Living With Tourists:
Local Effects of Home-Sharing

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Abstract

This paper empirically studies the potential impacts of short-term rental and home-sharing activities on neighborhood level outcomes. It focuses on the city Madrid and builds a comprehensive dataset of Airbnb activity and core neighborhood attributes (house prices, consumption amenities, and jobs) to argue that the increasing presence of touristic apartments affects each one of these core neighborhood attributes. I find that Airbnb activity increases house prices, consumption amenities that are highly demanded by tourists (restaurants), and low wage jobs. In addition, data on cross neighborhood mobility patterns is used to show that, both directly and indirectly through its effect on house prices, Airbnb activity reduces population density by preventing some of the in-migration of would be new residents of a neighborhood.

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1 Introduction

Short-term renting and home-sharing activities made through online platforms such as Airbnb have experienced a remarkable increase over the past decade. What are its potential impacts and how they affect residents of cities that are popular with tourists is an important question that is still unanswered.[1] Concerns that Airbnb apartments for hosting short-term visitors are increasing house prices, displacing permanent residents, and hollowing out neighborhoods have led to policies that strictly regulate home-sharing.[2] But housing prices and displacement are not the only neighborhood level effects of Airbnb, which could also boost local economic activity, contributing to increase the number of businesses and jobs. Understanding and measuring the different ways in which Airbnb expansion might affect local neighborhoods is therefore of fundamental importance for urban policy.

In this paper I provide evidence on the effects of the growth in Airbnb style apartments on three core neighborhood attributes: house prices, local consumption amenities (establishments), and job density. Additionally I provide suggestive evidence on whether these neighborhood attributes and Airbnb density itself are then relevant in predicting residents' decision of where to live. I do this by building a panel dataset with neighborhood-year level data on Airbnb activity, core neighborhood attributes, demographics, and mobility patterns. For each neighborhood, my data contains the number of Airbnb listings, the number of Airbnb guest reviews, average house prices, number of establishments in different categories, employment by broad industry type (or wage groups), basic demographic indicators (population density, education, age, region of birth), and the yearly inflow and outflow of residents. I use within-neighborhood longitudinal variation in Airbnb density along with all these other variables to estimate the relative importance of Airbnb in explaining neighborhood change.

I begin by illustrating the main descriptive facts of Airbnb growth and neighborhood change. A few essential facts come out clearly from this descriptive analysis. First, out-migration (residents that move out), which was very high is the beginning of the sample period, reduces everywhere regardless of Airbnb density. Second, in-migration (number of people who move in) increases only in areas with low penetration of Airbnb. These two facts together suggest the Airbnb's effect on displacement is concentrated on indirectly preventing new residents to move-in more than on actively pushing residents out.[3] And the third fact that appears in the descriptive analysis is that, out of the core neighborhood attributes, Airbnb's most striking correlation is with house price increases. This connects with the previous two facts because one way through which the expansion of tourist apartments may reduce the inflow of residents is by increasing house prices.

Next, I separately estimate the direct effects of Airbnb activity on each one of the core neighborhood attributes. First, I find positive and robust effects on house prices, which confirms the third fact of the descriptive analysis. Second, I find suggestive evidence of positive effects of Airbnb activity on the number of restaurants and food stores (businesses that benefit from tourist demand) and negative effects on establishments offering personal services (businesses that cater to locals). These effects are less robust than the ones found for housing prices and depend on the functional

[1] The well-being of tourists is also important to consider when looking at the overall effects of Airbnb, but the focus on the present paper is on the well-being in residents of cities where home-sharing activities have increased.

[2] Examples include Santa Monica (U.S.) and Berlin, which completely banned short-term rental of entire home units (the Berlin law has been changed to a more flexible regulation that allows touristic apartments under some circumstances); San Francisco, where short-term rental units cannot be rented for more than 90 days per year; Barcelona, where vacation rentals require a special tourist license which is limited to some neighborhoods; and Madrid, which currently has distinct city and estate (comunidad) level laws to regulate the activity of Airbnb like apartments.

[3] This is not to say that there are not cases in which residents are directly pushed out from a rented unit. The only thing that is suggested by the data is that this direct out-migration channel is not the dominant way through which Airbnb induced displacement in Madrid.

form assumed in the regressions. Third, I find no effects on overall employment but positive and significant effects on low wage jobs. Additionally, I find positive and robust effects on employment the hospitality industry. These two findings fit well together because most jobs created in hospitality (mostly restaurants and bars) are likely to be low wage jobs.

Then, I move on to showing that Airbnb activity is positively correlated with changes in the share of residents with university education and with the share of young adults, while it is negatively associated with changes population density and in the share of residents born in a non-OECD country (the best proxy I have for economically disadvantaged residents). Finally, in the last empirical part of the paper I use a basic residential location framework to investigate the potential causes of these correlations between Airbnb activity and neighborhood demographic indicators. I use data on the yearly number of in-movers to a neighborhood to estimate preference parameters for Airbnb density as well as for the core neighborhood attributes studied in this paper. I find that the number of establishments or jobs struggle to explain any variation in location decisions of in-movers, whereas Airbnb density and house prices appear as the most important drivers of individuals location decisions.

Three fundamental conclusions arise from the residential location model estimates. First, Airbnb's positive effect on house prices harms all kinds of demographic groups but it does so more strongly for poorer individuals, which helps explain Airbnb's positive association with education levels and negative correlation with immigrants from non-OECD countries. Second, regarding Airbnb's positive (but weak) association with the share of residents who are young adults. Although it is true that by increasing house prices it tends to reduce young adults' share relative to older adults, there are two counterbalancing effects: low wage jobs generated by Airbnb attract young adults relatively more than the older cohorts, and Airbnb's direct impacts on residents[4] hurt older residents utility more than they do so for the young. The third conclusion is that, even after controlling for all neighborhoods attributes, there is still significant variation in location decisions that is explained by Airbnb density, which suggests that Airbnb may affect residents' utility levels through mechanisms that my data is not able to capture, such as by reducing neighborhood community feeling and trust level among neighbors on the negative side, or by offering the possibility of making extra income with spare space on the positive one.

This paper builds on the existing literature from two distinct sources. On the one hand, I build on the large literature that studies gentrification, its drivers and its consequences. There's a growing interest on the topic of gentrification due to the increase in the net migration flows between suburbs and central neighborhoods in the U.S. over the two last decades. Of particular importance to my work and to my definition of the core neighborhood attributes is the investigation by Couture and Handbury (2017) of the main drivers of what the authors call "Urban Revival". Both Couture and Handbury (2017), Diamond (2016), and Su (2018) emphasize the importance of consumption amenities in driving location decisions. Other recent papers that also study the recent gentrification trends and effects are Aron-Dine and Bunter (2019), Baum-Snow and Hartley (2016), Glaeser, Kim, and Luca (2018), and Guerrieri, Hartley, and Hurst (2013). In terms of gentrification's effects on original residents' out-migration (as well as other well-being aspects) Brummet and Reed (2017) working paper uses micro-data from the U.S. census to show that most of the neighborhood level effects of gentrification tend to happen via changes in the characteristics of in-movers more than through direct out-migration effects. My results are in line with theirs, since most of the Airbnb effects I find on neighborhoods in my sample seem to be driven by changes related to in-migrants, both in terms of quantity and average demographics.

[4](By direct impacts I mean the effects that we know exist but are not explicitly included in the regression due to lack of data. Typical examples of direct impacts of Airbnb activity are *noise and congestion*.)

On the other hand, I also borrow from the recent and rapidly increasing empirical literature on the direct effects of short-term rentals and home-sharing. With respect to the housing market, Horn and Merante (2017), Barron, Kung, and Proserpio (2018), Segú (2018), and Koster, Ommeren, and Volkhausen (2018) all provide evidence of the positive effects of Airbnb on house prices in different contexts. My results in this paper are line with their findings. Regarding Airbnb's effect on local economic activity, Alyakoob and Rahman (2019) show that Airbnb expansion in New York City is associated with increases in restaurant employment in neighborhoods that were not touristic previous to Airbnb. Once more, my results also point in the same direction showing a positive effect of Airbnb activity on hospitality employment and no effects on other unrelated industries.

My main contribution is to try to bridge this two separate strands of literature. It is, to the best of my knowledge, the first attempt to study in the same empirical context (city) the effects of Airbnb activity on several neighborhood level outcomes and then to connect this to potential effects on residents mobility, neighborhood change, and gentrification. Although most of the estimates presented here are descriptive,[5] the main conceptual framework in which home-sharing expansion reallocates housing space from the residential to the short-term housing market, and simultaneously affects neighborhoods' core attributes and residents' residential choice seems to be a worthwhile area for further research.

The remaining of the paper is organized as follows. Section 2 describes the data and its sources. In Section 3, I present some basic facts about Airbnb growth and neighborhood change in Madrid. Section 4 separately estimates the effect of Airbnb on neighborhood house prices, consumption amenities, and jobs. Section 5 discusses a basic framework that illustrates the link between Airbnb effects on these core neighborhood characteristics and its potential impact on residents' mobility decisions. Section 6 concludes.

2 Data

The main unit of analysis throughout this paper is the neighborhood, which is the smallest administrative division within the city of Madrid for which yearly information on crucial variables such as house prices and demographics is available. There were 128 neighborhoods in Madrid in 2010, year when I observe the first Airbnb guest review. During the sample period, which goes up to December 2018, the number of neighborhoods increases to 131. Whenever possible (neighborhood creation and destruction is amenable for aggregation and disaggregation of relevant variables) I use a 2010 constant neighborhood definition. I collect data from a variety of sources and build a comprehensive dataset with information on various aspects of Madrid's neighborhoods over the last years. This section briefly describes the main types and sources of data used.[6]

2.1 Airbnb

Data regarding Airbnb activity was obtained from the "Inside Airbnb" project.[7] Using data provided by this source, I build a panel dataset capturing Airbnb activity at the neighborhood-year level in the city of Madrid. To that end, I make use of two key pieces of information for each listing scraped. First, I use review histories (exact date of each guest review) to proxy for the amount and timing of actual Airbnb activity, that is, when and how many guests specific listings actually

[5] The only outcome for which an attempt to make causal claims is carried out is for housing prices.

[6] Data that was used only occasionally and as second order supportive information is described in the specific sections in which they are used.

[7] Inside Airbnb is an independent, non-commercial project that periodically scrapes data directly from Airbnb's website and makes it available at http://insideairbnb.com/get-the-data.html.

received. Additionally, I use the latitude and longitude coordinates provided by Airbnb[8] to assign each listing to a neighborhood in the city.

With these two pieces of information in hand (location of listings and the timing of guest reviews) I build the two main measures of Airbnb activity used throughout the paper: *i*) number of active listings (listings with at least one guest review) and *ii*) estimated number of Airbnb guests (I do not observe actual bookings and I proxy it by guest reviews). Both measures are computed at the neighborhood-year level, for 128 neighborhoods from 2010 (year of first Airbnb guest review) to 2018, delivering a total of 1152 observations.

2.2 House Prices

Data regarding house prices was obtained from *Idealista*, the leading real estate online marketplaces in Spain. *Idealista*, which offers an online platform where sellers can post their offers and prospective buyers can look for houses on sale, periodically publishes its own Price Report.[9] The report, which in its annual version is called Annual Evolution of the Price of Second-Hand Housing, contains information on average prices over listings aggregated across distinct regions of Spain.[10] Hereafter, to avoid long and repetitive wording, whenever I use the term "house prices" I refer to this variable published by Idealista's report: the offer price (I don't observe the actual transaction price) of second-hand home.

Specifically for the Madrid area, average house prices is available every month for the city as a whole as well as for district wide averages (Madrid has 21 districts and 128 neighborhoods). However, at the narrower definition of neighborhoods, house price information is published by Idealista only once a year, so that all neighborhoods (even the smaller ones) have enough listings from which a representative sample can be obtained.[11] Therefore, the variable used in the analyses concerning house prices is the average offer price across all listings on *Idealista* in neighborhood i during year t.

2.3 City Hall Statistics

The Madrid City Hall has a statistics department which compiles data from different sources and makes them available for public use through two main channels: *i*) a general database website with infrequent updates but with data already cleaned and organized in ready to use formats,[12] and *ii*) an "Open Data", webpage where data is regularly uploaded in a somewhat raw format and users can download it to build their own datasets according to their specific needs.[13] From these two sources I obtain data on the evolution of neighborhood level demographics, employment, number of establishments by type of activity, and housing stock.

In terms of demographics, the data provided by the City Hall comes from the "Padrón Municipal" (or Municipal Census), which is the administrative record where residents of a municipality are registered.[14] I collected data on the yearly evolution of a number of different characteristics

[8]For privacy reasons, latitude and longitude provided by Airbnb, refer in fact to a random point in a circle of 150 meters centered around the true location of the listing. Such type of approximate location would be problematic for doing listing specific analyses, but since I aggregate listings at the neighborhood level, the "noise" should balance out across nearby neighborhoods and no bias should be introduced to the estimations.

[9]https://www.idealista.com/sala-de-prensa/informes-precio-vivienda

[10]As suggested by its name, the report excludes newly built house and the average prices are computed only for second-hand houses for sale

[11]https://st1.idealista.com/comunicacion/files/informe-de-precios/annio-2018.pdf

[12]http://www-2.munimadrid.es/CSE6/jsps/menuBancoDatos.jsp

[13]https://datos.madrid.es/portal/site/egob

[14]Any person living in Spain is obliged to register in the *Padrón Municipal* of the city in which they habitually reside. People should also report changes of address within the same municipality. Clearly, the municipal census may not reflect the exact reality of neighborhoods in a perfectly up-to-date manner if people change addresses but

of each neighborhood. The main ones are the size of the overall resident population, residents' education attainment, age structure, and place of origin. Unfortunately, the municipal census does not include any information whatsoever about residents' income.

Regarding employment, data offered by the City Hall's statistics department is compiled from social security records and includes yearly neighborhood level employment divided in broad classifications by industry types. For example, I observe total employment in the hospitality industry (accommodation and food/drink services) but not for restaurants or hotels separately. Thus, I include data on total employment as well as employment in each of the 21 different industry classes available. I also get employment levels for seven distinct professional categories as listed in the social security system. I use these professional categories to divide employment by wage group. In Section 4.3 this process is explained in detail.

With respect to the number of establishments in each neighborhood, I obtain information from the "Open Data" project of the City Hall that allows one to directly access data from the *Municipal Census of Establishments*, a record of all the establishments located in the City of Madrid with active licenses. Importantly, the tool offered by the City Hall provides snapshots of the census records of establishments at different points in time. However, since this a relatively recent project from the City Hall, the first period for which data is available is the end of 2013. For each establishment, I observe name, address, situation (open, inactive, under construction works), and type of activity carried out (clothing retail, restaurant, bakery, etc.). Using this data source I compute the yearly number of active establishments of different activity types for each neighborhood of the city.

Finally, some variables provided by the City Hall statistics service are not available at the neighborhood disaggregation level but are still used in the analyses that follows. Of particular importance is the citywide yearly number of tourists staying in hotels.

2.4 Tripadvisor

In order to further analyze the relationship between Airbnb tourists and local restaurant activity, I scrape data directly from Tripadvisor's website (Couture (2016) and Couture and Handbury (2017) show that restaurants are a very important consumption amenity driving both residents location choice as well as travelling behaviour within the city). From public-facing pages for each restaurant, I obtain two types of information. First I get basic information about each restaurant, such as name, type of food served, and street address. Second, I scraped the history of reviews written by customers. Importantly, for 74% of the customer reviews scraped I observe the user's location, which I use to divide customers in two types, locals or tourists. Reviewers who report their location of residence to be Madrid or any other city in the Community of Madrid are classified as locals, whereas reviewers reporting their location to by anywhere outside the Community of Madrid are considered tourists or visitors.[15]

Next, to aggregate restaurants at the neighborhood level I use Google Maps Geocoding API[16] to back out each restaurant's latitude and longitude coordinates and GIS software to assign each point to a neighborhood (addresses provided by Tripadvisor for each restaurant only includes street number and postal code, not the neighborhood). Ultimately, I combine the spatial information of each restaurant with costumer reviews to build neighborhood-year level data on the number of active restaurants (with at least one review), the number of distinct cuisines offered (Spanish,

take time to report it to the municipal authorities. Nevertheless, it is still the best information source available on population characteristics for small geographic areas (neighborhoods) with yearly updates.

[15] Reviews missing the user location are shown in some descriptive presentations of the data but are dropped for most analyses.

[16] https://developers.google.com/maps/documentation/geocoding/intro

Chinese, Italian, etc.), fraction of overall reviews left by tourists or locals, and the average rating by customer type (customer reviews include a rating from 0 to 5).

3 Basic Facts About Airbnb and Neighborhood Change

In spite of the amount media attention devoted to the effects of Airbnb on local neighborhoods,[17] there is still little empirical evidence that tries to jointly evaluate all the aspects that Airbnb expansion may potentially impact.[18] To provide a broader analysis of the neighborhood level effects of short-term rentals and home-sharing activity, this paper gathers data related to Airbnb and what I refer as *core neighborhood characteristics*, namely: house prices, commercial environment (consumption amenities) and job availability. My main interpretation of these core neighborhoods attributes is that they are important inputs into the utility function of residents and therefore drive their decision of where to live in a city. There is no doubt that other neighborhood attributes are also essential to the residential location decision of locals and in that sense should be included in the *core neighborhood characteristics*. Prime examples are school quality, crime levels and natural amenities (ocean view, mountains, parks, etc.). I do not include these variables either because of lack of data or because I don't expect Airbnb presence to have a major impact on them. I also collect data on snapshots of basic neighborhood demographics as well as residents' mobility patterns across neighborhoods with the intention of investigating whether Airbnb expansion, either by direct displacement[19] or by affecting core neighborhood attributes, may impact residents' location decisions and as a consequence the spatial distribution of demographics and population density across the city.

3.1 Summary Statistics by Airbnb Density Level

Table 1 describes some basic neighborhood characteristics for two groups, neighborhoods above (high Airbnb) and below (low Airbnb) the median level of Airbnb guest density. More specifically, I define Airbnb guest density as the number of guest reviews divided by the total residential units in a neighborhood, and divide neighborhoods between above and below the median for the 2018 values of this measure.[20] Then, I compute the average characteristics over neighborhoods in each group for 2013, 2018, as well as the change between these years (both in absolute and in percentage terms).[21]

Table 1 has three main parts. First, it brings data referring to Airbnb activity itself and a rough measure of hotel guests. Second, it includes information on neighborhood characteristics that I primarily interpret as factors that drive residents' decision of which neighborhood to live in. Lastly, it displays basic neighborhood demographics and mobility patterns that arise as a result of people's decision to move across neighborhoods in the city. It is certainly debatable whether the most adequate framework is to include neighborhood demographic features (e.g. share of residents

[17] Some examples of the infinite amount of media articles about Airbnb are:
www.bbc.com/news/business-45083954
www.theguardian.com/commentisfree/2018/aug/31/airbnb-sharing-economy-cities-barcelona-inequality-locals
www.elpais.com/ccaa/2018/11/06/madrid/1541517740_949384.html
www.newyorker.com/magazine/2019/04/29/the-airbnb-invasion-of-barcelona

[18] As mentioned in the Section 1, most papers is literature focus on one given factor that Airbnb may have an impact on, house prices and the hotel industry being the most commonly studied outcomes.

[19] I use the term direct displacement to refer to the case when a residential units is converted into a tourist apartment and the previous resident is pushed out.

[20] This is basically equivalent to dividing neighborhoods based on change on Airbnb tourist density over the sample period because neighborhoods start out with zero or very low level of Airbnb tourist density.

[21] Although the first year in which I observe Airbnb guest reviews is 2010, I do not have data on the number of establishments for years previous to 2013. In order to make Table 1 comparable across all variables I choose to describe the variables in 2013 and 2018.

with university education or higher) as a result or a driver of moving decisions, since the type of neighbors one had are an important determinant of utility and consequently of location decision. I choose to group these variables as results of location decisions since I see this as the most natural way to conceptualize the issue under study. That is, Airbnb density (in terms of listings or visitors depending on the application) affects the housing market, local consumption amenities (specially restaurants), and the types of jobs available, and these three core neighborhood attributes in turn impact people's location decision.

3.1.1 Airbnb Activity and Tourists

In terms of Airbnb activity it is clear that the difference between the two groups represented is extremely large. By 2018, the number Airbnb active listings (with at least one guest review during the year) in the average neighborhood was 8 times larger for the high Airbnb group. And regarding guest reviews, the difference between the two groups is even bigger, with the average neighborhood in the high Airbnb group having more than 13 times the number of reviews observed in the average low Airbnb neighborhood. The fact that the ratio is larger for reviews than for listings indicates that Airbnb popular areas do not only have more listings but they also tend to disproportionately concentrate more guests even conditional on the number of apartments listed. This is important because it may suggest that listings in neighborhoods in the high Airbnb density areas are being used more frequently than listings in other parts of the city and therefore are more likely to represent housing that is being permanently removed from the residential market.[22]

Another striking fact represented in Table 1 is the remarkable increase in Airbnb activity from 2013 to 2018. In the high Airbnb group, the average neighborhood received around 197 guest reviews in 2013, whereas in 2018 it received close to 5000 reviews, representing a percentage increase of more 2000%. Moreover, by looking at the changes in Airbnb listings and guest reviews one can get a sense of the nuances involved in estimating the effects of Airbnb growth. Although the absolute change in Airbnb activity (both listings and reviews) was substantially higher for the group of neighborhoods above the median activity level, the percentage growth is actually higher for the group below the median. This comes from the fact that although the actual Airbnb activity level is much higher for the above median density group, the low Airbnb group starts from such a low baseline level in 2013 that any absolute increase translates into huge percentage increases. This is important when one thinks about which measure of Airbnb to use when estimating its effects. Since many neighborhoods have very low levels of Airbnb activity (either in terms of listings or guest reviews) in the initial years of the sample, using log of Airbnb listings or reviews may be problematic because it gives relative high importance for small changes in Airbnb activity that represent larger percentage increases. That is, using log of listings as a measure of Airbnb activity would attribute the same importance to an increase in listings from 1 to 2 when to compared to an increase from 30 to 60. But in reality, an increase from 30 to 60 Airbnb listings is likely to bring about a more significant change in the neighborhood than an increase from 1 to 2. Certainly, this will depend on the application and using Airbnb density measures (reviews or listings per housing units) also has downsides, the main one being the very large concentration of Airbnb density in just a couple of neighborhoods, which ends up making the parameter estimates very sensitive to including or not these neighborhoods in the regressions.

Next, Table 1 also displays Airbnb active listings and guest reviews expressed as a percentage of the local housing stock. That is, how many active listings or guest reviews a neighborhood has for

[22]It is important to point out that although this story goes in line with the data, it is definitely not the only one that fits with it. It is possible that listings in both groups (high and low Airbnb) are in fact being advertised in a permanent (or occasional) basis, but listings in popular areas just have a higher occupancy rate.

Table 1: Neighborhood Characteristics by Airbnb Activity Level

Panel A: High Airbnb Density Neighborhoods

	2013	2018	Absolute Change	Percent Change
Airbnb Listings	20.25	260.28	240.03	1185.34
Airbnb Reviews	197.11	4724.34	4527.23	2296.81
Airbnb Listings per 100 Housing Units	0.18	2.33	2.14	1166.27
Airbnb Reviews per 100 per Housing Units	1.79	42.21	40.43	2261.24
Estimated Airbnb Guests*	788.44	18897.36	18108.92	2296.80
Estimated Hotels Guests**	91214.94	120903.90	29688.96	32.55
House Prices	2993.37	4115.55	1122.18	37.49
Number of Restaurants	157.64	187.31	29.67	18.82
Number of Groceries	21.86	30.39	8.53	39.03
Distinct Cuisines Types	8.37	15.72	7.35	87.78
Total Employees	16449.20	17670.63	1221.43	7.43
Hospitality Employees	1119.13	1377.56	258.44	23.09
Employees Aged between 20-24	633.20	993.61	360.41	56.92
High-pay Employees	2483.89	2874.17	390.28	15.71
% with University degree or Higher	36.07	42.84	6.77	18.77
% Aged Between 20 and 39	29.38	27.21	-2.17	-7.39
% from non-OECD country	9.76	8.54	-1.23	-12.56
Population	23099.47	22911.72	-187.75	-0.81
Moved Out***	2616.75	2241.531	-375.22	-14.34
Moved In***	2862.141	2851.875	-10.27	-0.36

Panel B: Low Airbnb Density Neighborhoods

	2013	2018	Absolute Change	Percent Change
Airbnb Listings	1.30	31.61	30.31	2337.35
Airbnb Reviews	5.41	353.66	348.25	6441.62
Airbnb Listings per 100 Housing Units	0.01	0.27	0.26	2286.16
Airbnb Reviews per 100 per Housing Units	0.05	2.99	2.95	6304.23
Estimated Airbnb Guests*	21.64	1414.64	1393	6437.15
Estimated Hotels Guests**	26298.84	30864.14	4565.30	17.36
House Prices	2236.67	2739.60	502.93	22.49
Number of Restaurants	87.97	109.44	21.47	24.40
Number of Groceries	15.13	20.02	4.89	32.33
Distinct Cuisines Types	2.96	6.57	3.61	122.01
Total Employees	7300.44	8717.44	1417.00	19.41
Hospitality Employees	404.77	465.08	60.31	14.90
Employees Aged between 20-24	308.83	406.33	97.50	31.57
High-pay Employees	1001.19	1351.94	350.75	35.03
% with University degree or Higher	26.65	31.38	4.73	17.76
% Aged Between 20 and 39	26.96	23.81	-3.15	-11.68
% from non-OECD countries	8.16	7.43	-0.74	-9.02
Population	27144.80	27429.27	284.47	1.05
Moved Out***	2605.87	2293.16	-312.71	-12.00
Moved In***	2771.70	2908.65	136.95	4.94

Notes: * Estimated Airbnb guests computed using a 60% review rate and 2.4 guests per booking. **Estimated hotels guests computed by multiplying the share of Madrid hotels located in neighborhood i by the total hotel guests in Madrid. ***Mobility related variables (Move Out and Move in) are for 2017, last year for which data is available.

each 100 housing units. These variables are shown because they are the main measures of Airbnb activity used throughout the paper to measure Airbnb density levels in distinct neighborhoods. In terms of levels it is interesting to note that even for the high Airbnb group in 2018, only 2.33% of the housing stock was being listed on Airbnb as tourist accommodation. Given that the housing stock moves very slowly and does not vary much in a 5 years period it is not surprising that the percentage increase displayed in Table 1 is very similar for Airbnb listings or reviews shown directly and for the case where these measures expressed in relation to the housing stock.

Lastly, Table 1 also shows estimated numbers of tourists staying in Airbnb apartments and hotels for the average neighborhood in each one of the two groups. The computation of estimated Airbnb guests uses the Airbnb 2016 Economic Activity Report for the Community of Madrid.[23] This report contains the total number of guests that stayed in an Airbnb unit in Madrid in the year of 2016 and also states that the average booking was made for 2.4 guests. With these two pieces of information and my observed number of reviews I can back out the average fraction of bookings that results in a review (not all guests leave a review). This calculation suggests that approximately 60% of the reservations resulted in a review. I use this review rate, the Airbnb informed 2.4 guests per booking, and the observed number of reviews to compute the estimated number of Airbnb guests in each neighborhood-year pair.

Regarding hotels, unfortunately there is no readily available information on the yearly incoming tourists staying in hotels at the neighborhood level. However I do observe yearly data on the hotel count for each neighborhood as well as the annual number of tourists staying in hotels in the entire city. Thus, I can compute yearly measures of the fraction of Madrid hotels located in each neighborhood and multiply it by the citywide number of incoming hotel guests to obtain an estimate of the neighborhood-year level number of hotel guests.[24] In spite of all the pitfalls of this measure, it is still useful to show that areas that are popular with Airbnb tend to be the same areas that concentrate more hotel tourists. Regarding the time variation, hotels guests are increasing over the sample period for both groups, indicating an overall surge in Madrid a tourist destination. Although the percentage increase in hotel guests is much more modest than the observed growth in Airbnb guests I would be hesitant to state whether this suggests that travellers are substituting from hotels to Airbnb as a short-term accommodation provider. As already mentioned, Airbnb starts out from very low baseline levels, which makes it hard to compare its percentage growth to other variables that already had a high baseline value in 2013 (it is physically impossible for hotels increase more than 2000% from 2013 to 2018). In reality, the incredible growth in Airbnb guests is probably a combination of new tourists that would not have travelled otherwise (e.g. by increasing the supply of accommodation for visitors in periods of peak demand when hotels are capacity constrained (Farronato and Fradkin 2018) Airbnb may "create" new travellers) with some degree of stealing of visitors that would have otherwise still travelled but stayed in hotels. Interestingly, hotel growth seems to be more spatially concentrated than Airbnb, since the areas that had a greater initial level of hotel guests presented, differently than for the case of Airbnb, higher increases both in absolute and in percentage terms.

3.1.2 Core Neighborhood Characteristics

In terms of neighborhood attributes Table 1 first displays average house prices. Not surprisingly, high Airbnb density areas are more expensive to live in. But not only that, the average neighbor-

[23] https://asiri.es/wp-content/uploads/2018/11/Spain-Madrid_ActivityReport-Airbnb.pdf

[24] This is the only measure of hotel guests at the neighborhood-year level I have so far. It is certainly a very rough approximation to the true number of hotel guests. To improve upon this measure I am scrapping data on guest reviews from hotel aggregator websites such as Tripadvisor. Future versions of the paper will include more accurate measures of yearly number of hotel guests in each neighborhood.

hood in the above median group also experienced stronger house price appreciation. Even starting from larger baseline house prices (absolute prices were 34% higher in the high Airbnb group in 2013), house prices grew by around 37% in the areas where Airbnb was more popular, whereas the price increase in the other group was around 22%.

Next, Table 1 shows data on two representative consumption amenities, restaurants and groceries.[25] I choose these types of consumption amenities because there is evidence that restaurants and groceries make up the largest share in consumer expenditure and are an important factor in explaining residents' utility and location decisions (Couture and Handbury 2017; Couture 2016). Maybe somewhat surprisingly, on average, the relative increase in the number of restaurant establishments is larger for neighborhoods in the low Airbnb group (24% versus 19%). This may have to do with the fact that high Airbnb density areas in 2013 had 80% more restaurants than low Airbnb neighborhoods. Since there are physical and legal (licensing and permits) limits to the amount of new restaurants that can be opened in a given neighborhood over the relatively short period of time of five years, this could help explain why the percentage increase was a bit lower for the group that already had a large number of open restaurants in 2013.[26] With respect to food stores the percentage increase was substantial in both groups, which makes sense given that the period from 2013 to 2018 is characterized by a marked economic recovery in Spain.

Still related to consumption amenities, I also include a measure of the diversity of the restaurant offer, I show the number of distinct cuisine types offered. For each restaurant listed on Tripadvisor I observe the main cuisine type it offers and I then aggregate the total number of distinct cuisines at the neighborhood level.[27] As one would expect, Airbnb popular neighborhoods also offer a wider range of cuisine types, with the average neighborhood in the high Airbnb group featuring almost 16 distinct types of cuisines, more than the double of the number present in the average low Airbnb neighborhood. The increase in this variable is two times larger in high Airbnb neighborhoods if one considers absolute changes, but relative growth is stronger in the the neighborhoods where Airbnb is less popular due to the very low diversity of cuisines these neighborhoods offered in 2013.

Following the variables related to consumption amenities are four dimensions of the jobs available in the average neighborhood of each Airbnb intensity group. Airbnb dense areas employ more people but went through lower job growth, both in terms of absolute and relative changes. However, if one classifies jobs by industry and considers only jobs in hospitality (accommodation and food service), high Airbnb neighborhoods, in spite of having almost three times the average hospitality employment of low Airbnb areas in 2013 (uneven baseline levels), still experienced a significantly higher percentage increase in hospitality jobs (23% versus 15%). Yet another way to segment total employment is by age. And when one looks at jobs held by people aged between 20-24 the pattern looks roughly similar to what happens to hospitality employment. That is, Airbnb popular areas had in 2013 higher number of jobs held by this age group (around the double of the average observed in low Airbnb neighborhoods), and yet growth for these areas was significantly larger even in percentage terms. Interestingly the ratios between percentage increases in high versus low Airbnb neighborhoods is very similar (around 1.6) for hospitality employment and for ages 20 to 24 employment categories. This may be due to the fact that many young adults first entering the labor force in Madrid actually find employment in the hospitality industry (waiters in restaurant or bars would a clear example).

[25] Restaurants include all eating and drinking places while groceries include all types of foo stores.

[26] Additionally, only looking at the stock of open restaurants in two points in time may miss the turn-over aspect of the possible changes occurring. That is, even if the high Airbnb neighborhoods did not experience a larger relative increase in the stock of open restaurants, it is possible that this areas are going through faster turn-over rates (opening and closing of restaurants). I do not explicitly test this hypothesis here, leaving it for future research.

[27] Every restaurant listed on Tripadvisor lists its main cuisine type, for example Mexican, Chinese, Mediterranean, etc.

The final variable related to employment refers to high-paying jobs. I define high-paying jobs based on the professional categories defined in the Spanish social security system. Essentially, for each professional category there is a minimum and maximum gross remuneration set by law, which in turn defines the amounts that each category should contribute with social security. There are seven professional categories and they are mostly based on the tasks performed by employees. Given the low variation in wage range across the seven categories (there are effectively only three distinct minimum pays) I define as high-paying jobs only those in the top category, which have a minimum pay significantly higher than other categories (21% higher than the middle category and 40% larger than the lower categories). We see that high paying jobs have come to represent a higher fraction of the overall number of jobs (they have experienced a larger percentage increase than the variable total jobs), but this pattern does not seem different across the two neighborhood types.

3.1.3 Demographics and Mobility

And finally, Table 1 displays data on three basic demographic indicators as well as population and total mobility. In terms of demographic indicators, high Airbnb areas are more college educated, and have slightly larger shares of young adults (between 20 and 39 years old) and residents born in non-OECD countries.[28]

With respect to education attainment, regardless of having a 10 percentage points higher baseline level of education attainment, neighborhoods in the high Airbnb group experienced a slightly larger relative change. This may be connected to increasing house prices and the heterogeneous ability to afford high housing costs across education levels (education tends to be very correlated with income). Regarding young adults, it is not surprising that all neighborhoods show decreasing trends, given that population aging is affecting the entire city. What is more novel is that in the group of neighborhoods where Airbnb thrived more the reduction in the fraction of the residents who are between 20 and 39 years old was substantially smaller. This may have to do with many factors, for example the higher willingness of young people to use Airbnb as a source of extra income or with an increasing preference of young adults for the sort of consumption amenities that are more prevalent in central neighborhoods (which are the same neighborhoods that concentrate more Airbnb listings). When it comes to the percentage of residents born in non-OECD countries, although there is a decreasing trend for all neighborhoods, the high Airbnb group seems to have experienced a somewhat stronger decline. Again, this may have to do with several factors, particularly with the increasing house prices, for which poorer immigrants are likely to be very sensitive to.

In terms of population there is a slight decline in Airbnb dense areas, whereas low Airbnb neighborhoods displayed an modest population growth. A closer look at mobility patterns revels that this difference in population changes is due to the differences in in-migrants. Although the average neighborhood in the group with low Airbnb density experienced a 5% increase in the number of in-migrants, for the high Airbnb group the total number of incoming residents reduced over the studied period. Interestingly, the number of out-migrants was substantially reduced in all neighborhoods, which is related to the economic recovery already mentioned previously. In fact, out-migration reduced even more for high Airbnb density neighborhoods, which suggest that the potential effects Airbnb may have in terms of substituting residential housing for tourist

[28] The gentrification literature in the U.S. has usually studied whether the share of blacks in gentrifying neighborhoods reduces (whites substituting blacks). In my context, since I do not observe neighborhood level ethnicity, I use place of origin as a proxy. The share of residents born in non-OECD countries proxies for disadvantaged immigrants which could be correlated with other measures of neighborhood vulnerability.

accommodation are more impactful in reducing the amount of in-migrants rather than directly pushing residents out. However, mobility numbers presented here are aggregates and represent all movers, which may mask substantial heterogeneity in the demographic types. For example, it is possible that out-migration is relatively similar for all neighborhoods, but out-migration of low education renters is higher in Airbnb dense areas (Brummet and Reed (2017) show that for the U.S. the effects of gentrification on out-migration is stronger for low education renters).

It is important to highlight that the numbers presented in Table 1 are only group averages and there are other aspects that differ between these two groups of neighborhoods that can also be driving the differential change patterns in the variables shown. Attempts to determine the causal effect of Airbnb on each of these neighborhood attributes are discussed in the Section 4.

3.2 Spatial Patterns in Airbnb, Neighborhood Attributes, and Mobility

In order to provide further insight into the main facts of the data, I plot maps that summarize the spatial and time variation in the main variables that will be used throughout the paper. The objective is to convey a big picture perspective of the recent changes in Airbnb activity, core neighborhoods attributes that drive people's location decision, and mobility patterns across neighborhoods.

3.2.1 Airbnb Activity

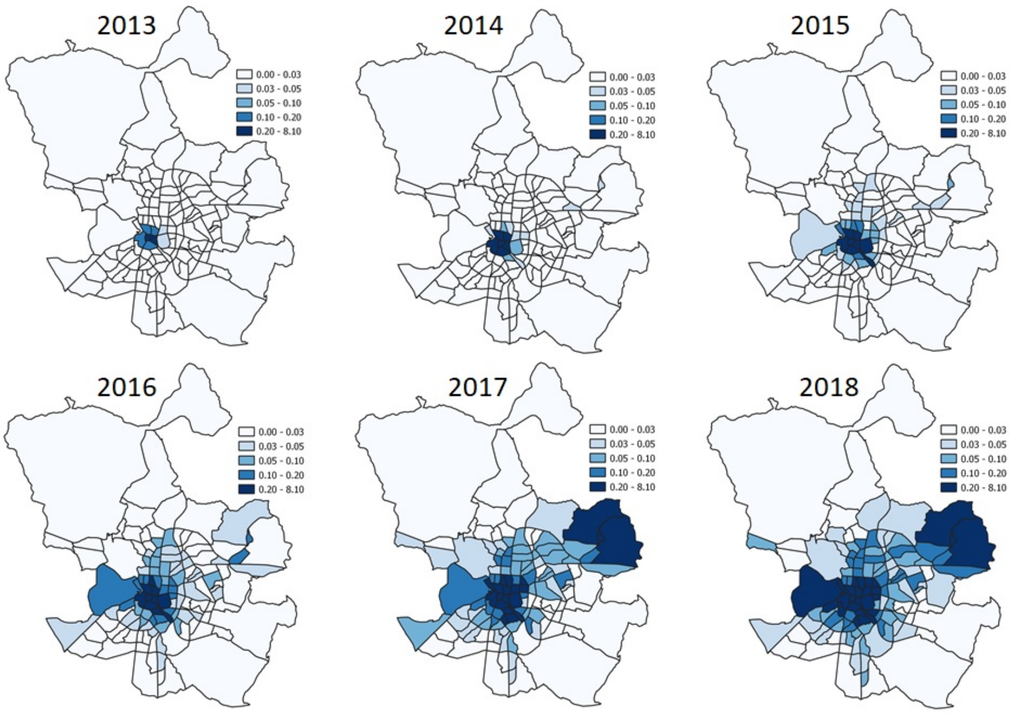
Figure 1 illustrates Airbnb activity growth from 2013 to 2018. Airbnb activity is expressed in terms of a density measure that normalizes neighborhoods according the number of households that reside in it. More specifically, the Airbnb measure used in Figure 1 is the number of reviews written guests divided by the total number of households in the neighborhood. From Figure 1, we see that Airbnb activity in Madrid went through a substantial increase over recent years. While in 2013 practically only the six neighborhoods in the "Centro" were hosting Airbnb guests, in 2018 the vast majority of neighborhoods received Airbnb guests. However, even in 2018, after Airbnb had already expanded to most neighborhoods in Madrid, the concentration of activity in central neighborhoods was still very strong. This can be appreciated by looking at the scale of the legend of the map for the year 2018. In this map, neighborhoods were divided in quintiles of equal count (number of neighborhoods), and the fact that the top quintile values of Airbnb activity range for from 0.2 to 8.1 gives a sense of the heterogeneity even within the neighborhoods that are most popular with Airbnb.

3.2.2 Core Neighborhood Characteristics

Next, in Figure 2 I plot maps with the percentage change between 2013 and 2018 in four variables that are representative of the core neighborhood attributes, house prices, total jobs, number of restaurants, and number of establishments that offer personal services (hair dresser, beauty saloon, tattoo shop, pet care, yoga center). With respect to housing, prices grew everywhere but the stronger percentage increases were in the more central neighborhoods. The map suggests a positive correlation between areas where Airbnb activity increased the most (shown in Figure 1) and areas where the percentage increases in house prices was larger.

In terms of the total number of employees that work in a neighborhood, we see a different pattern. More central neighborhoods, where Airbnb activity is relatively stronger, tended to have only moderate increases in jobs or even a decline in total employment. For example, the neighborhood of Cortes, with the second highest Airbnb density in Madrid, presented negative job growth. Conversely, some neighborhoods that are far from the city center (both to the north,

Figure 1: Airbnb Guest Reviews per Household



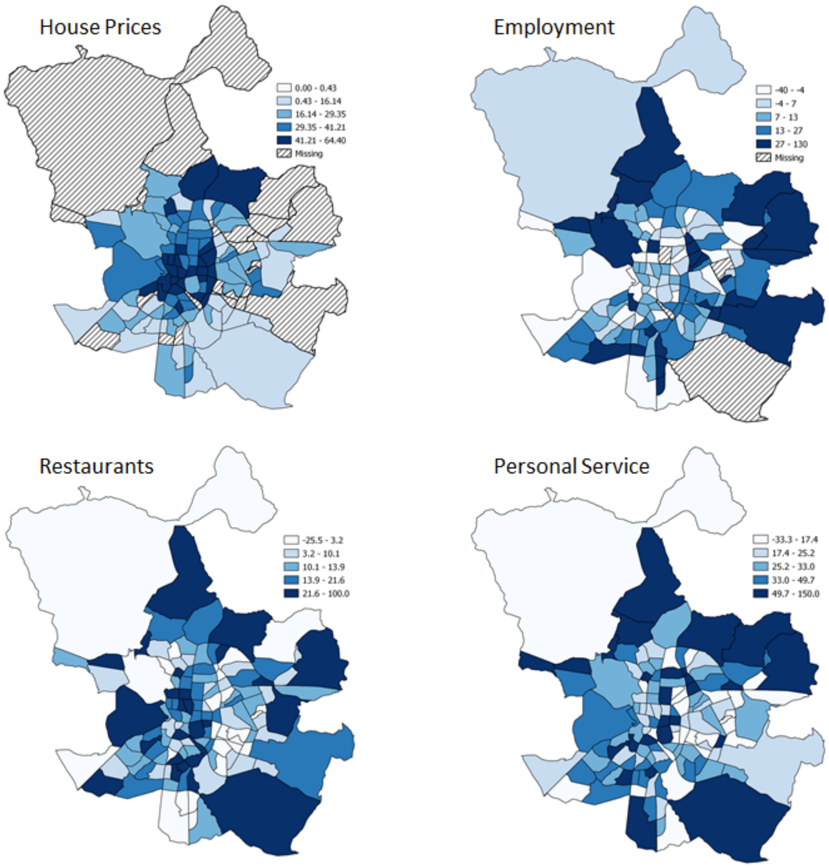
Notes: The legend refers to the number Airbnb guest reviews written for Airbnb listing located in a given neighborhood divided by the total number of households that live in that neighborhood. For example: the maximum value observed in 2018 is 8.1 for the neighborhood Sol, which means that in Sol, on average, there were 810 reviews for each 100 resident households.

east, south) and concentrate a pretty low level of Airbnb density went through the highest percentage increases in employment observed. Lastly, when it comes to consumption amenities, it harder to make any affirmative claims about correlations by looking at the maps only. There are neighborhoods with strong percentage increases in the number of restaurants or establishment offering personal services both in Airbnb dense areas and in neighborhoods where Airbnb is not popular. Regarding restaurants specifically, since Airbnb popular areas already had a very large baseline number of restaurants in 2013 (from Table 1) and still, some of these centrally located neighborhoods (Malasaña, Embajadores, Atocha, and neighborhoods in the district of Chamberí and Salamanca) are among the ones with the highest percentage growth in restaurants indicates of their particularly strong increase in restaurant activity.

3.2.3 Neighborhood Demographics

With respect to basic demographic indicators, I plot in Figure 3 the change in the share of residents with college degree or more, the share of residents aged between 20-39, and the share of residents born in a non-OECD country (in these maps changes are expressed in percentage points). The choice of these three basic demographic indicators follows the literature on gentrification that usually defines gentrifying neighborhoods as having higher (relative to other neighborhoods) increases the share of college educated, young adults, and white residents. Since I have no direct information on ethnicity, I use share of residents born in a non-OECD country as proxy for economically disadvantaged or otherwise more vulnerable residents (counterpart of share of black residents in the U.S. context of gentrification studies). The share of college educated residents is increasing everywhere, but it seems that it is growing even more in the areas where Airbnb also tends to be popular.

Figure 2: Percentage Change in Core Neighborhood Attributes (2013 - 2018)

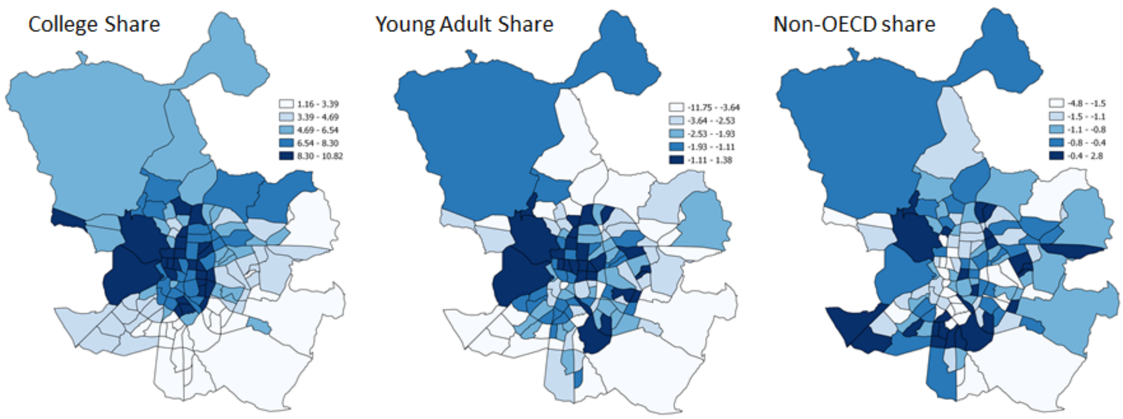


Notes: The legends refers to the percentage change in the relevant neighborhood characteristic from 2013 to 2018. For example, this highest number in the legend for establishments offering personal services is 150, which indicates that in one neighborhood the number of personal service establishments grew by 150% between 2013 and 2018.

Regarding the share of young adults, the spatial correlation is not as stark but there also seems to be the case that Airbnb dense areas are more attractive to young adults, which are declining in almost all neighborhoods (population aging) but at a lower rate in some central neighborhoods or even increasing, in particular in the districts of Chamberí and Salamanca. Finally, in terms of non-OECD born residents, the third maps of Figure 3 indicates a negative correlation between Airbnb growth and non-OECD share. In particular, neighborhoods that are in the *Centro* district, such as Embajadores, Sol, and Malasaña (officially called Universidad) all had remarkably large Airbnb density increases and a declining share of non-OECD residents.

The patterns for education levels and non-OECD residents are probably related in terms of the underlying reason driving the changes, income levels. If Airbnb dense areas are experiencing high house price increases, and both low education levels and being born in a non-OECD country are correlated with low income levels, it is expected that Airbnb popular neighborhoods will have rising levels of college educated residents and a declining share of non-OECD residents. The mixed pattern for the share of young adults may also hinge upon incomes, because even though young people may have a higher preference for amenities that are relatively more present in centrally located neighborhoods (Couture and Handbury 2017; Su 2018; Diamond 2016), if these neighborhoods are the same ones where housing price appreciation is strongest and young adults have lower incomes, then these two opposite effects may lead to the are mixed patters we see in the second map of Figure 3, with young people increasingly locating close to the city center, but not quite in the *Centro* district (the story of young adults having lower incomes may be particularly important in the context of Spain, where young adults unemployment or only part-time employment is a common reality that has persisted over the recent years).

Figure 3: Perc. Point Change in Basic Neighborhood Demographics (2013 - 2018)



Notes: The legends refers to the change in terms of percentage points in the relevant neighborhood demographic characteristic from 2013 to 2018. For example, this highest number in the legend for the share of residents with college education or higher is 10.82, which indicates that in one neighborhood the percentage of the resident population that have a university degree or more grew by 10.82 percentage points.

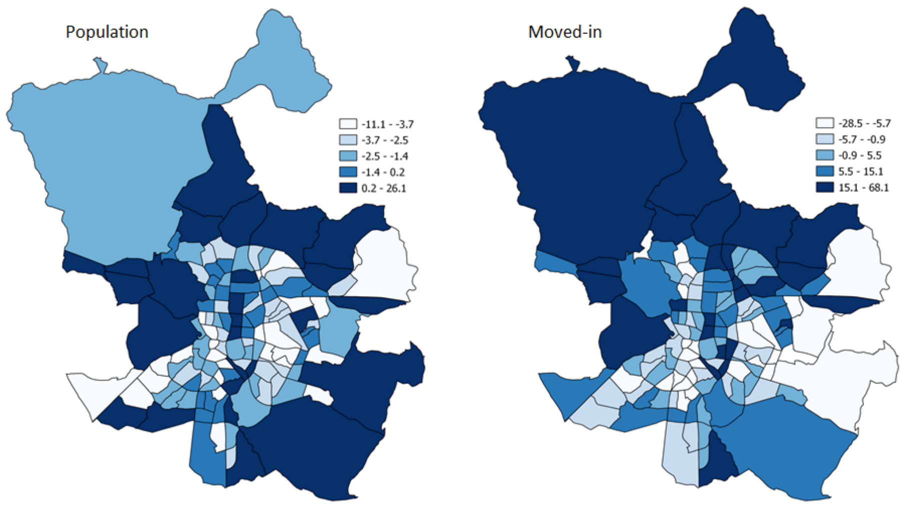
3.2.4 Population Size and Mobility

In Figure 4 I just provide further evidence of what was already discussed in Section 3.1.3 and displayed in the bottom part of Table 1. That is, that there seems to be a negative correlation between Airbnb and population growth and that this negative association seems to be driven by reducing the arrival of would be new residents. This association does not hold in all areas, neighborhoods in the district of *Salamanca* for example are above the median level of Airbnb density but still presented relatively high population growth. But the above mentioned negative relationship is specially salient in the neighborhoods of the *Centro* district. There, where Airbnb activity is the strongest (and likely constituted of more permanent rather then occasional listings), the left map in Figure 4 reveals that all neighborhoods lost population between 2013 and 2018. Moreover, Sol, Embajadores and Malasaña ranked in the bottom quintile, among the neighborhoods with the strongest population declines.

With respect the second map in Figure 4, we see that indeed population changes can be explained by in-coming residents, which increased substantially in neighborhoods in the north of Madrid while declined substantially in the Centro district. Once more, the district of Salamanca does not follow this pattern, since it has relatively high Airbnb activity (low comparing to Centro but high taking into account the low number in other areas of the city) while is also experiencing increasing levels in in-movers. This, as will be further discussed later, may indicate that Airbnb apartment in areas like Salamanca are probably not being originated from housing space that would have been otherwise occupied by residents, whereas in the Centro district, a fraction of Airbnb listings comes from dwellings that would have been used as housing for permanent residents.

In Section 5, I try to connect all the points summarized so far by investigating if and the extent to which the variation in demographic composition shown in Figure 3 is being shaped by changes in mobility patterns of residents of different demographic groups, which in turn are driven by changes in the core neighborhood characteristics presented earlier. But before that and in order to argue that Airbnb activity may ultimately have some effect on neighborhood demographic composition, I show reduced-form evidence of Airbnb's impact on each one the core neighborhood attributes.

Figure 4: Percentage Change in Population and Number of In-Migrants (2013-2018)



Notes: The legends refers to the percentage change in the population or total number of residents that moved-in the year of 2018 (2017 for moved-in as previously explained) in comparison to 2013. For example, this highest number in the legend for residents the moved-in is 68.1, which indicates that in one neighborhood of Madrid, the number of people who moved in during the year of 2017 was 68.1% higher in 2017 than the number of in-migrants in 2013.

4 Effects of Airbnb on Neighborhood Characteristics

4.1 House Prices

In order to build a step by step understanding of the relationship between Airbnb activity and housing prices, this section is divided into five subsections. First, I discuss the conceptual framework that naturally links Airbnb activity and the potential increase in house prices. Second, I include a basic description of the data on the overall evolution of Airbnb listings and house prices in Madrid. The third part discusses the basics of the estimation methodology and includes the baseline results. Next, estimation results are extended through the application of five alternative instruments in an attempt to mitigate endogeneity concerns. And finally, I include back of the envelope calculations to give a sense of the economic relevance of the effect of Airbnb on housing prices in Madrid.

4.1.1 Conceptual Framework

Conceptually, the link between Airbnb activity and house prices is straightforward. There are two main channels through which the emergence of Airbnb may impact housing costs. First, there is the direct channel that comes from (some) housing space being reallocated from the long-term housing market (permanent residences) to the short-term housing market (accommodation for visitors). This applies not only for entire houses being permanently advertised on the home sharing platform but also to rooms in shared apartments where, in the absence of Airbnb, the room would have been offered to a resident looking for a shared flat.[29] In practice, this amounts to a reduction in

[29]Since the financial crisis of 2008, living in a shared flat is becoming ever more common among Spanish adults. For media coverage of this situation, see for example this article published in *El País* https://elpais.com/economia/2016/02/17/vivienda/1455708137_795324.html.

the existing supply of residential housing space available to local residents, which would lead to an increase in house prices. Certainly, this framework does not apply to all Airbnb listings, since many of them may be housing units that would not be part of the effective supply of residential floor space even in the absence of Airbnb (e.g. a home owner that occasionally rents a spare room in his house to tourists but is not willing to rent it to a permanent resident). But to the extent that at least some Airbnb listings come at the expense of residential housing supply, this direct reallocation effect is likely to play a role in increasing local house prices.

Second, there is an indirect effect that comes from the fact the people living in a house can obtain extra income from renting spare space, be it a room that is permanently empty or renting out the entire home while residents are away (e.g. vacation period). In equilibrium, house prices should reflect what people are willing to pay to buy a house, which will equal the present value of long-term rents plus this new option value of renting in the short-term market (Barron, Kung, and Proserpio 2018). In other words, the possibility of making extra money by occasionally renting out spare space to tourists will be capitalized into house prices. Thus, even if the entire pool of Airbnb listings were comprised of people that occasionally share spare rooms as opposed to apartments permanently removed from the residential market, we should still expect some effect of the expansion of home-sharing on house prices.[30]

I should make clear that I am only talking about house prices and not about residents' welfare. Any claims about effects on overall residents' welfare will have to deal with more nuanced aspects of the problem such as the existing home ownership structure in the city (the increase in house prices will be beneficial to home owners, whereas renters will be hurt) and people's heterogeneous preferences (e.g. young people may be willing to sporadically rent out their homes to tourists to offset their higher housing expenses, whereas older residents may have a higher utility cost of doing so, and therefore will effectively bear a relatively larger share of the "costs" implied by higher house prices).

4.1.2 Descriptive Evidence

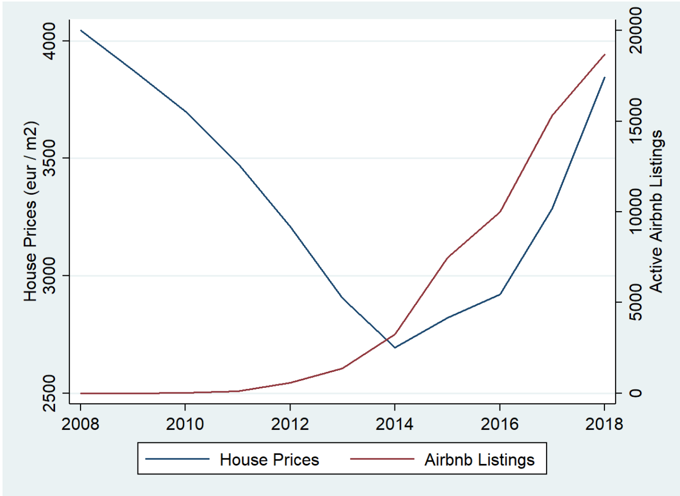
The recent increase in Airbnb listings across Madrid has coincided in time with a remarkable escalation in housing prices. Figure 5 plots the evolution of the average house prices across all *Idealista* listings of houses for sale posted in Madrid in a given year together with the number active Airbnb listing in the entire city. It includes the yearly evolution of these two variables since 2008, the year in which Airbnb was first launched.[31]

House prices (in euros per square meter) are represented in left y-axis, whereas Airbnb listings are pictured in the right y-axis. Figure 5 highlights two important aspects related to the task of empirically determining whether (and the extent to which) Airbnb activity impacts local house prices. The first one is that house prices start to increase around the same time when Airbnb activity in the city begins its striking growth path, which by 2018 seems to be still unfinished. This may indicate at first sight that one should certainly find a positive impact of Airbnb on house prices. However, the second aspect apparent in the picture is that the price increase that starts around 2014 is probably part of a more general housing market cycle, in which prices peaked around 2006 and 2007 and then went through substantial declines that persisted up to 2014. Thus, the main challenge in identifying Airbnb's effect on house prices is to separate what portion of the post 2014 surge in house prices variation was caused by the expansion of home-sharing from the

[30] In the extreme case where only the indirect effect (option value of renting spare) exists and no reallocation of housing takes place, from the perspective of a new buyer, increases in house prices should be offset by the extra income she could potentially make by renting spare space on Airbnb.

[31] Although Airbnb was launched in 2008, the first guest review I observe in Madrid is actually in 2010.

Figure 5: Evolution of Average House Prices and Total Airbnb Listings in Madrid

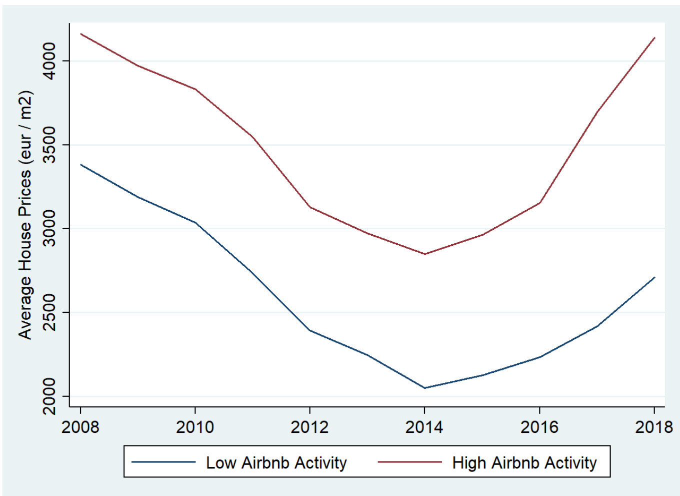


Notes: Airbnb active listings are listings that received at one guest review during the year. The house price variable is explained in detail in Section 2.2.

house price fluctuations that would have happened even in the absence of vacation apartments, just as a natural result of the economic downturn and the subsequent recovery.

In order to identify whether Airbnb had any causal impact on house prices I will use spatial variation in the increase in Airbnb listings as well as in the rates of increase in house prices. The idea is that neighborhoods where home-sharing flourished more relative to others should experience stronger price increases in the long-term housing market if Airbnb had any causal impact on residential house prices. To visually illustrate this idea, in Figure 6, I compute the growth in Airbnb activity (measured as the number of active Airbnb listings as percentage of the residential housing units) for all neighborhoods in the sample, divide them in above and below median Airbnb activity and plot the evolution of house prices for the average neighborhood in each group. The picture shows anecdotal evidence that after parallel pre-trends between 2008 and 2013 roughly, neighborhoods with high Airbnb density start to experience first slower decreases in prices and then, from 2014 on, faster increases in house prices.

Figure 6: Evolution of Average House Prices in Low and High Airbnb Activity Neighborhoods



Notes: Airbnb active listings are listings that received at one guest review during the year. The house price variable is explained in detail in Section 2.2.

4.1.3 Baseline Estimates

I use spatial and time variation in the expansion of Airbnb activity to identify its effect on local house prices. The spatial units of analysis are the 128 neighborhoods of Madrid and the time dimension is the year. More specifically, the baseline model I estimate is the following:

$$Ln(HousePrices)_{it} = \alpha + \beta AirbnbDensity_{it} + \gamma X_{it} + \eta_i + \delta_t(1 + \mathbb{1}\{M30\}_i) + \epsilon_{it} \quad (1)$$

The coefficient of interest is β, which captures the effect of an additional unit of Airbnb activity on neighborhood level log house prices. The variable $AirbnbDensity_{it}$ is constructed in a way that should reflect the heterogeneity in the intensity of Airbnb activity across time and space. My main measure of Airbnb activity at the neighborhood-year level is the number of active Airbnb listings in neighborhood i year t divided by total number of dwellings 2011 and multiplied by 100 to represent percentages (listings are considered active if they have at least one guest review during the year). In other words, my measure of Airbnb activity is the percentage of housing units in a neighborhood that hosted at least one Airbnb guest during the year.

There are a few important clarification points about this measure. First, I only consider listings that had at least one review in the year because data scrapped from Airbnb's website contain many "dead" listings. That is, listings that were posted at some point in the past, are not actually being used as tourist apartments anymore, but the owners never removed them from the website. Using guest reviews to proxy for a listing's activity provide a more up-to-date picture of which dwellings are actually receiving guests at a given point in time. Second, I divide active listings by the number of dwellings in a neighborhood to correct for the fact that neighborhood size is not homogeneous. For example, the exact same number of Airbnb listings will put more pressure on house prices in a small neighborhood than in a large one. Third, ideally I would use a time-varying measure of total dwellings, that is, the exact number of dwellings in neighborhood i year t. This kind of measure is provided by the Madrid Tax Agency (*Agencia Tributaria de Madrid*) using data from the Urban Land Registry (*Catastro Inmobiliario Urbano*), but unfortunately only includes the period from 2013 to 2017. Since my panel of Airbnb activity goes from 2010 to 2018, to use time-varying measure of dwellings, I would have to impute values for the remaining years. Taking into account that the total housing stock of a neighborhood does not experience substantial variation in short periods of time[32] and to avoid having to impute values I choose to, instead of using data from the Urban Land Registry, use the 2011 number of dwellings provided by the Housing Census[33]. Lastly, since the Airbnb measure is in essence the proportion of houses in a neighborhood that were used as vacation apartments it naturally connects to the idea of density. Thus, in what remains of Section 4.1 I indistinctly refer to Airbnb activity or Airbnb density as the same object.

The outcome variable $Ln(HousePrices)_{it}$ is the natural logarithm of the average price among all *Idealista* listings of houses for sale in neighborhood i in year t.[34] The baseline model also includes η_i, which is neighborhood fixed-effect that captures neighborhood-specific time-invariant characteristics affecting local house prices (e.g. a neighborhood's distance to the city centre), δ_t, which is a time-effect capturing time-varying shocks that affect all neighborhood equally (e.g. homogeneous component of overall economic activity cycles), as well as $\mathbb{1}\{M30\}_i$, which is a dummy variable that equals one if neighborhood i is located inside the the M-30 road, an orbital

[32] The Urban Land Registry data shows that total housing stock grew at 0.37% per year in the average neighborhood

[33] https://www.ine.es/en/censos2011_datos/cen11_datos_resultados_en.htm

[34] Section 2.2 explains in detail what exactly the house price variable is and how it is obtained.

highway that circles around the most central districts of Madrid.[35] This is done to account for the fact that neighborhoods that are closer to the center of the city may have differential trends in house prices. Lastly, Equation 1 also includes neighborhood-specific time-varying covariates that could also influence local house prices. Specifically, X_{it} contains the log of population, percentage of residents with college education of higher, the percentage of residents that are employed, percentage of residents aged between 20 and 39, percentage of residents from non-OECD. This last variable is included to account for the fact that neighborhoods with increasing presence of poorer immigrants may experience a reduction in house prices (Accetturo et al. 2014).

Table 2 shows the estimation results for the baseline model defined in Equation 1. Although the first Airbnb guest review observed is in 2010, I estimate Equation 1 using data between 2012 and 2018. That is because in the next section I will instrument for Airbnb density using characteristics of the housing structure in 2011, so I establish 2011 as the baseline year pre-estimation period.[36] Results are very similar when Equation 1 is estimated using the entire period since the first Airbnb review (2010 - 2018) and are not included for keeping the presentation concise.

Table 2: The Effect of Airbnb on House Prices: Baseline

	(1)	(2)	(3)	(4)
Airbnb Density	0.072***	0.028***	0.019***	0.010***
	(0.018)	(0.006)	(0.005)	(0.002)
Ln Population		0.024	0.006	0.143
		(0.027)	(0.021)	(0.182)
Perc. College		0.021***	0.018***	0.023***
		(0.001)	(0.001)	(0.003)
Perc. Aged 20-39		0.008**	0.004	-0.001
		(0.003)	(0.003)	(0.003)
Perc. non-OECD		0.004	-0.003	-0.001
		(0.003)	(0.003)	(0.005)
Perc. Employed		0.010***	0.001	0.001
		(0.002)	(0.002)	(0.001)
Year FE	No	No	Yes	Yes
M-30 Trends	No	No	Yes	Yes
Neighborhood FE	No	No	No	Yes
Observations	795	795	795	795

Dependent variable: Ln of house prices

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All specifications of Table 2 have the same outcome variable, log of house prices. In each specification I incrementally include covariates in addition to Airbnb density up to specification 4, which contains all the terms shown in Equation 1. The number of observations, 795, comes from the fact that although I potentially have 896 observations (128 neighborhoods times 7 years), for some years, small neighborhoods with a thin housing market have missing information regarding house prices.[37] Specification 1 is a simple pooled OLS model without any covariates or fixed effects. It

[35] The M-30 road circles the central districts of Madrid. It delineates what is known as the "Central Almond" (*Almendra Central*). Out of the 21 districts of the city, 7 are inside the M-30 road.

[36] To make estimates comparable across estimate in the OLS and IV estimation I estimate both models with data between 2012 and 2018. In any case, Airbnb activity was pretty low in 2010 and 2011 and most observations had zero Airbnb units in these two years (only 38 neighborhood-year pairs out 256 had non-zero Airbnb listings in these two years).

[37] 128 neighborhoods and 7 years gives me 896 observations, but in 101 neighborhood-year pairs *Idealista* leaves the house price variable as missing due to the low number of houses for sales on the website.

shows that Airbnb listings seem to locate in areas with high housing prices, with a one percentage point increase in Airbnb density being associated with approximately 7% higher housing prices. Obviously this does not imply any causality, and in fact the most reasonable interpretation is that some parts of the city are just nicer than others and this implies that they will command higher house prices and also attract tourists (and vacation apartments as a consequence). Specification 2 adds time-varying controls (the X_{it} previously discussed) and all the coefficients, except on the percentage of non-OECD residents, have the expected sign, with population, education level, share of young adults, and employment rate being positively associated with house prices (although population is not statically significant). Simply by adding these covariates, the association between Airbnb density and local house prices gets reduced by around 60%, which suggests that Airbnb density has a strong positive association with these basic demographic factors that positively correlate with house prices.

Next, specification 3 further adds the time-effects discussed previously, both the time-effects that affect all neighborhood equally and the time trend for the most central neighborhoods (inside M-30 road). Airbnb's association with house prices further get reduced by over 30% and the only other covariate that is still statistically significant in predicting house prices is the share of residents with college education or higher, which probably comes from the fact that education and income are usually strongly correlated.[38]

Finally, specification 4 adds the neighborhood fixed-effect (η_i) and the association of Airbnb density and house prices is further reduced to almost half of its previous value. Other covariates maintain a similar structure, with education levels being an important predictor of house prices. Since this model includes neighborhood fixed-effects, the estimation of a positive and statistically significant β indicates that changes in Airbnb density are positively correlated to changes in house prices. If one understands results of specification 4 as causal, it would mean that a one percentage point increase in Airbnb density leads to around 1% increase in house prices. However, it is still possible that results from specification 4 do not represent causal effects of Airbnb on house prices. It could be the case that time-varying neighborhood-specific unobserved factors are driving both house prices and Airbnb activity at the same time.

4.1.4 Instrumental Variables Estimates

To mitigate endogeneity concerns pointed out at the end of the last section, I present estimates of models similar to the one presented in Equation 1, but using alternative instruments to predict Airbnb density at the neighborhood-year level. More precisely, I estimate the following equation:

$$Ln(HousePrices)_{it} = \alpha + \beta_{IV} Airbnb\widehat{Density}_{it} + \gamma X_{it} + \eta_i + \delta_t(1 + \mathbb{1}\{M30\}_i) + \epsilon_{it} \quad (2)$$

$$AirbnbDensity_{it} = \theta + \beta_{1_{st}}(Instrument_{it}) + \gamma X_{it} + \eta_i + \delta_t(1 + \mathbb{1}\{M30\}_i) + \varepsilon_{it} \quad (3)$$

where Equation 2 is exactly the same as Equation 1 but only uses the variation in Airbnb density that is predicted by Equation 3. I use the general term *Instrument* because I will present estimates for five different instruments to show evidence that the effect of Airbnb on house prices seems to be robust to different choices of reasonable instruments. Below is a description of the five instruments used in alternative estimations of Equations 2 and 3:

[38] Unfortunately, there is no yearly data on neighborhood level income. The Urban Audit project does report neighborhood specific income data for Madrid, but it only include data for 2013, 2014, 2015, and 2016. I also estimate the same model imputing income data for the remaining years of 2012, 2017, and 2018 and results do not change.

- IV 1: This instrument is constructed by multiplying the number of establishments in the hospitality industry (bars, restaurants, hotels) in the year of 1998 by the Google Trends variable measuring the search interest for the search key "Airbnb" in each relevant year from 2012 to 2018. The intuition for these instrument is that neighborhoods with a higher number of establishments in hospitality tend to be locations that are more attractive to tourists, since they primarily use these kinds of services while visiting a city. I use the number of establishments in a year way before Airbnb existed to make sure I am not using Airbnb endogenously induced variation in hospitality establishments (1998 is the first year for which the number of hospitality establishments in each neighborhood is available). And by interacting this measure (that only varies spatially) with the search interest for the term "Airbnb" on Google (which only has time variation), I obtain a neighborhood-year specific variable. The assumption is that over time, as Airbnb becomes more well known among suppliers and consumers, landlords in areas that are more attractive to tourists are more likely to reallocate their housing units from long-term tenants to short-term guests relative to landlord in less touristic areas. This instrument was already used in the literature in the context of the United States (Barron, Kung, and Proserpio 2018) .

- IV 2: One may worry that the previous instrument only predicts well Airbnb activity because its time-component (Google search index for the term Airbnb) is strongly correlated to the Airbnb density measure and thus suffers the same endogeneity issues. To mitigate this concern, I build instrument 2, which is exactly the same as instrument 1, with the exception that I substitute the Google search index time-varying component of the instrument by the aggregate number of tourists arriving in Madrid in each year.

- IV 3: The two previous instruments were based from a more tourist demand point of view. They were based on the fact that areas with more establishments in the hospitality industry tend to be the areas of a city that receive relatively more tourists. For the next two instruments, I change the perspective to a more supply based framework. In essence, I use plausibly exogenous variation in the suitability of the physical characteristics of the housing stock across different neighborhoods. Taking into account the fact that the vast majority of Airbnb apartments tend to be small 1 or 2 bedroom apartments, I build instrument 3 from the share of the housing stock in neighborhood i in the pre-estimation year of 2011 (as reported by the Housing Census) that was constituted of houses having at most two rooms. In exact terms, Instrument 3 is obtained by computing the 2011 fraction of houses in each neighborhood that have 2 rooms or less and multiplying it by the same Google Trends search index measure already explained for Instrument 1.

- IV 4: For the same reasons already discussed for Instrument 2, I build Instrument 4 using the same cross-sectional variation of Instrument 3 (2011 share of small houses) but I multiply it by the total number of tourists arriving in Madrid each year of the estimation period.

- IV 5: Lastly, Instrument 5 combines information on three specific tourist attractions, their distances to different neighborhoods of the city, and their relative importance as a point of interest for tourists. In plain terms, the instrument is constructed by computing a weighted average of the inverse of the distance of each neighborhood's centroid to one of the three main tourist attractions in Madrid: the Prado National Museum, the Royal Palace, and the Real Madrid football stadium (Santiago Bernabéu).[39] This instrument is particularly appealing in

[39] The choice of these three tourist attractions is based on their popularity on Madrid's Tripadvisor page. They are the three most reviewed attractions in Madrid (excluding Retiro Park, which is highly reviewed by locals).

the context of Madrid, which has only a handful of quantitatively relevant tourist attractions when it comes to the number of visitors. For each neighborhood i year t, the instrument is a weighted average of the inverse of the distances between neighborhood i and each one of the before mentioned tourist attractions, where the weights are number of reviews received on Tripadvisor by each tourist attraction during year t (this is to proxy for the relative popularity of each attraction among tourists). The instrument's relevance hinges upon the idea that the closer a neighborhood i is from a tourist attraction and the higher the importance of that tourist attraction in terms of number of visitors in year t, the higher will be the Airbnb activity in that neighborhood and year. The exclusion restriction is that the increasing value of being close to tourist focused attractions only affects house prices through Airbnb (either by directly shifting some housing to Airbnb or by the enhancement of the option of making extra income with spare housing space). The exclusion restriction will fail if one believes that demand fundamentals for long-term housing from locals is changing over the relatively short period of 7 years. For example, if residents' preference for living closer to touristic attractions is rising over the sample period, then even β_{IV} would have an upward bias.

Table 3: The Effect of Airbnb on House Prices: Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Airbnb Density	0.010***	0.015***	0.014***	0.012***	0.012***	0.011***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Ln Population	0.143	0.200	0.190	0.163	0.164	0.151
	(0.182)	(0.176)	(0.178)	(0.182)	(0.186)	(0.183)
Perc. College	0.023***	0.023***	0.023***	0.023***	0.023***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Perc. Aged 20-39	-0.001	-0.000	-0.000	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Perc. non-OECD	-0.001	-0.000	-0.000	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Perc. Employed	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
M-30 Trends	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes	Yes
IV 1	No	Yes	No	No	No	No
IV 2	No	No	Yes	No	No	No
IV 3	No	No	No	Yes	No	No
IV 4	No	No	No	No	Yes	No
IV 5	No	No	No	No	No	Yes
Observations	795	795	795	795	795	795

Dependent variable: Ln of house prices

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 brings the results for estimations of Equation 2 using the five alternative instruments discussed above to predict Airbnb density as shown in Equation 3. Column 1 displays the results of a fixed-effects model that does not use any instrument for Airbnb density just for comparison with the IV estimates.[40] The first thing one notices is the stability of the results across all the different instruments used. Although the point estimates of all five IV regressions are above the point

[40]Column 1 of Table 3 displays results for the same model shown in Columns 4 of Table 2.

estimate of the fixed-effects model, considering the confidence intervals there is no statistically significant difference between these six estimates.

Columns 2 and 3 show the results for the two instruments based on the number of establishments in hospitality in each neighborhood in 1998, whereas columns 4 and 5 present results for the two instruments based on the share of small houses in each neighborhood in 2011. Looking at the difference between columns 2 and 3 (or 4 and 5), it becomes clear that it makes little difference if one uses the Google Trends index for the search term "Airbnb" or the city wide number of arriving tourists as the time-varying component of the instruments. This is reassuring because if in reality endogeneity is a big concern in the fixed-effects model and one worries about mechanical correlation of actual Airbnb growth and Google Search index growth (both having exponential growth over the sample period), changing the aggregate time series to the number tourists (which grows in a lower pace) should help mitigate this concern.

Next, looking at the difference between columns 2 and 4 (or 3 and 5) which use the same time-series component of the instrument but different cross-sectional variations in the suitability or profitability of maintaining an Airbnb tourist apartment, it also becomes clear that either using the density of hospitality establishment or small apartments provides very similar estimates. This is in spite of the fact that these two measures, although correlated, are clearly not the same.[41] My interpretation of these results is that Airbnb appears to have a causal impact on house prices. Moreover, the estimated impact in the fixed-effects model does not seem to be coming from an endogenous feature of areas attractive to tourists, since using Airbnb variation only coming from the physical structure of the housing stock also delivers very similar results (although the point estimates are slightly smaller).

Lastly, column 6 bring the results the Instrument 5, the weighted average of the inverse distance to three main tourist attraction as explained before. Once more, the main take away is that the estimated effect of Airbnb on house prices seems to be pretty stable. And there is no clear reason why the distance to tourist attractions should imply different increasing trends in prices in the long-term housing market via channels other than its impact on how likely it is that a housing unit will be used as vacation apartment through Airbnb.

Since the present context does not offer a natural experiment and Airbnb units are not randomly placed across neighborhoods, there is no certainty that results of Table 3 indicate a true causal impact of Airbnb on house prices. However, the robustness of the estimates to many different sources of variation that predict Airbnb activity for distinct reasons (pre-existing tourist amenities, housing physical structure, and time-variation in the relevance of being close to tourist attractions) suggests that it is likely that Airbnb does cause house prices to increase and that the actual magnitude of the effect should not be very different from the results reported in Table 3.

4.1.5 Economic Significance

To interpret the economic significance of the effect of Airbnb on house prices, we can compare what the estimates suggest in terms of price increase in relation to the actual observed house price growth. Out of the five instruments used in the last section, the median estimate coefficient is 0.012, which suggests that an additional 1 percentage point increase in Airbnb density (listings by 100 dwellings) leads to a 1.2% increase in local house prices.

One way to assess the economic relevance of such estimate is to look at averages. Over the sample period, 2012 to 2018, the average increase in Airbnb density (active listings per 100 housing units) was of 1.18 pp, which implies an 1.42% increase in house prices. The observed house price

[41] The correlation between share of small houses variable and proportion of hospitality establishments variable is of 50%.

growth over the same period was on average 20%. Thus, Airbnb explains approximately 7% of the actual house price increase, which points out two conclusions: *i*) Airbnb does impact house prices to some extent given that 7% of the observed growth is not negligible; *ii*) There are many other factors that contributed to the recent house price increases in Madrid and Airbnb alone does not seem to be the main driver behind the strong house price appreciation observed in the data.

One problem with looking at average economic impacts is that these averages do not really represent any true neighborhood. Thus, another way of evaluating the extent to which the estimated effects have any economic relevance is to choose key points along the distribution of Airbnb density to compare the estimated effects and observed changes for real neighborhoods. Table 4 displays the estimated effects of Airbnb on house prices, the observed house price growth, and the fraction explained by Airbnb for specific neighborhoods.

Table 4: The Effect of Airbnb on House Prices: Economic Significance

Pctile Airbnb Density Grow	Neighborhood	District	Estimated Airbnb Effect	Actual House Price Growth	Frac Explained by Airbnb
20	Estrella	Retiro	0.24%	29.34%	0.01
40	Pueblo Novo	Ciudad Lineal	0.41%	18.70%	0.02
60	Rejas	San Blas	0.69%	21.71%	0.03
80	Puerta del Angel	Latina	1.32%	38.53%	0.03
90	Almagro	Chamberí	2.03%	25.82%	0.08
94	Embajadores	Centro	11.19%	55.79%	0.20
95	Palacio	Centro	11.90%	38.48%	0.31
96	Universidad	Centro	11.35%	56.90%	0.20
97	Justicia	Centro	12.86%	49.46%	0.26
98	Cortes	Centro	15.73%	37.44%	0.42
99	Sol	Centro	27.58%	49.64%	0.56

Table 4 brings neighborhoods that lie in specific percentiles along the distribution of Airbnb density growth as well as the six neighborhoods in the *Centro* district, which are by far the neighborhoods with the largest Airbnb density in any given year of the sample.[42] That is, I compute the change in Airbnb as a percentage of housing units from 2012 to 2018, order all 128 neighborhoods from the smallest to largest change, and show the relative importance of Airbnb in explaining house price change for selected percentiles. The column named "Estimated Airbnb Effect" simply takes the observed change in Airbnb density and multiplies it by 1.2, the estimated percentage increase in house prices as a result of an additional percentage point in Airbnb density. For example, in *Sol*, the neighborhood with the highest density of Airbnb units, the increase in Airbnb as a percentage of housing units from 2012 to 2018 was of almost 23 percentage points[43] and therefore the estimated Airbnb effect on house prices is around 27%. The column "Actual House Price Growth" just displays the observed housing price appreciation in each neighborhood and finally, in the last column, I simply divide the growth predicted by Airbnb by the overall observed growth.

The main message of Table 4 is that the relevance of Airbnb in explaining house price increases varies a lot by neighborhood. In a nutshell, the fraction of the observed house price increases in the *Centro* district is between 20% in *Embajadores* or *Universidad* and 55% in *Sol*, whereas for other neighborhoods (even for the 90th percentile neighborhood in Airbnb density), the importance of

[42]Given the high concentration of Airbnb activity in the *Centro* district, it is important to study the impacts it may cause in this area of the city.

[43]This number of very similar to the actual density of Airbnb listings in 2018, since density levels in 2012 were rather low. Even for *Sol* the 2012 density was of less the 1 listing per 100 dwellings.

Airbnb in explaining the strong increase in house prices is substantially lower.

Before moving to the next section, two important caveats should be kept in mind in relation to the type of analysis presented here. First, the estimation method used does not account for spatial spillovers. That is, if increasing Airbnb units in neighborhood j significantly affect house prices not only in j but also in other neighborhoods of the city, the resulting estimates could be either biased towards zero or away from zero. If neighborhoods with high Airbnb density affect positively house prices of neighborhoods with low Airbnb density, then the estimates of the kind of model presented here would be biased towards zero. For example, if Airbnb increases in Embajadores and as a result house prices increase not only in Embajadores but also in low Airbnb density nearby neighborhood Acacias, then the difference in prices between the two neighborhoods will not be as large as it would have been in the absence of the spillover effects, thus biasing the estimated coefficient towards zero. However, if the relevant spillovers occur mostly among neighborhoods that all have high Airbnb density and do not spread to low Airbnb density areas, then the estimates would be biased away from zero. For example, if Airbnb expands in Embajadores and the spillover effects are concentrated mostly in other neighborhoods in the Centro district, then the difference in house prices between high Airbnb density areas and low Airbnb density areas will be larger than they would have been in the absence of the spillover effects. Reality is probably a mix of the two, but I judge the first case to be more widespread, that the spillover effects are mostly from Airbnb dense areas to areas with a somewhat lower Airbnb density (e.g. when residents move away from the city center to other neighborhoods where house prices are more affordable). If this conjecture is true, then the estimates presented in Table 3 could be interpreted as a lower bound for the true effect of Airbnb.

The second point refers to the assumption that Airbnb marginal effects on house prices is the same in all neighborhoods. This assumption could be more or less reasonable depending on the context. Ideally I would have investigated sources of heterogeneity of the effects, in particular with respect to listings that are permanently used as vacation apartment versus housing units that are occasionally offered as tourist accommodation. According to the discussion presented in Section 4.1.1, the effect should be larger for the former than for the latter. I leave for future research the task of a detailed empirical investigation about the mechanisms through which Airbnb affects house prices and what this implies for the heterogeneity in impacts across distinct neighborhoods.

4.2 Consumption Amenities

Similarly to the analysis of the effects of Airbnb on house prices, this section presents an empirical framework to try to estimate the impact of Airbnb activity on local consumption amenities. The presentation is broadly divided into three parts, a discussion of the conceptual framework, the estimation method and results, and finally a discussion of the economic relevance of the estimates.

4.2.1 Conceptual Framework

By consumption amenities I broadly refer to the local commercial environment and the range of retail and services available in a neighborhood. It is natural to suppose that Airbnb could potentially impact the performance of local businesses. The most logical way to think about how Airbnb expansion may affect the local commercial environment is to divide businesses into two categories, those that are used by locals and tourists and those that are almost exclusively used by locals. A leading example of the first category are restaurants and bars, the highest share of guest expenditure according to Airbnb.[44] And the main examples of the second class of businesses are

[44] https://press.airbnb.com/wp-content/uploads/sites/4/2019/03/2019-Madrid-Economic-Activity-Report.pdf

personal services, such as barbers, gyms, and beauty centers.

Since Airbnb growth essentially brings more tourists to different parts of the city, one would expect that it would have a positive impact on businesses that offer services that tourists consume a lot. And regarding businesses that are mostly cater to locals, Airbnb should have either no impact or a negative impact if it involves substitution of residential housing for vacation apartments and as a consequence of residents by tourists. In spite of the wide range of local consumption amenities that could potentially be affected by the recent growth in Airbnb activities, this section focuses on four consumption amenity categories: restaurants, food stores, clothing stores, and establishments offering personal services (hair dresser, beauty saloon, wax centers, tattoo shop, pet care, yoga).

With respect to restaurants, the Airbnb effects seems to be pretty direct. Airbnb visitors to a city will often eat out at local restaurants, suggesting a potential positive effect of Airbnb on restaurant's performance. Regarding groceries and food stores, the Airbnb effect is less straightforward and will depend on several factors. If Airbnb activity only represents extra tourists without a reduction in the number of residents, then demand for food stores may rise as a result of Airbnb growth. However, if Airbnb expansion comes together with permanent substitution of residents by a transient tourist population, then grocery stores may actually experience a demand decline. And crucially, these effects will depend on the kind of food store one is looking at. For example, small convenience stores (the typical stores called "Alimentación y Frutos Secos" in Spain) may benefit from the increasing presence of tourists while large supermarkets are less likely to benefit, since they more frequented by locals. Personal service establishments and clothing stores are mostly frequented by locals, so that Airbnb should have no effect or a negative effect if it displaces some original residents.

4.2.2 Estimation and Results

The main equation I estimate in order to identify the effect of Airbnb on consumption amenities is of the following type:

$$ConsumptionAmenity_{it} = \alpha + \beta Airbnb_{it} + \gamma X_{it} + \eta_i + \delta_t(1 + \mathbb{1}\{M30\}_i) + \epsilon_{it} \tag{4}$$

The consumption amenity variable represents the number of establishments in alternative categories, the Airbnb variable is the number of guest reviews per household living in the neighborhood, X_{it} is a vector is controls, and the other right-hand side variables are the same ones explained in Section 4.1. Table 5 displays the baseline estimates for four different types of consumption amenities, restaurants, food stores, clothing stores, and personal services. All models shown in the table have year dummies, central (inside M-30) specific trends, and neighborhood fixed-effects. Importantly, in addition to the demographic controls already discussed in the estimation of the effects on house prices, I also include here the number of hotels in each neighborhood as a way to control for the effect of tourists overall, not only Airbnb tourists.[45][46]

As previously discussed, depending on the extent to which to Airbnb activity comes from substituting residents by tourists the effects on the local commercial environment may differ. Primarily, we expect Airbnb activity to positively impact local restaurants, the local service that is likely to most complementary to Airbnb. This is confirmed in the first column of Table 5, which shows that there a positive association between Airbnb activity (reviews per household) and the number of active restaurants in a neighborhood.

[45]Ideally, I would include the yearly number of hotel bookings in each neighborhood, but unfortunately this kind of data is not available.

[46]Number of observations is smaller here than for house prices because I only observe the establishment count variable from 2013 on. Regressions are estimated using data between 2013 and 2018.

With respect to food stores, displayed in column 2, the effects of Airbnb also seem to be positive. This suggests that, on average, the extra demand brought by additional tourists exceeds that potential demand reduction arising from the removal of residential housing (and as a consequence residents). When it comes to businesses that mostly cater to locals, clothing stores and personal service establishments, the Airbnb effects seem to be negative. This is suggestive evidence that in neighborhoods where Airbnb density increases, the composition of businesses may be shifting towards establishments that offer services demanded by tourists.

Table 5: The Effect of Airbnb on Local Consumption Amenities

	(1) Restaurants	(2) Food Stores	(3) Clothing Stores	(4) Personal Services
Airbnb Activity	2.228**	0.998**	-1.392**	-3.085***
	(1.013)	(0.420)	(0.595)	(0.847)
Ln Population	20.808	-0.365	-3.653	2.717
	(13.935)	(5.783)	(8.192)	(11.657)
Perc. College	0.657	-0.517***	-0.571**	0.123
	(0.409)	(0.170)	(0.241)	(0.343)
Perc. Aged 20-39	-0.664*	-0.022	-0.089	-0.200
	(0.378)	(0.157)	(0.222)	(0.317)
Perc. non-OECD	-0.904	-0.399*	1.029***	-0.390
	(0.560)	(0.232)	(0.329)	(0.468)
Perc. Employed	0.064	0.034	-0.059	0.276**
	(0.159)	(0.066)	(0.094)	(0.133)
Hotel Count	1.639***	0.611***	0.470**	1.467***
	(0.319)	(0.132)	(0.187)	(0.267)
Year FE	Yes	Yes	Yes	Yes
M-30 Trends	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Observations	768	768	768	768

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, in Table 6 I also present estimates for restaurants (other consumption amenities not included for brevity) with the same instrumental variable approach described in Section 4.1, where the effects on house prices were estimated. I do not estimate Equation 4 with Instruments 1 or 2, because they were based precisely on the spatial distribution of hospitality establishments in 1998, which although consisted in a reasonable instrument for house prices would suffer from serious endogeneity concerns here, since the outcome variable is the number of restaurants, the most numerous establishment type in the hospitality industry.

Regarding the instrumental variable estimates, although Instrument 3 (share of small houses multiplied by Google Trends search index) is not statistically significant, the three Airbnb coefficients estimated point in the same direction, a large increase in the point estimate comparing to the fixed-effects estimate. My interpretation of this downward bias in the simple fixed-effects model is the following. Neighborhoods in the Centro district, which have disproportionately high levels of Airbnb activity (guest reviews per household) do not experience the same degree of disproportional increase in the number of restaurants. Thus, when estimating the non-instrumented version of the model, these neighborhoods drive estimates of the effect of an additional unit of Airbnb activity down (large increases in Airbnb activity associated with not so large increases in restaurants). However, when instrumenting for Airbnb, the predicted Airbnb activity assigned to these areas is smaller, which reduces this mismatch between the magnitude of Airbnb density in these neighborhoods and the lack of an increase in the number of restaurants of a proportionally large magnitude. In other words, the instrumental variables estimates assign lower levels of Airbnb density in the city center compared to they actually have in reality, and this increases the effect of marginal increase in Airbnb activity on restaurants establishments.

There are two ways to interpret the fact that neighborhoods in the Centro district tend to push estimates down. First, there are limits on the extent to which the number of restaurants in a given neighborhood can increase, specially in neighborhoods where the number of restaurants was already high in the initial year of the period used for estimation and it may be hard to find physical space and to get permits to open new restaurants. This would contribute for neighborhoods in Centro experiencing a much smaller marginal effect of Airbnb activity on the number of restaurants. And second, it is possible that Airbnb units that operate in Centro are different than those operating in less touristic neighborhoods. If Airbnb listings in Centro operate as permanent vacation apartments which replaced local residents, whereas listings in other neighborhoods are more of the occasional type, it is likely the overall Airbnb impact in neighborhoods of the Centro district combines the positive effect of increased tourist demand and the negative effects of less demand from residents, while in other neighborhoods the negative channel through the reduction in demand from locals is minimal or nonexistent.

Table 6: The Effect of Airbnb on the Number of Restaurants

	(1) Restaurants	(2) Restaurants	(3) Restaurants	(4) Restaurants
Airbnb Activity	2.228**	9.258	15.618**	13.978***
	(1.013)	(6.277)	(7.612)	(4.068)
Ln Population	20.808	30.708*	39.661**	37.352**
	(13.935)	(16.885)	(18.997)	(16.323)
Perc. College	0.657	0.655	0.652	0.653
	(0.409)	(0.425)	(0.463)	(0.451)
Perc. Aged 20-39	-0.664*	-0.443	-0.242	-0.294
	(0.378)	(0.439)	(0.490)	(0.435)
Perc. non-OECD	-0.904	-0.762	-0.634	-0.667
	(0.560)	(0.594)	(0.651)	(0.622)
Perc. Employed	0.064	0.077	0.089	0.086
	(0.159)	(0.166)	(0.181)	(0.176)
Hotel Count	1.639***	0.329	-0.856	-0.550
	(0.319)	(1.199)	(1.447)	(0.809)
Year FE	Yes	Yes	Yes	Yes
M-30 Trends	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
IV 3	No	Yes	No	No
IV 4	No	No	Yes	No
IV 5	No	No	No	Yes
Observations	768	768	768	768

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.3 Economic Significance

In the discussion of the economic relevance of the estimates I will focus on restaurant establishments, which I identify as the type of consumption amenity most directly affected by Airbnb expansion. Considering the estimates with Instrument 5, the weighted average of inverse distances to tourist attractions, each additional unit of Airbnb activity leads to almost 14 extra restaurants. This may sound like an extremely high number, however, Airbnb activity defined as reviews per household is a variable with changes that are very small in magnitude. For example, over the sample period the average increase in Airbnb activity was of 0.28, or 28 reviews per 100 households. This increase, multiplied the estimated Airbnb coefficient, suggests that Airbnb led to 3.83 additional restaurants in the average neighborhood. Taking into account that the observed average growth in restaurant count was of 15 units, this means that Airbnb was responsible for almost 25% of the observed increase.

However, if one is less confident in the instrumentation strategy and prefers to look at the fixed-effects estimate as an approximation to the causal effect of Airbnb on restaurants, then economic relevance is substantially lower. The 2.23 coefficient multiplied by the average change in Airbnb activity of 0.28 implies that Airbnb would have led to 0.61 additional restaurants on average. This represents only 4% of the actual increase in restaurants observed in the data.

4.3 Jobs

The third core neighborhood characteristic for which I study the effects of Airbnb relates to the jobs present in each neighborhood. I start by briefly discussing why Airbnb may affect local employment. Then, I present the baseline results for jobs divided by different wage levels as well as by industries that should be specially affected by Airbnb activity, hospitality and retail. Third, I bring suggestive evidence on the mechanism through which Airbnb may be affecting hospitality employment in particular. And lastly, show some back of the envelope calculation that give a sense of the economic relevance of the estimates.

4.3.1 Conceptual Framework

The mechanism through which Airbnb activity may affect local employment is straightforward. It basically depends on the boost in demand brought by the extra tourists that visit a city as a result of Airbnb's success. The size of the effect of Airbnb on local (neighborhood level) employment will depend on some key factors that are discussed below.

First, it will depend on the type of job. Jobs in activities that are closely related to what tourists demand will likely be positively impacted. Primary examples are jobs in restaurants and tourism related businesses such as travel agencies and tour guides. Since I only have data employment in broad categories (e.g. hospitality industry, retail industry), I cannot test whether jobs like tour guides are impacted by Airbnb growth. And taking into account that according the Airbnb's Economic Activity Report for the City of Madrid,[47] the two categories in which its visitors mostly spent money were on Eating Out and Shopping, I empirically evaluate the effects of Airbnb on hospitality employment and retail employment.

Second, the effect will depend on the extent to which Airbnb guests spend money locally, that is, in the same neighborhood where their accommodation is. If travellers only stay in a non-central neighborhood for a good deal on the price for accommodation but then travel to the city center

[47] https://press.airbnb.com/wp-content/uploads/sites/4/2019/03/2019-Madrid-Economic-Activity-Report.pdf

to go to restaurants or go shopping the local employment effects will be strongly heterogeneous across neighborhoods and estimating effects using neighborhood level data may be misleading.

Third, the effect on local jobs will depend on the extent to which Airbnb creates new tourists versus "steals" visitors that would have travelled anyways but would have stayed in hotels. If Airbnb tourists are in fact would be hotel guests, then causal impact of Airbnb on local jobs will smaller. Obviously, if Airbnb accommodation is cheaper than hotel accommodation this may free up extra money to be spent on local services, which would positively impact jobs. But in any case the degree of substitution versus "creation" of new tourists that would not otherwise have travelled is a key determinant of the causal impact of Airbnb on local employment.

Lastly, the effect will depend on the extent to which Airbnb tourist apartment are operated using housing space that would have been occupied by a local resident in the absence of Airbnb. If Airbnb is mostly about sharing space that would be otherwise empty (share a spare room in a house occupied by a permanent resident), then the extra tourist will be represent extra demand for local products and services. However, if Airbnb is mostly about removing residential units from the long-term residents to be reallocated to short-term visitors, then in addition to the growth in demand brought by tourists there will be a reduction in demand as a results of a smaller resident population.

With the data I have in hand at this stage I cannot explore all the nuances of the potential employment effects of Airbnb, its possible determinants, and heterogeneity aspects between different neighborhoods. However, I can still provide some initial insight into this question by trying to look whether there is suggestive evidence that it has impacted neighborhood jobs and whether the effects were distinct for different jobs in terms of wage level and industry/sector.

4.3.2 Estimation and Results

The main equation I estimate in order to identify the effect of Airbnb on local employment is the following:

$$Ln(Employment)_{it} = \alpha + \beta Airbnb_{it} + \gamma X_{it} + \eta_i + \delta_t(1 + \mathbb{1}\{M30\}_i) + \epsilon_{it} \tag{5}$$

The employment variable refers to the number of employees in neighborhood i year t for distinct categories of jobs, for example hospitality employment, high wage jobs, etc. The Airbnb activity measure I use is the log of Airbnb guest reviews.[48] I choose to use this measure because I want to allow different Airbnb listings to have differential impacts according to actual number of guests they receive, which is appropriate given that what ultimately affects employment are the Airbnb visitors that spend money in the city.

Table 7 displays the baseline estimates for the effects of Airbnb density on neighborhood total employment and also employment by wage brackets. As mentioned before, I use the professional category of each employee registered in the social security to construct three wage levels. More specifically, out of the seven categories that exist, I assign the top one to the high wage group (engineers, university degree holders and senior managers). Next, I assign two categories to the median wage group: "Technical Engineers and Assistants with some higher education" and "Administrative and Workshop Heads". And lastly, I include the four remaining categories into the low wage job types, since there is no variation whatsoever in the minimums and maximums set by law as the remuneration of these four categories.

In terms of Airbnb activity I show the main estimates using log of reviews instead of reviews per household because this measure delivers more stable results. Using reviews per household

[48] I use log of reviews plus one to avoid having to drop zeros.

as a measure of Airbnb density delivers similar results in qualitative terms, however it is very sensitive to including or dropping neighborhoods in the Centro district in the estimation sample (in particular estimates are sensitive to including or not the neighborhood Sol). That is because reviews per household in Sol is disproportionately large as compared to any other neighborhood and this extremely large levels of Airbnb density are not followed by correspondent increases in log employment.[49] It is simply not possible that Sol experiences percentage increases in jobs that order of magnitude larger than for other neighborhoods, thus regressions using guest reviews per household as the Airbnb density measure and deliver small effects of Airbnb to adjust for the outlier neighborhood Sol. Therefore, to avoid having to drop neighborhoods I present and discuss the baseline estimates using log of guest reviews as the main measure of Airbnb intensity in a neighborhood.

Table 7: Airbnb Impact on Local Jobs: Wage Levels

	(1) All Jobs	(2) High Wage Jobs	(3) Med. Wage Jobs	(4) Low Wage Jobs
Ln Airbnb Reviews	0.011	0.003	-0.028	0.021^{***}
	(0.007)	(0.015)	(0.020)	(0.008)
Ln Population	-0.016	0.823	1.207^{**}	-0.195
	(0.512)	(1.235)	(0.528)	(0.600)
Perc. College	0.010	0.042	0.015	0.004
	(0.012)	(0.026)	(0.022)	(0.013)
Perc. Aged 20-39	-0.021	-0.031	0.017	-0.024
	(0.016)	(0.039)	(0.023)	(0.018)
Perc. non-OECD	0.015	-0.009	0.010	0.025
	(0.014)	(0.033)	(0.023)	(0.016)
Ln Estab. Accommod.	-0.034	-0.059	0.008	-0.039
	(0.032)	(0.052)	(0.082)	(0.036)
Year FE	Yes	Yes	Yes	Yes
M-30 and Centro Trends	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Observations	768	768	768	768

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 reveals the importance of looking at different types of jobs when estimating the effects of Airbnb on employment. The first column shows that the association between Airbnb activity and local employment level is positive but statistically insignificant. However, splitting jobs into three level of wage, shows that actually Airbnb does seems to increase local jobs, but only low-wage ones. High wage jobs seems to have almost no relationship to Airbnb activity, while medium paying jobs show a negative but not statistically significant correlation. In fact, one thing that catches the attention across the columns of Table 7 is that there is no variable that is significant in explaining employment variation. That is because after including neighborhood fixed-effects and clustering standard errors at the neighborhood level, it is very hard to get precise estimates of time-varying factors that explain job growth (or decline) over a relatively short period of time (5 years). The estimated Airbnb effect in column 4 suggests that doubling the number of Airbnb guest reviews would increase the number of low wage jobs in a neighborhood by around 2%.

Next, Table 8 shows the estimated effects of Airbnb on neighborhood employment but separat-

[49] Sol had more than 8 reviews per household in 2018, while for most other neighborhoods this variable is below 0.1 and even in other neighborhoods in the "Centro" district, this variable is of the order of 2 reviews per households.

ing jobs into three large groups based on the industry of the company that employs the worker. Column one is the same of Table 7 and includes all types of jobs. Then, column 2 estimates the Airbnb effect on hospitality employment only (hotels, restaurants, and bars), columns 3 does the same for retail employment and column 4 estimates Equation 5 using the remaining jobs (excluding hospitality and retail). The choice of studying hospitality and retail employment in more detail comes from the fact that these two industries could benefit from the increase in incoming tourists that associated with Airbnb expansion.

Airbnb growth impacted hospitality employment positively but its effect on retail employment is statistically indistinguishable from zero. The positive impact on hospitality employment was already expected and there was descriptive evidence of this from Table 1. And in regards to the lack of an effect on retail employment may have to with the very broad nature of this category. It includes all types of retail stores, some of which may in reality be positively affected by Airbnb while others probably are negatively affected. For example, chain clothing stores (Zara, H&M, etc.) may be positively impacted by a boost in demand from the increasing numbers of tourists. However, the typical neighborhood stores (such stationery, small bookshops, florists, hardware store, etc.) are all likely to be negatively affected by Airbnb if at least some fraction of tourist apartments come from housing units previously occupied by local residents. Combining in the same category all these different types of retail jobs may be the reason why the Airbnb coefficient is so imprecisely estimated. In summary, Table 8 indicates that the relation of Airbnb expansion and local jobs is heterogeneous across industry types and the positive effect seem to be constrained to hospitality employment. And lastly, the results presented in Table 7 and Table 8 fit well together. That is, most of the increase in hospitality employment is probably related to restaurants and bars hiring waiters and lower level staff for the kitchen to accommodate the increasing demand for tourists. And these jobs are surely categorized into the low wage type of jobs represent in column 4 of table 7, which helps explain why both hospitality employment and low wage jobs are positively impacted by Airbnb. Results of column 2 suggest that doubling the number of Airbnb guests (proxied by reviews) leads to 3.4% increase in neighborhood level employment in hospitality, without any clear indication that jobs in other industries are being lost.

4.3.3 Hospitality Employment: The Mechanism

Given the significant positive association between Airbnb growth and hospitality employment growth I further study if there is evidence that tourists that stay in an Airbnb unit visit local neighborhood restaurants in the same area where their Airbnb apartment is. That would be the mechanism behind Airbnb increasing neighborhood employment in the hospitality industry. The alternative case would be one in which although guests stayed in Airbnb listings located in many distinct neighborhoods, visitors went only the most attractive neighborhoods of the city (mainly neighborhood in the city center) to eat out at restaurants.

In order to check whether there is suggestive evidence of tourists frequenting restaurants in the same neighborhood where their Airbnb listings are located, I use data from Tripadvisor to estimate a regression in which the main outcome variable is neighborhood's i share of Madrid's Tripadvisor tourist reviews in year t and the main explanatory variable is neighborhood's i share of Madrid's Airbnb guest reviews in year t. The main control variables (on top of the typical neighborhood dummies and year dummies) is neighborhood's i share of Madrid's Tripadvisor local residents' reviews in year t (popularity with locals). The intuition behind this regression to check whether areas that over time concentrate a higher proportion of Madrid's Airbnb guests also tend

Table 8: Airbnb Impact on Local Jobs: Hospitality and Retail Industries

	(1) All Jobs	(2) Hospitality Employees	(3) Retail Employees	(4) All the rest
Ln Airbnb Reviews	0.011	0.034**	0.012	0.005
	(0.007)	(0.015)	(0.010)	(0.004)
Ln Population	-0.016	-0.733	1.151***	0.710***
	(0.512)	(0.526)	(0.345)	(0.161)
Perc. College	0.010	-0.009	0.003	0.004
	(0.012)	(0.016)	(0.010)	(0.005)
Perc. Aged 20-39	-0.021	-0.018	-0.024**	-0.011***
	(0.016)	(0.014)	(0.009)	(0.004)
Perc. non-OECD	0.015	0.041*	-0.006	0.005
	(0.014)	(0.021)	(0.014)	(0.006)
Ln Estab. Accommod.	-0.034	-0.002	-0.082*	-0.064***
	(0.032)	(0.072)	(0.047)	(0.022)
Year FE	Yes	Yes	Yes	Yes
M-30 and Centro Trends	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Observations	768	768	768	768

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

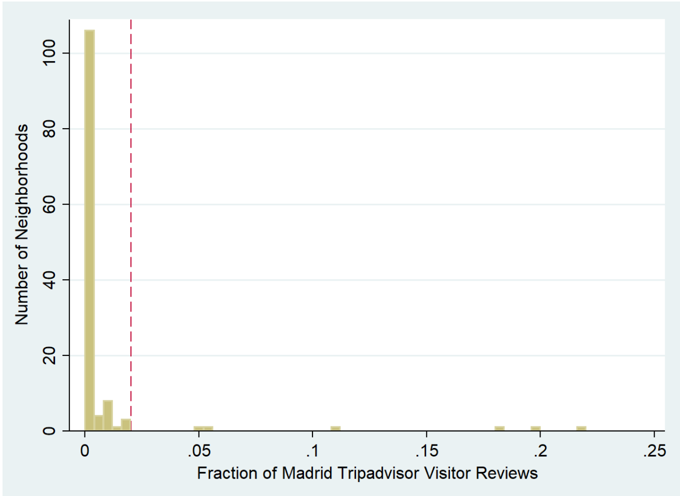
to concentrate higher shares of restaurant reviews made by tourists.[50]

In order to make a more extensive evaluation of this mechanism, I run the regression in three alternative samples. The entire sample with all neighborhoods in Madrid, a sample the excludes the most touristic neighborhoods, and lastly a sample restricted to neighborhoods that were not touristic at all as of 2009, before the first Airbnb guest reviews for Madrid was observed. To define which neighborhoods were touristic or not, I use Tripadvisor restaurant reviews for 2009 and compute the each neighborhood's fraction of Madrid's restaurants reviews made by tourists. Figure 7 plots the distribution of the fraction of city wide reviews made in each neighborhood. Neighborhoods to the right of the vertical dashed line are considered the main touristic neighborhoods, areas that already concentrated a significant proportion of restaurant tourist reviews before Airbnb existed. And only neighborhoods that had zero tourist reviews in their restaurants in 2009 are considered not touristic at all. In a nutshell, the first sample includes all neighborhoods, the second samples excludes the six neighborhoods that are to the right of the vertical dashed line in Figure 7, and lastly the third sample further excludes neighborhood to the left of the dashed line but that had a non-zero fraction of Madrid's restaurant reviews made by tourists in 2009. Table 9 displays the results for the three samples.

The main take away of Table 9 is that the expected positive association between Airbnb concentration of tourists going to local restaurants seem to hold in the data. That is, as a neighborhood captures a higher fraction of the overall Airbnb listings in Madrid, it also seems to capture a greater share of the restaurant reviews made by tourists in Madrid. The positive correlation holds for the three samples, suggesting that even in previously non-touristic neighborhoods, Airbnb guests, to some extent, use the service of local restaurants. Or put it in another way, it does not seem to be the case that Airbnb tourists staying in non-touristic neighborhoods go the city center every time they want to eat at a restaurant. At the same time, the fact that coefficients are much smaller than one could indicate that an important part of tourists do eat out in neighborhoods different than

[50] The data from Tripadvisor was explained in detail in Section 2.4

Figure 7: Neighborhood Fraction of Madrid Restaurant Tourist Reviews in 2009



Notes: Restaurant review made by tourist are reviews which the user location is any city outside the Community of Madrid.

Table 9: Airbnb guests and local restaurants

	Full Sample	Non-Touristic	Restricted Sample
Frac. Airbnb Guest Reviews	0.195***	0.108***	0.049***
	(0.033)	(0.009)	(0.017)
Frac. Restaurant Local Reviews	0.697***	0.554***	0.431***
	(0.066)	(0.030)	(0.025)
Frac. of Madrid Hotels	0.496***	0.114***	0.019***
	(0.059)	(0.020)	(0.007)
Year FE	Yes	Yes	Yes
M-30 and Centro Trends	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes
Observations	768	732	570
Number of Neighborhoods	128	122	95

the ones where their Airbnb listing is located. Lastly, the other main control variables have the expected sign, with more hotels also implying a higher share of the city's total restaurant reviews made by tourists, and with areas that are more popular with locals also being more popular with tourists (areas that simply have more, larger, or better restaurants).

4.3.4 Economic Significance

In this Section I have shown that Airbnb activity is positively associated with local employment, but not of all types. In fact, it had a positive effect only on low-wage jobs and jobs in the hospitality industry (which as discussed probably have a big overlap). Evaluation of the economic relevance of the estimates delivers results that seem too high comparing to what one would expect from the effect of Airbnb. This points to the fact that the effects of local jobs must better studied and that the actual magnitudes of the estimated effects may be sensitive to the kind of functional form assumed.

In terms of low wage jobs my estimates suggest that whenever Airbnb guests reviews doubles, there is a 2.1% growth in low wage jobs. Taking into account this coefficient, over the sample period, the observed increase in Airbnb reviews suggests that low wage jobs should have increased by around 9%. And since the actual observed increase was of 14%, the estimated suggest that Airbnb was responsible for 64% of the overall increase in low wage jobs in the average neighborhood. This number is implausibly high and points to the importance of further investigating better approaches to estimate causal effects of increased tourist activity in neighborhood outcomes such as employment.

And when it comes to employment in the hospitality industry my estimates suggest and even larger marginal effect of Airbnb. Whenever Airbnb reviews doubles, hospitality employment increases by 3.4%. Taking into account this marginal effect and the observed increase in Airbnb reviews in my sample, the implied effect on hospitality jobs is that it should increase by around 14% as a result of the growth in Airbnb guests. Since the actual observed growth in hospitality employment was of the order of 24%, Airbnb explains 58% of the actual increase in hospitality employment. Once again, these numbers are too high given all the other changes that have also influenced employment, such as the overall economic recovery, due to which jobs would have increased whether Airbnb existed or not. One reason why the implied economic significance seems out of range in these back of the envelope calculations is that estimated coefficients displayed in Tables 7 and 8 are supposed to represent the effect of a marginal increase in Airbnb guest reviews, but the back of the envelope calculations discussed here use observed changes in Airbnb reviews that far from marginal. That may imply that when computing the suggested Airbnb effects by simply multiplying the observed change in reviews by the estimated regression coefficient, we are actually using a poor approximation for the effect of large change by using the estimated linear effect on a marginal change.

5 Airbnb Effects on Mobility and Demographic Change

This section tries to bring together the aspects discussed in the previous parts of the paper in a unified framework. It starts by showing with a regression framework that Airbnb activity is associated with neighborhood demographics. Then, I move on to showing that, among the core neighborhood attributes previously discussed, house prices is the chief driver of residents location choices and that even after controlling for all neighborhood characteristics, Airbnb activity has a direct effect on residents location decisions, which I interpret as a combination of two factors: indirect (or exclusionary) displacement and unobserved factors that are also influenced by Airbnb but I cannot measure in my data.[51]

5.1 Airbnb Growth and Neighborhood Demographic Change

In this section I run a simple regression model with time fixed and neighborhood fixed effects tho show that Airbnb, as suggested in Table 1 and Figure 3, indeed is associated with changes in neighborhood demographics. More specifically, the regression is the following:

$$Demographic_{it} = \alpha + \beta AirbnbActivity_{it} + \eta_i + \delta_t + \epsilon_{it} \tag{6}$$

where $Demographic_{it}$ is one the four different previously discussed demographic characteristics, $AirbnbActivity_{it}$ is the usual measure of Airbnb activity used in most of the paper (Airbnb guest reviews divided by housing units), and η_i and δ_t are neighborhood and year dummies respectively.

[51] I adopt the formulation of Marcuse 1985, who defines direct displacement as the case in which original residents are pushed out of their housing units (out-migration) and indirect (or exclusionary) displacement for cases when people that would otherwise have moved-in are prevented from doing so.

Since I include neighborhood fixed-effects, the results of Table 10 are not showing correlation in levels but in changes.

Table 10: Airbnb and Neighborhood Demographics (full sample)

	(1) Pop. Density	(2) Perc. College	(3) Perc. Aged 20-39	(4) Perc. non-OECD
Airbnb Activity	-2.415***	0.812***	0.266**	-0.334***
	(0.435)	(0.130)	(0.115)	(0.078)
Year FE	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Observations	1152	1152	1152	1152

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first column shows that growth in Airbnb activity is associated with decreasing population density. This could be because of many factors, such as reallocation of residential housing space, or Airbnb induced house price increases. Certainly, I am not saying that the results are causal. For example, if there are other factors that also cause house prices to increase and these factors tend to be more present in the same areas where Airbnb activity grew more, then there will a bias in estimating a stronger negative relationship between Airbnb and population density than what the causal impact truly is. Next, from the second to the fourth columns I run the same regression model but substituting the outcome variable for the three basic demographic indicators already discussed through the paper. The signs of the correlations are the expected ones given the descriptive facts of the data laid out in Section 3. That is, a positive association with the residents' education attainment as well as with the share of young adults, while a negative association with the share of non-OECD residents. Again, none of these estimates should be interpreted as causal, but they at least indicate that Airbnb may be behind some of the demographic changes occurring across the neighborhoods of Madrid.

The results shows in Table 10 include data for the 128 neighborhoods that exist in the city for all years since the first Airbnb guest review is observed (2010) to the most recent year for which demographic variables are available (2018). However, in the next part of this section I will make use of the resident's mobility data, which is only available up to 2017, and the consumption amenities data (establishment count), which is only available from the end one 2013 on. And since I want to use Airbnb density together with neighborhood characteristics (including establishment count) as predictors of where people decide to locate, I can only include the years between 2014 and 2017. Therefore, for comparability I also include results for the same model illustrated in Table 6 but only using the same observations that I will be able to use in the next part of this section when estimating a simple residential location model (neighborhood-years for which both mobility, Airbnb, consumption amenities, and jobs data is available). Table 11 displays the results for the smaller sample. All the qualitative results are the same, although the association with the share of young adults in no longer statistically significant.

5.2 Estimating Preference for Neighborhood Characteristics

I now test whether the core neighborhood characteristics actually predict people decision of which neighborhood to live in. Borrowing from an extensive literature on urban economics (Holmes and Sieg 2015), I assume that individuals choosing where to live solve a discrete choice problem in which each neighborhood (product) is defined by a vector of characteristics. In my application the vector of decision relevant characteristics will be the core neighborhood attributes discussed

Table 11: Airbnb and Neighborhood Demographics (2014 - 2017 sample)

	(1) Pop. Density	(2) Perc. College	(3) Perc. Aged 20-39	(4) Perc. non-OECD
Airbnb Activity	-0.895**	0.606***	0.112	-0.276***
	(0.423)	(0.101)	(0.114)	(0.065)
Year FE	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes
Observations	454	454	454	454

Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

throughout the paper and Airbnb density directly.

In such discrete choice models, the structure of the decision problem delivers an estimation equation based on the share of the population of consumers that chooses each product, or equivalently, the share of the resident population that chooses to live in each neighborhood. For the purposes of my application, instead of focusing on the stock of population that resides in each neighborhood as it is usually done in the literature (Couture and Handbury 2017), I take advantage of the availability of mobility data (people that move-in in a given year) and estimate the location choice model with the share of movers that choose each neighborhood.[52] That is, conditional on moving, how does the menu of neighborhood characteristics available to choose from influence individual's decisions of which neighborhood to live in?

Three factors are the main reasons why I focus on in-movers rather than on the stock of residents. First, my time period is not very long and neighborhood demographic changes take time to realize, so using movers may provide more up-to-date information. Second, in Section 3 I show suggestive evidence that the Airbnb effects are more connected to in-migration patterns than to out-migration patterns. And third, the economics literature mostly finds that gentrification effects are driven more by changes on the in-migration than on the out-migration side of the residential flows.

In summary, the results displayed in the next tables come from estimating the following regression equation:

$$Share_{it} = \alpha + \beta_A Airbnb_{it} + \beta_P HousePrice_{it} + \beta_C ConsumAm_{it} + \beta_J Jobs_{it} + \eta_i + \delta_t + \epsilon_{it} \quad (7)$$

Airbnb activity is measured as guest reviews per residential housing unit existent in the neighborhood.[53] The other right-hand side variables are the three types of neighborhood core attributes discussed throughout the paper. The neighborhood fixed-effects are there to control for neighborhood size (large neighborhoods will attract Airbnb units as well as a large fraction of the overall number in-movers in the city) and neighborhood baseline demographic composition (a neighborhood that has a higher share of young adults will also attract a higher fraction of the young adults who are moving across the city). The outcome variable $Share_{it}$ is the fraction all in-movers in year t that choose neighborhood i. In-movers include both people moving from one neighborhood to another within the city of Madrid and people that come to Madrid from other cities or countries.

[52]The literature commonly uses the share of residents that live in each area of the city for lack of data on within city mobility. However, it seems natural to use data on the choice of in-movers, since this most closely parallels the IO literature that uses the share of buyers that choose each product, not the share of consumers that own each product.

[53]I use housing unit instead of households to avoid the mechanical correlation between the denominator of the Airbnb measure and the share choosing each neighborhood.

In either case, these in-movers have to choose a neighborhood where to live in Madrid and, conditional on moving, face the same menu of neighborhoods (defined by its characteristics) to choose from.

Table 12 shows the results of estimating Equation 7 with Airbnb activity as the only neighborhood attribute that characterizes a neighborhood. This is not realistic but it is still useful to have a first measure of the correlation between Airbnb growth and changes in the share of in-movers that choose each neighborhood. In each column I estimate the model for a different demographic group based on age and education. Column 1 considers all the migrants. And columns 2 through 5 restrict the in-movers to young adults with high education, young adults without college education, and so on. For example, in column 5, the outcome variable is the share, out of all older adults (40 years old or more) without college education that move in during year t, who choose neighborhood i. As expected, for all demographic groups, an increase in Airbnb activity is negatively correlated to the change in the share of people who, conditional on moving, choose that neighborhood to live in.

Table 12: Airbnb and the Residential Location Decision of In-Movers (1)

	(1) All	(2) Young High	(3) Young Low	(4) Old High	(5) Old Low
Airbnb Activity	-0.029***	-0.048***	-0.025**	-0.077***	-0.030**
	(0.009)	(0.018)	(0.012)	(0.014)	(0.012)
Year FE	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes
Observations	454	454	454	454	454

Standard errors in parentheses:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, to have a sense of the channels through which Airbnb may affect residents location decisions, Table 13 includes variables related to each one of the core neighborhood characteristics: house prices, four representative consumption amenities, and three types of jobs based on the professional categories and levels described in Section 4.3. I first briefly discuss the estimates for the core neighborhood attributes and then I talk about the estimated coefficients for Airbnb activity.

This first thing that deserves notice is that because the regressions include neighborhood fixed-effects and the number of years is small (four years, three changes), most neighborhood characteristics variables are not statistically significant. That comes from the fact that the share of movers that choose each neighborhood does not experience a very strong variation in such a short period of time. In spite of that, house prices are a powerful driver of changes in the share of people choosing where to live, with a negative and significant coefficient for all demographic groups except the older individuals with high education. The interpretation from a discrete choice model is that, in general, house prices are harmful for utility (as expected). The fact the the coefficient for older high education individuals is slightly positive indicates that there is still some unobserved neighborhood quality factor that probably has a positive correlation to house prices. Since older highly educated individuals tend to have higher incomes, they can afford to pay for these unobserved quality and this drives the positive correlation between the share of people in this demographic group that choose neighborhood with the level of prevailing prices.

In terms of restaurants the overall coefficients is zero but it is positive for low education individuals, while negative for high education ones. This suggests that the number of restaurants may be a poor measure of what actually provides utility to people, and in the future better measures of restaurant quality should be used instead. One attempt is made with the variable called Tripadvisor restaurants, which is the number of restaurants listed on Tripadvisor that a neighborhood has (assuming that on average restaurants listed on Tripadvisor tend have higher quality than other restaurants). In that case, the estimated coefficients, although not statistically significant do have the expected positive sign for all demographic groups, in particular for old adults with high education, who can afford these nicer restaurants. Regarding establishments offering personal services estimates are generally positive but almost never significant. And for food stores, coefficients are never significant and the sign varies with demographic group. This could indicate the the data coming from the *Censo de Locales* (Census of Establishemnts) may have limited use for future purposes. It may be contain information that is not up to date or divide establishment into classes that are too broad to give any meaningful structural interpretation. And regarding jobs, only medium wage and low wage jobs are consistent positive predictors of people's decision of where to live. In particular, low wage jobs positively predicts with strong statistical significance the location of young low education individuals, who are the most likely to work in low wage jobs.

Finally, with respect to the coefficient on Airbnb activity itself, it is consistently negative for all demographic groups. As expected, conditional on education level, it is more negative for older adults. That goes in line with the story that young adults are both more likely to enjoy the benefits (e.g. use Airbnb as extra source of income) as well as to suffer less with the damages (e.g. not as sensitive as the older people to loud noise from tourists). Moreover, conditional on age, the negative effect is stronger for high education individuals. This may be interpreted as suggestive evidence that, conditional on having the same cost of housing (I control for housing prices), low income individuals are more likely to use Airbnb as an income source whereas higher income individuals do not need that.

To finish this section of the paper, Table 14 shows the same results of the previous table but with the coefficients standardized to represent the effect of a one standard deviation of the relevant explanatory variable. I do that in order to able to compare the importance of the different variables in driving the choice of different demographic groups to live in different neighborhoods and explain how they connect to the correlations between Airbnb activity and neighborhood demographics showed in Table 10.

First, columns 3 and 5 show that for low education individuals, the most important predictor (in magnitude, be it negative or positive) are house prices. This helps to rationalize the fact that, in spite of having a less negative direct effect on lower education individuals, the (unconditional) correlation between Airbnb activity and education levels showed in Section 3 and Table 10 is positive. It seems that Airbnb, by increasing house prices, prevents lower education individuals from moving in, which generates the positive correlation of Airbnb activity and average education levels of a neighborhood.

Regarding the positive association between Airbnb and the share of young adults in a neighborhood there is more than one way to try to explain this fact. Regarding the direct effects, Airbnb is more tolerated by young adults than by older individuals, so this already would suggest a positive correlation between Airbnb and the share of young adults. Additionally, Airbnb increases the number of low wage jobs in the neighborhoods, as shown in Section 4.3, which is also a strong predictor of young adults with low education levels. On the other hand, by increasing house prices Airbnb reduces the share of young adults in a neighborhood, since, conditional education, the coefficients on house prices are always more negative for younger than for older cohorts. These effects going in opposite directions help explain why the correlation between Airbnb activity and the share of young adults was not as strong as for education and region of origin.

In terms on the negative relationship between Airbnb and the share of residents from a non-

Table 13: Airbnb and the Residential Location Decision of In-Movers (2)

	(1) All	(2) Young High	(3) Young Low	(4) Old High	(5) Old Low
Airbnb Activity	-0.020**	-0.037**	-0.004	-0.074***	-0.018
	(0.010)	(0.018)	(0.012)	(0.015)	(0.013)
Ln House Prices	-0.174***	-0.199*	-0.400***	0.026	-0.239***
	(0.057)	(0.107)	(0.074)	(0.089)	(0.076)
Ln Restaurants	-0.000	-0.593***	0.137	-0.151	0.138
	(0.067)	(0.126)	(0.087)	(0.105)	(0.090)
Ln Tripadvisor Restaurants	0.008	0.003	0.006	0.043*	0.017
	(0.015)	(0.029)	(0.020)	(0.024)	(0.021)
Ln Food Stores	-0.006	0.001	-0.016	0.018	-0.009
	(0.025)	(0.047)	(0.032)	(0.039)	(0.033)
Ln Personal Services	0.055	-0.062	0.021	0.110*	0.080
	(0.037)	(0.069)	(0.048)	(0.058)	(0.049)
Ln High Wage Jobs	-0.009	-0.054*	-0.027	-0.001	-0.001
	(0.017)	(0.032)	(0.022)	(0.026)	(0.023)
Ln Med. Wage Jobs	0.011	0.036	-0.004	0.013	0.011
	(0.018)	(0.034)	(0.024)	(0.028)	(0.024)
Ln Low Wage Jobs	0.031	0.027	0.111***	0.087*	0.013
	(0.030)	(0.056)	(0.038)	(0.046)	(0.040)
Year FE	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes
Observations	454	454	454	454	454

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

OECD country, there is no availability of data on in-movers with country of birth information (I only observe if in-movers are Spanish or foreigners). But given the expected correlation between country of birth and income levels, the main explanation seems to be, similarly to what was already discussed for education, based on the lower incomes and lower ability to afford the increased house prices that results from higher Airbnb density. Lastly, with respect to Airbnb's negative relationship with population density, both its effect of house prices and its direct effect go in the same direction, of lowering in-migration and reducing population density when compared to scenario where Airbnb did not exist.

Table 14: Residential Location Decision of In-Movers - Standardized Coefficients

	(1) All	(2) Young High	(3) Young Low	(4) Old High	(5) Old Low
Airbnb Activity	-0.021**	-0.029**	-0.003	-0.071***	-0.017
Ln House Prices	-0.149***	-0.128*	-0.239***	0.020	-0.176***
Ln Restaurants	-0.000	-0.728***	0.156	-0.224	0.194
Ln Tripadvisor Restaurants	0.022	0.006	0.012	0.105*	0.039
Ln Food Stores	-0.010	0.001	-0.017	0.025	-0.012
Ln Personal Services	0.091	-0.077	0.025	0.165*	0.114
Ln High Wage Jobs	-0.029	-0.133*	-0.062	-0.003	-0.003
Ln Med. Wage Jobs	0.030	0.076	-0.007	0.033	0.028
Ln Low Wage Jobs	0.070	0.046	0.176***	0.179*	0.025
Year FE	Yes	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes	Yes
Observations	454	454	454	454	454

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion

Short-term renting and home-sharing activities made through online platforms such as Airbnb have increased substantially over the past decade in most big cities in the world. This fact has attracted the attention of many researchers and policy makers in an attempt to understand and potentially regulate this relatively new and disruptive economic activity. Proposed regulation schemes such as imposing a limit to the number of days a residential home can be rented tourists, or in the number listings per host, mandatory presence of a permanent resident during the guests' stay, or outright prohibition, may all have large overall consequences as well as distributional impacts. Therefore, understanding whether and to what extent home-sharing may actually benefit or damage the well-being of city residents is an important policy question which is still not solved. To start answering this question, this paper builds a novel dataset that allows me to estimate the effects of Airbnb activity on important neighborhood characteristics as well as to fit this together in a more general framework of neighborhood demographic change.

My results suggest that Airbnb increases house prices, specially in centrally located neighborhoods that are more attractive to tourists. This suggests that local renters are harmed by Airbnb because they will have more difficulty in keeping up with housing costs. And this is particularly important for the case of central neighborhoods, which tend to feature higher rates of renter-occupied homes. On the other hand, homeowners benefit from home-sharing since their asset has a higher value. It also indicates that as houses increase in value, the importance of inheriting a home from family members grows, which could imply higher levels of generational persistence in inequality.

At the same time, Airbnb activity boosts some local businesses. In particular, home-sharing increases the number of restaurants and food stores in a neighborhood. However, there is also suggestive evidence that short-term rentals decrease the number of establishments focused on services that only locals consume. This suggests that Airbnb tourist apartments may, at least to some extent, be substituting resident population. One important distributional aspect is that although the increase in restaurants is likely to be enjoyed not only the residents of the neighborhood where they open (it is normal to go out to eat in a neighborhood different than the one you live in), the costs of losing establishments focused on locals necessities (barbers, gyms, etc.) is likely to fall on neighborhood residents that will have to travel to visit establishments that usually one consumes locally.

Airbnb activity is also associated with significant increases in local employment, although only lower wage types of jobs are positively affected by it. This is partially explained by the significant relation between Airbnb activity and local employment in the hospitality industry, which mostly offers low paying jobs. This could help young workers entering the labor force to get experience for getting better jobs later on, but won't solve long-run problems of neighborhoods in need of better quality jobs.

Additionally, Airbnb density is associated with significant changes in neighborhood level demographic variables. My results suggest a negative effect on population density, which mostly occurs through preventing people to move-in rather than directly pushing residents out. I also estimate a positive association of short-term rentals with neighborhood education levels, with the share of individuals that were born in an OECD country, and with the share of young adults in a neighborhood, although this last relationship is less robust. Using data on demographic characteristics on newly arrived residents in different neighborhoods I find evidence that the first two relations are mostly driven by increased house prices selecting higher income individuals, which tend to have higher education levels and higher probability of being from an OECD country. Regarding young adults, although increased house prices tend to reduce their presence relative to older individuals, Airbnb's positive effect on low wage jobs benefits the young the most. And it is also true that the unmeasured detrimental aspects for utility (noise, congestion...) tend to hurt young adults less than they do for the old.

Overall, my findings suggest that although Airbnb's effect on local neighborhood is multifaceted, the core neighborhood attribute that is both the most impacted by Airbnb activity and the most important in affecting residents utility are house prices. Thus, although policies may consider various angles of this issue, house prices should be the main outcome to consider. That being said, the heterogeneity of the economic relevance Airbnb's impact on house prices (Table 4) suggests that a city wide policy makes little sense. Given the high costs of total bans and strict limits, it could be more fruitful to think about policies that create incentives for spreading Airbnb activity more evenly throughout the city, so that the benefits of receiving visitors and the implied extra economic activity could be maintained, while avoiding that Airbnb's negative aspects fall entirely on the backs of residents of more touristic central neighborhoods. Improving tourist desirable amenities in usually non-touristic areas and having differential taxes for short-term rental apartments in distinct neighborhoods to adjust for their social costs are examples of policies that could be considered.

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