats to the identification of our main findings in the following ways. First, we check whether our main tenets hold whenever we change the functional form of our regression specification. Instead of using a level-level specification, we estimate a log-level equation by taking the logarithm of our dependent variable and also perform a control function IV non-linear model. We also show that our results also hold whenever we change how we measure short-term rental activity and control for spatial spillovers. Second, we focus on a different city and different samples to test that specific tracts do not drive our results. Finally, we use different aggregation scales as the unit of observation.

5.1.1 Alternative specification

For our baseline specification, we opted for a level-level form since many census tracts have only a few food and beverage establishments. Using a logarithmic transformation instead of levels, we would give more importance to small absolute changes than warrants. However, we estimate a log-level specification to show that our main findings are not model-specification-dependent. Moreover, we reestimate our IV equation specification using a novel control function IV approach that was proposed by Lin and Wooldridge (2019) and allows us to estimate non-linear scenarios with fixed effects. Table 3 shows that our results do not depend on the specific functional form of the model and are similar in magnitude: an increase in 10 Airbnb rooms translates to a 4% increase in food and beverage establishments.

As a second robustness check, we turn our attention to the way of measuring our dependent variable. The consumer-facing information retrieved from *Inside Airbnb* includes a great variety of size-related variables like the number of rooms, the number of beds and the maximum number of guests for each listing. Also, it provides information about the demand, such as the total number of reviews. The number of Airbnb rooms may not be the best measure of Airbnb activity as it may capture some housing characteristics of some areas of the city and does not reflect the actual level of demand. As each variable conveys different information from the listing, we decide to check whether our results are robust using different measures of Airbnb activity, like the number of Airbnb listings or the number of reviews for each listing. Again, the results in Table 3 show that our findings are not sensitive to alternative ways of measuring short-term rental activity.

In our baseline model specification, we assume that the Airbnb-induced tourism demand effect is restricted to the census tract where the Airbnb listing is located. This is a strong assumption considering the small size of our geographical unit of analysis. Although using census tracts allows us to better capture the effect of Airbnb on the number of food and beverage establishments, their reduced dimension makes them more prone to spillover problems from other short-term rental accommodations in the surrounding census tracts than bigger administrative units like neighborhoods or ZIP codes. Not taking into account the presence of spillovers makes us overestimate but also maybe underestimate the effect of Airbnb on the number of food and beverage establishments. On the one hand, the critical mass of potential customers increases with the Airbnb tourists of each census tract and the Airbnb guests of the neighbors' census tracts. On the other hand, Airbnb may be shifting demand away from census tracts without short-term rentals because of the creation of food and beverage clusters, leading to an increase in the number of food and beverage establishments in the census tracts with a strong Airbnb presence and a decrease in the surrounding neighborhoods.

To account for the potential spillover effects of the Airbnb presence in neighboring census tracks, we include the spatial lag of our variable of interest as another regressor: the weighted number of Airbnb rooms in census tracts neighbors.[13] Since Airbnb guests are more willing to consume only in nearby census tracts, we expect that Airbnb-induced tourism demand affects only nearby areas. As the weighted number of Airbnb rooms in census tract neighbors is probably endogenous, we instrument the spatial lag of Airbnb rooms with the interaction between worldwide Airbnb Google searches and the spatial lag of the share of rental houses in 2011.

Table 3 (E) shows the results of our baseline IV specification where we have augmented it, including the spatial lag of Airbnb activity and, as its instrument, the spatial lag of our shift-share variable. We see that once we consider potential spatial spillovers, our coefficient of interest does not change.[14] Therefore, we can conclude that our baseline model is defined at the appropriate level and it captures the full effect of Airbnb

[13]Census tracts neighbors are defined as all areas up to 500 meters away from each census tract centroid.

[14]The coefficient of the spatial lag of Airbnb activity is not significant in our specification.

on local consumption amenities.

Table 3: Robustness checks

Alternative specification	Coefficient	Alternative sample	Coefficient
A. Alternative specification (Log-log IV)	0.004***	F. Alternative sample (Barcelona)	0.154***
	(0.002)		(0.053)
B. Alternative specification (Poisson IV)	0.004***	G. Alternative sample (No hotel census tracts)	0.119***
	(0.002)		(0.029)
C. Alternative Airbnb measure (Listings)	0.1526***	H. Alternative sample (No city center and periphery)	0.116***
	(0.053)		(0.025)
D. Alternative Airbnb measure (Reviews)	0.002***	I. Alternative aggregation unit (Neighborhoods)	0.045***
	(0.012)		(0.010)
E. Spatial Spillover (Spatial Matrix)	0.068***	J. Alternative aggregation unit (Transport zones)	0.056***
	(0.014)		(0.006)

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. The dependent variable is the number of food and beverage establishments. All specifications are IV regressions with clustered standard errors at the census tract level in results A-H and neighborhood and transport zones in results I and J, respectively. We use the interaction between the share of rental houses in 2011 and worldwide Airbnb Google searches as an instrument for *Airbnb rooms* variable. Results A-E provide estimates of the effect of Airbnb on local consumption amenities where we modify our IV specification as follows: taking logarithms of the dependent variable (A), estimating a control function IV proposed by Lin and Wooldridge (2019) (B), changing the number of Airbnb rooms for the number of listings (C) and the number of reviews (D) and adding the spatial lag of the number of Airbnb rooms from census tract neighbors up to 500 meters away. Results F-J provide estimates of the effect of Airbnb on local consumption amenities where we modify our baseline sample in the following way: in result F, we estimate the same IV specification for Barcelona. Results G and H limit the sample to census tracts with no hotel rooms and census tracts outside the city center or near the airport, respectively. Finally, results I and J aggregate the data into neighborhood and transport zone areas.

5.1.2 Alternative sample

So far, we have seen that our baseline results do not depend on the functional form, the way of measuring our variable of interest, or the existence of spatial spillovers. In this section, we want to test the robustness of our results using different samples. First, we leverage that our instrumental variable strategy relies on open-access information accessible in every country to see whether our main tenets hold in other contexts. In particular, we have chosen the city of Barcelona, which has also undergone rapid tourism growth in short-term rental activity (Gutiérrez et al., 2017; Garcia-López et al., 2020). We have collected local consumption amenities information from the Barcelona City Council's census of business premises for the three cross-sections that corresponds to 2014, 2016, and 2019. We complement this information with the population, the proportion of foreign population, the average household income, the distance to the city center, and the number of traditional accommodation rooms. We apply our instrumental variable strategy as in our baseline IV specification (Column 5 in Table 2). The positive and statistically significant coefficient in F from Table 3 shows us that Airbnb spillover effects onto food and beverage services also hold in a context other than Madrid.

A potential violation of our exclusion restriction may stem from the non-random location of the Airbnb listings as most short-term rentals are in the city center and close to the airport. Because of this non-random Airbnb listing location, the main challenge is to disentangle the impact of Airbnb on food and beverage establishments from other effects triggered by traditional accommodations or local visitors. For instance, the number of food and beverage establishments may be increasing because of additional tourist flows coming from new or existing hotels in areas identified by our instrument as having a high share of rental houses prior to the arrival of Airbnb and, potentially, a large number of Airbnb rooms thereafter. This phenomenon is relevant to Madrid, where tourists are concentrated mainly in the city center (García-Palomares et al., 2015; Salas-Olmedo et al., 2018; Aparicio et al., 2021). That issue is partially solved by controlling for time-varying accommodation activities that directly affect tourist-related business like traditional accommodation rooms and distance to the city center time trends. Still, we cannot rule out other phenomena, such as a change in locals' taste toward eating out in the city center or a higher demand for the existing accommodations units.

We approach the problem of an increase in demand stemming from new or existing traditional accommodations or changes in locals' taste towards eating out in the city center as follows. In the first exercise, we remove the census tracts where a hotel is located. In this manner, we rule out potential spatial spillover effects from hotel users. In a second exercise, we remove census tracts in the city center or near the airport.[15] Results G and H in Table 3 rule out that city center characteristics or traditional accommodation confounders drive our results. In this regard, it seems that Airbnb has a more significant impact on non-tourist areas as these short-term rentals may be seen as a substitute for hotels Zervas et al. (2017). Therefore, the Airbnb-induced tourism effect is attenuated whenever other accommodations are around. Also, the opportunity cost of opening new establishments is lower in areas outside downtown because of a downward-sloping commercial rent gradient, although the COVID-19 disruption may attenuate this trend (Rosenthal et al., 2021).

[15] We are removing three city center neighborhoods and three neighborhoods close to the airport. In particular, we remove the following neighborhoods: Aeropuerto, Casco Histórico de Barajas, Alameda de Osuna, Palacio, Cortes, Justicia and Sol.

Finally, we further test whether our main tenets hold whenever we use the same regression specification and city but change our geographical unit of analysis. Instead of census tracts, we aggregate our data to the neighborhood level (128) and transport zones (481).[16] This exercise aims to address the ubiquitous statistical problem in spatial analysis framed as the Modifiable Areal Unit Problem (MAUP). Moreover, we reduce the concerns about spatial spillovers not captured in our spatial matrix specification by aggregating our data to larger administrative units, whose boundaries should be big enough to contain the effects of Airbnb spillovers.

Table 3 (G and H) shows that even though we find a positive and significant effect of Airbnb activity on the number of food and beverage establishments, this effect is higher in magnitude whenever we use our smaller geographical unit of analysis, the census tracts. The reduced size of that administrative unit of analysis allows us to better identify the tourism-induced effect of Airbnb as they are less heterogeneous than within neighborhoods or transport zones, which may explain the smaller magnitude of the coefficient.

5.2 Mechanism

Having explored Airbnb's impact on local consumption amenities and the robustness of our findings, we now turn to the mechanisms that may explain these results. First, we analyze whether Airbnb spillover effects on food and beverage establishment creation extend to employment in these activities, decomposing the overall Airbnb-induced employment effect between the intensive and the extensive margin. Second, we assess whether there are heterogeneous effects within the activities classified as local consumption amenities. We conclude by evaluating the impact of short-term rental activity on other local economic activities related to gentrification and urban revival.

[16] Transport zones (ZTs) constitute one of the basic spatial units for analysis and aggregation of information in Madrid. The Madrid Regional Transport Consortium defines them to collect information for doing surveys regarding the mobility patterns of Madrid's inhabitants. Its size approximates a scale of territorial division between the neighborhood and the census tract.

5.2.1 Employment

Along with the analysis, we have been focusing on the impact of Airbnb on the number of food and beverage establishments. However, employment in that activity may have grown as well. Unfortunately, we do not have access to restaurant employment at the census tract level, but only at the neighborhood level on a yearly basis. Therefore, to test whether employment in the restaurant industry has been affected by the entry of Airbnb in Madrid, we replicate our IV specification using the neighborhoods as our geographical unit of analysis and years as our time frame. Table 4 Column 1 summarizes the main findings.

Overall, the effect of Airbnb activity on employment is greater than the effect it has on the number of food and beverage establishments, as the employment variable is jointly picking up the effect of the extensive margin (positive variation in the number of restaurants) and the intensive margin (positive variation in the employment of restaurants). Because of the inaccessibility of individual employment data, we cannot disentangle one effect from the other. However, we can obtain a back-of-envelope estimate under the assumption that new restaurants and existing restaurants vary the employment equally.[17] The extensive and intensive margin evenly contribute to the increase in employment for food and beverage establishments.

Although we have previously ruled out the existence of different pre-trends in the change of the number of food and beverage establishments for census tracts where the share of housing rentals was high in 2011, we still do not know whether our instrumental strategy also satisfies the parallel trend assumption when the dependent variable is the employment of the restaurants. To check for parallel trends, we can use the employment level data for food and beverage establishments at the neighborhood level from 2010 onward.

Therefore, following Goldsmith-Pinkham et al. (2020), we run the following event study

$$Employment\, food\, beverage_{i,t} = \sum_{t \neq 2014} \lambda_t \times \delta Rental\, houses_{2011} + \rho X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t} \quad (3)$$

[17] The proof of the approximation decomposition is provided in Equation (4) and Equation (5) in the Appendix.

where we interact the share of rental houses in 2011, *Rental houses*, with year dummy variables λ_t, using 2014 as the base year. We choose 2014 as our base year as, in this year, Airbnb activity in Madrid became more significant. We control for the population, the proportion of the foreign population, the number of traditional accommodations and the distance to the city center time trends.[18] As our main results are driven mainly by areas where the share of rental houses is high, the main idea of this test is to check whether those areas were also experiencing a different trend in the evolution of the outcome variable. As can be seen in Figure V, the coefficients before Airbnb's entry are not different from zero. This result reassures us that it was Airbnb behind the increase in employment in the food and beverage sector. Therefore, we can conclude that there is no evidence that suggests a violation of the parallel trends assumption, or that Airbnb did not enter neighborhoods after observing an expansion in food and beverage amenities.

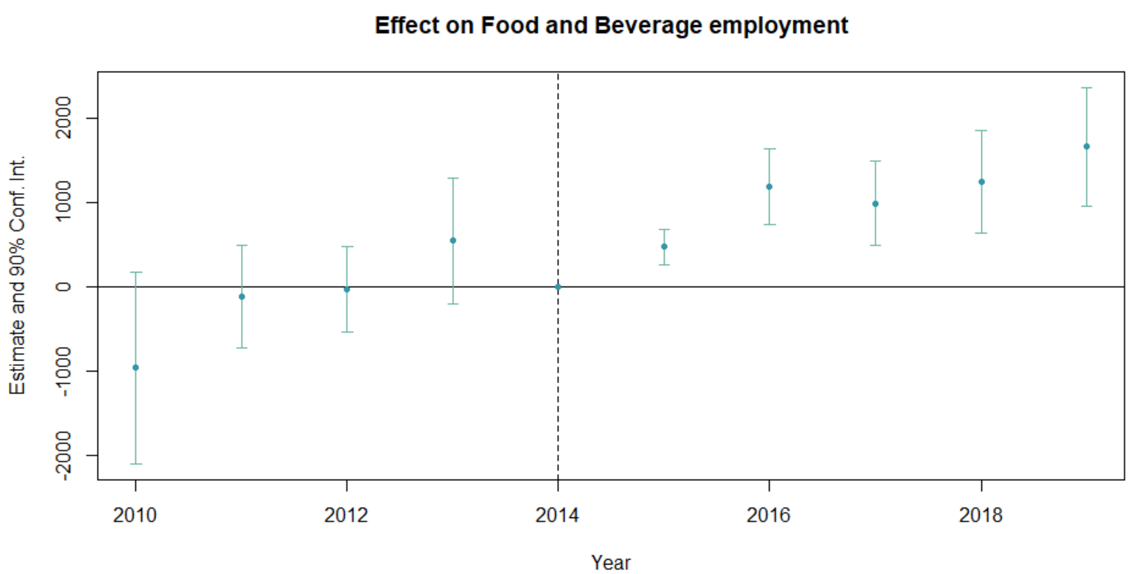


Figure V: Event study plots for employment 2010-2019.

5.2.2 Heterogeneous effects

So far, we have analyzed the Airbnb-induced tourism demand effect on the number of food and beverage establishments as a whole. However, our data set allows us to see

[18]The information about average household income is not available for years before 2014.

whether Airbnb also fosters the entry of some local consumption amenities individually. Therefore, in Columns 2-5 in Table 4, we run our preferred specification of the IV model using: the number of restaurants, the number of bars, the number of cafes and the number of clubs as dependent variables. We find a larger effect in the first category. This makes perfect sense since restaurants are the most tourist-oriented food and beverage establishments, whereas locals use bars and cafes regularly. In line with our previous findings, the sums of each category approximately return our coefficient, 0.071 food and beverage establishments per census tract per year, as expected since we are estimating a linear additive specification.

Table 4: Mechanism.

	Employment	Heterogeneous effects				Gentrification activities
	Food and Beverage	Restaurants	Bars	Cafes	Clubs	Cultural and creative industries
	(1)	(2)	(3)	(4)	(5)	(6)
Airbnb rooms	0.7976**	0.036***	0.023***	0.011**	-0.001	0.007
	(0.356)	(0.008)	(0.006)	(0.006)	(0.002)	(0.006)
Covariates	x	x	x	x	x	x
Census tract fixed effects	x	x	x	x	x	x
Year fixed effects	x	x	x	x	x	x
Distance × year	x	x	x	x	x	x

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. The dependent variable is the employment in food and beverage establishments in Column 1, the number of restaurants, bars, cafe and clubs in Columns 2-5, and the number of cultural and creative industries as in Behrens et al. (2018) in Column 6. All specifications are IV regressions with clustered standard errors at the neighborhood level (Column 1) and census tract level (Columns 2-6). We use the interaction between the share of rental houses in 2011 and the worldwide Airbnb Google searches as an instrument for *Airbnb rooms* variable. We remove El Viso and Castilla neighborhoods in our Column 1 specification due to inconsistent temporal data in the employment variable. Both neighborhoods are outside the city center.

5.2.3 The impact of Airbnb on other local economic activities

We are fully aware that, in our analysis, there might still be census-tract-specific time-varying unobservables correlated with Airbnb and the number of food and beverage establishments. To test that Airbnb and not other factors drive our findings, we exploit that short-term rental accommodations should affect only tourist-related activities, in general, and local consumption amenities in particular. Therefore, we perform our analysis on activities which may be related to a confounding phenomenon, like urban revival and cultural and creative sectors activities.[19] The existence of this confounder

[19]For a list of all activities related to those sectors, please refer to Table A4 in the Appendix. This information was collected from the Madrid City Council's census and matched with the Behrens et al. (2018) gentrifiers classification.

correlated with the presence of Airbnb and the number of food and beverage establishments may invalidate our identification strategy, as we will erroneously claim that Airbnb is behind the explosion in the number of food and beverage establishments. Conversely, if there is no unobserved time-varying trend, we should not find any effect of Airbnb on those economic activities as Airbnb fosters mainly tourist-related activities. Column 6 in Table 4 shows no effect of Airbnb on non-tourist-related activities.

6 Conclusions

This paper examines the impact of the most popular short-term rental company, Airbnb, on local consumption amenities. Using a fine-grained census of local store data sets and exploiting the exogenous variation created by the rapid and unequal entry of short-term rentals across the geography of Madrid, we find positive and significant effects on the food and beverage sector. Those effects are explained by displacement and new establishment creation alike. Interestingly, Airbnb spillover effects on local consumption amenities are heterogeneous within food and beverage activities, with restaurants the main activity that benefit from Airbnb disruption. Across the urban geography, we find that the impact is stronger in less touristic areas, which reinforces the idea that peer-to-peer accommodations help redistribute tourism consumption aound the city. Our results are very stable across different specifications: they are not driven by the functional specification form, the way of measuring Airbnb activity, or the presence of spatial spillovers. They are also robust to sample composition: using a different city, filtering out specific census tracts and using a different scale of analysis.

With this paper, we contribute to the debate about the effects of the platform economy on urban areas. We provide evidence about market expansion externalities brought by Airbnb into the city through higher employment and local consumption amenities. Moreover, market expansion effects are higher in touristic areas off-the-beaten, which may help to decongest tourism flows from central areas and redistribute tourism consumption across the city. However, other effects in the form of disamenities like noise and higher rental prices should also be taken into account to analyze the global effect of Airbnb on urban areas.

Hence, this study stresses the importance of taking into account the uneven effect of short-term rentals over urban geography. Considering the city as an homogeneous area entails the risk of masking heterogeneous effects, which may lead to inappropriate public policies. Therefore, our study yields notable policy implications regarding Airbnb regulation by providing some reasons to allow short-term rentals outside the city centers because of the potentially higher positive economic spillovers. In fact, current legislation is following that direction in cities like Madrid and Barcelona (Urquiaga et al., 2019). On top of that, the redistribution of tourist inflows within the city is key to the survival of the sector because its deleterious effects on residents in central areas may fuel reactions against tourists, which could jeopardize the entire sector (Allen et al., 2020).

Nevertheless, further research is needed. Although we have focused on this paper on the effect of short-term rentals on local consumption amenities, other economic activities may also be impacted by the arrival of short-term rentals. In this regard, a more holistic approach to how short-term rentals reshape cities is needed, considering the overall effect of short-term rentals across the geography of all economic activities. Since the IV approach we introduce in this paper is very general and can be applied to different cities, another possible future development is to extend our analysis to different urban areas other than Spanish cities. All things considered, the greater and undetermined externalities of short-term rentals deserve more consideration to understand their potential impact on urban areas.

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7 Appendix

7.1 Intensive and extensive margin:

The effect of Airbnb on food and beverage employment can be decomposed as follows:

$$\delta_L \times \Delta Airbnb = \underbrace{N_t \times \Delta S}_{IntensiveMargin} + \underbrace{\delta_N \times \Delta Airbnb \times (S_t + \Delta S)}_{ExtensiveMargin} \tag{4}$$

where δ_L represents the effect of Airbnb on employment (overall effect), $\Delta Airbnb$ the variation in the number of Airbnb rooms, N_t the number of food and beverage establishments, ΔS the variation in the average employment of the establishment, δ_N the effect of Airbnb on the number of food and beverage companies, and S_t the average employment of the establishment. The underlying assumption in the decomposition above is that both current restaurants and new restaurants vary the employment equally. We know all the parameters with the exception of the variation in the average employment of the establishment, ΔS. In turn, it can be computed with the other parameters as follows:

$$\Delta S = \frac{\Delta Airbnb \times (\delta_L - \delta_N \times S_t)}{N_t + \delta_N \times \Delta Airbnb} \tag{5}$$

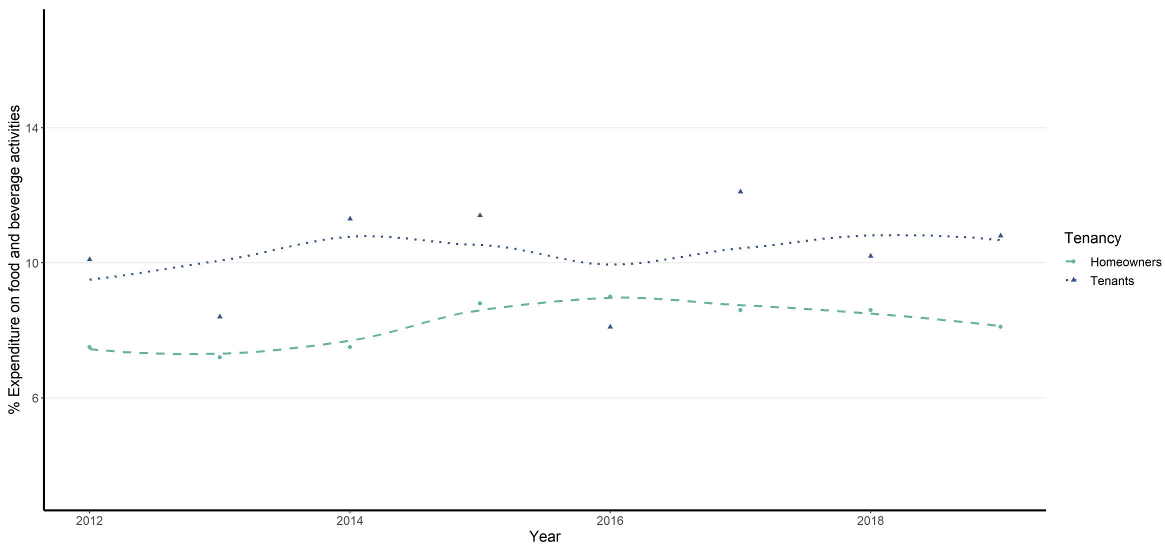
Table A1: Literature review for short-term rental studies.

Topic	Reference	Country/City	Period	Geographical unit	Dependent variable	Technique
Local economy and neighborhood amenities	Xu and Xu (2021)	USA (Chicago)	2015-2018 (quarterly)	Census tract (800)	Residential renovation project	Bartik instrument
	Bekkerman et al. (2022)	USA (15 cities)	2008-2019 (monthly)	ZIP code (608)	Residential permit	DiD
	Alyakoob and Rahman (2019)	USA (New York)	2007-2016 (yearly)	ZIP code (121)	Restaurant employment	DiD
	Basuroy et al. (2020)	USA (Texas)	2005-2018 (monthly)	ZIP code (1009)	Restaurant revenue	DiD
Housing	Batalha et al. (2022)	Portugal (Lisbon)	2018-2020 (quarterly)	Parish (24)	Housing price and Listings	DiD and IV
	Barron et al. (2021)	USA (100 CBSAs)	2011-2016 (monthly)	ZIP code (221)	Rental and housing price	Shift-share instrument
	Franco and Santos (2021)	Portugal (whole country)	2012-2016 (quarterly)	Municipalities (106) and civil parish (31)	Rental and Housing price	Shift-share instrument and DiD
	Valentin (2021)	USA (New Orleans)	2010-2018(monthly)	Individual data	Housing price	Difference-in-discontinuity
	Duso et al. (2021)	Germany (Berlin)	2016-2018 (monthly)	Building blocks	Number of long-term rental and rentals price	IV
	Bibler et al. (2021)	USA (San Francisco and Chicago)	2014-2019 (monthly)	County (192)	Housing price	DiD
	Garcia-López et al. (2020)	Spain (Barcelona)	2009-2017 (yearly)	Basic Statistical Area (221)	Rental and housing price	Shift-share instrument
	Chen et al. (2022)	USA (10 cities)	2014-2017 (monthly)	ZIP code (417)	Rental and housing price	DiD and Synthetic Control Method
	Garcia et al. (2022)	USA (LA county)	2014-2019 (yearly)	ZIP code (1360)	Housing price	Shift-share instrument and DiD
	Filippas and Horton (2020)	USA (New York)	2017	Individual data	Rental price	Structural model
	Hill et al. (2020)	Australia (Sydney)	2015-2018 (yearly)	Individual	Airbnb rent premia	IV
	Koster et al. (2021)	USA (Los Angeles County)	2014-2018 (monthly)	ZIP code (114)	Rental and housing price	Spatial Regression Discontinuity and DiD
	Horn and Merante (2017)	USA (Boston)	2015-2016 (weekly)	Census tracts (178)	Number and rental price	Hedonic modeling
Welfare and distributional impact	Farronato and Fradkin (2022)	USA (50 cities)	2011-2015 (monthly)	City (50)	Hotel performance outcome	IV
	Calder-Wang (2019)	USA (New York)	2010-2017 (monthly)	PUMA (55)	Housing rental and income	Structural model
	Almagro and Domınguez-Iino (2019)	Netherlands (Amsterdam)	2008-2019 (yearly)	Households and ZIP code (100)	Rents, amenities, and within-city migration	Structural model
Tourism	Fontana (2021)	UK (London)	2002-2019 (yearly)	Ward (624)	Discontent with tourism measures	Shift-share instrument
	Schaefer and Tran (2021)	France (Paris)	2017-2018 (daily)	District and hotel-level (20)	Hotel occupancy	Nested logit model
	Li and Srinivasan (2019)	USA (eight cities)	2014-2015 (monthly)	ZIP code–based subarea (51)	Hotel performance measures	Structural model
	Zervas et al. (2017)	USA (Texas)	2008-2014 (monthly)	City	Hotel revenue	DiD

Table A2: Variable definition and source.

Variable	Definition	Source
Dependent variables:		
Food and beverage establishments	Nº of food and beverage establishments	Madrid City Council's census
Employment food and beverage	Nº of employees in the food and beverage establishments	Madrid City Council Statistics department
Explanatory variables:		
Airbnb rooms	Nº of Airbnb rooms	Inside Airbnb
Population	Nº of inhabitants	*Padrón Municipal*
% Foreign population	Nº of foreign inhabitants divided by total number of inhabitants	*Padrón Municipal*
Average household income	Average household income	Spanish Household Income Distribution Atlas
Distance	Euclidean distance in meters to the city center from census tract centroid	Spanish National Geographic Institute
Hotel rooms	Nº of hotel and hostel rooms	Madrid City Council Statistics Department and Expedia
Instrument:		
Worldwide Airbnb Google searches	Index of the worldwide Airbnb Google searches	Google trends
Rental houses	% Rental houses in 2011	Spanish Census 2011

Figure A1: Percentage of expenditure on food and beverage by tenancy regime as percentage of overall expenditure.



Notes: % of overall expenditure on food and beverage by tenancy regime over the period 2012-2019. Microdata obtained from the Household Budget Survey (Spanish Statistical Office). Food and beverage activities comprise the following activities according to the Household Budget Survey: day menu in bars and restaurants (11111), lunches and dinners in bars and restaurants (11112), expenditure on bars and cafes (11113), and expenditure on fast and take-away food establishments (11116). Homeowners with and without mortgage are included in the homeownership category.

Figure A2: Bivariate map of the distribution of rental houses in 2011 and the change in the number of Airbnb rooms during the period 2014-2019.

Notes: Lighter colors reflects census tracts areas where the number of rentals houses were low in 2011 and the change in the number of Airbnb rooms during the period 2014-2019 was also low. Darker colors reflects census tracts where both the number of rentals in 2011 and the change in the number of Airbnb rooms were high. We do not show Airbnb and rental house information for city center neighborhoods for the sake of exposition.

Table A3: IV validity exercises

	No Airbnb census tracts	Parallel trend		Alternative instruments				
		2005-2010	2014-2019	Share Rental houses 2001	Total dwellings	Rental houses	Empty houses	Share rental + empty houses
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share Rental houses	0.006							
	(0.005)							
Change Airbnb rooms		0.004	0.064^{***}					
		(0.015)	(0.013)					
Airbnb rooms				0.064^{***}	0.123^{***}	0.086^{***}	0.096^{***}	0.065^{***}
				(0.013)	(0.028)	(0.020)	(0.034)	(0.014)
Covariates	x	x	x	x	x	x	x	x
Census tract FE				x	x	x	x	x
Year FE				x	x	x	x	x
Distance × year				x	x	x	x	x
F Stat				67.299	62.123	78.450	20.565	75.826
Observations	4,614	2,301	2,301	13,680	14,454	14,454	14,454	14,454

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. The dependent variable is the number of food and beverage establishments in Columns 1 and 4-8 and the change in the number of food and beverage establishments in Columns 2 and 3. The errors are clustered at the census tract level in 1 and 4-8 and robust in 2-3. We use as an instrument for *Airbnb rooms* variables the interaction between the share of rental houses in 2011 and worldwide Airbnb Google searches in Columns 2-3. From column 4, we keep the shift part, worldwide Airbnb Google searches, and we change the share in the following way: share of rental houses in 2001 in Column 4, the total number of dwellings in Column 5, number of rental houses in Column 6, number of empty houses in Column 7 and share of rental and empty houses in Column 8. Columns 1 is the reduced form regression, whereas columns 2-8 provide second-stage IV coefficients. The endogenous variable is the change in the number of Airbnb rooms in columns 2-3 and the number of Airbnb rooms in columns 4-8. Column 1 includes all census tracts with no Airbnb activity during our time period. Columns 2-4 include only census tracts which share the same boundaries as the 2011 definition. Columns 5-8 include all census tracts according to the 2011 boundary definition. Column 2 does not include income as covariate because of missing information about this variable previous to 2014 and includes distance as an additional regressor. We add distance time trends in Columns 1 and 4-8. We do not include income in the Column 3 specification for the purpose of comparison.

Table A4: Equivalence between gentrification businesses as in Behrens et al. (2018) and establishments in the Madrid City Council's census of business premises database

Pioneer business	**Madrid Activity codes**	**Madrid Activity description**
Motion Picture, and Video Production	591001	Motion picture, video and television activities (production, distribution, and exhibition)
Architectural Services/ Engineering Services	710001, 710002	Architectural and engineering technical services; technical testing and analysis; professional architectural and engineering offices
Musical Groups and Artists/ Sound Recording Studios	592001	Sound recording and music editing activities
Periodical Publishers/ Book Publishers	581001	Publishing of books, periodicals, and other publishing activities
Advertising Agencies/Public Relations Agencies	730001	Advertising, public relations, and market research
All Other Amusement and Recreation Industries	932007	Amusement and recreation halls and other recreational activities
Industrial Design Services/Graphic Design Services/ Interior Design Services	741001	Specialist design activities
Commercial Photography	477805	Retail trade in photographic and photographic equipment
Museums	910001	Activities of libraries, archives, museums. and galleries and exhibition halls without sale
All Other Speciality Food Stores	472910	Retail trade of cafe, tea, and chocolate
Computer Systems Design Services	582001	Software editing
Other Management Consulting Services	702001	Business management consultancy activities
Employment Placement Agencies	782001	Activities of temporary work agencies

Notes: We do not include consumption amenities present in Behrens et al. (2018) classification as they are part of our main dependent variable.