The Effect of Short-Term Rentals on House Prices and Residential Mobility: Evidence from Madrid

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Abstract

This study estimates the impact of Airbnb on housing prices and residential mobility in Madrid from 2010 to 2018. Using a comprehensive dataset that includes Airbnb activity, housing prices, and residential moves at the neighborhood-year level, I employ a shift-share instrumental variable approach that leverages variation in neighborhoods' attractiveness to tourists and Airbnb's rapid growth. My findings indicate that, on average, an increase of 100 Airbnb listings in a neighborhood leads to a 2% rise in housing prices and a corresponding decrease in the number of new residents moving into the neighborhood. Furthermore, results from a causal mediation analysis using the same instrumental variable reveal that the negative effect of Airbnb on residential inflows is primarily driven by its impact on house prices. Consistent with this result, the reduction in residential inflows caused by Airbnb's impact on house prices is predominantly driven by residents without a college degree. Together, these findings suggest that short-term rental platforms may trigger or intensify gentrification processes.

JEL Codes: R21; R31; Z30.

Keywords: Housing markets; Short-term rentals; Airbnb; Residential mobility.

*The data and codes to replicate this paper are available on http://dx.doi.org/10.6084/m9.figshare.26263979.

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1 Introduction

Over the past 10 to 15 years, the emergence of digital platforms has significantly influenced various economic activities, including ride-hailing services (Uber), international money transfers (Transferwise), start-up financing (Kickstarter), food delivery (Just Eat), freelance services (Upwork), and many others (Einav et al., 2016). Notably, Airbnb, a paradigmatic platform of the digital economy, has reshaped the market for short-term rentals (STR) and tourist accommodation. As of 2020, Airbnb hosted over 7 million listings worldwide.[1] This spectacular growth has increased competition for traditional hotels (Zervas et al., 2017) and enhanced travelers' welfare (Farronato and Fradkin, 2022).

Moreover, the rise in STR activity has significant implications for urban development and the quality of life for residents in cities with a high influx of tourists. Recent research suggests that STR platforms may elevate housing costs and rents (Garcia-López et al., 2020), increase the availability of local businesses catering to tourists, such as bars and restaurants (Hidalgo et al., 2024), and generate negative externalities such as increased noise and neighborhood turnover (Garcia et al., 2024). These factors are crucial considerations for residents when choosing which neighborhood to live in.

The previous discussion suggests that Airbnb's expansion might impact the patterns of residential mobility across neighborhoods within a city. To shed light on this issue, this paper examines the impacts of Airbnb on housing prices (a major input in residential location decisions) and residential mobility patterns. Specifically, I focus on Madrid, a major European city with a significant presence of Airbnb, and address three main questions. First, what is the effect of Airbnb on housing prices? Second, how does Airbnb affect the flows of residents moving into and out of a neighborhood? Third, quantitatively, what is the most important mechanism through which Airbnb impacts the flows of residential moves?

To answer these questions, I construct a detailed dataset that includes information on Airbnb activity, housing prices, and residential moves in Madrid at the neighborhood-year level for the period from 2010 to 2018. To address endogeneity concerns associated with Airbnb's expansion, I employ an instrumental variable approach that leverages cross-neighborhood variation in pre-existing tourist attractiveness and temporal variation in global awareness of Airbnb. Specifically, I exploit a shift-share instrument that interacts a weighted average of a neighborhood's inverse distance to tourist attractions with the number of worldwide Google searches for "Airbnb Madrid." Additionally, when examining Airbnb's influence on residential flows, I implement a novel mediation analysis designed for scenarios where both the primary variable of interest (i.e., Airbnb) and the mediator (i.e., housing prices) are endogenous, and only a single instrument is available (Dippel et al., 2022).

The empirical analysis begins with an examination of the effect of Airbnb on house prices. Results from the instrumental variable strategy described above show that Airbnb activity increased house prices in Madrid. Specifically, a 100-unit increase in Airbnb entire home listings in a neighborhood (close to the 2018 average level) leads to a 2% increase in house prices. This effect is economically significant, especially in neighborhoods close to the historic center, where Airbnb activity is more prevalent. For these areas, my estimates imply that the rise in house prices due to Airbnb is approximately 20%, accounting for nearly 40% of the actual price increase observed in those neighborhoods.

Next, I examine the effect of Airbnb activity on residential mobility. Using the same instrumental variable strategy, I find that Airbnb reduced the number of new residents moving into a neighborhood but did not affect the number of residents moving out. My preferred specification indicates that every two additional Airbnb listings cause a decrease of one new resident moving into the neighborhood. With the observed level of Airbnb activity

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

in the average neighborhood in 2018, these estimates suggest that the platform was responsible for a decrease of approximately 49 new residents moving in a given year, representing around 2% of the average yearly number of new residents.

To shed light on the mechanisms contributing to Airbnb's negative effect on residential inflow, I quantify the fraction of the effect that operates through Airbnb's impact on housing prices. Specifically, I estimate the causal mediation model proposed by Dippel et al. (2017, 2022). This model allows for decomposing the negative "total effect" of Airbnb on the inflow of residents into two components: an "indirect effect" that operates through increasing house prices and a "direct effect" that operates through all other channels.

Results from this mediation analysis show that the negative effect of Airbnb on residential inflows is primarily due to its impact on house prices. Conversely, the direct effect, which combines the effects operating through all other channels, is positive but comparatively small and not precisely estimated. Moreover, when breaking down in-movers by educational attainment, the analysis reveals that the reduction in residential inflows due to Airbnb's impact on house prices is entirely driven by residents without a college degree.

To further explore channels other than house prices, I estimate the impact of STR activity on the provision of specific consumption amenities. This analysis employs the same instrumental variable strategy used to estimate the effect of Airbnb on house prices. The results suggest that while Airbnb has increased the number of restaurants operating in a neighborhood, it has not significantly impacted their quality, as measured by online ratings. These modest but positive effects on consumption amenities, combined with potential negative externalities imposed by tourists, may explain the relatively small and imprecisely estimated effects of STR activity on residential inflows once we control for its impact mediated through house prices.

Related literature. This paper contributes to the growing body of empirical literature examining the effects of short-term rental platforms, such as Airbnb. Most studies have focused on evaluating the impact of short-term rentals on house prices and rents, with prominent examples including Garcia-López et al. (2020), Barron et al. (2021), and Koster et al. (2021). Similar to Garcia-López et al. (2020) and Barron et al. (2021), I adopt a shift-share instrumental variable strategy to estimate the impact of Airbnb on house prices. In addition, I extend this literature by providing evidence of the subsequent effects of housing prices on the residential mobility of individuals from different socio-demographic groups.

The literature has also explored additional effects of short-term rental platforms. For instance, Hidalgo et al. (2024), Alyakoob and Rahman (2022), and Basuroy et al. (2020) estimate the impact of Airbnb activity on the local provision of private consumption amenities, particularly focusing on restaurants. This paper is most closely related to Hidalgo et al. (2024), who also use data from Madrid and find that areas with stronger Airbnb activity experience an increase in both the number of restaurants and restaurant employment. Despite sharing the same empirical context, our studies differ significantly. While they focus on the effect of Airbnb on the restaurant industry, I place a stronger emphasis on house prices and residential mobility. Additionally, using data from Tripadvisor, this study provides evidence that although Airbnb may increase the number of restaurants, it does not affect their online ratings, suggesting that quality did not respond to increased STR activity.

Another key contribution of this study is the estimation of the effect of house prices on residential mobility decisions, leveraging variation in short-term rentals as a shock. This strategy resonates with the approaches of Calder-Wang (2021) and Almagro and Domínguez-Iino (2024). Both studies estimate structural models of a city's housing market where the emergence of STR platforms serves as the key shock providing variation to estimate the main parameters in the model. Specifically, Calder-Wang (2021), focusing on New York City, find that short-term rental activities predominantly affect the rent burden of high-income, highly educated renters. My findings offer a complementary perspective, showing that residents with lower education levels are prevented from moving to neighborhoods where short-term rentals have driven up housing costs, indicating that Airbnb may place significant welfare burdens on this group. Additionally, in relation to Almagro and Domínguez-Iino (2024), this study corroborates the positive effect of Airbnb on the supply of certain private consumption amenities like restaurants but reveals that these amenities exert a relatively minor impact on residential mobility decisions in the city.

Finally, in methodological terms, this paper relates to recent advancements in applying mediation analysis models using instrumental variables. This approach enables the quantification of the extent to which a causal effect, such as Airbnb's influence on residential mobility, is mediated through a specific channel like house prices. This methodology has been employed in studies such as Dippel et al. (2022), which explored how exposure to imports affected voting choices through local employment losses, and Nicoletti et al. (2023), which examined the extent to which the effect of maternal labor supply on children's academic achievements was mediated through changes in family income. Using this mediation model, I demonstrate that house prices are the primary channel through which Airbnb activity affects locals' residential relocation decisions. My results indicate that in a world where Airbnb did not increase house prices, its residual effect on residential inflows would likely be positive.

Roadmap. This paper is structured as follows. Section 2 provides a conceptual framework, briefly discussing the expected effects of short-term rental activity. Section 3 describes the data sources and variables used in the analysis. Section 4 estimates the effect of Airbnb on house prices. Section 5 examines the effect of Airbnb on residential moves and employs a mediation analysis to quantify the role of house prices in determining residential flows. Finally, Section 6 discusses the implications and concludes the paper.

2 Conceptual Considerations

This section outlines the primary impacts of short-term rental (STR) platforms on a city's residential market. The main objective is to provide a framework for the empirical analysis. Consequently, the discussion is centered on the effects of STR platforms that are investigated in the empirical part of the paper.

The advent of platforms such as Airbnb has integrated the long-term and short-term rental markets, allowing landlords to allocate their units to either long-term residents or short-term visitors. Consequently, the emergence of this platform may induce a reallocation of housing units from the conventional long-term rental market, which serves locals, to the short-term market, which serves tourists and travelers. Throughout the paper, I refer to this phenomenon as the "reallocation effect."

The "reallocation effect" leads to a leftward shift in the supply curve of long-term rental housing, resulting in increased long-term rents. As house prices reflect the expected present value of rents, this effect should also be evident in house prices (Barron et al., 2021). The extent of reallocation and the consequent rise in house prices depend on the difference between long-term rents before the emergence of STR platforms and the amount tourists are willing to pay for STRs. Several factors, such as the availability of tourist-oriented amenities, influence tourists' willingness to pay. Therefore, the more attractive a neighborhood is to tourists, the more we should expect an increase in house prices due to the reallocation effect caused by the emergence of short-term rental platforms.

In addition to direct housing reallocation, STR activity can have second-order effects on neighborhoods due to an increased influx of tourists. Two such effects are a boost in demand for certain types of businesses and the negative externalities that tourists may impose on residents. Unlike the reallocation effect, which pertains to landlords' decisions and shifts in the supply curve of residential housing, these second-order effects relate to changes in the desirability of a residential location from the perspective of local demand.

Regarding the impact of the increased tourist influx on local businesses, there is evidence that Airbnb has shifted the composition of private consumption amenities available in a neighborhood towards more tourist-oriented businesses (Hidalgo et al., 2023). For example, Airbnb has been beneficial to restaurants (Alyakoob and Rahman, 2022; Hidalgo et al., 2024). Conversely, STR platforms negatively impacted services that cater to locals, such as childcare facilities (Almagro and Domínguez-Iino, 2024). These effects arise because tourists and locals have different preferences, and local firms respond to the shift in the composition of their demand. Ultimately, how these changes affect the desirability of neighborhoods as residential locations will depend on how closely residents' preferences align with those of tourists.

With regard to the externalities generated by tourists, such as increased noise or overcrowding of streets, the direction of the effect is clear: they decrease the attractiveness of a neighborhood as a residential location. Garcia et al. (2024) provides evidence that regulations restricting STRs can lead to increased house prices by reducing tourist-related externalities. Importantly, since different demographic groups may assign varying levels of importance to these externalities, the extent to which housing demand changes will depend on the demographic composition of local residents.

Additionally, since short-term rental activity affects important attributes of neighborhoods, it is likely to influence residents' decisions about where to live. First, the reallocation effect, which drives up housing costs, should reduce the number of people choosing to live in neighborhoods with high Airbnb use. This effect is likely to disproportionately impact lower-income residents, who are more sensitive to price increases. Second, regarding Airbnb's second-order effects (consumption amenities and externalities), we cannot make a general statement about the direction of its impact on residents' moving decisions, as this will depend on the alignment of preferences between locals and tourists. Thus, we expect Airbnb's effect on the flow of residential moves to differ depending on demographic characteristics. For instance, young adults, who are more likely to place high value on eating out and be less concerned about noise, might be more attracted to neighborhoods with high Airbnb exposure compared to older residents.

3 Data

The analysis is conducted at the neighborhood-year level for the period between 2010 and 2018. Madrid is divided into 128 neighborhoods, each with an average population of about 25,000 inhabitants.[2] Neighborhoods are appropriate spatial units for this analysis because they likely reflect the areas that potential movers consider when evaluating alternative residential locations. Moreover, Idealista, the main online marketplace for long-term rentals in Spain, displays search results separated by neighborhood.

3.1 Sources

Airbnb. I obtained data on Airbnb activity from the "Inside Airbnb" project, an independent, non-commercial initiative that periodically scrapes data directly from Airbnb's website and makes it available for public use.[3] For Madrid, there are 15 snapshots available between July 2015 and February 2019. Each snapshot contains information

[2]There was an increase in the number of neighborhoods from 128 to 131 in 2017. For consistency, the paper uses 2010 constant boundaries.

[3]More information about this data is available on their website: http://insideairbnb.com/get-the-data.html.

about all properties listed on Airbnb, including variables such as geographical coordinates, nightly price, and the history of reviews from past guests.

My main measure of Airbnb activity is the number of "active" Airbnb listings in a neighborhood in a given year. To define when a listing is active, I follow the approach of studies such as Barron et al. (2021) and Garcia-López et al. (2020), considering a listing active in year t if it has received at least one guest review during that year.[4] I then use the latitude and longitude coordinates of each listing to assign them to a neighborhood.[5] The analysis focuses on "entire-home" listings, defined as accommodations where guests have exclusive access to an entire housing unit without sharing the space with permanent residents. This type of short-term rental is more indicative of the housing stock vulnerable to the reallocation effect, compared to other Airbnb listing categories such as private or shared rooms.

House Prices. Data on the evolution of house prices in Madrid comes from "Idealista," the leading online real estate marketplace in Spain. The company publishes an annual report indicating the neighborhood-level average price (in euros per square meter) of all second-hand housing units listed on its website in December of each year from 2007 to 2018. In the rest of the paper, the term "house prices" refers to this measure provided by Idealista.[6] Ideally, transaction prices would also be considered, but they are not readily available for public use. Nonetheless, Garcia-López et al. (2020), in a study focusing on Barcelona, shows that the effect of Airbnb on house prices was similar for both listed and transaction prices.

Neighborhood Demographics and Residential Moves. To examine the relationship between Airbnb activity and changes in the demographic composition of neighborhoods, the paper employs two types of data. First, I obtain basic socio-demographic information derived from the stock of the resident population in a neighborhood, including population size, number of households, age distribution, and the share of residents with a university degree. Second, I use data on the demographic characteristics of movers, individuals who change their place of residence during the sample period.[7]

The data, both on the stock and flows, originates from the "Padrón Municipal" (or Municipal Census). Although every person living in Spain is required to register in the Municipal Census of the city where they habitually reside and report changes of address within the same municipality, this source may measure moves with some degree of delay. Nevertheless, it is the only available source of information on residential moves at the neighborhood level with yearly updates. Further details on the potential biases that this type of mismeasurement may introduce are discussed in Section 5.2, which quantifies the impact of Airbnb activity on the flow of residential moves.

Consumption Amenities and Tourist Attractions. Data on private consumption amenities comes from two sources: the Madrid City Council's census of business establishments and scraped information from the online review platform Tripadvisor.[8] From the census, I compute the count of active establishments by type of activity in each

[4]Although reviews may not perfectly represent actual transactions, Airbnb reports that 72% of guests leave reviews. Despite the availability of snapshots starting only in 2015, we can infer a listing's prior activity by analyzing its review history, available in all snapshots.

[5]For privacy reasons, the coordinates provided by Airbnb correspond to a random point within a 150-meter radius of the actual location of the listing. While this approximation may be problematic for conducting listing-specific analyses, aggregating listings at the neighborhood level should mitigate the "noise" across nearby neighborhoods, thus avoiding introducing bias to the estimations.

[6]More information about Idealista's report is available at www.idealista.com/en/press-room/property-price.

[7]Data on neighborhood snapshots is computed in January of each year and is publicly available at https://datos.madrid.es/portal/site/egob. Information on movers was constructed on demand and generously provided by Madrid's "Subdirección General de Estadística".

[8]Data from the Madrid Census of Business Establishments is publicly available and can be accessed by navigating to https://datos.madrid.es/portal/site/egob and searching for "Censo de Locales".

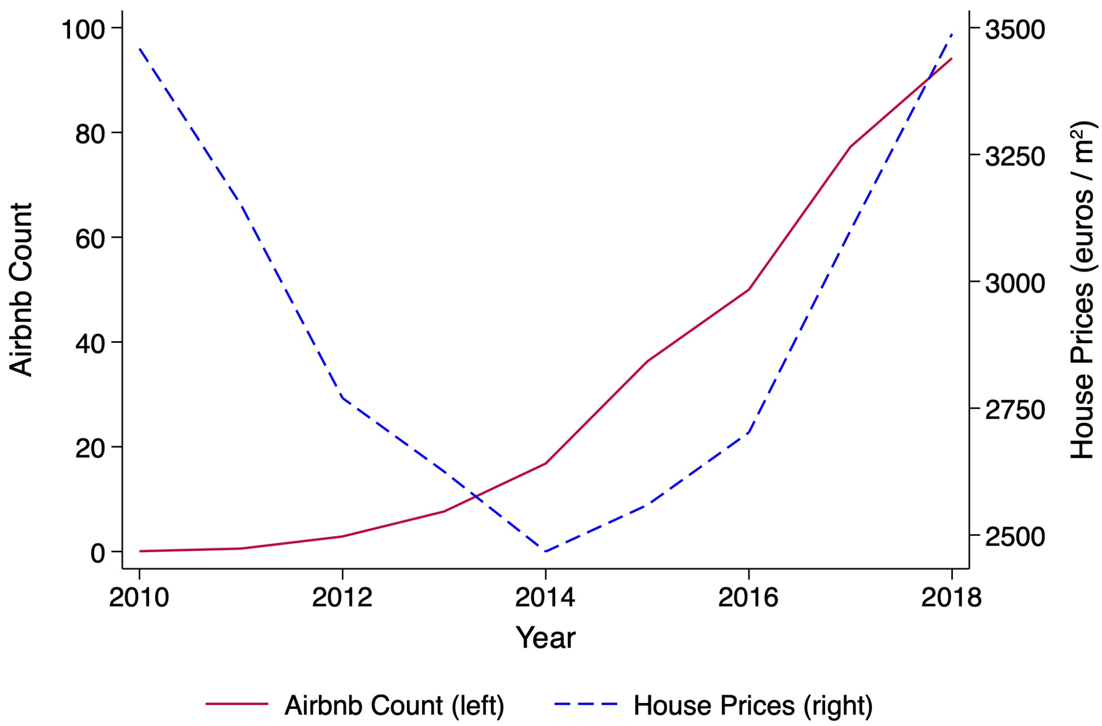
neighborhood-year. From Tripadvisor, I obtain consumer reviews for restaurants listed on the website. I use these measures to explore the potential impact of Airbnb activity on both the quantity and quality of restaurants operating in a neighborhood.

Additionally, I use Tripadvisor data to compute the instrument, which is based on a neighborhood's proximity to amenities valued by tourists. Specifically, I access Madrid's profile on this website and obtain a list of the most popular tourist attractions in the city. The attractiveness of each neighborhood to tourists is then computed as a weighted average of the inverse distances to each tourist attraction, with the weight of each attraction determined by the number of tourist reviews on Tripadvisor. This measure, capturing cross-sectional variation in tourist appeal, is combined with yearly data from Google Trends on worldwide interest in the search term "Airbnb Madrid." More information about the construction of the instrument can be found in Section 4.1.

3.2 Descriptive Statistics

Figure 1 displays the average Airbnb activity and house prices across all neighborhoods in Madrid. The number of entire home listings on Airbnb, my baseline measure of Airbnb activity, increased rapidly after the first guest review in 2010. By 2018, the average neighborhood in Madrid had 94 active listings, while neighborhoods in the top decile of Airbnb activity had 325 active listings. Regarding house prices, we observe two distinct periods with opposite movements. First, following the global financial crisis, prices fell. Then, from around 2014 onward, as the most troubling years of the post-crisis period passed, house prices entered a period of strong growth that continued until the end of the sample period.

Figure 1: Evolution of Neighborhood Average Airbnb Listings and House Prices



Notes: Neighborhood averages of the count of active Airbnb listings (red solid line, left vertical axis) and house prices (blue dashed line, right vertical axis). Airbnb data is from Inside Airbnb. Data on house prices is from Idealista.

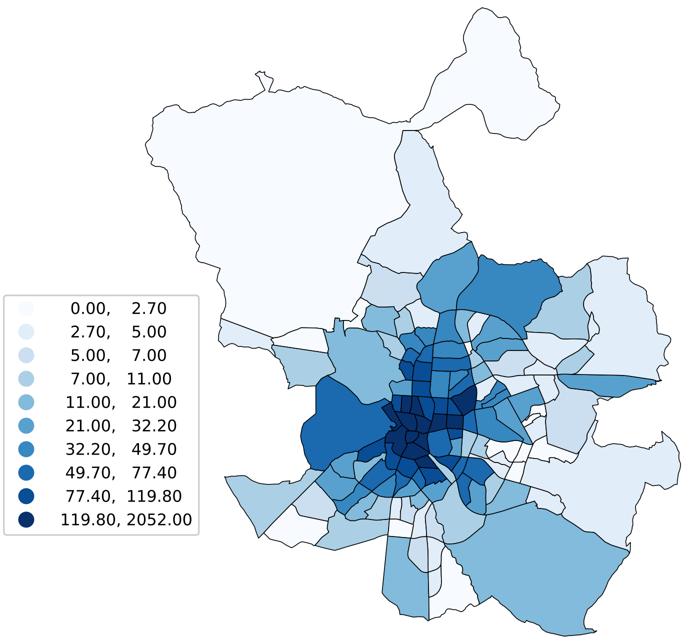
Shifting from temporal to spatial variation, Figure 2 illustrates the distribution of Airbnb activity across neighborhoods in Madrid. By 2018, most neighborhoods had some Airbnb presence, but the activity was highly concentrated in a few areas. Even within the top decile of Airbnb activity, neighborhoods varied substantially in the number of properties listed on the platform. The largest Airbnb market, the Embajadores neighborhood, had over 2,000 entire-home listings that received at least one guest review in 2018.

As previously discussed, the expansion of Airbnb activity is likely to have affected house prices as well as the provision of private consumption amenities highly demanded by tourists, such as restaurants. Figures 3a (house prices) and 3b (restaurants) show that, from a descriptive point of view, these hypotheses align with the observed patterns. Specifically, neighborhoods with stronger Airbnb growth also experienced more pronounced increases in house prices and a larger rise in the number of operating restaurants.

Moreover, since I am also interested in Airbnb's effect on the spatial distribution of the resident population, Figures 4a and 4b illustrate how population size and residential inflows have changed between 2013 and 2018 across different neighborhoods. These figures provide suggestive evidence that, consistent with the dynamics described in Section 2, Airbnb growth is negatively correlated with changes in population size and the number of in-movers.

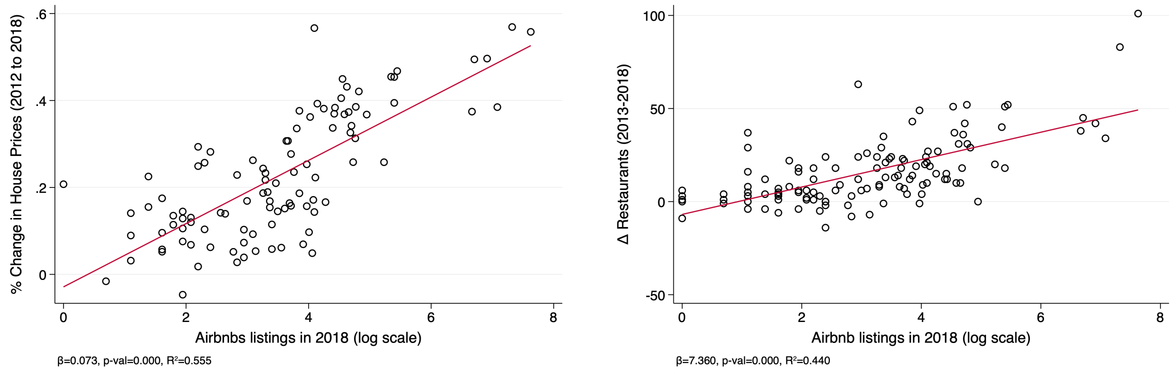
To conclude this section, Table 1 presents averages for some of the previously variables, such as house prices, as well as additional variables used in subsequent parts of the paper, including neighborhood-level sociodemographic characteristics. I provide the neighborhood means for the years 2012 and 2018 for two different samples: all neighborhoods and high Airbnb neighborhoods (those in the top quartile of the Airbnb listings distribution in 2018).

Figure 2: Airbnb Entire-Home Listings Across Neighborhoods in 2018



Notes: Distribution of Airbnb listings across Madrid's neighborhoods in 2018. Only entire-home listings with at least one guest review in that year are included. Neighborhoods are divided into deciles based on Airbnb presence. Airbnb data is from Inside Airbnb. Information on the city's administrative divisions is from the Madrid City Council, available at https://www.madrid.es.

Figure 3: Airbnb Activity and Changes in Neighborhood Characteristics

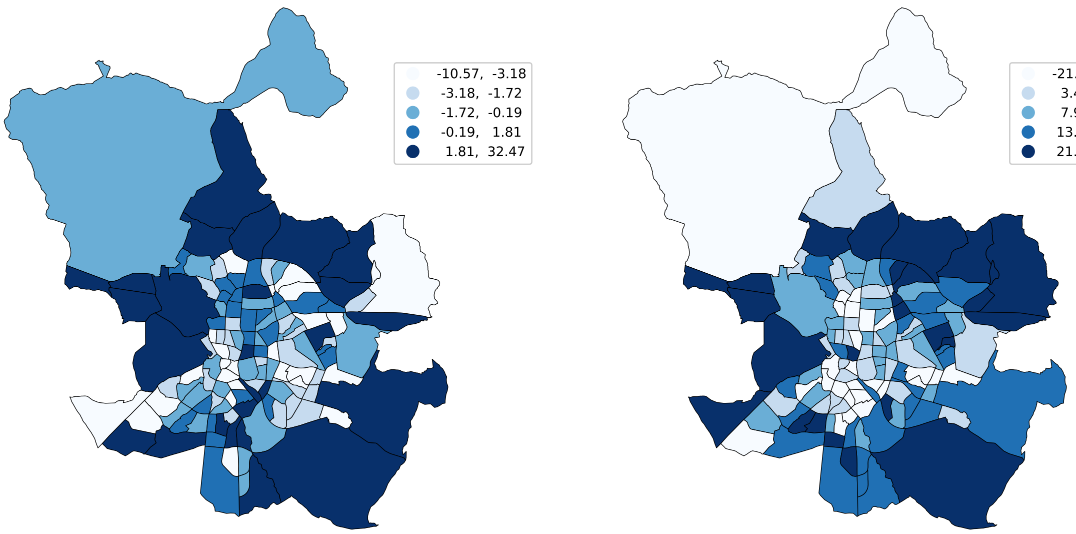


(a) House Prices

(b) Food and beverage establishments

Notes: Correlation between Airbnb activity and house prices (left) and restaurants (right). The bottom left of each plot reports statistics from a univariate regression $y_i = \alpha + \beta \log(\text{Airbnb})_i + \epsilon_i$, where i represents neighborhoods and y_i is the outcome reported on the vertical axis of each plot. Airbnb data is sourced from Inside Airbnb. Data on house prices comes from Idealista. Restaurant counts are compiled from Madrid's Census of Establishments.

Figure 4: Percentage Change in Population and Residential Inflow (2013 to 2018)



(a) % Change in Population

(b) % Change in Number of In-Movers

Notes: Neighborhood-level changes in population size (left) and residential inflow (right) between 2013 and 2018, measured in percentage points. In each figure, neighborhoods are divided into quintiles according to the outcome being represented. Data on population size is publicly available at https://datos.madrid.es/portal/site/egob. Information on movers was constructed on demand and generously provided by Madrid's "Subdirección General de Estadística".

Table 1: Descriptive Statistics: Selected Neighborhood Characteristics in 2012 and 2018

	2012		2018	
	All neighborhoods	High Airbnb neighborhoods	All neighborhoods	High Airbnb neighborhoods
Airbnb Listings	2.88	10.63	94.17	324.78
House Prices (eur/m^2)	2770	3456	3488	4769
Population	25296	25659	25170	25016
% High Education	0.30	0.39	0.37	0.49
Median Age	42.27	43.47	44.39	44.75
Food and Beverage Estab.*	116	210	131	242
Distinct Cuisines	4.82	9.22	11.18	21.75
Rating of Avg. Restaurant	3.83	3.80	3.55	3.72
Total In-movers	2294	2744	2457	2777
% In-movers High Educ.	0.27	0.40	0.36	0.53

Notes: Columns 1 and 3 present the mean values for all neighborhoods, while Columns 2 and 4 display the data for neighborhoods with high Airbnb activity. High Airbnb neighborhoods are defined as those within the top quartile of Airbnb listing activity in 2018. The counts of food and beverage establishments in the left columns are from 2013, the earliest year for which Census of Establishments data is available. Data is sourced from Inside Airbnb, Idealista, Madrid's Padrón Municipal and Census of Establishments, and Tripadvisor. See Section 3.1 for details on data sources.

4 The Effect on House Prices

4.1 Empirical Framework

I start with the following baseline specification:

$$\log(House\ Prices_{it}) = \beta Airbnb_{it} + \gamma' X_{it} + \mu_i + \delta_t + \epsilon_{it} \tag{1}$$

where $House\ Prices_{it}$ represents the average posted price of second-hand housing listed on Idealista in neighborhood i in year t and $Airbnb_{it}$ is the number of entire-home listings on Airbnb in neighborhood i with at least one guest review in year t. The vector X_{it} includes time-varying controls aimed at capturing neighborhood-specific urban revival or gentrification trends that may impact both house prices and Airbnb growth. The baseline specification also accounts for year fixed effects (δ_t) and neighborhood fixed effects (μ_i).

With regards to time-varying controls, I follow Garcia-López et al. (2020) and include demographic characteristics that correlate with gentrification trends. Specifically, X_{it} contains population density (in logs), the proportion of foreign residents, the median age, the average household income, and the proportion of residents with a higher education degree. In the most demanding specifications, I include the interaction between a linear time trend and the distance to the city center to allow for different trends in house prices depending on the neighborhood's location relative to Madrid's central point, "Puerta del Sol."

Instrumental Variables Approach. Even with the inclusion of time-varying sociodemographic controls and neighborhood fixed effects, Airbnb may still be endogenous in Equation 1. This could be due to gentrification processes or other neighborhood-specific dynamics not fully captured by the demographic controls. To address these concerns, I employ a shift-share instrument. The instrument consists of two components: a share component, which captures pre-Airbnb cross-sectional variation in neighborhoods' appeal to tourists, and a shift component, which measures aggregate time variation in Airbnb's overall popularity:

$$Instrument_{it} = \sum_{k \in K} \frac{w_k}{d_{ik}} \times \text{Google Search Index for ``Airbnb Madrid''}_t \tag{2}$$

Each neighborhood's measure of touristic interest is calculated as the weighted average of the inverse of its distance d_{ik} to a set of K tourist attractions. The weight assigned to each attraction is proportional to the number of reviews it has on Tripadvisor, denoted by w_k. To capture time variation in Airbnb's overall popularity, I use data from Google Trends, which provides yearly variation in worldwide searches for "Airbnb Madrid" on Google.

My baseline strategy employs a parsimonious instrument that includes the three most popular tourist attractions in Madrid according to Tripadvisor: the Prado National Museum, the Royal Palace, and the Santiago Bernabéu Stadium (home of Real Madrid). To ensure that the share component of the instrument is exogenous to Airbnb, I compute the weights w_k based exclusively on Tripadvisor reviews prior to 2010, the year when I observe the first Airbnb listing in Madrid. This avoids endogeneity concerns that would arise from using current-day reviews, as variation in weights w_k could be partly driven by Airbnb guests.[9]

The instrument's relevance is based on two insights. First, proximity to tourist attractions should predict levels of Airbnb across space. Tourists' willingness to pay is higher for neighborhoods close to attractions of interest, which provides more incentives for landlords to switch to the short-term market. Second, conditional on location, the Google search index variable predicts when Airbnb will appear. The larger the popularity of Airbnb online, the more likely people are to learn about and want to use it, both travellers and landlords.

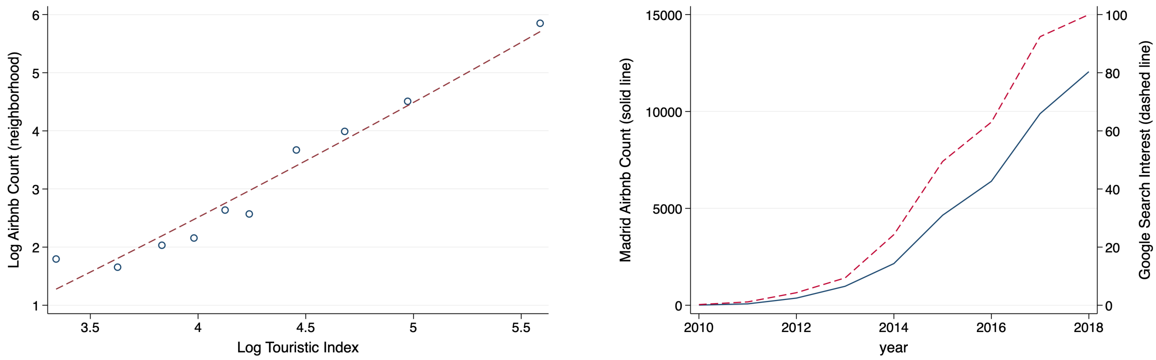
The previous argument is illustrated in Figure 5. The plot on the left shows that proximity to tourist attractions predicts the number of Airbnb listings in a neighborhood. Furthermore, the plot on the right demonstrates that the trends in worldwide Google searches for "Airbnb Madrid" closely follow the actual growth of Airbnb listings.

Examining the Exclusion Restriction. As shown by Goldsmith-Pinkham et al. (2020), in shift-share designs like mine, the identification of causal effects relies on the exogeneity of the share component of the instrument. Specifically, identification requires that a neighborhood's proximity to tourist attractions influences house prices over time solely through its effect on the neighborhood's exposure to Airbnb activity. A potential violation of the exclusion restriction would occur if residents' demand for living near tourist attractions changes during the sample period. For instance, if, even before Airbnb's emergence, areas closer to tourist attractions were already becoming more desirable as residential locations due to location-specific public investment projects, house prices in these areas would be expected to increase at a faster rate, even if STR platforms had never been invented.

As is common in IV settings, there is no definitive way to directly test the exclusion restriction. However, I provide suggestive evidence consistent with the exogeneity of the shift-share instrument. The idea behind this test is that, under the exclusion restriction, proximity to tourist attractions should not explain changes in housing prices before Airbnb's arrival. Figure 6 shows trends in house prices for three groups of neighborhoods, divided based on an index measuring proximity to important tourist attractions. The trends in house prices across the three groups of neighborhoods are very similar before Airbnb's emergence, which provides suggestive evidence of the validity of the instrument.

[9] To test the robustness of the instrument concerning the number of tourist attractions, I also estimate the effect of Airbnb using specifications where $K = 20$. While I have the full review history with timestamps for the three primary tourist attractions mentioned above, for these additional attractions, I only have access to their total review count. This means that the weights for these extended tourist attractions also include Tripadvisor reviews submitted in recent years when Airbnb was already popular.

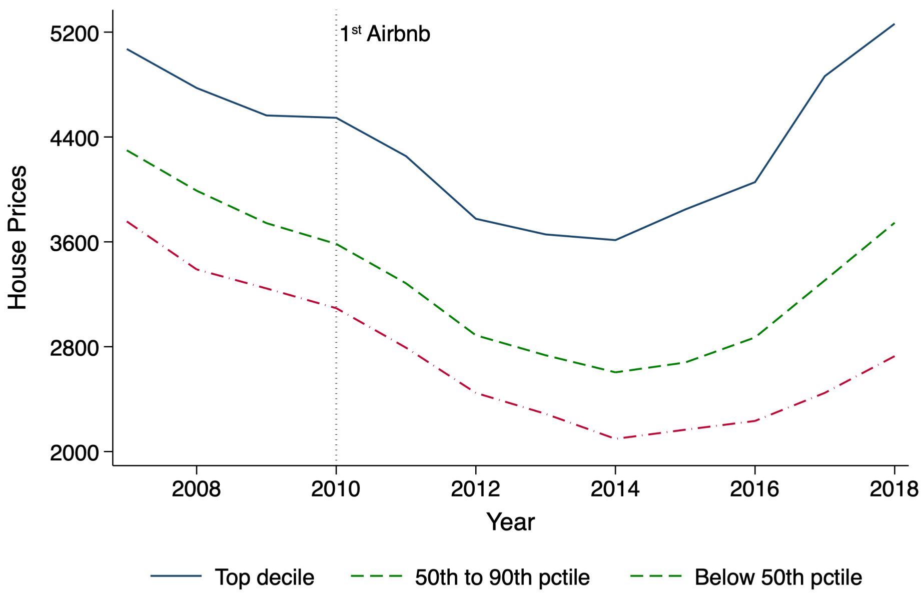
Figure 5: Relevance of Shift-Share Instrument



(a) Tourist attractions and Airbnb activity (b) Google search interest and Airbnb activity

Notes: Plot (a) shows the relevance of the instrument's share component with a binned scatter plot of the number of Airbnb listings as a function of proximity to tourist attractions (weighted by the number of reviews). Each dot represents a decile of the distribution of the share component of the instrument. Plot (b) demonstrates the relevance of the shift component, showing the yearly evolution of total Airbnb listings in Madrid and worldwide Google search intensity for the term "Airbnb Madrid." Airbnb data is sourced from Inside Airbnb. Information on tourist attractions is obtained from Tripadvisor. Data on search interest is from Google Trends. See Section 3.1 for details on data sources.

Figure 6: Instrument Pre-trend Analysis: House Prices by Neighborhood Tourist Index



Notes: Average house prices for three groups of neighborhoods along the distribution of the tourist interest index (the share component of the instrument): top decile (blue line), between the 50th and 90th percentiles (green dashed line), and below the 50th percentile (red dashed line). House prices are sourced from Idealista. Data on tourist attractions is from Tripadvisor. See Section 3.1 for details on data sources and Section 4.1 for details on the instrument.

4.2 Baseline Results

Table 2 shows the results of estimating Equation 1, both using the full variation in Airbnb activity (OLS columns) and using only the variation predicted by the instrument in Equation 2 (IV columns). The dependent variable is the log of house prices and the independent variable is the number of Airbnb entire home listings (measured in 100 units). Thus, coefficients should be interpreted as the percentage change in house prices resulting from an increase of 100 homes listed on Airbnb.[10]

Table 2: Effect of Airbnb on Log of House Prices

	OLS					IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Airbnb Count (x100)	0.061***	0.024***	0.025***	0.015***	0.014***	0.020***	0.022***
	(0.017)	(0.007)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)
Controls		X		X	X	X	X
Neighborhood FE			X	X	X	X	X
Year FE			X	X	X	X	X
Dist. Center $\times$ Trend					X		X
Observations	1,029	1,029	1,029	1,029	1,029	1,029	1,029
1^{st}-stage F-stat						20.691	15.955

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome variable is the log of house prices. Controls include: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. IV regressions use the baseline instrument: proximity to the top 3 tourist attractions (weighted by Tripadvisor reviews) multiplied by worldwide Google search interest for "Airbnb Madrid." House prices are sourced from Idealista. Data on Airbnb is compiled from Inside Airbnb. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the construction of the instrument.

Column 1 demonstrates that, in the cross-section, neighborhoods with more Airbnb listings also tend to have higher house prices. Interestingly, the reduction in the coefficient from a pooled OLS regression without controls (column 1) to a pooled OLS regression with time-varying demographic controls (column 2) is similar to the reduction observed when running a two-way fixed effects model without controls (column 3). In both cases, the effect decreases by roughly one-third. In column 4, incorporating both controls and fixed effects further reduces the effect of Airbnb to about one-fourth of the coefficient value in column 1. Finally, including city-center-specific time trends has minimal impact on the results.[11]

Moving to columns 6 and 7, I repeat the specifications from columns 4 and 5, but instrument Airbnb listings with my baseline shift-share variable based on the top three tourist attractions and Google Trends data. Point estimates increase by one-third in the specification without city-center-specific trends and by 50% in my preferred specification. These results suggest a downward bias in the OLS regressions, where, conditional on all controls, Airbnb listings tend to appear more often in neighborhoods where house prices are increasing slower than average.

From a conceptual standpoint, it can be argued that the most common endogeneity concern would suggest a bias in the opposite direction (see Section 2). Neighborhoods undergoing gentrification processes would attract Airbnb activity and experience other unobserved trends driving stronger growth in house prices. However, the

[10]The analysis uses data on 128 neighborhood for a period of 10 years (2010-2018). The number of observations is smaller than 1280 because a few neighborhoods do not have data on house prices when the number of listings on Idealista is not large enough in a given year.

[11]The city center is measured as the distance from Puerta del Sol, one of the city's main squares and a central hub of the metro line.

reallocation effect described earlier can also generate a negative bias. In neighborhoods where the unobserved demand for permanent housing (attractiveness for locals) is increasing rapidly, rents (and prices) will grow faster, and landlords will have lower incentives to switch to Airbnb. This type of simultaneity bias, as observed by Barron et al. (2021), may create a negative correlation between Airbnb activity and house prices.[12]

To interpret the magnitude of the effect, I focus on column 7, my preferred specification. The point estimate implies that an increase of 100 Airbnb listings in a given neighborhood raises house prices by 2.2%. Given that the average neighborhood in Madrid had 94 active Airbnb listings by 2018, these estimates imply an increase in house prices of approximately 2.1%. Furthermore, considering that the average house price increased by about 21% by the end of 2018, my baseline estimates suggest that Airbnb was responsible for approximately 10% of the overall growth in house prices on average.

Given the substantial heterogeneity in Airbnb activity across neighborhoods (see Figure 2), it is important to evaluate the implied effects at different levels of Airbnb penetration. For neighborhoods far from the city center, with very low Airbnb penetration, the implied effect is virtually zero. Conversely, for neighborhoods in the historic center, with a large number of Airbnb homes, the implied effect is economically significant. Among the six neighborhoods situated in the historic center, with an average of 900 Airbnb homes by 2018, my estimates imply that Airbnb increased house prices by 20%, which accounts for approximately 40% of the actual price increase observed in these areas.

4.3 Robustness

Measure of Airbnb Activity. I tested whether the results were sensitive to how Airbnb activity was measured. Instead of using the raw number of listings as the independent variable, two alternative measures were used: i) Airbnb density, measured as listings per housing unit in a neighborhood, and ii) the log of listings. Results presented in Table B.1 in the appendix demonstrate that the baseline results remain consistent across these alternative measures of Airbnb activity.

Sociodemographic-specific time trends. Given the overall economic recovery and substantial increases in house prices across Madrid during the sample period, it is important to evaluate whether different neighborhoods exhibited distinct house price trends independent of Airbnb activity. To address this concern, I augmented the baseline specification with interaction terms between neighborhood demographics in 2010 and a linear time trend. Results in Table B.2 show that although the OLS estimates decrease with the inclusion of these trends, the IV regression results remain unchanged. These findings provide additional confidence that the instrument effectively addresses the issue of common trends influencing both Airbnb activity and house prices.

Alternative instruments. A potential concern with the baseline instrument is that the proximity of tourist attractions to the city center may complicate the interpretation of results, particularly if residents' preferences for living near the city center are changing during the sample period. Although incorporating city-center-specific trends mitigates some of these concerns, I also reestimate the baseline model using alternative instruments. I recomputed the spatial component of the instrument using the number of hospitality establishments in a neighborhood in 1998 and three alternative housing stock characteristics as of 2011. The former predicts a neighborhood's attractiveness to tourists, while the latter three predict the ease with which landlords can shift to the short-term market. The time dimension

[12]The downward bias in the OLS estimates of the effect of Airbnb is also consistent with results from Hidalgo et al. (2024), who mention measurement error in Airbnb activity as a potential explanation for downward-biased OLS estimates.

of the instrument remains the same, Google Trends search interest. Results are presented in Table B.3. All point estimates are positive and significant, with the estimated effect of an additional 100 Airbnb units ranging from 1.8% to 3.2%.

Dropping selected neighborhoods. Given the high concentration of Airbnb activity in a few neighborhoods, I tested whether the effects were robust to dropping each of the six neighborhoods where Airbnb was most popular. The results of this analysis are presented in Table B.4 and confirm that the effects remained similar when each of these neighborhoods was removed from the sample. The percentage increase in house prices from each additional 100 properties listed on Airbnb ranged from 2.1% to 2.5%.

4.4 Mechanism: Evidence of Reallocation

Ideally, one would directly test the reallocation effect by estimating the impact of Airbnb growth on the number of long-term rental contracts signed. Unfortunately, there is no publicly available data on rental contracts at the neighborhood level that goes back in time long enough to carry out the fixed effects panel regression that constitutes my core empirical strategy. Thus, I resort to investigating whether Airbnb expansion impacts the size of the resident population of a neighborhood. I estimate regressions similar to Equation 1, using either a neighborhood's population size or the number of households as the dependent variable. Table 3 presents the results.

Airbnb activity is measured by the number of entire home listings, and the outcome variables are measured in levels. Therefore, the coefficients in Table 3 indicate the impact of an additional home listed on Airbnb on the number of residents (Panel A) or households (Panel B) in a neighborhood. To address concerns that changes in Airbnb listings and population (or households) measured in levels might be disproportionately larger in neighborhoods with a larger population, columns 3 and 6 include a time trend interacted with the baseline value of the dependent variable.

Table 3 shows that Airbnb growth reduces the resident population and the number of households, providing evidence of the reallocation effect. On average, an additional home listed on Airbnb reduces a neighborhood's population by 1 to 3 residents. Importantly, this result cannot be attributed to a correlation between Airbnb expansion and pre-existing trends of decreasing average household size. Panel B demonstrates that Airbnb activity also leads to a decrease in the number of households residing in a neighborhood. My preferred specification (column 6), which instruments Airbnb activity using the shift-share strategy described previously, suggests that an additional Airbnb listing results in one fewer household in the neighborhood.

5 The Effect on Residential Mobility

5.1 Empirical Framework

Model 1: Total Effect. I begin by estimating the total impact of Airbnb activity on the flow of residents moving in and out of Madrid's neighborhoods. To achieve this, I employ the same model used to estimate the effects on house prices, but with a different outcome variable. Specifically, I estimate the following two-stage model:

$$\text{First Stage:} \qquad T_{it} = \gamma_T^Z Z_{it} + \gamma_T^X X_{it} + \mu_{i1} + \delta_{t1} + \varepsilon_{it1} \tag{3}$$

$$\text{Second Stage:} \qquad Y_{it} = \beta_Y^T \widehat{T}_{it} + \beta_Y^X X_{it} + \mu_{i2} + \delta_{t2} + \varepsilon_{it2} \tag{4}$$

Table 3: Effect of Airbnb on Population and the Number of Households

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Outcome: Population					
Airbnb Count	-1.482***	-2.778***	-2.874***	-4.708**	-4.021**	-3.432***
	(0.443)	(0.704)	(0.809)	(2.145)	(2.011)	(1.288)
Panel B	Outcome: Number of Households					
Airbnb Count	-0.161**	-0.610**	-0.819***	-1.280*	-2.017**	-1.209***
	(0.076)	(0.289)	(0.306)	(0.717)	(0.829)	(0.430)
Neighborhood FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Controls (X_{it})		X	X		X	X
$X_{i,2010} \times$ Lin. Trend		X	X		X	X
$Y_{i,2010} \times$ Lin. Trend			X			X
Observations	1,152	1,151	1,151	1,152	1,151	1,151
1^{st}-stage F-stat				15.183	13.076	13.468

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome variable is population (Panel A) and number of households (Panel B). The vector of baseline characteristics $X_{i,2010}$ includes: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. Controls include the same variables as in $X_{i,2010}$ except for population density, which is mechanically correlated with the outcome variable. IV regressions use the baseline instrument: proximity to the top 3 tourist attractions (weighted by Tripadvisor reviews) multiplied by worldwide Google search interest for "Airbnb Madrid." Columns 3 and 6 include a time trend interacted with the value of the dependent variable at baseline ($Y_{i,2010}$). House prices are sourced from Idealista. Data on Airbnb is compiled from Inside Airbnb. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the construction of the instrument.

Throughout this section, I adopt a shorter notation for clarity and ease of presentation. Specifically, T_{it} (treatment) denotes the number of Airbnb listings in neighborhood i in year t, Y_{it} represents the number of individuals moving into or out of a neighborhood, and Z_{it} signifies the shift-share instrument based on proximity to tourist attractions and Google search intensity. This notation will be particularly useful when discussing the causal mediation model in the next subsection.

There are two important points to keep in mind about Model 1. First, the coefficient of interest is β_Y^T, which represents the total effect of Airbnb on the volume of residential inflows or outflows. Second, the identification strategy, as in Section 4, relies on the exogeneity of the instrument. Specifically, a causal interpretation requires that proximity to tourist attractions is not associated with other neighborhood characteristics that are themselves linked to unobservable shocks to residential demand from locals.

Since data on residential moves are only available from 2011 onward, visual tests for parallel pre-trends cannot be conducted. However, evidence supporting the exogeneity of the instrument concerning house prices, combined with the strong comovement between population and house prices, suggests that it is reasonable to assume the instrument is exogenous with respect to residential moves. A comparison between Figures 1 and A.1 illustrates this comovement between population and house prices.

Model 2: Mediation Analysis. To unpack Airbnb's total effect on the number of residential moves and investigate the role of housing prices as a potential mediator, I employ the causal mediation model proposed in Dippel et al. (2017). Similar to traditional mediation analysis (e.g., Baron and Kenny (1986)), the causal mediation model aims to decompose the total effect (TE) of a treatment variable (Airbnb activity) on a final outcome (residential moves) into two components: an indirect effect (IE) that runs through the main mediator (house prices) and a direct effect (DE) that runs through the combination of all other channels.[13]

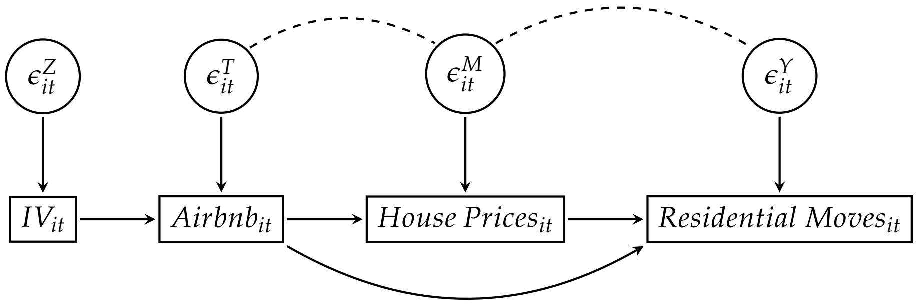
The key innovation introduced by Dippel et al. (2017) is to adapt the causal mediation analysis framework to settings where the treatment is endogenous with respect to both the mediator and the final outcome, and there is only one instrument available.[14] This setup fits well my application, where the combination of proximity to tourist attractions and Google search interest constitute the instrument, which is then used to predict variation in Airbnb that's exogenous with respect to neighborhood specific unobservable shocks that affect house prices and residential flows. Figure 7 illustrates the proposed model, with T, M, Y, and Z denoting the treatment, mediator, outcome, and instrument, respectively.

The outcome, residential moves into or out of neighborhood i during year t, results from individuals choosing where to live based on neighborhood characteristics. All else being equal, higher house prices in a location should discourage people from moving there. Since Airbnb changes house prices, this is one channel in which it (indirectly) affects movers' location choices. Additionally, other neighborhood characteristics influence people's preferred locations. One key example is the availability and type of private consumption amenities in a neighborhood, which can also be affected by Airbnb. Therefore, even in a hypothetical scenario where Airbnb did not impact house prices, it could still affect residential flows through other channels. This is represented by the curved arrow directly linking Airbnb and the outcome.

[13] In mediation analysis, the effect that runs through the mediator variable measured and explicitly accounted for in the analysis, is known as the indirect effect. Describing Airbnb's impact on residential flows through housing prices as "indirect" may seem counterintuitive since housing prices appear to be the most direct channel of interaction. Nonetheless, to maintain consistency with the terminology used in mediation analysis, I refer to the portion of Airbnb's impact on residential flows that operates through housing prices as the indirect effect.

[14] Other approaches to mediation analysis in setting where variables are endogenous and instruments are used, for example Frölich and Huber (2017), require separate instruments for the treatment and for the mediator.

Figure 7: Diagram Illustrating the Causal Mediation Model



In Figure 7, the absence of a direct link between unobservables driving Airbnb activity and residential moves is a key assumption of this model. The identifying assumption is that the endogeneity of Airbnb (treatment) in a regression of residential flows (outcome) on Airbnb primarily arises due to omitted variables that also affect house prices (mediator). For example, in the urban economics literature (Garcia-López et al., 2020; Barron et al., 2021), the main endogeneity concern in a regression of house prices on Airbnb activity is that unobservable shocks to local housing demand may drive changes in both Airbnb listings and house prices. It is reasonable to argue that the same shocks affect the number of residential moves, as this variable also reflects locals' preferences for neighborhood characteristics.

While unobserved variables may affect the relationship between Airbnb penetration and housing prices (which is precisely why an IV is used), as well as the relationship between house prices and subsequent residential moves, it is challenging to identify unobserved shocks that are orthogonal to house prices but significantly impact the relationship between Airbnb growth and changes in the number of movers into (and out of) a neighborhood. For instance, unobserved neighborhood-specific shocks related to the hotel industry might be a candidate for violating this assumption, as they could affect Airbnb activity without strongly impacting house prices. My identification strategy relies on the premise that these types of shocks are not significant drivers of residential moves.

Equations 5 through 8 describe the causal mediation model, which is constituted of two instrumental variable estimations. The first estimates the effect of Airbnb on house prices. Section 4 carried out this same type of estimation, but I restate the model here to facilitate the interpretation of all the parameters involved in the mediation analysis. The second part of the model is more novel. It estimates the effect of house prices on residential moves while controlling for Airbnb activity and only using the variation in house prices that arises from the shift-share instrument.

$$\text{First Stage (A):} \quad T_{it} = \gamma_T^Z Z_{it} + \gamma_T^X X_{it} + \mu_{i1} + \delta_{t1} + \varepsilon_{it1} \tag{5}$$

$$\text{Second Stage (A):} \quad M_{it} = \beta_M^T \widehat{T}_{it} + \beta_M^X X_{it} + \mu_{i2} + \delta_{t2} + \varepsilon_{it2} \tag{6}$$

$$\text{First Stage (B):} \quad M_{it} = \gamma_M^Z Z_{it} + \gamma_M^T T_{it} + \gamma_M^X X_{it} + \mu_{i3} + \delta_{t3} + \varepsilon_{it3} \tag{7}$$

$$\text{Second Stage (B):} \quad Y_{it} = \beta_Y^M \widehat{M}_{it} + \beta_Y^T T_{it} + \beta_Y^X X_{it} + \mu_{i4} + \delta_{t4} + \varepsilon_{it4} \tag{8}$$

Ultimately, I am interested in the β parameters from the two second-stage regressions. The direct effect (DE) of Airbnb on residential moves is captured by β_Y^T, which measures the impact of Airbnb on the number of movers into (or out of) a neighborhood in a hypothetical world where house prices remain fixed. The indirect effect (IE), on the other hand, is formed by the multiplication of two parameters: β_M^T from Equation 6 and β_Y^M from Equation 8. The former measures the impact of Airbnb on house prices and the second the subsequent effect of house prices on the number of movers. Finally, by summing the direct and indirect effects, one can recover the total effect (TE) of Airbnb on residential flows, which is analytically same as β_Y^T from Equation 4 in Model 1.

Before moving to the discussion of results, it is helpful to examine Equation 7, which represents the most novel aspect of this mediation model. In this equation, the instrument is used to predict changes in house prices conditional on Airbnb activity. The insight from Dippel et al. (2022), when applied to my setting, is that, conditional on observed levels of Airbnb activity, proximity to tourist attractions will partly reflect shocks to the demand for housing from locals, which is the primary candidate for bias in the first place.

Landlords decide how to allocate their housing unit by comparing payoffs in the two markets. Since payoffs in the short-term market increase with the proximity to tourist attractions, one reason why neighborhoods at different levels of proximity to attractions (the instrument) can actually have the same number of Airbnb units is if they have different underlying demands from locals. Otherwise, neighborhoods closer to tourist attractions should have more Airbnb units. Thus, conditional on the number of Airbnb listings, neighborhoods closer to tourist attractions will tend to feature positive demand shocks from locals. This argument is supported by the fact that estimated values of γ_M^Z in Equation 7 are always positive.

5.2 Main Results

Model 1: Total Effect. I focus on the effect of Airbnb expansion on residential inflows and outflows, that is, the coefficient β_Y^T in Equation 4. Table 4 presents the results and shows that while Airbnb activity appears to have reduced the inflow of new residents (panel A), it has not resulted in an increase in the outflow of existing ones (panel B). This conclusion can be observed in all IV regressions, shown in columns 4 through 7. For completeness, I also include the results of OLS regressions in columns 1 through 3.

Column 1 shows that when pooling all observations together, Airbnb activity is higher in areas with greater resident turnover. However, Columns 2 and 3, which control for neighborhood and year fixed effects, indicate that there is almost no relationship between Airbnb activity and residential moves. Despite this, Airbnb's activity is endogenous, and its expansion across space may correlate with other dynamics driving residential flows. Instrumenting Airbnb activity with proximity to tourist attractions and Google search intensity (column 4) reveals that it reduces the yearly arrival of movers. The coefficient for outflows, however, remains insignificant. These conclusions are robust to variations of the instrument used, either by changing the shift component from Google trends to the number of yearly visitors to each attraction (column 5) or by expanding the share component to include a larger set of tourist attractions (column 6).[15]

The last column shows the results of including house prices as a covariate in the regression. It is important to note that house prices are added as a standard control and not as a mediator, so we cannot interpret the coefficients as the "effect" of prices on residential flows. For instance, unobserved shocks to the desirability of a neighborhood as a residential location will drive price increases and more in-moves, which likely explains the marginally significant and positive coefficients in panel A. Furthermore, since house prices are influenced by Airbnb and also affect residential flows, they represent a "bad control." Including them may distort our estimates of the effect of Airbnb, moving them further from the true causal effect we seek (Angrist and Pischke, 2009).

It is worth highlighting that none of the regressions displayed in Table 4 include neighborhood demographic time varying controls. The reason for this choice is that in the analysis that follows I will specifically look into the

[15]The number of yearly visitors to each of the top 3 tourist attractions (Prado Museum, Royal Palace, Santiago Bernabeu Stadium) was obtained directly from their websites.

Table 4: Effect of Airbnb on the Number of Movers

	OLS			IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A	Outcome: Number of In-Movers						
Airbnb Count	1.725***	-0.123	-0.167	-0.564***	-0.560***	-0.529***	-0.597***
	(0.593)	(0.082)	(0.125)	(0.181)	(0.211)	(0.171)	(0.184)
Log House Prices							296.826*
							(158.677)
Panel B	Outcome: Number of Out-Movers						
Airbnb Count	1.062**	-0.208*	-0.117	-0.175	0.045	-0.170	-0.135
	(0.494)	(0.111)	(0.077)	(0.152)	(0.147)	(0.152)	(0.173)
Log House Prices							172.180
							(108.353)
Year FE		X	X	X	X	X	X
Neighborhood FE		X	X	X	X	X	X
$X_{i,2010}$ × Trend			X	X	X	X	X
IV-share (N of Attractions)				Top 3	Top 3	Top 20	Top 3
IV-shift				Google	N Visitors	Google	Google
Observations	1,024	1,024	1,024	1,024	1,024	1,024	914
1^{st}-stage F-stat				18.023	24.410	15.946	20.668

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: The outcome variable is the number of in-movers in panel A and the number of out-movers in panel B. The analysis is conducted at the neighborhood-year level for the period from 2011 to 2018. The vector of baseline characteristics $X_{i,2010}$ includes population size, log of population density, average income, share of foreigners, median age, and share of residents with a higher education degree. IV regressions alternate between different instruments: the share component can use either the 3 or the 20 most popular attractions on Tripadvisor, and the shift component can be either the Google search index variable or the yearly number of visitors to each attraction. Data on residential moves is sourced from Madrid's Municipal Census. Data on Airbnb is compiled from Inside Airbnb. House prices are sourced from Idealista. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the construction of the instrument.

effects on in-moves by demographic group and I want to avoid a mechanical correlation between the outcome variable (e.g. number of high education in-movers) and potential controls (share of high education residents). However, to allow for the possibility that trends in residential mobility may differ across neighborhoods that looked different before Airbnb appeared, I include interactions between baseline demographic controls and a time trends, similarly to what we have done in Section 4.

The key takeaway is that Airbnb activity reduces residential inflows but does not increase outflows of existing residents. The former result aligns with expectations, while the latter may be surprising. The reallocation effect suggests that as landlords convert their housing units from long-term to short-term rentals, existing renters may be displaced and would have to move out. There are two explanations that, in combination, help rationalize this lack of effect.

The first explanation involves potential measurement error in the outcome variable. Although everyone living in Spain is required to register in the Municipal Census of the city where they habitually reside and report changes of address within the same municipality, anecdotal evidence suggests that not everyone reports address changes promptly. People making intercity moves (to or from Madrid) have more incentives to report their address change.

For example, to have full access to Madrid's public health system, one needs to be registered as a city resident. On the other hand, individuals changing neighborhoods within Madrid have fewer reasons to report their residential move. This difference in reporting incentives between intercity and intracity moves, combined with the fact that Madrid's population is increasing during the period of most intense Airbnb activity (see Figure A.1), helps explain why most of the effects appear among in-movers.

The second explanation has to do with the high volume of within neighborhood moves. These types of moves are not included in the computation of the outcomes used regression shown in Table 4, but a inspection of the data reveals that the largest flows of intra-city moves occurs in cases where the origin and destination are the same neighborhood. This phenomenon is particularly salient for neighborhoods close in the historic center, where Airbnb is very popular.

Model 2: Mediation Analysis. Having estimated Airbnb's total effect on residential flows in Madrid, I now present the results of the causal mediation analysis. As shown previously, Airbnb expansion primarily impacted the inflow rather than the outflow of residents. Therefore, the mediation analysis focuses exclusively on in-movers.

Table 5 provides a summary of the results. The bottom part of Panel A presents the key coefficients of interest, including the total, direct, and indirect effects of Airbnb on the yearly arrival of new residents into a neighborhood. Panel's A top section features estimates of the two parameters that make up the indirect effect, namely, the impact of Airbnb on house prices (β_M^T) and the effect of house prices on the inflow of new residents (β_Y^M). These coefficients are part of the mediation model, fully characterized by the set of four equations numbered 5 to 8.

All models presented in Table 5 control for neighborhood and time effects. Identification concerns may arise due to neighborhood-specific trends that could simultaneously correlate with changes in Airbnb activity, house prices, and residential moves. For instance, Airbnb activity may correlate with gentrification trends, which could bias our estimates. The direction of the bias is unclear, as gentrification may lead to an influx of new residents but also a shift towards more affluent residents with smaller households. The goal of the instrumental variable strategy based on proximity to tourist attractions is to tackle this kind of endogeneity concern. Section 4.1 argues that the spatial heterogeneity in Airbnb expansion predicted by the instrument is mainly due to tourist demand rather than unobserved shocks to demand from residents.

I do not include neighborhood time-varying demographic characteristics (e.g. share of high education residents), as the in-movers themselves generate changes in these characteristics. However, to control for neighborhood-specific trends that may be correlated with both the expansion of Airbnb and trends in the number of in-movers, each column from 2 to 5, incrementally includes time trends interacted with neighborhood characteristics in the baseline year of 2010.

I begin by examining the parameters in the top panel, which summarize the effects mediated by house prices. Specifically, regarding the impact of Airbnb on house prices denoted by β_M^T, the estimates suggest that an increase of 100 Airbnb listings correlates with a 3% to 5% rise in neighborhood house prices per year, varying by the model specification. These findings align with those reported in Section 4.[16]

The second row of the top panel provides estimates of the effect of house prices on the number of in-movers, denoted as β_Y^M. This coefficient is derived using a 2SLS framework, where house prices are instrumented through a shift-share instrument based on proximity to tourist attractions. The coefficients consistently reveal a negative relationship, indicating that higher house prices deter people from moving into the area. Since house prices are

[16]It is important to note that in this analysis, I have not normalized the number of Airbnb listings by 100. Additionally, the minor discrepancies in the coefficient estimates shown in the first row of Table 5 compared to those in Table 2 are due to the absence of neighborhood time-varying controls in this section.

Table 5: Mediation Analysis: Airbnb, House Prices, and the Inflow of New Residents

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mediation Analysis Model						
Intermediary Parameters: β_M^T, β_Y^M						
Airbnb on House Prices: β_M^T		0.0005***	0.0005***	0.0004***	0.0003***	0.0003***
		(0.00006)	(0.00006)	(0.00004)	(0.00004)	(0.00006)
House Prices on In-Movers: β_Y^M		-2000.92***	-2100.38***	-2100.31***	-2800.84***	-2800.84***
		(400.39)	(400.37)	(400.75)	(600.69)	(900.49)
Main Parameters						
Total Effect (TE)		-0.741***	-0.690***	-0.457***	-0.541***	-0.541***
		(0.155)	(0.140)	(0.091)	(0.102)	(0.165)
- Direct Effect (DE): β_Y^T		0.323**	0.334***	0.332**	0.355**	0.355
		(0.127)	(0.126)	(0.148)	(0.161)	(0.254)
- Indirect Effect (IE): $\beta_M^T \times \beta_Y^M$		-1.064***	-1.023***	-0.789***	-0.896***	-0.896***
		(0.255)	(0.243)	(0.195)	(0.232)	(0.345)
IE / TE		1.436	1.484	1.726	1.655	1.655
Panel B: Standard 2SLS Model (Airbnb Instrumented and House Prices as a Covariate)						
Airbnb Count	-0.741***	-1.147***	-1.070***	-0.731***	-0.733***	-0.733***
	(0.167)	(0.258)	(0.237)	(0.144)	(0.144)	(0.216)
House Prices		797.42***	793.93***	739.80***	615.63***	615.63***
		(204.96)	(200.48)	(172.04)	(158.71)	(203.92)
Year FE	X	X	X	X	X	X
Neighborhood FE	X	X	X	X	X	X
$X_{i,2010} \times$ Trend			Population	+ Med. Age	+ % College	$\sim$ (5)
Standard Errors	Robust	Robust	Robust	Robust	Robust	Clustered i
Observations	914	914	914	914	914	914

Notes: The outcome is the number of in-movers. The analysis is conducted at the neighborhood-year level for the period from 2011 to 2018. Panel A displays core parameters of the mediation model, denoted as *Model 2* in Section 5.1. Panel B shows the effect of Airbnb on the number of movers using a standard instrumental variable approach, denoted as *Model 1* in Section 5.1. House prices are in logs. Heteroskedasticity-robust standard errors are used in all columns except column 6, where standard errors are clustered at the neighborhood level. Each column from 3 to 5 includes an additional baseline neighborhood characteristic interacted with a time trend. When a new characteristic is added, the previous one remains in the regression. All regressions use the baseline instrument based on the top 3 tourist attractions on Tripadvisor and the Google search index variable. Data on residential moves is sourced from Madrid's Municipal Census. Data on Airbnb is compiled from Inside Airbnb. House prices are sourced from Idealista. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the construction of the instrument.

expressed in log units, the point estimates suggest that a 1% increase in house prices results in approximately 20 to 30 fewer residents moving into the neighborhood.

It is important to note the distinctions between the mediation model (panel A) and the standard regression model, which includes house prices as an additional covariate (panel B). The addition of house prices as a control in a model that instruments just for Airbnb results in significantly different coefficients of house prices. For instance, in column 2, which solely incorporates neighborhood and time fixed effects, the mediation model implies that higher prices decrease the arrival of new residents, whereas the standard regression, which does not instrument for prices, suggests that higher prices attract more residents.

This discrepancy underscores the necessity of using instrumental variables not only for Airbnb activity (the treatment) but also for house prices (the mediator). Specifically, areas gaining popularity among residents—likely due to increasing unobservable amenities—are expected to experience faster than average increases in house prices and and in the influx of new residents. This dynamic is reflected in the positive coefficients observed in the last row of the table.

In analyzing the key coefficients of interest (middle section of Table 5), I first examine the indirect effect (IE). The estimates range from 0.79 to 1.06, suggesting that each additional Airbnb listing typically reduces the number of people moving into the neighborhood by approximately one. It is crucial to note that the indirect effect, mediated by house prices, is consistently larger (in absolute terms) than the total effect. Therefore, if the sole impact of Airbnb on neighborhood dynamics were to increase house prices, the decrease in the influx of new residents would be even more pronounced than the effect actually observed (the total effect).

Additionally, the direct effect (DE) is generally positive but small compared to the indirect effect. Furthermore, in column 7, my preferred specification, which clusters standard errors at the neighborhood level, the DE is not statistically significant. Potential second-order effects of Airbnb that might contribute to the DE include changes in the composition of private consumption amenities and negative externalities from tourists, such as noise. While the latter suggests a negative prediction for the DE, the former could potentially influence residents' propensity to move to a neighborhood either positively or negatively. On one hand, the supply of tourist-oriented services, such as restaurants, could become more diverse and/or of higher quality. On the other hand, these services may displace those primarily utilized by locals, such as hardware stores, gyms, or hair salons and barbershops. These opposing effects could explain why the DE is relatively modest and not precisely estimated.

Effects by Education Level. As Table 5 shows, Airbnb's total effect of decreasing the number of in-movers into a neighborhood works primarily through its link to the housing market. The remaining effects seem to be either zero or even positive. If this analysis is correct and Airbnb's effect on the number of people moving into a location varies depending on whether we consider indirect effects via housing prices or direct effects through other channels, then we would expect to see differences in impact across demographic groups that are more or less sensitive to changes in housing prices. Unfortunately, there is no data on movers' income, but I observe their educational attainment. Specifically, I have information on the inflow of new residents with and without a college degree, which serves as a reasonable proxy for income.

Table 6 presents the results of the mediation model estimated separately for low- and high-education in-movers in panels B and C. For comparison purposes, the table also includes results obtained when the outcome variable includes all in-movers (panel A). The findings suggest that Airbnb's negative effect on the inflow of residents (via its effects on house prices) is driven by residents without a university degree. This conclusion holds true both for plain two-way fixed-effects regressions (column 1) and models that include trends based on neighborhood characteristics at baseline (columns 2 through 6).

Table 6: Mediation Analysis: Airbnb and the Inflow of New Residents, by Education

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**All:** total number of in-movers					
Total Effect (TE)	-0.741***	-0.690***	-0.457***	-0.541***	-0.541***	-0.520***
	(0.155)	(0.140)	(0.091)	(0.102)	(0.165)	(0.156)
- Direct Effect (DE)	0.323**	0.334***	0.332**	0.355**	0.355	0.299
	(0.127)	(0.126)	(0.148)	(0.161)	(0.254)	(0.244)
- Indirect Effect (IE)	-1.064***	-1.023***	-0.789***	-0.896***	-0.896***	-0.819**
	(0.255)	(0.243)	(0.195)	(0.232)	(0.345)	(0.325)
IE / TE	1.436	1.484	1.727	1.655	1.655	1.575
Panel B	**Low education:** number of in-movers without university degree					
Total Effect (TE)	-0.919***	-0.961***	-0.707***	-0.741***	-0.741***	-0.696***
	(0.135)	(0.133)	(0.088)	(0.093)	(0.178)	(0.163)
- Direct Effect (DE)	0.129	0.222**	0.252**	0.272**	0.272	0.175
	(0.103)	(0.100)	(0.124)	(0.138)	(0.219)	(0.195)
- Indirect Effect (IE)	-1.048***	-1.183***	-0.960***	-1.014***	-1.014***	-0.871***
	(0.203)	(0.217)	(0.184)	(0.214)	(0.327)	(0.290)
IE / TE	1.140	1.232	1.357	1.368	1.368	1.251
Panel C	**High education:** number of in-movers with university degree					
Total Effect (TE)	0.178***	0.272***	0.251***	0.200***	0.200**	0.177**
	(0.067)	(0.060)	(0.046)	(0.048)	(0.079)	(0.076)
- Direct Effect (DE)	0.194***	0.111*	0.079	0.081	0.081	0.123
	(0.063)	(0.063)	(0.077)	(0.078)	(0.094)	(0.093)
- Indirect Effect (IE)	-0.016	0.161*	0.173**	0.119	0.119	0.054
	(0.099)	(0.086)	(0.080)	(0.084)	(0.124)	(0.123)
IE / TE	-0.092	0.592	0.687	0.595	0.595	0.303
Year FE	X	X	X	X	X	X
Neighborhood FE	X	X	X	X	X	X
$X_{i,2010}$ × Trend		Population	+ Med. Age	+ % College	$\sim$ (4)	$\sim$ (4)
N Attrac. in IV	Top 3	Top 3	Top 3	Top 3	Top 3	Top 20
Cluster SE	Robust	Robust	Robust	Robust	Cluster *i*	Cluster *i*
Observations	914	914	914	914	914	914

Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome is the total number of in-movers in panel A, in-movers without college education in panel B, and in-movers with a college degree in panel C. Analysis at the neighborhood-year level for the period of 2011 to 2018. Coefficients shown are the core parameters of interest of the mediation model (*Model 2* in Section 5.1). Heteroskedasticity robust standard errors in all columns except columns 5 and 6, where standard errors are clustered at the neighborhood level. Columns from 2 to 4 includes an additional baseline neighborhood characteristics interacted with a time trend. When a new characteristic is added, the the previous remains in the regression. Columns 1 to 5 use the baseline instrument based on the top 3 tourist attractions on Tripadvisor and the Google search index variable. Column 6 uses the top 20 attractions to build the instrument. Data on residential moves is sourced from Madrid's Municipal Census. Data on Airbnb is compiled from Inside Airbnb. House prices are sourced from Idealista. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the construction of the instrument.

While clustering standard errors at the neighborhood level (columns 5 and 6) reduces the precision of the estimates, the negative indirect effect on the number of low-education in-movers remains significant at the 1% level. Finally, in column 6, I test the robustness of the instrument by including additional tourist attractions in the computation of its share component. Specifically, the baseline instrument only includes the top 3 tourist attractions in the city, while column 6 uses an instrument that includes the top 20 attractions in Madrid ranked by the number of reviews on Tripadvisor.

When considering the total effect of Airbnb on residents with different levels of education, we observe a negative impact on those with low education and a positive impact on those with high education. One possible explanation is that consumption amenities impacted by the influx of tourists, such as restaurants and bars, are more important for high education residents, since they more disposable income to spend on this kind of activity. However, the estimated direct effect, which accounts for changes in house prices, does not provide clear support for this explanation. Overall, the direct effects are poorly estimated and never significant when we cluster standard errors, regardless of the demographic group.

5.3 Another Mechanism: Consumption Amenities

In Tables 5 and 6, Airbnb's direct effect (DE) on residential inflows combines impacts running through all channels apart from housing prices. The modest estimates of the DE might stem from the fact that different underlying mediators have both positive and negative impacts, depending on individual preferences and circumstances. To shed light on one of the channels that contributes to the DE, I investigate the effect of short-term rental activity on the provision of private consumption amenities.

Consumption amenities relate to the local commercial environment, covering the array of retail and services available in a neighborhood. The potential impact of Airbnb on this local commercial environment stems from the idea that tourists and locals have different demands. For instance, a report by Airbnb shows that restaurants and bars constitute the largest portion of guest expenditures.[17] On the other hand, services such as repair shops or clothing stores are more frequented by local residents.

To estimate the effect of Airbnb activity on the provision of consumption amenities in a neighborhood, I employ models similar to those used in Section 4. That is, I instrument the number of Airbnb listings using my baseline shift-share approach. The outcome variables include four specific types of private amenities: repair shops, clothing stores, groceries, and restaurants.[18] Data for these variables are sourced from the Municipal Census of Business Establishments. Additionally, for restaurants, which are particularly susceptible to shifts in tourist demand, I utilize data from Tripadvisor reviews to explore the potential impact of Airbnb on the average quality available in the market.

Table 7 presents a summary of the results, with each panel displaying a different outcome variable related to the quantity or quality of local consumption amenities. Due to data limitations, the number of observations in this table is smaller compared to previous regressions in this paper. Specifically, the Census of Establishments only features data from 2013 onwards, and some neighborhoods do not have restaurants listed on Tripadvisor for some years in the sample period. To ensure a fair comparison of the parameters, I only include observations in the regression for which all outcome variables could be computed.

[17] Source: airbnb.com/Madrid-Economic-Activity-Report

[18] The category of repair shops includes establishments offering repair services for various items such as bikes, clothes, shoes, computers, etc.

Table 7: The Effect of Airbnb on Private Consumption Amenities

	OLS				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A	Outcome: Number of Repair Shops (census)						
Airbnb Count (x100)	0.738***	-0.063	-0.064	-0.096	0.049	-0.005	-0.032
	(0.253)	(0.136)	(0.110)	(0.117)	(0.160)	(0.172)	(0.179)
Panel B	Outcome: Number of Clothing Stores (census)						
Airbnb Count (x100)	12.860***	-0.760	-0.757	-0.763*	-0.166	0.145	0.039
	(2.182)	(0.506)	(0.467)	(0.448)	(0.625)	(0.620)	(0.643)
Panel C	Outcome: Number of Groceries (census)						
Airbnb Count (x100)	5.002***	1.144***	1.158***	0.993***	1.736***	1.446***	1.461***
	(0.680)	(0.166)	(0.130)	(0.147)	(0.314)	(0.275)	(0.277)
Panel D	Outcome: Number of Restaurants (census)						
Airbnb Count (x100)	36.185***	3.997***	3.717***	3.162***	4.934***	3.771***	3.988***
	(6.025)	(0.501)	(0.466)	(0.458)	(0.904)	(0.898)	(0.901)
Panel E	Outcome: Rating of Average Restaurant (Tripadvisor)						
Airbnb Count (x100)	0.004	0.030***	0.025***	0.017**	0.026	0.009	0.004
	(0.005)	(0.008)	(0.005)	(0.008)	(0.016)	(0.022)	(0.022)
Year FE		X	X	X	X	X	X
Neighborhood FE		X	X	X	X	X	X
$X_{i,2010}$ × Trend			X	X	X	X	X
Controls				X		X	X
N Attrac. in IV					Top 3	Top 3	Top 20
Observations	641	641	641	641	641	641	641

Standard errors clustered at the neighborhood level $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcomes are indicated in the title of each panel. Analysis conducted at the neighborhood-year level from 2013 to 2018. Coefficients represent the effect of 100 Airbnb listings. Controls include: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. These variables are also included in the vector of baseline characteristics $X_{i,2010}$. Columns 5 and 6 utilize the baseline instrument based on the top 3 tourist attractions on Tripadvisor and the Google search index variable. Column 7 employs the top 20 attractions to construct the instrument. Data on the count of businesses is sourced from Madrid's Census of Establishments. Airbnb data is compiled from Inside Airbnb. House prices are obtained from Idealista. Information on tourist attractions and restaurant ratings is from Tripadvisor. For detailed information on data sources and the construction of the instrument, see Sections 3.1 and 4.1.

Panels A (repair shop) and B (clothing) focus on consumption amenities that are more likely to be demanded by locals than by tourists. Overall, the IV regressions show no effect of Airbnb activity on these types of businesses. Therefore, the hypothesis of crowding out has no support in the data. Panel C shows the results for a type of service demanded by both locals and tourists: groceries. The observed increase in grocery stores likely stems from two factors. First, compared to hotel tourists, Airbnb guests are more likely to cook at home. Second, mini-markets offering a small selection of food-related products until late at night, which match well the kind of things demanded by tourists, are also counted as grocery stores in the Census of Establishments.

Panels D and E focus on restaurants. As expected, Airbnb activity increases the availability of restaurants. The results in column 7 of panel D suggest that for every 100 additional Airbnb units in a neighborhood, the overall number of restaurants increases by approximately four. These estimates align with those obtained by Hidalgo et al. (2024), whose study estimates the effects of Airbnb on restaurants using data from Madrid. Panel E, on the other hand, examines the quality dimension by estimating the effect on the rating (a proxy for quality) of the average restaurant in a neighborhood.[19] The data shows no evidence that the tourist influx brought by Airbnb increased restaurant quality.

To summarize, the weakly positive DE suggests that factors beyond the negative externalities caused by tourism are at play. The results in Table 7 indicate that an increase in the variety of restaurants (and, to a lesser extent, food stores) may be one of the compensating factors that contribute to the positive DE. Furthermore, there is no evidence of crowding out services that cater to locals, supporting the argument that the net effect through consumption amenities is positive, offsetting some of the negative externalities.

Moreover, the lack of effect on restaurant quality is informative for understanding the potential heterogeneity of the effects of short-term rentals across different demographic groups. If Airbnb had affected not only the quantity but also the quality of restaurants, one would have expected different types of consumers to benefit differently. For instance, higher-income consumers may be more attracted to locations with higher-quality restaurants, even if it means higher prices. The fact that Airbnb does not affect the quality of restaurants is consistent with the DE not being different between low- and high-education residents.

6 Conclusion

The rise of platforms like Airbnb has resulted in a significant expansion of short-term renting activity. Numerous regulatory proposals have been put forth, such as capping the number of days a residential unit can be rented to tourists, requiring the presence of a permanent resident during guests' stays, or an outright ban. Therefore, it is crucial to comprehend the potential impact of home-sharing on the welfare of city residents.

This paper investigates the effects of Airbnb activity on house prices and residential mobility in Madrid, a large European capital with large affluence of tourists. Adopting an instrumental variable approach based on spatial variation in neighborhoods' attractiveness to tourists and the rapid expansion of Airbnb over time, I establish that short-term rental activity raised house prices and reduced the number of in-movers into a neighborhood. Specifically, for a neighborhood with average Airbnb activity, my results suggest that: i) house prices have risen by 2%, and ii) the number of in-movers without a college education has dropped by 65. These findings suggest that the

[19] My aim is to understand Airbnb's impact on the desirability of neighborhoods as residential locations from the perspective of local residents. Therefore, in Panel E, to measure quality, I only include reviews from Tripadvisor users who report residing in Madrid. Locals and tourists submit systematically different ratings, with tourists being less stringent.

growth of short-term rental platforms may trigger or intensify gentrification processes, often leading to a shift in the demographic makeup of the local population towards highly educated residents.

Furthermore, using a causal mediation analysis, the study demonstrates that Airbnb's impact of reducing the inflow of low-education residents is entirely mediated by its effect of raising housing costs. Effects running through other channels are positive but small. This indicates that second-order effects of short-term rentals, such as the improvement of private consumption amenities, have only modest impacts on attracting new residents. In support of this argument, I provide evidence that Airbnb increased the number of restaurants in a neighborhood but not their quality.

Overall, this study contributes to policy debates surrounding strategies to regulate short-term rental platforms. My findings indicate that, in the context of Madrid, the main impact of Airbnb on residents' welfare is related to its effect of increasing housing costs. Consequently, policies that restrict Airbnb activity will generally harm homeowners and benefit renters.

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Appendix

A Extra Figures

Figure A.1: Evolution of Population and Average Demographics Characteristics

Notes: Evolution of cross-neighborhood averages for population size, the proportion of residents with a higher education degree, and median age. The red solid line represents population size (left scale). The blue and green dashed lines depict demographic characteristics (right scale). Neighborhood demographics are derived from data provided by Madrid's City Council statistics department, available at https://datos.madrid.es/portal/site/egob.

B Extra Tables

Table B.1: Effect of Airbnb on Log of House Prices: Alternative Measure of Airbnb

	OLS			IV		
	(1) Count (x100)	(2) % Housing	(3) Log Count	(4) Count (x100)	(5) % Housing	(6) Log Count
Airbnb Activity	0.014***	0.016***	0.015***	0.022***	0.022***	0.130***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.033)
Controls	X	X	X	X	X	X
Neighborhood FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Trend × Dist. Center	X	X	X	X	X	X
Observations	1,029	1,029	1,029	1,029	1,029	1,029
1^{st}-stage F-stat				15.974	24.715	10.528

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome variable is the log of house prices. Column names indicate how Airbnb Activity is measured. Controls include: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. IV regressions use the baseline instrument: proximity to the top 3 tourist attractions (weighted by Tripadvisor reviews) multiplied by worldwide Google search interest for "Airbnb Madrid." House prices are sourced from Idealista. Data on Airbnb is compiled from Inside Airbnb. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the instrument, respectively.

Table B.2: Effect of Airbnb on Log of House Prices: Alternative Time Trends

	OLS					IV				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Airbnb Count (x100)	0.014***	0.013***	0.012***	0.014***	0.008***	0.022***	0.021***	0.019***	0.023***	0.022***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)
Controls	X	X	X	X	X	X	X	X	X	X
Neighborhood FE	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X
$X_{i,2010}$ × Trend	Dist. Center	Income	Med. Age	% College	All	Dist. Center	Income	Med. Age	% College	All
Observations	1,029	1,029	1,029	1,029	1,029	1,029	1,029	1,029	1,029	1,029
1^{st}-stage F-stat						15.974	22.166	28.878	21.678	17.658

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome variable is the log of house prices. Controls include: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. Row $X_{i,2010}$ × Trend indicates which neighborhood characteristics are interacted with a linear time trend. IV regressions use the baseline instrument: proximity to the top 3 tourist attractions (weighted by Tripadvisor reviews) multiplied by worldwide Google search interest for "Airbnb Madrid." House prices are sourced from Idealista. Data on Airbnb is compiled from Inside Airbnb. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the instrument, respectively.

Table B.3: Effect of Airbnb on Log of House Prices: Alternative Instruments

	Baseline		Alternative Instruments			
	(1)	(2)	(3)	(4)	(5)	(6)
Airbnb (x100)	0.014***	0.022***	0.018***	0.028***	0.025***	0.032**
	(0.003)	(0.005)	(0.004)	(0.006)	(0.008)	(0.013)
Controls	X	X	X	X	X	X
Neighborhood FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Trend × Distance	X	X	X	X	X	X
IV share component		Proximity to Tourist Attract.	Number of Hospitality Estab.	Share of Rented Houses	Share of Small Houses	Share of Empty Houses
Observations	1,029	1,029	1,029	1,029	1,029	1,029
1^{st}-stage F-stat		15.974	34.032	15.006	8.408	4.448

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome variable is the log house prices. Controls are: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. All IV regressions use the Google search interest for "Airbnb Madrid" as the instrument's shift component. The row "IV share component" indicates the variable used to construct the share component of the instrument. Data on Airbnb is compiled from Inside Airbnb. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the instrument, respectively.

Table B.4: Effect of Airbnb on Log of House Prices: Drop Selected Neighborhoods

	Baseline		Drop One Neighborhood					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Airbnb (x100)	0.014***	0.022***	0.025***	0.024***	0.022***	0.021***	0.022***	0.021***
	(0.003)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Controls	X	X	X	X	X	X	X	X
Neighborhood FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Trend $\times$ Distance	X	X	X	X	X	X	X	X
IV		X	X	X	X	X	X	X
Neigh. Dropped			Palacio	Embajadores	Cortes	Justicia	Universidad	Sol
Observations	1,029	1,029	1,020	1,020	1,020	1,020	1,020	1,020
1^{st}-stage F-stat		15.974	10.438	14.698	9.885	14.631	14.654	13.682

Standard errors clustered at the neighborhood level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: Outcome variable is the log house prices. Controls are: log of population density, proportion of foreign residents, median age, log of average household income, and proportion of residents with a higher education degree. IV regressions uses the baseline instrument: proximity to the top 3 tourist attractions (weighted by Tripadvisor reviews) times worldwide Google search interest for "Airbnb Madrid". Columns 3 through 8 alternatively drop one of the six most popular neighborhoods in terms of Airbnb listings. Data on Airbnb is compiled from Inside Airbnb. Information on tourist attractions is from Tripadvisor. See Sections 3.1 and 4.1 for details on data sources and the instrument, respectively.