POLITECNICO DI TORINO
Repository ISTITUZIONALE

The uneven effect of Airbnb on the housing market. Evidence across and within Italian cities

Original
The uneven effect of Airbnb on the housing market. Evidence across and within Italian cities / Congiu, Raffaele; Pino, Flavio; Rondi, Laura. - In: JOURNAL OF REGIONAL SCIENCE. - ISSN 0022-4146. - ELETTRONICO. - (2024), pp. 1-53. [10.1111/jors.12737]

Availability:
This version is available at: 11583/2992937 since: 2024-12-03T15:25:13Z

Publisher:
Wiley-Blackwell

Published
DOI:10.1111/jors.12737

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

(Article begins on next page)

26 December 2024

Check for updates

Received: 11 January 2023 | Revised: 28 May 2024 | Accepted: 15 September 2024

DOI: 10.1111/jors.12737

RESEARCH ARTICLE

JOURNAL OF REGIONAL SCIENCE WILEY

The uneven effect of Airbnb on the housing market: Evidence across and within Italian cities

Raffaele Congiu | **Flavio Pino** | **Laura Rondi**

Department of Management, Politecnico di Torino, Turin, Italy

Correspondence

Laura Rondi, Department of Management, Politecnico di Torino, Corso Duca degli Abruzzi, 24, 10129 Turin, Italy.

Email: laura.rondi@polito.it

Funding information

Ministero dell'Istruzione, dell'Università e della Ricerca

Abstract

We investigate if Airbnb diffusion affects residential property values differently across and within cities leveraging the heterogeneity of five Italian cities in terms of tourist attractiveness, local housing markets, and socioeconomic conditions. We find that Airbnb density growth leads to increases in house prices in all cities. Within-city, the impact is positive both in centers and in the suburbs in more touristic towns, but only in the center in the others. Moreover, Airbnb may increase or decrease the center–periphery price gap. Our results suggest that the different impact of Airbnb on housing submarkets is driven by local disparity conditions.

KEYWORDS

Airbnb, core–periphery submarkets, housing market, sharing economy, spatial inequality, tourism

1 | INTRODUCTION

Airbnb is probably the most well-known face of the sharing economy. The platform's claim is to provide guests with an affordable and personal accommodation experience and hosts with an additional source of income from unused capacity. While this appears economically efficient, the diffusion of short-term rentals has been criticized by residents and local administrators complaining that they benefit landlords and tourists at the expense of local

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2024 The Author(s). *Journal of Regional Science* published by Wiley Periodicals LLC.

renters.[1] Not surprisingly, a growing number of academic studies has provided empirical evidence of their impact on the real-estate market and inquired into the positive and negative externalities of home-sharing platforms (Ayouba et al., 2020; Barron et al., 2020; Duso & Michelsen, 2020; Filippas & Horton, 2018; Franco & Santos, 2021; Garcia-López et al., 2020; Horn & Merante, 2017; Koster et al., 2021; Thackway et al., 2022). Recently, the literature has raised the issue of an Airbnb impact on welfare distribution within cities, driven by an endogenous increase of local amenities and private investments that reinforces location sorting and inequality across neighborhoods (Almagro & Domínguez-lino, 2021; Calder-Wang, 2021; Xu & Xu, 2021).

Motivated by the idea that short-term rental platforms may concur with a spatial dimension of inequality within cities, this paper investigates whether the diffusion of Airbnb reduces or exacerbates the differences between central and suburban areas by affecting residential property values. To find comprehensive evidence that may inform the policy debate on urban housing issues, we leverage on the heterogeneity that five Italian cities—Rome, Florence, Milan, Turin, and Naples—exhibit in terms of tourist and business vocation, housing markets, socio-economic conditions, and disparity across center and periphery.[2] Indeed, preliminary descriptive evidence reveals that Airbnb diffusion and growth greatly differ amongst the five cities (from lowest in Turin to highest in Florence) as well as between the suburbs and the center, where it is most concentrated. Such heterogeneity provides the geographical scope that instructs the conceptual framework behind our empirical analysis.

In this paper, we estimate the aggregate and the city-specific effects of an increase in Airbnb density on house sale prices and rental rates between 2014 and 2019. Then, for the aggregate and for each city, we investigate whether the effect differs between the center and the periphery. The empirical analysis uses quarterly data on individual Airbnb listings sourced from AirDNA, a provider of short-term rental analytics, house sale prices and rental rates provided by Idealista, a major online real-estate portal, data on housing market characteristics provided by Osservatorio del Mercato Immobiliare (OMI), the Italian Registry of the Real-Estate Market, and Census data. Airbnb density is the number of listings in a neighborhood divided by the number of housing units. The neighborhood, our unit of observation, is the area into which Idealista divides housing markets.

We find that, in our sample, Airbnb growth has determined an increase in house prices both overall and in each city.

Moreover, the impact is significant only in the center in less touristic cities where house prices are lower and decreasing (viz., Naples and Turin), while in Florence, Rome, and Milan, sale prices are also affected in the suburbs. When we calculate the quantitative effects in Euros, price increases generated by Airbnb diffusion are quite different across and within cities. In Milan and Rome—the two cities with the largest subcity income and property value inequality—our results show that the center–periphery difference in house prices increases overtime, whereas in Florence, where initial subcity disparity is lower, the price trends in center and periphery appear to converge.

Overall, these findings suggest that Airbnb amplifies the initial gap between property values in the center and the suburbs where the gap was already wide, and that initial subcity disparities between the center and the suburbs influence how differently Airbnb affects property values within cities.

Estimating the impact of Airbnb on house prices and rents raises several endogeneity concerns. We address the omitted variable problem by including a large set of control variables, and we account for identification threats due to the potential correlation between tourist attractiveness and centrality by including area-specific year and quarter fixed-effects (FEs) and neighborhood-level time-varying controls associated with urban revival processes. Then, we implement an instrumental variable (IV) approach that exploits the interaction between an out-of-sample score of

[1] Counterfactual evidence of the inflationary impact on the housing market is provided by Thackway and Pettit (2021), who show that, during the COVID-19 pandemic, the reduced Airbnb activity has contributed to a decline in rental prices by up to 7% in areas with higher Airbnb diffusion.

[2] A previous version of the manuscript—titled "Airbnb and the housing market in Italy—evidence from six cities"—also included the analysis of the city of Venice. However, as we shifted the focus towards within-city and spillover effects, we realized that the geographical layout of Venice did not allow us to examine such effects. Indeed, the city center of Venice covers most of the municipality, while what would be referred to as suburbs are scattered through the few islands surrounding the city.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

tourist attractiveness—derived from Tripadvisor—and a time-varying measure of public awareness of Airbnb—derived from worldwide Google searches (Barron et al., 2020).

Our paper contributes to the literature in the following ways. First, despite Italy's strong tourist vocation, this is the first study that estimates the impact of Airbnb on the Italian housing market delving into differences across and within cities, to the best of our knowledge. Second, by focusing on five cities where housing markets and socioeconomic characteristics differ from each other, we provide evidence of an overarching effect but also of the need for bespoke policies, as the positive effect we find at the city level is stronger in cities with higher touristic attractiveness. Third, by disentangling Airbnb's effect within cities, we find that the quantitative impact is not homogeneous and typically larger in the city center, in line with the recent literature that studies the distributional impact of home-sharing platforms. Overall, our findings can help understanding whether, and why, Airbnb diffusion may benefit some parts of the city while leaving other neighborhoods behind, and the conditions that make this effect more likely. These findings highlight the need for policymakers to take a subcity approach when they address the impact of short-term rental platforms, focusing on the local initial conditions that concur to determine what kind of effect will affect residents in the center and in the suburbs, to avoid an increase in inequality.

The paper is organized as follows. In Section 2, we present the geographical scope of our study, highlighting the differences across the five cities. In Section 3, we review the relevant literature from which we draw our conceptual framework and the empirical implications for the local housing markets. Section 4 describes the data and Section 5 the empirical strategy. In Section 6, we present the results of the analyses and in Section 7 the conclusions. The appendices include additional material and analyses.[3]

2 | GEOGRAPHICAL SCOPE AND EMPIRICAL IMPLICATIONS

This section explains the geographical scope of our analysis by describing how the cities in our sample—Florence, Milan, Naples, Rome, and Turin—differ in terms of Airbnb density, housing market and economic indicators, and center/periphery disparity. This heterogeneity could explain why short-term rental platforms may affect the housing (sub) market of each city with respect to their specific characteristics.

Our choice of cities is driven by their importance in the economic and political life of the country, tourist attractiveness, and inherent variety. Such variety allows us to conjecture a different response to the diffusion of Airbnb and a different impact on the housing market. In Figure 1, the left pane shows their location, population, and the number of visitors in 2019, while the right pane reports the quarterly trend of the aggregate number of listings, testifying to the explosive growth of the platform.

Figure 2 describes the evolution of rents and sale prices and of Airbnb density—the number of listings in a neighborhood divided by the number of housing units—in each city and in the center (dark area).[4] The housing market is tracked from 2012, while Airbnb's presence is traced from the end of 2014, when it became less negligible. Sale prices and rents have been declining in all cities until 2015–2016, thereafter stabilizing or soaring, depending on the city (e.g., house prices escalated in Florence and Milan, but not in the other cities). In Appendix A, Table A2 reports housing market data of each city at the beginning and at the end of the period, and Table A3 breaks down the information across city centers and peripheries. The table reveals that center and suburbs starkly

[3]The appendices cover a synoptic table on the empirical literature, additional descriptive statistics, a detailed description of the data and empirical methods, the sensitivity analysis, an extension of the analysis to the impact of Airbnb on rental rates, and to potential spillovers effects on house prices in the suburbs that might originate from the growth of Airbnb density in the city center.

[4]It is worth noting that the scales of the five figures are very different from each other, as the listing density in Florence is almost twice the density in Milan and Rome, and more than six times that of Turin. The distinction between center and suburbs is based on a classification by OMI, the Italian register of the real-estate market of the Internal Revenue Service. See Section 4 for a detailed description of the data set.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

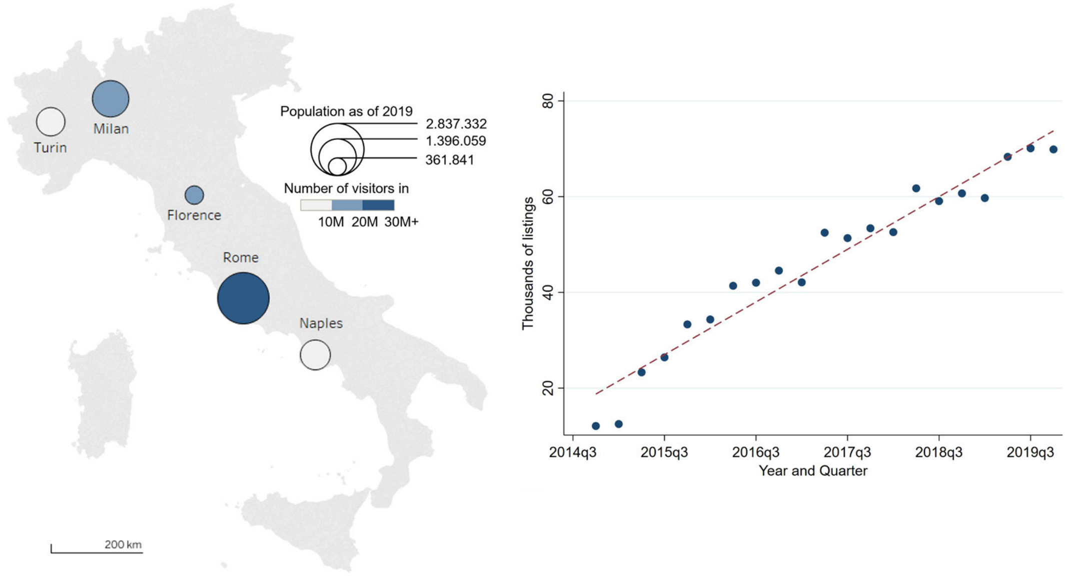

FIGURE 1 The five cities. (Left pane) Location, number of residents and visitors as of 2019. (Right pane) Total number of listings (the dashed line is the linear fit). *Sources*: AirDNA and Italian National Institute of Statistics (ISTAT). [Color figure can be viewed at wileyonlinelibrary.com]

differ in terms of house sale prices, Airbnb diffusion, store, and amenity density (the latter defined as the number of bars, restaurants, and pubs per km^2), particularly in Milan, Naples, and Rome.[5]

The maps in Figure 3 show Airbnb's density and tourist attractiveness based on Tripadvisor (explained in Appendix C) in each neighborhood—our geographical unit of observation—and in the center, delimited by the thick black line. Finally, Table 1 provides within-city descriptive evidence on sociodemographic characteristics based on 2011 Census data, while Table 2 documents within-city inequality in terms of income per capita and growth in the supply of amenities between 2014 and 2019, revealing that disparity is stronger in Milan and Rome and much weaker in Florence. We now briefly summarize the main characteristics of each city.

Rome—Italy's capital—is the largest and most visited city, with almost 3 million citizens and over 33 million visitors in 2019. Airbnb density is above the sample average, with peaks of about 15% in the center, where tourist attractions are concentrated. Housing market values are in line with those of the other cities. However, sale prices decrease throughout the period, whereas the descent of rents stabilizes from 2014 (Figure 2 and Table A2). The data show a wide gap between center and periphery (Table A3) with regard to sale prices, rents, demographic indicators, and income distribution, with a ratio between the richest and poorest neighborhoods of 4.2. Moreover, the supply of tourism-related amenities per km^2 highlights a substantial increase in the city center, which is almost tenfold that in the suburbs (Tables 1 and 2).

Milan, the second largest Italian city and second most visited, is the economic and financial capital, with the higher and faster-growing growing per capita income. In 2015 it hosted the World Expo. Rents and sale prices are much higher than in Rome and have rapidly grown in recent years, whereas Airbnb density is similarly skewed towards the center. The contrast between center and suburbs is also similar in terms of house prices and rents, income inequality, with the highest ratio (5.3) between high- and low-income neighborhoods, and amenity density growth, with the second highest ratio center to suburbs ratio (6.55), after Rome.

[5]We thank one referee who has suggested us to provide the statistics that document the difference in amenity density between center and periphery and how the densities have changed over time.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Florence is the smallest city, but reports the highest tourist and Airbnb density. The limited size of the center and the presence of many historical buildings and museums obviously constrain the expansion of Airbnb (but also of building capacity). Therefore, while Airbnb's distribution is still skewed towards the center, high density levels are also registered in the suburbs, as the relatively short distance from the center may increase their convenience. Notably, Florence shows the lowest income inequality in our sample, the lowest house price difference and the smallest gap between the growth of amenity supply in the center and the periphery.

Naples and Turin, despite their size and importance in Italy's economy, are characterized by much lower house sale prices, average income, and tourist intensity (Tables A2 and A3). Airbnb penetration is low and slow in Turin, where listing density reaches 3% only in some central neighborhoods, and higher in Naples, where it is concentrated in the center. In both cities, house prices have been decreasing over time, particularly in the suburbs.

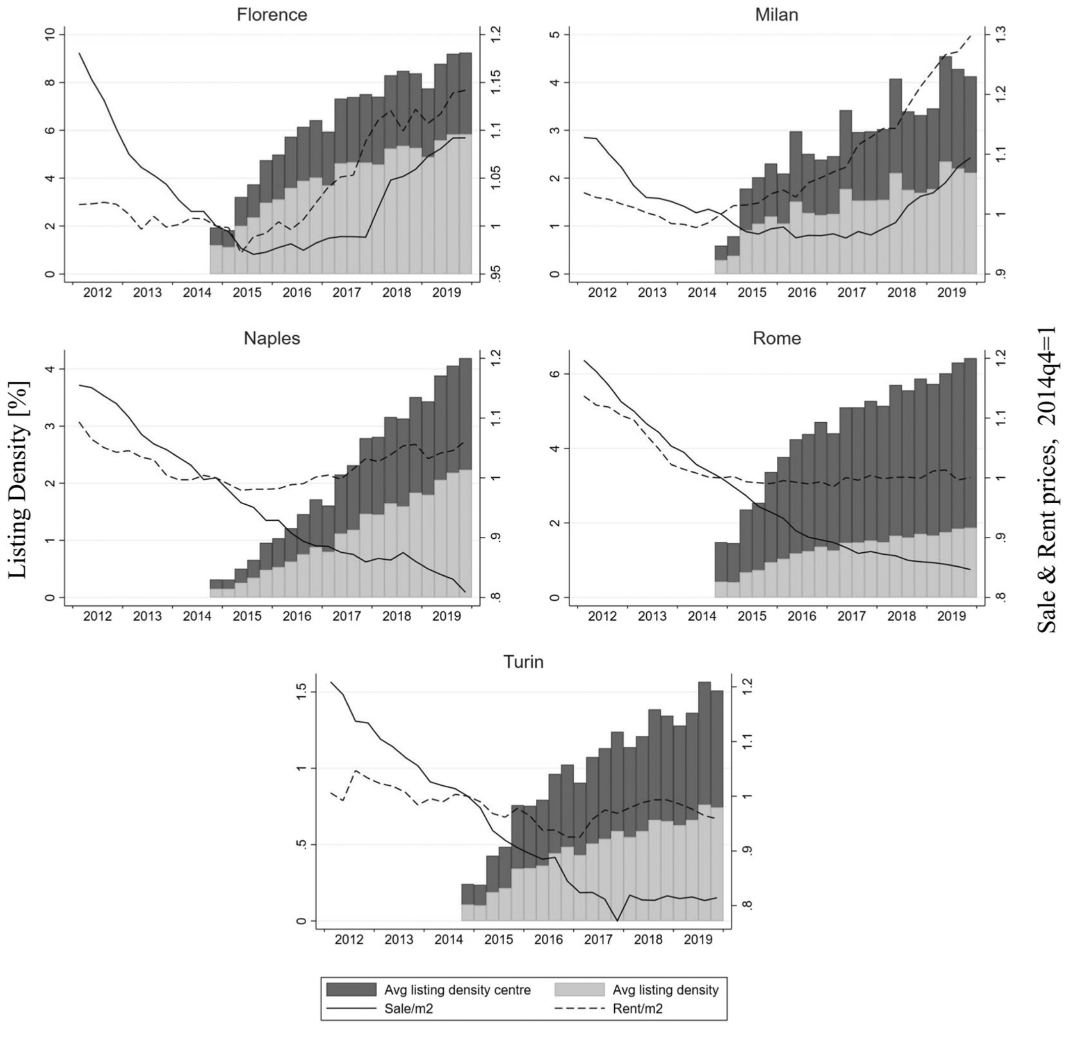

FIGURE 2 Airbnb density, rents, and house prices from 2012 to 2019 (average data by neighborhood). This figure shows the evolution over time of average rents, sale prices and Airbnb density for each city. Rents and sale prices are shown from the first quarter of 2012 and are normalized to the last quarter of 2014. The average listing density is shown from the last quarter of 2014 for both the average neighborhood (light gray) and for the city center (dark gray). *Sources*: AirDNA, Idealista, and Osservatorio del Mercato Immobiliare.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

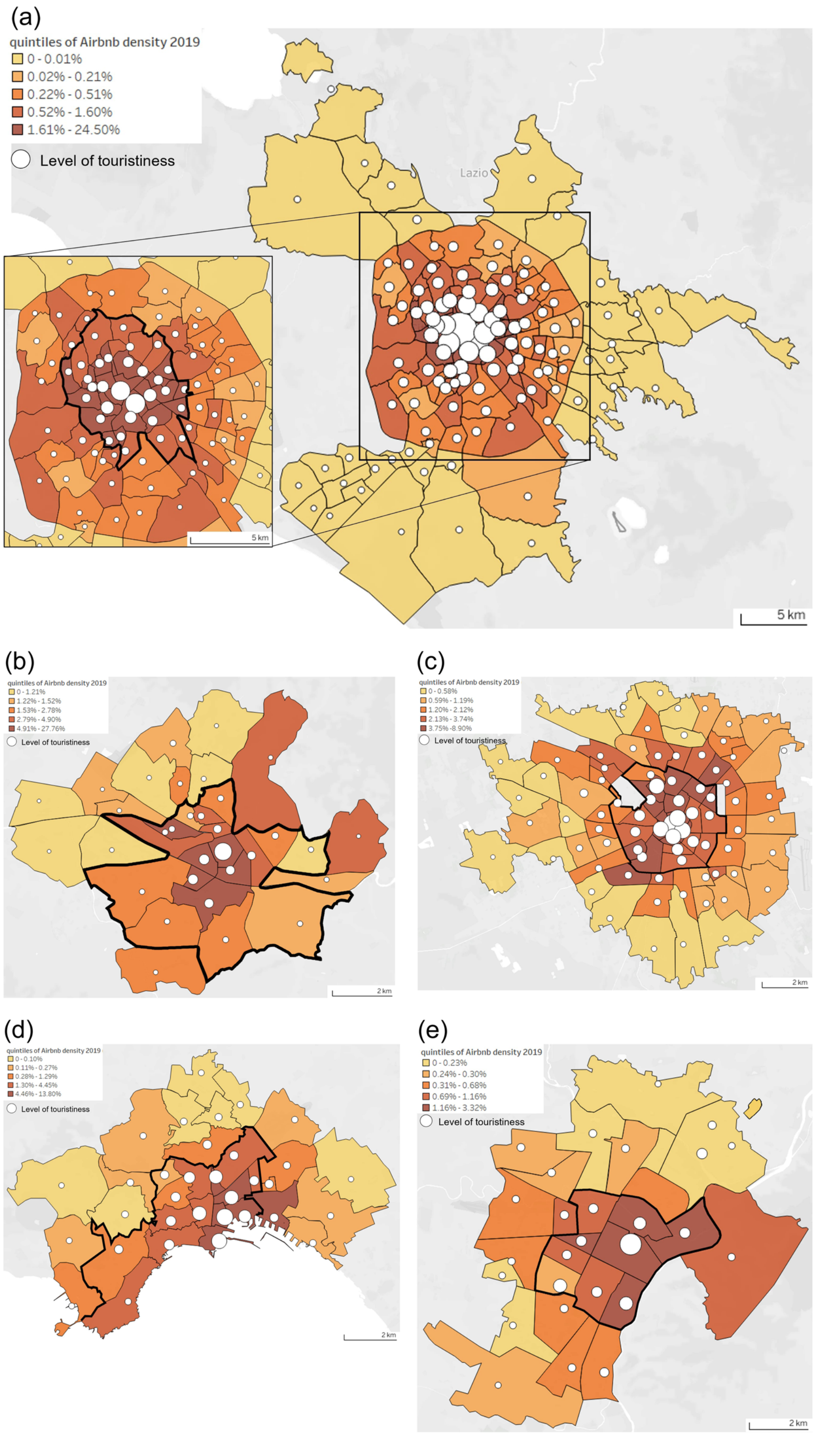

FIGURE 3 (See caption on next page).

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

3 | RELATED LITERATURE AND CONCEPTUAL FRAMEWORK

In this section, we first highlight the relevant literature that helps us frame our contribution. Next, we propose a conceptual framework which helps us link our empirical findings to the economic mechanisms that have been extensively researched in the previous literature.

3.1 | Related literature

The literature on the impact of home-sharing platforms on the housing market has highlighted that, by reducing transaction and information costs in the short-term rental market (Einav et al., 2016), they make it convenient for homeowners to switch from long-term to short-term rentals. Although this substitution effect has a direct impact on rents, it also affects sale prices. First, since house value can be measured by the present value of all future revenues and costs, including incomes from renting (Poterba, 1984), changes in the rental market convey to the sale market with a larger magnitude. Second, as short-term rental platforms allow hosts to rent unused capacity, the prospect of an additional source of income can further raise sale prices and even lead investors to acquire dwellings for commercial use. Third, whenever the housing supply cannot be increased due to geographical or building constraints, the impact on property values will be stronger (Gyourko and Molloy, 2015, Chap. 19).

The empirical literature supports this effect mainly at the aggregate or at the city level (Barron et al., 2020; Duso & Michelsen, 2020; Garcia-López et al., 2020; Sheppard & Udell, 2016), but only a few studies have investigated the differences across cities. For example, Ayouba et al. (2020) compare the impact of Airbnb on rental rates in eight French cities and find that the effect is larger in those with higher tourist attractiveness, whereas Franco and Santos (2021) estimate a positive overall impact on sale prices (but not on rents) in Portugal, which is stronger in more touristic cities, like, Lisbon and Porto.

Recently, some studies have highlighted the importance of disaggregating the analysis of housing prices into the submarkets of the metropolitan area (see, e.g., Bangura and Lee, 2021, 2022), thus contributing to the microfoundation of the housing markets (Rothenberg, 1991).[6] This literature shows that a city's housing market is composed of a set of submarkets (Keskin & Watkins, 2017) which depend on socioeconomic and environmental conditions, geographical and political boundaries (Bourassa et al., 2003), information constraints and search costs (Palm, 1978). These insights motivate us to analyze the impact of Airbnb by considering local, subcity characteristics that might explain not only the different responses of the housing market, but also the different diffusion of Airbnb within cities. Among the studies that examine the impact within cities, Franco and Santos (2021) show that the effect of Airbnb's presence on house prices in Lisbon and Porto is larger in the historical center and in touristic neighborhoods. Similarly, Koster et al. (2021) find a larger effect in highly touristic neighborhoods of Los Angeles, like, Hollywood's Walk of Fame, whereas Horn and

FIGURE 3 Maps of the five cities. Each map shows a city divided into the Idealista neighborhoods. The thick black line delimits the city center from the suburbs (the classification into the two classes is described in Section 4). The neighborhoods' colors reflect the level of Airbnb density as of 2019, divided into quintiles. The size of the white circles refers to the level of touristiness of each neighborhood, computed as in Section 3. The size of the circles is relative to each city and, as such, is not comparable across cities. (a) Rome, (b) Florence, (c) Milan, (d) Naples, and (e) Turin. [Color figure can be viewed at wileyonlinelibrary.com]

[6] For the theoretical underpinnings of tiered housing markets, see also Jones et al. (2012).

TABLE 1 Sociodemographic and economic time-invariant characteristics within the city.

	% Owner-occupancy	% > 60 years	% Graduates	% Working	Household size
Suburbs					
Average	64.83	22.43	14.56	40.03	2.24
Florence	69.14	26.26	14.64	42.04	2.16
Milan	63.31	25.44	16.43	43.13	2.03
Naples	46.00	15.45	6.14	23.02	3.00
Rome	68.56	20.57	15.88	41.45	2.29
Turin	67.23	25.95	10.84	39.00	2.13
Center					
Average	64.43	24.16	26.69	41.87	2.06
Florence	68.21	26.30	23.72	43.70	2.02
Milan	62.91	23.59	34.32	47.54	1.95
Naples	58.52	20.33	17.72	30.40	2.52
Rome	67.32	25.60	28.66	41.81	1.99
Turin	61.03	22.90	21.49	43.01	1.98

Note: This table shows—at the city center and suburbs level for each city—average values for owner-occupancy, percentage of residents older than 60, percentage of graduates, percentage of employed, and average household size. *Source*: 2011 Census, Italian National Institute of Statistics.

TABLE 2 Disparity measures within cities.

Panel A	Lowest income ZIP code	Highest income ZIP code	High-to-low ratio
Florence	20,523	40,527	1.97
Milan	18,926	100,489	5.31
Naples	13,462	47,316	3.51
Rome	16,298	68,264	4.19
Turin	18,158	64,094	3.53
Panel B	**Amenity density increase in suburbs (per km^2)**	**Amenity density increase in the center (per km^2)**	**Center to suburbs ratio**
Florence	249	819	3.29
Milan	773	5066	6.55
Naples	552	2016	3.66
Rome	234	2234	9.55
Turin	400	1936	4.84

Note: Panel A of this table shows the income per capita in the lowest and highest average income ZIP codes neighborhoods in each city as of 2019. *Source*: MEF—Italian Ministry of Economics and Finance. Panel B shows the increase in the number of amenities per km^2 between 2014 and 2019 in the suburbs and in the city center for each city, as well as the ratio between the increases. *Source*: Italian Chambers of Commerce.

Abbreviation: ZIP, Zone Improvement Plan.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Merante (2017) show that, in Boston, the substitution effect is stronger in the city center, where the housing supply is inelastic. In contrast, Thackway et al. (2022), delve into the fragmented nature of the Sydney housing market and, using Geographically Weighted Regressions with individual house prices, find that Airbnb impact on house prices is positive and significant in areas where the tourist market is less developed, not in the more touristic locations of Sydney. In Appendix A, Table A1 presents an overview of the results, scope, and methods of this empirical literature.

Another strand of literature has instead focused on how rental platforms can shape the directions of a city's development at the suburban level. First, as the diffusion of short-term rentals extends to suburban, less touristic areas, they may improve their residents' living conditions by attracting renovation projects and service supply to meet tourists' tastes, thereby raising housing demand and prices (Coles et al., 2018; Farronato & Fradkin, 2018; Xu & Xu, 2021).[7]

Second, urban and tourism economics have long shown the importance of tourism-driven amenities for urban success (see Glaeser et al., 2001, for a seminal contribution and, more recently, Broxterman et al., 2019).[8] Drawing on this insight, recent studies have shown how online rental platforms can redistribute a city's welfare through the reinforcement of residential sorting (Almagro & Domínguez-Iino, 2021; Calder-Wang, 2021). In this framework, the substitution between long and short-term rental can be endogenously enhanced if the growing number of tourists boosts the supply of local amenities (shops, bars, restaurants, theaters, and museums), in areas where tourists flock to, that is, typically the center. Such substitution may lead to a price escalation, which eventually hurts those residents whose preferences are aligned with those of tourists, but who cannot afford the higher housing market prices. As these residents have to move out of the center, the demand shift will raise the house prices in other city areas, for example, suburban and neighborhoods (Calder-Wang, 2021; Couture et al., 2019). Recent evidence by Hidalgo et al. (2023) has shown that short-term rental markets in Madrid has prompted tourist-oriented businesses at the expense of resident-oriented services, leading to an endogenous reshaping of the urban space. This effect is also highlighted by Garcia-López and Rosso (2023), who find comparable results in the city of Turin.

Finally, a few studies have addressed the issue of negative externalities generated by Airbnb in cities where visitors' inflows and Airbnb density are particularly high (Barron et al., 2020; Filippas & Horton, 2018; Sheppard & Udell, 2016). In particular, whenever Airbnb density and visitor turnover makes the neighborhood noisy, congested and unsafe, residents may decide to leave the area, reducing the overall demand increase generated by Airbnb, and the pressure over sale prices and rents.

3.2 | Conceptual framework

As the aim of our study is primarily empirical, we do not propose a new economic mechanism through which short-term rental platforms impact the housing market, but we draw upon the literature that has extensively investigated numerous direct and indirect channels. Therefore, to frame our research questions and the hypotheses underlying our empirical specifications, we briefly describe such channels, how they interact, and how they may generate different effects in the city center and in the suburbs.

[7]Xu and Xu (2021) find that Airbnb diffusion increases the number of residential renovation projects, as landlords make their entry into the short-term rental market, and that the investment response has been stronger in nongentrified, declining neighborhoods, possibly due to lower investment costs.

[8]Lanzara and Minerva (2019) have found that large tourist inflows spur economic activity and employment, but could also hurt local residents by raising prices and rents. Li and Xia (2022) delve deeper into the connection between amenities and house prices by analyzing the emergence of new economic poles in Beijing. Letdin and Shim (2019) have proposed a housing location choice model where households face a trade-off between proximity to the place of employment and proximity to amenities, while Wang and Chen (2019) have built an equilibrium-sorting model which considers how the job market, amenity supply and local spillovers affect destination choices in China.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

First, the literature has highlighted how the additional revenues generated by short-term rental platforms shifts the housing supply from the long-term to the short-term rental market, leading to a substitution effect that increases rental rates (Ayouba et al., 2020; Barron et al., 2020; Duso & Michelsen, 2020; Franco & Santos, 2021; Garcia-López et al., 2020; Horn & Merante, 2017; Koster et al., 2021; Sheppard & Udell, 2016). The rent increase translates into higher sale prices, as the prospects of additional future cashflows improve the performance of investing in the housing market (Poterba, 1984).

Second, as short-term rental platforms allow more tourists to satisfy their desire to stay in the city center, they also lead to a higher concentration of touristic amenities, further boosting tourists' demand for accommodation. This endogenous redistribution of consumption amenities spurs the substitution effect and increases house prices in the center (Almagro & Domínguez-Iino, 2021; Calder-Wang, 2021).[9]

Third, the high density of Airbnb listings may turn more touristic areas overcrowded, noisy and unsafe, reducing the housing demand by residents (Barron et al., 2020; Filippas & Horton, 2018; Sheppard & Udell, 2016). This effect might be particularly strong in central areas, where Airbnb density is higher.

Fourth, the substitution effect previously described may lead to residents leaving the city center in favor of the suburbs (Calder-Wang, 2021; Couture et al., 2019). The lower housing demand by residents may thus reduce the pressure on the rental market in the city center, tempering the positive effect of online platforms and, possibly, leading to a revaluation of prices in the suburbs. In particular, we expect such demand shifts to be stronger in cities where the suburbs are closer to the city center and offer more favorable living conditions. Indeed, the proximity between the city center and the suburbs—both physical and figurative—is expected to raise the center–suburbs substitutability for residents, leading to higher demand shifts the higher the prices in the center increase. Conversely, wherever the initial center–periphery gap is wider in terms of income inequality, property values and amenity supplies, the residents' willingness to move out of the center will not reduce and the pressure on the house prices in the city center will not be relieved.

On the basis of this conceptual framework, we thus formulate the following hypotheses regarding the expected outcomes of the empirical analysis:

1. Airbnb diffusion is expected to positively influence housing prices in more touristic cities.
2. The positive effect should be stronger in more touristic areas, such as city centers, both due to higher Airbnb density and to the endogenous increase in touristic amenities. This trend is expected to increase the difference between house prices in the center and in the suburbs.
3. However, wherever Airbnb density boosts, such increase may be tempered by the negative externalities caused by high touristic pressure, leading residents to leave the center.
4. The residential demand shift from center to suburbs should be stronger in cities with appealing suburbs (i.e., more similar initial conditions). Such shift, by decreasing demand in the center and increasing it in the suburbs, may lead to a convergence in housing prices.

On the basis of the characteristics of the cities in our sample, described in Section 2, we thus expect to find positive effects of Airbnb's density on housing prices in all city centers and in those suburbs which exhibit the highest Airbnb density. In particular, in cities with strong disparities between the center and the suburbs, such as Rome and Milan, we expect Airbnb's presence to strongly increase prices in the city center with respect to the suburbs, as residents are willing to pay more in exchange for better living conditions. Conversely, in Florence, where suburbs are close to the city center and offer fair living conditions, we expect a strong increase in housing prices in the suburbs, which could even be comparable with that in the city center.

[9]For evidence of the positive impact of tourism growth on the supply of services and amenities in Italian cities, see Lanzara and Minerva (2019).

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

4 | DATA

In this section, we briefly describe the data we used and their sources. A more detailed description of the data set and the merging process between data from various sources is provided in Appendix B. We employ four data sources: AirDNA for daily data on Airbnb's dwellings (AirDNA, 2021), Idealista for trimestral data on rent and sale prices (Idealista, 2021), OMI (the Italian register of the real-estate market) for time-varying attributes of the real estate and Italian National Institute of Statistics (ISTAT) for predetermined control variables on demographics, occupation, education and housing characteristics (ISTAT, 2021).

A first crucial aspect of our analysis is the division of cities into neighborhoods, which are our geographical unit. For the cities' subdivision, we rely on data from Idealista, which splits the cities in our sample into a total of 287 neighborhoods. As Idealista is a specialized real-estate portal, its subdivision minimizes area-specific heterogeneity and related information costs. Thus, Idealista neighborhoods are heterogeneous both in size and in the number of residents, but we use listing density, not an absolute number, as the variable of interest, and we include neighborhood FEs in the panel regressions. We can think of the identification of a neighborhood as being equivalent to that of a relevant market.

A second relevant feature of our analysis is how to distinguish between central and peripheral neighborhoods. Some recent works have distinguished neighborhoods based on the distance from the city center (see, e.g., Gupta et al., 2021; Moreno-Maldonado & Santamaria, 2022). In this work, we rely on OMI data because the Italian register of the real-estate market is the main source used by the government, both on a national and a township level, to evaluate a city's characteristics. In particular, OMI divides each city into small homogeneous neighborhoods, each of them characterized as central, semicentral, peripheral, suburban, and rural. central neighborhoods represent the urban center of the cities, while semicentral neighborhoods are contiguous to the central ones and well connected to the center by public transports. Peripheral neighborhoods are poorly connected with the center, while suburban and rural neighborhoods are completely disconnected from it. We construct a binary variable to identify whether a neighborhood belongs to the "city center" when it is located in a central or semicentral neighborhood, or to the "suburbs" or "periphery" if located in a peripheral, suburban or rural areas. We exploit this dichotomy to investigate whether the impact of Airbnb penetration differs contingent on the centrality of the neighborhood and to account for centrality-driven unobserved factors through time-varying area FEs.

Table 3 presents summary statistics at the neighborhood-trimester level.

5 | EMPIRICAL METHODS

We start by estimating the impact of Airbnb diffusion on sale prices for the five cities altogether and individually. Then, we turn to the analysis within cities, to investigate the differences between Airbnb impact in the city center and in the periphery. Finally, in Appendix F, we provide a tentative analysis of the spillover effects that Airbnb growth in the center may have on the property values in the suburbs.

Our research strategy accounts for endogeneity concerns in several ways. First, we add a large set of sociodemographic, urban and housing market controls to reduce the omitted variable bias. Second, we add spatial (city, area, and neighborhood) and time (year and quarter) FEs and their interactions that control for different time trends and seasonality amongst and within cities, so as to capture different dynamics of pricing (such as different trends of house prices in nicer and less nice areas) and urban development, which might generate spurious correlations. Indeed, in Section 2, we described how the five cities are differently exposed to tourist and business-related flows and seasonality, while also differing in terms of average income, inequality, and degree of marginalization of the peripheries. Third, we lag the variable of interest for one period (i.e., one quarter) as the response of the market (and particularly house sale prices) to the increase in Airbnb density is not likely to be simultaneous. Lagging one period also contributes to reduce reverse causality concerns. Fourth, we

TABLE 3 Summary statistics by neighborhood.

	Mean	SD	Minimum	Maximum	*N*
Idealista					
Rent (€/m^2)	12.60	3.65	4.41	32.22	6027
Sale (€/m^2)	3131.35	1391.56	694.44	10,889.59	6027
Airbnb					
Airbnb listings	161.06	370.62	0	5353.00	6027
Airbnb density	0.016	0.034	0.00	0.311	6027
OMI					
House density %	43.89	33.46	0.61	161.09	6027
Store density %	12.75	12.94	0.22	75.95	6027
Garage density %	15.69	11.25	0.28	43.77	6027
Average house rooms	5.11	0.67	3.78	9.19	6027
Average store m^2	45.06	13.44	9.84	98.29	6027
Census					
Number of residents	20,301	13,683	1072	71,855	6027
Owner-occupancy	0.65	0.10	0.29	0.83	6027
20–39 years	0.24	0.04	0.17	0.45	6027
> 60 years	0.22	0.05	0.06	0.36	6027
Graduates	0.19	0.10	0.03	0.44	6027
Working	0.41	0.06	0.18	0.57	6027
Foreigners	0.10	0.06	0.01	0.37	6027
Full houses	0.93	0.06	0.61	1.00	6027
Number of houses	9675.36	6477.95	248.57	30,495.69	6027
Houses in poor condition	0.15	0.13	0.01	0.78	6027

Note: This table shows summary statistics for the main variables used in the empirical analysis. The geographic unit is the Idealista neighborhood.
Sources: AirDNA, Idealista, Italian National Institute of Statistics, and Osservatorio del Mercato Immobiliare (OMI).

estimate a two-stage least squares (2SLS) model. Our IV strategy uses a shift-share instrument (Bartik, 1991) which exploits, for the cross-sectional (share) part, reviews of the top 150 Tripadvisor's attractions for each city to measure the tourist attractiveness of a given neighborhood. This instrument has been already used in this literature (Barron et al., 2020; Garcia-López et al., 2020) and is thoroughly described in Appendix C, where we also provide visual representations of its effectiveness. In Appendix D, we provide tests to check its validity (viz., parallel pretrends, a placebo test, and test of the impact of the IV on neighborhoods that do not present Airbnb activity). Finally, we allow for dynamic effects in the housing market by estimating a dynamic panel data model which uses the generalized method of moments (GMM)-System estimator (Appendix G) as an alternative IV estimation.

We cluster standard errors at the neighborhood level to account for correlation across the time dimensions within neighborhoods. Moreover, because neighborhood effects may exhibit patterns of mutual dependence across

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

neighborhoods, we allow for spatial correlation by calculating Driscoll and Kraay (1998) standard errors that are reported below the neighborhood-clustered standard errors.

In Appendix G, we present a battery of sensitivity analyses and robustness tests. Specifically, we report the results of the System-GMM model and of an additional set of 2SLS estimates using an alternative instrument that measures tourist attractiveness based on Lonely Planet guidebooks (instead of Trip Advisor). Moreover, we employ two alternative measures of Airbnb supply, that is, listings by creation date and the number of listings, and we present the results when using the log of rents instead of the log of sale prices as a dependent variable.[10]

To estimate the overall impact of Airbnb, we start with a baseline ordinary least squares (OLS) equation that includes time-varying and time-invariant sociodemographic, urban and structural characteristics at the neighborhood level and year FEs. We then add neighborhood FEs and city- and area-specific time (quarterly) effects. To account for spurious correlation, we include neighborhood-level time-varying housing characteristics associated with urban revival processes (e.g., gentrification) and center- and suburbs-specific year-level FEs that control for the fact that high tourist attractiveness might be a proxy of centrality of a neighborhood.

The FE model we estimate thus includes two sets of interacted time and location FEs, at different levels of spatial disaggregation, as follows:

$$\log(Y_{n,t}) = \beta \text{Airbnb Intensity}_{n,t-1} + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t}, \tag{1}$$

where $Y_{n,t}$ is the average house sale price in neighborhood n at year–quarter t, Airbnb Intensity$_{n,t-1}$ is the listing density in neighborhood n at time $t-1$, $X_{n,t}$ is a matrix of time-varying controls in neighborhood n at time t, $\pi_{s,i}$ is the interaction between city i and quarter s (to account for city-specific seasonality), $\tau_{y,i,a}$ is the interaction among the year, the city and the area, that is, city center versus periphery, and μ_n is a neighborhood-specific FE.

In the third model, we turn to IV estimation, using the touristic attractiveness instrument based on Trip Advisor reviews, and in the fourth model we include the time-invariant sociodemographic and housing Census controls interacted with the population growth rate of each city (base year is 2011) to capture some of the trends that may affect house values beyond Airbnb. These four models are then re-estimated by adding an estimate of the growth in the supply of local amenities, as a further control variable. Although this variable is arguably correlated with the set of year-area FEs and potentially endogenous, its inclusion is an important robustness check of whether the Airbnb impact on sale prices holds when the change in amenities is accounted for.[11]

Next, we investigate the impact of Airbnb density by city modifying the previous specification as follows:

$$\log(Y_{n,t}) = \beta \text{Airbnb Intensity}_{n,t-1} \times \text{city}_i + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t}, \tag{2}$$

where Airbnb Intensity$_{n,t}$ × city$_i$ is the interaction between listing density in neighborhood n at time t with the city i.

We then address the potential heterogeneity of the impact of short-term rental platforms within cities, and we turn to investigating if the impact of Airbnb differs between the center and the suburbs. To this end, we first re-estimate Equation (1) with a specification that adds to the four models described above an interacted term multiplying Airbnb density by a binary variable denoting the city center. If significant, the interaction term would suggest that the impact on housing prices in the city center differs from the impact in the suburbs. Then, to estimate whether Airbnb impact in each city differs between the center and the suburbs, we modify Equation (2) as follows:

$$\log(Y_{n,t}) = \beta \text{Airbnb Intensity}_{n,t-1} \times \text{city}_i \times \text{area}_b + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t}, \tag{3}$$

[10]The results with rental rates are found to be less informative for our purposes. Indeed, the rental market in Italy is influenced by a housing policy that grants below-market rents in the social housing sector, assigns favorable tax-regimes to assisted tenancies and restricts free-market rents to long-term contracts (4 years) (Baldini & Poggio, 2012). As a consequence, rents may be less responsive to increases in Airbnb density. The results are in Appendix H.

[11]We thank one referee for suggesting us to perform this further sensitivity analysis.

where Airbnb $\text{Intensity}_{n,t} \times \text{city}_i \times \text{area}_b$ is the interaction among listing density in neighborhood n at time t with city i and with an indicator variable area_b denoting either the center or the periphery. To check whether the price effect of Airbnb in the center and in the suburbs differs significantly, we first test, for each city, the restriction that two interacted coefficients are equal. Then, we modify Equation (2) by adding for each city the interaction multiplying Airbnb density by the binary variable denoting the city center, so as estimate if the impact on prices differs significantly between the center and the periphery in each city. Finally, we test if we can reject the hypothesis that the five interacted terms identifying the center–suburb differences are jointly zero. The results of these analyses are in Appendix E, for reason of space.

6 | RESULTS

In this section, we present the results of our analysis. We find significant evidence of a positive impact of Airbnb's diffusion on sale prices, both in the overall sample and in the individual cities.

6.1 | The overall and by city impact of Airbnb density

Table 4 presents the results estimating the impact of an increase in Airbnb density on the house prices for the five Italian cities altogether from 2014 to 2019.

We find that Airbnb estimated coefficients are positive and significant throughout the columns. They remain highly significant also when we account for spatial correlation. Column (1) reports the OLS estimates after controlling for both time-varying and time-invariant control variables (for reasons of space, we omit the coefficients of control variables, but the full set of results is available on request). Column (2) presents the FE results that allow for neighborhood specific FEs, year–city–area, and quarter–city time effects. Columns (3) and (4) report the 2SLS regressions using Tripadvisor's *touristiness* as the instrument. In Column (4) we add, for each city, time-invariant neighborhood-level controls interacted with the growth rate of the population to control for remaining spurious correlations after including space-time interactions. The IV coefficient is statistically significant at the 1% level, and its size of 0.618 implies that an increase of one percentage point in Airbnb density leads to a 0.618% increase in price per square meter. At the bottom of the table, the first-stage results show that the correlation between Airbnb density and the instrument is strong.

When we use the Airbnb density coefficient in Column (4) to calculate the quantitative effects,[12] we find that the increase in Airbnb density from 2014 to 2019 leads to a 5-year increase in sale prices of 43.39 €/m^2. We compute the effect of the annual density increase on the price of the average house in each city. Considering an average house surface of 98 m^2 (Agenzia delle Entrate, 2019), the total effect of the annual increase of Airbnb density on the price of the average house is 860 €. As a comparison, Barron et al. (2020) have found, for the United States, a price increase of 1800$.

To check the robustness of the analysis, we re-estimate the entire set of regressions including, as an additional control, the growth in the number of amenities. Unfortunately, only data on the number of amenities at the start and at the end of the sampling period are available. To overcome this limitation, we assume that the number of amenities has followed a parabolic trend over the years. The results in Table 5 show that, in all columns, the effect of Airbnb density on house prices remains positive and significant even when directly controlling for the increase in

[12]Our model estimates an impact in terms of percentage change in sale prices as a consequence of a one percentage point increase in Airbnb density. To express this in meaningful economic terms, we convert it to the change in Euros of the sale prices per m^2 across the 5 years. We consider the change in Airbnb density in the 5 years at the neighborhood level, and we multiply the average of neighborhood-specific changes with the estimated coefficient of Airbnb intensity, β. Finally, we express this impact in Euro terms by multiplying it by the average sale price of all the neighborhoods in the sample.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 Airbnb density and house sale prices in five Italian cities.

Dependent variable: Log(Sale price)	(1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at *t* − 1	0.937	0.561	0.630	0.618
	(0.479)*	(0.149)***	(0.161)***	(0.157)***
	(0.121)***	(0.0701)***	(0.117)***	(0.114)***
First stage				
Touristiness at *t* − 1			5.82e − 11	5.80e − 11
			(6.21e − 12)***	(6.16e − 12)***
			(7.68e − 12)***	(7.67e − 12)***
F statistic excluded instrument			87.712	88.689
			57.370	57.167
Controls				
Time-invariant (census) controls	×			
Time variant controls	×	×	×	×
Interacted census controls				×
Fixed effects				
Year FE	×			
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
Time-varying controls:	House density, Store density, Garage density, Average house rooms, Average store m^2			
Time-invariant controls:	Number of residents, % Owner-occupancy, % 20–39 years, % > 60 years, % Graduates, % Working, % Foreigners, % Houses in use, Number of houses, % Houses in poor conditions			
Observations	5740	5740	5740	5740
Adjusted R^2	0.799	0.981		

Note: The dependent variable is the natural logarithm of the sale price. Estimation of Equation (1). OLS estimates in Column (1); FE estimates in Column (2); 2SLS estimates in Columns (3) and (4), where we include the interactions between the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics and the growth rate of each city population in the base year 2011. The instrument in Columns (3) and (4) is $a_n^{TA} \times g_t$. For each coefficient, the first parenthesis shows robust standard errors clustered by neighborhood, the second shows Driscoll–Kraay standard errors. The same order is followed when showing the *F* statistic of the excluded instrument.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares; TA, Trip Advisor.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

the number of touristic amenities in each neighborhood. Not surprisingly, the growth in amenity supply, a proxy for attractiveness, also positively affects sale prices.[13]

[13]We thank one referee for suggesting this analysis.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 5 Airbnb density and house sale prices in five Italian cities, including amenities.

Dependent variable: Log(Sale price)	(1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at $t-1$	0.750	0.305	0.303	0.315
	(0.392)*	(0.144)**	(0.170)*	(0.168)*
Number of touristic amenities	0.157×10^{-3}	0.135×10^{-3}	0.135×10^{-3}	0.128×10^{-3}
	(0.313×10^{-4})***	(0.364×10^{-4})***	(0.364×10^{-4})***	(0.3690×10^{-4})***
First stage				
Touristiness at $t-1$			5.82e − 11	5.80e − 11
			(6.21e − 12)***	(6.16e − 12)***
F statistic excluded instrument			87.712	88.689
Controls				
Time-invariant (census) controls	×			
Time variant controls	×	×	×	×
Interacted census controls				×
Fixed effects				
Year FE	×			
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
Time-varying controls:	House density, Store density, Garage density, Average house rooms, Average store m^2			
Time-invariant controls:	Number of residents, % Owner-occupancy, % 20–39 years, % > 60 years, % Graduates, % Working, % Foreigners, % Houses in use, Number of houses, % Houses in poor conditions			
Observations	5740	5740	5740	5740
Adjusted R^2	0.81	0.98		

Note: The dependent variable is the natural logarithm of the sale price. Estimation of Equation (1). OLS estimates in Column (1); FE estimates in Column (2); 2SLS estimates of in Columns (3) and (4), where we include the interactions between the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics and the growth rate of each city population in the base year 2011. The instrument in Columns (3) and (4) is $a_n^{TA} \times g_t$.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares; TA, Trip Advisor.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Next, we turn to the analysis of the impact of Airbnb diffusion in each individual city. Results from estimating Equation (2) are reported in Table 6.[14] We find that all five coefficients show a positive effect on house prices, which is always statistically significant in the IV estimates and are numerically quite different from each other.

[14]Results with the full set of robust standard errors—clustered by neighborhood and allowing for spatial correlation—are in Table G1.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 Airbnb density's impact on house sale prices by city.

Dependent variable: Log(Sale price)	(1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at $t-1$ in:				
Florence	−0.134	0.439	0.437	0.438
	(0.303)	(0.106)***	(0.139)***	(0.140)***
Milan	2.098	2.233	2.509	2.508
	(1.414)	(1.029)**	(1.276)*	(1.275)*
Naples	0.380	1.447	1.778	1.981
	(1.293)	(0.760)*	(0.712)**	(0.772)**
Rome	2.244	0.198	0.410	0.404
	(0.524)***	(0.149)	(0.144)***	(0.144)***
Turin	−27.48	11.24	12.05	12.04
	(8.124)***	(2.670)***	(3.384)***	(2.967)***
Controls				
Time-invariant controls	×			
Time-varying controls	×	×	×	×
Interacted census controls				×
Fixed effects				
Year FE	×			
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
H0: Coefficients of all cities are equal to 0	8.99	8.57	7.31	8.06
F statistic (*p* value)	0.000***	0.000***	0.000***	0.000***
Observations	5740	5740	5740	5740
Adjusted R^2	0.83	0.98		

Note: OLS, FE, and 2SLS estimates of Equation (2). See notes in Table 4.
Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

To evaluate the magnitude of the impacts in each city, the coefficients have to be adjusted to the house prices in their respective housing markets, which also differ widely. Using the results in Column (4), we apply to the city-specific coefficients the same approach we followed to quantify the overall effect in Table 4, and we compute, for each city, the 5-year increase in sale prices due to a 5-year increase in Airbnb density in that city. Translated into percentage changes with respect to each city's average prices, our results suggest that Airbnb diffusion may have contributed to price increases ranging from 0.6% in Rome to 7.7% in Turin, while the impact in the other cities lies between 2% and 4%.[15]

[15]Our estimates are comparable to those of Garcia-López et al. (2020), who estimate an increase in transaction prices of 5.24% for Barcelona over a 5-year period.

It is worth noting, however, that sale prices have been decreasing over time in Naples, Rome, and Turin (see Figure 2). Hence, the diffusion of online rental platforms might have contributed to mitigate the contraction of property values in these cities. As to the other cities, Airbnb impact on property values is significant both in Florence, which has the highest tourist presence in our sample, and in Milan and Turin, where the business-related component of visitors is comparatively more important. Our results thus suggest that both tourist and business communities seem to take advantage of Airbnb supply to satisfy their needs. This evidence confirms that the role of Airbnb has gone well beyond the accommodation of tourists in search of a "sharing" experience, but has grown into a major player in the short-term housing market.

6.2 | Airbnb's impact within cities

Motivated by the idea that short-term rental platforms may concur to a spatial dimension of inequality within cities (Almagro & Domínguez-Iino, 2021; Calder-Wang, 2021; Xu & Xu, 2021), we now disentangle the impact of Airbnb growth on the prices in the center and in the suburbs, based on the mechanisms described in the conceptual framework. To this end, we have divided each city into a central and a suburban area, as described in Section 4. As the analysis focuses on intraurban differences, it is worth noting that in Italy and in Continental Europe, contrary to many US cities, the center is typically the area where well-off and middle-class people live, while the periphery often houses the working class, immigrants and more disadvantaged people. The descriptive statistics in Section 2 and in the appendix provide documental evidence on the disparity conditions between the center and the suburbs in our data.

As a first step to investigate the suburban impact of short-term rental platforms, we test if a statistically significant difference in the Airbnb effect between the center and the periphery can be found when estimating the effects for the five cities altogether. Table 7 presents the results of a model which adds to Equation (1) the interaction between Airbnb density and a binary variable denoting the city center.

The results show that there is a statistically significant difference between the effect of Airbnb density in the peripheries and in the city center. Although the sum of the coefficients indicates that the effect is positive both in the center and in the suburbs, the negative coefficient on the interacted term suggests that the impact of a one percentage point increase in Airbnb density on the house prices in the suburbs is stronger than in the center. This is not surprising because Airbnb density is very low in the peripheries (0.10%, on average in 2014, 0.7% in 2019); hence, a hypothetical one percentage point density increase would imply a stronger percentage increase in the suburbs than in the city center, where Airbnb density is much higher (1.05% in 2014 and 5.58% in 2019, on average).

Driven by the above evidence, we turn to the analysis by city and we estimate if the impact of Airbnb density on the central and peripheral submarkets differs in each city. We then quantify the magnitude of the effects on prices over the period at subcity level. We use Equation (3) to separately estimate how increases in Airbnb density in the center and in the suburbs affect house prices in the respective submarkets and we test whether the differences between each pair of coefficients are statistically significant. The magnitude of the estimated effects is then calibrated using the area-specific listing density changes and submarket characteristics. The results are in Table 8.[16]

Looking at the IV estimates in Column (3), we find that the coefficients on Airbnb density are significantly positive both in the center and in the suburbs of Florence, Milan, and Rome. In contrast, in Naples and Turin, the

[16]Table 8 reports the individual subarea effects, which enables us to compute the quantitative effects of Airbnb density throughout the time window of our sample. In addition, we estimate an alternative specification of Table 8, similar to Table 7 that allows us to test directly the significance of the difference between the effects in the center and in the suburbs and we report the results in the appendix (Table E1). We thank the referee who has suggested us to perform this analysis.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 7 Airbnb density and house sale prices in five Italian cities, difference between center and periphery.

Dependent variable: Log(Sale price)	(1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at $t-1$	6.003	2.294	5.238	5.329
	(1.633)***	(1.650)	(2.041)**	(2.055)**
Airbnb density at $t-1\times$center	−5.005	−1.797	−4.633	−4.736
	(1.588)***	(1.644)	2.005)**	(2.020)**
First stage				
Touristiness at $t-1$			5.82e − 11	5.80e − 11
			(6.21e − 12)***	(6.16e − 12)***
F statistic excluded instrument			87.712	88.689
Controls				
Time-invariant (census) controls	×			
Time variant controls	×	×	×	×
Interacted census controls				×
Fixed effects				
Year FE	×			
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
Time-varying controls:	House density, Store density, Garage density, Average house rooms, Average store m^2			
Time-invariant controls:	Number of residents, % Owner-occupancy, %20–39 years, % > 60 years, % Graduates, % Working, % Foreigners, % Houses in use, Number of houses, % Houses in poor conditions			
Observations	5740	5740	5740	5740
Adjusted R^2	0.80	0.98		

Note: The dependent variable is the natural logarithm of the sale price. Estimation of Equation (1). OLS estimates in Column (1); FE estimates in Column (2); 2SLS estimates in Columns (3) and (4), where we include the interactions between the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics and the growth rate of each city population in the base year 2011. The instrument in Columns (3) and (4) is $a_n^{TA}\times g_t$.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares; TA, Trip Advisor.

***$p<0.01$; **$p<0.05$; *$p<0.1$.

impact on sale prices is significant only in the city center. Notably, based on our tests of the restriction that, for each city, the two coefficients are equal, we find that the difference between the impact on the center and the suburbs is statistically significant (at least) at the 10% level in all cities, except Turin.[17] In Appendix F, the specification we

[17]The p values of the city-specific tests that the coefficient of the impact on prices in the center is equal to the coefficient of the impact in the periphery are 0.06 for Florence, 0.07 for Milan, 0.07 for Naples, 0.09 for Rome and 0.45 for Turin. In other words, the tests reject the null for all cities except Turin.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 8 Effects on house sale prices within cities.

Dependent variable: Log(Sale price)	(1) FE	(2) 2SLS	(3) 2SLS
Airbnb density at $t-1$ in:			
Florence suburbs	0.528	4.194	4.206
	(1.406)	(2.013)**	(2.017)***
Florence central	0.438	0.469	0.468
	(0.106)***	(0.149)***	(0.150)***
Milan suburbs	4.534	8.950	8.937
	(1.734)***	(4.185)**	(4.194)**
Milan central	1.106	2.458	2.451
	(0.760)	(1.167)**	(1.166)**
Naples suburbs	−2.773	−1.876	−3.273
	(1.343)**	(3.433)	(3.021)
Naples central	1.902	1.849	1.969
	(0.440)***	(0.636)***	(0.702)***
Rome suburbs	3.463	5.548	5.519
	(1.798)*	(3.065)*	(3.055)*
Rome central	0.167	0.312	0.303
	(0.148)	(0.141)**	(0.142)***
Turin suburbs	26.57	−10.53	−6.463
	(6.503)***	(26.90)	(26.79)
Turin central	9.163	12.84	12.53
	(2.782)***	(2.950)***	(3.057)***
Controls			
Time-varying controls	×	×	×
Interacted census controls			×
Fixed effects			
Year FE			
Neighborhood FE	×	×	×
Quarter#City FE	×	×	×
Year#City#Area FE	×	×	×
Observations	5740	5740	5740
Adjusted R^2	0.98		

Note: FE and 2SLS estimates of Equation (3). See notes in Table 4.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

estimate in Table E1 allows one to test, altogether, the differences between center and periphery by adding, for each city, the interaction between Airbnb density and a binary variable for the city center (similar to Table 7). We find that we can reject the joint hypothesis that the coefficients estimating the differential Airbnb impact in the center are equal to zero, which allows us to reject the null that, overall, there is no difference between the within-city effects.

The estimated coefficients in Table 8 suggest that the within-city effects also quantitatively differ when compared across the five cities. Our calculations show that, in Florence, Airbnb's growth between 2014 and 2019 has respectively led to house price increases of 132.20 €/m^2 in the city center (where Airbnb density is both high and fast growing) and 159.76 €/m^2 in the suburbs (where density has grown, but remains comparatively low). This finding suggests that Airbnb has generated a value-increasing process, apparently greater in the suburbs than in the center, notwithstanding the higher tourist concentration in the center (for a similar result, see Thackway et al. (2022), who also found that Airbnb diffusion in Sydney has a more substantial positive impact on suburbs with fewer tourist attractions). Hence, over time, this process might reduce the disparity of property values between the two submarkets. In contrast, Milan shows an opposite trend: Airbnb growth accounts for a 5-year increase of 503.59 €/m^2 in the center and 262.34 €/m^2 in periphery, thus suggesting that the attractiveness and the housing demand of Milan's city center have increased much faster than in the suburbs, widening the gap between property values in the two areas. The evidence is similar in Rome, where the price increase is much larger in the center, where Airbnb density has doubled over time, than in the suburbs, where density is low and stable.[18]

The contrasting results of Florence on one side and of Milan and Rome on the other side, may derive from their different initial conditions documented in Section 2. In Florence, where the suburbs are not too far from the historical center, income and house price disparities between center and periphery are not large, suggesting that relatively favorable living conditions in its suburbs that satisfy and attract both local residents and Airbnb users.

Conversely, in Milan and Rome, the gap between property values in the center and in the periphery, income inequality between the richest and the poorest postcode districts (5.3 and 4.2 times higher for Milan and Rome, respectively), and the ratio between the increase in tourist amenities' density in the center and in the suburbs (6.5 and 9.5 for Milan and Rome, respectively) are higher than in any other city. Hence, their city centers are plausibly more attractive to both tourists and local residents, driving up house prices. Finally, in Naples and Turin, the two cities with the lowest income per capita and listing density in our sample, the impact on sale prices is significantly positive only in the city center, as the effect in the suburbs does not survive in IV estimation.

To sum up, in Milan and Rome the diffusion of Airbnb appears to widen the existing gap between property values in the center and the suburbs, whereas in Florence it seems to lead to a convergence of house prices over time. In Turin and Naples, Airbnb seems to bring an advantage only to the city center, where it revamps property values that are low and even decreasing over time, but no benefit to the suburbs.

6.3 | Discussion of results

Overall, our results show that the impact of Airbnb on the metropolitan housing markets is not neutral, highlighting the importance of estimating the effect both by city and within cities. Airbnb almost certainly increases property values in the center but, in the peripheries, our results are mixed, as we find a positive effect on the house prices in the suburbs of Milan, Rome, and Florence, but no significant evidence in Naples and Turin.

Our results also suggest that the response of the housing submarkets to the penetration of Airbnb depends on the initial conditions in the local economy. Although the price impact in Milan, Rome, and Florence is positive both in the center and the suburbs, we find that sale prices tend to diverge in Rome and Milan and to converge in

[18]Recall that quantitative effects are calculated using the initial (i.e., 2014) prices in central or suburban neighborhoods. Hence, although the magnitude of the coefficients is larger in the suburbs than in the center, the price increase in Euro terms is larger the higher the initial price level in that area.

Florence. By considering this evidence having in mind the subcity urban and demographic characteristics, we realize that the Airbnb-related price gap between center and suburbs increases in cities where the pre-existing disparities on average income, amenity supply and property values are larger, and decreases where the initial inequality is lower. The diversity of the price trends in the center and in the periphery thus suggests that the overall Airbnb impact, and even the city-specific effects are not informative enough for policymakers. In fact, they should also take the local characteristics below the metropolitan level into account to enlighten a bespoke policy approach that pays attention to pre-existing conditions and distributional effects at the subcity level. Being part of an empirical literature that struggles to find univocal effects, our work contributes by proposing a research approach—that is, focusing on the submarket level and the extent and sign of diversity and inequality between subareas—that may be generalized to other cities, situations and settings.

Our study on the impact of Airbnb on the Italian housing market focuses solely on the period between 2014 and 2019. Thus, the impact of COVID-19 is outside our temporal scope. This is a limitation of our study, as the business and travel restrictions may have asymmetrically affected not only the short-term rental market, but also the inequality indicators at the subcity level. Still, we can conjecture how the COVID-19 shock might have affected our results, as the travel restrictions related to the pandemic had a significant impact both on Airbnb supply and touristic flows. For example, Shen and Wilkoff (2022) find that Airbnb's supply decreased as far as 25%, and dwellings that did remain open have seen their occupancy drop by as far as 20% while Alekseev et al. (2023) show that COVID-19 also impacted both touristic and nontouristic amenities.

Under the circumstances, the drop in Airbnb demand/supply, coupled with the crisis faced by local amenities, should have led to a sharp decrease in both house and rental prices. Indeed, Thackway et al. (2022) have shown that, in Sidney, the reduced Airbnb activity during the pandemic can be associated with a decline in rental rates. As also in Italy tourist and amenity activities shut down, the pressure on the housing market probably diminished especially in the city center where Airbnb density was higher and the substitution effect between long and short-term rental more intense. However, the aftermath of COVID-19 might be short-lived, as Airbnb activity has already bounced back from the COVID-19 impact in 2022 and listing bookings in 2022 have surpassed those in 2019.[19] In addition, the 2023 annual report of the Italian Federation of Public Establishments highlights that the consumption of restaurants, pubs and bars has almost bounced back to prepandemic levels, suggesting that also the amenity supply has promptly responded to the recovery in (local and tourist) demand. On the basis of this evidence, we may speculate that our findings could still hold, in the aftermath of the renewed travel activity, as all the main components of our transmission mechanism have recovered in the last 2 years. If any, we might expect that the recovery of the price effects in the suburbs may be slower, given the lower Airbnb density, especially in cities where the disparity between center and periphery is larger.

7 | CONCLUSIONS

The diffusion of home-sharing platforms has recently sparked interest in their potential distributional impact on the participants in the housing market, suggesting that they may concur to a spatial dimension of inequality within cities. In this paper, we have studied how Airbnb' growth has affected house prices in five important cities, which aptly represent the heterogeneity of the Italian housing market: Florence, Milan, Naples, Rome, and Turin. On the basis of a rich and inspiring literature and on the intrinsic variety of our sample of cities, we derived a conceptual framework to disentangle the different impacts of Airbnb density on property values at the metropolitan and submarket levels, leveraging on the differences in their initial conditions. Then, we have estimated the impact of Airbnb diffusion on the housing market for the five cities altogether and individually, calculating the quantitative

[19]Airbnb Bookings Climb Past Pre-Pandemic High in 2022. Statista, March 9, 2023.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

effects in Euros. Finally, we turned to investigating Airbnb impact on the house prices in the city center and in the suburbs and whether they differ.

Our findings suggest that Airbnb diffusion has caused an increase in house prices. The aggregate results for the five cities indicate that an increase of 1 percentage point in Airbnb density leads to an average 0.63% rise in sale prices. The positive effect differs across cities though, with prices increases ranging from 0.6% in Rome to 7.7% in Turin. These results are consistent with those of the previous literature (Barron et al., 2020; Garcia-López et al., 2020). When focusing within cities, we find that in Florence, Milan, and Rome the diffusion of online rental platforms positively affects property values not only in the center but also in the suburbs, while in Turin and Naples, the impact on sale prices is statistically significant only in the center. Moreover, in cities where Airbnb affects both the center and the suburbs, price trends quantitatively differ at the subcity level, as the property value gap increases in Milan and Rome and shrinks in Florence. We thus find, over time, a convergence of house prices in some cities and a divergence in another. Do these trend correlate with local conditions? Indeed, initial conditions in the housing submarkets appear to be crucial when assessing the magnitude of the effects: the price increases in the centers of Milan and Rome—where the center–periphery disparity on average income, house prices and amenity supply are larger—are much higher than in the suburbs, whereas in Florence—where within-city inequality is lower—the price increase is higher in the periphery.

To conclude, our results speak of an overarching impact on the housing markets, but also of heterogeneous trends at the subcity level that require context-specific policies that evaluate the consequences on house prices on a case-by-case basis to better understand when and how Airbnb's diffusion may benefit some area of the city while leaving others behind. One further step in this direction would be to study the spillovers of Airbnb diffusion on different submarkets so as to frame, both theoretically and empirically, how the growing concentration of short-term rental platforms in the city center may affect the housing market and the living conditions in the periphery. Using a descriptive approach, we tentatively addressed this problem in the appendix, but the complexity of the underlying transmission mechanisms suggests that we pursue this research question in the future. Using a descriptive approach, we tentatively addressed this problem in the appendix, but the complexity of the underlying transmission mechanisms suggests that we pursue this research question in the future, equipped with more detailed and time-varying data at the subcity level. Similarly, by extending the sample period to more recent years, our future agenda may also cover the relevant question, unaddressed in the present study, of the impact of COVID-19's on the short-term rental industry and the local housing markets, as the shock to tourism, travels and business activity, and the subsequent recovery have certainly affected center and suburbs in a different way.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the real-estate portal *Idealista* and the Italian register of the real-estate market *OMI* (*Agenzia delle Entrate—Territorio—Osservatorio del mercato immobiliare*) for kindly providing data on the Italian rental market. For useful comments and suggestions, the authors thank Laura Abrardi, Luigi Benfratello, Federico Boffa, Marc Bourreau, Elena Cefis, Gilles Duranton, Tomaso Duso, Sauveur Giannoni, Francesco Luigi Milone, Lorien Sabatino, Raffaele Scuderi, Dominique Torre, Huaxin Wang-Lu, and all participants to the XIX SIEPI Workshop, the 62nd SIE Conference, the 9th iCare Conference and the 1st The Economics of Airbnb Workshop. This research has been partially supported by Ministero dell'Istruzione, dell'Università e della Ricerca Award TESUN-83486178370409 finanziamento dipartimenti di eccellenza CAP. 1694 TIT. 232 ART. 6. Open access publishing facilitated by Politecnico di Torino, as part of the Wiley - CRUI-CARE agreement.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

DATA AVAILABILITY STATEMENT

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

ORCID

Flavio Pino http://orcid.org/0000-0002-2916-299X
Laura Rondi http://orcid.org/0000-0002-7683-1164

REFERENCES

Agenzia delle Entrate. (2019). *Gli immobili in Italia—2019*. https://www1.finanze.gov.it/finanze/immobili/public/contenuti/immobili_2019.pdf

AirDNA. (2021). *AirDNA—Short-term rental analytics—Vrbo & Airbnb Data*. https://www.airdna.co/

Alekseev, G., Amer, S., Gopal, M., Kuchler, T., Schneider, J. W., Stroebel, J., & Wernerfelt, N. (2023). The effects of COVID-19 on US small businesses: Evidence from owners, managers, and employees. *Management Science*, *69*(1), 7–24.

Almagro, M., & Domínguez-Iino, T. (2021). *Location sorting and endogenous amenities: Evidence from Amsterdam* [Working Paper]. https://m-almagro.github.io/Location_Sorting.pdf

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Ayouba, K., Breuillé, M.-L., Grivault, C., & LeGallo, J. (2020). Does Airbnb disrupt the private rental market? An empirical analysis for French cities. *International Regional Science Review*, *43*(1–2), 76–104. https://doi.org/10.1177/0160017618821428

Baldini, M., & Poggio, T. (2012). Housing policy towards the rental sector in Italy: A distributive assessment. *Housing Studies*, *27*(5), 563–581. https://doi.org/10.1080/02673037.2012.697549

Bangura, M., & Lee, C. L. (2021). The determinants of homeownership affordability in Greater Sydney: Evidence from a submarket analysis. *Housing Studies*, *38*(2), 206–232.

Bangura, M., & Lee, C. L. (2022). Housing price bubbles in Greater Sydney: Evidence from a submarket analysis. *Housing Studies*, *37*(1), 143–178.

Barron, K., Kung, E., & Proserpio, D. (2020). The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science*, *40*(1), 23–47. https://doi.org/10.1287/mksc.2020.1227

Bartik, T. (1991). *Who benefits from state and local economic development policies? (Books from Upjohn Press)*. W.E. Upjohn Institute for Employment Research.

Benítez-Aurioles, B., & Tussyadiah, I. (2021). What Airbnb does to the housing market. *Annals of Tourism Research*, *90*(100), 103108. https://doi.org/10.1016/j.annals.2020.103108

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Borusyak, K., Hull, P., & Jaravel, X. (2018). *Quasi-experimental shift-share research designs* [Working Paper No. 24997]. National Bureau of Economic Research. https://doi.org/10.3386/w24997

Bourassa, S. C., Hoesli, M., & Peng, V. S. (2003). Do housing submarkets really matter? *Journal of Housing Economics*, *12*(1), 12–28.

Broxterman, D., Coulson, E., Ihlanfeldt, K., Letdin, M., & Zabel, J. (2019). Endogenous amenities and cities. *Journal of Regional Science*, *59*(3), 365–368.

Calder-Wang, S. (2021). *The distributional impact of the sharing economy on the housing market* (SSRN Scholarly Paper No. ID 3908062). Social Science Research Network. https://doi.org/10.2139/ssrn.3908062

Christian, P., & Barrett, C. B. (2017). *Revisiting the effect of food aid on conflict: A methodological caution* [Policy Research Working Papers No. WPS8171]. The World Bank. https://doi.org/10.1596/1813-9450-8171

Coles, P., Egesdal, M., Ellen, I. G., Li, X., & Sundararajan, A. (2018). Airbnb usage across New York City neighborhoods: Geographic patterns and regulatory implications. In N. M. Davidson, M. Fink, & J. J. Infranca (Eds.), *The Cambridge handbook of the law of the sharing economy* (pp. 108–128). Cambridge University Press. https://doi.org/10.1017/9781108255882.009

Couture, V., Gaubert, C., Handbury, J., & Hurst, E. (2019). *Income growth and the distributional effects of urban spatial sorting* [Working Paper No. 26142]. National Bureau of Economic Research. https://doi.org/10.3386/w26142

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, *80*(4), 549–560. https://doi.org/10.1162/003465398557825

Duso, T., Michelsen, C., Schäfer, M., & Tran, K. D. (2020), *Airbnb and rents: Evidence from Berlin* [DIW Berlin Discussion Paper No. 1890]. DIW. https://doi.org/10.2139/ssrn.3676909

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Einav, L., Farronato, C., & Levin, J. (2016). Peer-to-peer markets. *Annual Review of Economics*, *8*(1), 615–635. https://doi.org/10.1146/annurev-economics-080315-015334
Farronato, C., & Fradkin, A. (2018). *The welfare effects of peer entry in the accommodation market: The case of Airbnb* [w24361]. National Bureau of Economic Research. https://doi.org/10.3386/w24361
Filippas, A., & Horton, J. J. (2018). *The tragedy of your upstairs neighbors: Externalities of home-sharing* [Working Paper].
Franco, S. F., & Santos, C. D. (2021). The impact of Airbnb on residential property values and rents: Evidence from Portugal. *Regional Science and Urban Economics*, *88*, 103667. https://doi.org/10.1016/j.regsciurbeco.2021.103667
Garcia-López, M.-n., Jofre-Monseny, J., Martínez-Mazza, R., & Segú, M. (2020). Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona. *Journal of Urban Economics*, *119*, 103278. https://doi.org/10.1016/j.jue.2020.103278
Garcia-López, M. A., & Rosso, G. (2023). Let's visit the consumer city: The role of tourism in reshaping Urban Amenities. Available in SSRN 4959434.
Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, *1*(1), 27–50.
Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624. https://doi.org/10.1257/aer.20181047
Gupta, A., Mittal, V., Peeters, J., & Van Nieuwerburgh, S. (2021). Flattening the curve: Pandemic-induced revaluation of urban real estate. *Journal of Financial Economics*. *146*(2), 594–636. https://doi.org/10.1016/j.jfineco.2021.10.008
Gyourko, J., & Molloy, R. (2015). Regulation and housing supply. In G. Duranton, J. V. Henderson, & W. C. Strange (Eds.). *Handbook of regional and urban economics* (Vol. 5, pp. 1289–1337). Elsevier. https://doi.org/10.1016/B978-0-444-59531-7.00019-3
Hidalgo, A., Riccaboni, M., & Velazquez, F. J. (2023). When local business faded away: The uneven impact of Airbnb on the geography of economic activities. Cambridge. *Cambridge Journal of Regions, Economy and Society*, *16*(2), 335–348.
Horn, K., & Merante, M. (2017). Is home sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics*, *38*, 14–24. https://doi.org/10.1016/j.jhe.2017.08.002
Idealista. (2021). *Idealista—Case e appartamenti, affitto e vendita, annunci gratuiti*. https://www.idealista.it/
ISTAT. (2021). *Istat.it—15° censimento della popolazione e delle abitazioni 2011*. https://www.istat.it/it/censimenti-permanenti/censimenti-precedenti/popolazione-e-abitazioni/popolazione-2011
Jones, C., Coombes, M., Dunse, N., Watkins, D., & Wymer, C. (2012). Tiered housing markets and their relationship to labour market areas. *Urban Studies*, *49*(12), 2633–2650.
Keskin, B., & Watkins, C. (2017). Defining spatial housing submarkets: Exploring the case for expert delineated boundaries. *Urban Studies*, *54*(6), 1446–1462.
Koster, H. R. A., van Ommeren, J., & Volkhausen, N. (2021). Short-term rentals and the housing market: Quasi-experimental evidence from Airbnb in Los Angeles. *Journal of Urban Economics*, *124*, 103356. https://doi.org/10.1016/j.jue.2021.103356
Lanzara, G., & Minerva, G. A. (2019). Tourism, amenities, and welfare in an urban setting. *Journal of Regional Science*, *59*(3), 452–479.
Letdin, M., & Shim, H. S. (2019). Location choice, life cycle and amenities. *Journal of Regional Science*, *59*(3), 567–585.
Li, L., & Xia, F. (2022). City sub-center as a regional development policy: Impact on the property market. *Journal of Regional Science*, *63*(3), 643–673.
Moreno-Maldonado, A., & Santamaria, C. (2022). *Delayed childbearing and urban revival* [Working Paper]. https://drive.google.com/file/d/1ENRNKGYO6dtsGWglxshC4QKF29FMDSlj
Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417–1426. https://doi.org/10.2307/1911408
Palm, R. (1978). Spatial segmentation of the urban housing market. *Economic Geography*, *54*(3), 210–221.
Poterba, J. M. (1984). Tax subsidies to owner-occupied housing: An asset-market approach. *The Quarterly Journal of Economics*, *99*(4), 729–752. https://doi.org/10.2307/1883123
Rothenberg, J. (1991). *The maze of urban housing markets: Theory, evidence, and policy*. University of Chicago Press.
Shen, L., & Wilkoff, S. (2022). Cleanliness is next to income: The impact of COVID-19 on short-term rentals. *Journal of Regional Science*, *62*(3), 799–829.
Sheppard, S., & Udell, A. (2016). *Do Airbnb properties affect house prices*? [Williams College Department of Economics Working Papers, 3].
Thackway, W. T., Ng, M. K. M., Lee, C.-L., Shi, V., & Pettit, C. J. (2022). Spatial variability of the 'Airbnb Effect': A spatially explicit analysis of Airbnb's impact on housing prices in Sydney. *ISPRS International Journal of Geo-Information*, *11*(1), 65.
Thackway, W. T., & Pettit, C. J. (2021). Airbnb during COVID-19 and what this tells us about Airbnb's impact on rental prices. *Findings*, 23720.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Wang, Z., & Chen, L. (2019). Destination choices of Chinese rural–urban migrant workers: Jobs, amenities, and local spillovers. *Journal of Regional Science*, *59*(3), 586–609.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51.

Xu, M., & Xu, Y. (2021). What happens when Airbnb comes to the neighborhood: The impact of home-sharing on neighborhood investment. *Regional Science and Urban Economics*, *88*, 103670. https://doi.org/10.1016/j.regsciurbeco.2021.103670

How to cite this article: Congiu, R., Pino, F., & Rondi, L. (2024). The uneven effect of Airbnb on the housing market: Evidence across and within Italian cities. *Journal of Regional Science*, 1–53. https://doi.org/10.1111/jors.12737

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

APPENDIX A: EMPIRICAL LITERATURE AND ADDITIONAL DESCRIPTIVE TABLES

See Tables A1–A3.

TABLE A1 Overview of the literature on the impact of Airbnb on house prices and rents: Empirical methods and results.

Author	Aim and context	Method	Control variables	Results
Sheppard and Udell (2016)	Impact of Airbnb on house prices in New York City.	Fixed-effect (FE) model (hedonic) and difference-in-differences SE clustered at the census tract level.	Information about the house being sold; areas of interest; tax lot; census tract level information on education, racial and ethnic demographics, employment measures; crimes by precinct. Year of sale and neighborhood FEs.	Doubling the number of Airbnb listings in a 300-m radius around a property leads to a 6%–11% increase in its value.
Horn and Merante (2017)	Impact of Airbnb on asking rents and on the number of houses available for rent in Boston.	FE model. Asking rents used with a 1-month lag with respect to the Airbnb density measure. SE clustered at the census tract level.	Number of beds and bathrooms, size, number of newly built rental units in each tract. Population, housing units, crime level, building permits, and restaurant licenses issuance at the tract level. Census tract and month FE.	An increase in the 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%.
Barron et al. (2020)	Impact of Airbnb on house prices and rents in the USA.	Instrumental variable (IV) is the interaction of Google Trends global search index with a measure of how touristy a Zone Improvement Plan (ZIP) code is in 2010. SE clustered at the ZIP code level.	ZIP code level 5-year estimates of income level, population, education, employment rate, owner-occupancy rate. One-year estimates of housing vacancy rates in the metropolitan area. ZIP code FEs, area time-varying effects, correlated with number of listings.	A 1% increase in Airbnb listings leads to a 0.018% increase in rents and 0.026% in sale prices, decreasing with the share of owner-occupiers.
Koster et al. (2021)	Impact of Airbnb on house prices and rents in L.A. County.	Spatial regression discontinuity design which compares changes in prices across municipality borders after localized bans to Airbnb. Difference-in-differences to estimate the effect on rents. SE clustered at the census block level.	Property and neighborhood characteristics, location controls. Census block and area-month FEs.	The legislation on short-term rentals resulted in a decrease of 2% in both rent and sale prices.

(Continues)

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE A1 (Continued)

Author	Aim and context	Method	Control variables	Results
Ayouba et al. (2020)	Impact of Airbnb on asking rents in eight French cities.	Hedonic regression allowing for heteroskedasticity and spatial error autocorrelation of unknown forms. B-spline functions for some controls. Lagged variables to limit endogeneity.	Structural characteristics of dwellings, accessibility to jobs and services, socioeconomic context, and environmental quality around housing. Time FEs.	A 1% increase in Airbnb density in a given neighborhood leads to a 0.5% increase in rents in Pairs. When focusing on commercial listings, the impact more than doubles to 1.2%.
Garcia-López et al. (2020)	Impact of Airbnb on the housing market in Barcelona.	FE models (hedonic). IV is the interaction of Google Trends local search index with a measure of how touristy a ZIP code is. SE clustered at the neighborhood level.	Neighborhood and time FEs. neighborhood level time trends and demographic effects.	Airbnb led to 7% increase in rents and a 17% and 14% increase in transaction prices in Barcelona's areas most popular with tourists.
Duso and Michelsen (2020)	Impact of Airbnb on asking rents in Berlin.	IV using an exogenous shock: introduction of a ban on the use of apartments as short-term rentals, only affecting “entire home” dwelling types. SE clustered at the ZIP code level.	Neighborhood characteristics: restaurants, bus stops, supermarkets, noise level, air quality, age of buildings. Apartment characteristics: size, rooms, parking lot. Linear and quadratic monthly trends and ZIP codes FE.	An additional Airbnb listing increases by at least seven cents the average monthly rents per square meter.
Franco and Santos (2021)	Impact of Airbnb on house prices and rents in Portugal.	IV is the interaction of Google Trends global search index with a measure of how touristy a municipality or parish is pre-Airbnb expansion. Difference-in-differences to compare results. SE clustered at the municipality or parish level.	Census data on sociodemographic characteristics, number of dwellings, and population. Further data at the parish level for the cities of Porto and Lisbon. List of time-invariant amenities. Year–quarter FEs.	A one percentage point increase in Airbnb density results in a 3.7% increase in house prices; no evidence on rents. The impact on sale prices is greater in city centers and tourist areas.
Thackway et al. (2022)	Impact of Airbnb on house prices in Sydney.	Hedonic property valuation model, IV is the interaction of Google Trends global search index with a measure of how touristy a municipality or parish is pre-Airbnb expansion and Geographically Weighted Regressions.	Apartment characteristics, time-invariant amenities in the house proximity, location w.r.t. landmarks.	1% increase in Airbnb density causes a 2% increase in sale price. The effect is insignificant in Sydney's central business district and positive in less touristic areas.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE A2 Housing market data by city at the beginning and the end of the period.

	2014q4				2014	
	Monthly rent	Sale price	Airbnb density (%)	Store density (%)	Revenue	Tourists/capita
Average	12.11	3338.79	0.41	12.45	24,954	7.52
Florence	12.90	3504.76	1.20	8.64	23,624	22.82
Milan	13.65	3557.11	0.29	17.48	30,156	7.73
Naples	9.28	2759.34	0.15	15.28	19,880	2.96
Rome	12.63	3633.47	0.43	9.87	24,577	8.26
Turin	7.90	1945.49	0.11	9.83	22,542	3.39
	2019q4				**2019**	
	Monthly rent	**Sale price**	**Airbnb density (%)**	**Store density (%)**	**Revenue**	**Tourists/capita**
Average	13.47	3147.18	2.32	12.98	26,019	9.75
Florence	14.73	3827.65	5.84	8.81	24,444	30.28
Milan	17.71	3891.87	2.11	18.90	32,330	8.92
Naples	9.85	2231.41	2.23	15.59	19,757	4.00
Rome	12.65	3076.66	1.87	10.01	25,262	11.11
Turin	7.57	1584.09	0.74	10.15	23,793	4.27

Note: This table shows average values for monthly rent, sale price, listing, and store densities in percentage—overall and by city—for the last quarter of 2014 and 2019. Average revenue and tourists per capita at the yearly level are shown for years 2014 and 2019. Rent and sale prices are expressed in euros per square meter.

Sources: AirDNA, Idealista, ISTAT, and Osservatorio del Mercato Immobiliare.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE A3 Airbnb presence and housing market characteristics within the city.

	Suburbs					Center				
	Monthly rent	Sale price	Airbnb density (%)	Store density (%)	Amenities Density (per km^2)	Monthly rent	Sale price	Airbnb density (%)	Store density (%)	Amenities Density (per km^2)
2014q4										
Average	11.09	2817.53	0.10	6.97	808	14.18	4392.28	1.05	23.51	4122
Florence	12.41	3193.87	0.25	3.77	423	13.28	3746.57	1.94	12.44	1386
Milan	12.24	2764.23	0.16	8.50	1370	17.08	5487.60	0.59	39.34	8153
Naples	8.19	2300.23	0.02	8.04	1095	10.58	3310.27	0.31	23.96	3653
Rome	11.49	3116.82	0.06	6.46	404	15.92	5114.53	1.49	19.64	4052
Turin	7.45	1778.04	0.04	6.08	747	8.79	2280.38	0.24	17.35	3365
2019q4										
Average	12.22	2487.49	0.70	7.35	1249	16.02	4480.45	5.58	24.36	6536
Florence	14.01	3372.26	1.46	3.85	672	15.29	4181.84	9.25	12.66	2205
Milan	15.93	2709.56	1.29	9.31	2143	22.04	6770.54	4.13	42.24	13,219
Naples	8.16	1759.23	0.60	8.23	1647	11.88	2798.04	4.19	24.42	5670
Rome	11.43	2595.42	0.28	6.68	638	16.14	4456.20	6.42	19.57	6285
Turin	7.07	1321.08	0.36	6.27	1148	8.58	2110.10	1.51	17.91	5301

Note: This table shows average values for monthly rent, sale price, listing, and store density in percentage—in the suburbs and in the city center—for the last quarter of 2014 and 2019.

Sources: AirDNA, Idealista, and Osservatorio del Mercato Immobiliare.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

APPENDIX B: DATA

Rent and sale prices data and neighborhood definition

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 neighborhoods, that is, geographical areas sharing common characteristics. Idealista data cover 287 neighborhoods from the first quarter of 2012 to the first quarter of 2020, and the number of neighborhoods per city varies significantly according to each city's characteristics. For each neighborhood, Idealista provides an estimate of the monthly rental rates and the transaction prices per square meter at the trimester level. We can thus think of the identification of a neighborhood as being equivalent to that of a relevant market. By choosing Idealista's neighborhoods as our definition of neighborhood, we can approximate the geographical scope of the individual housing market, as the real estate company has likely chosen the neighborhoods to minimize the area-specific heterogeneity and the information costs. This mapping allows us to compare different neighborhoods both across and within cities controlling for unobserved neighborhood-level factors and helps us identify the impact of Airbnb.

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 data sets: a property one and a daily one. The property data set provides information on dwelling characteristics, ownership, and rental conditions. The daily data set provides, for each dwelling, rental outcomes such as whether the dwelling was blocked, available, rented and, if so, 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 data sets report the coordinates of each dwelling, albeit with a margin of error. For privacy reasons, in fact, Airbnb scrambles these coordinates so that the reported location of the dwelling is within a 150-m radius from the actual ones. As the anonymized data change over time, AirDNA provides an average of these values, therefore increasing geolocation precision.

We merge the AirDNA and the Idealista data sets by assigning the listings to the neighborhoods, and we finally obtain two measures of Airbnb intensity at the neighborhood-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 really active. The latter is defined as the ratio between the number of listings and the number of houses in a given neighborhood.

Final data set

To characterize each neighborhood according to the attributes of its real estate and the sociodemographic and economic dimensions, we rely on two additional sources: the OMI (the Italian register of the real estate market) data set and the Italian 2011 census by the ISTAT.

OMI provides, for its own geographical partitions, the annual number of housing units, their average number of rooms, the number of commercial activities, their average size in square meters, and the number of garages. Data are available from 2016 to 2019 for every city but Rome, for which they start from 2017. To match the time series of Airbnb data, we extrapolate the OMI data for 2015 (also 2016 for the city of Rome) and the last quarter of 2014, assuming a linear trend. We assigned Idealista neighborhoods to their respective OMI partitions—with some minor approximation. OMI partitions are smaller than Idealista's neighborhoods and, typically, they are contained within the Idealista's neighborhood. When the two geographical units do not completely overlap, we merge the respective data (under the assumption that the real estate market is uniformly distributed within the OMI partition) and assign a share equal to the percentage of overlap to the Idealista neighborhood. OMI partitions are further characterized as central, semicentral, peripheral, suburban and rural. We make use of this distinction to define a binary variable—which we call area—that identifies an Idealista neighborhood as belonging to either the “city center” or the "suburbs." We define a neighborhood as belonging to the city center area if it is either a central or semicentral neighborhood. Conversely, a neighborhood is defined as belonging to the suburbs area if it is either peripheral, suburban or rural. In the empirical analysis, we exploit this dichotomy to investigate whether the impact of Airbnb diffusion differs contingent on the centrality of the neighborhood and to account for centrality-driven unobserved factors through time-varying area FEs.

Through OMI data, now attributed to the Idealista neighborhood, we calculate Airbnb density as the ratio between the number of listings and the number of houses. Similarly, we compute the housing, store and garage densities by dividing the corresponding stock to the area of the Idealista neighborhood, expressed in hectares.

To find additional predetermined control variables we exploited the 2011 census which provides a wealth of (time-invariant) data on demographics, education, occupation, and housing characteristics (ISTAT, 2021) at the census tract level for the cities in the analysis. We collected the number of residents, characterized by age, education level, employment status and citizenship; the number of owner-occupiers; the number of houses, further characterized by occupancy and physical condition. To give an idea of the geographical resolution of census data, note that, while Rome is divided into 117 Idealista neighborhoods, it consists of about 13,000 census tracts. Therefore, by appropriately rearranging the data, it is possible to characterize an Idealista neighborhood accurately with census variables.

The resulting data set consists of a balanced panel of 6027 observations at the neighborhood-trimester level. It comprises 287 neighborhoods and 21 time intervals from the last trimester of 2014 to the last of 2019.

APPENDIX C: INSTRUMENT'S CONSTRUCTION

Our shift-share instrument combines the cross-sectional variation across neighborhoods of a measure of tourist attractiveness, and an aggregate time variation of a measure of Airbnb growth awareness. For the cross-sectional (share) part we use reviews of the top 150 Tripadvisor's attractions for each city to measure the tourist attractiveness a_n^{TA} of a given neighborhood.[20] The shift-share instrument's temporal part (shift) is a measure of Airbnb awareness over time: we derive it from Google Trends by retrieving the number of worldwide searches of the word "Airbnb" at the monthly level.

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

$$a_n^{TA} = \sum_k^K \frac{\text{reviews}_k}{\text{dist}_{n,k}},$$

where n represents the neighborhood, k the tourist attraction, reviews_k the number of reviews of attraction k, and $\text{dist}_{n,k}$ the distance of attraction k from the centroid of neighborhood n expressed in kilometers. This variable predicts where Airbnb listings locate, as the presence of tourist attractions increases tourists' willingness to pay, which in turn raises both listing price and Airbnb activity (Garcia-López et al., 2020).

In addition, we construct an alternative measure of tourist attractiveness that we use as a robustness test, based on Lonely Planet guidebooks and website. Lonely Planet lists the top 10 sites of interest for each city, ordering them by popularity. We geolocate these sites using Google Maps' API to get the coordinates, and we define the alternative share component as follows:

[20] In Appendix G we conduct a robustness check by instead using the top 10 attractions for each city provided by Lonely Planet

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

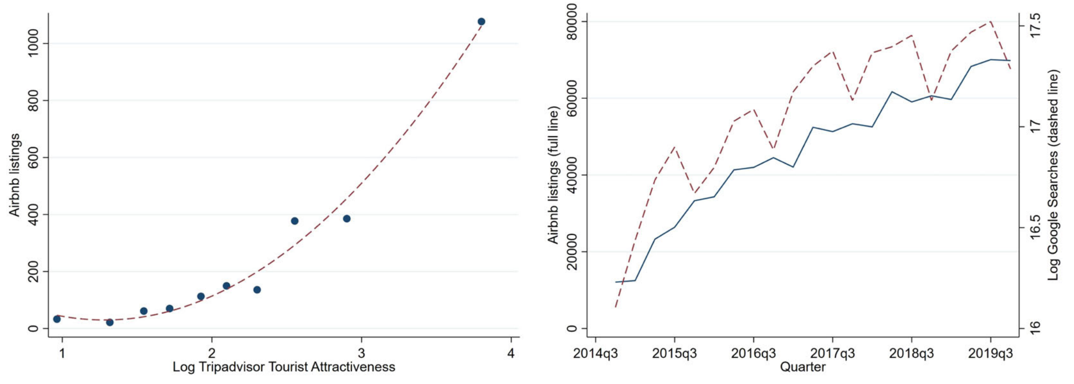

FIGURE C1 Instrumental variable. On the left pane, the figure shows the number of Airbnb listings as a function of the natural logarithm of the tourist attractiveness score. The dots are the deciles of the tourist attractiveness distribution, while the dashed line is the quadratic fit. On the right pane, the figure shows the number of Airbnb listings by quarter (blue line) and the natural logarithm of Google worldwide searches of the word "Airbnb" (dashed line). [Color figure can be viewed at wileyonlinelibrary.com]

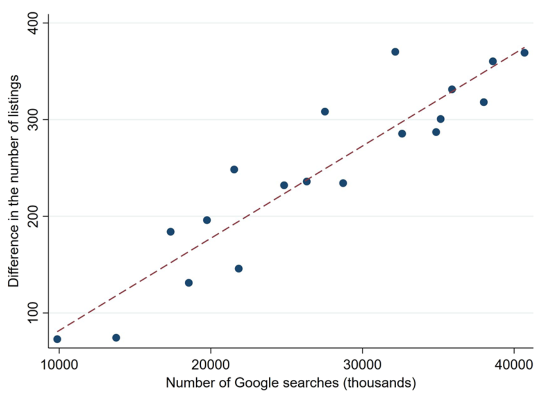

FIGURE C2 Instrument effectiveness. This figure shows the average difference in the number of listings between high- and low-tourist attractiveness neighborhoods—that is, the neighborhoods above or below the median—as a function of the number of Google worldwide searches of the word "Airbnb" (blue dots). The dashed line is the linear fit. [Color figure can be viewed at wileyonlinelibrary.com]

$$a_n^{\mathrm{LP}} = \sum_{k}^{10} \frac{1/\mathrm{position}_k}{\mathrm{dist}_{n,k}},$$

where $\mathrm{position}_k$ 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 refer to as g_t and we derive from Google Trends by retrieving 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 numbers of searches for the last 12 months. This variable provides a proxy of Airbnb intensity by representing the extent of public awareness of the platform on both the demand and supply sides. As pointed out by Barron et al. (2020), the limited time window of the analysis makes it unlikely that the shift component reflects the growth of overall tourism demand, while it should reflect the growth of the short-term housing supply only where caused by

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Airbnb. Notably, we use a global measure of searches rather than a city-specific one so that correlation with tourist flows at the local level is unlikely.

Our instrument, referred to as *touristiness*, is thus the product of the cross-sectional and temporal components (see Barron et al., 2020; Garcia-López et al., 2020 for a similar approach), as follows:

$$z_{n,t} = a_n^{TA} \times g_t.$$

Its intuitive rationale is that the attractiveness score a_n^{TA} predicts where Airbnb listings appear, while the number of searches g_t predicts when they are offered. Figure C1 illustrates the relation between the instrument and Airbnb listings.

The left pane shows the number of listings in a neighborhood as a function of the natural logarithm of the tourist attractiveness score, where the dots are the deciles of the tourist attractiveness distribution. We can see how neighborhoods with a higher tourist attractiveness score have a larger number of listings. The right pane shows the number of listings over time and the number of Google searches of the word Airbnb. We can see how the number of Google searches approximates well the number of listings in a given quarter. While Figure C1 provides graphical evidence of the relevance of the instrument, in Section 6.1 we provide further proof by reporting the first-stage estimates.

The effectiveness of the instrument hinges on the fact that property owners become increasingly likely to offer their property on Airbnb 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 tourist and nontourist neighborhoods.[21] Figure C2 provides a visual representation that the hypothesis holds, as this difference increases with the number of Google searches.

APPENDIX D: INSTRUMENT VALIDITY

The popularity of shift-share instruments has spurred a number of studies that discuss their validity conditions (Borusyak et al., 2018; Christian & Barrett, 2017; Goldsmith-Pinkham et al., 2020) and show that the consistency of the estimator can derive from the exogeneity of either of its terms, even when the other is endogenous.[22] However, this literature also underlines that the main identification threats usually come from the share component (Goldsmith-Pinkham et al., 2020). In our case, the exogeneity of the shares requires that the tourist attractiveness a_n^{TA} is uncorrelated with unobservable neighborhood-specific time-varying shocks captured by the error term $\varepsilon_{n,t}$. That is to say, the tourist attractiveness of a neighborhood should be correlated with changes in house prices and rents only through the density of Airbnb—after controlling for our set of covariates and FEs. Our empirical strategy accounts for identification threats from the high correlation between tourist attractiveness and centrality by including center- and suburbs-specific year-level FEs and neighborhood-level time-varying controls associated with urban revival processes. However, in this section, we make three further arguments for why the exogeneity condition is likely to hold in our setting.

D.1 | Parallel pretrends

Noting that the shift-share instrument makes use of level differences in the share component, Goldsmith-Pinkham et al. (2020) argue that the validity of the following assumption should be assessed: the shock (i.e., awareness of the Airbnb platform, as opposed to pre-existing conditions) is what determines the difference in the changes in house

[21]We split neighborhoods according to tourist attractiveness depending on whether they are below or above the median.

[22]Among others, consistency of the estimator can derive from the sole shift component where a long time series having weak serial dependence is present, even when there is a single shock per period (Borusyak et al., 2018).

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

FIGURE D1 Parallel pretrends. This figure shows average house price (left pane) and rents (right pane), normalized to the first quarter of 2012. On each pane, the two curves represent the averages across tourist (blue line) and nontourist neighborhoods (red line). The vertical dashed line, coinciding with the first quarter of 2014, approximates the entry of Airbnb in the market. [Color figure can be viewed at wileyonlinelibrary.com]

prices and rents. We test the assumption by looking at the trends in changes before the shock, as in parallel pretrend tests in difference-in-differences analysis.

We date the entry of Airbnb at the beginning of 2014, when AirDNA first started recording data, as its activity was previously irrelevant in Italy.[23] We therefore take the first quarter of 2014 as the treatment period. Instead, our data on rents and sale prices date back to the first quarter of 2012. We use the tourist attractiveness score a_n^{TA}, to distinguish between nontourist neighborhoods (first quartile of the distribution of a_n^{TA}, our control group) and tourist neighborhoods (the other three quartiles, the treatment group). Figure D1 shows the average house price (left pane) and rents (right pane), normalized to the first quarter of 2012.

No differential pretrends appear between tourist and nontourist neighborhoods for both house prices and rents before the treatment period: that is, the trends start to diverge only after the diffusion of Airbnb began to intensify. This graphical evidence suggests that the neighborhoods with a different tourist attractiveness score did not generally have different long-run house price and rent trends.

D.2 | IV impact on non-Airbnb neighborhoods

Our second test checks whether the touristiness instrument has a statistically significant effect on prices in neighborhoods that never registered an impactful Airbnb activity. For the instrument to be valid, the effect should be significant only in neighborhoods where listings are present. If an effect is found outside of those cases, the instrument does not predict prices only through the Airbnb density and is therefore capturing a spurious correlation.

We estimate Equation (1) with the interacted census controls, our most complete specification, regressing the natural logarithm of sale prices directly on the instrumental variable (without 2SLS) on three subsamples:

1. neighborhoods that never registered any Airbnb activity,
2. neighborhoods that registered very little Airbnb activity,
3. neighborhoods that registered a significant Airbnb activity.

[23]Looking at the creation date of the listings, we note that the number of listings registered between 2008 and the end of 2013 is barely noticeable.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE D1 Correlation between instrument and house prices in neighborhoods with no Airbnb presence.

Dependent variable:	Log(Sale price) (1)	(2)	(3)
Touristiness at $t-1$	4.87e − 10	3.54e − 10	1.67e − 11**
	(3.15e − 10)	(3.45e − 10)	(8.35e − 12)
Controls			
Time-varying controls	×	×	×
Interacted census controls	×	×	×
Fixed effects			
Neighborhood FE	×	×	×
Quarter#City FE	×	×	×
Year#City#Area FE	×	×	×
Observations	680	1040	2860
Adjusted R^2	0.969	0.951	0.986

Note: Fixed effects (FE) estimates of Equation (1). The dependent variable is the natural logarithm of the sale price, while the variable of interest is the lagged touristiness. Columns (1)–(3) show the coefficients for the three different subsamples according to Airbnb activity. All columns include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population from the base year 2011. Robust standard errors clustered by neighborhood in parenthesis.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Subsample 2 consists of neighborhoods having at most 100 listings throughout the entire time period, that is, a maximum average of five listings per quarter. Subsample 3 covers neighborhoods belonging to the top three quartiles of the distribution of listings. We do not limit the analysis to the first and third subsamples because the neighborhoods that have no listings throughout the period are very few. Table D1 reports our findings, where the three columns represent the different subsamples.

Columns (1) and (2) of the table show that there is no evidence of a statistically significant relationship between our instrument and house prices. The effect is significant only for the third column, where neighborhoods with Airbnb activity are considered. This finding provides further evidence that the instrument predicts house prices only through the Airbnb intensity.

D.3 | Placebo test

We further assess the exogeneity of our instrument with a placebo test, following Barron et al. (2020) and Christian and Barrett (2017), that allows us to check if the effects we estimate can be reasonably attributed to a causal relation or depend on spurious time trends. To this end, we randomize our measure of Airbnb intensity by swapping the number of listings among neighborhoods that have at least some degree of Airbnb penetration by the end of the time period (i.e., one listing by the last quarter of 2019). The swap is consistent between periods: if neighborhood i is swapped with neighborhood j, this is true for every quarter t. We keep constant every other variable of our analysis. Through this transformation we maintain any pre-existing correlation between a hypothetical omitted variable and the overall trend in Airbnb's diffusion, while losing any relationship between the instrument and the

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE D2 Placebo test.

Effect	Percentage of significant iterations			
	Sale (%)		Rent (%)	
	(1)	(2)	(3)	(4)
Overall	1.10	1.32	0.00	0.00
Florence	1.64	1.54	0.44	0.36
Milan	0.02	0.04	0.02	0.00
Naples	1.88	1.68	1.44	1.36
Rome	0.50	0.56	0.00	0.00
Turin	5.52	3.28	0.34	0.00
Controls				
Time-varying controls	×	×	×	×
Interacted census controls		×		×
Fixed effects				
Neighborhood FE	×	×	×	×
Quarter#City FE	×	×	×	×
Year#City#Area FE	×	×	×	×

Note: The table shows, out of the 5000 iterations, the percentage of them in which the coefficient of the variable of interest of Equations (1) and (2) (i.e., overall and by city) estimated with 2SLS is significant at the 5% level. Columns (1) and (2) show results for sale prices, (3) and (4) for rental rates. Columns (2) and (4) include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population in the base year 2011.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects.

number of listings in each neighborhood.[24] As a consequence, should the significance of our 2SLS coefficients be driven mainly by a spurious correlation with whether a neighborhood has any Airbnb presence, we would expect the resulting 2SLS estimates to be significant also in the placebo. Conversely, if it is the intensity of Airbnb that truly drives our results, then the instrument should become weak, and the coefficients in the placebo should be insignificant.

We perform 5000 iterations, reassigning Airbnb listings to different neighborhoods in each one. We then estimate the 2SLS specification of Equations (1) (overall effect) and (2) (effect by city) with the scrambled data set. Table D2 reports the share of iterations in which the estimated coefficient is significant at the 5% level, that is, those that challenge the validity of the instrumental variable. In particular, in Columns (2) and (4), the IV regression adds the interacted census controls, to further account for spurious correlation. In both specifications, the results for the overall impact show that the 2SLS placebo coefficient is insignificant at the 5% level in 100% of the randomized draws in the rents regressions and in about 99% of the draws in the regressions for house prices. As such, we do not identify any spurious time trends.

The evidence is similar when looking at the impact by city: the share of significant coefficients in the placebo tests in both specifications is well below 2% in all cities except for Turin's sale prices, which reaches 5.52% in Column (1). As shown in Table A2, Turin has, by far, the lowest Airbnb density among the five cities, and we will be

[24]Barron et al. (2020) aptly describe it as preserving the impact of touristiness on the *extensive margin* of Airbnb's diffusion (whether there are any listings) while eliminating its impact on the *intensive margin* (how many listings are there).

particularly cautious when assessing this city's coefficients. However, do note that these numbers drop significantly when including interacted census controls in Column (2), suggesting that adding these controls lowers any residual spurious correlation for the city.

Overall, these preliminary tests suggest that the touristiness variable we employ in the instrumental variable estimations is effective and that spurious time trends should not bias the results in our main analysis, providing evidence in favor of the robustness of our identification strategy.

APPENDIX E: TESTING DIFFERENCES OF AIRBNB IMPACT WITHIN CITIES: ALTERNATIVE VERSION OF TABLE 8

In Table E1, we estimate the average effect of Airbnb density in each city, and the difference between the effects between the centers and the suburbs by estimating an alternative version of Table 8 which allows us to directly test if we can reject the hypothesis that the center-suburbs differences are jointly insignificant.

The estimates suggest that the effect of Airbnb density on house prices is significantly different between the city center and the suburbs for all cities except Turin. In particular, Florence, Milan, and Rome show a stronger effect in the suburbs (as the coefficient for the central areas is negative), whereas Naples shows a stronger effect in the city center. As to Turin, the evidence shows that there is no difference between the center and the suburbs. Finally, the *F* tests on the joint hypotheses that the five city coefficients as well as the five interactions are both statistically significant.

TABLE E1 Effects on house sale prices within cities.

Dependent variable: Log(Sale price)	(1) FE	(2) 2SLS	(3) 2SLS
Airbnb density at $t-1$ in:			
Florence	0.528	4.194	4.206
	(1.406)	(2.013)**	(2.017)**
Milan	4.534	8.950	8.937
	(1.734)***	(4.185)**	(4.194)**
Naples	−2.773	−1.876	−3.273
	(1.343)**	(3.433)	(3.021)
Rome	3.463	5.548	5.519
	(1.798)*	(3.065)*	(3.055)*
Turin	26.57	−10.53	−6.463
	(6.503)***	(26.90)	(26.79)
Florence central	−0.0903	−3.725	−3.738
	(1.401)	(1.959)*	(1.963)*
Milan central	−3.428	−6.492	−6.486
	(1.686)**	(3.564)*	(3.571)*
Naples central	4.675	3.725	5.242
	(1.394)***	(3.361)	(2.872)*
Rome central	−3.296	−5.237	−5.216

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE E1 (Continued)

Dependent variable: Log(Sale price)	(1) FE	(2) 2SLS	(3) 2SLS
	(1.798)*	(3.053)*	(3.043)*
Turin central	−17.41	23.37	18.99
	(6.795)**	(25.51)	(24.96)
Controls			
Time-varying controls	×	×	×
Interacted census controls			×
Fixed effects			
Year FE			
Neighborhood FE	×	×	×
Quarter#City FE	×	×	×
Year#City#Area FE	×	×	×
H0: Coefficients of all cities are equal to 0	12.88	6.15	2.46
F statistics (*p* value)	0.000***	0.000***	0.0337**
H0: Coefficients of all cities' centers are equal to 0	9.32	4.90	2.33
F statistics (*p* value)	0.000***	0.003***	0.0430**
Observations	5740	5740	5740
Adjusted R^2	0.98		

Note: FE and 2SLS estimates of Equation (3). See notes in Table 4.
Abbreviations: 2SLS, two-stage least squares; FE, fixed effects.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

APPENDIX F: EXPLORATORY ANALYSIS OF SPILLOVER EFFECTS FROM CENTER TO SUBURBS

In this section, we address the distributional impact of Airbnb intensity with an exploratory analysis that investigates whether and how its diffusion in the center might affect property values in the periphery. To this end, we conduct the city-by-city analysis on the subsample composed of suburban neighborhoods. For each city, we calculate the aggregate Airbnb density in the center, which is now the variable of interest and include Airbnb density in each suburban neighborhood as a control. The model we estimate is the following:

$$\log(Y_{n,t}) = \beta_1 \text{Airbnb Intensity}_{n,t-1} \times \text{city}_i + \beta_2 \text{Airbnb Intensity center}_{i,t-1} \times \text{city}_i + \gamma X_{n,t} + \pi_{s,i} + \tau_{y,i,a} + \mu_n + \varepsilon_{n,t}. \quad \text{(F1)}$$

This model investigates whether the diffusion of Airbnb in the center (i) also affects property values in suburban neighborhoods (n), controlling for the effect of Airbnb density in each suburban neighborhood. The dependent variable is the average house price in each suburban neighborhood, and the variable of interest is the average listing density in the city-center, to estimate its impact on the house prices in the suburbs.

In addition, we control for the price effects of Airbnb density in each suburban neighborhood. The FE and IV specifications add the usual set of neighborhood-specific and time–space interacted FEs, which include

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE F1 Spillover effects on sale prices from city center to suburbs (controlling for the local impact of Airbnb diffusion in the suburbs).

Dependent variable: Log(Sale prices) in suburban neighborhoods	**(1) FE**	**(2) 2SLS**	**(3) 2SLS**
Spillover effect of Airbnb's density in the center on house prices in the suburbs			
Florence	−4.086***	−0.201	−0.214
	(1.235)	(9.707)	(9.748)
Milan	−2.680**	−11.35***	−11.35***
	(1.057)	(3.117)	(3.123)
Naples	1.894	−30.77	−32.33
	(5.984)	(67.09)	(67.52)
Rome	−3.855***	−5.022***	−5.022***
	(0.471)	(1.721)	(1.724)
Turin	−17.45***	−34.82	−34.06
	(6.546)	(26.03)	(26.21)
Direct effect of Airbnb's density in the suburbs on house prices in the suburbs			
Florence	0.616	16.02	16.04
	(1.692)	(14.29)	(14.38)
Milan	5.304***	17.42***	17.43***
	(1.754)	(5.695)	(5.709)
Naples	−3.263***	−0.295	−2.482
	(1.046)	(4.294)	(3.545)
Rome	3.873**	7.494**	7.541**
	(1.835)	(3.384)	(3.383)
Turin	28.71***	−12.51	−15.26
	(6.394)	(30.58)	(32.94)
Controls			
Time-varying controls	×	×	×
Interacted census controls			×
Fixed effects			
Neighborhood FE	×	×	×
Quarter#City FE	×	×	×
Year#City#Area FE	×	×	×
Observations	3840	3840	3840
Adjusted R^2	0.94		

Note: FE and 2SLS estimates of Equation (F1). Estimation is on the subsample of suburban neighborhoods. See notes from Table 4.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

time-specific effects for both center and periphery of each city as well as the product between time-invariant sociodemographic characteristics of the neighborhood and the growth rate of the population.

In the IV regressions, we instrument both Airbnb Intensity$_{n,t-1}$ and Airbnb Intensity center$_{i,t-1}$. Airbnb intensity in the individual suburban neighborhood is instrumented with its respective *touristiness*, while Airbnb in the city center is instrumented by the average level of *touristiness* in the center.

The FE and 2SLS results for sale prices are shown in Table F1. The upper panel in the table reports the estimates of the spillover effect, that is, the relationship between the aggregate Airbnb density in the center and the sale prices in each suburban neighborhood. In the lower panel, the results show, for each suburban neighborhood, the direct impact of localized increases in Airbnb density on house sale prices.

Focusing on IV results in Columns (2) and (3) in the upper panel, we find that house prices in the suburbs are negatively related to increasing Airbnb pressure in the center in all cities, although the coefficients are significant only in Milan and Rome. This finding suggests that the growing Airbnb pressure in central Rome and Milan negatively affects property value in their peripheries, even though the direct effect of the local diffusion of short-term rental—estimated in the lower panel—is positive. Not surprisingly, the results on the local effects are qualitatively similar to the estimates for suburbs in Table 8. At face value, our estimates imply that all else equal and controlling for the local impact of listing density in the suburbs, an increase of one percentage point in Airbnb density in the center leads to a decrease in the price per square meter in the suburbs of 5.02% in Rome and 11.35% in Milan.[25]

These findings suggest that, at least in the two largest cities in Italy, the rise in property values following Airbnb growth in the center seems to lead to a setback in the periphery. This process may result from the center's increasing power to attract, not only tourists, but also a greater supply of amenities (as documented in panel B of Table 2), renovation investments and, ultimately, the housing demand of local residents keen on living in the center. This evidence is in line with Xu and Xu (2021), who finds a positive effect of Airbnb on private capital investments, and with the ongoing debate on the overtourism in major cities. As highlighted by Almagro and Domínguez-Iino (2021) and Calder-Wang (2021), city centers increase their profitability as they evolve to accommodate every tourist's desires. As tourist services and investments focus on the center, the suburbs may pay the cost by becoming more marginalized, even though Airbnb diffusion has, per se, a positive effect on house prices in the suburbs (as we find in Milan, Rome, and Florence).

In the case in point, the negative core–periphery spillover of Airbnb takes place in those cities where the contrast between the poorest and the richest neighborhoods is higher, the increase in amenity supply is larger in the center, and the spread between house prices in the center and the suburbs is wider, hence where inequality is also (comparatively) higher. This suggests that initial conditions matter in driving how short-term rental platforms affect property values in peripheral neighborhoods, generating a contraction that exacerbates distributional effects. Indeed, because the fraction of owner-occupancy is typically higher in the periphery, a devaluation of many families' most valued asset is likely to have a negative impact on household wealth, further increasing inequality.

As to Florence, where Airbnb intensity is very high in the center, we do not find a spillover effect, but the results in Table 8 show that its diffusion seems to bring central and suburban prices to converge over time. The center of Florence is a small and closely regulated jewel that does not allow real estate developments, leaving room in the nearby suburbs for further expansion of Airbnb as well as for local residents. Indeed, as shown in Section 2, the initial gap between core and periphery is not large. Suburbs may thus become a viable alternative for those who may prefer to move away from the congested center, renting their house in the center on

[25]Note that the magnitude of this effect is computed on a density increase of one percentage point, which implies a different percentage increase depending on the city and the area at hand. For example, an increase of one percentage point in Airbnb density in Milan's city center from a density value of 0.59% in 2014, implies a 169% increase in density. In Rome, where the listing density in 2014 was 1.49%, a one percentage point density increase in the city center entails a 67% increase in density.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

the short-term rental market. In sum, the positive effect of Airbnb on house prices in the suburbs seems to occur both via the endogenous growth in the supply of amenities and renovation investments and through substitution effects.

APPENDIX G: ROBUSTNESS

In this section, we perform a battery of robustness tests to challenge our evidence of a positive effect of Airbnb's diffusion on the real estate market.

G.1 | Driscoll–Kraay standard errors in the by-city estimation

In Table G1, we allow for spatial correlation in the by-city estimation by calculating Driscoll and Kraay (1998) standard errors that are reported below the neighborhood-clustered standard errors.

G.2 | Allowing for dynamic effects in the housing market: A dynamic panel model

A dynamic approach is complementary to the scope of this work: housing units (and, in turn, rental prices) are often evaluated by comparison with similar dwellings, and their prices are then adjusted to account for differences. Similarly, it is reasonable to assume that a house valuation strongly depends on its previous values and that prices and rents are persistent over time (see, e.g., Benítez-Aurioles & Tussyadiah, 2021, on London's housing market). In this section, we estimate the following dynamic version of the model that studies the relationship between sale or rental prices and Airbnb density:

$$\log(Y_{n,t}) = \alpha \log(Y_{n,t-1}) + \beta \,\text{Airbnb Intensity}_{n,t-1} + \gamma X_{n,t} + \tau_t + \mu_n + \varepsilon_{n,t}. \tag{G1}$$

This specification includes the lagged dependent variable $Y_{n,t-1}$ to account for its persistence over time. To account for the *dynamic panel bias* that arises from the correlation between the lagged dependent variable and the FE in the error term (Nickell, 1981), we adopt the GMM-SYS approach (Arellano & Bond, 1991; Blundell & Bond, 1998).[26] Both the lagged dependent variable and the variable of interest (i.e., Airbnb's density) are treated as endogenous and are instrumented with the GMM approach.[27] For the validity of the GMM estimates, it is crucial that the instruments are exogenous, so we report the appropriate tests: the Arellano and Bond (1991) autocorrelation tests to control for first-order and second-order correlation in the residuals, and the two-step Sargan–Hansen statistic to test the joint validity of the instruments. The temporal effects control for seasonality at the city level as well as for year effects at the area level (i.e., center and suburbs) in each city. Standard errors are robust to heteroskedasticity and arbitrary patterns of auto-correlations within firms.

In Table G2, we report the one-step GMM-SYS estimates of the dynamic specification and the (inconsistent) FEs results for comparison.

Comfortingly, the GMM-SYS estimates show that also when we account for dynamic effects and apply a different estimator, Airbnb intensity affects positively and significantly sale prices, consistent with our previous

[26]We use the Blundell–Bond estimator with Windmeijer's finite sample correction (Windmeijer, 2005), dealing with situations where the lagged dependent variable is persistent (i.e., the autoregressive parameter is large). This model estimates a system of first-differenced and level equations and uses lags of variables in levels as instruments for equations in first-differences and lags of first-differenced variables as instruments for equations in levels, in which the instruments must be orthogonal to the firm-specific effects.

[27]To keep the number of instruments under control, we constrain the moment conditions regarding time intervals, depending on the individual specifications, reporting the ratio between instruments and groups at the bottom of the table. We include both the temporal effects and the instrumental variables for touristiness (based on Google searches and Tripadvisor's tourist attractiveness score) as external instruments in the estimation.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE G1 Airbnb density's impact on house sale prices by city.

Dependent variable: Log(Sale price)	(1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at $t-1$ in:				
Florence	−0.134	0.439	0.437	0.438
	(0.303)	(0.106)***	(0.139)***	(0.140)***
	(0.124)	(0.0642)***	(0.0803)***	(0.0808)***
Milan	2.098	2.233	2.509	2.508
	(1.414)	(1.029)**	(1.276)*	(1.275)*
	(0.767)**	(0.340)***	(0.719)***	(0.706)***
Naples	0.380	1.447	1.778	1.981
	(1.293)	(0.760)*	(0.712)**	(0.772)**
	(0.329)	(0.575)**	(0.608)***	(0.534)***
Rome	2.244	0.198	0.410	0.404
	(0.524)***	(0.149)	(0.144)***	(0.144)***
	(0.314)***	(0.101)*	(0.133)***	(0.133)***
Turin	−27.48	11.24	12.05	12.04
	(8.124)***	(2.670)***	(3.384)***	(2.967)***
	(1.999)***	(1.633)***	(2.795)***	(2.928)***
Controls				
Time-invariant controls	×			
Time-varying controls	×	×	×	×
Interacted census controls				×
Fixed effects				
Year FE	×			
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
Observations	5740	5740	5740	5740
Adjusted R^2	0.83	0.98		

Note: The dependent variable is the natural logarithm of the sale price. Estimation of Equation (2). OLS estimates in Column (1); FE estimates in Column (2); 2SLS estimates in Columns (3) and (4), where we include the interactions between the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics and the growth rate of each city population in the base year 2011. The instrument in Columns (3) and (4) is $a_n^{TA} \times g_t$. For each coefficient, the first parenthesis shows robust standard errors clustered by neighborhood, the second shows Driscoll–Kraay standard errors. The same order is followed when showing the *F* statistic of the excluded instrument.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares; TA, Trip Advisor.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE G2 GMM-SYS-lagged density in GMM (both in levels and in difference).

Dependent variable:	Log(Sale price) (1) FE	(2) GMM-SYS	Log(Rent) (3) FE	(4) GMM-SYS
Dependent variable at $t-1$	0.651***	0.890***	0.439***	0.496***
	(0.030)	(0.013)	(0.022)	(0.051)
Airbnb density at $t-1$	0.098	0.100**	0.173*	0.444***
	(0.072)	(0.044)	(0.089)	(0.131)
House density	0.0004	−0.0002***	−0.0003	−0.0008***
	(0.0009)	(0.00008)	(0.0014)	(0.0002)
Store density	0.0049	0.0004**	0.0021	0.0018***
	(0.0042)	(0.0001)	(0.0049)	(0.0005)
Garage density	−0.0016	0.0003*	−0.0001	0.0003
	(0.0029)	(0.0002)	(0.0041)	(0.0004)
Average house rooms	−0.0084	−0.0052	−0.0001	−0.0339***
	(0.0219)	(0.0036)	(0.0501)	(0.0094)
Average store Mq	0.0022**	0.0002**	0.0015	0.0002
	(0.0010)	(0.0001)	(0.0011)	(0.0003)
Controls				
Time-varying controls	×	×	×	×
Fixed effects				
Neighborhood FE	×	×	×	×
Quarter#City FE	×	×	×	×
Year#City#Area FE	×	×	×	×
Number of instruments		261		135
Number of instruments/p		0.91		0.47
AR(1)		−9.38***		−9.99***
AR(2)		0.95		−0.21
Hansen test (p value)		0.124		0.085
Observations	4879	4879	4879	4879

Note: Estimates of Equation (G1). One-step GMM-SYS estimates (Columns 2 and 4) and inconsistent FEs results (Columns 1 and 3) for comparison. The dependent variable is the natural logarithm of sale (Columns 1 and 2) and rent prices (Columns 3 and 4). The variable of interest is the lagged Airbnb density, both in levels and in differences. Robust standard errors clustered by neighborhood in parenthesis.

Abbreviations: AR, autoregressive; FE, fixed effects; GMM, generalized method of moments; SYS, system.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

evidence.[28] Moreover, the coefficient of the lagged dependent variable confirms that prices in the housing market are quite persistent, particularly sale prices.

G.3 | Alternative measure of tourist attractiveness in the IV analysis

We test the sensitivity of our results to the touristiness instrument based on Trip Advisor by constructing an alternative shift-share variable. In the new instrument, the share component (i.e., tourist attractiveness) is based on the list by Lonely Planet guidebooks and website of the 10 "must-see" locations in each city, chosen by the authors of the city guide based on their expertise (refer to Appendix C). The shift component remains the same, based on worldwide Google searches of the word Airbnb.

The rationale behind this alternative instrument is similar to the one based on Tripadvisor but differs in two respects. On the one hand, the Lonely Planet instrument, largely based on time-invariant tourist–artistic–archeological, and geographical sites, may be less precise and responsive in the identification of the most popular locations. On the other hand, compared with the Tripadvisor rating system, the tighter but steadier classification of Lonely Planet attractions is less sensitive to tourist trends and fads, hence ultimately less influenced by Airbnb diffusion (a feature that motivated us to scrape the data for the Tripadvisor share component at a date earlier than our estimation period).

Tables G3 and G4 report the 2SLS estimates overall and by city, in Columns (2) and (4) using the new IV, while showing in Columns (1) and (3) the corresponding 2SLS results of the main analysis, for ease of comparison.

Looking at Table G3, we find that the coefficient for sale prices is significant and larger than the baseline result. The first-stage results show a strong correlation between Airbnb density and the instrument based on Lonely Planet. Turning to the analysis by city, we note that the results for sale prices are very similar to those obtained when we use the instrument based on Trip Advisor.

G.4 | Alternative measures of Airbnb supply: Listings by creation date

The literature has highlighted the difficulty of precisely measuring Airbnb activity either through scraping Airbnb's website or using publicly available databases. For example, many of the previous studies had to rely on data sets that captured listings' activity (i.e., whether they are blocked, available for rent, or reserved) through occasional scrapes of the platform's website, thus requiring some degree of approximation when quantifying the number of active listings per time period. In this paper, we could instead leverage on the fine-grained detail of the AirDNA database, which is based on daily scrapes, an information that allows one to determine the activity of each listing on a daily basis.[29]

To estimate supply when data are occasionally scraped, one can ultimately apply one of the following strategies. First, one can assume that the listing's entry date is the date of its first review and that, thereafter, the listing never exited the market, thus possibly overestimating Airbnb supply. A different strategy defines active as any listing that has received at least a review during the quarter, which may underestimate Airbnb supply as listings can be active even when they do not receive a review for a period (however, Airbnb strongly incentivizes guests and hosts to leave reviews, reducing the size of the bias). Finally, one can use the host's registration date to proxy the listing's entry, which may also overestimate supply since a host can open additional listings after the first one, but all subsequent listings are erroneously backdated to the time of the earliest apartment.

[28]The autocorrelation tests for second-order correlation in the residuals and the two-step Sargan–Hansen statistic suggest that our estimates are valid (although in the rent equation we can reject the null that instruments are invalid at the 5%, but not at the 10% level). The ratio between instruments and groups is well below one.

[29]See Barron et al. (2020), Garcia-López et al. (2020), Horn and Merante (2017), and Sheppard and Udell (2016). Ayouba et al. (2020) is the only work we are aware of that, like us, uses daily scrapes to measure Airbnb supply.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE G3 IV Lonely Planet—Overall effect.

Dependent variable:	Log(Sale price) (1) TA	(2) LP	Log(Rent) (3) TA	(4) LP
Airbnb density at $t-1$	0.618***	1.135***	0.116	0.250
	(0.157)	(0.293)	(0.128)	(0.242)
First stage				
Touristiness at $t-1$	5.80e − 11***	7.63e − 7***	5.80e − 11***	7.63e − 7***
	(6.16e − 12)	(1.39e − 7)	(6.16e − 12)	(1.39e − 7)
F statistics excluded instrument	88.689	30.214	88.689	30.214
Controls				
Time-varying controls	×	×	×	×
Interacted census controls	×	×	×	×
Fixed effects				
Neighborhood FE	×	×	×	×
Quarter#City FE	×	×	×	×
Year#City#Area FE	×	×	×	×
Observations	5740	5740	5740	5740

Note: 2SLS estimates of Equation (1). The dependent variable is the natural logarithm of sale (Columns 1 and 2) and rent prices (Columns 3 and 4). The instrument in Columns (2) and (4) is $a_n^{LP} \times g_t$, while Columns (1) and (3) report the results from Column (4) of Tables 4 and H1—where the instrument is $a_n^{TA} \times g_t$—for ease of comparison. All columns include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population from the base year 2011. Robust standard errors clustered by neighborhood in parenthesis.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; IV, instrumental variable; LP, Lonely Planet; TA, Trip Advisor.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

As a robustness test, we estimate the impact of Airbnb intensity by using the approach based on the listing's creation date that assumes no exit, and we compare the results with our previous findings in Tables 4, H1, 5, and H2. The results are in Columns (2) and (4) of Appendix Tables G5 and G6.

We find that using listings' creation date leads to lower estimates of the impact, with coefficients being about half as large as in Columns (1) and (3), thus confirming that measuring Airbnb intensity with the creation date approach leads to underestimating its impact on the real estate market.[30]

G.5 | Alternative measures of Airbnb intensity: Number of listings

The impact of Airbnb's diffusion can also be tested by using the number of listings to measure Airbnb intensity, instead of listing density (e.g., Barron et al., 2020; Garcia-López et al., 2020, among the others). The main reason to prefer listing density (e.g., as opposed to the number of listings) is that it allows us to control for the size differences among the various neighborhoods, which are very heterogeneous in our data set.

[30]The difference is statistically significant at the 1% level for the overall coefficients, at least at the 5% level for significant coefficients of the analysis by city except for Milan and Naples (10% level).

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE G4 IV Lonely Planet—By city effect.

Dependent variable:	Log(Sale price) (1) TA	(2) LP	Log(Rent) (3) TA	(4) LP
Airbnb density at $t - 1$ in:				
Florence	0.438***	0.476***	0.299**	0.318**
	(0.140)	(0.134)	(0.142)	(0.157)
Milan	2.508*	3.479***	−1.517	−2.251**
	(1.275)	(1.191)	(1.222)	(1.105)
Naples	1.981**	1.972***	1.763***	2.419***
	(0.772)	(0.553)	(0.436)	(0.491)
Rome	0.404***	0.458***	0.131	0.206
	(0.144)	(0.149)	(0.150)	(0.163)
Turin	12.04***	8.689*	−1.039	−0.832
	(2.967)	(5.016)	(1.195)	(1.430)
Controls				
Time-varying controls	×	×	×	×
Interacted census controls	×	×	×	×
Fixed effects				
Neighborhood FE	×	×	×	×
Quarter#City FE	×	×	×	×
Year#City#Area FE	×	×	×	×
Observations	5740	5740	5740	5740

Note: 2SLS estimates of Equation (2). The dependent variable is the natural logarithm of sale (Columns 1 and 2) and rent prices (Columns 3 and 4). The instrument in Columns (2) and (4) is $a_n^{\mathrm{LP}} \times g_t \times \mathrm{city}_i$, while Columns (1) and (3) report the results from Column (4) of Tables 5 and H2—where the instrument is $a_n^{\mathrm{TA}} \times g_t \times \mathrm{city}_i$—for ease of comparison. All columns include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population from the base year 2011. Robust standard errors clustered by neighborhood in parenthesis.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; IV, instrumental variable; LP, Lonely Planet; TA, Trip Advisor.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

However, for completeness, in this section, we re-estimate our models using the number of listings as the variable of interest (while the size of each neighborhood is absorbed by the FE specification). The results in Table G7 show the overall effect of an increase of 100 listings in a given neighborhood on sale prices and rent. Looking at the 2SLS results in Column (4), our estimates imply that an increase of 100 listings in a neighborhood leads to an increase of 0.6% in sale price.

The impact of Airbnb on sale prices across cities computed using the number of listings instead of their density gives comparable results to the one presented in Section 6.1: we find an increase in sale prices of 40.67 €/m^2 during the analyzed time period.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE G5 Listing density by creation date—Overall effect for the five cities.

Dependent variable:	Log(Sale price) (1) Baseline	(2) Creation date	Log(Rent) (3) Baseline	(4) Creation date
Airbnb density at $t-1$	0.618***	0.289***	0.116	0.0543
	(0.157)	(0.0725)	(0.128)	(0.0596)
Controls				
Time-varying controls	×	×	×	×
Interacted census controls	×	×	×	×
Fixed effects				
Neighborhood FE	×	×	×	×
Quarter#City FE	×	×	×	×
Year#City#Area FE	×	×	×	×
Observations	5740	5740	5740	5740

Note: 2SLS estimates of Equation (1). The dependent variable is the natural logarithm of sale (Columns 1 and 2) and rent prices (Columns 3 and 4). The instrument is $a_n^{LP} \times g_t$. Columns (1) and (3) report the results from Column (4) of Tables 4 and H1 for ease of comparison. In Columns (2) and (4), the measure of Airbnb density in the first stage is obtained from the listings' creation date. All columns include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population from the base year 2011. Robust standard errors clustered by neighborhood in parenthesis.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; LP, Lonely Planet.

***p < 0.01; **p < 0.05; *p < 0.1.

TABLE G6 Listing density by creation date—By city effect.

Dependent variable:	Log(Sale price) (1) Baseline	(2) Creation date	Log(Rent) (3) Baseline	(4) Creation date
Airbnb density at $t-1$ in:				
Florence	0.438***	0.205***	0.299**	0.142**
	(0.140)	(0.0654)	(0.142)	(0.0668)
Milan	2.508*	1.297**	−1.517	−0.776
	(1.275)	(0.651)	(1.222)	(0.633)
Naples	1.981**	1.146**	1.763***	1.012***
	(0.772)	(0.444)	(0.436)	(0.254)
Rome	0.404***	0.184***	0.131	0.0621
	(0.144)	(0.0672)	(0.150)	(0.0691)
Turin	12.04***	4.730***	−1.039	−0.410
	(2.967)	(1.184)	(1.195)	(0.469)
Controls				
Time-varying controls	×	×	×	×
Interacted census controls	×	×	×	×

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE G6 (Continued)

Dependent variable:	Log(Sale price) (1) Baseline	(2) Creation date	Log(Rent) (3) Baseline	(4) Creation date
Fixed effects				
Neighborhood FE	×	×	×	×
Quarter#City FE	×	×	×	×
Year#City#Area FE	×	×	×	×
Observations	5740	5740	5740	5740

Note: 2SLS estimates of Equation (2). The dependent variable is the natural logarithm of sale (Columns 1 and 2) and rent prices (Columns 3 and 4). The instrument is $a_n^{LP} \times g_t \times city_i$. Columns (1) and (3) report the results from Column (4) of Tables 5 and H2 for ease of comparison. In Columns (2) and (4), the measure of Airbnb density in the first stage is obtained from the listings' creation date. All columns include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population from the base year 2011. Robust standard errors clustered by neighborhood in parenthesis.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; LP, Lonely Planet.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

TABLE G7 Airbnb number of listings—Overall effect.

Dependent variable:	Log(Sale price) (1) OLS	(2) FE	(3) 2SLS	(4) 2SLS	Log(Rent) (5) OLS	(6) FE	(7) 2SLS	(8) 2SLS
Listings/100 at $t-1$	0.0151***	0.00417**	0.00603***	0.00592***	0.0111***	0.00117	0.00102	0.00111
	(0.00325)	(0.00164)	(0.00215)	(0.00213)	(0.00278)	(0.00130)	(0.00130)	(0.00130)
Controls								
Time-invariant controls	×				×			
Time-varying controls	×	×	×	×	×	×	×	×
Interacted census controls				×				×
Fixed effects								
Year FE	×				×			
Neighborhood FE		×	×	×		×	×	×
Quarter#City FE		×	×	×		×	×	×
Year#City#Area FE		×	×	×		×	×	×
Observations	5740	5740	5740	5740	5740	5740	5740	5740
Adjusted R^2	0.80	0.98			0.71	0.96		

Note: OLS estimates of Equation (1) in Columns (1) and (5); FE estimates of (1) in Columns 2 and 6; 2SLS estimates of (1) in Columns (3), (4), (7), and (8). Columns (4) and (8) include the interaction of the time-invariant neighborhood-level controls for demographic, education, occupation, and housing characteristics with the growth rate of each city population from the base year 2011. The dependent variable is the natural logarithm of sale (Columns 1–4) and rent prices (Columns 5–8). The variable of interest is the lagged number of listings/100. The instrument in Columns (3), (4), (7), and (8) is $a_n^{TA} \times g_t$. Robust standard errors clustered by neighborhood in parenthesis.

Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

APPENDIX H: RENTS

Overall effect of Airbnb density

Table H1 estimates the models with the log of rental monthly rates as the dependent variable. The evidence is weaker, though, compared with house sale prices.

The OLS specification in Column (1) tells us that an increase of one percentage point in Airbnb density leads to an increase of 0.438% of rent per square meter. Most control variables correlate with rents similarly to sale prices. An exception is the positive coefficient on foreign residents, probably because it correlates to neighborhoods where the rental turnover is higher, thus enabling the landlord to increase the rent more often. When we move to the specification in Column (2), with neighborhood and space-time FEs, the coefficient drops to 0.174, while the IV estimates in Columns (3) and (4) are insignificant, despite the good performance of the instrument in the first-stage

TABLE H1 Airbnb density and house rents in five Italian cities.

Dependent variable:	Log(Rent) (1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at $t-1$	0.438	0.174	0.106	0.116
	(0.362)	(0.138)	(0.128)	(0.128)
	(0.0740)***	(0.0708)**	(0.115)	(0.117)
House density	−0.000727	−0.000971	−0.000819	−0.00222
	(0.000606)	(0.00234)	(0.00239)	(0.00220)
	(0.000121)***	(0.00100)	(0.000963)	(0.00165)
Store density	0.00631	0.00965	0.00900	0.0117
	(0.00176)***	(0.00925)	(0.00924)	(0.00896)
	(0.000157)***	(0.00471)*	(0.00434)*	(0.00471)**
Garage density	−0.00586	0.00157	0.00165	0.00186
	(0.00137)***	(0.00449)	(0.00448)	(0.00442)
	(0.000100)***	(0.00225)	(0.00226)	(0.00242)
Average house rooms	−0.0792	−0.108	−0.108	−0.118
	(0.0212)***	(0.0708)	(0.0709)	(0.0661)*
	(0.00932)***	(0.0182)***	(0.0182)***	(0.0181)***
Average store Sq m	−0.00104	0.00174	0.00177	0.00172
	(0.000707)	(0.00173)	(0.00173)	(0.00161)
	(0.000106)***	(0.000812)**	(0.000854)*	(0.000843)*
Number of residents	0.00000717			−0.000000312
	(0.00000502)			(0.000000280)
	(0.00000121)***			(0.000000170)*
Owner-occupancy	−0.251			0.0249
	(0.148)*			(0.0187)
	(0.0132)***			(0.0177)

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE H1 (Continued)

Dependent variable:	Log(Rent) (1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
20–39 years	−1.329			0.0386
	(0.542)**			(0.0741)
	(0.139)***			(0.0343)
> 60 years	0.369			−0.125
	(0.370)			(0.0569)**
	(0.0602)***			(0.0200)***
Graduates	1.345			0.0193
	(0.204)***			(0.0291)
	(0.0418)***			(0.0111)*
Working	1.963			−0.0106
	(0.362)***			(0.0690)
	(0.0607)***			(0.0415)
Foreigners	0.692			−0.0239
	(0.253)***			(0.0178)
	(0.0828)***			(0.00884)**
Houses in use	0.399			0.0561
	(0.199)**			(0.0297)*
	(0.0534)***			(0.00854)***
Number of houses	−0.0000200			0.000000723
	(0.0000113)*			(0.000000580)
	(0.00000308)***			(0.000000358)*
House in poor condition	0.0121			−0.0167
	(0.0827)			(0.00556)***
	(0.0126)			(0.00643)**
First stage				
Touristiness at $t-1$			5.82e − 11	5.80e − 11
			(6.21e − 12)***	(6.16e − 12)***
			(7.68e − 12)***	(7.67e − 12)***
F statistics excluded instrument			87.712	88.689
			57.370	57.167
Controls				
Interacted census controls				×
Fixed effects				
Year FE	×			

(Continues)

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE H1 (Continued)

Dependent variable:	Log(Rent) (1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
Observations	5740	5740	5740	5740
Adjusted R^2	0.699	0.962		

Note: OLS, FE, and 2SLS estimates of Equation (1) for rents. See notes from Table 4.
Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE H2 Airbnb densities' impact on house rents by city.

Dependent variable:	Log(Rent) (1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Airbnb density at $t-1$ in:				
Florence	−0.334	0.240	0.293	0.299
	(0.187)*	(0.172)	(0.142)**	(0.142)**
	(0.0549)***	(0.0865)**	(0.148)*	(0.146)*
Milan	4.100	−0.0131	−1.533	−1.517
	(1.220)***	(0.609)	(1.222)	(1.222)
	(0.404)***	(0.326)	(1.022)	(1.034)
Naples	1.251	1.838	1.909	1.763
	(1.206)	(0.320)***	(0.420)***	(0.436)***
	(0.133)***	(0.300)***	(0.390)***	(0.423)***
Rome	1.306	−0.218	0.121	0.131
	(0.341)***	(0.181)	(0.151)	(0.150)
	(0.153)***	(0.116)*	(0.0978)	(0.102)
Turin	−32.65	−2.466	−2.140	−1.039
	(7.210)***	(1.269)*	(0.941)**	(1.195)
	(1.971)***	(0.784)***	(1.086)*	(1.430)
Controls				
Time-invariant controls	×			
Time-varying controls	×	×	×	×
Interacted census controls				×
Fixed effects				
Year FE	×			

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE H2 (Continued)

Dependent variable:	Log(Rent) (1) OLS	(2) FE	(3) 2SLS	(4) 2SLS
Neighborhood FE		×	×	×
Quarter#City FE		×	×	×
Year#City#Area FE		×	×	×
Observations	5740	5740	5740	5740
Adjusted R^2	0.83	0.98		

Note: OLS, FE, and 2SLS estimates of Equation (2) for rents. See notes from Table 4.
Abbreviations: 2SLS, two-stage least squares; FE, fixed effects; OLS, ordinary least squares.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

regression. Using the estimates of Column (3), an increase of one percentage point in Airbnb density leads to an increase in average monthly rent per square meter of 0.106%, corresponding to a 3 €cent/m^2 rent increase over the analyzed time period.

The effect of Airbnb density by city

We estimate Equation (2), focusing on rent prices. Once again, we find weaker evidence when compared with the effect on sale prices (Table H2).

By examining the IV estimates of Column (4), we find that the effect is significant and positive in Florence and Naples, insignificant in Milan and Rome, even negative in Turin. Average rents are more similar across cities than house prices, with Milan ranking first and Turin last. Based on coefficients from Column (4), the estimated impacts over the period show increases of 37 and 19 €cent/m^2 in Naples and Florence. While these values may seem low, they are significant when compared with the rental rates variation from 2014 to 2019.

14679787, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.12737 by Politecnico Di Torino Sist. Bibl Del Polit Di Torino, Wiley Online Library on [02/12/2024]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License