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The effect of short-term rentals on local consumption amenities: Evidence from Madrid

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Abstract

This paper examines the impact of the arrival of Airbnb on local consumption amenities in Madrid. We exploit the exogenous variation created by the timing and uneven distribution of Airbnb listings in the city to determine the impact 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 of 14 Airbnb rooms in a given census tract leads to almost one more restaurant, and the same increase in a given neighborhood generates 11 new tourist-related employees. The results are robust to the specification and sample composition. This paper contributes to the literature on the economic impact 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

1 | INTRODUCTION

The economic landscape in urban areas is rapidly changing as peer-to-peer (P2P) accommodation platforms move into cities (Ferreri & Sanyal, 2018). In a short time, Airbnb, the leader in this sector, has grown from a few thousand properties in 2009 to more than seven million in 2020 in more than 100,000 cities worldwide.[1] The explosion of

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

short-term rentals in urban areas has sparked a fierce debate about their economic impact. Several studies have pointed out the negative effects of the increase in housing prices and rents on the housing market (Barron et al., 2021; Franco & Santos, 2021; Garcia-López et al., 2020), the negative impact on hotel performance (Schaefer & Tran, 2021; Zervas et al., 2017) and the impact on the welfare of residents and tourists (Almagro & Domınguez-Iino, 2019; Calder-Wang, 2021; Farronato & Fradkin, 2022).

The rise of short-term rental platforms calls for a closer examination of their impact on local economies, highlighting potential differences across areas. Tourists and residents have different consumption patterns, which affects local economic activity differently. As short-term residents take the place of long-term residents, Airbnb-induced demand increases, potentially impacting stores *locally*. The influx of short-term residents could promote a local market expansion effect that increases demand for nearby consumption facilities, such as restaurants and retail services, as tourists tend to spend relatively more at these facilities compared with locals (Allen et al., 2020; Aparicio et al., 2022; Meltzer & Capperis, 2017; Meltzer & Schuetz, 2012). Moreover, the uneven distribution of short-term rentals in the city redistributes the economic impact of tourism throughout the urban area. Consequently, this new form of lodging could expand the benefits of tourism beyond traditional tourist hotspots. These disparate impacts support recent actions by local authorities to restrict short-term rentals in city centers while allowing them in peripheral areas (Valentin, 2021).

To analyze the impact of short-term rentals on tourism-related activities, we focus on how the arrival of Airbnb has fostered Madrid's food and beverage establishments. Four conditions allow us to pinpoint the impact of short-term rentals on local consumption 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 spread unimpeded into existing dwellings across the city. The ability to bring visitors to nontouristic areas allows us to separate the effect of Airbnb from other accommodations; (ii) the rapid spread of Airbnb. The flexibility and lack of regulation have led to a sudden increase in these accommodations, which would be unthinkable with other regulated accommodation types; (iii) food and beverage establishments quickly respond to changes in local demand due to low start-up costs. This is especially important in a country like Spain, which welcomed more than 83 million tourists in 2019, making it the second most visited country in the world (World Travel Tourism Council, 2019); (iv) as hotel customers, Airbnb users are likely to spend a large portion of their time budget in the immediate vicinity of the accommodation (Shoval et al., 2011). Therefore, it is expected that Airbnb will redesign the surrounding area to better meet the needs of its new customers.

In this study, we introduce a novel methodological approach to exploit the exogenous variation generated by the uneven entry of Airbnb across the Madrid geography. To measure the impact of Airbnb on local consumption amenities, we use a Bartik-like instrumental variables (IVs) approach that uses the share of rental housing in 2011 (before Airbnb's arrival 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 housing before Airbnb's arrival to explain the increase in the number of short-term rentals thereafter. We exploit the sharp geographic and temporal variation in the availability of short-term rentals by using census tracts and neighborhoods as our main geographic units of analysis.

Our results show that Airbnb's entry into the market has had a positive impact on both employment and the number of food and beverage establishments: an increase of 14 Airbnb rooms in a given census tract translates into almost one more food and beverage establishment. The same increase in one neighborhood adds 11 new food and beverage workers. The new and displaced businesses contribute equally to the creation of local consumption amenities. Moreover, the employment effects of Airbnb are equally explained by the intensive and extensive margins. Interestingly, the spillover effects of Airbnb on local consumption amenities are heterogeneous within the food and beverage industry, with restaurants benefiting the most from Airbnb penetration. Across the urban geography, Airbnb effects are stronger in less touristic areas, supporting the idea that P2P accommodations help redistribute tourism consumption across the city. We find no evidence of pretrends, 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 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 available geographical unit of analysis: census tracts. Using a narrow geographic unit of analysis helps overcome the problems of heterogeneity within larger spatial units, such as zone improvement plan (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. We also examine the distributional effect of Airbnb and changes in the composition of the urban landscape. We find that the overall Airbnb-induced establishment effect is equally explained by a compositional shift within commercial real estate between food and other retail sectors and by an increase in the conversion of land to commercial use. Finally, we decompose the overall Airbnb-induced employment effect between the intensive and extensive margins and show that the positive effects also extend to incumbents.

Third, we contribute a new Bartik-like instrument to resolve the endogeneity of the Airbnb activity variable: the interaction between the share of rental houses for each census tract before Airbnb's 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 because the distinction between commercial and residential areas is more nuanced in European urban areas than in the United States, although the difference is diminishing over time (Gordon & Cox, 2012). In particular, the mixed-use areas prevalent in Europe offer Airbnb more opportunities to transform the urban landscape compared with the United States. This research is of particular importance given the role of tourism in Spain, the world's second most visited country, with Madrid seeing a staggering 60% increase in tourist flows from 2014 to 2019. It is expected that the introduction of short-term rentals in residential areas will have a significant impact on business configuration and favor 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. Sections 3 and 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 is devoted to analyzing the impact of short-term rentals on the real estate sector, documenting the negative effects of Airbnb on housing prices and rents (Barron et al., 2021; Batalha et al., 2022; Garcia-López et al., 2020). The reallocation of housing from long-term to short-term rentals triggered by P2P accommodations has led to an increase in housing rental prices. Similarly, the increase in housing prices has been attributed to an increase in the option value of owning a home,

[2]Not related to our research question, the only papers that analyze other Airbnb externalities in European contexts are Garcia-López et al. (2020), which look at the impact of Airbnb on rental prices in Barcelona, Gálvez-Iniesta et al. (2023) analyzing the impact of Airbnb on employment in Spain from a regional perspective, Almagro and Domınguez-Iino (2019), which examine the impact of Airbnb on neighborhood amenities in Amsterdam, and Fontana (2021), which examines tourist dissatisfaction resulting from Airbnb-induced tourism flows in London.

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

thanks to the possibility of short-term rentals and the capitalization of higher rental prices. The disruptive impact of home-sharing platforms goes beyond the housing sector, negatively affecting the performance of traditional accommodations (Li & Srinivasan, 2019; Zervas et al., 2017), tax evasion (Garz & Schneider, 2023) but at the same time contributing to a more diversified supply of accommodation and lowering prices as hotels face capacity constraints during periods of peak demand (Farronato & Fradkin, 2022; Schaefer & Tran, 2021).

Although most literature to date has emphasized the negative effects of Airbnb on local economies, the advent of short-term rentals has also brought positive externalities by stimulating neighborhood and residential investment (Bekkerman et al., 2023; Xu & Xu, 2021). Specifically, Alyakoob and Rahman (2022) and Basuroy et al. (2020) analyze whether Airbnb has had a positive impact on local food and beverage services. Alyakoob and Rahman (2022) 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 strategy that exploits the different timing and intensity of Airbnb's entry in different geographical areas. In this way, they can determine the impact of Airbnb, measured by the number of reviews or the number of reviews per household, on restaurant performance by comparing high and low Airbnb intensity zones before and after Airbnb entry. Both studies conclude that Airbnb has a positive impact on restaurant outcomes, although the intensity of the effect varies widely: a 1% increase in the number of reviews per household leads to a 1.7% increase in restaurant employment in New York (Alyakoob & Rahman, 2022); 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). The available studies focus on the US context and do not consider the different effects across the geography of cities or among different types of establishments. Against this background, our study provides evidence of the overall impact of Airbnb on local consumption amenities in a European context. In addition, we rely on a different instrumental strategy and analyze Airbnb's effects across the geography and within the food and beverage sector.

Our study also relates to the literature on urban consumption (Glaeser et al., 2001). Several works have shown how densely populated areas benefited from a large diversity and supply of food establishments (Couture, 2013; Couture & Handbury, 2020; Mazzolari & Neumark, 2012; Schiff, 2015). The main channels explaining this trend include the overrepresentation of young people and the heterogeneity of citizens of ethnic origin in urban areas. Both the number of local consumption amenities and their quality have been shown 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 pricing patterns of cities. Many papers emphasize 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 their homes. This is critical to our study as 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' perspective, we focus instead 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 finest level of analysis available. Therefore, our primary geographic units of analysis are Madrid's census tracts. Census tracts are the smallest statistical unit in Spain. In particular, the city of Madrid is divided into districts (21), neighborhoods (128), and census tracts (2409), from the largest to the smallest administrative unit (see Figure 1). Because the census tracts are constructed to represent a similar population (1000–2500 people) at a narrowly defined geographic resolution, they are suitable for analyzing local effects.[4]

[4]We create consistently defined census tracts by setting the boundaries to the 2011 definition.

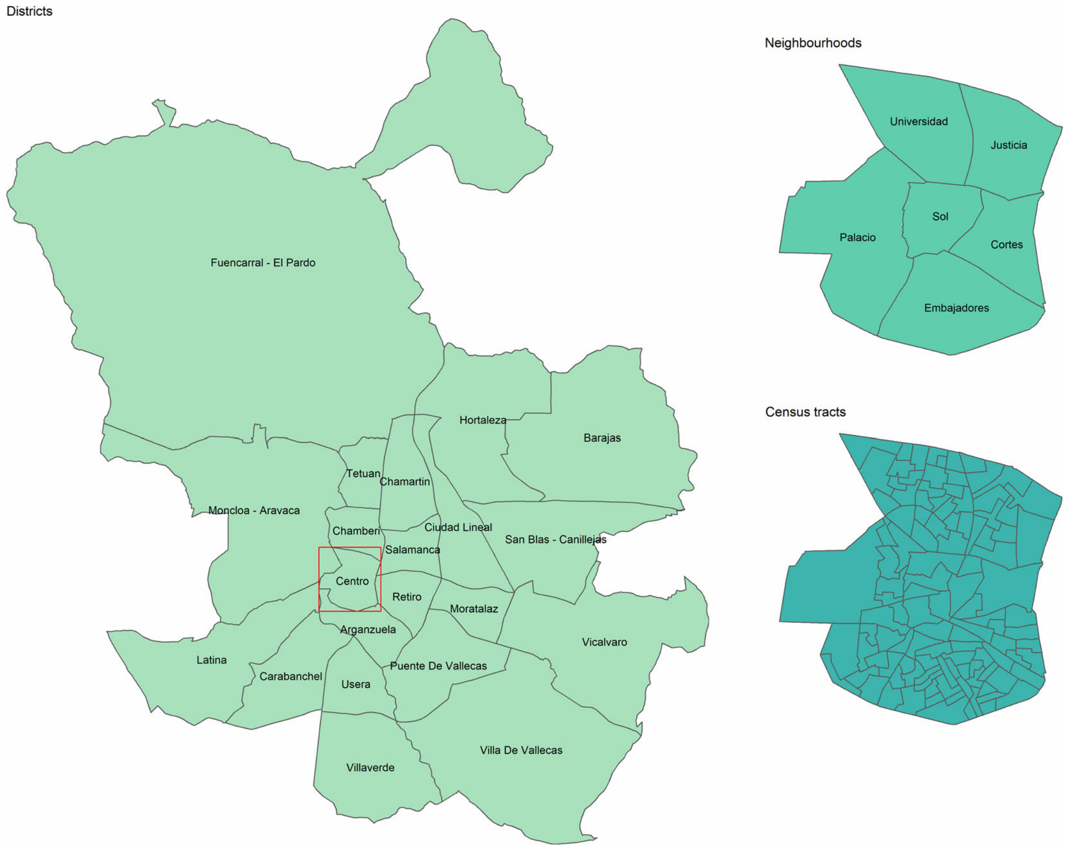

FIGURE 1 Administrative units in Madrid. [Color figure can be viewed at wileyonlinelibrary.com]

3.1 | Airbnb

We create the Airbnb activity variable by collecting annual 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 provides listing information at different points in time from different cities around the world. For our purposes, we are most interested in the information on the geographical coordinates of the listing, size, and insights into short-term rental activity in Madrid.

We need to find a way to define when a listing is active or not. To do this, we use the date of the first and the last reviews as proxies for the beginning and the end of the period in which the listing was active on the platform. In addition, we consider the number of rooms in each accommodation as a proxy for its size. In this way, we identify the potential impact of Airbnb on food and beverage establishment users.[6] Finally, we decided to remove shared

[5]*Inside Airbnb* provides annual snapshots of the evolution of the short-term rental sector in Madrid since 2015. As Airbnb appears in Madrid before 2015, we can recover the 2014 supply by considering the date of the first review as a proxy of a listing's opening, provided that the supply has not yet been deleted from the platform. At the end of our sample period, the Madrid City Council adopted a regulatory plan for short-term rentals (*Plan Especial de Hospedaje*). Under the new regulation, short-term rental activities were restricted to certain areas of the city. However, since the impact of such regulation was negligible (Ardura Urquiaga et al., 2019), we decided to include 2019 in our sample. The exclusion of the year 2019 does not affect our results.

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

and private rooms and while keeping entire flats whenever we build our measure of Airbnb activity. Including shared and private rooms could confound the effect on local spending for Airbnb-induced tourists with the composition effect of owner-present and Airbnb users.

3.2 | Local consumption amenities

We have obtained annual 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 population 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 undergoing reform). Since the objective of the study is to assess the impact of Airbnb on local consumption amenities, we focus on food and beverage establishments (NACE I.56), which account for the majority of tourist spending in Spain (INE, 2020). Previous research has shown for the Madrid case that tourists' spending is mainly concentrated in restaurants (Aparicio et al., 2022). For this reason, our main dependent variable will be the total number of food and beverage establishments at the census tract level.[7]

We also have access to annual employment data for food service establishments from the Madrid City Council Statistics Department. However, since employment data are confidential, we only have access to neighborhood-level employment statistics from 2010 to 2019, so we consider the number of employees in the food and beverage service sector at the neighborhood level as the second dependent variable.

3.3 | Control variables

We augment our data set with a set of variables to control for other factors related to either establishments or employment in the food and beverage industry. Previous studies have shown that these factors, such as population, proportion of foreigners, average household income, distance to the city center, and number of rooms in hotels and hostels, are important determinants (Mazzolari & 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 the statistics of the Registry of Residents (*Padrón Municipal*), whereas information on traditional accommodations was obtained from the Madrid City Council Statistics Department and Expedia. Average household income was taken from the Spanish Household Income Distribution Atlas and distance to the city center from the Spanish National Geographic Institute.[8] For a final list of all variables used, see Table A2 in the appendix.

3.4 | Descriptive statistics

Airbnb activity and the number of food and beverage establishments have increased in Madrid during the period studied. At the same time, the total supply of hotel rooms has changed only slightly (see Table 1 and Figure 2). This divergence is explained in part by local planning ordinances that restrict the location of traditional accommodations

[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, for example, museums, performance arts, and sports events, and (2) they are not fully tourist-oriented, for example, grocery, clothing, and gyms.

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

TABLE 1 Descriptive statistics.

	2014			2019		
	Sum	Mean	SD	Sum	Mean	SD
Food and beverage establishments	15,660	6.501	8.124	17,212	7.145	9.094
Airbnb listings	2153	0.894	3.516	12,763	5.298	16.598
Airbnb rooms	3288	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	1314.431	508.245	3,278,988	1361.141	668.755
Average household income	86,736,299	36,005.105	14,876.846	99,176,288	41,169.069	17,359.439

Note: N = 14,454, census tracts = 2409. Descriptive statistics for census tract level observation.

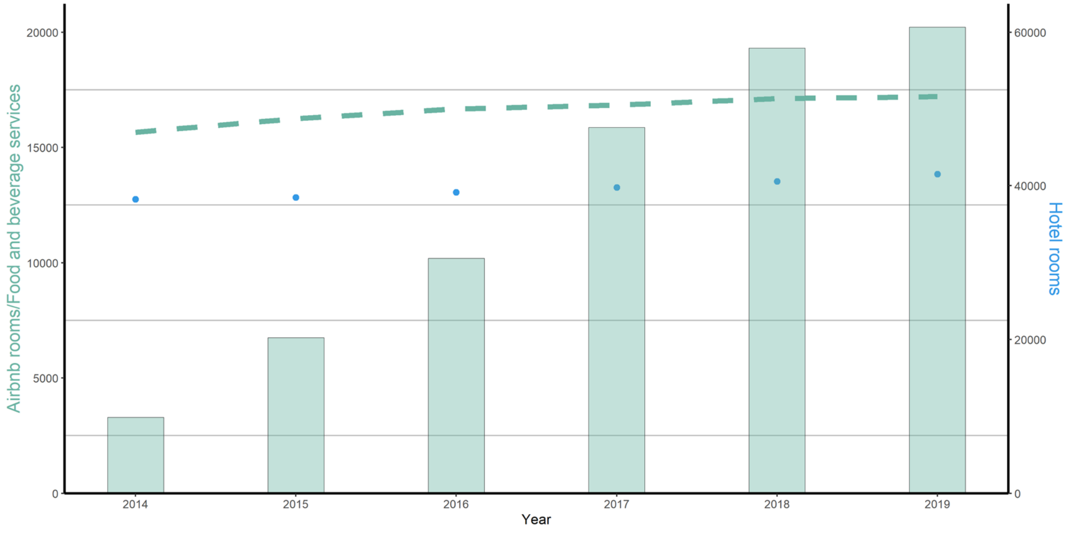

FIGURE 2 Number of food and beverage establishments, Airbnb and hotel rooms from 2014 to 2019. Left scale is for food and beverage establishments (dashed) and Airbnb rooms (bars). Right scale is for the evolution of hotel rooms (dots). [Color figure can be viewed at wileyonlinelibrary.com]

and the flexibility of short-term rental supply based on already existing dwellings. We can also observe how sociodemographic indicators such as average household income or population size improve over the period studied. This is the result of the recovery process that took place in Madrid in the years following the Great Recession and the bursting of the Spanish housing bubble.

The positive correlation between short-term rentals and food and beverage establishments holds spatially as well, as we can see in Figure 3. The uneven distribution of short-term rentals across the city suggests that Airbnb is boosting local consumption not only in the city center (where the number of Airbnb listings has increased the most) but also in more peripheral areas. Because P2P accommodations are based on owners' dwellings, they can quickly spread across the urban geography. In turn, Airbnb listings tend to localize not only near tourist attractions, which in the case of Madrid coincide with the city center and surrounding areas, but also in other nontouristic neighborhoods.

FIGURE 3 Spatial correlation in the change of the number of Airbnb rooms and consumption amenities during the period 2014–2019. 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. [Color figure can be viewed at wileyonlinelibrary.com]

4 | METHODOLOGY

4.1 | Model specification

The objective of this article is to investigate the impact of Airbnb's entry into Madrid on the local food and beverage sector. We argue that the entry of Airbnb might have a positive impact on local food and beverage activities, especially in nontouristic areas. To answer our research question, we start with our baseline specification, which takes the following form:

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

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. To account for time-invariant characteristics, like the size area, we add census tract fixed effects. We include year-time fixed effects for cyclical changes. 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.

Above all, we are interested in β of Equation (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 exactly when they are active and when they are not since we approximate the number of active Airbnb rooms with the number of listings with customer reviews. Therefore, our empirical setting requires an IV strategy to account for 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 depends on the local supply of rental houses that can be let out for Airbnb. As Airbnb grows globally over time, the number of Airbnb listings increases at different rates in different census tracts due to the availability of houses that can be rented out for Airbnb. As a result, census tract housing supply, which is primarily historically determined, causes different tracts to experience different levels of Airbnb penetration. We use this variation in the growth of short-term rentals in the census tract to measure the effects on food and beverage establishments.

It is easy to see that the shares explain either the extensive or the intensive margin of the treatment, while the shift describes the timing. More formally,

$$\textit{Shift-Share}_{i,t} = \textit{Share Rental houses}_{i,2011} \times \textit{Worldwide Airbnb Google Searches}_t, \tag{2}$$

where $\textit{Share Rental houses}_{i,2011}$ are the share rental houses in census tract i in 2011, and $\textit{Worldwide Airbnb Google Searches}_t$ are the normalized worldwide Airbnb Google searches. The relevance of our instrument is based on the fact that, as Horn and Merante (2017) have shown, the main mechanism by which Airbnb expands in the real estate sector is by decreasing the stock of long-term rentals and increasing the supply of short-term rentals. Indeed, we can observe that there is a positive and significant relationship between the share of rental houses in each census tract and subsequent Airbnb activity (in Figure 4, panel a). We can also observe that the evolution of worldwide Airbnb Google searches mimics Airbnb growth (in Figure 4, panel b).

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 a 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 center, 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 4, 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).

Regarding the exclusion restriction, it is highly unlikely that global Airbnb Google searches are directly correlated with the increase in Madrid's overall attractiveness. Airbnb is a global company with a presence in more than 100,000 cities in over 190 countries. Therefore, we can confidently claim that our Bartik-like instrument's shift part is exogenous to local conditions in Madrid. To satisfy the exclusion restriction, our share instrument $\textit{Share Rental houses}_{i,2011}$ 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

[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 annually and is normalized to 100 for the year with the highest number of searches.

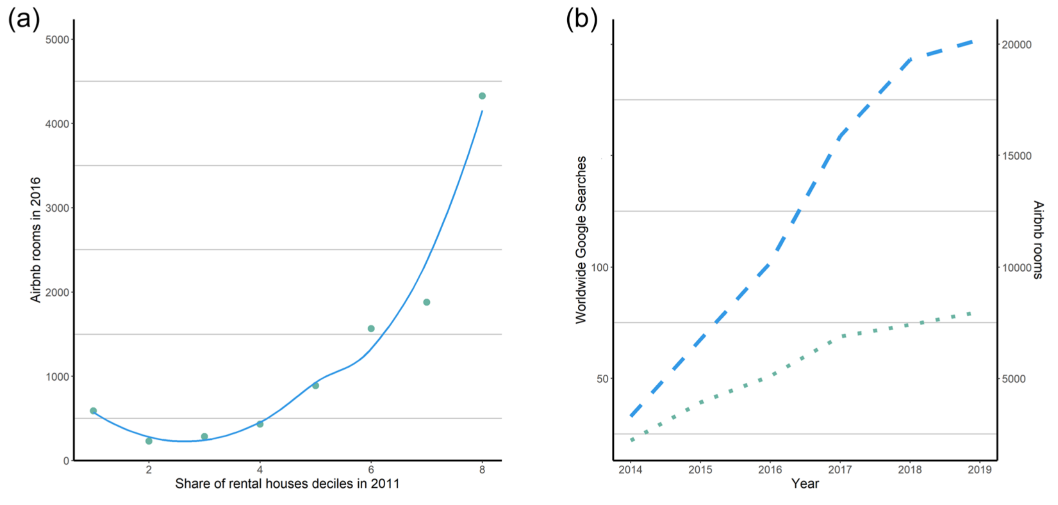

FIGURE 4 Shift-share instrument relevance. Subplot (a) depicts how Airbnb supply in 2016 is positively correlated with the share of rental houses divided by deciles. Subplot (b) shows the evolution of worldwide Airbnb Google searches (dashed-dotted line) and the growth of Airbnb in Madrid (dashed line). [Color figure can be viewed at wileyonlinelibrary.com]

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 condition as follows.

First, we check whether our share instrument predicts 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 find no significant relationship 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 Equations (1) and (2) in Column 1 from Table 2).

Second, a key concern with the instrument is that census tracts with a high proportion of rental houses can explain changes in local consumption amenities even before Airbnb's arrival (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). On the one hand, as can be seen in Figure A1, long-term residents' taste for tourism-related activities hardly changed over the period of study, regardless of the type of tenancy. On the other hand, to show that the parallel trends hold in our setting, we regress the change in the number of food and beverage establishments in the preperiod 2005–2010 against the change in Airbnb rooms in 2014–2019 predicted by the share of rental houses in 2011.[10] We control for population size, share of foreign population, distance to the city center, and number of traditional accommodation rooms measured in 2005. We find that the coefficient of interest is not statistically significant for the period before Airbnb's entry. However, for the 2014–2019 period, where we repeat the same specification but use contemporaneous data on local consumption establishments, it is significant (see Columns 2 and 3 in Table 2 and for the event study version Figure 5). All in all, our results show that historical areas with a high proportion of rental houses are not located in census tracts that already underwent different trends correlated with the evolution of local consumption amenities.

Having demonstrated the validity of our proposed instrumental strategy, we now turn to analyze the impact of Airbnb's arrival on the food and beverage establishments in Section 5.

[10]We have obtained annual information on local consumption amenities from the census of commercial premises of the Madrid region. This database contains information on all establishments in the Madrid region for the period 1998–2010. For our purposes, we restrict the data on consumption amenities to the city of Madrid.

TABLE 2 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	×	×	×	×	×	×	×	×
Census tract FE				×	×	×	×	×
Year FE				×	×	×	×	×
Distance year				×	×	×	×	×
F statistics				67.299	62.123	78.450	20.565	75.826
Observations	4614	2301	2301	13,680	14,454	14,454	14,454	14,454

Note: 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 that 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 a 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.

Abbreviations: FE, fixed effects; IV, instrumental variable.

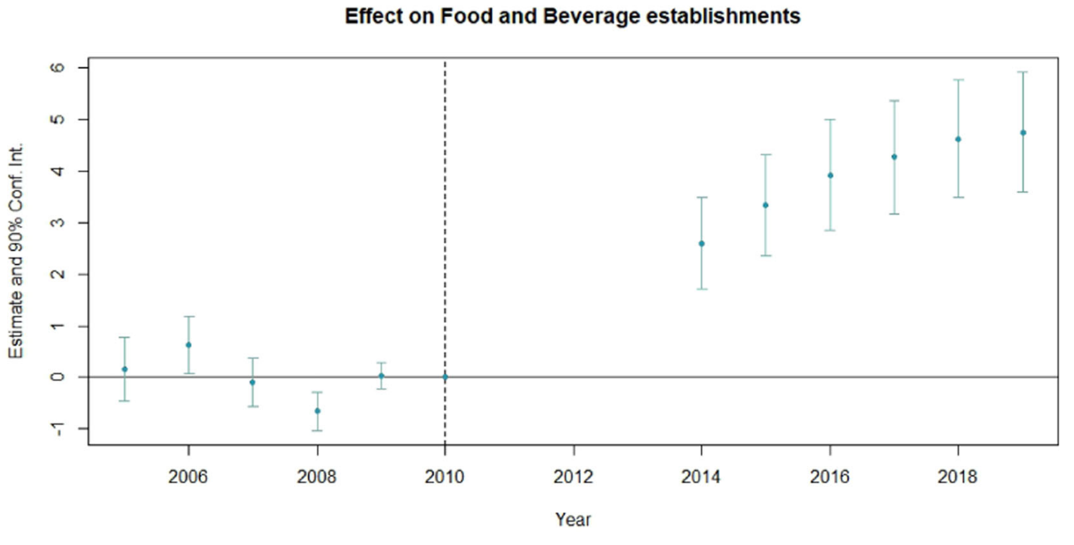

FIGURE 5 Event study plot for establishments 2005–2019. Omit data from the years 2011 to 2013 due to unavailability of food and beverage establishment information. [Color figure can be viewed at wileyonlinelibrary.com]

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. We then decompose the overall effect into displacement and net food and beverage establishment creation.

Table 3 presents the results of our baseline Ordinary Least Squares (OLS) and IV specifications. Our baseline sample includes 2409 census tracts for 6 years. Our dependent variables are the number of food and beverage establishments in Columns 1–5 and the number of new and established business premises, 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 2–7. 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.

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. In this way, our results confirm previous findings in the literature that have shown a positive link between Airbnb and consumption amenities (Alyakoob & Rahman, 2022; Basuroy et al., 2020; Xu & Xu, 2021). 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 IV 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

TABLE 3 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	×	×	×	×	×	×	×
Census tract fixed effects		×	×	×	×	×	×
Year fixed effects		×	×	×	×	×	×
Distance × year			×		×	×	×
Adjusted R^2	0.450	0.986	0.987				
F statistics, excluded instrument				48.466	68.246	68.246	68.246

Note: [a]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, and the number of existing food and beverage establishments in Column 7[b]7 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.

Abbreviations: FE, fixed effects; IV, instrumental variable; OLS, Ordinary Least Squares.

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.

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]

It is noteworthy that the IV coefficient (Column 5) is more than twice as large as the OLS coefficient (Column 2). This result is consistent with previous studies that also found a downward bias in the OLS specification (Barron et al., 2021; Fontana, 2021; Garcia-López et al., 2020). A potential reason for this downward bias is that measurement error presents a challenge in accurately determining the number of active listings in the market, particularly with respect to Airbnb listing entry and exit rates (Barron et al., 2021; Garcia-López et al., 2020; Xu & Xu, 2021). This uncertainty introduces noise into the data that can bias the estimated coefficients. As a result, the OLS estimates may be biased downward. We attempt to address this issue by using the date of the first and last reviews as a proxy for the beginning and end of the period in which the listing has been active on the platform.

In economic terms, our estimates show that each addition of 14 Airbnb rooms increases the number of food and beverage establishments in each census tract by one more consumption amenity and leads to annual Airbnb-induced tourism expenditures totaling 342,881 euros.[12] In terms of the number of establishments, the change in

[11]One potential criticism of our share instrument is that the proportion of rental houses may be affected by Airbnb's 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 2 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 2 show that our main tenets hold 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]On the basis of an average occupancy rate of 55% (INE, 2023c) and assuming two people per room, this translates to 5621 overnight stays per year in 2019. Considering that the average daily expenditure of an urban tourist in Spain is 225 euros, of which 27% spent on restaurants (INE, 2023b), tourists in Madrid spend about 61 euros per day on food and beverages. Thus, the 14 Airbnb rooms would contribute a direct expenditure of 342,881 euros to this sector. In addition, the average turnover of a restaurant in Madrid in 2019 was 267,877 euros (INE, 2023a). Therefore, the total effect is split between local spending by tourists nearby and in other parts of the city and between established and newly added businesses.

the number of Airbnb rooms per tract from 2014 to 2019 averaged 5. Consequently, our estimates suggest that a tract with the average influx of Airbnb rooms had about one-third of an additional establishment (0.335), an increase of about 46% over the baseline number of consumption amenities in the tract.

Finally, our coefficient may mask crowding out effects from other nonlocal consumption amenities. To rule out the possibility that Airbnb's entry is associated with pure displacement effects and to understand compositional changes within the urban landscape, we divide our main dependent variable, the number of food and beverage establishments, into two groups: the construction of new storefronts that offer food service and established storefronts that switch to food service establishments. New establishments represent the opening of new physical business premises, taking the number of establishments present in 2014 as the reference.[13] We can observe that the growth in local consumption amenities led by Airbnb is equally attributable to new and existing establishments. The sums of the individual groups approximate our coefficient of 0.071 food and beverage establishments per census tract per year, as expected, given that we estimate a linear additive specification. As a result, we find that Airbnb contributes to changing the urban landscape by shifting the composition within commercial real estate between food and other retail sectors and converting land to commercial use through the opening of new physical stores.

5.1 | Robustness checks

We address the threats to the identification of our main findings in the following way. First, we check that our main findings hold even if we change the functional form of our regression specification. Instead of a level–level specification, we estimate a log-level equation by taking the logarithm of our dependent variable and also running a control function IV nonlinear model. We also show that our results hold even when we change the measure of 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 re-estimate our IV equation specification using a novel control function IV approach that was proposed by Lin and Wooldridge (2019) and allows us to estimate nonlinear scenarios with fixed effects. Table 4 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

[13]As an example, a business premise that offered hairdresser services in 2014 and starts to offer restaurant services in the following years would be in our group of established business premises which switch the service offer. The construction of new business premises that offer food and beverage services would be in the new establishment group. Therefore, the growth in consumption amenities can occur through two channels: (1) the opening of new business premises, that is, the construction of new physical stores, and (2) the switching activities within an existing business premise that was already established.

TABLE 4 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)

Note: 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.

Abbreviation: IV, instrumental variable.

Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

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 4 show that our findings are not sensitive to alternative ways of measuring short-term rental activity.[14]

In our baseline specification of the model, we assume that the Airbnb-induced effect on tourism demand is limited to the census tract where the Airbnb listing is located. This is a strong assumption, given the small size of our geographic unit of analysis. Although using census tracts allows us to better capture the impact of Airbnb on the number of food and beverage establishments, their smaller size makes them more susceptible to spillover issues from other short-term rental accommodations in surrounding census tracts than larger administrative units, such as

[14]To compare the magnitude of these coefficients to our baseline specification, we calculated the average number of listings, reviews, and bedrooms per census tract from 2014 to 2019. We then multiplied these numbers by the appropriate coefficient in each specification. The results are summarized in Table A3, where we report the mean values, coefficients, and average effects for each variable. As can be seen, the coefficients are quite similar in magnitude. Our baseline specification can be considered the more conservative of the three measurements. These calculations support our claim that the results are not sensitive to different ways of measuring short-term rentals.

neighborhoods or ZIP codes. If we do not account for the presence of spillover problems, we overestimate the impact of Airbnb on the number of food and beverage establishments, but we may also be underestimating it. On the one hand, the critical mass of potential customers increases with Airbnb tourists from each census tract and Airbnb guests from neighboring census tracts. On the other hand, by creating food and beverage clusters, Airbnb could shift demand away from census tracts without short-term rentals, leading to an increase in the number of food and beverage establishments in census tracts with a strong Airbnb presence and a decrease in surrounding neighborhoods.

To account for the distributional effect of the Airbnb presence in neighboring census tracts, we include the spatial lag of our variable of interest as another regressor: the weighted number of Airbnb rooms in census tracts neighbors.[15] Since Airbnb guests are more likely to consume only in nearby tracts, we expect Airbnb-induced tourism demand to affect only nearby areas. Since the weighted number of Airbnb rooms in nearby census tracts is likely endogenous, we instrument the spatial lag of Airbnb rooms with the interaction between global Airbnb Google searches and the spatial lag of the share of rental houses in 2011.

Table 4 (E) shows the results of our baseline IV specification we have extended by including the spatial lag of Airbnb activity and, as its instrument, the spatial lag of our shift-share variable. We see that our coefficient of interest does not change when we account for potential spatial spillovers.[16] Therefore, we can conclude that our baseline model is defined at the appropriate level, and it captures the full effect of Airbnb on local consumption amenities.

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 test the robustness of our results using different samples. First, we leverage that our IV 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 (Garcia-López et al., 2020; Gutiérrez et al., 2017). We have collected local consumption amenities information from the Barcelona City Council's census of business premises for the three cross-sections that correspond to 2014, 2016, and 2019. We complement this information with the population, the proportion of the foreign population, the average household income, the distance to the city center, and the number of traditional accommodation rooms. We apply our IV strategy as in our baseline IV specification (Column 5 in Table 3). The positive and statistically significant coefficient in F from Table 4 shows that Airbnb spillover effects onto food and beverage services also hold in a context other than Madrid, despite the fact that the Barcelona sample comes from a different data set and covers a different time period, which may contribute to the observed difference in magnitude.

A potential violation of our exclusion restriction may stem from the nonrandom location of the Airbnb listings, as most short-term rentals are in the city center and close to the airport. Because of this nonrandom 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 before 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 (Aparicio et al., 2022; García-Palomares et al., 2015; Salas-Olmedo et al., 2018). That issue is partially solved by controlling for time-varying accommodation activities that directly affect tourist-related

[15]Census tract neighbors are defined as all areas up to 500 meters away from each census tract centroid.
[16]The coefficient of the spatial lag of Airbnb activity is not significant in our specification.

businesses 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 accommodation units.

We approach the problem of an increase in demand stemming from new or existing traditional accommodations or changes in locals' taste toward 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.[17] Results G and H in Table 4 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 nontourist 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., 2022).

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 (ZTs) (481).[18] This exercise aims to address the ubiquitous statistical problem in spatial analysis framed as the Modifiable Areal Unit Problem. 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 4 (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 ZTs, which may explain the smaller magnitude of the coefficient.

5.2 | Extensions

Having examined the impact of Airbnb on local consumption amenities and the robustness of our results, we now turn to the mechanisms that might explain these results. First, we analyze whether Airbnb's spillover effects on establishment formation extend to employment in these activities by disaggregating the total Airbnb-induced employment effect between the intensive and extensive margins. Second, we evaluate whether there are heterogeneous effects within activities classified as local consumption amenities. Finally, we evaluate the impact of short-term rentals on other local economic activities related to gentrification and urban revitalization.

5.2.1 | Employment

Along with the analysis, we focused on the impact of Airbnb on the number of food and beverage establishments. However, employment in this sector may have also increased. Unfortunately, we do not have access to restaurant employment numbers at the census tract level, only at the neighborhood level on an annual basis. Therefore, to test

[17]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.

[18]ZTs constitute one of the basic spatial units for analysis and aggregation of information in Madrid. The Madrid Regional Transport Consortium defines them as collecting 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.

TABLE 5 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	×	×	×	×	×	×
Census tract fixed effects	×	×	×	×	×	×
Year fixed effects	×	×	×	×	×	×
Distance × year	×	×	×	×	×	×
F statistics, excluded instrument	0.27777	0.98363	0.98368	0.99453	0.17362	0.97535
R^2	0.27777	0.98363	0.98368	0.99453	0.17362	0.97535

Note: The dependent variable is the employment in food and beverage establishments in Column 1, the number of restaurants, bars, cafes, and clubs in Columns 2–5, and the number of cultural and creative industries as in Behrens et al. (2024) 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.

Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

whether restaurant employment has been affected by Airbnb's entry into Madrid, we repeat our IV specification using neighborhoods as the geographic unit of analysis and years as the time frame. Table 5 Column 1 summarizes the main results.

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 in employment equally.[19] The extensive and intensive margins contribute equally to the increase in food and beverage employment.

Although we have previously ruled out the existence of different pretrends 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:

$$\textit{Employment food beverage}_{i,t} = \sum_{t \neq 2014} \lambda_t \times \delta \textit{Rental houses}_{2011} + \rho X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}, \tag{3}$$

[19]The proof of the approximate decomposition is provided in Equations (A1) and (A2) 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 chose 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. 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 6, the coefficients before Airbnb's entry are not different from zero. This result reinforces our conclusion that it was Airbnb that was responsible for the increase in employment in the food and beverage sector. Thus, we can conclude that there is no evidence of a violation of the parallel trends assumption or that Airbnb did not enter the neighborhoods after observing an expansion of the food and beverage sector.

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 whether Airbnb also fosters the entry of some local consumption amenities individually. Therefore, in Columns 2–5 in Table 5, 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. Consistent with our previous findings, the sums of the individual categories roughly yield our coefficient of 0.071 food and beverage establishments per census tract per year, as expected, given that we estimate a linear additive specification.

5.2.3 | The impact of Airbnb on other local economic activities

We are well aware that there may still be census-tract-specific, time-varying, unobservable variables in our analysis that correlated with Airbnb and the number of food and beverage establishments. To test that Airbnb and not other factors influence our results, we exploit that short-term rental accommodations should affect only tourist-related activities, in general, and local consumption amenities in particular. Therefore, we conduct our analysis on activities that could be related to a confounding factor, such as urban revival and cultural and creative sectors activities.[20] The presence of this confounding factor, which correlates with the presence of Airbnb and the number of food and beverage establishments, could invalidate our identification strategy, as we would falsely 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 mainly promotes tourist-related activities. Column 6 in Table 5 shows no effect of Airbnb on nontourist-related activities.

6 | CONCLUSIONS

This article examines the impact of Airbnb, the most popular short-term rental company, on local consumption amenities. Using a fine-grained census of local business datasets and exploiting the exogenous variation created by the rapid and uneven entry of short-term rentals into Madrid's geography, we find positive and significant effects

[20]For a list of all activities related to those sectors, please see Table A4 in the appendix. This information was extracted from the Madrid City Council's census and cross-checked with the Behrens et al. (2024) classification of gentrifiers.

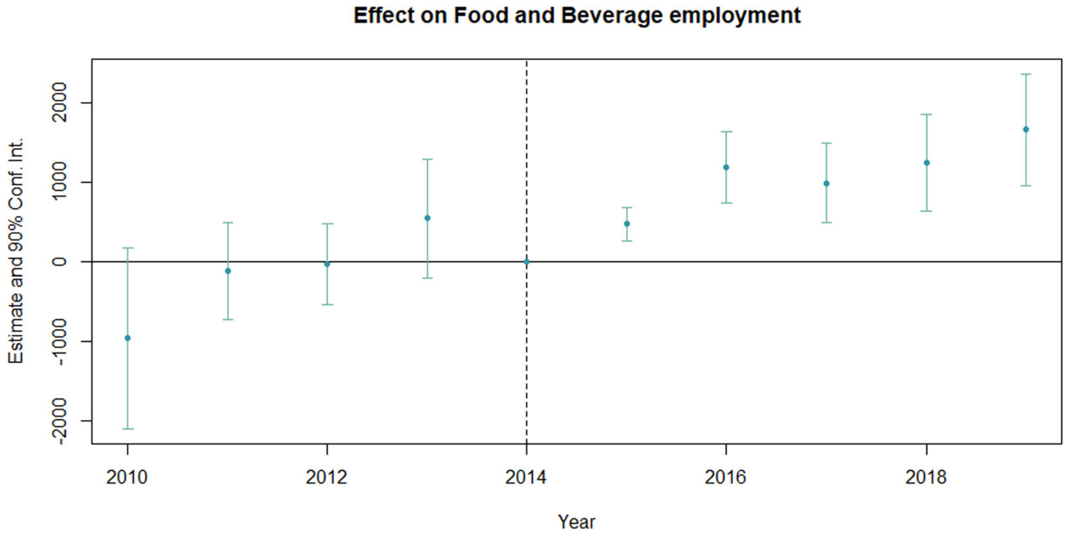

FIGURE 6 Event study plots for employment 2010–2019. [Color figure can be viewed at wileyonlinelibrary.com]

on the food and beverage sector. These effects can be explained by both displacement and the creation of new establishments. Interestingly, the spillover effects of Airbnb on local consumption amenities are heterogeneous within the food and beverage industry, with restaurants benefiting the most from Airbnb disruption. We find that the effects are stronger in less touristic areas, supporting the idea that P2P accommodations help redistribute tourism consumption in the city. Our results are very robust across different specifications: they are not affected by the form of the functional specification, the way Airbnb activity is measured, 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.

In this paper, we contribute to the debate on the impact 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 tourist areas off-the-beaten, which may help relive tourist flows from central areas and redistribute tourism consumption in 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 highlights the importance of taking into account the uneven effect of short-term rentals over urban geography. Viewing the city as a homogeneous area entails risks obscuring heterogeneous effects, which may lead to inappropriate public policies. Therefore, our study yields noteworthy policy implications regarding Airbnb regulation by providing some rationale for allowing short-term rentals outside the city centers due to their potentially higher positive economic spillovers. Indeed, current legislation is following that direction in cities, like, Madrid and Barcelona (Ardura Urquiaga et al., 2019). On top of that, the redistribution of tourist flows within the city is key to the survival of the sector, as the negative effects on residents of central areas may provoke reactions against tourists that could jeopardize the entire sector (Allen et al., 2020).

Nevertheless, further research is needed. Although we have focused on the effect of short-term rentals on local consumption amenities in this study, other economic activities may also be affected by the arrival of short-term rentals. In this regard, a more holistic approach is needed to examine how short-term rentals reshape cities by considering the overall impact of short-term rentals on the geography of all economic activities. Since the IV approach we present 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 in all, the larger and undetermined externalities of short-term rentals deserve more attention to understand their potential impact on urban areas.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

A.1 | Intensive and extensive margin

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

$$\delta_L \times \Delta Airbnb = \underbrace{N_t \times \Delta S}_{\text{Intensive Margin}} + \underbrace{\delta_N \times \Delta Airbnb \times (S_t + \Delta S)}_{\text{Extensive Margin}}, \tag{A1}$$

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

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. (2023)	USA (15 cities)	2008–2019 (monthly)	ZIP code (608)	Residential permit	DiD
	Alyakoob and Rahman (2022)	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

TABLE A1 (Continued)

Topic	Reference	Country/city	Period	Geographical unit	Dependent variable	Technique
	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 (2021)	USA (New York)	2010–2017 (monthly)	PUMA (55)	Housing rental and income	Structural model
	Almagro and Domınguez-lino (2019)	Netherlands (Amsterdam)	2008–2019 (yearly)	Households and ZIP code (100)	Rents, amenities, and within-city migration	Structural model
Tourism	?	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

Abbreviations: CBSA, core-based statistical area; DiD, Difference-in-Differences; IV, instrumental variable; ZIP, zone improvement plan.

TABLE A2 Variable definition and source.

Variable	Definition	Source
Dependent variables		
Food and beverage establishments	Number of food and beverage establishments	Madrid City Council's census
Employment food and beverage	Number of employees in the food and beverage establishments	Madrid City Council Statistics Department
Explanatory variables		
Airbnb rooms	Number of Airbnb rooms	Inside Airbnb
Population	Number of inhabitants	*Padrón Municipal*
% Foreign population	Number 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	Number 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

TABLE A3 Sensitivity analysis.

Variable	Mean	Coefficient	Average effect
Supply bedrooms	5	0.071	0.335
Supply listings	3	0.152	0.456
Supply review	214	0.002	0.428

TABLE A4 Equivalence between gentrification businesses as in Behrens et al. (2024) 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

TABLE A4 (Continued)

Pioneer business	Madrid activity codes	Madrid activity description
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

Note: We do not include consumption amenities present in Behrens et al. (2024) classification as they are part of our main dependent variable.

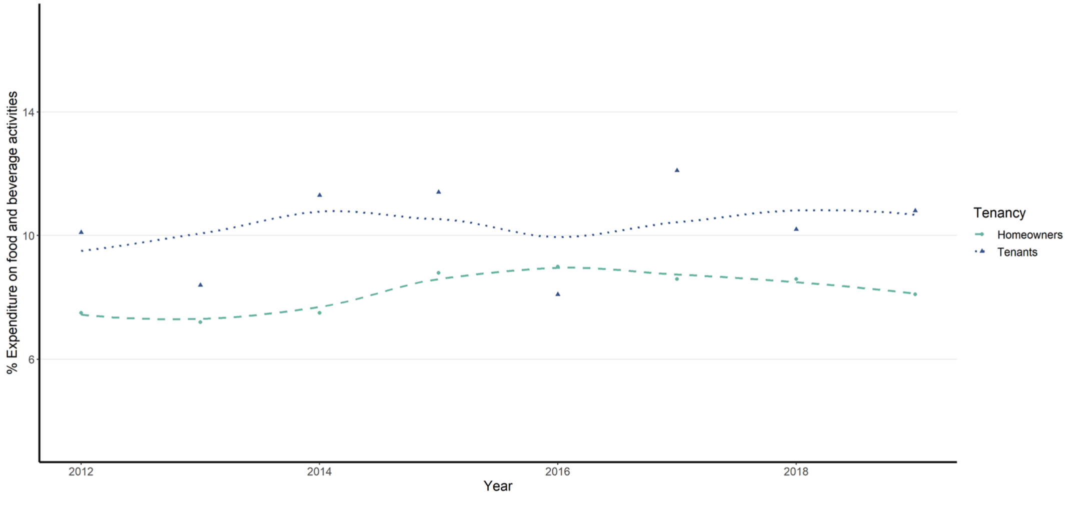

FIGURE A1 Percentage of expenditure on food and beverage by tenancy regime as percentage of overall expenditure. % of overall expenditure on food and beverage by tenancy regime over the period 2012–2019. Microdata obtained from the Household Budget Survey (Spanish Statistical Office). Food and beverage activities comprise the following activities according to the Household Budget Survey: day menu in bars and restaurants (11,111), lunches and dinners in bars and restaurants (11,112), expenditure on bars and cafes (11,113), and expenditure on fast and take-away food establishments (11,116). Homeowners with and without mortgage are included in the homeownership category. [Color figure can be viewed at wileyonlinelibrary.com]

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. Lighter colors reflect census tracts areas where the number of rentals houses was low in 2011 and the change in the number of Airbnb rooms during the period 2014–2019 was also low. Darker colors reflect 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. [Color figure can be viewed at wileyonlinelibrary.com]

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 (Tables A1–A4 and Figures A1 and A2):

$$\Delta S = \frac{\Delta Airbnb \times (\delta_L - \delta_N \times S_t)}{N_t + \delta_N \times \Delta Airbnb}. \quad (A2)$$