When Local Business Faded Away: The Uneven Impact of Airbnb on the Geography of Economic Activities

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Abstract

This paper investigates the unequal effect of Airbnb on the spatial organisation of economic activity in Madrid, Spain. Using establishment-level data from Madrid City Council and consumer-facing information from this short-term rental company, we find that Airbnb reshapes the urban space by encouraging tourist-oriented businesses, defined as businesses where tourists spend more than locals, at the expense of businesses primarily oriented to locals. These findings prove that short-term rentals do displace not only the local population but also resident-oriented businesses. Eventually, we show that our results are not driven by the method of measuring digital accommodation activity, other touristic actors, and confounders related to gentrification and the rise of online purchasing.

Keywords: digital platform, short-term rentals, Airbnb, neighbourhood change, retail sector, tourism

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Introduction

The rise of 'home-sharing' economic platforms is posing numerous challenges to urban planners and policy makers (Ferreri and Sanyal, 2018). While much of the public debate and academic literature have focused on the negative impact of short-term rentals on housing affordability (Garcia-López et al., 2020), there is still a lack of understanding about how platforms like Airbnb are changing the economic landscape of urban areas (Celata et al., 2017). Specifically, it is still unclear to what extent the expansion of short-term rentals is affecting the mix of economic activities within cities. In that regard, the expansion of the short-term rentals phenomenon differs from other touristification processes as short-term rentals not only increase the accommodation capacity in certain areas, but also spread throughout urban geography, ultimately exacerbating problematic relations between residents and tourists as local businesses may be displaced. In turn, the loss of local businesses may lead to a decline in the local population, as they no longer have access to the services they need for daily living.

The main focus of this paper is to examine the consequences of the displacement of residents by tourists on the economic landscape. Tourists tend to have different consumption patterns than residents, and the influx of these new customers can affect various businesses in different ways. This impact is primarily local, as residents and tourists often spend a large portion of their time in the areas surrounding their accommodations. Local businesses[1] that serve the needs of residents are more likely to be negatively impacted by the arrival of tourists if their offerings do not match the preferences of tourists. On the other hand, businesses that cater to tourists may benefit from the influx of tourists facilitated by Airbnb, as short-term rentals expand their potential demand. Finally, the spatial organisation of urban economic activity may also be affected by Airbnb, as short-term rentals do not concentrate only in city centre areas but expand across the urban geography, blurring the touristic city. Therefore, a central research question is the extent to which Airbnb influences the economic landscape of urban areas.

To investigate the impact of Airbnb on the spatial organisation of economic activity, we study the case of Madrid, Spain. Using establishment-level data from the Madrid City Council and consumer-facing data from Airbnb, we analyse how the local economy was affected by Airbnb from 2014 to 2019. We first assess the impact of Airbnb on the birth and death of establishments. We go beyond traditional measures of establishment turnover to examine transitions, or establishments that were open in 2014 or 2019 but have changed their primary activity. We are interested in whether Airbnb promotes establishments that cater to tourists, intended as businesses where tourists spend relatively more than locals, and whether local businesses are being replaced by establishments in different sectors, such as restaurants or souvenir shops replacing drugstores or butcher shops. To do this, we take advantage of the temporary nature of our data and the uneven distribution of short-term rentals to isolate the impact of Airbnb from other trends related to e-commerce or gentrification.

Our main findings suggest that Airbnb contributes to business formation, particularly the creation of establishments that cater to tourists, such as restaurants and bars, and to a lesser extent, tourist-oriented retail shops like souvenir or gift stores. Conversely, we observe a decline in resident-oriented establishments, including both tradable and non-tradable businesses. Our results show that the increase in tourist-oriented establishments comes at the expense of local businesses. We complement our results with an instrumental variable strategy and show that our baseline results are robust to alternative measures of short-term rental activity, other factors contributing to tourism gentrification aside from Airbnb, and confounders related to gentrification and the growth of online shopping occurring at the same time as the disruption of digital accommodation. This study adds to the literature on the economic impact of platform economies by providing the first evidence of the unequal effect of Airbnb on the spatial economic organisation within a city. Additionally, we propose a new methodology and classification to identify which businesses are at risk of decline due to Airbnb disruption in local areas.

The rest of the paper is organised as follows. In the next section, we provide a brief review of the previous literature. Afterwards, we describe our data and methodology in detail. Subsequently, we present our results and the corresponding robustness checks. Finally, we conclude by drawing our findings together in the last section.

Tourism gentrification and neighbourhood change

Over the last decade, urban tourism flows have skyrocketed, spurred by the outbreak of the digital platform economy (Stabrowski, 2017). Regardless of other tourist accommodations like hotels and hostels, digital platform-mediated short-term rentals have leveraged the existing stock of local housing to develop their activity. Flexibility and the lack of ad-hoc regulation in the early stages explain why we have recently witnessed enormous growth in short-term rentals. However, platform accommodation-induced tourism has not come without a cost. Several studies have noted how the proliferation of short-term rentals in urban areas is related to the increase in housing and rental prices (Garcia-López et al., 2020; Barron et al., 2021). In that regard, 'home-sharing accommodations' have accelerated the already existing gentrification process (Wachsmuth and Weisler, 2018; Yrigoy, 2019; Ardura Urquiaga et al., 2020; Cocola-Gant and Gago, 2021). In particular, the widespread use of digital platforms nowadays spurs the expansion of digital accommodation companies across countries, intensifying transnational gentrification dynamics where worldwide higher-income classes appropriate local urban space (Sigler and Wachsmuth, 2015; Bantman-Masum, 2020).

Tourism gentrification, understood as a subset of the transnational gentrification process, diverges from other local population displacement processes. Classical gentrification displaces the resident population with higher-income individuals. Conversely, tourism gentrification implies a substitution of residents for tourists who do not settle down permanently (Lees and Ley, 2008). Looking at the consequences, both processes modify urban space. Unlike classical gentrification, which contributes to business transformations in line with the needs of the new affluent residents, tourism gentrification triggers urban changes to better satisfy tourists' needs (Behrens et al., 2018; Jover and Díaz-Parra, 2020). Despite those differences, the two processes may sometimes overlap as residents may also mimic broader tourist lifestyle attitudes (Novy, 2018). Short-term rental disruption adds another layer to the complexity of tourism-led gentrification. On the one hand, home-sharing accommodations allow landlords to generate extra income by renting unused housing space as rooms (Guttentag, 2015). However, commercial actors have monopolised the sector in recent years (Gil and Sequera, 2020). Therefore, to what extent Airbnb displaces the local population is context-specific and depends on the magnitude of Airbnb's professionalisation. Moreover, the geographic distribution of short-term rentals differs from other traditional accommodations. Home-sharing accommodations are more dispersed than hotels, which are concentrated in the city centre (Gutiérrez et al., 2017; Xu and Xu, 2021). The possibility of bringing tourists to residential areas could exacerbate the tension between local serving businesses and tourist-oriented activities but, at the same time, it contributes to decongesting tourism from central city areas. Besides, traditional accommodations already provide consumption amenities within their facilities; therefore, the potential impact on the local area is attenuated.

In the empirical literature about gentrification impacts on neighbourhood outcomes, only a handful of studies have gone beyond demographic and housing market changes, focusing on the transformation of business activities in those neighbourhoods (Lester and Hartley, 2014; Schuetz, 2014; Meltzer, 2016; Behrens et al., 2018; Glaeser et al., 2020). In this literature, leisure amenities and cultural and creative sectors have been marked as the primary services brought in by gentrifiers. The literature on Airbnb-led gentrification and business transformation is scant, and most papers have focused on the spillover of Airbnb effects on consumption amenities (Alyakoob and Rahman 2019; Basuroy et al. 2020; Hidalgo et al. 2022b). This paper contributes to filling this gap, taking a broader approach to investigate how short-term rentals reshape urban space, considering the overall effect of short-term rentals across the spatial organisation of retail businesses.

Methodology

Data

Study area

Our study takes place in the city of Madrid. We choose the city of Madrid as a compelling case study since it is one of the most prominent destinations in Europe by the number of Airbnb listings (Statista, 2019), and it is the most visited city in Spain (INE, 2020a). These characteristics make Madrid a valuable case study for examining the impact of the accommodation platform economy on the urban economic landscape.

Dependent variable

For our study, we used administrative records from the Madrid Statistical Department, specifically the Madrid City Council's census of business premises. This dataset contains monthly information on all business premises in the Madrid municipality from 2014.[2] We focused on establishment dynamics in October 2014 and October 2019. We choose the same month to avoid seasonality problems. To eliminate the influence of new urban development on our analysis, we only consider business premises that were present in the dataset throughout the entire study period. This allows us to focus on changes in establishment dynamics driven by local demand rather than supply factors. The dataset includes information on the location and accessibility of each premise, as well as data on the business activities of each establishment.

For our purposes, we are interested in businesses that cater to tourists or residents and whose consumption is local. The local consumption condition is key in our analysis since we are exploiting the fact that Airbnb users spend a high proportion of their time budget in nearby areas of their accommodation, ultimately impacting the urban economic landscape. To classify the establishments as tourist-oriented or resident-oriented, we rely on already-existing classifications and adapt them to our setting (Meltzer and Schuetz, 2012; Meltzer and Capperis, 2017; Allen et al., 2020; Aparicio et al., 2021). For the purpose of this classification, we consider establishments to be tourist-oriented if the expenditure of tourists is higher than that of residents. As a result, mostly tourist-oriented activities comprise local consumption amenities such as restaurants, bars and coffee shops. Previous research has shown that Airbnb is behind the rise in food and beverage establishments (Alyakoob and Rahman 2019; Basuroy et al. 2020; Hidalgo et al. 2022b). On top of that, food and beverage services correspond to the main expenditures made *in situ* by tourists (INE, 2020b; Aparicio et al., 2021). We complement this group with other stores that target tourist needs like clothing, souvenirs, gifts, or currency exchange stores.

For resident-oriented establishments, we select those activities that fulfil the basic needs of daily life. In particular, we cover a broad set of neighbourhood amenities that serve local consumer demand directly (Meltzer and Capperis, 2017). We include in this group tradable and non-tradable services. Among the tradable category are food-related stores such as butcheries or fishmongers and device-related stores like drugstores, phone and newsagent stores. The non-tradable group includes personal care and education services: hairdressers, depilation, and nursery schools. We decided not to include higher-level education and health services in our analysis as they might not have only local consumption. We do not include other potential local businesses, such as pharmacies or tobacco shops, as the location is regulated and responds to local planning ordinances, and therefore their location is not subject to the same potential displacement as other neighbourhood uses. In order to avoid the overlap of activities that cater to tourists or locals, businesses that host both tourist-and resident-oriented activities are not classified as either tourist-or local-oriented establishments. Table I shows our proposed classification.

After classifying establishments based on their target population and their activity, we calculated the first set of business dynamics variables: birth and death. *Birth* (*Death*) is a binary variable that is assigned a value of 1 for establishments that were closed (opened) in 2014 and opened (closed) in 2019. In order to understand the impact of Airbnb on business activities, we further distinguished birth and death by our proposed classification of tourist- and resident-oriented businesses. As a result, our first group of business dynamics variables consists of: *birth*, *birth-tourist*, *birth-resident*, *death*, *death-tourist*, and *death-resident*.

[Insert Table I here]

As a second step, we focused on transitions, i.e., business premises that changed their main activity and storefront name between 2014 and 2019.[3] Therefore, we created a binary variable *transition* that is assigned a value of 1 for business premises that were open in both years but changed their activities during the period 2014-2019. This group is of particular interest because it allows us to measure the effect of Airbnb on business displacement. Unlike other business dynamics metrics such as births or deaths, transitions better reflect the reorientation of local supply because they refer to establishments that are open in our five-year period but change their service offerings. Births and deaths, on the other hand, might be more closely tied to long-term business trends. For the case of births, we do not have information about the business premises prior to 2014. For the case of deaths, we are unable to go beyond 2019 because of the COVID-19 outbreak, which has caused unprecedented disruption to business dynamics. In particular, the implementation of furlough schemes in the tourism sector in Spain prevents us from including recent years in our time frame because of the difficulty of distinguishing the impact of the decline in tourist flows due to public aid (Hidalgo et al., 2022a).

As we are interested in examining whether Airbnb-induced tourism contributes to the displacement of establishments towards tourist-oriented activities, we defined two binary dependent variables, *transition-tourist* and *transition-resident*, which are assigned a value of 1 for business premises that changed their offerings in 2019 towards tourist-or resident-oriented activities, respectively. Additionally, it is possible that Airbnb may contribute to the displacement of establishments towards tourist-oriented activities at the expense of businesses that are more focused on serving the needs of local residents. To test this hypothesis, we focus on two specific transitions: *transition resident-tourist* and *transition tourist-resident. Transition resident-tourist* (*transition tourist-resident*) is assigned a value of 1 for establishments that became tourist-oriented (resident-oriented) in 2019, given that they were resident-oriented (tourist-oriented) in 2014. Figure I provides evidence of spatial displacement of resident-oriented businesses by tourist-oriented activities in the trendy tourist neighbourhood of Embajadores in Madrid.

[Insert Figure I here]

Short-term rental activity

To measure short-term rental activity, we used consumer-facing information from the largest company in the sector, Airbnb. Specifically, we obtained data from Inside Airbnb, an independent, non-commercial website that scrapes information directly from the Airbnb site for various cities and countries worldwide.[4] The entry of Airbnb in Madrid is not evenly distributed, concentrated in the city centre and spreading to the periphery (Gil and Sequera, 2020; Hidalgo et al., 2022b). As a result, establishments in Madrid are differently exposed to Airbnb-induced tourism depending on the location of Airbnb listings. To consider this pattern of short-term rental activity and its influence on the retail business sector, we draw a 150-meter radius buffer around each business premise in 2014 and 2019.[5] Then, we count the number of short-term rentals within each buffer and calculate the absolute difference in the number of short-term rentals in each buffer over the five-year period. Figure II shows the creation of the buffer using the Embajadores neighbourhood as in Figure I. We preferred our Airbnb intensity measure for aggregating short-term rental data instead of census tracts or neighbourhoods because both are based on arbitrary boundaries that may not reflect the Airbnb-induced tourism effect around each business premise. Additionally, buffers are homogeneous measures in size and shape, while other predefined spatial partitions may be heterogeneous in shape and scale. In that regard, the creation of buffers around each establishment allows for measuring its potential demand in a more reliable way compared with pre-established administrative measures, where the location of the establishment is not necessarily central. Lastly, we address the issue of jittering coordinates by Airbnb by using a 300-meter circumference area.

[Insert Figure II here]

Control variables

We complement our dataset with socio-demographic information which contributes to explaining urban establishment dynamics such as population and average household income at the census tract level. We also add distance to the city centre as an additional covariate to control for city centre trends. Finally, we include a dummy variable to measure the accessibility level of the establishment (ground level or within a mall). A final list with all the variables used can be found in Table AI and its main descriptive statistics in Table AII in the Appendix.

Specification

The purpose of this paper is to investigate the impact of Airbnb's entry into urban business transformation. Specifically, we aim to determine to what extent Airbnb has affected business dynamics metrics such as the probability of openings, business closures, or changes in business activity, distinguishing between establishments oriented towards tourists and those oriented towards residents. To address our research question, we use the following linear probability model specification:

$$\Pr(Establishments\ dynamics_i^{2019-2014}) = \beta Airbnb_i + \rho X_c + \delta Z_i + \alpha_s + \gamma_n + \epsilon_i \tag{1}$$

where $Establishments\ dynamics_i^{2019-2014}$ refers to the business dynamics outcome variables in Table AI depending on the specification. Our main coefficient of interest is β, which measures the effect of a change in the number of short-term rentals around a 150-meters radius buffer of business premises i on the probability that the establishment undergoes any change in business activity. We expand our specification to control for socio-demographic characteristics measured in 2014 at the census tract level X_c, such as population and the average household income. We measure them at the beginning of our sample period to avoid potential contamination effects from our treatment variable. To account for different geographical business dynamics trends depending on the location of the economic activity, we add the distance to the city centre as an explanatory variable. We include establishments-specific characteristics Z_i related to its accessibility (ground level or within a mall) and we control for activity α_s and neighbourhood γ_n fixed effects.[6] In this way, we account for potential trends in the emergence or decline of certain economic activities in the city and unobserved time-invariant characteristics at the neighbourhood level. We cluster the standard errors at the neighbourhood level as business premises share commonalities at a higher treatment level. Besides, we avoid the potential problem of overlapping buffers.

One potential concern in our baseline specification is that general trends may influence the dynamics of tourist and local-oriented establishments in addition to the presence of Airbnb. While we have controlled for socioeconomic trends and included time-invariant location characteristics and activity-specific trends, there may still be some unconfounded factors that our ordinary least squares (OLS) specification cannot control for. To address this issue, we used an instrumental variable (IV) strategy. We use the number of rental houses in 2011 as an instrument for our Airbnb variable, following the approach of Hidalgo et al. (2022b). The idea behind this instrument is that short-term rentals are more likely to grow in areas with a higher stock of rental houses since Airbnb's entry into the market reduces the supply of long-term rentals to capitalise on the short-term rental price premium (Horn and Merante, 2017; Garcia-López et al., 2020; Barron et al., 2021).

We obtained rental house data from the Spanish 2011 Census, which is available only at the census tract level. Since our buffers are larger than the median census tract area in Madrid, we imputed the number of rental houses in each buffer using the proportion of the area of each census tract within the buffer (See Figure AI in the Appendix).[7]

Results

This study aims to investigate the effect of short-term rentals on the dynamics of urban establishments, using the city of Madrid as a case study. The units of analysis in this study are business premises. We examine whether business premises in Madrid experienced any changes in their business status between October 2014 and October 2019. In the first stage of the analysis, we investigate the effect of Airbnb on the probability that an establishment opens or closes, and whether this change in activity status is driven by the orientation of the establishment to tourists or residents. In the second stage, we focus on transitions: establishments that were open in 2014 and 2019 but changed their main activity. We also differentiate between tourist-oriented and resident-oriented businesses in our analysis of transitions to understand the nature of retail change. Finally, we investigate whether the transitions related to tourism come at the expense of local businesses.

Table II presents the results of the first set of business dynamics variables using a baseline linear probability model specification. The sample size for each specification varies because of the different comparison groups. In the case of the birth group, we include only inactive establishments that were present between 2014 and 2019, and establishments that were born in 2019 and closed in 2014. In the death group, we include all establishments that were open in both 2014 and 2019, and those that were closed in 2019 but opened in 2014. When examining the impact of being a tourist-oriented or resident-oriented business on birth or death probabilities, we use only establishments in the respective category (births and deaths) as the comparison group.

[Insert Table II here]

The results in Table II show that Airbnb has a positive effect on the creation of new establishments (Column 1), but does not seem to affect the probability of closure (Column 4). This finding is consistent with the work of Jiménez et al. (2022), who found that Airbnb has a positive impact on the arrival of tourists in several Spanish cities, including Madrid. The positive effect of short-term rentals on business openings may be due to the additional income flows generated by Airbnb-induced tourism. However, it is worth noting that the impact of Airbnb on business premises' service offerings is not uniform. In particular, Airbnb increases the probability of entry of tourist-oriented businesses (Column 2) but decreases the probability of the creation of resident-oriented establishments (Column 3). A reverse pattern is observed for the case of closures, with an increase in the probability of closure for resident-oriented establishments (Column 6).

Table II provides insights into the impact of the arrival of short-term rentals on the dynamics of businesses in Madrid, but we must be cautious in interpreting the results because of the coefficient of interest in these specifications. Airbnb listings may be self-selecting in areas of the city where some form of urban revitalisation is occurring. In this case, the positive effect on the birth and the null effect on the death specification may be due to unobserved city-specific events that would have occurred even in the counterfactual scenario where Airbnb did not enter these areas. To address this issue, we perform an instrumental variable analysis and report the results in Table AIII. These results confirm the findings from the baseline model, and in some cases, the effects are even stronger under the instrumental variable model.

Last, the birth and death specifications are subject to left and right censoring due to data limitations. Therefore, we complement our first set of business dynamics variables with the transition group to try to partially address censoring. Table III summarises the main results.

[Insert Table III here]

The results of our second set of business dynamics metrics confirm the findings from the previous analysis: Airbnb increases the probability that business premise will transition to a tourist-oriented activity (Column 8). Specifically, an increase of 15 Airbnb listings (the average Airbnb listing change within the buffer) around a business premises that undergoes any type of transition increases the probability of transitioning to a tourist-oriented establishment by 1 percentage points, which represents a 4% increase over the mean of the dependent variable. At the same time, this increase in short-term rentals decreases the probability of transitioning to a local business by a similar magnitude (Column 9). As shown in Figure III, the increase in the probability of transitioning to a tourist-oriented business is driven mainly by clothing stores, restaurants, bars and cafe services. These establishments typically have more flexible opening hours that are more convenient for tourists, as they are open during the day and at night, while souvenir or gift shops are usually only open during the day.

[Insert Figure III here]

So far, we have found that Airbnb contributes to the rise of tourist-oriented business in Madrid, measured through births and transitions. At the same time, short-term rental negatively affects local businesses by increasing the probability of closure and decreasing the probability of birth and transition. We claim that the main mechanism behind our findings is the substitution of residents for tourists whose consumption patterns differ from those of residents. While the growth of businesses that cater to tourists may be part of a larger trend related to the growth of the short-term rental sector in Spain and Madrid (Jiménez et al., 2022), it is also possible that other factors are contributing to the decline of businesses that cater to residents. To pinpoint the specific role of Airbnb in this shift, we have analysed whether the transition of businesses to those that cater to tourists is occurring at the expense of other sectors or, more specifically, at the expense of local-oriented businesses. We have found that Airbnb has a greater impact on the displacement of non-tourist related activities

(See Columns 10 and 11 of Table III for the OLS baseline model and Table AIV for the IV model). Indeed, whereas Airbnb increases the probability that an establishment becomes tourist-oriented, conditional on being a local business in the past, we do not observe the opposite. To get a better picture of which types of local activities are being displaced by touristic business, we reproduce in Figure IV the transition from resident to tourist-oriented activities. We can observe that consumption amenities account for most resident-tourist transitions in both directions, i.e., from food-oriented local businesses to food-oriented tourist establishments. Moreover, other non-tradable local businesses such as beauty salons or clothing textile activities are also crowded out, reflecting that the displacement of local activities is not concentrated in specific sectors.

Consequently, our findings reveal the important role that Airbnb has played in the reconfiguration of economic activity in the city of Madrid, a case that can be extended to other European tourist cities where ad-hoc regulations are being introduced to cope with the diffusion of short-term renting (Valentin et al., 2019).

[Insert Figure IV here]

Robustness checks

In this section, we test the robustness of our main results from Table III in different ways. First, we control whether our main tenets hold whenever we modify the way we measure short-term rental activity. Second, we leverage the heterogeneous distribution of short-term rental activity across Madrid by removing from our sample all observations within a neighbourhood where a new hotel settles to avoid contamination of tourist effects stemming from traditional accommodations. Third, we test whether the transitions towards tourism-oriented business and the decline in resident-oriented establishments mask other business-related phenomena beyond Airbnb-induced tourism, such as gentrification and e-commerce.

Short-term rental measurement

To account for the fact that some businesses may be more exposed to local demand shocks caused by Airbnb than others, we have used a 150-meter radius buffer around each business premises as our main variable of interest to calculate the change in the number of short-term rentals over a five-year period. This approach allows us to avoid using administrative units such as census tracts or neighbourhoods, which may not accurately reflect the specific impact of Airbnb on business dynamics. However, this method does not take into account the size of each accommodation unit or its demand. To address this issue, we used the maximum number of guests that a listing can accommodate as an alternative measure of Airbnb activity, calculating the difference between 2019 and 2014 for each buffer. We also considered the number of reviews for each listing as another measure of Airbnb activity, calculating the difference between 2019 and 2014 for each buffer. Furthermore, we have varied our buffer by 50 meters up and down in alternative specifications to test the robustness. Results A, B and C, and D from Table IV show that our main findings hold regardless of the method used to measure Airbnb activity.

Traditional accommodations

To further assess the impact of Airbnb on local businesses, we have examined whether our main findings hold when we remove certain neighbourhoods from our sample where new traditional accommodations have opened.[8] We are deleting mainly city centre neighbourhoods where the bulk of the short-term rental activity is concentrated. Our decision is conservative as we do not expect all economic activities in the neighbourhood to be affected by the arrival of a new hotel, but only those closest to it. However, our decision to exclude these neighbourhoods is also motivated by the fact that the location of new hotels can be seen as a proxy for the overall tourist attractiveness of an area. As such, it is likely that changes in the economic activity in these neighbourhoods are driven by overall tourist flows rather than short-term rentals-induced tourism. The results in E from Table IV provide evidence that business displacement is driven mainly by Airbnb's arrival and not other trends in the tourism sector. In principle, this is because Airbnb concentrates not only on tourist enclaves but also on other residential areas with good public transit and cultural cachet (Gutiérrez et al., 2017; Wachsmuth and Weisler, 2018; Deboosere et al., 2019). We can observe that once touristic neighbourhoods are removed, the probability of a transition to a tourist-oriented business doubles. Therefore, outside the touristic area of the city, the effect of Airbnb is even more intense and disruptive.

[Insert Table IV here]

Gentrification and e-commerce

Our business classification for tourism is made up mainly of amenities for consumption, such as food and beverage establishments. While tourists often spend a significant amount of their financial budget on food while on vacation, local residents also consume these amenities. In this case, 'touristification' may be confused with the adoption of tourist-like behaviours and consumption habits by local residents. Moreover, the proliferation of food and beverage establishments has been connected to the process of gentrification in several studies (Novy, 2018; Almagro and Dominguez-Iino, 2022). If Airbnb enters areas where locals are more likely to adopt tourist-like consumption patterns, our results may not accurately capture the pure effect of Airbnb-induced tourism. To address this potential confounder, we conduct a falsification exercise by replacing tourist-oriented activities with those that have been linked to gentrification.[9] Our findings, shown in Result H in Table IV, suggest that gentrification does not account for our previous results. These findings align with the idea that Airbnb does not necessarily concentrate on gentrifying areas and can be found beyond central business districts with high rates of traditional accommodations, as noted by Wachsmuth and Weisler (2018).

The prevalence of tradable establishments in our local-business category makes our empirical analysis exceptionally sensitive to shocks related to this sector. One possible explanation for the decline in local businesses could be the rise of e-commerce. If this trend is happening in the same areas where Airbnb is present, we would be capturing the combined impact of online shopping and tourist activity driven by Airbnb. To ensure that our results are specifically due to a local demand shock caused by Airbnb and not any other factors, we restrict our resident-oriented category to only non-tradable businesses.[10] Additionally, in another exercise, we exclude clothing businesses, ready-made meal providers, and limited-service eating places from our classification of businesses oriented towards tourists. We made this decision because the concentration of short-term rentals and clothing stores in the city centre of Madrid makes it difficult to distinguish the effects of Airbnb-induced tourism from other local spending effects. We also chose to exclude ready-made meals and limited-service eating places due to their potential relationship with the growth of ridesharing businesses (Gorback, 2020). Finally, we did not include newsagents in our classification of businesses oriented towards residents because their decline may be due to the death of print media. Result G in Table IV confirms that our main findings are not affected by broader trends.

As a final check, we employ sensitivity analysis tools for regression models developed by Cinelli and Hazlett (2020) to assess whether our results are robust to the potential existence of confounders, interacting non-linearly. Table AVI in the Appendix confirms our main findings.

Discussion and conclusion

The emergence of the accommodation platform economy, with Airbnb being a prominent player, has significantly impacted the spatial organisation of urban economies. However, this impact varies across locations and different types of businesses. Using Madrid as a case study, we found that short-term rentals reshaped the urban space to better meet the needs of tourists. However, the impact on the economy, driven largely by the growth of tourist-oriented businesses, masks negative effects on non-touristic sectors. In particular, businesses that cater to the needs of local residents are particularly impacted by the arrival of short-term rentals, indicating that Airbnb does displace resident-oriented businesses. Our findings are robust to alternative measures of Airbnb activity, and to other tourist actors or confounding factors related to gentrification and the rise of online shopping.

The present study makes meaningful contributions to tourism gentrification and neighbourhood change literature. We show that the effect of Airbnb exposition expands beyond the city centre. In this way, short-term rentals may fuel uneven geographies by contributing to expelling the population from non-central neighbourhoods. At the same time, Airbnb-induced tourism can help to decongest the city centre of tourists and redistribute them better across the city. The uneven effect on the spatial organisation of the economic activity demands local authorities to address two issues: the levels of short-term rentals that are considered globally desirable in the city and the manner in which they are distributed throughout the territory. Therefore, policymakers should take into account the uneven impact of Airbnb on businesses depending on their target consumers, possibly undertaking initiatives such as food security measures to ensure that the basic needs of local residents are met. In addition, the loss of local businesses may compromise the 15-minute city strategy, which is already in place in a growing number of cities. Otherwise, there is a risk of eroding the collective city space in the affected neighbourhoods, thus amplifying the touristification phenomenon already taking place in urban areas. We believe that our results may help design policy interventions that consider not only its immediate effect on the housing rental market but also the structural change in the geography of economic activities.

Further research is necessary to confirm our findings across cities and over time. Our methodology, which is based on existing classifications of tourist-oriented versus local-oriented businesses, publicly available information on short-term rentals, and business register data, can be easily replicated in other contexts. However, it is worth noting that there are some limitations to our study. Sometimes, tourist-oriented and local-oriented establishments may overlap in terms of their target consumers, and future research could complement our proposed methodology by using surveys and establishment reviews from recommendation platforms to better classify activities and thoroughly examine the touristification phenomenon. It is also important to determine the persistence of the transition from resident-oriented to tourist-oriented activities and whether it may be influenced by factors such as urban geography and socio-demographic characteristics. The disruption caused by the COVID-19 pandemic provides a unique opportunity to evaluate the resilience of urban areas that were previously reliant on tourist amenities.

Notes

[1]We will use the terms 'local business', 'resident-oriented', or 'local-oriented establishment' to refer to activities that serve the needs primarily of the local community.

[2]In our dataset, a business premise refers to the physical property where an establishment conducts its activities. For more information about the dataset, please see Appendix.

[3]For example, a transition in our study would refer to a business premise that offered DVD rental services in 2014 but changed its storefront name and activity to offer mobile phone accessories at a later date. Our dataset does not allow us to identify ownership, so it is possible that the same owner changed the focus of their business or that a new owner took over the premise.

[4]Inside Airbnb began collecting Airbnb data for Madrid in 2015. To obtain data for 2014, we used the date of the first review as a proxy for when the listing was first opened, assuming it had not been deleted from the platform. Additionally, we applied the following filter to remove any inactive listings from our dataset: we only included listings that received at least one review in the previous year. similar to the approach taken in Zervas et al. (2017) and Garcia-López et al. (2020). Therefore, we excluded listings that did not receive a review since October 2018 for available listings in October 2019. Similarly, we dropped listings that did not receive a review since 2013 for available listings in October 2014. We chose October as our reference month to account for potential seasonal fluctuations in the number of short-term rentals in Madrid.

[5]Previous contributions in the STRs literature have relied on different aggregation measures such as census tracts (Horn and Merante, 2017; Xu and Xu, 2021; Hidalgo et al., 2022b), ZIP codes (Koster et al., 2021; Bekkerman et al., 2022; Chen et al., 2022), and neighbourhoods (López et al., 2020; Batalha et al., 2022). Only a few studies have used rings as aggregation measures (Sheppard et al., 2016; Zou, 2020; Venerandi et al., 2022).

[6]We include activity fixed effects at the current activity level for *birth*, *death* and *transition* specifications. Conversely, we include activity fixed effects at the previous activity level for *transition tourist* and *transition local tourist* specifications to prevent them from interfering with our dependent variable. Whenever we condition birth or death to be a tourist-or resident-oriented activity, we do not include any activity fixed effects because of collinearity with the dependent variable.

[7]Our imputation procedure relies on the assumption that rental homes in 2011 were evenly distributed within census tracts, which may not be accurate for some large tracts located far from the city centre but is reasonable for most tracts, which have a similar size. It is worth noting that only a few of the census tracts within the boundaries of the Madrid municipality are highlighted because of their large size and low population density, as these tracts are primarily made up of parks.

[8]The neighbourhoods where new hotels locate are Sol, Cortes, Justicia, Universidad, Casco H. Vallecas, Castilla, Nueva España, Prosperidad, Casco Histórico de Barajas, Arguelles, Cuatro Caminos and Recoletos.

[9]The list of gentrification activities can be found in Table AV in the Appendix. That classification comprises mainly leisure amenities and cultural and creative sectors. It is important to bear in mind that the classification above is based on Behrens et al. (2018), who focuses on a different context and time frame (New York 2000-2010).

[10]The non-tradable resident-oriented establishments are: Textile laundry, Tailor, Furnishing services, Hairdresser, Beauty and depilation salon, Driving and Nursery school.

References

Allen, T., Fuchs, S., Ganapati, S., Graziano, A., Madera, R., and Montoriol-Garriga, J. (2020). Is tourism good for locals? Evidence from Barcelona. *Dartmouth College, mimeograph.*

Almagro, M. and Dominguez-Iino, T. (2022). Location sorting and endogenous amenities: Evidence from Amsterdam. *Available at SSRN 4279562.*

Alyakoob, M. and Rahman, M. S. (2019). Shared prosperity (or lack thereof) in the sharing economy. *Available at SSRN 3180278.*

Aparicio, D., Hernández Martín-Caro, M. S., García-Palomares, J. C., and Gutiérrez, J. (2021). Exploring the spatial patterns of visitor expenditure in cities using bank card transactions data. *Current Issues in Tourism*, pages 1–19.

Ardura Urquiaga, A., Lorente-Riverola, I., and Ruiz Sanchez, J. (2020). Platform-mediated short-term rentals and gentrification in Madrid. *Urban Studies*, 57(15):3095–3115.

Bantman-Masum, E. (2020). Unpacking commercial gentrification in central Paris. *Urban Studies*, 57(15):3135–3150.

Barron, K., Kung, E., and Proserpio, D. (2021). The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science*, 40(1):23–47.

Basuroy, S., Kim, Y., and Proserpio, D. (2020). Estimating the impact of Airbnb on the local economy: Evidence from the restaurant industry. *Available at SSRN 3516983.*

Batalha, M., Gonçalves, D., Peralta, S., and dos Santos, J. P. (2022). The virus that devastated tourism: The impact of covid-19 on the housing market. *Regional Science and Urban Economics*, 95:103774.

Behrens, K., Boualam, B., Martin, J., and Mayneris, F. (2018). Gentrification and pioneer businesses. *Available at SSRN 3278671.*

Bekkerman, R., Cohen, M. C., Kung, E., Maiden, J., and Proserpio, D. (2022). The effect of short-term rentals on residential investment. *Marketing Science.*

Celata, F., Hendrickson, C. Y., and Sanna, V. S. (2017). The sharing economy as community marketplace? Trust, reciprocity and belonging in peer-to-peer accommodation platforms. *Cambridge Journal of Regions, Economy and Society*, 10(2):349–363.

Chen, W., Wei, Z., and Xie, K. (2022). The Battle for Homes: How Does Home Sharing Disrupt Local Residential Markets? *Management Science*.

Cinelli, C. and Hazlett, C. (2020). Making sense of sensitivity: Extending omitted variable bias. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 82(1):39–67.

Cocola-Gant, A. and Gago, A. (2021). Airbnb, buy-to-let investment and tourism-driven displacement: A case study in Lisbon. *Environment and Planning A: Economy and Space*, 53(7):1671–1688.

Deboosere, R., Kerrigan, D. J., Wachsmuth, D., and El-Geneidy, A. (2019). Location, location and professionalization: A multilevel hedonic analysis of Airbnb listing prices and revenue. *Regional Studies, Regional Science*, 6(1):143–156.

Ferreri, M. and Sanyal, R. (2018). Platform economies and urban planning: Airbnb and regulated deregulation in London. *Urban Studies*, 55(15):3353–3368.

Garcia-López, M.-À., Jofre-Monseny, J., Martínez-Mazza, R., and Segú, M. (2020). Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona. *Journal of Urban Economics*, 119:103278.

Gil, J. and Sequera, J. (2020). The professionalization of Airbnb in Madrid: Far from a collaborative economy. *Current Issues in Tourism*, pages 1–20.

Glaeser, E. L., Luca, M., and Moszkowski, E. (2020). Gentrification and neighborhood change: Evidence from yelp. Technical report, National Bureau of Economic Research.

Gorback, C. (2020). Your Uber has arrived: Ridesharing and the redistribution of economic activity. *Job Market Paper*.

Gutiérrez, J., García-Palomares, J. C., Romanillos, G., and Salas-Olmedo, M. H. (2017). The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism management*, 62:278–291.

Guttentag, D. (2015). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current issues in Tourism*, 18(12):1192–1217.

Hidalgo, A., Martín-Barroso, D., Nunez-Serrano, J. A., Turrión, J., and Velázquez, F. J. (2022a). Does hotel management matter to overcoming the COVID-19 crisis? The Spanish case. *Tourism management*, 88:104395.

Hidalgo, A., Riccaboni, M., and Velázquez, F. J. (2022b). The effect of short-term rentals on local consumption amenities: Evidence from Madrid. *Available at SSRN 4000918*.

Horn, K. and Merante, M. (2017). Is home sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics*, 38:14–24.

INE (2020a). Tourist Expenditure Survey (Egatur). Retrieved December 10, 2020 from: https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177002&menu=ultiDatos&idp=1254735576863.

INE (2020b). Tourist Expenditure Survey (Egatur). Retrieved December 10, 2020 from: https://www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736177002&menu=ultiDatos&idp=1254735576863.

Jiménez, J. L., Ortuño, A., and Pérez-Rodríguez, J. V. (2022). How does AirBnb affect local Spanish tourism markets? *Empirical Economics*, 62(5):2515–2545.

Jover, J. and Díaz-Parra, I. (2020). Gentrification, transnational gentrification and touristification in Seville, Spain. *Urban Studies*, 57(15):3044–3059.

Koster, H. R., Van Ommeren, J., and Volkhausen, N. (2021). Short-term rentals and the housing market: Quasi-experimental evidence from Airbnb in Los Angeles. *Journal of Urban Economics*, 124:103356.

Lees, L. and Ley, D. (2008). Introduction to special issue on gentrification and public policy. *Urban Studies*, 45(12):2379–2384.

Lester, T. W. and Hartley, D. A. (2014). The long term employment impacts of gentrification in the 1990s. *Regional Science and Urban Economics*, 45:80–89.

López, F. A., Mínguez, R., and Mur, J. (2020). ML versus IV estimates of spatial SUR models: Evidence from the case of Airbnb in Madrid urban area. *The Annals of Regional Science*, 64(2):313–347.

Meltzer, R. (2016). Gentrification and small business: Threat or opportunity? *Cityscape*, 18(3):57–86.

Meltzer, R. and Capperis, S. (2017). Neighbourhood differences in retail turnover: Evidence from New York City. *Urban Studies*, 54(13):3022–3057.

Meltzer, R. and Schuetz, J. (2012). Bodegas or bagel shops? Neighborhood differences in retail and household services. *Economic Development Quarterly*, 26(1):73–94.

Novy, J. (2018). 'Destination'Berlin revisited. From (new) tourism towards a pentagon of mobility and place consumption. *Tourism Geographies*, 20(3):418–442.

Schuetz, J. (2014). Do art galleries stimulate redevelopment? *Journal of Urban Economics*, 83:59–72.

Sheppard, S., Udell, A., et al. (2016). Do Airbnb properties affect house prices. *Williams College Department of Economics Working Papers*, 3(1):43.

Sigler, T. and Wachsmuth, D. (2015). Transnational gentrification: Globalisation and neighbourhood change in Panama's Casco Antiguo. *Urban Studies*.

Stabrowski, F. (2017). 'People as businesses': Airbnb and urban micro-entrepreneurialism in New York City. *Cambridge Journal of Regions, Economy and Society*, 10(2):327–347.

Statista (2019). Number of Airbnb listings in selected European cities as of 2019. Retrieved November 30, 2020 from: https://www.statista.com/statistics/815145/airbnb-listings-in-europe-by-city.

Valentin, M. et al. (2019). The effects of regulating the housing short-term rental market: Evidence from New Orleans. *Available at SSRN*, 3329964.

Venerandi, A., Feliciotti, A., Fleischmann, M., Kourtit, K., and Porta, S. (2022). Urban form character and Airbnb in Amsterdam (NL): A morphometric approach. *Environment and Planning B: Urban Analytics and City Science*, page 23998083221115196.

Wachsmuth, D. and Weisler, A. (2018). Airbnb and the rent gap: Gentrification through the sharing economy. *Environment and Planning A: Economy and Space*, 50(6):1147–1170.

Xu, M. and Xu, Y. (2021). What happens when Airbnb comes to the neighborhood: The impact of home-sharing on neighborhood investment. *Regional Science and Urban Economics*, 88:103670.

Yrigoy, I. (2019). Rent gap reloaded: Airbnb and the shift from residential to touristic rental housing in the Palma Old Quarter in Mallorca, Spain. *Urban Studies*, 56(13):2709–2726.

Zervas, G., Proserpio, D., and Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of marketing research*, 54(5):687–705.

Zou, Z. (2020). Examining the impact of short-term rentals on housing prices in Washington, DC: Implications for housing policy and equity. *Housing Policy Debate*, 30(2):269–290.

Tables

Table I: Tourist-oriented and resident-oriented activities classification

Establishment type	Activity code	Activity description
Tourist-oriented		
Souvenirs	661002, 477807, 477808	Exchange currency, Expositions, Gift shop
Restaurant	561001, 561004	Restaurant, Bar restaurant
Bar	561005, 563002, 563005	Bar with kitchen, Bar without kitchen, Bar with performance
Ice-cream parlour	472902,472903, 472904	Ice-cream parlour (in-place elaboration), Ice-cream take-away
Cafe	561006, 561007	Cafe, Teahouse
Limited-Service Eating places	472406, 472407	Take-away (in-place elaboration), Take-away
Ready-made meals	471101	Ready-meal store
Pastry shops	472402, 472403	Pastry, Pastry with baked goods
Clothing store	477101	Retail trade of clothing in specialised stores
Resident-oriented		
Clothing textile	464201,952004, 960101	Textile shop, Textile laundry, Tailor
Furnishing	475903, 433001	Furnishing
Retail food	471104, 472907, 472102, 472203, 472302	Convenience, Fruit, Butchery, Fishmonger, Candy
Retail non food	477801, 474201, 931008	Drugstore, Phone store, Gym
Beauty salon	960206, 960203,960201	Hairdresser, Beauty salon, Depilation
Car workshop	452002,472102, 855001	Car workshop, Driving School
Newsagent	476201, 821001	Newsagent, Print shop
Nursery	851001	Nursery school

Notes: Activity codes refer to the most disaggregated information about business service offerings. These codes are based on the classification of activities used by the Madrid City Council. The proposed classification is not exhaustive as other activities which are not categorised as either tourist or local-oriented are not considered as they do not satisfy the local consumption assumption and expenditure patterns, despite being present in the Madrid City Council census of business premises.

Table II: Linear probability model for establishments birth and death dynamics OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Pr(Birth = 1)	Pr(Birth, tourist = 1)	Pr(Birth, resident = 1)	Pr(Death = 1)	Pr(Death, tourist = 1)	Pr(Death, resident = 1)
Airbnb buffer	0.010***	0.015***	-0.012***	0.001	-0.004	0.015**
	(0.004)	(0.006)	(0.004)	(0.001)	(0.012)	(0.007)
Mean dependent variable	0.792	0.193	0.238	0.0233	0.195	0.262
Marginal percentage effect	1.120	7.756	5.036	4.298	2.052	5.730
R^2	0.17657	0.06799	0.03202	0.02464	0.13997	0.09923
Observations	7,732	6,123	6,123	74,227	1,868	1,868

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. The standard errors for the estimates are clustered at the neighbourhood level. The Airbnb buffer variable represents the absolute change in the number of short-term rentals within a 150-meter radius ring around each establishment between 2014 and 2019. The coefficient for this variable is scaled by 15, which represents the average Airbnb listing change within the buffer. The model also includes control variables such as the logarithm of the population, average household income at the census tract level, a dummy variable to identify the accessibility of the establishment (grouped or storefront), and distance to the city centre. Neighbourhood fixed effects are included in each specification, and activity codes fixed effects are included in the first and fourth columns. The number of observations varies across each specification depending on the reference comparison group. The birth group comprises only inactive establishments that were present between 2014 and 2019, and establishments that were born in 2019 and closed in 2014. The death group includes all establishments that were open in both 2014 and 2019, and those that were closed in 2019 but open in 2014. When examining the impact of being a tourist-oriented or resident-oriented business on birth or death probabilities, we use only establishments in the respective category (establishments that were born in 2019 and closed in 2014 for births and establishments that were closed in 2019 but open in 2014) for deaths as the comparison group.

Table III: Linear probability model for establishments transitions dynamics (OLS)

	(7)	(8)	(9)	(10)	(11)
Dependent Variable:	Pr(Transition = 1)	Pr(Trans, tourist = 1)	Pr(Trans, resident = 1)	Pr(Trans, resident-tourist = 1)	Pr(Trans, tourist-resident = 1)
Airbnb buffer	0.003***	0.010*	-0.007**	0.025***	-0.004
	(0.0001)	(0.006)	(0.004)	(0.007)	(0.004)
Mean dependent variable	0.109	0.244	0.219	0.217	0.197
Marginal percentage effect	2.752	4.098	3.196	11.520	2.030
R^2	0.228	0.184	0.107	0.169	0.218
Observations	85,791	9,334	9,334	1,518	1,600

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. The standard errors for the estimates are clustered at the neighbourhood level. The Airbnb buffer variable represents the absolute change in the number of short-term rentals within a 150-meter radius ring around each establishment between 2014 and 2019. The coefficient for this variable is scaled by 15, which represents the average Airbnb listing change within the buffer. The model also includes control variables such as the logarithm of the population, average household income at the census tract level, a dummy variable to identify the accessibility of the establishment (grouped or storefront), and distance to the city centre. Neighbourhood fixed effects are included in each specification, and activity codes fixed effects are included in the first and fourth columns. The number of observations varies across each specification depending on the reference comparison group. The transitions group is comprised of all establishments that were open both in 2014 and 2019 with no change and establishments that were open in both 2014 and 2019 and change activity and storefront name. The transition-tourist and transition-residents group is comprised only of transition establishments. The transition resident-tourist (transition tourist-resident) group is comprised only of transition establishments whose previous activity was local-oriented (tourist-oriented).

Table IV: Robustness checks

Dependent Variable:	Pr(Transition = 1)	Pr(Trans, tourist = 1)	Pr(Trans, resident = 1)	Pr(Trans, resident-tourist = 1)	Pr(Trans, tourist-resident = 1)
A. Airbnb buffer (Guests)	0.003***	0.010**	-0.005**	0.025***	-0.003
	(0.0001)	(0.005)	(0.0003)	(0.005)	(0.004)
B. Airbnb buffer (Reviews)	0.002***	0.008*	-0.006*	0.019*	-0.007*
	(0.0001)	(0.004)	(0.003)	(0.010)	(0.003)
C. Airbnb buffer (Radius 100m)	0.004***	0.019**	-0.010	0.054***	-0.001
	(0.001)	(0.009)	(0.007)	(0.016)	(0.007)
D. Airbnb buffer (Radius 200m)	0.001***	0.007	-0.004**	0.016**	-0.004
	(0.0001)	(0.004)	(0.003)	(0.006)	(0.003)
E. Airbnb buffer (No hotel neighbourhoods)	0.003**	0.018***	-0.004	0.022**	-0.004
	(0.001)	(0.003)	(0.004)	(0.009)	(0.004)
F. Airbnb buffer (Only non-tradables)	0.003***	0.010*	-0.004**	0.033**	0.009
	(0.0001)	(0.006)	(0.001)	(0.016)	(0.004)
G. Airbnb buffer (Broader trends)	0.003***	0.009*	-0.007**	0.025**	0.009
	(0.0001)	(0.003)	(0.001)	(0.008)	(0.015)
Dependent Variable:	**Pr(Transition = 1)**	**Pr(Trans, gentrifiers = 1)**	**Pr(Trans, resident = 1)**	**Pr(Trans, resident-gentrifiers = 1)**	**Pr(Trans, gentrifiers-resident = 1)**
H. Airbnb buffer	0.003***	-0.001	-0.007**	-0.004	-0.034
	(0.0001)	(0.001)	(0.004)	(0.004)	(0.036)

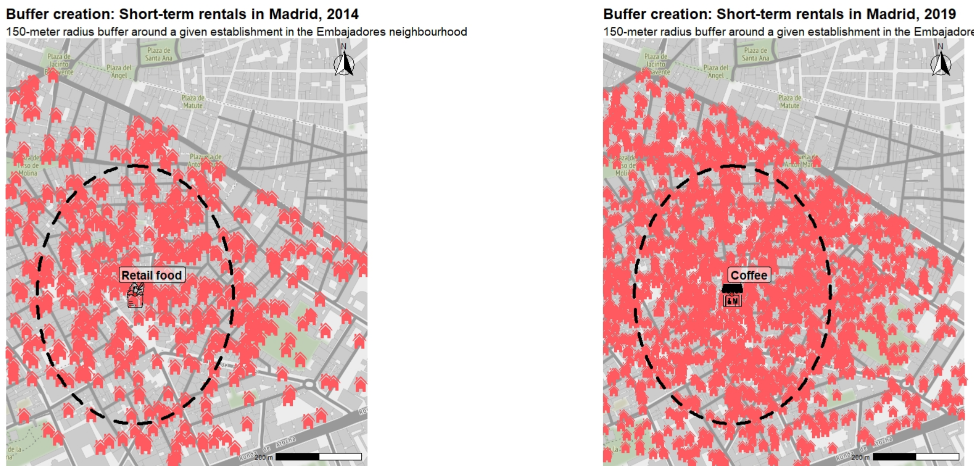
Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the neighbourhood level. Airbnb buffer guests variable represents the absolute change in the total capacity (maximum number of guests) in each Airbnb listing within a 150-meter radius ring around each establishment between 2014 and 2019. The Airbnb buffer reviews variable represents the absolute change in the total number of reviews for each Airbnb listing within a 150-meter radius ring around each establishment between 2014 and 2019. Airbnb buffer variable represents the absolute change in the number of short-term rentals within a 150-meter radius ring around each establishment between 2014 and 2019 in rows E-G, a 100-meter radius in row C, and a 200-meter radius in row D. The coefficient for each variable has been multiplied by the average increase in the Airbnb measure in each specification, i.e., 1000, 50, and 15 for reviews, guests, and Airbnb listing measures, respectively. The model also includes control variables such as the logarithm of the population, average household income at the census tract level, a dummy variable to identify the accessibility of the establishment (grouped or storefront), and distance to the city centre. Neighbourhood fixed effects are included in each specification, and activity codes fixed effects are included in all specifications. The number of observations varies across each specification depending on the reference group. The transitions group is made up of all establishments that were open in both 2014 and 2019 with no change and establishments that were open in both 2014 and 2019 and change activity and storefront name. The transition-tourist and transition-residents group is comprised only of transition establishments, The transition resident-tourist (transition tourist-resident) group is comprised only of transition establishments whose previous activity was local-oriented (tourist-oriented).

Figures

Figure I: Resident-oriented establishments displaced by tourist-oriented

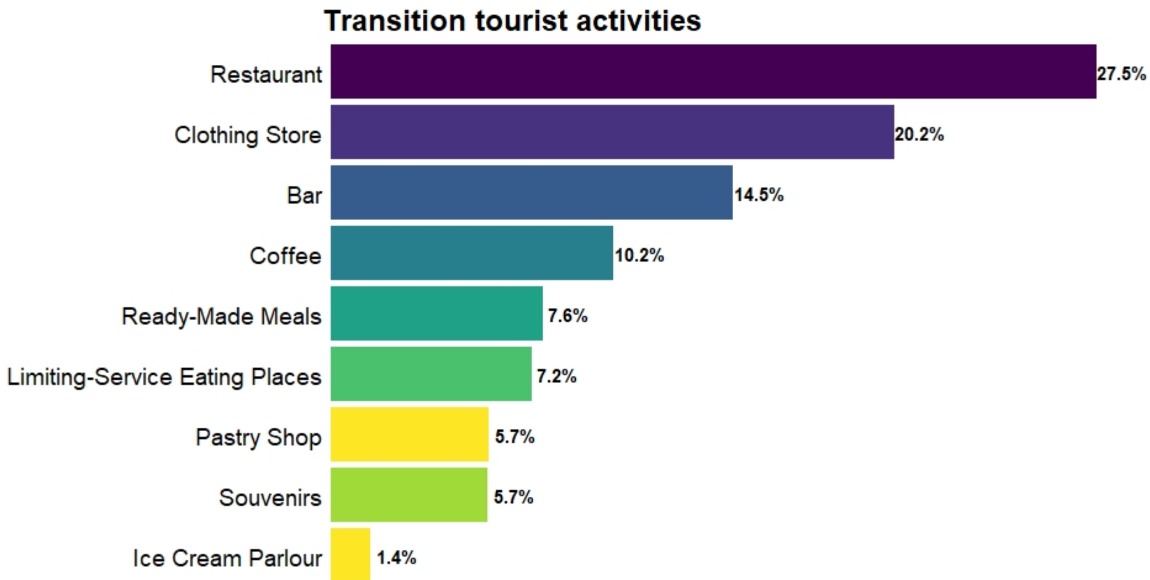
Notes: Business premises hosting resident-oriented activities in 2014 (left) and the same business premises hosting tourist-oriented activities in 2019 (right) in the Embajadores neighbourhood in Madrid.

Figure II: Buffer creation



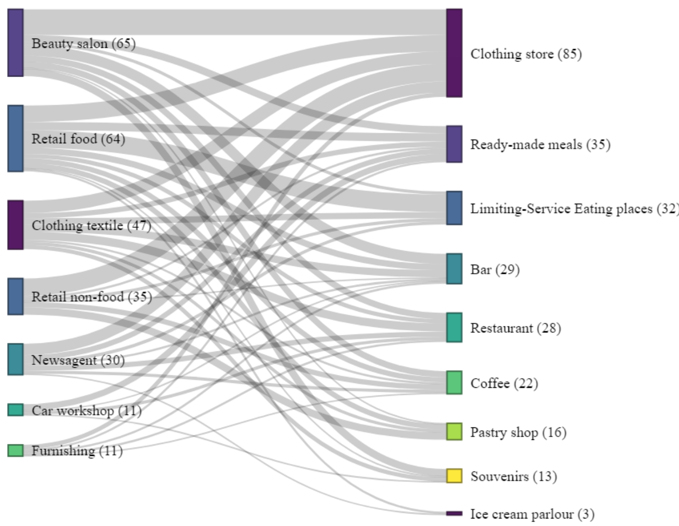
Notes: Short-term rentals (represented by red house icons) located near a business premise that provides retail food in the Embajadores neighbourhood in 2014 (left). On the right, you can see short-term rentals near the same business in 2019, but now offering Cafe services.

Figure III: Tourist-oriented transitions



Notes: Business premises transitions toward tourist-oriented establishments during the period October 2014-October 2019.

Figure IV: Resident-oriented establishments displaced by tourist-oriented establishments



Notes: Transitions towards tourist services in 2019 (right) conditional on offering resident-oriented activities in 2014 (left).

Appendix

Madrid City Council's census of business premises database

The Madrid Statistical Department has recently made available a dataset that includes information on all business premises in Madrid. A business premise refers to the physical location where an establishment carries out its activities. Each establishment is classified into one or more categories based on 21 sections, 87 divisions, and 448 codes. The dataset also includes details such as the name, location, accessibility, and current status of each establishment. The data is available from March 31, 2014, to December 31, 2014, in quarterly updates, and from January 1, 2015 onward in monthly updates. In this study, we consider data only from October 2014 to October 2019 to evaluate any changes in the status or activities of each establishment over a five-year period. We excluded observations related to establishments that entered or left the dataset during this period, as these may be influenced by factors such as urban expansion rather than local consumer demand driven by Airbnb.

In our study, we are primarily interested in the types of services offered by each establishment and whether they are targeted towards tourists or residents. We classify establishments as belonging to one of these two groups if they offer any of the services listed in Table I. To avoid overlap, if an establishment offers both tourist and local services, we do not classify it as either tourist- or resident-oriented. For example, a butcher that opens a lunch counter would not be classified as either tourist- or resident-oriented. We consider an establishment to have undergone a change if it has altered its service offerings or changed its name. As we do not have information on the ownership or management of each establishment, we use a change in name as an indicator of a change in the establishment.

Table AI: Variable definition and source

Variable	Definition	Source
Dependent variables:		
Birth	1 if an establishment opened during the period 2014-2019, 0 otherwise	Madrid Statistical Department
Birth, tourist	1 if a tourist-oriented establishment opened during the period 2014-2019, 0 otherwise	Madrid Statistical Department
Birth, resident	1 if a resident-oriented establishment opened during the period 2014-2019, 0 otherwise	Madrid Statistical Department
Death	1 if an establishment closed during the period 2014-2019, 0 otherwise	Madrid Statistical Department
Death, tourist	1 if a tourist-oriented establishment closed during the period 2014-2019, 0 otherwise	Madrid Statistical Department
Death, resident	1 if a resident-oriented establishment closed during the period 2014-2019, 0 otherwise	Madrid Statistical Department
Transition	1 if an establishment was open during the period 2014-2019 but changed activity, 0 otherwise	Madrid Statistical Department
Transition, tourist	1 if an establishment was open during the period 2014-2019 but changed activity towards tourist services, 0 otherwise	Madrid Statistical Department
Transition, resident	1 if an establishment was open during the period 2014-2019 but changed activity towards local services, 0 otherwise	Madrid Statistical Department
Transition, resident-tourist	1 if an establishment was a tourist business in 2019 conditional on being a local business in 2014, 0 otherwise	Madrid Statistical Department
Transition, tourist-resident	1 if an establishment was a resident-oriented business in 2019 conditional on being a tourist business in 2014, 0 otherwise	Madrid Statistical Department
Explanatory variables:		
Airbnb	Absolute change in the number of Airbnb listings within a 150-meter radius buffer around each establishment between 2014 and 2019	Inside Airbnb
Population	Number of inhabitants in a given census tract	Municipal Register
Average household income	Average household income in a given census tract	Ministry of Development
Distance	Euclidean distance in meters to the city centre from census tract centroid	Spanish National Geographic Institute
Accessibility	1 if the business premises is a street-level establishment	Madrid Statistical Department

Table AII: Descriptive statistics

	ΔOctober 2019 - October 2014					
Dependent variables		Sum	Mean	Sd		
Birth		6565	0.05	0.22		
Birth, tourist		1184	0.008	0.09		
Birth, resident		1459	0.010	0.10		
Death		2236	0.016	0.12		
Death, tourist		364	0.003	0.06		
Death, resident		489	0.003	0.06		
Transition		9762	0.074	0.26		
Transition, tourist		2352	0.017	0.13		
Transition, resident		2105	0.015	0.14		
Transition, resident-tourist		284	0.002	0.04		
Transition, tourist-resident		403	0.003	0.05		
	October 2014			**October 2019**		
Explanatory variables	Sum	Mean	Sd	Sum	Mean	Sd
Airbnb buffer	765908	5.796	15.086	2780702	21.043	47.37
Population	3130308	3243940	1319.691	508.4846	1387.485	654.0428
Avg. Household Income	85488590	36040.72	14782.41	85488590	36040.72	14782.41

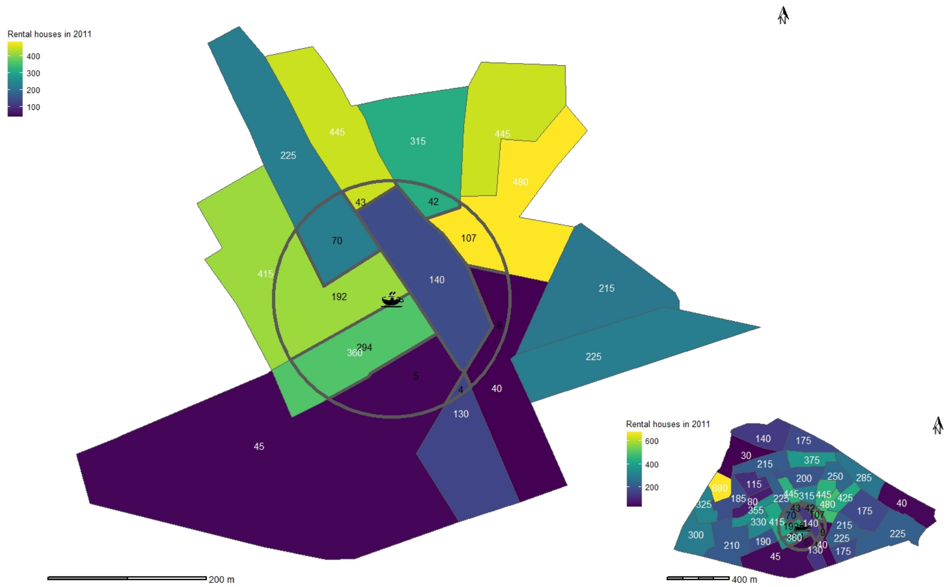


Figure AI: Instrumental variable construction

Notes: Rental houses imputation for a particular establishment in Embajadores neighbourhood. The imputed number of rental houses, represented by the black numbers, is calculated by multiplying the area of the census tract touched by the buffer by the actual number of rental houses in 2011 (white numbers).

Table AIII: Linear probability model for establishments birth and death dynamics (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Pr(Birth = 1)	Pr(Birth, tourist = 1)	Pr(Birth, resident = 1)	Pr(Death = 1)	Pr(Death, tourist = 1)	Pr(Death, resident = 1)
ex1 Airbnb buffer	0.004***	0.004***	-0.0004	0.0007**	-0.004	0.006*
	(0.001)	(0.001)	(0.001)	(0.0003)	(0.002)	(0.003)ex1
Mean dependent variable	0.792	0.193	0.238	0.0233	0.195	0.262
Marginal percentage effect	1.120	7.756	5.036	4.298	2.052	05.730
Observations	7,732	6,123	6,123	74,227	1,868	1,868

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the neighbourhood level. The Airbnb buffer is the absolute change in the number of short-term rentals around a 150-meter radius ring for each establishment between 2014 and 2019. The coefficient is scaled by 15, representing the average Airbnb listing change within the buffer. We have instrumented that variable with the number of rental houses in 2011. Control variables included in each specification are the logarithm of the population and average household income measured at the census tract level, a dummy variable to identify establishment accessibility (grouped or storefront) and distance to the city centre. Neighbourhood fixed effects are included in each specification. Activities codes fixed effects are included only in the first and fourth columns. The number of observations varies across each specification depending on the reference comparison group. The birth group comprises only inactive establishments that were present between 2014 and 2019, and establishments that were born in 2019 and closed in 2014. The death group includes all establishments that were open in both 2014 and 2019, and those that were closed in 2019 but open in 2014. When examining the impact of being a tourist-oriented or resident-oriented business on birth or death probabilities, we use only establishments in the respective category (establishments that were born in 2019 and closed in 2014 for births and establishments that were closed in 2019 but open in 2014) for deaths as the comparison group.

Table AIV: Linear probability model for establishments transitions dynamics (IV)

	(7)	(8)	(9)	(10)	(11)
Dependent Variable:	Pr(Transition = 1)	Pr(Transition, tourist = 1)	Pr(Transition, resident = 1)	Pr(Transition, resident-tourist = 1)	Pr(Transition, tourist-resident = 1)
ex1 Airbnb buffer	0.013**	0.028	-0.010	0.138**	-0.013
	(0.006)	(0.019)	(0.013)	(0.067)	(0.024)ex1
Mean dependent variable	0.109	0.244	0.219	0.217	0.197
Marginal effect	0.110	0.217	0.262	0.151	0.175
Observations	85,791	9,334	9,334	1,518	1,600

Notes: Statistical significance at the 1, 5 and 10% levels is indicated by ***,** and *, respectively. Cluster standard errors at the neighbourhood level. The Airbnb buffer is the absolute change in the number of short-term rentals around a 150-meter radius ring for each establishment between 2014 and 2019. The coefficient is scaled by 15, representing the average Airbnb listing change within the buffer. We have instrumented that variable with the number of rental houses in 2011. Control variables included in each specification are the logarithm of the population and average household income measured at the census tract level, a dummy variable to identify establishment accessibility (grouped or storefront) and distance to the city centre. Neighbourhood fixed effects are included in each specification. Activities codes fixed effects added in all specifications. The number of observations varies across each specification depending on the reference comparison group. The transitions group is comprised of all establishments that were open in both 2014 and 2019 with no change and establishments that were open in both 2014 and 2019 and change activity and storefront name. The transition-tourist and transition residents group is comprised only of transition establishments, The transition resident-tourist (transition tourist-resident) group is comprised only of transition establishments whose previous activity was local-oriented (tourist-oriented).

Table AV: 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 office
Musical Groups and Artists/ Sound Recording Studios	592001	Sound recording and music editing activities
Full-Service Restaurants	561001,561004	Restaurant, Bar restaurant
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 photography equipment
Museums	910001	Activities of libraries, archives, museums and galleries and exhibition halls without sale
All Other Speciality Food Stores	472910	Retail trade of coffee, 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

Sensitivity analysis

Results F, G, and H in Table IV provide evidence that our results are not driven by confounders related to lifestyles, gentrification and the e-commerce process. However, the way to rule out the existence of those unobserved confounders might be wrong whenever they are not manifested through either the proposed list of gentrification businesses or tradable services. To assess that our results are not biased because of the presence of those unobserved confounders, we employ sensitivity analysis tools for regression models developed by Cinelli and Hazlett (2020).

Cinelli and Hazlett (2020) proposed two measures to check the extent to which any unobserved confounders are likely to bias our results:

- The *Robustness Value* (RV): It provides a convenient reference point for assessing the overall robustness of a coefficient to confounders. Suppose the association of our coefficient of interest β and our dependent variable *transition tourist local* (measured as partial R^2) are both assumed to be less than RV. In that case, the confounders cannot explain away the observed effect.

- $R^2_{Transition\ tourist\ local \sim Airbnb\ buffer|X}$: It is the proportion of the variation in the outcome (*Transition tourist local*) explained exclusively by the treatment (*Airbnb buffer*). It reveals how strongly a confounder that explains 100% of the residual variance of (*Transition tourist local*) would have to be associated with (*Airbnb buffer*) in order to eliminate the effect.

To make some meaningful sense of the magnitude of the value for those two measures, Cinelli and Hazlett (2020) suggests using some covariate to bound the strength of unobserved confounders. In our setting, we choose the average household income variable related to either gentrification or the rise in e-commerce. Table AVI reports that information. As we can observe, a confounder as strong as average household income can at most explain 0.9% of the residual variation of our outcome variable (transition tourist-local) and 4.6% of the treatment (Airbnb buffer). As both numbers are below the robustness value of 8.2%, we can conclude that our point estimate is robust to a confounder(s) as strong as average household income.

Table AVI: Sensitivity analysis

Outcome: *Transition, tourist-resident*

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Airbnb buffer	0.002	0.001	3.048	0.9%	8.9%	3.3%
df = 1073		*Bound (1x income)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 1.2\%$, $R^2_{D\sim Z\|\mathbf{X}} = 4.6\%$				

Notes: Y refers to our outcome variable, transition tourist-resident, D, our variable of interest, Airbnb buffer, X the set of controls, and finally, Z the unobserved confounder(s).

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