Airbnb and the housing market in Italy

Evidence from six Cities*

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Abstract

We study how the growth of Airbnb has affected the housing market in six important Italian cities – Milan, Turin, Venice, Florence, Rome, and Naples. These cities differ in terms of tourist attractiveness, seasonality of visitors, business and industry vocation, and morphological constraints to their boundaries. Our empirical strategy accounts for omitted variable bias as well as for reverse causality. We apply an instrumental variable approach by using two alternative measures of city-specific "touristiness" that vary within cities, according to the relevance of touristic attractions as reviewed by Tripadvisor and Lonely Planet, and over time, based on a measure of Airbnb popularity as proxied by GoogleTrends.

We find that Airbnb density leads to increases in rents and sale prices, but the effect varies greatly across cities and, even more, within cities (centre and suburbs). For some cities this impact is virtually non-existent, even in the town centre; for some is weak or even negative, but for others is sizeable. However, the overall quantitative effect remains modest, thus suggesting that attempts to regulate home-sharing and short-term rentals (from this point of view) have to be calibrated with much attention.

Keywords: Sharing economy, Airbnb, Housing market, Tourism, Core-periphery submarkets.

JEL Codes: R31, R21, L83, Z30

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1 Introduction

Airbnb's growth worldwide has been steady since the platform's launch, becoming a major economic actor in the real estate market. Italy is one of the countries most affected by this phenomenon, being Airbnb's fourth largest market after the USA, France and Spain. However, in recent years, concerns were raised about possible negative externalities of this expansion. Aside from a possible unfair competition to hotels, Airbnb short-term rentals might have a negative impact on both the long-term rental and the sale markets. To temper these negative effects, many national and municipal regulators have thus introduced policies that aim to limit the platform's expansion. For example, France and Japan introduced a cap on rental periods at 120 days per year. The city of Berlin instead banned the rental of entire homes in 2016; however the regulation has been revised in 2018, allowing for the rental of entire homes but introducing a 90 days cap for second homes (Duso et al., 2020). Other cities, like Barcelona and New Orleans, have introduced restrictions for specific zones in order to reduce Airbnb's presumed negative impact on the most attractive areas. The city of New York has instead introduced a policy that limits the number of listings to one per address. In Italy, in 2017, the government passed a legislation that required a registration of short-term rentals and obliged Airbnb to directly collect taxes on them, in order to lower tax evasion in the market. However, Airbnb fought this legislation, and in 2019 the State Council decided that this policy falls under the European Court of Justice (ECJ) jurisdiction. At present, the ECJ has yet to rule on the Italian case.[b]

Although the response by policymakers has been diverse and widespread, few studies have tried to identify the existence of a causal link between the diffusion of the platform and the effects on the housing market (see for example, Horn and Merante, 2017; Garcia-Lopez et al., 2020, Barron et al. 2020, Duso et al. 2020). The uncertainty surrounding the recent regulatory developments and the actual need of regulating on-line accommodation platforms provide a strong motivation to estimate the effects that Airbnb can have on the real estate market of the cities most affected by this branch of the sharing economy.

The aim of this paper is to provide evidence on the effect of Airbnb listings on housing rents and prices in six Italian cities – Milan, Turin, Venice, Florence, Rome, and Naples – which aptly represent the heterogeneity within the Italian housing market. To study this effect,

[b] In 2019, for a similar case in France, the ECJ ruled in favour of Airbnb, but then in 2020 another ECJ's decision established that national and municipal governments have the right to ask for the registration or authorisation of short-term rentals.

we collected data for each city from a variety of sources. Individual Airbnb listings were obtained from AirDNA, a large data provider of short-term rental analytics (AirDNA, 2021). Rent and sale prices were provided by Idealista, a major online real estate portal in Italy (Idealista, 2021).

Our research strategy starts by testing the impact of Airbnb on rents and sale prices for the six Italian cities altogether, and then takes the heterogeneity of their housing markets into account by estimating, for each city, the effect of Airbnb's intensity on rents and prices. The selected cities differ from each other in terms of touristic attractiveness, artistic heritage and safe-guards, business vocation, short- vs. long-term rental needs, size and geographical constraints, house building capacity, and seasonality of Airbnb demand. Because of this heterogeneity, we can obtain further insights by exploiting differences in the town-specific exposure of the real estate markets to Airbnb in central and peripherical areas, which also vary in terms of potential attractiveness for Airbnb listings, economic situation, and dynamics of the housing markets. This allows us to provide some evidence on whether the magnitude of Airbnb's effect only depends on the city itself or if it is contingent on the level of urbanisation of the different zones constituting the city.

We address potential endogeneity problems that may derive from omitted variable bias as well as simultaneity problems that may derive from shocks that cause a rental or sale price increase, influencing the decision to list the apartment. Since one of these shocks may be related to the attractivity of (some) areas, we apply an instrumental variable strategy that exploits the interaction of a potentially endogenous cross-sectional exposure variable (a measure of touristiness) with a reasonably exogenous time-series (Bartik, 1991; Barron et al., 2020, Garcia-López et al., 2020). We employ two alternative measures of touristiness derived from Tripadvisor (an American online travel company) and Lonely Planet (a travel guid book publisher). This required collecting data from Tripadvisor reviews and from Lonely Planet guidebooks of each city's touristic attractions, in order to compute the "touristiness" level of the different neighbourhoods at a pre-sample date (2011). We then interacted these scores with a worldwide Airbnb searches according to Google Trends.

We find that Airbnb intensity, measured by its density as well as by the number of listings in a zone, is positively related to both rents and house prices. Our empirical analysis shows that on average, an increase of 1 percentage point in Airbnb density leads to an increase of 0.38.% in sale prices and of 0.37% in monthly rents. The impact of Airbnb on house prices and rents, however, differs by city and, within each city, between the centre and the suburban areas. The evidence is stronger in Florence, Naples, Rome, and Turin (where we find a positive effect on sale prices but a negative impact on rents), less so in Venice and Milan. Interestingly, however, the magnitude of the effect is stronger in these two cities, where an increase of one standard deviation of city-specific Airbnb listing density leads to an estimated price increase of 124 €/m^2 and 76 €/m^2 respectively. The positive relationships persist when controlling for a large number of factors (to reduce the omitted variable bias), to various forms of yearly or quarterly time trends (by city and by area), and zone fixed effects. Our results are also robust to the implementation of the IV strategy, as the coefficients remain significant.

Our contribution to this growing literature is manifold. First, we are the first to analyse the impact of Airbnb's diffusion on rents and house prices for the Italian market. Second, by focusing on six cities that represent strongly heterogenous housing markets, we are able to capture the differentiated effect that Airbnb's diffusion can have, providing valuable information to policymakers of the need of a bespoke approach. Third, we examine the effects not only by city but also by sub-areas in each city, allowing us to pin down whether and to what extent the effect of Airbnb differs across the centre and the periphery. Obviously, the effects are larger in certain cities and in certain areas than in others, and here is where our selection of towns may be most useful. The evidence we have gathered so far motivates further studies.

The paper is organized as follows. In Section 2, we review the relevant literature from which we derive the conceptual framework. In Section 3, we describe the geographical scope of our study and describe Airbnb activity in the six cities. In Section 4, we describe the data and, in Section 5, the empirical strategy. In Section 6, we present the results and in Section 7 we conclude.

2 Related literature and conceptual framework

2.1 Empirical evidence

Our work is related to a growing literature that studies the economic impact of short-term rentals on the housing market.

Sheppard and Udell (2016) study Airbnb's impact on the value of New York City's residential property. They argue that Airbnb's diffusion can increase property value – e.g., by offering new income streams to house owners, thus reducing the cost of ownership; increasing the demand for space due to a growth in local tourist population; raising the quality of a neighbourhood due to the local economic impact of tourists – or decrease it, as the presence of tourists can impose negative externalities to residents. They find that doubling the number of Airbnb listings in a 300m radius around a property is linked with a 6% to 11% increase in its value. Horn and Merante (2017) inquire into the short-term effects on rents of Airbnb's penetration in Boston. They find that an increase in density of Airbnb listings equal to a standard deviation rises rents by 0.4% and reduces the number of units offered for rent by 5.9%. The increase in rent reaches 3.1% for neighbourhoods in the top decile for Airbnb density. Barron et al. (2020) study the impact of Airbnb on housing prices and rents in the USA. They find that a 1% increase in Airbnb listings leads to a 0.018% increase in rents and 0.026% in prices. They underline how these estimates change according to the degree of owner-occupancy of Airbnb listings, suggesting that the effect is driven by a reallocation of supply from the long- to the short-term.

Turning to the papers examining the impact in European cities, Ayouba et al. (2019) investigate whether Airbnb listings affect rental prices in eight French cities. They find that an increase in the number of Airbnb listings is linked to a raise in rental prices for some cities. A one percent increase in Airbnb density in a given neighbour leads to a 0.5 percent increase in rents in Pairs, which is the town that registers the highest impact. However, when considering commercial listings, the impact more than doubles to 1.2 percent. In some cities, Airbnb impact surprisingly increases with the share of home-occupiers, and it decreases with hotel density. Garcia-López et al. (2020) study the impact of Airbnb's diffusion in Barcelona's housing market. Their findings suggest that Airbnb had a significant effect on housing rents and sale prices in Barcelona, especially in the most touristic parts of town, where they attribute to Airbnb's presence a 7% increase in rents and a 17% and 14% increase in transaction and posted prices. They impute this to the reduction in the supply of housing units. Finally, Duso et al. (2020) assess Airbnb's impact on the rental prices in Berlin. They differ from previous studies in that they can exploit an exogenous shock caused by the enforcement of a law that limits short-term rentals to identify the impact of rents in the instrumental variable regressions. They find that an additional Airbnb listing increases by at least seven cents the average monthly rents by square meter. Table 1 provides a summarised view of the empirical methods adopted by the reviewed literature.

Table 1: Literature review

Author	Objective	Method	Dependent var	Independent var	Control variables
Sheppard and Udell (2016)	Effect of Airbnb on house prices in New York City.	Fixed-effect model (hedonic) and diff-in-diff. SE clustered at the census tract level.	Sale price of a specific house. Data from 2003 to 2015	Number of active listings in a 300m radius from the property sold. Active starting from first feedback. Alternative measures: price, capacity, bedroom, beds, reviews. 12 points in time during 2015-2016.	Information about the house being sold; presence of areas of interest (e.g., parks, cemeteries, airports, subway entrances); tax lot; census tract level information on education, racial and ethnic demographics, employment measures; crimes by precinct.[3] Year of sale and neighbourhood fixed effects. Not all data is at census-tract level.
Horn and Merante (2017)	Effect of Airbnb on asking rents and on the number of houses available for rent in Boston.	Fixed-effect model. Asking rents used with a 1-month lag with respect to the Airbnb density measure supposedly minimize the risk of reverse causation. SE clustered at the census tract level.	Asking rent of a specific house at a given month. Data for the six months from 08-2015 to 01-2016.	Density of Airbnb in a given census tract in the previous month. Density defined as number of listings over number of housing units.	Number of beds and bathrooms in the rented house, square footage. Number of newly built rental units in a given tract. Population, housing units, crime level, building permits and restaurant licenses issuances at the tract level. Census tract and month fixed effects.
Ayouba et al. (2019)	Effect of Airbnb on asking rents in eight French cities.	Hedonic regression allowing for heteroscedasticity and spatial error autocorrelation of unknown forms. Distinction between nonprofessional and professional renters[4] and on all tenancy agreements and only new ones. B-spline functions for some controls. Lagged variables to limit endogeneity.	Asking monthly rent of a specific apartment at a given year for 2014-2015.	Density of Airbnb listings in a given neighbourhood for a given year (from AirDNA). A differentiation in made between professional and nonprofessional hosts.	Structural characteristics of dwellings, accessibility to jobs and services, socioeconomic context, environmental quality around housing. Time fixed effects
Duso et al. (2020)	Effect of Airbnb on asking rents in Berlin.	IV using an exogenous shock: introduction of ban on the use of apartments as short-term rentals. They consider only “entire home” dwelling types because only these are affected by the law. SE clustered at the zipcode level.	Asking monthly rent per square meter of a specific apartment for 2013-2018.	Number of active listings in a 250m radius from the property sold. Monthly data from 2015 to 2018.	Neighbourhood characteristics such as number of restaurants, level of noise, air quality, age of buildings. Apartment characteristics such as the size, number of rooms, availability of parking. Points-of-interest such as bus stop, restaurants, supermarkets. Linear and quadratic monthly trend and zipcodes fixed effects.
Garcia-López et al. (2020)	Effect of Airbnb on housing market in Barcelona.	Fixed-effect models (hedonic). IV defined as the interaction of a measure of proximity to touristic amenities with Google trends.	Average residual resulting from hedonic regression of log rents on or prices on time dummies and unit characteristics. Data from 2007 to 2017.	Number of Airbnb listings. 21 points in time, from 2015 to 2018.	Neighbourhood and time fixed effects. Neighbourhood level time trends and demographic effects (i.e., average age, population density, average household occupancy rate, unemployment rate, relative income, and percentage of foreign residents).
Barron et al. (2020)	Effect of Airbnb on house prices and rents in the USA.	IV is the interaction of Google Trends global search index with a measure of how touristic a zipcode is in base year 2010 (measured as the number of establishments in the accommodation and food industries). SE clustered at the zipcode level. Variety of robustness checks.	Median sale price of houses at zipcode-month level. Median long-term rental price of houses at zipcode-month level.	Number of active listings in each zipcode (active starting from host join date). Data from 2008 to 2016.	Zipcode level 5-year estimate of income level, population, education, employment rate, owner-occupancy rate.[5] 1-year estimates of housing vacancy rates at the metropolitan area (CBSA). Zipcode fixed effects, CBSA time varying effects, correlated with number of listings.

[3] Not all data are available at the same geographic scale.
[4] For French law, a professional renter is one who rents either several “entire home” dwellings (regardless of the number of days) or an “entire home” dwelling for more than 120 days a year
[5] As these are not available at a monthly level, the authors linearly interpolate/extrapolate to the monthly level using the 2007-2011 and the 2011-2015 ACS 5-year estimates at the zipcode level.

2.2 The effect of home-sharing on the housing market

Beside estimating the impact of Airbnb on the housing market, this literature has analysed the mechanism of transmission of the impact, underlining how these effects can often go in opposite directions.

First and foremost, home-sharing has reduced many of the frictions that were present in the short-term rental market, both on a transactional and on a trust level (Einav et al., 2016). This attractiveness increase can lead some owners to switch from the long-term to the short-term rental market. Since housing supply is inelastic in the short term, this leads to a price increase in the former and to a price reduction in the latter, as observed by Horn and Merante (2017) and Zervas et al. (2017). The magnitude of the switching effect depends on many factors, some in favour of short-term rentals while others not. Short-term rental prices are usually higher than long-term prices, and they often elude or are subject to a more lenient revenue taxation. Owners can be attracted by the fewer restrictions given by short-term contracts, especially so in jurisdictions with strong tenant protection laws. On the other hand, owners could prefer long-term rentals due to risk aversion (e.g., due to fear of property depreciation caused by impolite short-term renters) or to reduce effort costs required by managing a short-term rental. In the long run, the quantity of houses that can supply short- and long-term rentals should increase, reducing the impact of home-sharing on the supply side. However, the magnitude of this effect is linked with multiple factors such as land availability and building regulations, as documented by Gyourko and Molloy (2015).

Second, home-sharing platforms can increase the attractiveness of previously less interesting city areas: this effect, documented in Farronato and Fradkin (2018) and Coles et al. (2018), can drive both long-term and short-term prices upwards due to a general demand increase. Relatedly, harsh increases of tourists' presence may lower the attractiveness of an area for local residents, as pointed out by Filippas and Horton (2018).

Finally, home-sharing effects on rent prices also reflect on sale prices. House value can be measured by the present value of all future revenues and costs, including possible incomes from renting (Poterba, 1984). As such, any change in the rental market is reflected on the sale market with a higher magnitude. Moreover, since home-sharing allows the owner to rent unused capacity, this additional source of possible future income should drive up sale prices even further.

Although the literature identifies various – and, to some extent, discordant – effects, both theoretical and empirical studies suggest that the predominant one is the substitution effect. Therefore, we expect to see an increase in rents prices where Airbnb activity is higher, and an even larger increase in sale prices due to the compounding effect of the sum of future revenues originating from the rental.

3 Geographical scope

3.1 National overview

As of 2011, the year of the latest nation-wide census, in Italy there were approximately 31 million houses, 24 million of which were either owner-occupied or rented. The remaining 7 million include empty houses, holiday homes, or occasional dwellings. This ratio may have facilitated Airbnb entry, giving homeowners a new channel to exploit underused capacity. As we can see from Figure 1, Airbnb growth in Italy has been steady from its entry in 2014, resulting in more than 450,000 listings as of 2019 (6.4% of the 7 million potentially available).

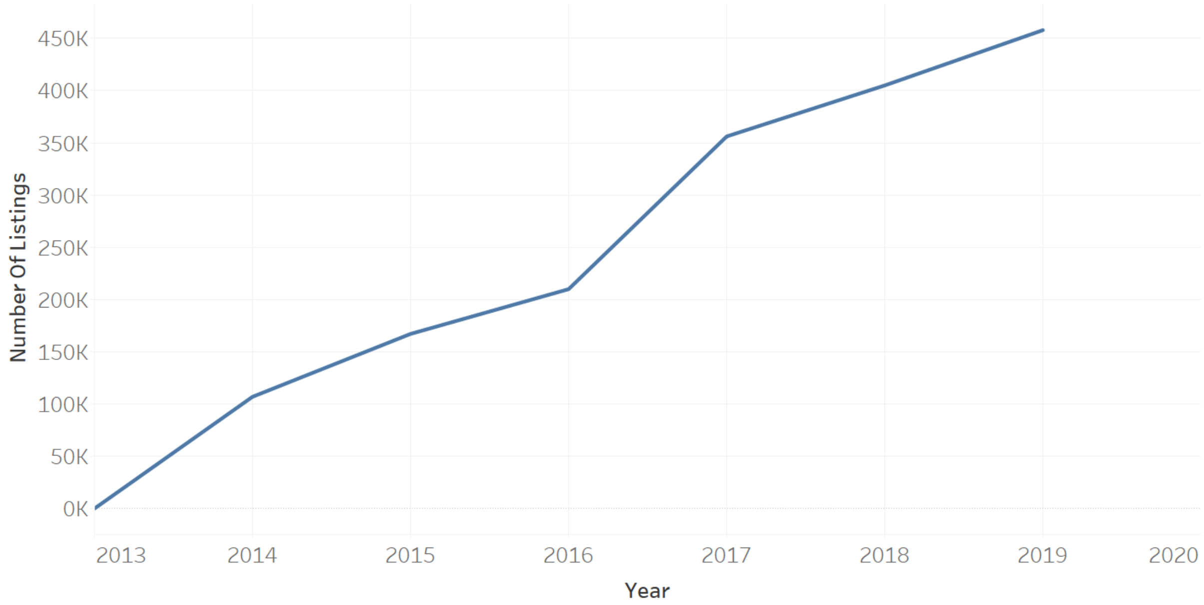


Figure 1: Number of Airbnb listings in Italy per year.

Figure 2 provides a measure of the activity of the Italian real estate market by reporting the yearly Normalised Transaction Number (NTN) from 2011 to 2019. The NTN is calculated by weighting each transaction according to the percentage of the property that is being transferred. The NTN followed a V-shaped curve, mostly due to the 2008 economic crisis.

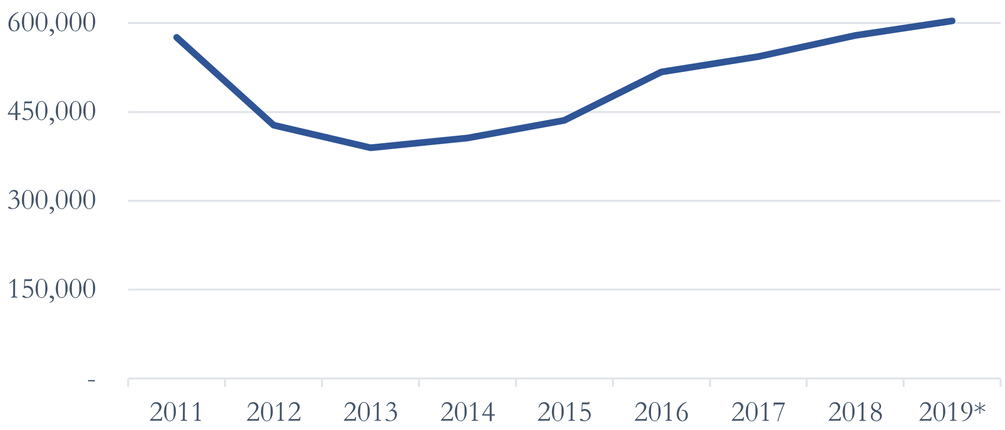


Figure 2: Yearly NTN for residential properties and buildings. Source: *OMI*.

Figure 3 reports the average rent and sale prices per square meter from 2012 to 2019. Sale prices have been steadily declining over time, while rent prices followed a V-shaped curve that closely resembles that of the NTN.

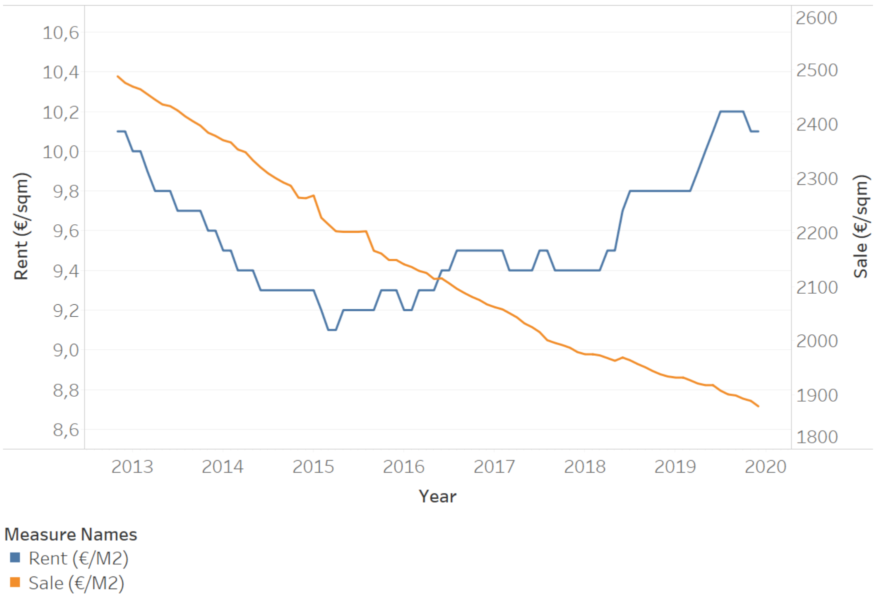


Figure 3: Average rent and sale price for square metre in Italy, from November 2012 to December 2019. Source: *OMI*.

Price trends differ greatly between rent and sale: while rent prices in the last years started to recover from the economic crisis, sale prices are still decreasing.

Overall, we find that the Italian real estate market fluctuated greatly in the last decade, both in demand and prices, despite a steady growth of Airbnb's presence in Italy. However, it is well known that Airbnb market presence is concentrated in sites with high tourist attraction: thus, we focus our study on cities where tourist demand is above average. Moreover, we include cities which attract residents through job opportunities or quality of life; this enables us to study the effect of a sizeable presence of Airbnb in markets where the real estate demand is also above average.

3.2 An overview of the six Cities of this study

Figure 4 shows the location of the six cities as well as their population as of 2020.

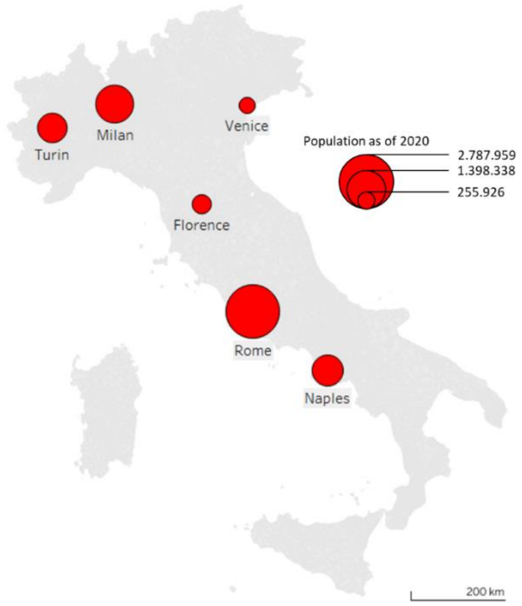


Figure 4: Location and population of the six cities.

The choice of this sample of city as an object for this study is driven by their inherent variety, their relative importance in the economic and political life of the country, and in the symbolic, worldwide fame as a touristic attraction. Rome and Milan are the two most populous cities in Italy and are respectively the first and second most visited cities. While their touristic attractiveness is undoubted, they also represent major points of interest for Italian citizens. Rome, being the capital of Italy, is home to most of the political headquarters: thus, it attracts many people looking to work in this sector. Moreover, some multinationals have their national headquarters in its peripheral area, which further amplifies the supply of jobs within the city. Milan, on the other hand, is the most economically active city in Italy, ranking first as the city with the highest income per capita. In the last decade, it has attracted workforce from all Italy and Europe, with a steady growth in population since 2001. These cities are characterised by a high demand for both short-term and long-term rental, and by an elastic supply: while existing homeowners can decide to offer their property, the real estate market can be easily expanded with the construction of new buildings.

Venice and Florence present a different situation: while they respectively rank third and fourth as most visited cities in Italy, their geographical extension is extremely limited when compared to Rome and Milan. Both Venice and Florence are capitals of their respective regions and have well established universities, attracting workforce and students as well as tourists. This results in a high demand both for short-term and long-term rentals, as well as real estate. However, the supply differs from the previous cities: while homeowners can still choose to offer their property, the possibility of constructing new buildings is very limited due to the already high density of these cities. This is particularly true for Venice, being it built on a lagoon.

Finally, Turin and Naples complete our analysis. These cities attract less tourists than the previous ones, ranking respectively tenth and sixteenth as most visited cities. However, they still are a major point of interest for Italian workforce: both Turin and Naples have been a staple for manufacturing and are home to various multinationals headquarters. Compared to previous cities, the demand for short-term rentals is lower, while the demand for long-term rentals and real estate is comparable. Moreover, since Naples is mostly visited due to its seaside, it allows us to analyse a case in which the tourist attractiveness is highly seasonal.

Table 2 reports descriptive statistics for the years 2015 (the first full year for which we have Airbnb data) and 2019. It presents the zone yearly average of two samples: all zones and high Airbnb density zones (i.e., those belonging to the top decile of the Airbnb listing density distribution). The table shows the extent to which Airbnb is concentrated in selected areas. In 2019, high Airbnb density zones had a higher occupancy rate and had about five times more listings than the average zone.

The data also testifies to the growth of the Airbnb phenomenon: in just four years, the average number of listings per zone almost tripled, the occupancy rate doubled, reservation days and revenues multiplied by five and six folds, respectively. This increase is similar for the high Airbnb density zones. Meanwhile, rents registered a small increase, while sale prices slightly reduced in the average zone (although they increased in the high Airbnb density ones). The number of houses and stores did not change significantly. In Appendix A, we report a table where this information is provided by city.

Table 2: Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m²]	12.44	16.78	13.83	18.71
Sale [€/m²]	3,367.11	5,001.12	3,316.41	5,326.48
Listings	144	694	324	1,556
Listing Density	2%	7%	3%	15%
Airbnb Revenue	€224,519	€1,269,693	€1,350,466	€8,103,833
Occupancy Rate	18%	25%	35%	41%
Reservation Days	2,318	12,328	12,101	66,267
(OMI) N. Houses	11,352	11,784	11,532	12,002
(OMI) N. Stores	3,019	5,103	3,112	5,160

Figure 5 shows, for each city, the evolution over time of zone averages in rents, sale prices and Airbnb listing density (computed as the number of listings divided by the number of dwellings in a given zone). Average listing density is given also for the zones belonging to the top decile of the Airbnb listing density distribution. Price trends in the six cities vary greatly from the national average previously analysed.

Airbnb density varies greatly between cities: while Rome, Florence and Venice all reach maximums of over 20% for the zones in the top decile, Milan, Turin and Naples barely reach 10%. This difference is mainly driven by the most central zones: while the first three cities have some central zones, which are almost completely dedicated to tourism, the latter three have city centres which mix both attractions for tourists and points of interest for citizens. Moreover, the real estate market trends are also heterogeneous: while cities like Florence and Milan have experienced a raise in both rent and sales prices, others show opposite trends. Turin has experienced a drop in both rent and sale prices, while in the other cities they have loosely followed the national average, with a slight recover of rents and a steady decrease in sale prices.

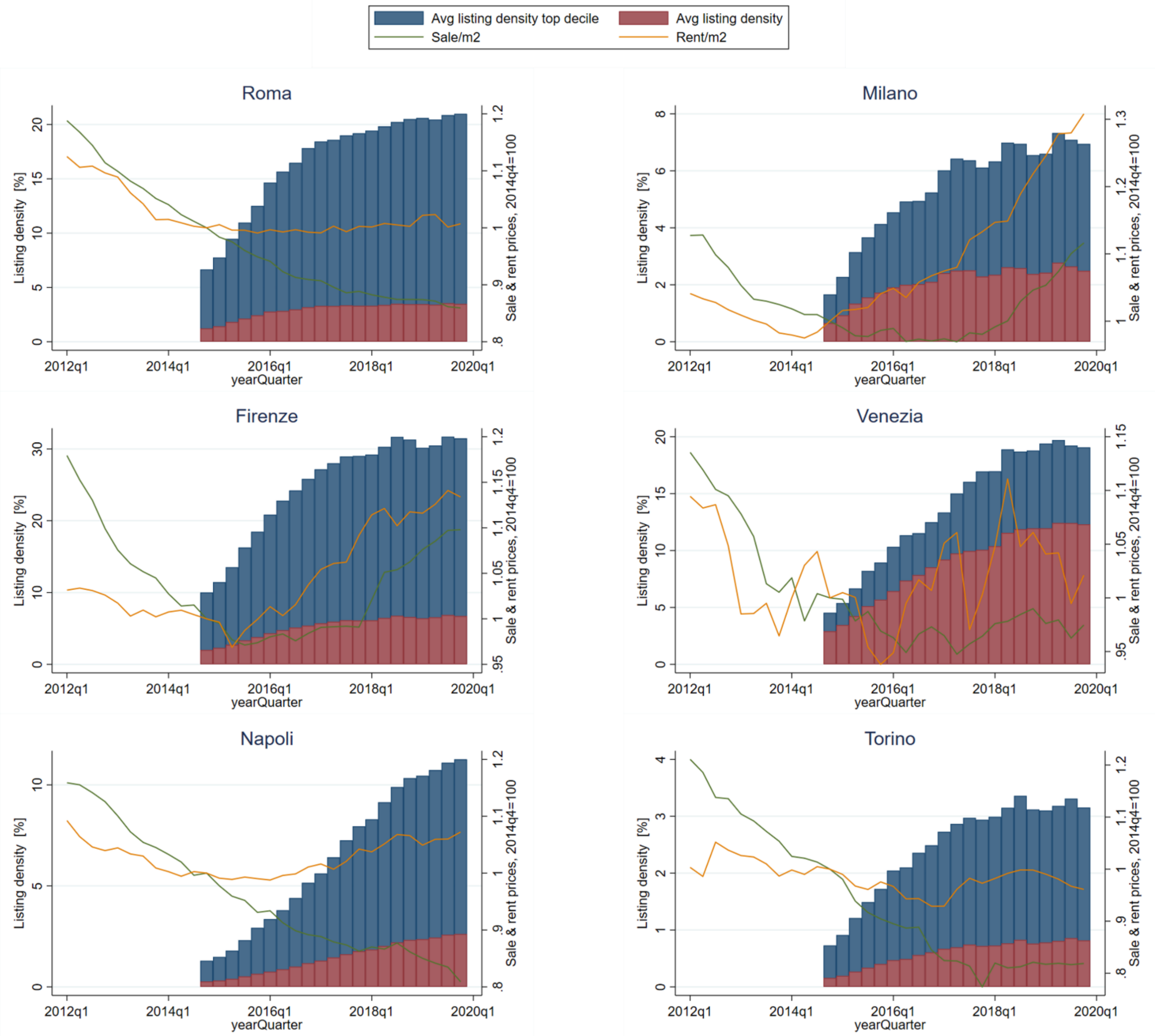


Figure 5: Airbnb density, rent and sale prices from 2012 to 2019.

4 Data

4.1 Rent and sale prices data and geographical aggregations

Our source of rent and sale prices is Idealista, a major online real estate portal operating in the Italian market (Idealista, 2021). Idealista divides each city into zones, that is, areas sharing common characteristics. Overall, for the six cities, Idealista data cover 301 zones from the first quarter of 2012 to the first quarter of 2020, and the number of zones for each city varies significantly according to each city's characteristics. For each zone, Idealista provides an estimate of the rental rates and transaction prices per square meter at the trimester level . We can thus think of the identification of a zone as being equivalent to that of a relevant market. By choosing Idealista's zones as our definition of neighbourhood, we can approximate the geographical scope of the individual housing market, as the real estate company has likely chosen the zones to minimise the area-specific heterogeneity and the information costs. This mapping allows us to compare different zones both across and within cities controlling for unobserved zone-level factors and helps us identify the effect of Airbnb. In the empirical analysis, we use two additional levels of geographical aggregation, both deriving from the *Osservatorio del Mercato Immobiliare* (OMI, the register of the real estate market in Italy): the OMI area and a measure of centrality. OMI is a branch of the Italian Taxation Authority, which provides techno-economic data on the Italian real estate market (OMI, 2021).[6] Like Idealista, the OMI divides each city into homogenous territorial areas sharing similar economic and socio-environmental conditions, the smallest being OMI zones, while the largest being OMI areas. OMI zones are typically smaller than Idealista's and are often contained within them. OMI areas are central, semi-central, peripheral, suburban and rural, although not every city has all of them. We assigned Idealista zones to their respective OMI areas – with some minor approximation. Furthermore, we introduced a measure of centrality given by a dummy equal to one when the OMI area is either central or semi-central and zero otherwise. Therefore, our geographic unit is the Idealista zone, which is further characterised by an OMI area (from now on referred to only as area) and by being central or peripheral (i.e., the suburbs).

4.2 Airbnb data

Data on Airbnb come from AirDNA, a provider of short-term rental data and analytics, which collects information directly from Airbnb's website (AirDNA, 2021). AirDNA provides two datasets: a property one and a daily one. The property dataset provides information on dwelling characteristics and rental conditions. The daily dataset provides, for each dwelling, rental outcomes such as whether the dwelling was available, rented, blocked and, if rented, at what price. This fine-grained detail allows us to measure Airbnb supply reliably: rather than using reviews or the listing's creation date as a proxy of activity, we can look at the actual days in which the property was available or rented. AirDNA data covers the period from October 2014 to December 2019. The datasets report the coordinates of each dwelling, albeit with a margin of error: for privacy reasons, Airbnb scrambles these coordinates so that the reported location of the dwelling is within a 150m radius from the actual ones. As the anonymised data changes over time, AirDNA provides an average of these values,

[6] OMI also provides of rents and prices of houses. However, these data are value estimates rather than based on transactions, and they are thus less appropriate for this analysis.

therefore increasing geolocation precision. Finally, these datasets allow identifying listings belonging to the same owner (i.e., a multi-host).

From these datasets, we obtain two measures of Airbnb intensity at the zone-trimester level: the number of listings and the listing density. The former is derived as the number of listings being offered for rent in a given trimester and reserved at least once during the year – a constraint needed to expunge listings that are not actually active. The latter is defined as the ratio between listings and houses in a given zone – where the number of houses is a measure sourced from the OMI dataset, as explained in the following subsection. As a refinement, we restrict our selection to those listings having a high chance to substitute long-term rents, which we refer to as commercial listings. A listing is labelled as commercial if it refers to a whole apartment while either being reserved for at least 90 days per year or belonging to a multi-host.

We merge the two datasets by assigning the listings to the zones. We drop the zones for which Airbnb data are missing while keeping those for which they are zero.

4.3 Control variables

Our control variables come from two sources: the OMI and the Italian 2011 census by the Italian National Institute of Statistics (ISTAT).

The OMI provides, at a year-OMI zone level, several measures that characterise the real estate stock. These are the number of housing units and their average number of rooms, the number of commercial activities and their average size in squared meters, the number of garages. These data are available from 2016 to 2019 for every city but Rome, for which they start from 2017. Furthermore, we extrapolate the data for 2015 (also 2016 for the city of Rome) and the last quarter of 2014, assuming a linear trend. While often an OMI zone is entirely contained within an Idealista zone, a degree of overlap exists in some cases. When this happens, we merge the data under the assumption that the real estate is uniformly distributed within the OMI zone and assigning a share equal to the percentage of overlap between the two areas to the Idealista zone. We derive the housing, store and garage density by dividing the corresponding stock to the area of the Idealista zone, expressed in hectares. We then use the number of houses at the Idealista zone level to calculate Airbnb density.

The 2011 census provides a wealth of data on demographics, education, occupation and housing characteristics (Istat, 2021). These are the number of residents, further characterised by age, education level, employment status and nationality; the number of owner-occupiers; the number of houses, further characterised by occupancy and physical condition. These data are provided at the census tract level for the cities in the analysis, and they are time-invariant and relative to 2011. To give an idea of the geographical resolution, note that, while Rome is divided into 117 Idealista zones, it consists of about 13,000 census tracts. Therefore, it is possible to characterise an Idealista zone with census data precisely.

4.4 Instrument

The cross-sectional part (share) of the shift-share instrument is a measure of tourist attractiveness of a given zone, which we obtain from Tripadvisor. For each city, we scrape the list of the top 150 tourist attractions, their coordinates and their respective number of reviews until the end of 2013; that is, before the start of our analysis' time window. We define a measure of the tourist attractiveness of a zone as follows:

$$Tourist\ Attractiveness\ TA_n = \sum_k^K \frac{reviews_k}{dist_{n,k}}$$

where n represents the zone, k the tourist attraction, $reviews_k$ the number of reviews of attraction k, $dist_{n,k}$ the distance of attraction k from the centroid of zone n expressed in kilometres.

Furthermore, we define an additional measure of tourist attractiveness that we use as a robustness test. We get the data from the Lonely Planet website, which lists the top 10 attractions by city, ordering them by popularity. We geolocate them through Google Map's API to get the coordinates. We define the additional measure as follows:

$$Tourist\ Attractiveness\ LP_n = \sum_k^{10} \frac{1/position_k}{dist_{n,k}}$$

where $position_k$ is the position of the attraction in Lonely Planet's list, and the other terms have the same meaning as before.

The shift-share instrument's temporal part (shift) is a measure of Airbnb intensity over time, which we derive from Google Trends. We get the number of worldwide searches of the word "Airbnb" at the monthly level. Google Trends provides percentages relative to the month with the highest number of searches. We convert these into absolute numbers by matching them with data from WordTracker, a website that provides absolute numbers of searches for the last 12 months.

Our instrument, referred to as "touristness", is thus the product of the cross-sectional and temporal components (see Garcia_Lòpez et al., 2020 and Barron et al., 2019 for a similar approach).

4.5 Final dataset

The resulting dataset consists of a balanced panel of 5,544 observations at the zone-trimester level. It comprises 264 zones and 21 time intervals from the last trimester of 2014 to the last of 2019. Table

3 presents summary statistics at the zone-trimester level except for census variables, which are time invariant.

Table 3: Summary statistics.

	Mean	SD	Min	Max	Observations
Idealista					
Rent [€/m²]	13.00	3.75	4.41	32.22	5499
Sale [€/m²]	3,292.84	1,427.41	694.44	10,889.59	5544
Airbnb					
Airbnb Listings	261.37	514.49	0.00	7281.00	5544
Airbnb Density	0.03	0.05	0.00	0.44	5544
OMI					
House Density	47.60	33.22	0.15	161.09	5544
Store Density	13.96	13.43	0.03	75.95	5544
Garage Density	16.21	11.52	0.00	43.77	5544
Avg. House Rooms	5.09	0.62	3.78	7.24	5544
Avg. Store m²	44.52	13.28	9.84	98.29	5544
Num. Residents	20,437.05	14,030.20	1,072.05	71,855.31	5544
CENSUS					
% Owner-occupancy	0.64	0.10	0.29	0.83	5544
% 20-39 years	0.23	0.03	0.17	0.37	5544
% >60 years	0.24	0.05	0.08	0.36	5544
% Graduates	0.20	0.10	0.03	0.44	5544
% Working	0.41	0.06	0.18	0.53	5544
% Foreigners	0.10	0.06	0.01	0.37	5544
% Full houses	0.93	0.06	0.56	1.00	5544
Num. Houses	9812	6625	249	30496	5544
% House in poor condition	0.15	0.14	0.01	0.78	5544
IV					
Touristness - Tripadvisor	347,899,480.70	444,183,179.58	18,148,189.31	5,268,453,471.83	5544
Touristness - Lonely Planet	28,494.89	31,309.34	1,927.31	289,738.75	5544

5 Empirical methods

We start by estimating the following baseline model:

$$\log(Y_{n,t}) = \beta Airbnb\ Intensity_{n,t-1} + \gamma X_{n,t} + \delta F_n + \tau_y + \varepsilon_{n,t} \qquad (1)$$

where $Y_{n,t}$ is either rents or sale prices in zone n at year-quarter t. $Airbnb\ Intensity_{n,t-1}$ is the listing density in zone n at time $t-1$.[7] $X_{n,t}$ is a matrix of time-varying controls in zone n at time t and F_n

[7] Listing density is the ratio between the total number of Airbnb listings and the total housing stock in the zone. In the robustness section, we will also use the number of listing to measure the presence of Airbnb.

is a matrix of time-invariant characteristics of zone n. τ_y are year fixed effects. $\varepsilon_{n,t}$ is a mean-zero error term.

Our main coefficient of interest in (1) is β, which captures the overall effect of the Airbnb intensity measure on the dependent variable. We lag the variable of interest to reduce reverse causality concerns, and we address the risk of omitted variable bias by controlling for time-varying and time-invariant demographic and structural characteristics at the zone level. We cluster standard errors at both the zone and city-area levels to account for correlation across the time-dimension within zones as well as for spatial correlation across the city-areas (see Cameron et al., 2011, and, for the empirical implementation in Stata, Baum, Nichols and Schaffer, 2011).

Next, we add the zone fixed effects to this specification (thereby losing all time-invariant zone level characteristics) and, starting from the third model, we control for more sophisticated time effects to account for different time trends across cities, within cities, and seasonality. The 6 cities are indeed differently exposed to touristic flows, business trips, occurrence of exhibitions and fairs (with different seasonality), as well as characterised by different economic performance and business cycles, so that we can safely assume that the housing market dynamics may differ not only across cities but also within cities. The different exposition to touristic flows and Airbnb presence of the centre and the periphery of metropolitan cities like Milan or Naples may well imply different pricing dynamics, and this we try to take into account. We thus refine the specification by introducing an appropriate set of interacted time and location fixed effects, at different level, as per the following model:

$$\log(Y_{n,t}) = \beta Airbnb\ Intensity_{n,t} + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t} \qquad (2)$$

where all terms have the same meaning as before, except for μ_n which is a zone-specific fixed effect, $\pi_{s,i}$ is the interaction between city *i* and quarter *s* (to account for city-specific seasonality) and $\tau_{y,i,a}$ is the interaction among year, city and city-centre (vs. periphery) effects that controls for the different economic and housing market trends. Note, however, that when we add the zone fixed effects, all time-invariant controls cannot be estimated.

Equations (1) and (2) do not allow to estimate a city-specific effect of the impact of Airbnb nor to allow for different effects between the city centre and its periphery. To investigate these further issues, we estimate the following models:

$$\log(Y_{n,t}) = \beta Airbnb\ Intensity_{n,t}\#city_i + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t} \qquad (3)$$

and:

$$\log(Y_{n,t}) = \beta Airbnb\ Intensity_{n,t}\#city_i\#centre_b + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t} \qquad (4)$$

where all terms have the same meaning as before, except for $Airbnb\ Intensity_{n,t}\#city_i$ which is the interaction between listing density in zone n at time t with the city i, and $Airbnb\ Intensity_{n,t}\#city_i\#centre_b$, which is the interaction among listing density in zone n at time t with city i and the indicator variable that denotes the city centre.

5.1 Instrumental variable

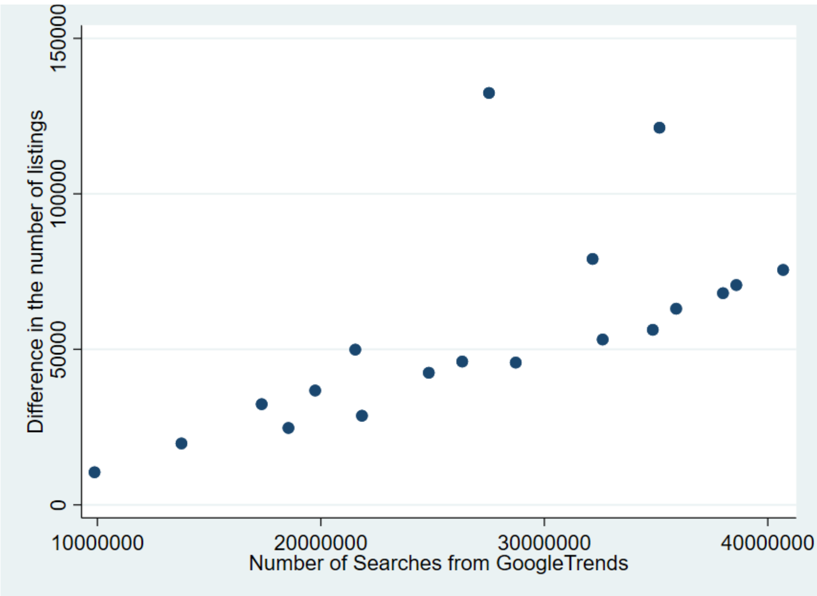
Our previous specifications control for unobserved factors at the zone and city-year and city-quarter level, but do not yet account for unobserved zones-specific and time-varying factors contained in the error term $\varepsilon_{n,t}$ and correlated with the measure of Airbnb intensity $Airbnb\ Intensity_{n,t}$. To address these and other endogeneity concerns, we also re-estimate our models using two-stage least square regressions. Following the approach introduced by Bartik (1991), we make use of a shift-share instrument combining a cross-sectional variation across zones of a measure of touristic attraction, and an aggregate time variation of a measure of Airbnb intensity (see details on how it is obtained in Section 4.4). Such an instrument has been adopted in the literature on the analysis of Airbnb's impact on the housing market by Garcia-López et al., (2020) and Barron et al. (2020).

Our shift component is given by the number of worldwide Google searches of the word "Airbnb" in a trimester. This measure acts as a proxy of Airbnb intensity by representing the extent of public awareness of the platform on both the demand and supply sides. Using a global measure makes it unlikely for it to be correlated with tourism trends at the local level. Finally, as pointed by Barron et al. (2020), the measure should reflect the growth of the short-term housing supply only where caused by Airbnb.

The share component is given by the level of touristic attractiveness of a zone in the base year 2013. We follow the approach by Garcia-López et al., (2020) of estimating it by calculating the distance of each Tripadvisor touristic attractions from the centroid of a zone, where the attraction is weighted using the number of reviews (see Section 4.4). However, to prevent reverse causality issues, rather than using all reviews, we use only reviews written before the year 2013 (our Airbnb data start in 2014). This way, we derive an ex-ante, out-of-sample measure of touristiness, avoiding the simultaneity problem we would have as the increase of Airbnb intensity would determine a higher number of reviews. A zone with a higher score of touristic attraction is expected to exert a stronger pull on tourists, as it underlines a closeness to attraction points.

The effectiveness of the instrument hinges on the fact that property owners must become increasingly likely to offer their property on Airbnb online portal after becoming aware of the platform. Following Barron et al. (2020), we test this hypothesis by looking at the relationship between Google searches and the difference in the number of listings between touristic and non-touristic zones.[8] Figure 6 provides a visual representation that the hypothesis holds, as this difference increases with the number of Google searches (with two possible outliers).

Figure 6: Difference in the number of listings between high- and low-touristiness zones.



The validity of the instrument requires that the interaction of the shift and share components be uncorrelated with the error term $\varepsilon_{n,t}$. For this to happen, it is sufficient that either the ex-ante touristic attractiveness in 2013 is uncorrelated with time-varying zone-level shocks, or the Google searches of the word Airbnb are not correlated with them in a systematic way so that the correlation is stronger or weaker in more touristic zones (Barron et al., 2020).

The resulting instrument is reasonably uncorrelated with the error term $\varepsilon_{n,t}$, but it is highly correlated with listing number or density as confirmed by first-stage estimates.

[8] We split zones according to touristness depending on whether they are below or above the median.

6 Results

6.1 The overall effect of Airbnb density

Table 4 and Table 5 present the results of the overall impact of Airbnb on the sale prices and rents (€/m^2) for the six Italian cities over the period 2014-2019. Columns from (1) to (3) report the OLS and fixed effect results while columns (4) and (5) present the IV estimates with instruments derived from Tripadvisor and Lonely Planet, respectively, and with the first-stage results at the bottom of the table. The intensity of Airbnb is measured by listing density (number of listings divided by number of dwellings) in the Idealista market zone.[9] Therefore, our estimates represent the semi-elasticity of rents and prices with respect to Airbnb intensity.

In Table 4, results show that the listing density positively affects house prices. In our simplest specification, the coefficient implies that an increase of 1 percentage point in Airbnb density leads to an increase of 0.750% in house prices, but the estimate is not statistically significant at the conventional levels. In Column (1), however, we can evaluate the relationships between house prices and our large set of control variables. We find that, on average, dwellings are more expensive in zones where the density of shops is higher and parking lots are scarce (presumably the city centre). Moreover, house units are more expensive in zones where the proportion of elderly and more educated people is higher. In contrast, the average price is lower in zones where many non-EU immigrants and unemployed people live. Finally, house prices appear lower in zones where the share of owner-occupier is higher (in line with evidence by Ayouba et al., 2019 and Barron et al., 2020). When the owner lives in her home, there may be no reallocation from the long-term to the short-term rental markets, but she can sell through Airbnb unused capacity, thereby increasing short-term supply and, therefore, decreasing rental rates and, in turn, house value. Although the coefficient is not significant at conventional levels, we will further exploit the presence of owner-occupiers to investigate the issue of city space reallocation.

When we move to more robust specifications that include zone and time interacted fixed effects in Columns (2) and (3), the estimated coefficients of the variable of interests turn significant. In Column (2) the coefficient is highly significant and rises to 0.922. However, when we control for city- and area-specific time effects, the size of the coefficient shrinks to 0.311, i.e., a 0.311% increase in house prices following a one percentage point increase in Airbnb density. Based on the more conservative estimate, we find that a density increase of 5 percentage points (one standard deviation) leads to a sale price increase of 1.56%. Using the average sale price in Table 3 as a basis, that would

[9] In the robustness section, we report the results when using the number of listings as the variable of interest.

amount to a 52.2 €/m^2 increase. Finally, Columns (5) and (6) report the estimated coefficients of the 2SLS regressions. Notably, the first-stage results show that the correlation between Airbnb density and the instrument is very strong for both. We find that the Tripadvisor-based IV coefficient is 0.384, similar to the fixed effect results in Column (3). The instrument based on Lonely Planet touristic attractions leads to estimate a much stronger effect, with a coefficient of 0.769 that would imply a sale price increase of 128.6 €/m^2 in zones where Airbnb density increases by 5 percentage points. While the similar coefficient in Column (4) may suggest that the effect of omitted factors in Column (3) is small or, if any, they cancel each other out, the higher estimate in Column (5) hints at a possible underestimation of the effect. This could derive from a measurement error in the availability for booking of the number of listings used to calculate Airbnb density (Barron et al., 2020). This possibility motivates a further analysis where we try to account not only for availability for booking, but also for the presence of professional listings.

Table 5 repeats the regressions with the (log of) rental monthly rates as the dependent variable. The evidence is much weaker, and the density coefficient is significant only in Column (2), where we include zone and year fixed effects. When we control for city, area and season specific fixed effects the coefficients are insignificant, also in the IV estimates, in spite of the good performance of the instruments in the first-stage regressions. However, in Column (1) we find that many control variables correlate to rents in the same direction as they did with sale prices. One exception is the sign on the share of foreigners, which is now positive, probably because in these zones the turnover, and the possibility to increase the rate, is higher. Moreover, we find that average number of rooms of the house unit bears a negative coefficient, probably because the dependent variable is the monthly rate at the m^2. Using the estimates of Column (2), an increase of one percentage point in Airbnb density leads to an average monthly rate increase of 0.366% in the zone. This corresponds to an increase of 24 €cent/m^2. We suspect that the weak significance of the overall Airbnb effect in the rental market might be due to the heterogeneity across the six cities, thus providing a further motivation for the next step of our analysis, where we allow for city-specific effects.

6.2 The effect of Airbnb density by city

When we turn to the estimates by city, in Table 6, we find that the effects differ greatly across the six towns. The size of the coefficients, however, has to be adjusted considering the actual prices in the housing markets of the different cities, which we report in Appendix A. For example, 2019 prices in Venice and Rome more than double those in Turin, while prices in Florence and Milan are a bit lower than in Venice and much higher than in Naples. Interestingly, we observe that the estimated coefficients in Columns from (3) to (5) are very similar and more stable, including the IV estimates generated by different instruments, thus suggesting that trying to estimate an overall Airbnb effect across a pool of highly different cities is a difficult exercise. We verify a cross-specification stability of coefficients on both sale prices and rental rates (though at a lesser extent). Notably, if we look at the IV results, the impact of Airbnb density on house prices is always positive, though significant for four out of six cities. The effect on rental rates is instead positive and significant for three cities but negative for two.

Looking at Column (4) of Table 6, the impact on house prices is significant in Florence, Naples, Rome and Turin, while in Milan and Venice the coefficients are positive but not far from significance. Possibly in Venice the market is already saturated, and the turnover low.

Using the estimates in Column (4), the effect of an increase of one percentage point in Airbnb density may lead to a 9.7% increase of sale prices in Turin (where the sale price point in 2015 was 1820 €/m^2), 2.2% in Milan (3465 €/m^2), 1.37% in Naples (2633 €/m^2) and (just) 0.14% in Rome (3947€/m^2) or 0.58 in Venice (with 4129 €/m^2, i.e., the highest average price).

Calculating the quantitative effects based on the 2015-2019 average city-specific listing density in the 2015-2019 period (Appendix A), we find that house price increases (€/m^2) range from 124 €/m^2 in Venice (the highest) to 11 €/m^2 in Rome and Naples (the lowest), with Milan at 76 €/m^2, Turin 53 €/m^2 and Florence 29 €/m^2. However, looking at the city-specific values in high density zones in 2019, where Florence scores 31% and Rome and Venice 19%, it is reasonable to conclude that the price increases would be much higher than what implied by the sample period averages we have used.

Turning to the results for rental rates in Table 7, we find again that the coefficients are not only more stable than the overall estimates in Table 5, but also more precisely estimated. Interestingly, and perhaps surprisingly, the impact on rents is negative in Turin and (insignificantly so) in Milan. It remains positive and strong in Naples, Florence and Rome, and statistically insignificant in Venice. The city-level rents are, on average, more similar, with the highest in Venice and lowest in Turin. Back-of-the-envelope calculations based on Column (3) of the table show that the monthly rate increase in Rome and Florence is very modest, 5-6 €cent/m^2. The evidence at the city level confirms that results depend very much on the size and the boundaries of the housing market's definition that we apply to district-related characteristics. This is not surprising, as we have already emphasised the extent of the differences across the six cities in this study, which leads us to the next step, where we explore the different Airbnb impact in the central and peripheral zones of each city.

6.3 The different impact of Airbnb in the city centre and in the periphery.

Table 8 and Table 9 report the results obtained estimating equation (3) where Airbnb density is interacted twice, with each city and with central and peripheric zones, so as to show possibly different effects in magnitude and in sign. Same as before, the quantitative effects have to be calibrated based on the area-specific density and house market characteristics. Comfortingly, we find that in most cases coefficients are quite stable, especially across the results in Columns from (3) to (5). Focusing on house prices from Table 8, we find that the impact of Airbnb is always positive only in Florence and in Milan (where it is significant only in the city centre). Conversely, we find that in Turin and in Naples the effect is positive in the centre and negative in the periphery, while in Rome and Venice we find that the presence of Airbnb does not affect house prices in the centre but seems to negatively influence prices in the suburbs. Although the literature has considered potentially negative externalities related to heavy densities of Airbnb (Barron et al., 2020; Filippas and Horton, 2018), the negative signs are not easy to rationalise, especially because they materialize in the suburbs. This could suggest the presence of some omitted variable, escaping our set of multiple time and area interactions, or a perverse effect of the success (and profit opportunity) of Airbnb in the city centre, causing an increase in the demand of unoccupied central dwellings. In other words, a run towards the centre instead of away from the centre. In this regard, a useful twist in the analysis would be to control whether the effect is particularly strong in zones where the number of unoccupied units is higher.

Turning to the effect on rental rates in Table 9, we find a similar pattern of alternate signs in the city centre and in the suburbs. We find that rents significantly increase in the centre of Florence, Rome and Naples, and decrease in the centre of Turin and of Milan, denoting a specular trend if compared to sale prices. Conversely, there is no effect in the centre of Venice (which is expected to be quite saturated) but we note a positive impact in the suburbs, which in the case of Venice include the Lido and some of the small islands in the Laguna, in contrast with the decrease in sale prices we have found in Table 8. Perhaps the rent increase is due to substitution effect between short- and long-term rental, thus reducing the supply in rental space.

7 Conclusions (preliminary)

We have studied how the growth of Airbnb presence has been affecting the housing market in six important Italian cities – Milan, Turin, Venice, Florence, Rome, and Naples - which differ in term of tourist or visitor attractiveness, seasonality of inflows, business and industry vocation, and morphological constraints to the extension of their boundaries. Notably, the real estate markets in these cities are also very heterogeneous, as average prices and rents can even vary from one city to another by 100%.

Our empirical strategy accounts for omitted variable bias as well as for reverse causality. We applied an instrumental variable approach which employs two alternative measures of city-specific “touristiness” that vary within cities, according to the presence and relevance of touristic attractions as reviewed by Tripadvisor and Lonely Planet, and over time, according to a measure of Airbnb popularity over the years proxied by GoogleTrends.

We have found that Airbnb density and numerosity of listings lead to increases in rents and sale prices, but the effect varies greatly across and within cities. For some cities it is virtually non-existent, not even in the town centre, for some is weak, and for others is more evident. However, the quantitative effects in (at least some cities) remain modest, thus suggesting that any attempt to regulate (from this point of view) home sharing and short-term rentals have to be calibrated with much attention.

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Table 4: Airbnb Density and house prices

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	IV Tripadvisor	IV Lonely Planet
Airbnb Density at t-1	0.750^	0.922***	0.311**	0.384***	0.769**
	(0.472)	(0.239)	(0.120)	(0.128)	(0.287)
House Density	-0.00107	-0.00480	0.00387*	0.00363	0.00232
	(0.000883)	(0.00425)	(0.00222)	(0.00211)	(0.00220)
Store Density	0.00729***	0.0629***	0.0161	0.0171	0.0227*
	(0.00208)	(0.0173)	(0.0110)	(0.0115)	(0.0120)
Garage Density	-0.00736**	0.0165*	-0.000495	-0.000558	-0.000890
	(0.00310)	(0.00868)	(0.00489)	(0.00498)	(0.00550)
Avg. House Rooms	0.0499	-0.0562	0.0320	0.0312	0.0266
	(0.0333)	(0.0662)	(0.0517)	(0.0520)	(0.0524)
Avg. Store Mq	-0.000981	-0.00133	0.00582*	0.00576*	0.00544
	(0.00157)	(0.00386)	(0.00326)	(0.00323)	(0.00316)
Num. Residents	0.00000954				
	(0.00000769)				
% Owner-occupancy	-0.382^				
	(0.225)				
% 20-39 years	1.323				
	(1.098)				
% >60 years	1.560***				
	(0.527)				
% Graduates	2.410***				
	(0.428)				
% Working	2.171***				
	(0.627)				
% Foreigners	-1.338***				
	(0.428)				
% Full houses	0.0725				
	(0.410)				
Num. Houses	-0.0000223				
	(0.0000172)				
% House in poor condition	-0.0525				
	(0.110)				
First-stage results					
TA Touristness at t-1				7.98e-11***	0.00000100***
				(5.48e-12)	(0.000000276)
F-stat. excluded instrument				58.841	93.417
Control variables					
Year FE	X	X			
Zone FE		X	X	X	X
Quarter#City FE			X	X	X
Year#City#Area FE			X	X	X
Observations	5,280	5,280	5,280	5,280	5,280
Adjusted R2	0.79	0.97	0.98		

Table 5: Airbnb Density and Rental Rates

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	IV Tripadvisor	IV Lonely Planet
Airbnb Density at t-1	0.301	0.366*	0.0779	0.0784	0.212
	(0.381)	(0.189)	(0.109)	(0.0956)	(0.282)
House Density	-0.000863	0.00130	0.000583	0.000582	0.000129
	(0.000817)	(0.00334)	(0.00214)	(0.00206)	(0.00231)
Store Density	0.00565**	0.0378***	0.00940	0.00941	0.0113
	(0.00212)	(0.0102)	(0.0126)	(0.0126)	(0.0108)
Garage Density	-0.00655*	0.0141	0.000201	0.000201	0.0000902
	(0.00321)	(0.00912)	(0.00624)	(0.00624)	(0.00620)
Avg. House Rooms	-0.0907***	0.00496	-0.0469	-0.0469	-0.0484
	(0.0258)	(0.0821)	(0.0645)	(0.0645)	(0.0644)
Avg. Store Mq	-0.00202^	-0.00694**	0.00235	0.00235	0.00223
	(0.00123)	(0.00259)	(0.00163)	(0.00162)	(0.00162)
Num. Residents	0.00000604				
	(0.00000872)				
% Owner-occupancy	-0.295				
	(0.190)				
% 20-39 years	-0.983				
	(0.682)				
% >60 years	0.570				
	(0.432)				
% Graduates	1.352***				
	(0.333)				
% Working	1.990***				
	(0.490)				
% Foreigners	0.597*				
	(0.324)				
% Full houses	0.334				
	(0.332)				
Num. Houses	-0.0000184				
	(0.0000200)				
% House in poor condition	-0.0115				
	(0.0871)				
First-stage results					
TA Touristness at t-1				7.97e-11***	0.000000999***
				(5.51e-12)	(0.000000278)
F-stat. excluded instrument				58.841	93.417
Control variables					
Year FE	X	X			
Zone FE		X	X	X	X
Quarter#City FE			X	X	X
Year#City#Area FE			X	X	X
Observations	5,237	5,237	5,237	5,237	5,237
Adjusted R2	0.69	0.95	0.96		

Table 6: Airbnb Density and house prices by City

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	IV Tripadvisor 2nd stage	IV Lonely Planet 2nd stage
Airbnb Density at t-1 in:					
Florence	-0.00318	1.367***	0.254***	0.282***	0.310***
	(0.311)	(0.291)	(0.0300)	(0.0669)	(0.0586)
Milan	2.913*	3.858***	1.681	2.211	2.985*
	(1.446)	(0.747)	(1.310)	(1.627)	(1.470)
Naples	0.274	0.231	1.126^	1.372**	1.356**
	(0.603)	(0.974)	(0.656)	(0.648)	(0.497)
Rome	1.719***	0.0607	0.0809**	0.139*	0.152
	(0.331)	(0.258)	(0.0340)	(0.0760)	(0.0925)
Turin	-19.71**	-0.955	8.334***	9.718***	7.356***
	(8.341)	(3.723)	(2.258)	(0.714)	(1.312)
Venice	1.006***	0.602***	-0.0296	0.585	0.634
	(0.326)	(0.159)	(0.426)	(0.411)	(0.460)
Time invariant controls	X				
Time varying controls	X	X	X	X	X
Year FE	X	X			
Zone FE		X	X	X	X
Quarter#City FE			X	X	X
Year#City#Area FE			X	X	X
Observations	5,280	5,280	5,280	5,280	5,280
Adjusted R2	0.82	0.98	0.98		

Table 7: Airbnb Density and Rental Rates by City

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	IV Tripadvisor	IV Lonely Planet
Airbnb Density at t-1 in:					
Florence	-0.236	0.587***	0.132***	0.168***	0.181***
	(0.290)	(0.163)	(0.0459)	(0.0494)	(0.0510)
Milan	3.422***	3.191***	-0.197	-1.333	-1.917
	(1.041)	(1.031)	(0.706)	(1.446)	(1.220)
Naples	1.000	1.378***	1.430***	1.524***	1.974***
	(0.668)	(0.457)	(0.302)	(0.334)	(0.352)
Rome	0.913***	-0.380	-0.123	0.167*	0.243*
	(0.318)	(0.329)	(0.135)	(0.0943)	(0.123)
Turin	-24.40***	-3.018^	-2.028*	-1.945***	-1.643*
	(7.706)	(1.901)	(1.085)	(0.520)	(0.809)
Venice	0.359	0.0728	-0.216^	-0.105	0.0922
	(0.257)	(0.116)	(0.134)	(0.334)	(0.337)
Time invariant controls	X				
Time varying controls	X	X	X	X	X
Year FE	X	X			
Zone FE		X	X	X	X
Quarter#City FE			X	X	X
Year#City#Area FE			X	X	X
Observations	5,237	5,237	5,237	5,237	5,237
Adjusted R2	0.78	0.96	0.96		

Table 8: Airbnb Density and House Prices by City, City Center and Suburbs

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	IV Tripadvisor	IV Lonely Planet
Airbnb Density at t-1 in:					
Florence suburbs	4.676**	6.860***	-0.134*	3.366**	3.818*
	(2.133)	(1.458)	(0.0742)	(1.570)	(1.877)
Florence central	0.0790	1.225***	0.256***	0.294***	0.330***
	(0.275)	(0.231)	(0.0298)	(0.0746)	(0.0700)
Milan suburbs	1.346	3.701***	3.835	7.604	7.989
	(1.857)	(1.089)	(2.686)	(6.002)	(5.551)
Milan central	3.263**	3.443***	0.220	2.065*	2.782***
	(1.264)	(0.730)	(0.593)	(1.061)	(0.823)
Naples suburbs	0.487	-5.980***	-2.223*	-1.457	-2.488**
	(1.911)	(1.490)	(1.150)	(1.292)	(0.916)
Naples central	0.717	0.507	1.442***	1.444**	1.457***
	(0.590)	(0.729)	(0.387)	(0.583)	(0.408)
Rome suburbs	7.081	-6.942*	-1.901***	-5.516**	-5.440**
	(5.169)	(3.934)	(0.646)	(1.999)	(1.933)
Rome central	1.733***	0.0144	0.0789**	0.108	0.127
	(0.349)	(0.249)	(0.0364)	(0.0800)	(0.0948)
Turin suburbs	-83.29***	-25.63***	18.26***	-7.280***	-26.69***
	(14.95)	(5.460)	(0.685)	(1.260)	(2.336)
Turin central	-15.17***	1.309	6.817***	10.12***	7.586***
	(2.907)	(1.508)	(0.251)	(0.272)	(0.291)
Venice suburbs	8.598***	0.904	-7.239***	-5.138***	-4.809**
	(2.168)	(0.954)	(0.777)	(1.551)	(1.685)
Venice central	1.060***	0.523***	0.0987	0.523*	0.581
	(0.304)	(0.160)	(0.143)	(0.298)	(0.337)
Time invariant controls	X				
Time varying controls	X	X	X	X	X
Year FE	X	X			
Zone FE		X	X	X	X
Quarter#City FE			X	X	X
Year#City#Area FE			X	X	X
Observations	5,280	5,280	5,280	5,280	5,280
Adjusted R2	0.85	0.98	0.98		

Table 9: Airbnb Density and Rental Rates by City, City Center and Suburbs

	(1)	(2)	(3)	(4)	(5)
	OLS	FE	FE	IV Tripadvisor	IV Lonely Planet
Airbnb Density at t-1 in:					
Florence suburbs	1.730	1.177	-2.013***	-1.035	-0.887
	(1.156)	(0.959)	(0.152)	(2.706)	(3.018)
Florence central	-0.139	0.511***	0.145***	0.158**	0.172**
	(0.251)	(0.132)	(0.0372)	(0.0564)	(0.0611)
Milan suburbs	4.334**	5.492***	0.980	-0.0956	0.646
	(2.035)	(1.014)	(1.004)	(2.830)	(2.956)
Milan central	2.542**	1.409^	-0.981**	-1.401	-2.106**
	(1.178)	(0.849)	(0.468)	(1.351)	(0.883)
Naples suburbs	0.727	-1.763**	-0.268*	-0.936	0.143
	(2.033)	(0.676)	(0.147)	(2.458)	(3.340)
Naples central	1.216*	1.482***	1.596***	1.603***	1.999***
	(0.692)	(0.323)	(0.181)	(0.204)	(0.252)
Rome suburbs	4.377	-11.28**	-1.111	5.555	5.849
	(3.789)	(4.280)	(0.832)	(3.421)	(3.451)
Rome central	0.905**	-0.365	-0.121	0.165*	0.239*
	(0.324)	(0.276)	(0.131)	(0.0924)	(0.120)
Turin suburbs	-80.49***	-14.28***	1.459^	-5.742	-1.349
	(13.97)	(3.717)	(0.867)	(5.046)	(7.673)
Turin central	-20.03***	-2.759**	-2.536***	-1.781***	-1.466*
	(2.857)	(1.063)	(0.328)	(0.568)	(0.755)
Venice suburbs	1.885	-0.702	1.631***	2.268	2.610*
	(1.324)	(0.493)	(0.407)	(1.449)	(1.447)
Venice central	0.309	0.0236	-0.240**	-0.0958	0.0897
	(0.225)	(0.0969)	(0.0929)	(0.334)	(0.340)
Time invariant controls	X				
Time varying controls	X	X	X	X	X
Year FE	X	X			
Zone FE		X	X	X	X
Quarter#City FE			X	X	X
Year#City#Area FE			X	X	X
Observations	5,237	5,237	5,237	5,237	5,237
Adjusted R2	0.82	0.96	0.96		

Appendix A

Table A1: Milan. Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m^2]	13.93	19.40	17.32	23.61
Sale [€/m^2]	3464.53	6014.27	3789.51	7292.56
Listings	124.84	306.39	231.83	603.18
Listing Density	1%	3%	2%	7%
Airbnb Revenue	€163,265	€555,253	€733,291	€2,687,268
Occupancy Rate	18%	24%	38%	42%
Reservation Days	1693	4832	6857	20683
(OMI) N. Houses	0.58%	0.84%	0.59%	0.87%
(OMI) N. Stores	0.18%	0.52%	0.19%	0.55%

Table A2: Turin. Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m^2]	7.70	9.58	7.67	9.56
Sale [€/m^2]	1819.87	2708.97	1581.69	2929.17
Listings	61.11	370.13	165.02	895.88
Listing Density	0%	1%	1%	3%
Airbnb Revenue	€47,896	€347,250	€299,291	€1,983,290
Occupancy Rate	14%	20%	36%	38%
Reservation Days	750	4973	4762	28060
(OMI) N. Houses	0.59%	0.87%	0.59%	0.88%
(OMI) N. Stores	0.10%	0.26%	0.10%	0.27%

Table A3: Venice. Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m^2]	14.14	15.70	14.77	16.04
Sale [€/m^2]	4129.15	5015.81	4086.48	4836.59
Listings	239.35	279.25	627.63	748.00
Listing Density	5%	7%	12%	19%
Airbnb Revenue	€695,463	€903,478	€4,240,895	€5,157,343
Occupancy Rate	30%	33%	35%	41%
Reservation Days	5004	6024	27766	33633
(OMI) N. Houses	0.21%	1.15%	0.22%	1.16%
(OMI) N. Stores	0.09%	0.54%	0.09%	0.53%

Table A4: Florence. Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m^2]	12.75	15.79	14.53	18.46
Sale [€/m^2]	3429.33	4167.66	3800.60	5023.16
Listings	175.45	945.25	396.43	2031.42
Listing Density	3%	15%	6%	31%
Airbnb Revenue	€330,890	€2,057,351	€1,920,491	€11,460,842
Occupancy Rate	24%	33%	37%	42%
Reservation Days	3563	20923	16392	90712
(OMI) N. Houses	0.32%	0.62%	0.32%	0.63%
(OMI) N. Stores	0.09%	0.26%	0.09%	0.27%

Table A5: Rome. Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m^2]	13.58	18.95	13.78	19.00
Sale [€/m^2]	3947.13	5786.68	3537.58	5297.08
Listings	199.79	1251.41	404.72	2592.78
Listing Density	2%	9%	3%	19%
Airbnb Revenue	€298,702	€2,267,740	€1,895,907	€15,255,758
Occupancy Rate	17%	25%	33%	42%
Reservation Days	3186	21634	16633	118943
(OMI) N. Houses	0.41%	0.69%	0.42%	0.69%
(OMI) N. Stores	0.13%	0.27%	0.13%	0.27%

Table A6: Naples. Variables' means across zones for 2015 and 2019.

	2015		2019	
	All zones	**High Airbnb density zones**	**All zones**	**High Airbnb density zones**
Rent [€/m^2]	9.11	11.01	9.69	13.77
Sale [€/m^2]	2633.16	2898.89	2294.14	2882.21
Listings	50.73	215.42	287.33	1244.92
Listing Density	0%	2%	2%	11%
Airbnb Revenue	€47,161	€224,639	€674,312	€3,376,196
Occupancy Rate	14%	23%	26%	35%
Reservation Days	727	3411	9340	44062
(OMI) N. Houses	0.51%	1.02%	0.53%	1.05%
(OMI) N. Stores	0.15%	0.44%	0.16%	0.43%