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Who is my neighbour? Short-term renting and civic engagement in London

Nicola Fontana

TEP Working Paper No. 0525

July 2025

Trinity Economics Papers
Department of Economics

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Nicola Fontana †

1st July 2025

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Abstract

Urbanization has transformed cities into the economic hubs of high-income countries, yet concerns about declining social capital persist. This paper investigates the impact of changes in neighbourhood composition on social capital within London. I show how neighbourhoods with higher short-term renting penetration experience a reduction in charitable organizations and increased feelings of loneliness. These results cannot be attributed uniquely to a change of composition in the long-term residents, but they also reflect changes in the behaviours of residents. Moreover, I find that higher short-term renting penetration is associated with a decrease in neighbourhood quality.

JEL Codes: P00, A13, Z18

Keywords: Civic Engagement, Social Capital, Short-term Renting

*This paper is a revised version of the paper "Backlash against Airbnb: Evidence from London". I am extremely grateful to Guy Michaels for his invaluable advice and guidance throughout this project. I thank Andrea Alati, Tim Besley, Fabio Bertolotti, Filippo Biondi, Nicolas Chanut, Luca Citino, Gaia Dossi, Tillman Hönig, Monica Langella, Nicola Limodio, Stephen Machin, Marco Manacorda, Alan Manning, Steve Pischke, Łukasz Rachel, Maddalena Ronchi, Kilian Russ, Viola Salvestrini, Matteo Sandi, Vincenzo Scrutinio, Alessandro Sforza, Mark Schankerman, Tommaso Sonno, Daniel Sturm, Guido Tabellini, Marco Tabellini, Di Song Tan, Martina Zanella and seminar participants at CEMFI, LSE, Tor Vergata University, Trinity College Dublin, University College Dublin, University of Bologna, University of Tokyo for useful comments. I thank Dr. Lindsay Relihan, Nick Groome, and the Ordnance Survey team for their support with Digimap data. I thank Bhavya Shrivastava and Sonny Stenson for excellent research assistance. All remaining errors are mine.

†Dept. of Economics & CEPH & TIME & TRiSS, Trinity College Dublin; CEP, London School of Economics; nicola.fontana@tcd.ie

1 Introduction

With more than 80% of the high-income countries' population living in cities (World Bank Data), urban settlements represent the backbone of developed countries. While cities often displayed high universalist moral values (Enke, 2020), there are concerns on lacking communal support and deteriorating interpersonal relationships (Putnam, 2000, Turkle, 2015). Despite a vast literature that correlates social capital and civic engagement with economic (see for example, Guiso et al., 2006, Falk et al., 2018, Chetty et al., 2022a), political (Nannicini et al., 2013), mental health (Xue et al., 2020), and crime outcomes (Buonanno et al., 2009), relatively little is known about what shapes social capital and civic engagement in urban contexts and within cities.

In order to study this question, I leverage the impact of short-term renting accommodation as a shock to local community composition and study what is the consequent impact on residents' civic engagement and interpersonal ties. Arguably, short-term stayers are not likely to be involved in neighbourhoods' social capital formation, and for this reason, they represent an ideal shock to study how communities would react.

Despite a slowdown during the Covid-19 pandemic, tourism is booming in many cities with a full recovery to pre-pandemic levels (United Nations World Tourism Organization). Based on the official statistics presented in UNWTO (2020), the number of international overnight tourists grew to 1.5 billion in 2019, which is 53.4 per cent higher than in 2010.[1] A concern is that, however, this growth has been highly concentrated in a handful of destinations around the world, with almost 50 per cent of global tourism concentrated in 100 cities (Yasmeen, 2019). The same is likely to be true also within cities, with benefits highly concentrated among a few operators.

City governments in some of these hotspots are trying to cope with so-called "over-tourism", a term coined by the media to describe the consequences of having too many visitors that may fuel the backlash against tourists. While it is recognized that tourists are beneficial for some local areas and sectors, such overcrowding brings costs, which are borne by residents. Tourists may increase the cost of living, with locals "crowd out" of touristic neighbourhoods (Gurran and Phibbs, 2017). Moreover, residents may find that pavements and public transport are clogged by tourists, and they may deal with late-night misbehaviours (Gallagher, 2018).[2] Finally, and most importantly for this paper, there are rising concerns among policymakers and sociologist of lower levels of social interaction across class lines (Fischer and Mattson, 2009; Smith et al., 2014; Putnam, 2016 Doob, 2019), especially in cities and neighbourhoods most affected by residential isolation will experience a loss of social capital and civic engagement (Wang et al., 2018; Athey et al., 2020).

[1] From 2008 to 2019, in London, the number of rooms available on Airbnb grew from 0 to 140,000, almost matching the number of hotel rooms at 159,000. See Quattrone et al. (2016) for a discussion on Airbnb spread in London.

[2] "Airbnb Party flats" are well-known issues, *e.g.* The Guardian (2017) *It sounded like Fabric was upstairs' - Airbnb rental used for all-night party*.

Motivated by these facts, I investigate whether social capital is affected by Airbnb penetration in London. I discuss whether neighbourhoods experience a population change and a change in attitudes by stayers. To do so, I consider a standard measure of social capital, official statistics, as well as a unique survey to investigate attitudes of London's residents. I then study why short-term renting had such a profound impact by looking at its impact on the neighbourhood. First, I look at the relationship between Airbnb penetration in London and backlash against tourism. Then, I study the pecuniary and non-pecuniary roots of the observed discontent against tourists. In particular, I investigate whether the grievances against tourism stem from higher house prices and rents, or the worsening of quality of life in the neighbourhoods, and discuss the potential mechanisms behind it. The intuition is simple: gains from tourism are likely to be highly concentrated, while costs are equally spread among the residents. I provide evidence on whether results are specific to short-term renters or more generally to the tourism industry.

I perform my analysis in the context of London, for which I construct a rich and spatially disaggregated dataset at electoral ward-year level, where wards represent the primary unit of English electoral geography. My dataset has two novel features.

First, I construct a dataset with a rich set of neighbourhood quality measures (anti-social behaviour crime rates and proxies for congestions of local services), proxies for social capital (number of charitable organizations), and attitudes of stayers, thanks to a unique individual survey that tracks social cohesion and inclusion. These measures allow me to shed light on non-pecuniary mechanisms and social implications, so far unexplored by the existing literature.

Second, I complement this dataset with explicit complaint measures. The main proxy of backlash against tourists tracks complaints against tourists, which I build from a unique source of geo-localized complaints sent to local authorities. Thanks to this direct measure, I can test precisely the relationship between Airbnb penetration and backlash against tourism. Such a measure allows me to capture those unhappy with the status quo, even when these groups represent a minority whose discontent would not be captured by vote shares or average house prices, which are standard measures typically used in political economy or urban economics to explore analogous questions. Moreover, I can measure complaints about different quality aspects of the neighbourhood, providing a complement to the actual statistics to disentangle perceptions and realized outcomes.

Depending on the outcome variable, the empirical analysis is performed at the electoral ward-year-month or electoral ward-year level, always controlling for ward fixed characteristics as well as flexible time effects for each local authority within London.[3] In the baseline specification, I also include a wide range of pre-determined and geographic characteristics interacted with year-month or year fixed effects to control for different evolution depending on initial and fixed characteristics.

[3]See Appendix Section A.1 for details on London administrative structure. Each ward is uniquely assigned to one of the 33 London local authorities (or boroughs).

In addition, I use a shift-share instrumental variable strategy, as in Barron et al. (2020), to address the concern that Airbnb penetration might be itself influenced by time-varying ward conditions not captured by the demanding set of controls described. The "share" part of the IV exploits the spatial variation of historical points of touristic interests. The "shift" component exploits time variation in Airbnb worldwide popularity. The validity of this strategy hinges on two critical assumptions, conditional on controls: i) determinants of the spatial distribution of historical sites from hundreds of years ago are not informative of current trends, and ii) worldwide Airbnb popularity is not informative of wards' unobservable trends.

Notably, hotel penetration is not a confounding factor in my identification strategy. First, hotel penetration is almost constant in the sample period considered; therefore, mostly absorbed by ward fixed effects. Second, controlling for flexible trends (by the local authority or by "central" wards) ensures that common trends are captured. Third, adding hotel penetration as a regressor alters neither the significance nor the magnitude of my results. The same is true if I proxy tourist penetration with the number of bars, restaurants, and nightclubs in the area.

Thanks to the described setting, I provide evidence that neighbourhoods with higher penetration of short-term renters, which are assumed to be less involved in the local area, display lower social capital. Following Guiso et al. (2016), I measure social capital by the number of charitable organizations. For each additional tourist for every 100 residents, which represents the average impact in London in 2019, the number of charitable organizations drops by 4.5 per cent.[4] A change in population composition, towards more mobile and less involved residents, does not fully explain these results. I still find a drop in social capital when I look at wards with low residents' turnout. This suggests that the results are not simply driven by a change in population composition, but also by a change in attitudes of residents.

This explanation is documented thanks to a unique survey run in 2018. Leveraging on a granular survey, I show how individuals living in areas more exposed to short-term renting feel that they belong less to the local area, feel lonely more often, and are less likely to have contact with neighbours. They also feel that they are less likely to influence the area and have lower life satisfaction. These results suggest that neighbourhoods with residents with no involvement in the local area are harmful for social capital formation. This is consistent with a large literature that has discussed the importance of social ties in forming social capital (Putnam, 2016; Doob, 2019; Wang et al., 2018; Athey et al., 2020). Consistent with what is shown with ward-level data, these results are not driven entirely by responders who have just moved into the area.

To rationalize the results presented, I then discuss evidence on the impact that Airbnb had on

[4] However, the magnitude of the effect can vary widely given the heterogeneity of Airbnb presence across London. As an example, the cumulated Airbnb penetration in central London in 2019 is twenty times larger than in the median ward.

neighbourhoods: in the remainder of the paper, I present the impact that short-term renting has on residents, which, in turn, makes them less prone to contribute to the local area. I begin this analysis by documenting a positive relationship between Airbnb penetration and backlash against tourists. For each additional tourist every 100 residents, the probability of a complaint against tourists increases by 1.9%. There exist at least two explanations for this finding. First, discontent might arise from the impact that a permanent reallocation of housing supply, from long to short-term rentals, has on prices. Second, the high turnout of tourists in residential areas might affect the quality of the neighbourhood.

Evidence on the first channel comes from Barcelona (Garcia-López et al., 2020), Amsterdam (Almagro and Domínguez-Iino, 2025), Los Angeles (Koster et al., 2019), Berlin (Duso et al., 2024) or the entire US (Barron et al., 2020). These papers show how an increase in Airbnb penetration is linked to a rise in prices caused by the permanent shift of properties from long to short-term renting in cities with fixed housing supply. This is also true in London, with the effect concentrated in small properties which are, on average, more profitable for Airbnb hosts.

I explore the second channel, documenting how neighbourhood quality is impacted by Airbnb's presence. I do this in several ways. First, I show that complaints against misbehaviours such as rubbish in the street or incorrect car parking are increasing. These measures of complaints are a unique and disaggregated proxy of neighbourhood quality, but could hide two different aspects.[5] First, complaints may be rising as actual incidents are increasing, suggesting a decrease in neighbourhood quality. Second, higher complaints may be due to more engaged citizens.

I first show how incidents are increasing. I document a rise in crime rates for anti-social behaviours. The estimated effects are sizeable: anti-social behaviour crime rates increase by 4.7 per cent in a ward with average Airbnb penetration. Also, proxies of residents' misbehaviour increase, such as the number of parking notices. While this may be partially due to local authorities not investing in areas with high Airbnb penetration, I cannot find evidence on this explanation in the data, suggesting that the increase in complaints is due to tourists' and residents' misbehaviour.

Second, I discuss how not all complaints are increasing, and that the ratio between complaints and actual incidents is not increasing. This reassures that higher complaints are not due to more active and engaged citizens.

These results suggest that the roots of backlash are also linked to non-pecuniary motivations, which cannot be captured only by dynamics in house prices. A potential explanation is that, while house prices just capture a net, average effect, benefits and costs are unequally distributed and perceived across different subgroups of residents. My direct approach to measuring complaints and neighbourhood quality allows for capturing such heterogeneity and unveiling new patterns. To

[5]The advantage of these complaint measures lies in the spatial and temporal coverage, and in the detailed description of the incidents, compared to the actual incidents not available for the entire period and the universe of wards.

the best of my knowledge, this is the first paper to explicitly link Airbnb penetration to the backlash against tourism and to provide evidence that this occurs through a decline in neighbourhood quality.

To validate my results, I highlight the differences between short-term renting and traditional accommodations in hotels. As mentioned above, I discuss how my empirical strategy is not simply capturing tourists' penetration and tourism trends. Furthermore, I document how Airbnb has two distinctive characteristics that differentiate short-term renting from traditional hotel accommodations. First, as Airbnb supply is extremely flexible and not regulated, local services may fail to adjust, and hosts do not internalize the impact of an increasing number of visitors on congestion of public services (*quantity* externality). Second, the absence of formal monitoring over guests may induce both negative behaviours from tourists and negative selection, with more disruptive tourists choosing Airbnb properties to take advantage of looser constraints (*quality* externality).

Consistent with this hypotheses, I provide evidence that negative externalities are triggered by a lack of control from Airbnb hosts. I observe fewer complaints in areas where most guests rent just one room and share the property with the host, rather than renting the entire property. This suggests that monitoring through the presence of hosts mitigates negative behaviours from guests.

I conclude the paper by discussing how the benefits from short-term renting are concentrated among a few and absent homeowners. While the costs of the above-described externalities are borne by the entire community, the benefits from the influx of short-term stayers are highly concentrated among a few hosts, often not London-based. I document how, among Airbnb hosts, only 60% report living in London and around 5 per cent control 65 per cent of all Airbnb booked nights in 2019. Moreover, I show that, consistent with the importance of regular monitoring, areas with more professional hosts or absent hosts are more likely to experience an increase in complaints.

Previous literature My paper contributes to three strands of the literature. First, it is related to the growing body of research on the impact of short-term renting. A first set of papers highlights the impact on the house and long-term rent prices. Sheppard and Udell (2016), Garcia-López et al. (2020), Koster et al. (2019), Duso et al. (2024) and Barron et al. (2020) find that house and long-term rent prices increase, taking advantage of a similar empirical strategy as the one presented here, in New York, Barcelona, Los Angeles, Berlin and the United States, respectively.[6] Calder-Wang (2020) uses a structural model of residential choice to estimate the effect of the increased opportunity for landlords to rent short-term on the equilibrium rents across different housing types and demographic groups. A second set of papers studies the impact of Airbnb on the hotel industry, showing how Airbnb's presence negatively affected hotel revenues (Zervas et al., 2017; Farronato and Fradkin, 2018; Schaefer and Tran, 2020). A paper close to mine is Rodon et al. (2025), which focuses on the electoral consequences of Airbnb penetration in Barcelona, and shows how

[6]Differently from other studies, Koster et al. (2019) takes advantage of discontinuous regulation between Los Angles county and neighbourhood areas. Duso et al. (2024) takes advantage of policy changes in Berlin.

areas with more Airbnb experience higher abstention and are more likely to vote for the party that campaigned in favour of home-sharing regulations. Jin et al. (2024) shows how short-term rental regulation in Chicago reduces the burglaries near buildings that limit Airbnb listings, while Lutz et al. (2024) study the perceived impact of short-term renting platforms.

I complement this recent literature in four ways. First, I discuss and provide direct evidence of the linkage between Airbnb penetration and the observed backlash against tourists. Second, I present novel evidence of an additional non-pecuniary impact of short-term renting on neighbourhood quality. I also highlight the consequences of the deterioration of local amenities on social capital and residents' attitudes. Third, I suggest that the lack of monitoring by Airbnb and Airbnb hosts is a key difference from standard hotel tourism, which represents the mechanism driving the documented backlash. Fourth, I introduce a new measure of Airbnb penetration. While the literature has focused mainly on the number of listings, I define penetration as the number of Airbnb guest nights over the resident population. The measure that I use has two key advantages: i) it does not suffer from the problem of inactive listings not removed from Airbnb website, as it uses actual reviews to infer the number of guests in the area; and ii) it accounts for the heterogeneity in the size of listings and length of stay of guests.

The second strand of the literature I contribute to is the one examining the determinants of neighbourhood quality. From business composition (Almagro and Domínguez-Iino, 2025, Glaeser et al., 2023) to school quality (Bayer et al., 2007), several explanations have been advanced.[7] Complement to these works, Avetian and Pauly (2025) study how influx of tourists affect locals' satisfaction with amenties. My contribution is to highlight the role played by the short-term renting industry and its potential impact on residents' behaviour. My working hypothesis is that disruption experienced by residents may induce a lower willingness to contribute to the neighbourhood quality. This is consistent with the idea that, in neighbourhoods in which social networks are tighter, the willingness to contribute to the local area is higher. This has been shown by comparing homeowners and long-term rentals (González-Pampillón, 2022 and Billings and Soliman, 2024 look for example at the impact on crime rates), and it becomes even more salient if short-term renters are present (Putnam, 1993; Sims, 2007; Billings and Soliman, 2023). Not only will tourists misbehave, but their misbehaviour may induce similar responses by residents.

Finally, my work is related to the growing literature explaining how social capital is shaped, and the role played by social interactions.[8] This has been mainly done across countries or, at best, across cities. In this paper, I provide evidence also within a single urban settlement. Starting from

[7] Almagro and Domínguez-Iino (2025) uses a structural approach to study the endogenous link between amenities and residents' location sorting, and how this shapes welfare distribution. Airbnb, in their context, drives the shift in housing supply. They also document an increase in house and long-term rent prices.

[8] How to define social capital is widely discussed; I follow Guiso et al. (2016). Durante et al. (2024) discuss the different aspects associated with the concept of social capital.

the seminal work in Alesina et al. (1999) that shows how ethnic fragmentation is an important determinant of public good provision, the literature has discussed the role played by social interaction. Oldenburg (1999) discusses the role played by gathering places in shaping society. Putnam (2021) traces the determinants of social capital in the US in the last century, highlighting the role of social interactions. Bailey et al. (2020) and Bailey et al. (2020), leveraging novel Facebook data, discuss the determinants of social connectedness in Europe and in New York City, respectively. Bailey et al. (2021) and Chetty et al. (2022b), leveraging on the same Facebook data, show that the role of international trade and socioeconomic status in explaining social connection. Finally, Choi et al. (2024) shows the importance of network ties, facilitated by the opening of new neighbourhood cafés, in facilitating entrepreneurship.

The remainder of the paper is organized as follows. Section 2 presents the data. Section 3 lays out the empirical strategy and presents the first stage results from the IV strategy. Section 4 documents the consequences of short-term visitors on social capital and residents' attitudes. Section 5 studies the impact of Airbnb penetration on the neighbourhood, looking at costs and benefits and their pecuniary and non-pecuniary roots. Section 6 discusses why the results are not simply driven by tourism presence, and Section 7 discusses the benefits associated with Airbnb and their distribution. Section 8 summarizes the main robustness checks, which are then described in detail in the Appendix. Section 9 concludes and provides policy considerations.

2 Data

My analysis relies on a panel of 624 London electoral wards for years between 2006 and 2019, where each ward is uniquely assigned to a local authority (or "borough").[9] To study the economic and political effects of Airbnb penetration, I combine data from several sources. Appendix B fills in the details. Appendix Table C.1 reports summary statistics for the main variables.

2.1 Airbnb Penetration

Data on Airbnb penetration comes from InsideAirbnb.com and Tomslee.net, independent sources that web scrape the Airbnb website monthly and collect all publicly available information. My measure of Airbnb penetration is defined as follows:

$$Airbnb\,penetration_{it} = \frac{Cumulative\,Airbnb\,tourists\,nights_{it}}{Residents\,nights_{i2007}} \tag{1}$$

It represents the cumulative number of tourists that have used Airbnb until time t (year or month, depending on the specification) over the population of ward i. The numerator in Equation 1 is

[9] I fix the boundaries at 2011 electoral wards. See Appendix Section A.1 for details on the London administrative structure. I exclude the sample City of London local authority due to its unique characteristics.

computed in the following way:

$$Airbnb\,tourists\,nights_{it} = \sum_j Reviews_{jit} \times \frac{1}{0.69} \times Guests_j \times Nights_j \tag{2}$$

where $Reviews_{jit}$ is the number of reviews received at time t by listing j in ward i.[10] To convert the number of reviews into the number of Airbnb visits, I rescale the former by 0.69, which is the percentage of guests that leave a review (Fradkin et al., 2020). I obtain the number of $Airbnb\,tourists\,nights$ by taking into account the number of guests the property can accommodate ($Guests_j$) and the number of minimum nights a host requests ($Nights_j$). The measure of Airbnb tourists' visits produces an overall figure for 2018 that is in line with official statistics in Airbnb (2018), 2.2 million vs 2.28 million. The denominator in Equation 1 is the number of residents in 2007 in ward i times 350, assuming each resident spends 15 days outside London.[11]

Airbnb penetration before 2008 is set to zero, as the platform was founded in 2008 in San Francisco. Web scraped data starts in 2013, which is the first year Airbnb's presence became relevant in London and most of the popular destinations (see *e.g.* Garcia-López et al., 2020). However, I can recover Airbnb penetration before 2013 by looking at the number of reviews ever received by the listings in 2013, conditional on the listing not being removed from the platform. Results are analogous when restricting the sample to 2013-2019, which still represents the longest panel of Airbnb presence in the literature.

This measure of Airbnb penetration captures the intensity of Airbnb tourism with respect local population, and it departs from previous literature, Garcia-López et al. (2020), Barron et al. (2020), Almagro and Domínguez-Iino (2025), Duso et al. (2024), or Koster et al. (2019), which studies housing market outcomes using the number of properties listed on the Airbnb website. This approach has two main advantages: i) since it considers only actual reviews, it automatically excludes listings present on the Airbnb website but not active; ii) it represents more precisely the number of tourists in the area, as it takes into account the size of the flat and duration of stay.

To further explore the mechanisms and heterogeneity of my results, I distinguish between hosts renting a room or an entire property. I define a host professional when they are renting 5 or more properties in a given month. I leverage self-declared residence to assign the host location (same neighbourhood as the property, from London or the UK).

In Figure 1, I plot the geographic distribution of *Airbnb penetration* in 2019, where areas more (less) exposed are denoted in red (yellow), and bins are defined according to 2019 quintiles.

[10] I assign each listing based on latitude and longitude. Airbnb alters the exact location by a factor ranging between 0 and 150 meters, given the size of each ward, the number of wrongly assigned listed is negligible. Since guests have 14 days maximum to fill a review, the time of filling is, therefore, representative of the period of the visit.

[11] Here and in the rest of the paper when considering per residents measure I fix local population at its 2007 level (source: Office of National Statistics).

Exposure is decreasing with distance from the city centre, except for a cluster at the extreme west denoting the Heathrow Airport area. In 2013 (see Appendix Figure C.1), Airbnb was more concentrated in the city centre and surrounding areas were overall less exposed.[12] Conversely, the number of hotels in 2019 (the dots in the maps) shows a higher concentration in fewer locations, mainly in Centre-West London (Westminster and Chelsea area).

2.2 Outcomes of interests

Social capital Given my interest in understanding how a high turnout of residents may affect social capital, following Guiso et al. (2016), I measure social capital as the number of charitable organizations.[13] The source of these data is the "Point of Interest" dataset (2011-2019) from Digimap, which reports the exact coordinates and a precise sector categorization.

Survey of Londoners In order to provide evidence on the sentiments of residents about their neighbourhood, I leverage unique survey data. From the Survey of Londoners 2018-19 (run by the Greater London Authority), I collect individual opinions on various aspects regarding local networks and involvement in the community. This is a unique survey because it allows a granularity that all the widely used surveys do not provide, with a significant sample size (6601 individuals precisely geolocalized in London). Thanks to this survey I construct various measure of connections and life satisfaction at individual level: a dummy whether the individual feels that they belong to the local area/to London; a dummy whether the individual has never felt lonely; a dummy whether the individual has had contacts with their neighbours; a dummy whether the individual agrees that they can influence the area; a dummy whether the individual report a life satisfaction index below or equal to 4. Please refer to the Appendix Table C.2 for the detailed questions.[14] Importantly for my analysis, respondents also report how long they have lived in the area, which allows me to distinguish between long-term residents and newcomers.

[12] While the Olympic Games 2012 and years before saw a very modest presence of Airbnb, a turning point event is also represented by the acquisition of London-based rival CrashPadder.

[13] Unfortunately, there are no data on how many people volunteer at such a granular level. The closest we can get is the London Volunteer project that collects expressions of interest. The data, however, are available only from 2018, leaving very little time variation given that the main sample is restricted to 2019. Another natural variable to consider as a proxy of social capital would be voter turnout. Three issues prevent me from using it. First, national election results are not available at my unit of analysis (*i.e.* ward) but only at the constituency level. There are 73 parliamentary constituencies in Greater London, with only 4 general elections in the 2006-2019 period. I suffer from small sample biases. Electoral calculus presents estimates for turnout at ward level, but they are all ex post interpolations, predicting values from the constituency results using the control variables included in my analysis. Second, local elections (for which we have results at the ward level) are not representative. Third, the electorate reported is an endogenous variable, as to vote, individuals have to register. Information on the number of people meeting criteria to be able to register is not available at the ward-year level.

[14] An alternative source to explore connections would be the Meta Social Connectedness Index presented in Bailey et al. (2018). This novel measure tracks the intensity of social connectedness between locations. Unfortunately, this is available only at the NUTS3 level, which is a level of aggregation even larger than local authorities, and as a unique snapshot in time.

Complaints against tourists To shed light on how residents perceive their neighbourhood, I also collect data on the complaints submitted to their local authority. I web scrape "FixMyStreet", an online service where residents can submit geolocalized complaints which are forwarded to the local authority in charge. Data collected span the period 2007-2019 and contain around 424 thousand complaints in 17 categories.[15]

I construct a dummy equal to one whether a complaint is reported to the local authority in ward i in month t for each category. I consider complaints about rubbish in the street (susceptible to the presence of tourists and change in residents' behaviour), complaints about dog fouling, abandon vehicles and car parking (susceptible to change in residents' behaviour but not to the presence of tourists) and complaints about road status green areas' status (placebo category, to verify that it is not the case that i) residents are complaining more in general, or that ii) local authorities are not investing at all in very touristic areas).

Finally, I also measure backlash against tourism with a dummy equal to one if a complaint contains in its description specific keywords (*e.g.* "tourist", "Airbnb", etc.) related to the tourist industry. Classic measures of backlash against specific groups, such as political support or newspaper articles (Tabellini, 2020, Dustmann et al., 2019 or Colantone and Stanig, 2018) are non-applicable in this context, given the granularity of the analysis.

Differently from measures of backlash proposed by the political economy of discontent (*e.g.* vote shares) or measures of net welfare change proposed by the urban economics literature (*e.g.* house prices), my outcome variable capture directly those unhappy with the status quo, even when these groups represent a minority, whose discontent would not be captured by previously cited measures. An additional key advantage of my measure is that it consists of actual complaints, and it does not require any sentiment analysis to infer a negative attitude towards tourists.

A key advantage of this measure is the granularity and consistency of the data. Actual incidents presented below are, unfortunately, not present for all periods and wards of interest. Complaints and actual incidents complement each other to shed light on neighbourhood quality.

Housing market A permanent shift towards short-term rents may induce an increase in long-term rents and house prices, which is a potential source of discontent among residents. This is why I collect data on both long-term rents and residential property prices.

Rent data comes from Urban Big Data Centre (UBDC), with the primary source being Zoopla, a popular UK property comparison online platform. I match each transaction with Energy Performance Certificates to recover the size of the property, and compute the median price for properties with 1 or 2 rooms and for properties with 3 rooms or more in ward i and year-month t. Small properties are the most likely to be affected by the short-term renting market as they are the

[15] In Appendix Table C.3 I report the 17 categories, see Appendix Figure C.2 for aggregate take-up rates.

ones with the highest returns.[16]

Data on house prices are from the UK Land Registry, which reports the universe of transactions from 1995. I match each transaction with Energy Performance Certificates to recover the size of the property, and compute the median price per square meter in ward i and year-month t.

Both sources report the exact postcode of the property, which maps uniquely into a ward. I adjust prices using the CPIH index (2015=100, source: ONS, and to guarantee representativeness, I exclude ward-year-month observations with less than 5 transactions. [17]

Rateable Values Following Heblich et al. (2020), I measure the value of non-domestic property values in London using rateable values, which correspond to the annual flow of rent for the use of land and buildings (source: Valuation Office Agency). I consider the rateable value per square meter and the floorspace available for non-domestic properties in each ward from 2006 to 2019.

Neighbourhood quality To quantify the actual impact of resident turnout, via Airbnb presence, I also measure proxies of neighbourhood quality. I consider the number of anti-social behaviour crimes at the ward-year-month level. Anti-social behaviour is defined by the police as "behaviour by a person which causes, or is likely to cause, harassment, alarm or distress to persons not of the same household as the person" (Anti-social Behaviour Act 2003 and Police Reform and Social Responsibility Act 2011). An important characteristic of this measure is the non-subjective nature of crime rates, which are derived from official reports, hence verified by Police officers, and are less affected by residents' biased reporting nuisances.[18]

To complement the above data and the data on complaints by residents, I collect information on parking fines and fly-tipping incidents. In particular, I consider the total number of Parking Charge Notice (PCN) for each ward i in month t and a dummy equal to one whether a fly-tipping incident was recorded in ward i in a given month t.[19] These data are not available at the centralized level, and I submit individual requests to each of the 33 local authorities. Unfortunately, not all local authorities were available to provide such detailed data, and the analysis is therefore limited to the data that can be credibly trusted. I collect data at the local authority level and use the aggregate data to benchmark the more disaggregated data. The resulting dataset is an unbalanced panel of the local authorities that provided good quality data, see Appendix Table C.4.[20]

[16] Zoopla reports advertised, not realized, rent prices.

[17] Results similar by considering different thresholds. These steps are similar to those presented in Ahlfeldt et al. (2023). Ahlfeldt et al. (2023) presents data at MSOA-year level for the UK following the same strategy, the data I collected allows for a more disaggregated analysis as I computed monthly indexes.

[18] Original data are provided at the month-LSOA level. I thank the CEP Community - Crime group for sharing the data with me up to September 2018. I collect the remaining months from the MET police website. Appendix Section B.3.1 presents detailed definitions of anti-social behaviours.

[19] While what constitute a PCN is constant across all local authorities, fly-tipping incidents definitions vary depending on the local authority. That is why I consider a continuous variable for the PCNs, while for fly-tipping incidents, I rely on a dummy variable.

[20] Quality of the data has been assessed using London Councils data for PCN data. Fly-tipping data are benchmarked

2.3 Additional variables

Demographic variables I include in my dataset various demographic variables. From the 2011 and 2021 Censuses, I collect data on population by age group, educational attainment, tenure in the UK, and whether they lived at the same address one year ago (2021 only). I collect the share of workers by sector (2001 Census). All variables are collected at the Output Area level, which maps uniquely into wards.[21] To complement these sources, I also collected information on the total electricity consumption at ward-year level as an alternative proxy of population (source: UK Government, Department for Business, Energy & Industrial Strategy; 2013-2019).

Moreover, I collect public data on schools to check whether ward population composition is changing over time. From data at the school level, I collect information for each ward i in year t on the total number of pupils enrolled; the share of pupils for which English is not the first language; the share of pupils with Special Education Needs (SEN); the share of pupils entitled to free meals in ward i and year t. All variables are provided by the UK Government and are available for the period 2011-2019. Schools in London are highly competitive, and almost all of them run admissions locally, considering small catchment areas. Pupils enrolled in a school can be considered a reliable proxy of the wards' pupil population.

Geographic variables Taking advantage of GIS software, I compute the following measures of "centrality" for each ward: the distance from each ward centroid to Charing Cross, which is considered the London city centre and the distance from each ward to the closest underground station, as the underground network represents a crucial characteristic of London structure, and it is a proxy of how well-connected to other locations a ward is.

Hotel penetration Data on the number of tourists in hotels are not available at the unit of analysis used in this paper. More generally, they are usually provided by professional data providers that take advantage of detailed surveys. To estimate the number of tourists using the hotel industry at the ward-year-month level, I proceed in the following way. Similarly to Airbnb penetration (Equation 1) I define hotel penetration as:

$$Hotel\,penetration_{it} = \frac{Cumulative\,Hotel\,Tourists\,nights_{it}}{Residents\,nights_{i2007}} \tag{3}$$

using WasteDataFlow data. Both sources provide data only at the local authority level.

[21] The ONS also presents data on population by age group at the ward-year level from 2002 to 2019. Caveats on these population counts may apply in this context as ONS can only provide estimates from secondary sources (see Suárez Serrato and Wingender (2016) for an example of mismeasurement in population estimates in non-Census years).

It represents the cumulative number of tourists using hotels up to time t in ward i divided by the ward population. [22] The numerator is computed in the following way:

$$\begin{aligned} &Hotel\,Tourists\,nights_{it} = \\ &= N.\,London\,rooms_t \times \frac{N.\,Hotels_{it}}{Tot.Hotels_t} \times 3 \times 365 \times Occupation\,rate_t \end{aligned} \tag{4}$$

where I consider the total number of hotel rooms reported by van Lohuizen and Smith (2017) and PwC UK Hotel forecast (2016, 2017, 2018, and 2019). Total hotel rooms are assigned proportionally across London according to the distribution among wards of hotels in period t.[23] I then assume that each room can fit on average 3 guests, giving the number of guests that can potentially be present each day in a ward i. I then consider the yearly equivalent by multiplying 365 by the average annual occupation rates reported by van Lohuizen and Smith (2017) and PwC UK Hotel forecast. The denominator of hotel penetration is the number of residents in ward i in 2007.

In Figure 1, I plot (blue dots) the number of hotels in 2019. The geographic distribution displays a clear cluster in Centre-West London (namely, Westminster and Chelsea area) and one in the Heathrow Airport area. Moreover, I do not observe any remarkable change in the geographical distribution over time, see for example the same variable in 2013 reported in Appendix Figure 1. In Appendix Figure C.3, I plot the median ward, 25$^{\text{th}}$ percentile ward, and 75$^{\text{th}}$ percentile ward from the distribution of the number of hotels per square kilometre. It confirms that the number of establishments is relatively fixed over time.

Bars, restaurants and nightclubs To make sure that the results are not driven by the presence of bars, restaurants, and nightclubs, I collect data on the number of these establishments in each ward. I use the "Point of Interest" dataset (2011-2019) from Digimap, which reports the exact coordinates and a precise sector categorization.[24]

3 Empirical Strategy

This project aims to study how fewer connections within cities may affect social capital. To do that, I leverage the penetration of Airbnb. Short-term renters are arguably less likely to develop relationships and invest in the local neighbourhood than homeowners and long-term renters. Leveraging on this assumption, I study the social and economic effects of a change in Airbnb penetration with the following model:

[22] For hotels, I considered any "serviced" room, which includes hotel rooms, bed and breakfast, and hostels.

[23] Source of the number of hotels in ward i-period t is Digimap, which is available only from 2011 onwards. For all previous years, I considered the average distribution over the 2011-2019 period.

[24] I consider the following categories: Banqueting and function rooms; Cafes, Snack bars and tea rooms; Fast food and takeaway outlets; Fast food delivery services; Fish and chip shops; Internet cafes; Pubs, bars and inns; Restaurants; Cinemas; Discos; Nightclubs; Theatres and concert halls; Adult venues.

$$Y_{ibt} = \beta Airbnb\, Penetration_{ibt} + X_{it}\gamma + \eta_i + \delta_{bt} + \epsilon_{ibt} \tag{5}$$

where Y_{ibt} represents the outcome of interest in ward i, local authority b and time t, and *Airbnb Penetration* is the measure described in Section 2.1. Depending on the outcome variable considered, I will look at yearly or monthly data. X_{it} is a rich set of interactions between time dummies and the 2001 share of workers by sector, the 2001 log of house prices per square meter, distance from ward centroid to Charing Cross, and distance from ward boundaries to the closest underground station. I also include ward i fixed effects (η_i) and local authority b time trend (δ_{bt}). Inclusion of local authority-specific time trend is important given the peculiarity and autonomy of each local authority. This rich set of fixed effects implies that β is estimated from changes in Airbnb penetration within the same ward over time, compared to other wards in the same local authority in a given year (or year-month) and compared to wards with similar pre-determined and geographical characteristic in a given year (or year-month). While extremely demanding, a year-month specification would account precisely for the high degree of seasonality in tourism and Airbnb tourism.[25] This is why, whenever possible, I consider year-month variation.

Standard error computation follows Conley (1999) and Hsiang (2010) with a spatial correlation parameter of 14 km and a serial correlation parameter of 2 years or 24 months.[26]

Two opposite forces may bias results. On the one hand, we may expect Airbnb penetration to be higher in wards becoming more attractive due to local amenities and in higher quality neighbourhoods. On the other hand, Airbnb penetration might settle in otherwise declining wards, where residents and long-term renters do not want to live. The concern is that, despite the rich set of controls, any time-varying unobservable variation included in ϵ_{ibt} that correlates both with Airbnb penetration and the outcome of interest will lead to biased OLS estimates for β in Equation 5.

To address these concerns, I instrument Airbnb penetration following a shift-share IV strategy as in Garcia-López et al. (2020), Barron et al. (2020), or Almagro and Domínguez-Iino (2025). The "share" part of the IV exploits spatial variation from the spatial distribution of historical monuments and buildings per square kilometre, as their presence represents an attractive feature for tourists. The "shift" part exploits time variation in the worldwide popularity of Airbnb as proxied by the Google search volume for the word "Airbnb".[27]

[25] In Appendix Figure C.4, I present quarterly aggregated data for international visitors and Airbnb visitors nights.

[26] Parameters choice follows from the fact that the radius of the median local authority would be 2 km if they were perfect circles. This implies that I am assuming that spatial correlation vanishes in 3 complete local authorities from each ward centroid. For the autocorrelation parameter, I consider 2 years, note Airbnb started in London in 2009, and that Greene (2018) recommends at least $T^{0.25}$. Results are similar by changing parameter values as described in Appendix Section D.5 and reported in Appendix Figure E.4.

[27] In Appendix Figure C.5, I plot the geographical distributions of historical monuments and buildings, notably they are not only concentrated in the city centre. In Appendix Figure C.6, I plot the time evolution of the trend for the word "Airbnb" according to Google, denoting a stable growth over time.

$$Airbnb\,Penetration_{it} = Historical\,Sites_i \times Google\,Trend\,Airbnb_t \tag{6}$$

The exclusion restriction can be expressed as follows. Both factors are orthogonal to unobservable ward temporal variation ϵ_{ibt}, conditional on covariates and fixed effects. First, I do not expect worldwide Airbnb popularity to be informative of ward-specific unobservable trends. Second, I assume that determinants of the spatial distribution of monuments from hundreds of years ago are not informative of current trends that may affect the outcome of interests.

Similarly, we can say that the key identifying assumption behind the instrument is that wards with a higher number of historical monuments must not be on different trajectories for the evolution of economic and social conditions in subsequent years (as suggested by Goldsmith-Pinkham et al., 2020, this setting mimic a DiD setting).[28] This assumption can be violated if the characteristics of wards with a higher number of historical monuments had persistent confounding effects on tourism patterns as well as on changes in the outcomes of interest.

Following Goldsmith-Pinkham et al. (2020), I deal with this concern in two different ways. First, I show that the pre-period change in outcomes of interest is uncorrelated with subsequent changes in Airbnb penetration predicted by the instrument (Appendix Section D.1). Second, in my baseline specification, I control for interactions between year (or year-month) dummies and several 2001 wards characteristics and proxies of "centrality" that might be linked to a higher number of historical monuments and may have a time-varying effect on economic and social conditions.

In terms of instrument relevance, in all my specifications, I obtain a strong first stage relation. Appendix Table E.1 presents first stage results for the relationship between Airbnb penetration and my instrument. Kleibergen-Paap F statistic for weak identification, using the described spatially-corrected standard errors, is reported. In Column 1, I consider yearly data with ward FE and local authority flexible time trends. Column 2 adds the interactions between year dummies and the 2001 share of workers by sector and the 2001 log of house prices per square meter. Column 3, which reports my baseline specification, includes the interaction between year dummies and the distance to Charing Cross and the distance to the closest underground station. Columns 4 to 6 report the same specifications with monthly data. In all cases, the F-stat is well above 10, and there is a strong and significant relationship between Airbnb penetration and the instrument proposed. Appendix Section D.1 further explores the robustness of this empirical strategy.

3.1 Count Variables

As explained in Wooldridge (2010) and Wooldridge (2015), when facing count variables such as the number of non-profit organizations, a robust approach is to consider a Poisson Fixed Effect

[28] Given the setting, the identification proposed by Borusyak et al. (2020) does not apply as the identification is entirely driven by the exogeneity of the shares.

estimation, with an exponential mean function using a control function approach. The steps, in this case, are the following: First, run the first stage and predict the residuals with a standard OLS, taking into account all controls and fixed effects described in Equation 5. Second, run a Poisson Fixed Effect including the endogenous regressor and the control function (the prediction in the previous stage), including once again all controls and fixed effects. To correctly compute the standard errors, I bootstrap them with 300 iterations. I report the 90% bias-corrected confidence interval for the variables of interest. I will also report the 90% bias-corrected confidence interval on the control function as it can be interpreted as a test on the exogeneity of the independent variable.

This approach, on top of the IV identifying assumptions stated above, not only requires conditionally mean independence of the instrument, but I should also assume that the endogenous variable is linearly separable in the exogenous part from the endogenous part (Petrin and Train, 2010; Wooldridge, 2015). Reassuringly, including nonlinear terms of Z in the first stage (quadratic and cubic terms) does not improve the fit of the first stage regression, suggesting evidence that the linear separability assumption holds (results available upon request).

4 Consequences of Airbnb penetration

In this Section, I present the main results of this project. I study what happens when neighbourhoods experience an influx of stayers with a lower level of engagement with the community. To do that, I leverage the assumption that a higher Airbnb penetration is associated with lower investments in the area, as short-term renters have no interest in doing that. I first discuss the consequences of Airbnb penetration on a widely used social capital measure, and I further discuss potential mechanisms behind this result.

Social capital has been used to explain an impressive range of phenomena (economic growth Knack and Keefer, 1997; institutions' design and performance Djankov et al., 2003, etc.). Its determinant and the role of social connections, however, have not been fully understood. That is particularly true in cities where we observe higher levels of progressive views and universalist moral values (Enke, 2020) but a decreasing level of volunteers and other proxies of social capital (Putnam, 2000, Turkle, 2015).

4.1 Social Capital

In Table 1, I study the impact of Airbnb penetration on one of the most common social capital measures: the number of non-profitable organizations (see, for example, Guiso et al., 2016). Throughout the paper, Panels A and B always present, respectively, IV and OLS estimates. I also report the KP F-stat for weak instruments and years considered for each specific outcome variable.

In Columns 1 and 2, I consider the count model as described in Section 3. Column 1 considers only ward FE and local authority flexible time trends, while Column 2 also includes interactions between year dummies and several 2001 ward characteristics and geographic variables. Irrespective of the specification, I document a decrease in the number of charitable organizations. Looking at Panel A, Column 2, an increase of 1 Airbnb tourist per 100 residents is associated with a drop of 4.5 per cent in the number of charitable organizations per resident.

When looking at the intensive (Columns 3 and 4) and extensive margin (Columns 5 and 6), it seems that the results are driven by the former. Looking at wards where we have a profitable organization (83% of the sample), I document a decrease of 7.2 per cent in the number of non-profitable organizations active. I find no statistically significant results for the dummy representing the presence of at least one non-profitable organization in the ward.

The influx of short-term residents may trigger different reactions that explain the results presented above. I propose and discuss two alternatives.

Population changes A vast literature (starting with Tiebout, 1956) has discussed the concept of "voting with your feet" where residents sort themselves in different areas depending on their preferences, making it harder to interpret electoral support for a certain party. Similarly, I investigate whether a major shift in population or in population composition may be detected. This would certainly be true in a frictionless city; however, constraints as homeownership and school enrollment may limit movements and increase dissatisfaction with the status quo (Hirschman, 1970). In Table 2, I look at various measures of population and find little change in the ward population. Despite (almost) all point estimates being negative, only one is statistically significant. In Columns 1 and 2, I look at the population counts from the 2011 and 2021 Censuses. When looking at the full specification, we do observe a significant drop in population in areas more exposed to Airbnb presence. Columns 3 and 4 discuss, as an alternative measure, the total electricity consumption and find no effect, similar to the number of pupils enrolled in the schools in the neighbourhood (Columns 5 and 6). This is consistent with the idea that residents with higher constraints are less likely to move. School admission is a relevant constraint to moving, given that most schools in London run admission locally with small catchment areas.

To further verify whether neighbourhood composition is affected, I consider the impact of Airbnb penetration on i) the age composition, ii) the share of individuals holding a degree, iii) the share of people born in the UK vs those arrived less than two years ago and iv) the share of pupils that are more likely to be part of families with higher moving constraints. In Table 3, Columns 1-5, I check whether the age composition of the ward population is affected. I observe changes in the age structure, with more residents below 24 (Column 1) and above 65 years old (Column 5), and fewer with age between 50 and 64 years old (Column 4). While the share of individuals with a degree (Column 6) is not affected, I document a shift towards residents that are recently arrived in the UK (Column 8) at the expense of UK-born residents (Column 7).

To further verify whether neighbourhood composition is affected, I consider the impact of

Airbnb penetration on i) the ward-specific share of pupils entitled to a free meal registered in a school (Column 9), ii) the ward-specific share of pupils for which English is not the primary language (Column 10) and iii) the share of pupils with Special Education Needs (Column 11). The results of these Columns confirm that families with higher constraints are less likely to move.

Just population change? As previous literature (Wilson, 2000) have shown how volunteering and other forms of social capital peak among middle age, highly educated and natives individuals, results presented in Table 3 suggest that the population composition change, towards individuals less likely to be involved, may explain the drop in the number of charitable organizations documented in Table 1. While this represents a potential mechanism and an interesting result per se, it is important to note that the observed decrease in social capital is not only driven by a change in composition. The documented drop is indeed more present in wards with a higher share of individuals who are living at the same address or who have been living in the UK for more than 2 years. To show this, in Appendix Table E.2, I consider, starting from Columns 4 and 6 of Table 1, the following specification:

$$Y_{ibt} = \beta_1 Airbnb\,Pen_{ibt} + \beta_2 Airbnb\,Pen_{ibt} * HD_{ibt} + \gamma X_{it} + \eta_i + \delta_{bt} + \epsilon_{ibt} \tag{7}$$

where $Airbnb\,Pen$ represents the Airbnb penetration measure described in Section 2 and HD is a dummy variable capturing the heterogeneous effects of residents living at the same address as last year (Columns 1 and 3). The definition of such dummy is that it represents areas that in 2021 had an above median share of residents living at the same address as last year.[29] I instrument Airbnb penetration with the shift-share instrument described in Section 3, and the interaction $Airbnb\,Pen * HD$ with the interaction between the instrument and the HD dummy.[30]

Results reported in Appendix Table E.2 indicate that, although changes in population composition may have contributed to the decline in social capital, this effect is also present in wards where most of the residents have not just relocated to the area. This suggests that changes in the behaviour of long-term residents play a significant role in explaining the observed reduction in social capital.

Residents' attitude Even without any population change, we may expect a change in long-term residents' attitude towards their community when exposed to residents with a very low level of engagement as short-term renters. This may explain the drop documented in Table 1. To study

[29]Unfortunately, the 2011 Census does not report the share of residents living in the same address as last year, that is why I verify that my results hold also with an imperfect measure of long term residents, *i.e.* those living in the UK for more than 2 years, in Columns 2 and 4 of Appendix Table 1.

[30]HD_{ibt} is fixed over time, and it is absorbed by ward Fixed Effects. This specification is extremely demanding, and the F-stat of the first stage occasionally falls below 10, while when excluding the wide set of controls interacted with year fixed effects, the F-stat is always above 10. Moreover, given the added complexity, F-stat is computed starting from standard errors clustered at ward level, while standard errors reported are corrected following Conley (1999), parameters considered: 14 km and 2 years.

this, I leverage a survey run in October 2018. This survey is unique for the detailed questions asked to a relevant sample size within the same city. Given the nature of the survey, I cannot exploit the panel structure of my data, but the empirical strategy remains similar. I estimate the following equation:

$$Y_{jib} = \beta Airbnb\,Penetration_{jib} + \theta W_j + \gamma X_i + \delta_b + \epsilon_{ib} \quad (8)$$

where Y_{jib} is the answer to a question by individual j in ward i and local authority b, $Airbnb\,Penetration_{ib}$ represents the Airbnb penetration in October 2018, W_j is a set of individual characteristics and X_i is a set of ward level characteristics, and δ_b are local authority fixed effects.[31] I instrument $Airbnb\,Penetration_{ib}$ with the shift-share IV described in Section 3.

Results are reported in Table 4. In Column 1, I observe a drop in the share of people who feel that they belong to the area when exposed to higher Airbnb penetration. The same is not true when asked about their feeling about belonging to London (Column 2), suggesting a neighbourhood-specific effect. Consistent with the idea that short-term stayers make it harder to create connections, I observe that people more exposed to Airbnb penetration are less likely to never feel lonely, as well as having contact with their neighbours (Columns 3 and 4). Moreover, residents feel less likely to be able to influence the local community (Column 5). Finally, the probability of reporting a life satisfaction below 5 is higher when exposed more to Airbnb penetration (Column 6).[32] All these results are consistent with the hypothesis that communities with weaker ties due to the high turnout of residents have deeper consequences on life satisfaction and engagement in the local community.

New residents' attitudes? As presented in the previous Section, the change in population composition may be a potential mechanism behind the drop in social capital. To study this, I leverage the same survey data and interact with the main explanatory variable with a dummy equal to one if the respondent has been living in the area for less than 2 years. Results presented in Appendix Table E.3 suggest that the impact on residents' attitudes is not only driven by new residents but also present among long-term residents. In particular, those living in the area for more than 2 years are less likely to feel that they belong to the area, they are less likely to have any contact with neighbours, and are less likely to feel that they can influence the local community. This suggests that the impact of Airbnb penetration is not only driven by new residents but also by long-term residents' attitudes towards their community.

Evidence presented in this Section confirms the concerns of the many who oppose this new

[31] Individual controls are: age band dummies, female dummy, homeownership dummy, dummy if completed a university degree, income score, years living in London, and whether the survey was conducted online. Ward controls are: 2001 share of workers by sector, 2001 log of house prices per square meter, distance from ward centroid to Charing Cross, distance from ward boundaries to the closest underground station.

[32] When looking at life satisfaction indexes, 5 is often the modal value and considered the threshold value below which people are "unhappy", see for example Ortiz-Ospina and Roser (2017) or Abdallah et al. (2008).

wave of tourism (the media even refer that to that as "overtourism"): such a high turnout of temporary residents is harmful for social capital and local networks formation, civic engagement and may favour lack of social connectedness (Gallagher, 2018).[33]

5 Impact of Airbnb on the neighbourhood

This Section outlines potential mechanisms behind the results found. Airbnb penetration is associated with backlash from residents (Section 5.1) and more complaints. Second, I study what the causes of observed backlash against tourists are concerning Airbnb penetration, in particular looking at pecuniary and non-pecuniary channels discussing both the impact on house and long-term rental (Section 5.2), and the decrease in neighbourhood quality (Section 5.3).

5.1 Backlash against Tourism

Where does the disconnection with the local community come from? Is it a sign of dissatisfaction among residents? Abundant anecdotal evidence suggests that the increase in short-term renting in London, as well as in other European cities, has fuelled residents' discontent. Airbnb, as one of the earliest and most widespread players, has often been accused of fostering "touristification" and "killing" city centres.[34] Motivated by this discussion, in Table 5, I study the effect of Airbnb penetration on the probability that a complaint is received by local authorities in a given month from a particular ward. I will consider the full specification presented in section 3.

In Column 1 of Table 5, I find that there is a positive relation between Airbnb penetration and the probability that a complaint against tourism is reported. Results confirm that backlash against tourism and Airbnb presence are linked. This is particularly valuable in a setting where considerable heterogeneity in the distribution of gains and losses is present. This would not be possible using standard measures typically used in the political economy (*e.g.* vote shares) or the urban economics (*e.g.* house prices) literatures, as they would capture just a net effect. My outcome variable, on the contrary, can reflect those unhappy with the status quo, even when these groups represent a minority, whose discontent would not be captured by the previously cited measures.

5.2 House and long term rental prices

So far, the literature has focused on the impact of Airbnb on the housing market, looking at house prices and long-term rents. The documented positive effect of Airbnb on both prices was then, anecdotally, linked to the backlash received by Airbnb in many popular destinations. It is then natural to start my analysis of the potential roots of the previously described backlash from these outcomes. Results are presented in Appendix Table E.4.

[33]The Guardian, January 2020, *Overtourism in Europe's historic cities sparks backlash*.

[34]Financial Times, September 2019, *Are Airbnb investors destroying Europe's cultural capitals?*; The Guardian, May 2019, *How Airbnb took over the world*.

In Columns 1 and 2, I consider the impact of Airbnb penetration on the log of the number of ads for properties to rent. I document a decrease in the number of long-term renting ads by 11.1% for small properties (Column 1), which are the most likely to be affected, as these are the ones more profitable on Airbnb. This is not the case for larger properties (Column 2). This drop in supply is reflected in median rent (Column 3). At the same time, house prices are marginally affected (Column 6) with an overall small increase in the median price per square meter. Finally, I consider the impact of Airbnb penetration on business rates in the area (Columns 7 and 8). I find no significant effect on the floorspace available and the rateable values. This is reassuring as it rules out the possibility that rising business rents priced out non-profit organizations' offices.

These results mirror the previous literature, which found a positive and significant effect of Airbnb penetration on house prices and rents consistently. My findings are robust to using as an alternative measure of Airbnb penetration, the number of entire Airbnb properties over the number of dwellings in 2011, which is closer to the ones proposed by the literature, see Appendix Section B.2.1 for details on how I construct this measure.

Just looking at house prices in London or at previous studies, and assuming house prices internalize all benefits and costs for residents, we may be tempted to conclude that Airbnb has a positive effect on the welfare of residents. Heterogeneity of the impact of Airbnb across population subgroups is key to reconcile such positive (or null effect for large properties) with the rise of backlash, which I documented above in the paper and which is in line with what trade or migration and trade literature has found (*e.g.* Tabellini, 2020, Autor et al., 2020). House prices just capture an average effect: while few homeowners benefit from the rise in house prices, many long-term renters are paying the cost.

To unveil such inequality, it is crucial to explore alternative measures of residents' welfare, such as neighbourhood quality, which is what I do in the next subsection.

5.3 Neighbourhood quality

In this Section, I explore the impact of Airbnb on neighbourhood quality as a source of backlash against tourists.

Complaints about local area The rise in complaints against tourists is paralleled by an increase in complaints about neighbourhood quality. Table 5 presents these results. In Column 2, I examine the probability that a local authority receives a complaint about rubbish in the street. The IV specification indicates that higher Airbnb penetration leads to a 3 percentage point increase in the likelihood of such complaints, suggesting a decline in neighbourhood quality. As discussed in Section 2, this measure reflects negative behaviours by both tourists and residents.

Consistent with the idea that Airbnb penetration may affect social capital, I also document how residents' behaviour and civic engagement deteriorate in areas more affected by Airbnb. In

Columns 3 to 5 of Table 5, I report the impact of Airbnb penetration on complaints on dog fouling, abandoned vehicles, and car parking, which are misbehaviours linked to residents and not directly affected by the presence of tourists.

In all cases, I observe an increase in misbehaviour by residents: Airbnb penetration not only has a direct impact on neighbourhood quality due to the presence of tourists, but it also deteriorates social capital and residents' civic engagement. This is in line with previous literature comparing the behaviour of homeowners and long-term renters (Sims, 2007), and it is even more salient if short-term renters are present. In neighbourhoods in which local networks are weaker, the willingness to contribute to the local area is lower (Putnam, 1993).

More complaints or lower quality? An increase in complaints may be explained by two non-mutually exclusive factors: i) an actual decrease in the quality of the neighbourhood, or ii) more active and engaged citizens in reporting incidents.

In Table 6 Column 1, in support of the first factor, I report how an increase in Airbnb penetration is associated with a 4.7 per cent increase in anti-social behaviour crime rates. As described in Section 2, Police crime rates are a more objective measure as crimes are verified by Police officers. This helps mitigate concerns about biased reporting by residents, which instead may affect the complaints reported directly by residents. This result confirms how neighbourhood quality is negatively affected by Airbnb presence. This finding is consistent with Jin et al. (2024), which shows that when short-term renting is less prevalent, this reduces the burglaries in the area. Moreover, comparing the result in Table 6 Column 1 to the magnitudes usually uncovered by the crime literature, I find this is a sizeable effect. In Draca et al. (2011), a 10 per cent increase in police activity reduces crime by around 3 to 4 per cent. In my context, a similar impact is obtained by decreasing Airbnb penetration by around 1 tourist per 100 residents, which is close to the average Airbnb penetration in 2019. An increase in crime rate is also consistent with the recent ”Work From Home” literature that shows how the presence of residents in the neighbourhood is a deterrent for crime (Matheson et al., 2024).

Moreover, in Column 2, I report how the number of Parking Charging Notes is increased by 6.6 per cent, consistent with the idea of less civic engagement by residents. The probability of an incident that required rubbish collection is not statistically significant, but unfortunately, this measure is not consistently reported by every local authority, as explained in Section 2.

It is worth mentioning that it is not the case that local authorities have disinvested from areas more affected by Airbnb penetration. In Table 5, I look at the effect of Airbnb penetration on complaints about road (Column 6) and green area status (Column 7), local amenities that are not expected to be influenced by the presence of Airbnb tourists or residents' misbehaviour and can be thought as placebo measures. Consistent with my prior, I find no effects. I also report in Column 8 of Table 5 the impact on the probability of receiving any complaint by local authority.

This is not affected by Airbnb penetration. Overall, all the above results document a decrease in neighbourhood quality due to short-term renters' and long-term residents' misbehaviours.

As mentioned, an increase in complaints may be justified by citizens more prone to report incidents. However, when taking the ratio between the number of complaints and the actual incidents of either parking or rubbish misbehaviour, I find no effect of higher Airbnb presence (Columns 4 and 5 in Table 6). This suggests that the dominant factor in the increase in the number of complaints is related to an actual deterioration of the neighbourhood rather than more active citizens.

5.4 Timing

While the main empirical strategy is silent on the exact timing of the effects, in Appendix Figure E.1 I plot the dynamic effects of Airbnb penetration on two main outcomes: the number of non-profitable organizations (Panel A) and the number of anti-social behaviour crime reports (Panel B). I consider a simple difference in differences specification with the following equation:

$$Y_{it} = \beta_0 + \sum_{k=2011}^{2019} \beta_k Airbnb\,Penetration_{ik} + \eta_i + \delta_t + \epsilon_{it} \tag{9}$$

where I take 2012 as the base year. I include ward fixed effects η_i and year (or year-month) fixed effects δ_t. I consider spatially corrected standard errors as described in Section 3.

From both Panels, I observe that the effect of Airbnb penetration is realized right after the first years of sizeable Airbnb presence in London, which can be marked with the acquisition of London-based rival CrashPadder and the growth in popularity from 2013 onwards (see also Figure 2).

6 Different from hotels

In the previous sections, I document a drop in social capital and lower civic engagement in neighbourhoods more affected by Airbnb presence, and I discuss how this may be due to citizens being exposed to lower-quality neighbourhoods. A potential concern with the current identification strategy is that I am simply capturing hotel and tourist penetration rather than a disruption to the local community via short-term renting. In this section, I first discuss how hotels are not a confounder of my empirical strategy. I then present evidence on how this effect may arise for two key distinctive characteristics that differentiate short-term renting from hotel accommodations: a more pervasive penetration and the lack of monitoring.

6.1 Airbnb or Hotel tourists?

A potential concern is that the effects described are not due to the presence of short-term stayers, but it is just a proxy of overall rising tourism. While in principle this can be true, I tackle this issue in different ways. See Section 2.3 where I describe how I construct a measure of hotel tourists' penetration comparable to Airbnb tourists' penetration.

First, the hotel industry is relatively fixed. In my data, I observe only minor changes in the supply of hotels. When looking at the total number of hotel rooms, they increase only by 21,600 from 2013 to 2019, while the Airbnb number of rooms increased by almost 121,300, see Figure 2. In Appendix Figure C.3, Panel A, I plot the median ward, 25th percentile ward, and 75th percentile ward from the distribution of the number of hotels per square kilometre. It confirms that the number of establishments is relatively fixed. Even more important, the geographic distribution of hotels is almost constant with the clusters identified in Figure 1, in which I am plotting hotel distribution for 2019. This appears evident when compared to the same variable in 2013, see Appendix Figure C.1. This guarantees that most of the variation in the tourists using hotel rooms will be captured by ward fixed effects. Moreover, even if a set of neighbourhoods (*e.g.* a specific local authority or all areas closer to the city centre) are becoming more popular, it will be captured by the specific trends described in Section 3.

Second, when adding the predicted number of hotel tourists per resident as a regressor, the results are not affected. In Table 7 I am reporting the OLS and IV specifications of Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) adding Hotel Penetration measure described in Section 2.3. No results are affected.[35]

6.2 Short-term renting peculiarities

In this section, I discuss two peculiar aspects of Airbnb that differentiate it from the hotel industry.

Quantity externality First, Airbnb supply can adjust almost immediately to market demand (Farronato and Fradkin, 2018).[36] As a consequence, local services, which face higher adjustment costs, may fail to timely react, causing a drop in overall neighbourhood quality and higher congestion. I refer to this effect as a *quantity* externality.

The inflow of tourists staying in Airbnb can be easily shown in aggregate. Figure 2 shows how the Airbnb number of rooms increased from 19,400 in 2013 to roughly 140,700, almost matching the number of hotel rooms that increased only by 21,600 over the same period, reaching 159,500 in 2019. When looking at the geographical distribution, similar concerns regarding the *quantity* externality can be drawn. In Figure 1, I plot the geographic distribution of *Airbnb penetration* in 2019, where areas more (less) exposed are denoted in red (yellow), and bins are defined according to 2019 quintiles. Exposure is decreasing with distance from the city centre, except for a cluster

[35] Various concerns to this regression apply: i) it is hard to think of a credible instrumental strategy for hotel penetration; ii) hotel penetration may be a bad control if Airbnb penetration also heavily affects hotel presence and businesses as suggested by Farronato and Fradkin (2018).

[36] Central planner has no control over where Airbnb properties will be; this is not the case in the hotel industry, which is heavily regulated. See Sections 55 and 57 of the Town and Country Planning Act 1990 for further details.

at the extreme west denoting the Heathrow Airport area. In 2013 (see Appendix Figure C.1), Airbnb was more concentrated in the city centre and surrounding areas were overall less exposed.[37] Conversely, the number of hotels in 2019 shows a higher concentration in fewer locations, mainly in Centre-West London (Westminster and Chelsea area), and fairly constant over time.

Quality externality Second, neither hosts nor Airbnb monitors guests during their visits. Airbnb advertises its service saying that guests can "live like a local" and "feel at home". An absent host may induce: i) negative behaviours, ii) negative selection on the type of guests as they may want to take advantage of the absence of monitoring, and iii) more disruptive behaviours not only in the property but also in the local area due to the lack of any verification procedures.[38] I call this a *quality* externality.

To back the intuition that this is a key factor that distinguishes short-term accommodation from hotels, and a factor that may drive negative behaviours and negative selection of guests, I show that when monitoring is easier because hosts are present (room renting), complaints are reduced. To do so, I consider the specification presented in Equation 7 where HD is now a dummy variable capturing the heterogeneous effects of hosts renting just a room. The definition of such a dummy is that it represents areas that in 2015 had above median nights booked in listings with hosts that are renting just a room (and not the entire flat).[39]

In Table 8, Column 1, I present the described specification. Results show that the number of complaints in the area decreases by 5.5 percentage points when most of the tourists are in rooms. This is consistent with the idea that the absence of monitoring may foster negative behaviours or negative selection and confirms that, on the contrary, monitoring by hosts prevents negative behaviours or negative selection.

An alternative explanation is that negative sorting is not driven by the absence of monitoring, but rather by lower prices in Airbnb accommodation, with most disruptive tourists attracted by lower prices. The average price per night per room in an Airbnb accommodation is £82, while a hotel room costs, on average, £170 in London. At the same time, renting just a room is cheaper than renting an entire property (59 *vs* 102 per room). If negative selection is driven by lower prices, we should observe more disruptive behaviours when most of the tourists are using cheaper accommodations. However, the result presented in Column 1 of Table 8 suggests that, when most tourists in the area are renting just rooms, there are fewer complaints in the area.

[37] While the Olympic Games 2012 and years before saw a very modest presence of Airbnb, a turning point event is also represented by the acquisition of London-based rival CrashPadder.

[38] "Airbnb Party flats" are well-known issues, *e.g.* The Guardian (2017) *It sounded like Fabric was upstairs' - Airbnb rental used for all-night party*. Incentives on the hosts' side are limited, as hosts are often offered an insurance plan by Airbnb itself to protect their flat from damage. Moreover, consider that in a hotel, an ID and a payment card are immediately registered, whereas in Airbnb, everything is carried out online, posing a question of traceability.

[39] I consider 2015 to compute this dummy.

Other touristic amenities An additional concern is the role of touristic amenities, like bars, restaurants, and nightclubs. An increase in their density, driven by the growth in tourist clientele, could serve as a direct mechanism for some observed effects, such as increased complaints and anti-social behaviour. Similar to what was presented for hotels, I construct a measure of touristic amenities' density in the area, which is described in Section 2.3, mainly based on the number of restaurants, bars, and nightclubs in the area.

Similar to when considering hotel presence, the density of bars and nightclubs is relatively fixed as shown in Appendix Figure C.3, Panel B where I plot the median ward, 25$^{\text{th}}$ percentile ward and 75$^{\text{th}}$ percentile ward from the distribution of number of restaurants, bars and nightclubs per square kilometre.

Moreover, when adding the number of bars, restaurants, and nightclubs as a regressor, the results are not affected. In Table E.5 I am reporting the OLS and IV specifications of Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) adding the log number of bars, restaurants and nightclubs. No results are affected.[40]

7 Gains not in the city

In the previous Section, I discuss the negative impact of Airbnb penetration. However, there are also benefits linked to the influx of tourism in certain areas. Airbnb (2018) claims a £342 million income earned by local households via Airbnb and £1.3 billion in economic activity generated by hosts and guests between July 2017 and June 2018. However, while the costs of short-term renting are paid by the entire community, the benefits are concentrated in the hands of a few.

Among Airbnb hosts in London in 2019, only 62% are reporting to live in London (was 86% in 2013) and around 5 per cent controls 65 per cent (was 60 per cent) of all Airbnb booked nights, suggesting a high level of professionalism which may contribute to a rising inequality not captured by measures such house prices.[41] In Appendix Figure C.7, I plot, on the horizontal axis, the hosts from the one controlling the largest share of booked nights in 2019 to the one with the smallest, while the vertical axis represents the cumulative percentage of booked nights in 2019 for those hosts. It is evident how a very small portion of hosts control most of the Airbnb supply.

Coherent with these results, I find that areas where benefits (*i.e.* revenues from short-term renting) are less likely to "stay local" we do observe more complaints. In Table 8, I consider Equation 7 where HD dummy represents: i) host location (Columns 2-4) or ii) type of host (Column 5). The definition of such a dummy is that it represents areas that in 2015 had more than 50% of nights

[40] Various concerns to this regression apply: i) it is hard to think a credible instrumental strategy for the number of these touristic amenities; ii) the number of bars, restaurants and nightclubs may be a bad control if Airbnb penetration heavily affects also their presence as suggested by Almagro and Domínguez-Iino (2025).

[41] These statistics are consistent with Gyódi (2023), where the author studies the growth of professional hosts in Barcelona, Berlin, and London.

booked in listings with hosts not based in the neighbourhood (Column 2), in London (Column 3), or the UK (Column 4). In Column 5, it represents areas that in 2015 had more than 50% of nights booked in listings with hosts with 5 or more listings.

In all cases, we notice that complaints are higher in areas with higher concentrations of hosts, not from the area, as displayed by the interaction coefficients in Columns 2 to 4. Moreover, I observe an increasing pattern when we move from hosts not from the neighbourhood but potentially still from London/UK (Column 2) to hosts not from the UK (Column 4). I also document an increase in complaints in areas with a higher concentration of professional hosts (Column 5). All these categories are more likely to retain benefits outside the neighbourhood.

8 Robustness

A number of robustness checks to the main results and preferred specifications have already been presented in the text. In this Section, I present additional checks and I refer to Appendix Section D for further details.

The validity of the shift-share instrument constructed in Equation 6 rests on one key assumption: areas with a higher share of historical sites must not be on different trajectories for the evolution of economic and social conditions in subsequent years (see also Goldsmith-Pinkham et al., 2020 and Borusyak et al., 2020). In Appendix Table E.6, I test for pre-trends, regressing the pre-period change in various outcomes of interest against the subsequent change in Airbnb penetration predicted by the instrument. Reassuringly, coefficients are never statistically significant. Also, and importantly, they are quantitatively different from the baseline IV estimates. These results indicate that historical sites are not in wards that were already undergoing economic changes.

In Appendix Section D.1, I discuss the robustness of first stage results reported in Column 6 of Appendix Table E.1. First, I consider an alternative measure for historical sites, using historical buildings from Historic England, and an alternative measure for the shift component, using Google Trends for "Airbnb London". Second, I construct alternative measures of Airbnb presence. Appendix Table E.7 shows that results are robust in each of these cases. Finally, I verify the robustness of the first stage results by i) modifying the starting year of analysis (Appendix Figure E.2) and ii) excluding one local authority at the time (Appendix Figure E.3).

In Appendix Section D.2, D.3 and D.4, I replicate the OLS and IV specifications of Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) using measures of Airbnb penetration built in different ways. First, I show that results are similar if I consider the number of beds rather than the number of people a property can accommodate in the expression for Airbnb Penetration. This is done to tackle the concern that the number of people a property can accommodate may be inflated with hosts not providing proper accommodation for each guest (Appendix Table E.8).

Second, I check that my results are not driven by the fact that data before 2013 have been imputed conditional on properties being still listed on Airbnb. When restricting the sample to 2013 onwards, all results are robust, except the count model on the number of charitable organizations. Alternative specifications are, however, robust to this sample restriction (Appendix Table E.9).[42]

Third, I consider, as an alternative measure of Airbnb penetration, the number of entire properties listed on Airbnb over the number of dwellings, in line with previous literature (Garcia-López et al., 2020; Barron et al., 2020). My results do not change (Appendix Table E.10), except for the count model on the number of charitable organizations.

In Appendix Table E.11, I include a squared term for Airbnb penetration in the OLS and IV specifications. Results are robust to this specification, suggesting that the relationship between Airbnb penetration and outcomes is linear.

In Appendix Section D.5 I discuss parameter choice (14 km, 2 years) for standard errors' correction following Conley (1999) and Hsiang (2010) in the main results of Column 4, Panel A, Table 1. Significance is not affected by parameter values (Appendix Figure E.4).

Finally, in Appendix D.6, I discuss multiple hypothesis testing procedures that I run to ensure that my results are not false rejections of the null hypothesis of no statistical significance. Results are presented in Appendix Table E.12. Irrespective of the method considered, I am reassured that I find that p-values computed using standard procedures are unaffected by potential problems arising due to multiple hypothesis testing.

9 Conclusions

In this paper, I discuss the impact that a high turnout of residents has on social capital, civic engagement, and attitudes of residents. I leverage the rise of short-term renting as a shock to the local composition of neighbourhoods, assuming that short-term renters are not likely to be involved in building social capital and relationship ties in the area.

Using a monthly panel dataset with unique features in terms of information richness and spatial-time disaggregation, and demanding OLS and IV specifications, I find that short-term tourists' penetration in London is associated with decreasing social capital, lower civic engagement, and worsening citizens' attitudes towards their neighbourhood and their sense of community. These results cannot be fully explained by the change in population composition, suggesting that residents' attitudes are also affected. These findings are particularly important given the urban context studied and open up the way for a new avenue of research.

These results are backed up by the hostile reactions triggered by Airbnb's presence. Exploring the causes of such discontent, I provide evidence that resident backlash is unlikely to have only pecuniary roots via the housing market and long-term rent increase. One key driver of backlash

[42] As data on population are available only for 2011 and 2021, I do not report a robustness test for Table 2.

is, instead, declining neighbourhood quality. I find that Airbnb penetration increases anti-social behaviour crime rates as well as an increase in misbehaviour by residents. Exploiting variation in the type of accommodations chosen, I document that residents' backlash is lower if tourists are monitored (*i.e.*, hosts are present as they rent just a room), suggesting that lack of control is a potential key difference between Airbnb and hotel tourism.

Tourism, as international trade and immigration, despite a beneficial economic impact, may trigger opposition due to non-pecuniary roots. The fact that Airbnb penetration induces a drop in social capital confirms that it can have profound effects on social dynamics and political views. The parallel with the cited literature is also confirmed by the evidence supporting how, while externalities costs are faced by the entire neighbourhood, the benefits are highly concentrated in the hands of a few, often not even residents in the area.

The findings proposed by this paper may be somewhat linked to the specific characteristics of London neighbourhoods. However, they are generalizable in many respects, and they may be relevant for the design of policies aimed at dealing with the economic and social effects of tourism around the world and, more generally, to the increasing distance among citizens. As shown by Enke et al. (2024), geographic and social distance are strongly related to political preferences.

Future research should engage in a formal comparison between rural and urban areas, both within the UK and across countries, studying cities that have been most affected by Airbnb penetration and more generally by high turnout of residents. The cross-cities comparison becomes particularly relevant to get a deeper understanding of the link between tourism and social capital, described for the first time in this paper.

At the same time, a separate analysis should address the inequality implications of the fact that Airbnb benefits accrue to a few homeowners while most residents are paying the costs. Finally, studying in greater detail the difference among types of tourists and the selection induced by short-term renting is a challenging area of research. Even in the post Covid-19 era, it will be important to regulate tourist flows to make sure that the latter will not disproportionately redirect to destinations that are not well-prepared to welcome a significant mass of people. Airbnb and low-cost flights allow high flexibility in location choices, and this is why these are important phenomena to monitor.

Tables and Graphs

Table 1: **Social Capital**

	N. Charitable Organizations		ln(N. Charitable Organizations)		At least one Charitable Organization	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.047	-0.045	-0.082	-0.072	-0.007	0.004
Penetration (x100)	[-0.158;-0.021]	[-0.239;-0.002]	(0.020)***	(0.022)***	(0.008)	(0.013)
Panel B: OLS						
Cumulative Airbnb	-0.016	0.000	-0.006	0.017	0.001	0.005
Penetration (x100)	[-0.036;-0.001]	[-0.021;0.019]	(0.008)	(0.008)**	(0.005)	(0.004)
Observations	5616	5616	4689	4689	5616	5616
F-Stat FS	48.7	56.9	49.9	54.3	48.7	56.9
90% C.I. C.F.	[0.006;0.151]	[0.006;0.217]				
Ward FE	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X
Vars 2001 x Year FE		X		X		X
Geo x Year FE		X		X		X
Years	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. All Columns consider yearly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. Columns 1 to 2 consider the count model presented in Section 3.1, where the dependent variable is the number of charitable organizations (source: Digimap). Columns 3 to 6 consider the 2SLS presented in Section 3. In Columns 3 and 4, I consider the log of the number of charitable organizations. In Columns 5 and 6, I consider a dummy equal to 1 if at least one charitable organization is present. In Columns 1, 3, and 5, I include ward fixed effects and local authority time trends. Columns 2, 4, and 6 add the interaction of year dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and interaction of year dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Columns 1 and 2 report the 90% bootstrap confidence interval after 300 iterations. Similarly, they report the 90% bootstrap confidence interval of the control function. Conley (1999) standard errors are reported in Columns 3 to 6, parameters considered: 14 km and 2 years. *** p<0.01; ** p<0.05; * p<0.1.

Table 2: **Population**

	ln(Population)		ln(Electric Consumption)		ln(Pupils Enrolled)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.007	-0.006	-0.003	-0.006	0.007	-0.015
Penetration (x100)	(0.004)	(0.003)**	(0.005)	(0.007)	(0.010)	(0.022)
Panel B: OLS						
Cumulative Airbnb	-0.003	-0.002	0.001	-0.001	0.010	0.006
Penetration (x100)	(0.003)	(0.001)	(0.003)	(0.003)	(0.006)*	(0.007)
Observations	1248	1248	3744	3744	5595	5595
F-Stat FS	225.9	292.2	40.1	46.1	48.1	55.7
Ward FE	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X
Vars 2001 x Year FE		X		X		X
Geo x Year FE		X		X		X
Years	2011-2021	2011-2021	2013-2019	2013-2019	2011-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1-2 consider data from the 2011 and 2021 Censuses with all the explanatory variables measured in 2011 and 2019, respectively. Columns 3-6 consider yearly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. The dependent variable in Columns 1 and 2 is the log of ward population. In Columns 3 and 4, it is the log of total electricity consumed in the ward (no data for 2014). In columns 5 and 6, it is the log of the number of pupils enrolled in a school in the ward. In Columns 1, 3, and 5, I include ward fixed effects and local authority time trends. Columns 2, 4, and 6 add the interaction of year dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and interaction of year dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 2 years. *** p<0.01; ** p<0.05; * p<0.1.

Table 3: **Population Composition**

	Share of population					Share of population			Share of pupils enrolled with		
	0-24	25-34	35-49	50-64	65+	Degree	born UK	in UK 0-2 years	free meals	first lang. not English	SEN
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: IV											
Cumulative Airbnb	0.271	0.072	-0.023	-0.358	0.079	0.028	-0.781	0.419	0.946	-0.466	0.705
Penetration (x100)	(0.136)**	(0.071)	(0.081)	(0.042)***	(0.029)***	(0.032)	(0.094)***	(0.022)***	(0.473)**	(0.725)	(0.276)**
Panel B: OLS											
Cumulative Airbnb	0.064	-0.103	0.005	-0.062	-0.041	-0.037	-0.401	0.295	0.185	0.749	0.518
Penetration (x100)	(0.058)	(0.056)*	(0.019)	(0.046)	(0.016)**	(0.030)	(0.041)***	(0.054)***	(0.075)**	(0.176)***	(0.118)***
Observations	1248	1248	1248	1248	1248	1248	1248	1248	5595	5595	5595
F-Stat FS	292.2	292.2	292.2	292.2	292.2	292.2	292.2	292.2	55.7	55.7	55.7
Ward FE	X	X	X	X	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X	X	X	X	X
Years	2011-2021	2011-2021	2011-2021	2011-2021	2011-2021	2011-2021	2011-2021	2011-2021	2011-2019	2011-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1-38 consider data from the 2011 and 2021 Censuses, with all the explanatory variables measured in 2011 and 2019, respectively. Columns 9-11 consider yearly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per* km^2 *times Airbnb Google Trend/100*. In Columns 1 to 5, the dependent variable is the share of the population by age group. In Column 6, the dependent variable is the share of the population with at least a University Degree. In Columns 7 and 8, the dependent variable is the share of the population born in the UK (Column 7) or arrived in the UK in the last two years (Column 8). In Columns 9 to 11, it is the share of pupils (over total pupils enrolled in the ward) entitled to free meals, for whom English is not their first language, and with Special Education Needs (SEN). All Columns include ward fixed effect, local authority time trends, and the interaction of year dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and the interaction of year dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 2 years. *** p<0.01; ** p<0.05; * p<0.1.

Table 4: **Residents' attitudes**

	Feel belong to the area	to London	Never felt lonley	Any contact with neighbours	Agree can influence area	Life satisfaction index ≤ 4
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.046	-0.030	-0.016	-0.008	-0.029	0.036
Penetration (x100)	(0.007)***	(0.004)***	(0.007)**	(0.003)**	(0.010)***	(0.018)*
Panel B: OLS						
Cumulative Airbnb	-0.030	-0.022	-0.018	-0.010	-0.023	0.019
Penetration (x100)	(0.013)**	(0.009)***	(0.003)***	(0.004)***	(0.001)***	(0.008)**
Observations	3358	3340	3363	3359	3073	3288
F-Stat FS	231.4	242.6	229.6	231.7	241.8	233.6
Individual controls	X	X	X	X	X	X
Ward controls	X	X	X	X	X	X

Note: The sample includes individual responses from the Survey of Londoners 2018-19 (run by the Greater London Authority). *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100* in October 2018. The dependent variable in Column 1 is a dummy equal to 1 if the respondent feels they belong to the local area. In Column 2 is a dummy equal to 1 if the respondent feels they belong to London. In Column 3 is a dummy equal to 1 if the respondent never felt lonely. In Column 4 is a dummy equal to 1 if the respondent had any contact with their neighbours. In Column 5 is a dummy equal to 1 if the respondent feels that they can influence the local area. In Column 6 is a dummy equal to 1 if the life satisfaction index is less than or equal to 4 (on a scale from 0, Not at all satisfied, to 10, Completely Satisfied). Individual controls are: age band dummies, female dummy, homeownership dummy, dummy if completed a university degree, income score, years since in London, and whether the survey was conducted online. Ward controls are: 2001 share of workers by sector, 2001 log of house prices per square meter, distance from ward centroid to Charing Cross, distance from ward boundaries to the closest underground station. All Columns include local authority fixed effects. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km. *** p<0.01; ** p<0.05; * p<0.1.

Table 5: **Complaints to local authority**

	At least one complaint to the local authority about							
	Tourists	Rubbish	Dog Fouling	Abandoned vehicle	Car Parking	Road conditions	Green areas	Anything
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: IV								
Cumulative Airbnb	0.019	0.030	0.019	0.031	0.015	0.014	0.002	-0.012
Penetration (x100)	(0.007)***	(0.016)*	(0.006)***	(0.010)***	(0.006)**	(0.019)	(0.009)	(0.016)
Panel B: OLS								
Cumulative Airbnb	0.010	0.012	0.006	0.010	0.004	0.000	0.002	-0.009
Penetration (x100)	(0.004)***	(0.004)***	(0.002)***	(0.004)***	(0.002)*	(0.006)	(0.003)	(0.005)*
Observations	97344	97344	97344	97344	97344	97344	97344	97344
F-Stat FS	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0
Ward FE	X	X	X	X	X	X	X	X
LLA x Year-Month FE	X	X	X	X	X	X	X	X
Vars 2001 x Year-Month FE	X	X	X	X	X	X	X	X
Geo x Year-Month FE	X	X	X	X	X	X	X	X
Years	2007-2019	2007-2019	2007-2019	2007-2019	2007-2019	2007-2019	2007-2019	2007-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. All Columns consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. Dependent variables are dummies equal to 1 if at least one complaint about each category was reported in the ward i in month t. All Columns include ward fixed effect, local authority time trends, and the interaction of year-month dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and the interaction of year-month dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 24 months. *** p<0.01; ** p<0.05; * p<0.1.

Table 6: **Externalities**

	ln(Number of ASB incidents)	ln(Number of Parking Notices)	At least one Flytipping incidents	Complaints over real incidents on Parking	Complaints over real incidents on Rubbish
	(1)	(2)	(3)	(4)	(5)
Panel A: IV					
Cumulative Airbnb	0.047	0.066	-0.032	0.035	-0.606
Penetration (x100)	(0.015)***	(0.019)***	(0.119)	(0.106)	(0.456)
Panel B: OLS					
Cumulative Airbnb	0.013	0.021	0.016	0.026	-0.099
Penetration (x100)	(0.005)***	(0.009)**	(0.008)*	(0.059)	(0.045)**
Observations	67391	14020	17875	14020	15818
F-Stat FS	61.8	59.8	11.3	59.8	13.8
Ward FE	X	X	X	X	X
LLA x Year-Month FE	X	X	X	X	X
Vars 2001 x Year-Month FE	X	X	X	X	X
Geo x Year-Month FE	X	X	X	X	X
Years	2011-2019	2008-2019	2006-2019	2008-2019	2007-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. In Columns 2 to 5, a sample restriction has been imposed due to data quality; see Appendix Sections B.3.2 and B.3.3 for details. All Columns consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km*^{2} *times Airbnb Google Trend/100*. The dependent variable in Column 1 is the log of anti-social behaviour (ASB) crime (source: Police statistics). In Column 2 is the log of the number of Parking Notice Charges (PCN). In Column 3 is a dummy equal to 1 if a fly-tipping incident was recorded. In Column 4 is the ratio between the complaints about parking received by the local authority and the number of PCNs (x1000). In Column 5 is the ratio between the complaints about rubbish received by the local authority and the number of fly-tipping incidents recorded. All Columns include ward fixed effect, local authority time trends, and the interaction of year-month dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and the interaction of year-month dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 24 months. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 7: **Include Hotel Penetration**

	N. Charitable Organizations	ln(N. Charitable Organizations)	ln(Population)	At least one complaint about Tourists	Rubbish	ln(Number of ASB incidents)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.064	-0.094	-0.004	0.019	0.034	0.046
Penetration (x100)	[-0.340;-0.004]	(0.028)***	(0.001)***	(0.008)**	(0.019)*	(0.019)**
Cumulative Hotel	0.040	0.049	-0.005	0.001	-0.005	0.001
Penetration (x100)	[-0.004;0.143]	(0.019)***	(0.007)	(0.002)	(0.005)	(0.008)
Panel B: OLS						
Cumulative Airbnb	-0.002	0.022	0.002	0.007	0.012	0.003
Penetration (x100)	[-0.026;0.018]	(0.008)***	(0.002)	(0.003)**	(0.005)**	(0.005)
Cumulative Hotel	0.006	-0.010	-0.008	0.004	0.001	0.021
Penetration (x100)	[-0.020;0.030]	(0.012)	(0.001)***	(0.001)***	(0.002)	(0.004)***
Observations	5616	4689	1248	97344	97344	67391
F-Stat FS	18.9	18.2	15.8	21.8	21.8	20.3
90% C.I. C.F.	[0.013;0.393]					
Ward FE	X	X	X	X	X	X
LLA x Time FE	X	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X	X
Geo x Time FE	X	X	X	X	X	X
Timing	Year	Year	Year	Year-Month	Year-Month	Year-Month
Years	2011-2019	2011-2019	2011-2021	2007-2019	2007-2019	2011-2019

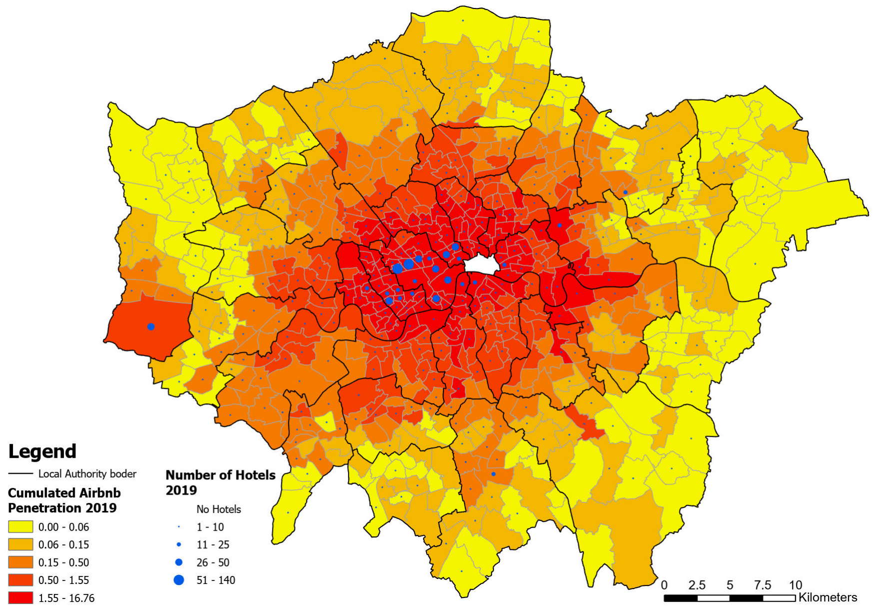
Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1-2 consider yearly data; Column 3 considers data from the 2011 and 2021 Censuses with all the explanatory variables measured in 2011 and 2019, respectively. Columns 4 to 6 consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. All specifications control for *Cumulative Hotel penetration*, see 2.3 for details. Column 1 considers the count model presented in Section 3.1 where the dependent variable is the number of charitable organizations (source: Digimap). Columns 2 to 6 consider the 2SLS presented in Section 3. In Column 2, the dependent variable is the log of the number of charitable organizations. In Column 3 is the log of ward population. In Columns 4 and 5 dependent variables are dummies equal to 1 if at least one complaint about each category was reported in the ward i in month t. In Column 6 is the log of anti-social behaviour (ASB) crime (source: Police statistics). All Columns include ward fixed effect, local authority time trends and the interaction of year (or year-month) dummies with 2001 share of workers by sector, 2001 log of house prices per square meter and interaction of year (or year-month) dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument Conley (1999) standard errors, parameters considered: 14 km and 2 years (Columns 1 to 3) or 24 months (Columns 4 to 6). *** p<0.01; ** p<0.05; * p<0.1.

Table 8: **Mechanisms: Gains not in the City**

	At least one complaint to the local authority about Rubbish				
	(1)	(2)	(3)	(4)	(5)
Panel A: IV					
Cumulative Airbnb	0.034	0.015	-0.004	-0.046	-0.186
Penetration (x100)	(0.015)**	(0.015)	(0.012)	(0.026)*	(0.103)*
Cumulative Airbnb Penetration x	-0.055	0.017	0.033	0.073	0.213
Heterogeneity Dummy	(0.022)**	(0.008)**	(0.009)***	(0.019)***	(0.094)**
Panel B: OLS					
Cumulative Airbnb	0.013	0.005	0.000	0.001	0.029
Penetration (x100)	(0.004)***	(0.005)	(0.005)	(0.007)	(0.029)
Cumulative Airbnb Penetration x	-0.014	0.010	0.022	0.012	-0.017
Heterogeneity Dummy	(0.011)	(0.004)**	(0.005)***	(0.007)*	(0.029)
Heterogeneity	Rent just a room	Host not from neighbourhood	Host not from London	Host not from UK	Professional host
Observations	92040	92040	92040	92040	92040
F-Stat FS	11.4	4.2	8.5	10.3	12.5
Ward FE	X	X	X	X	X
LLA x Year-Month FE	X	X	X	X	X
Vars 2001 x Year-Month FE	X	X	X	X	X
Geo x Year-Month FE	X	X	X	X	X
Years	2007-2019	2007-2019	2007-2019	2007-2019	2007-2019

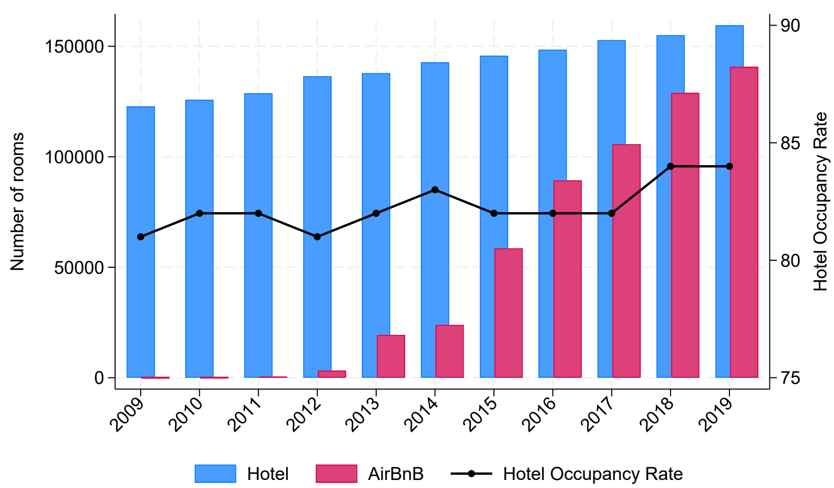
Note: The sample includes a panel of 624 electoral wards in Greater London. All Columns consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km*^{2} *times Airbnb Google Trend/100* and its interaction with the heterogeneity dummy. The dependent variable is a dummy equal to 1 if at least one complaint about rubbish was reported in the ward i in month t. *Host not from neighbourhood* is a dummy equal to 1 if the ward i has a share of nights rented by hosts that live outside the neighbourhood above the median. *Host not from London* is a dummy equal to 1 if the ward i has a share of nights rented by hosts that live outside London above the median. *Host not from UK* is a dummy equal to 1 if the ward i has a share of nights rented by hosts that live outside the UK above the median. *Professional host* is a dummy equal to 1 if the ward i has a share of nights rented by professional (managing 5 or more properties) hosts above the median. *Rent just a room* is a dummy equal to 1 if the ward i has a share of tourists-nights spent not in the entire property that is above the median. All the heterogeneity dummies are defined using 2015 data and are fixed over time. All Columns include ward fixed effect, local authority time trends, and the interaction of year-month dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and the interaction of year-month dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument Conley (1999) standard errors, parameters considered: 14 km and 24 months. *** p<0.01; ** p<0.05; * p<0.1.

Figure 1: **Airbnb Penetration in 2019**



Note: Airbnb penetration (Equation 1) in 2019 x 100 at ward level. Bins are represented by the 2019 quintiles of Airbnb penetration. Dots represent the number of hotels in 2019 at the ward level.

Figure 2: **Evolution hotel and Airbnb rooms in London**



Note: Plotting number of hotel rooms in London (blue, source: Greater London Authority and PwC) and number of Airbnb rooms (red, source: Tomslee.net and InsideAirbnb.com) on the left axis. Plotting hotel occupancy rate (black line, source: PwC) on the right axis.

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A Online Appendix: Institutional background

A.1 London administrative structure

Greater London is formed by 33 local authorities or “boroughs”. I exclude “City of London” given its peculiarity, it contains the historic centre with the first settlement located here, and the primary central business district of London. It is also a separate ceremonial county, being an enclave surrounded by Greater London, and is the smallest county in the United Kingdom.[43]

Median area of a local authority is 38.7 km^2 while median population (2011 Census) is 255,511 residents. Each borough is administered by borough councils, which are elected every 4 years. Boroughs are the principal local authorities in London and are responsible for running most local services, such as schools, social services, waste collection, and roads. Some London-wide services are run by the Greater London Authority, and some services and lobbying of government are pooled within the London Councils. Some councils group together for services such as waste collection and disposal. Each borough council is a local education authority.

The Greater London Authority (GLA), known colloquially as City Hall, is the devolved regional governance body of London, with jurisdiction over both the City of London and the regional county of Greater London. It is a strategic regional authority, with powers over transport, policing, economic development, and fire and emergency planning. The GLA is responsible for the strategic administration of Greater London. It shares local government powers with the councils of 32 London boroughs and the City of London Corporation.

B Online Appendix – Data Sources and Description

B.1 Data management

The unit of analysis of this paper is the electoral ward. Each ward is fully contained in a borough. In my sample, I consider 624 wards. Median area is 1.86 km^2 while median population (2011 Census) is 13,015 residents. The ward is the primary unit of English electoral geography.

B.1.1 Census Geography

The main geographies directly associated with the Census are Output Areas (OA). The OA is the lowest geographical level at which census estimates are provided. Output areas are fully contained in electoral wards, so whenever data are provided at the OA geography level, the mapping is straightforward. OAs are further aggregated at the lower layer super output areas (LSOA), and then into the middle layer super output areas (MSOA).

[43] It is a common practice to exclude City of London, see for example Draca et al. (2011).

B.1.2 Mapping different geographies

Thanks to Office for National Statistics (ONS) mapping tables, it has been possible to map:[44]

- Output areas 2001 Census into Output areas 2011 Census
- LSOA or MSOA 2011 Census into 2011 electoral wards. LSOA or MSOA are not perfectly contained in a ward. When looking at absolute numbers (*e.g.* number of police records of anti-social behaviours), I compute the share of the area in which each LSOA or MSOA is split across different wards and I assign proportional data to the corresponding ward. When looking at relative numbers (*e.g.* crimes per person), I compute the shares of the ward represented by each specific LSOA or MSOA forming the ward and use them to compute a weighted average of the index of interest.
- Postcodes into Output areas 2011 Census.

B.2 Airbnb Penetration

Data on Airbnb penetration comes from InsideAirbnb.com and Tomslee.net, independent sources that web scrape the Airbnb website monthly and collect all publicly available information. InsideAirbnb is a more reliable source than Tomslee. In Appendix Table C.5, I report the dates and sources of each web scraped as reported by InsideAirbnb.com and Tomslee.net. Each web scrape can be thought of as a "snapshot" of all publicly available information on Airbnb.com. Given InsideAirbnb reports a much richer set of variables in case two "snapshots" from different sources are available, I prioritize InsideAirbnb. If two "snapshots" from the same source are available for the same month, I kept the one closer to the 15th of the month. After applying these restrictions, I have one snapshot in 2013, one in 2014, four snapshots in 2015, eight snapshots in 2016, five snapshots in 2017, eight snapshots in 2018, and twelve snapshots in 2019. In Appendix D.3, I discuss results when restricting years after 2013, given that it is the year in which the series of snapshots started.

Thanks to these data, I can compute the following measure of Airbnb penetration:

$$Airbnb\,penetration_{it} = \frac{Cumulative\,Airbnb\,tourists\,nights_{it}}{Residents\,nights_{i2007}}$$

It represents the cumulative number of tourists that have used Airbnb until time t (year or month, depending on the specification) over the population of ward i. The numerator of the above Equation

[44] I am deeply grateful to the Open Geography portal from the Office for National Statistics (ONS) for their constant support throughout this project. They provided excellent support for all my data inquiries regarding mapping and boundaries of different geography levels.

is computed in the following way:

$$Airbnb\,tourists\,nights_{it} = \sum_j Reviews_{jit} \times \frac{1}{0.69} \times Guests_j \times Nights_j$$

To compute $Airbnb\,tourists\,nights_{it}$, I started from the number of reviews each listing j received in a given time t.[45] Each listing is assigned to a ward i given its latitude and longitude.[46] I adjust the number of reviews reported, taking into account that only 69% of guests leave a review, following results in Fradkin et al. (2020), obtaining the number of visits using Airbnb. Results are similar if ignoring this adjustment given it is just a constant multiplicative factor. Notice that reviews are hidden until either guests or hosts submit a review or 14 days have expired. Prior 8th May 2014, both guests and hosts had 30 days after the checkout date to review each other, and any submitted review was automatically posted to the website. The review rate before 8th May 2014 was 68%. I multiply the resulting number of visits by the number of guests the property can accommodate and by the number of minimum nights a host requests.[47] Results are similar if considering the number of beds in the property, as explained in Appendix Section D.2. The measure of Airbnb tourists' visits produces an overall figure for 2018 that is very similar to official statistics in Airbnb (2018), 2.2 million vs 2.28 million.

The denominator of $Airbnb\,penetration_{it}$ is the number of residents in 2007 in ward i times 350, where I assume each person spends 15 days outside London.

B.2.1 Alternative measure

Literature, as Garcia-López et al. (2020), Barron et al. (2020), Almagro and Domínguez-Iino (2025), Duso et al. (2024) or Koster et al. (2019), has mainly focused on the number of properties listed on Airbnb website. To replicate their results, I consider:

$$Airbnb\,penetration_{it} = \frac{Entire\ Properties\ on\ Airbnb_{it}}{Number\ Dwellings_{i2011}} \tag{10}$$

where at the numerator I am considering the number of entire properties listed on the Airbnb website in ward i and time t, while at the denominator I consider the number of dwellings in 2011 (source: Census 2011). It can be interpreted as the share of properties that are on the short-term market. Assuming a constant supply of dwellings in London, it measures the shift in housing space from residents to tourists. As the rest of the literature has been focusing on housing market it makes sense to consider this types of measures, however, given my context, I preferred to capture

[45] Guests have 14 days maximum to fill a review; they are then representative of the period of the visit.

[46] Exact location is not provided, Airbnb alters the exact location by a factor ranging between 0 and 150 meters. Given the size of each ward, the number of wrongly assigned listed is negligible.

[47] This information has been fixed at the last available date

the intensity of Airbnb penetration, in terms of tourists in the area, more precisely by: i) taking into account the size of the flat; ii) taking into account the duration of stay.

Notice that a recurrent concern with this type of measure, as in Equation 10, is that it relies on the assumption that only active listings are left on the platform. This issue is tackled in the literature in various ways (*e.g.* by restricting only to the one receiving reviews, see Barron et al., 2020) but concerns still apply, especially when constructing the panel dataset for periods for which a web scrape is not available where the standard approach is to assume that a listing has been active since the first day of listing continuously. My measure presented in Section 2.1 leverages the actual reviews received. I will then capture activity by the number of reviews, even if a non-active listing is still present on the website, it won't be an issue. However, I may still suffer from the problem that I am only leveraging listings that manage to survive at least till 2013 (the first year for which I have a web scrape). The same issue applies, however, to the measure discussed in Equation 10.

Results are unchanged when I replicate my analysis with this measure (Appendix Section D.4).

B.3 Neighbourhood quality

B.3.1 Anti-social behaviours definition

Anti-social behaviour is defined by the police as "behaviour by a person which causes, or is likely to cause, harassment, alarm or distress to persons not of the same household as the person" (Anti-social Behaviour Act 2003 and Police Reform and Social Responsibility Act 2011).

London Metropolitan Police website divides anti-social behaviours into three main categories, depending on how many people are affected:

- Personal antisocial behaviour is when a person targets a specific individual or group.
- Nuisance antisocial behaviour is when a person causes trouble, annoyance, or suffering to a community.
- Environmental antisocial behaviour is when a person's actions affect the wider environment, such as public spaces or buildings.

Under these main headings, antisocial behaviour falls into one of 13 different types: vehicle abandoned; vehicle nuisance or inappropriate use; rowdy or inconsiderate behaviour; rowdy or nuisance neighbours; littering or drugs paraphernalia; animal problems; trespassing; nuisance calls; street drinking; prostitution-related activity; nuisance noise; begging; misuse of fireworks.

B.3.2 Parking Charge Notices (PCNs)

To proxy civic responsibility by residents, I collect the number of Parking Charge Notices (PCNs) recorded by each local authority by month. I do not distinguish by type of PCN nor by the receivers' characteristics. The definition of what triggers a PCN is constant across local authorities.

There are no centralized databases for such a detailed dataset. I then request from each of the 33 local authorities the data. Unfortunately, not all local authorities were available to provide such detailed information, and the analysis is therefore limited to the data that can be credibly trusted.

To benchmark the data disaggregated at ward-month level, I aggregate the data at local authority-fiscal year level and leverage on the data reported on the London Councils data.

The resulting dataset is an unbalanced panel of the local authorities that provided good quality data (Appendix Table C.4, Panel A).

B.3.3 Fly-tipping incidents

To proxy local misbehaviours by residents and tourists, I collected the number of fly-tipping incidents recorded by each local authority by month.

There are no centralized databases for such a detailed dataset. I then request from each of the 33 local authorities the data. Unfortunately, not all local authorities were available to provide such detailed information, and the analysis is therefore limited to the data that can be credibly trusted. Moreover, consider that, unlike the PCNs data, the definition of fly-tipping incident differs depending on the local authority.

To benchmark the data disaggregated at ward-month level, I aggregate the data at local authority-quarter level and leverage the data reported on the WasteDataFlow data.

The resulting dataset is an unbalanced panel of the local authorities that provided good quality data, see Appendix Table C.4, Panel B.

B.4 Demographic and geographic variables

As a control in baseline specification, I consider the share of workers by sector. Sectors considered are: i) Agriculture, hunting and forestry (A), Fishing (B), Mining and quarrying (C), Manufacturing (D), Electricity, gas and water supply (E), Construction (F); ii) Wholesale and retail trade, repairs of motor vehicles, motorcycles and personal and households goods (G), Hotels and restaurants (H), Transport, storage and communications (I), Financial intermediation (J), Real estate, renting and business activities (K), Public administration and defence, compulsory social security (L), Education (M), Health and social work (N), Other community, social and personal services activities (O), Activities of private households as employers and undifferentiated production activities of private households (P), Extraterritorial organizations and bodies (Q).[48]

I further consider the 2001 log of house prices per square meter (source: UK Land Registry). As described in Section 2, I match each transaction with Energy Performance Certificates to recover the size of the property. To guarantee representativeness, I exclude observations with fewer than 5 transactions. Each transaction reports the exact postcode of the property, which maps

[48]The letter in parentheses refers to the NACE Rev. 1.1 section reported in the original data.

uniquely into a ward.

Finally, to proxy "centrality" of each ward, I compute, taking advantage of GIS software, the distance from each ward centroid to Charing Cross, which is considered the London city centre and the distance from each ward to the closest underground station (source: Transport For London), as the underground network represents a crucial characteristic of London structure, and it is a proxy of how well-connected to other locations a ward is.

C Online Appendix – Additional Tables and Figures

Table C.1: **Summary Statistics**

	Mean	Sd	Min	Median	Max	Obs	Sample
Panel A: Monthly variables							
Cumulative Airbnb tourists nights over 2007 resident (x100)	0.17	0.69	0.00	0.00	16.76	104,832	2006-2019
Cumulative Hotel tourists nights over 2007 resident (x100)	47.2	168.3	0.0	11.3	3,365.2	104,832	2006-2019
At least one complain about rubbish	0.17	0.38	0.00	0.00	1.00	97,344	2007-2019
At least one complain	0.50	0.50	0.00	1.00	1.00	97,344	2007-2019
Anti social behaviour crimes	41.9	31.5	0.0	34.0	498.0	67,392	2011-2019
N. Parking Charge Notice	707.2	1,271.2	0.0	345.0	15,823.8	14,022	2008-2019
N. flytipping incidents	24.5	38.6	0.0	12.0	621.0	17,876	2006-2019
Panel B: Yearly variables							
N. of Charitable Organizations	3.7	6.6	0.0	2.0	137.0	5,616	2011-2019
At least one Charitable Organization	0.8	0.4	0.0	1.0	1.0	5,616	2011-2019
Population (Census)	13,590.8	2,936.8	5,114.0	13,491.0	32,713.0	1,248	2011-2021
Share of population 0-24 (Census)	31.1	5.3	17.2	30.1	63.5	1,248	2011-2019
Share of population 25-34 (Census)	18.7	6.0	6.7	17.6	39.0	1,248	2011-2019
Share of population 35-49 (Census)	22.5	2.1	15.1	22.4	29.0	1,248	2011-2019
Share of population 50-64 (Census)	16	3	7	16	24	1,248	2011-2019
Share of population 65+ (Census)	11.9	4.1	3.4	11.1	26.6	1,248	2011-2019
Share of population with at least a University Degree (Census)	42.21	13.24	12.53	41.28	74.45	1,248	2011-2019
Share of population born in the UK (Census)	61.96	13.18	29.26	60.76	94.94	1,248	2011-2019
Share of population living in the UK less than 2 years (Census)	4.33	3.05	0.16	3.70	19.82	1,248	2011-2019
Total Domestic Electric Consumption	17,612,058.00	4,489,104.50	7,813,331.00	16,930,764.00	53,452,444.00	3,744	2013-2019
N. pupils enrolled in school	2,135.32	1,157.95	0.00	1,932.00	8,494.00	5,596	2011-2019
Share of pupils entitled to freemeals	23.05	12.74	0.00	21.54	69.38	5,595	2011-2019
Share of pupils with English not as first language	35.78	18.98	0.00	35.32	92.60	5,595	2011-2019
Share of pupils with Special Educational Needs	8.18	5.78	0.00	8.06	42.11	5,595	2011-2019
Panel C: Constant variable							
Area (km^2)	2.55	2.58	0.39	1.86	29.03	624	2011
Panel D: Survey variables							
Feel belong to the area	0.75	0.44	0.00	1.00	1.00	6,482	2018-2019
Feel belong to London	0.83	0.38	0.00	1.00	1.00	6,458	2018-2019
Never felt lonley	0.73	0.45	0.00	1.00	1.00	6,426	2018-2019
Any contact with neighbours	0.90	0.29	0.00	1.00	1.00	3,973	2018-2019
Agree can influence area	0.34	0.47	0.00	0.00	1.00	3,609	2018-2019
Life satisfaction index ≤ 4	0.12	0.32	0.00	0.00	1.00	6,235	2018-2019

Note: Column Sample reports the year for which a variable is available. *Cumulative Airbnb tourists nights over 2007 resident (x100)* represents the main measure of Airbnb presence, called *Airbnb Penetration* and described in Section 2. Please check Appendix Table C.2 for a detailed description of the variables presented in Panel D.

Table C.2: **Survey questions**

Variable	Definition	Survey question	Possible answers
Feel belong to the area	Dummy equal to 1 if the respondent feel to belong to the local area (very or fairly strongly)	How strongly belong to the local area?	Very strongly; Fairly strongly; Not very strongly; Not at all strongly
Feel belong to London	Dummy equal to 1 if the respondent feel to belong to London (very or fairly strongly)	How strongly belong to London?	Very strongly; Fairly strongly; Not very strongly; Not at all strongly
Never felt lonley	Dummy equal to 1 if the respondent occasionally, hardly ever or never felt lonley	How often feel lonely?	Often/always; Some of the time; Occasionally; Hardly ever; Never
Any contact with neighbours	Dummy equal to 1 if the respondant has any contact with neighbours	Frequency of face-to-face contact with neighbours	At least once a day; 4-6 times a week; 2-3 times a week; Around once a week; Around once a fortnight; Around once a month; Less than once a month; Never
Agree can influence area	Dummy equal to 1 if the respondant definitely or tend to agree that she can influence decisions affecting the local area	Can personally influence decisions affecting local area	Definitely agree; Tend to agree; Tend to disagree; Definitely disagree
Life satisfaction index ≤ 4	Dummy equal to 1 if life satisfaction is below or equal 4	Satisfaction with life nowadays	From 0 (not at all satisfied) to 10 (completely satisfied)
Age band	Grouped age variable, six categories		16-24; 25-34; 35-49; 50-64; 65-79; 80+
Female	Dummy equal to 1 if classified as Woman and 0 if Man	Gender self-classification	Man; Woman; Transman; Transwoman; Non-binary / Genderqueer / Agender / Gender fluid / Intersex
Homeowner	Dummy equal to 1 if the respondent is a homeowner	Household tenure	Being bought on a mortgage; Owned outright by household; Rented from Local Authority; Rented from Housing Association / Trust; Rented from private landlord; Other - please specify; Shared ownership (RAISED CODE); Student accommodation / student halls
Born in UK	Dummy equal to 1 if respondent is born in the UK	Country of birth	List of countries
Have a degree	Dummy equal to 1 if respondent is educated at university level	Whether educated to university level	Yes; No
Income Score	Income Score	Income	Income level
Years in London	Number of years the respondent has lived in London	How long respondent has lived in London	Less than 1; 1-2; 2-3; 3-5; 5-10; 10 or more; Always lived in London
Years in the area	Number of years the respondent has lived in the local area	How long respondent has lived in local area	Less than 1; 1-2; 2-3; 3-5; 5-10; 10 or more; Always lived in the area

Note: Source: Survey of Londoners 2018-2019.

Table C.3: **FixMyStreet complaints categories**

Complaints about	Share over total	Complaints about	Share over total
Rubbish	23.0%	Drain	1.7%
Road status	21.9%	Car parking	1.6%
Flytipping	21.1%	Dead animal	1.0%
Green area status	6.8%	Dog foul	0.9%
Street lights	5.9%	Admin	0.8%
Abandoned vehicle	5.6%	Street furniture	0.3%
Flyposting	4.5%	Dangerous structure	0.1%
Other	2.4%	Public toilet	0.0%
Traffic sign	2.3%		

Note: Categories in FixMyStreet after aggregating similar ones and share of complaints over total number of complaints (2007-2019).

Table C.4: **Externalities dataset coverage**

	Data available	
Local Authority	From	To
Panel A: PCN data		
Bexley	04-2016	03-2019
Brent	01-2017	12-2019
Bromley	04-2016	03-2019
Camden	04-2013	12-2019
Greenwich	04-2017	12-2019
Hackney	06-2016	12-2019
Harrow	01-2010	12-2019
Havering	01-2013	12-2019
Lambeth	04-2014	12-2019
Tower Hamlets	10-2019	12-2019
Waltham Forest	01-2018	12-2019
Westminster	01-2008	12-2019
Panel B: Flytipping data		
Barking and Dagenham	11-2017	12-2019
Bexley	06-2012	12-2019
Bromley	01-2004	12-2019
Camden	04-2017	12-2019
Ealing	01-2013	12-2019
Hammersmith and Fulham	01-2017	12-2019
Hillingdon	03-2019	10-2019
Hounslow	02-2013	12-2019
Islington	01-2017	12-2019
Kensington and Chelsea	03-2019	12-2019
Lambeth	01-2017	12-2019
Merton	11-2016	12-2019
Redbridge	09-2005	12-2019
Sutton	01-2018	12-2019
Tower Hamlets	03-2016	12-2019

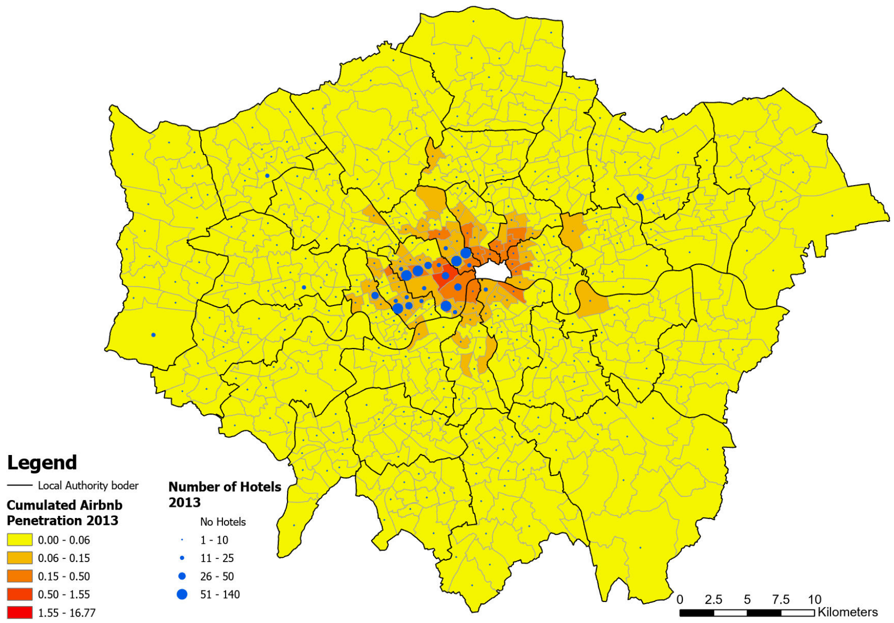
Note: List of local authorities providing good quality data and period of coverage. Each local authority has been individually contacted. PCN data benchmarked using London Councils data. Fly-tipping data benchmarked using WasteDataFlow data.

Table C.5: **Webscrape dates and source**

Webscrape date	Source	Webscrape date	Source
2013-12-21	Tomslee	2018-05-11	InsideAirbnb
2014-05-13	Tomslee	2018-07-07	InsideAirbnb
2015-01-17	Tomslee	2018-08-08	InsideAirbnb
2015-04-06	InsideAirbnb	2018-09-10	InsideAirbnb
2015-09-02	InsideAirbnb	2018-10-06	InsideAirbnb
2015-12-25	Tomslee	2018-11-04	InsideAirbnb
2016-01-09	Tomslee	2018-12-07	InsideAirbnb
2016-02-02	InsideAirbnb	2019-01-13	InsideAirbnb
2016-03-03	Tomslee	2019-02-05	InsideAirbnb
2016-06-02	InsideAirbnb	2019-03-07	InsideAirbnb
2016-08-07	Tomslee	2019-04-09	InsideAirbnb
2016-09-22	Tomslee	2019-05-05	InsideAirbnb
2016-10-03	InsideAirbnb	2019-06-05	InsideAirbnb
2016-12-26	Tomslee	2019-07-10	InsideAirbnb
2017-01-21	Tomslee	2019-08-09	InsideAirbnb
2017-03-04	InsideAirbnb	2019-09-14	InsideAirbnb
2017-04-19	Tomslee	2019-10-15	InsideAirbnb
2017-06-19	Tomslee	2019-11-05	InsideAirbnb
2017-07-28	Tomslee	2019-12-09	InsideAirbnb
2018-04-08	InsideAirbnb		

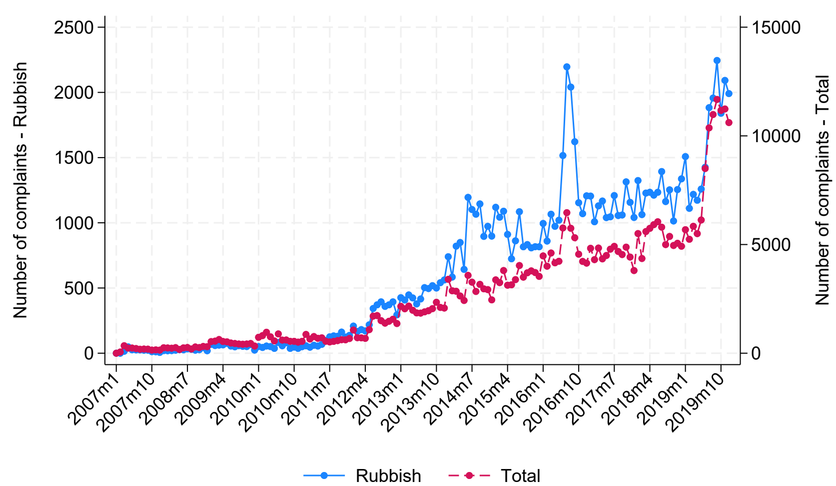
Note: Dates of webscrapes carried on by InsideAirbnb.com and Tomslee.net.

Figure C.1: **Airbnb Penetration in 2013**



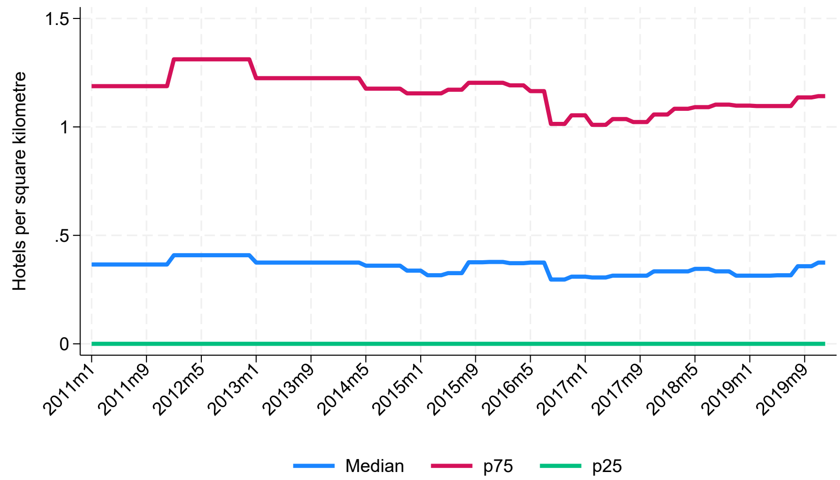
Note: Airbnb penetration (Equation 1) in 2013 x 100 at ward level. Bins are represented by the 2019 quintiles of Airbnb penetration. Dots represent the number of hotels in 2013 at the ward level.

Figure C.2: **Number of complaints on FixMySteet**

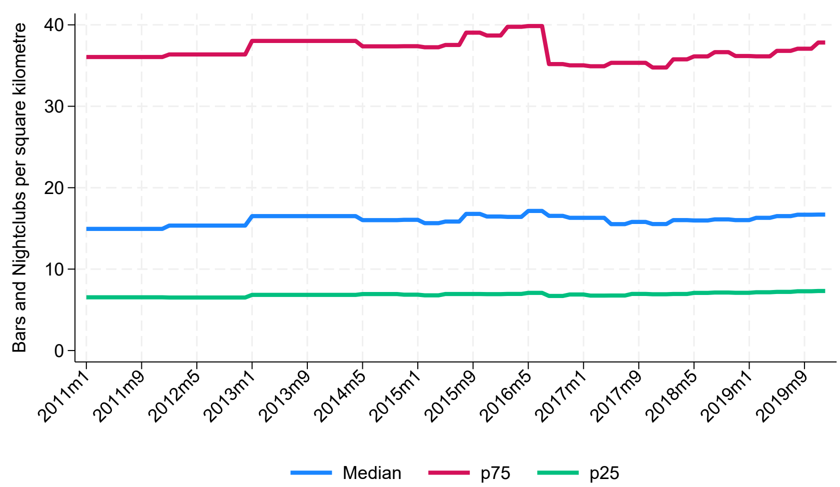


Note: Plotting total number of complaints (right y-axis) and number of complaints for the most common category (Rubbish, left y-axis). Source: FixMyStreet (founded in 2007).

Figure C.3: **Hotels and Bars/Nightclubs' evolution**



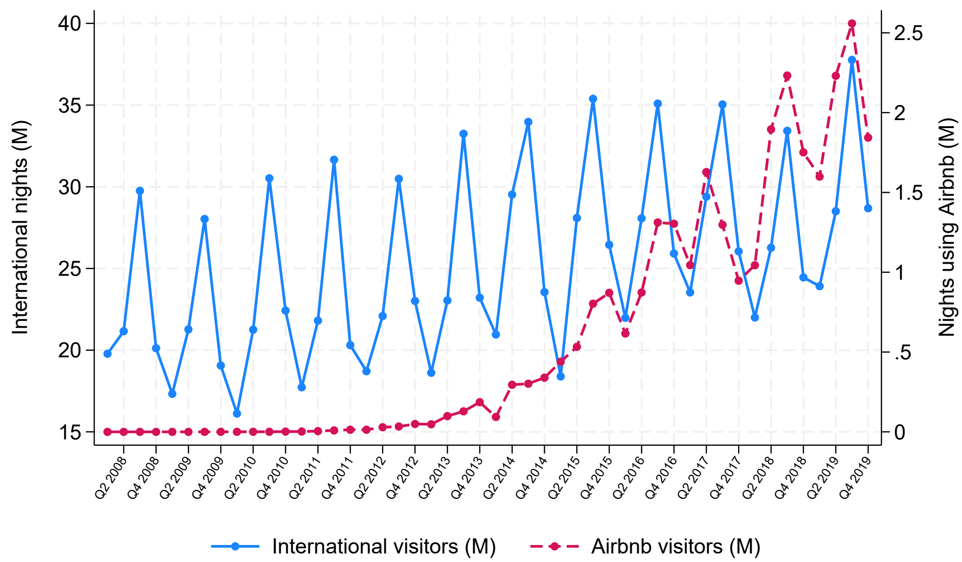
(a) Hotels per square kilometre



(b) Bars and Nightclubs per square kilometre

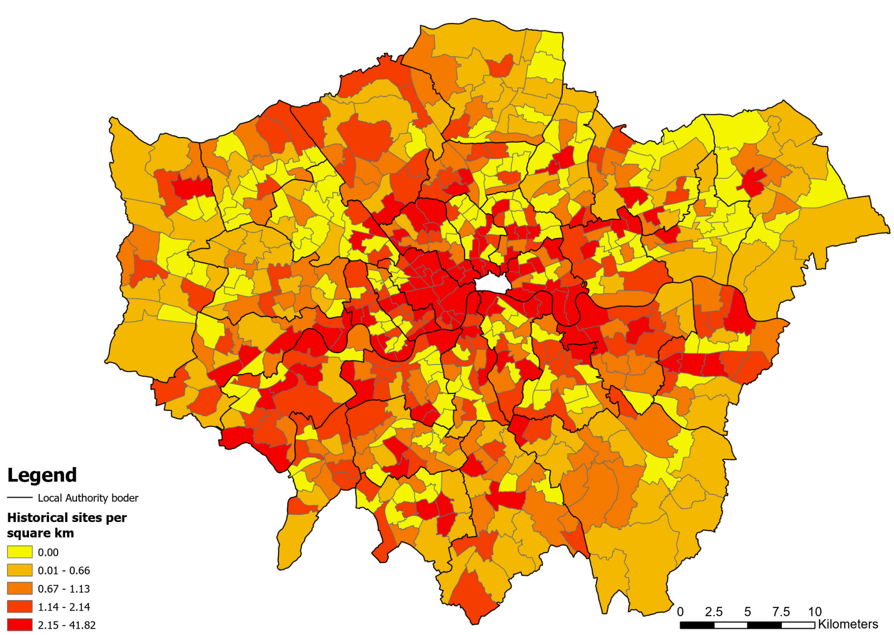
Note: Panel A plots the number of hotels per square kilometre for the median ward, 25$^{\text{th}}$ percentile ward, and 75$^{\text{th}}$ percentile ward from the distribution of number of hotels per square kilometre. Panel B plots plotting number of bars and nightclubs per square kilometre for the median ward, 25$^{\text{th}}$ percentile ward, and 75$^{\text{th}}$ percentile ward from the distribution of number of bars and nightclubs per square kilometre.

Figure C.4: **Seasonal variation in tourists nights**



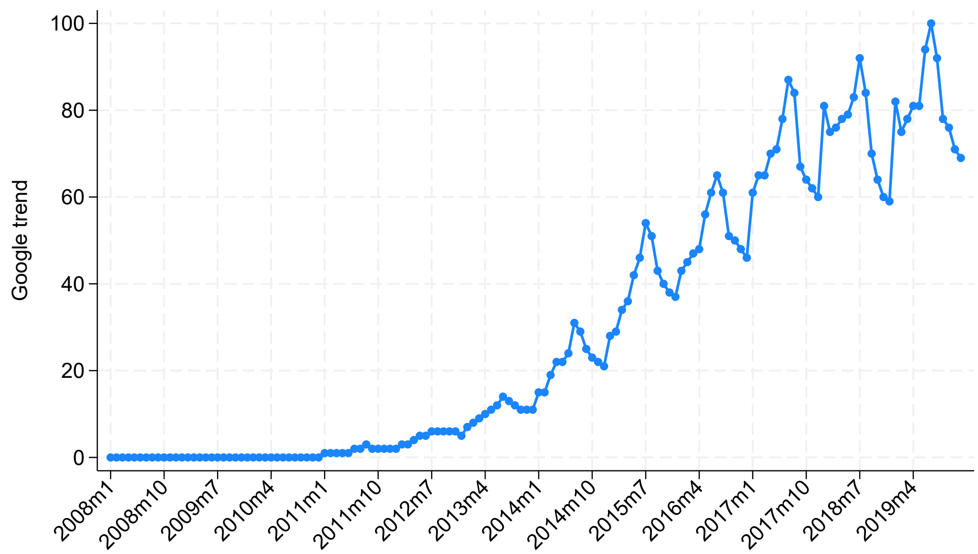
Note: Plotting number of international visitors nights (left y-axis) and nights of tourists using Airbnb (right y-axis) by quarter. Sources: Visit Britain and InsideAirbnb.

Figure C.5: **Geographical distribution of point of historical touristic interest**



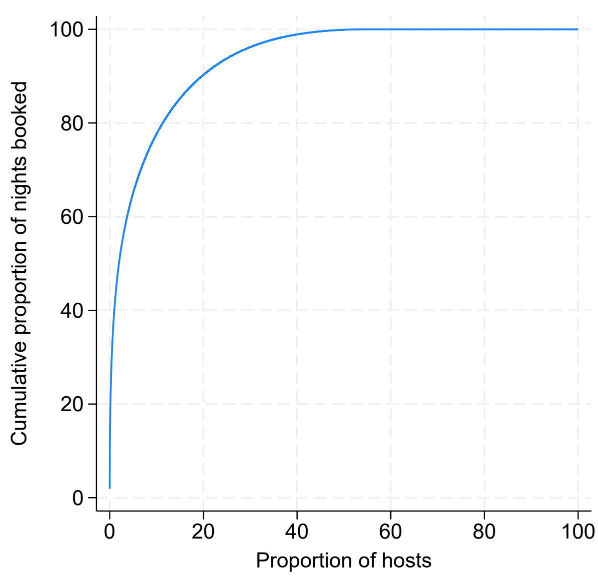
Note: Plotting number of historical monuments and buildings by square kilometres (source: Digimap). Bins represent quintiles of the distribution.

Figure C.6: **Airbnb Google Trend**



Note: Plotting time evolution of worldwide search volume for the word “Airbnb” (source: Google Trend).

Figure C.7: **Concentration in Airbnb market**



Note: Plotting the hosts on the x-axis from the one controlling the largest share of booked nights in 2019 to the one with the smallest share. The y-axis represents the cumulative percentage of booked nights in 2019 for each host.

D Online Appendix – Additional Results and Robustness

D.1 First Stage Robustness

In this Section, I provide robustness checks for the IV strategy proposed in Section 3.

Pre-trends The validity of the shift-share instrument constructed in Equation 6 in the main text rests on one key assumption: areas with a higher share of historical sites must not be on different trajectories for the evolution of economic and social conditions in subsequent years (see also Goldsmith-Pinkham et al., 2020 and Borusyak et al., 2020). In Appendix Table E.6, I test for pre-trends, regressing the pre-period (2002-2005) change in the outcomes of interest against the 2006-2019 change in Airbnb penetration predicted by the instrument. The estimated Equation controls for local authority fixed effects, 2001 share of workers by sector, 2001 log of house prices per square meter, distance ward centroid to Charing Cross, and distance ward to the closest underground station:

$$Y_{ib}^{2005} - Y_{ib}^{2002} = \beta(Airbnb_{ib}^{2019} - Airbnb_{ib}^{2006}) + \gamma X_i + \delta_b + \epsilon_{ib} \tag{11}$$

Among my outcomes, I can only consider the total population from ONS yearly estimates and the number of selling transactions and prices from the UK Land Registry. Reassuringly, coefficients are never statistically significant. Also, and importantly, they are quantitatively different from the baseline IV estimates. These results indicate that historical sites are not in wards that were already undergoing economic changes.[49] Despite not having a long time series, I can also test for pre-trends in the total floorspace available for businesses and the rateable values (pre-period 2006-2008), in the number of complaints received by local authorities (pre-period 2007-2008), and finally the number (or the presence) of charitable organizations as well as the number of antisocial behaviours (pre-period 2011-2012).[50] Once again, irrespective of the variables considered, I do not reject the null hypothesis of no pre-trends.

In the remainder of the Section, I describe various modifications to the baseline specification of the first stage presented in Appendix Table E.1.

Alternative shift and shares As a first robustness check, I consider alternative measures both for the shares and the shifts of Equation 6. I consider a different source for the "share" component in Column 1 of Appendix Table E.7 using the number of historical buildings of grade I and II stars reported by Historic England. In Column 2, I modify the "shift" component and consider the

[49] I am considering standard errors clustered at ward level as Hsiang (2010) procedures fail to deliver spatially corrected standard errors.

[50] The pre-period difference is regressed against a post period as described above, the post period would then be adjusted according to the pre-period considered, it would be either 2009-2019 or 2013-2019.

Google Trends for "Airbnb London". In both cases, results are robust to these modifications. I will present robustness only for the specification of Column 4 of Appendix Table E.1 with the full set of controls.[51]

Alternative specifications Second, I consider instead of *Airbnb Penetration* alternative specifications. In Column 3 of Appendix Table E.7, I consider the month-year Airbnb penetration level (so not computing the cumulative up to that month). In Column 4, I consider just the numerator of Equation 1.

Alternative measures of Airbnb presence Third, to verify that my results do not depend strictly on the assumptions made in constructing the measure of Airbnb penetration, I consider alternative proxies of Airbnb presence. In Column 5 of Appendix Table E.7, I consider in the numerator of Equation 1 the number of beds per listing instead of the number of people a listing can accommodate. In Column 6, I consider as the numerator of Equation 1 the number of Airbnb visits (*i.e.*, ignoring adjustment by the number of guests the property can accommodate and the minimum number of nights to consider) and as the denominator the 2007 residents. In Column 7, to reconcile with the literature on the impact of Airbnb on house prices and the hotel industry, I consider the number of entire properties listed on Airbnb over the number of dwellings in 2011. All these modifications do not alter the relevance of my instrument. Finally, to verify whether my instrument is capturing Airbnb penetration or simply a higher presence of tourists using hotels, in Column 8, I consider the number of accommodation establishments per square kilometre. In this case, I do not find any first stage suggesting that my instrument is not predicting the presence of hotels, and then of "regular" tourists, but only of Airbnb tourists.

Starting year Baseline specification includes all sample years from 2006 onwards. Airbnb, however, was born in 2008 in Los Angeles, and it became popular in 2013. Moreover, in 2013, it is the first year I observed data; all previous years have been imputed using reviews of listings still existing in 2013. To make sure that my results did not follow from the starting year, I progressively modify the starting year, moving the first year of analysis one year earlier in each first stage regression. The specification is one of Column 6, Appendix Table E.1. Results are presented in Appendix Figure E.2, where I am reporting the coefficient of each regression, where I am changing the starting year of the analysis reported on the x-axis. Results are stable until the very end, when the coefficient is not significantly different from zero anymore. Moreover, the F-statistic drops below ten when 2017 (or later) is the starting year. Most likely, both these issues arise due to the wide set of different trends I am including in the regression. However, it is important to notice that even if I restrict my attention after 2008 (when Airbnb was born) or after 2013 (when Airbnb became popular and when my data collection starts), I do not observe any significant difference

[51] All the other specifications are robust to the modification proposed; results available upon request.

from the baseline specification.

Exclude one by one a local authority In Appendix Figure E.3, I report estimates of Column 6, Appendix Table E.1, where I am excluding, one by one, a local authority. None of these exclusions changes the results.

D.2 Data quality robustness: beds

As described in Appendix Section B.2 I take advantage of the information on how many people a listing can accommodate to infer the number of visitors in a given listing. A potential concern is that this information misrepresents real numbers, as Airbnb hosts may inflate it by allowing people to stay on sofas, etc. To make sure that this is not a problem in Appendix Table E.8 I replicate OLS and IV specifications of Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) replacing number of people a flat can accommodate with number of beds in the flat when computing *Airbnb tourists nights* in expression 2. Results are unchanged.

D.3 Data quality robustness: webscrape dates

As described in Appendix Section B.2, the first "snapshot" of reviews is available in 2013. That means that all information before 2013 has been inferred conditional on the listing being still active in 2013. To make sure that this is not a problem in Appendix Table E.9 I replicate OLS and IV specifications of Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) restricting my sample from 2013 onwards. All results are robust, except the count model on the number of charitable organizations. Alternative specifications (see Column 2) are, however, robust to this sample restriction.

D.4 Alternative measure of Airbnb penetration

I replicate OLS and IV specifications of Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) using as a measure of Airbnb penetration the number of entire flats listed on Airbnb over the number of dwellings described in Appendix Section B.2.1. Results are reported in Appendix Table E.10, and they are unchanged, except for the count model on the number of charitable organizations. Alternative specifications (see Column 2) are, however, robust to this sample restriction..

D.5 Standard Errors

As described in Section 3 throughout the paper, I consider standard errors corrected following Conley (1999), and Hsiang (2010) with the following parameter choice: 14 km and 2 years. The parameters choice follows from the fact that the radius of the median local authority is 2 km if they were perfect circles. That implies that I am assuming that spatial correlation vanishes 3 complete local authorities from each ward centroid. For the autocorrelation parameters, I considered 2 years as Airbnb started its presence in London in 2009, and that Greene (2018) recommends at least $T^{0.25}$, even considering the longest panel (2009-2019), I am being more conservative.

To validate my choice, I report in E.4 the 10% confidence intervals of Table 1, Panel A, Column 4 specification when changing the parameters of interest. In particular, I report all the combinations with the time parameter equal to 1, 2, 5, 10, and the distance parameter equal to 1, 5, 10, 14, 15, 20, 25. When turning our attention to parameter combinations, it is evident how the "time" parameter marginally alters confidence intervals, while it is mainly the distance parameter that determines how wide the confidence intervals will be. Around the parameter choice (14 km and 2 years), results remain significant, and confidence intervals are almost identical. Wider standard errors appear when considering a high distance parameter. Given that this is happening for parameter choices far from the baseline specification, I am reassured about my choice.

D.6 Multiple hypothesis testing

Given the numerous outcomes considered under the same treatment, a concern is that we may falsely reject at least some null hypotheses of no effect. A vast literature has tackled the issue of multiple hypothesis testing. I perform various tests.

False Discovery Rate (FDR) q-values One of the most popular ways to deal with this issue is to follow Anderson (2008) to compute sharpened False Discovery Rate (FDR) q-values.[52] The FDR is the expected proportion of rejections that are type I errors (false rejections). The procedure is extremely simple because this takes the p-values as inputs, I can consider p-values coming after Conley (1999) correction. A drawback of this method is that it does not account for any correlations among the p-values. Anderson (2008) notes that in simulations the method seems to also work well with positively dependent p-values, but if the p-values have negative correlations, a more conservative approach is needed.[53]

Familywise error rate (FWER) An alternative procedure aims to control the familywise error rate (FWER), which is the probability of making any type I error. I calculate Westfall-Young (Westfall and Young, 1993) stepdown adjusted p-values, which also control the FWER and allow for dependence among p-values.[54]. This method uses bootstrap resampling to allow for dependence across outcomes. Given the added complexity imposed by the fact that I am now controlling for dependence among p-values, I consider standard errors clustered at ward level[55]

[52] Code is available from Anderson's website.

[53] Note that sharpened q-values can be less than unadjusted p-values in some cases when many hypotheses are rejected because if there are many true rejections, you can tolerate several false rejections too and still maintain the false discovery rate low.

[54] Stata code available as `randcmd`.

[55] I report bootstrap-t as it is generally considered superior to the -c because its rejection probabilities converge more rapidly asymptotically to nominal size, Hall (1992). I consider 1999 randomization iterations

Joint test that no treatment has any effect A third approach, suggested in Young (2018), rather than adjusting each p-value for multiple testing, it conducts a joint test of the hypothesis that no treatment has any effect, and then uses the Westfall-Young approach to test this across equations.[56] Also here, given the added complexity imposed by the fact I am now controlling for dependence among p-values, I consider standard errors clustered at ward level. Looking at randomization-c p-value for the joint-test of the significance of treatment measure in each equation as a whole is 0.0044 while randomization-t p-value for the Westfall-Young multiple testing test of the significance of any treatment measure in each equation as a whole is 0.0041. We can then reject the hypothesis that no treatment has any effect.

In Appendix Table E.12, I report original p-values in Column 1, sharpened q-values following Anderson (2008) in Column 2, and p-values corrected following Westfall and Young (1993) in Column 3. I tested all main specifications, considering always yearly specifications, even when, in the main text, I was reporting monthly specifications.[57] This is why some p-values may be different. I consider Panel A and B of Table 1 (Columns 4 and 6), 2 (Columns 2, 4 and 6), 3 (all Columns), 5 (all Columns), 6 (all Columns).

Comparing Columns 1 and 2 p-values and sharpened q-values following Anderson (2008) are similar. Also, in columns 1 and 3, differences are limited to a few cases.

[56] Stata code available as `randcmd`.

[57] I ignore, as not directly comparable, the survey analysis in Table 4 as well as specification containing hotel penetration (Table 7) or interactions (Table 8).

E Online Appendix – Robustness Tables and Figures

Table E.1: **First Stage**

	Cumulative Airbnb Penetration (x100)					
	(1)	(2)	(3)	(4)	(5)	(6)
Historical Sites x	0.244	0.192	0.186	0.204	0.163	0.158
Google Trend/100	(0.035)***	(0.025)***	(0.024)***	(0.023)***	(0.021)***	(0.021)***
Observations	8736	8736	8736	104832	104832	104832
F-Stat FS	50.0	58.0	58.6	80.8	60.1	59.1
Ward FE	X	X	X	X	X	X
LLA x Time FE	X	X	X	X	X	X
Vars 2001 x Time FE		X	X		X	X
Geo x Time FE			X			X
Timing	Year	Year	Year	Year-Month	Year-Month	Year-Month
Years	2006-2019	2006-2019	2006-2019	2006-2019	2006-2019	2006-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1 to 3 consider yearly data; Columns 4 to 6 consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. *Historical Sites* is the number of historical sites per km^2 (source: Digimap) and *Google Trend* represents the worldwide search volume of the word "Airbnb" in Google. In Column 1 (4), I include ward fixed effects and local authority time trends. Column 2 (5) adds to Column 1 (4) the interaction of year (year-month) dummies with the 2001 share of workers by sector, and the 2001 log of house prices per square meter. Column 3 (6) adds to Column 2 (5) the interaction of year (year-month) dummies with the distance ward centroid to Charing Cross, and the distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for a weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 2 years (Columns 1 to 3) or 24 months (Columns 4 to 6). *** p<0.01; ** p<0.05; * p<0.1.

Table E.2: **Long term Residents' Social Capital**

	ln(N. Charitable Organizations)		At least one Charitable Organization	
	(1)	(2)	(3)	(4)
Panel A: IV				
Cumulative Airbnb	-0.093	-0.099	0.016	0.009
Penetration (x100)	(0.029)***	(0.024)***	(0.019)	(0.015)
Cumulative Airbnb Penetration x	-0.505	-0.374	0.351	0.098
Heterogeneity Dummy	(0.252)**	(0.107)***	(0.269)	(0.097)
Panel B: OLS				
Cumulative Airbnb	0.012	0.017	0.005	0.004
Penetration (x100)	(0.009)	(0.009)*	(0.005)	(0.005)
Cumulative Airbnb Penetration x	-0.140	-0.004	-0.032	-0.020
Heterogeneity Dummy	(0.074)*	(0.038)	(0.020)	(0.018)
Heterogeneity	Same address last year	UK more 2 years	Same address last year	UK more 2 years
Observations	4689	4689	5616	5616
F-Stat FS	10.9	9.3	11.6	10.9
Ward FE	X	X	X	X
LLA x Year FE	X	X	X	X
Vars 2001 x Year FE	X	X	X	X
Geo x Year FE	X	X	X	X
Years	2011-2019	2011-2019	2011-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. All Columns consider yearly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. In Columns 1 and 2, I consider the log of the number of charitable organizations. In Columns 3 and 4, I consider a dummy equal to 1 if at least one charitable organization is present. *Same address last year* is a dummy equal to 1 if the ward i has a share of residents that in the 2021 Census report living in the same address as in the previous year, above the median. *UK more 2 years* is a dummy equal to 1 if the ward i has a share of residents who in the 2011 Census reported to live in the UK for more than two years above the median. All Columns include ward fixed effect, local authority time trends, and the interaction of year dummies with 2001 share of workers by sector, 2001 log of house prices per square meter, and the interaction of year dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. Conley (1999) standard errors are reported, parameters considered: 14 km and 2 years. *** p<0.01; ** p<0.05; * p<0.1.

Table E.3: **Long term Residents' attitudes**

	Feel belong to the area	Feel belong to London	Never felt lonley	Any contact with neighbours	Agree can influence area	Life satisfaction index ≤ 4
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.038	-0.026	-0.010	-0.016	-0.026	0.026
Penetration (x100)	(0.006)***	(0.016)	(0.022)	(0.006)***	(0.009)***	(0.018)
Cum. Airbnb Penetration x	-0.021	-0.010	-0.029	0.034	-0.018	0.038
Less than two years	(0.014)	(0.022)	(0.025)	(0.006)***	(0.007)**	(0.022)
Less than two years	-0.138	-0.053	0.105	-0.067	0.032	-0.085
in the area	(0.029)***	(0.031)	(0.035)	(0.025)***	(0.016)*	(0.026)
Panel B: OLS						
Cumulative Airbnb	-0.022	-0.019	-0.020	-0.005	-0.022	0.016
Penetration (x100)	(0.011)**	(0.001)***	(0.011)	(0.006)	(0.012)	(0.002)***
Cum. Airbnb Penetration x	-0.013	-0.006	0.003	-0.012	-0.005	0.011
Less than two years	(0.010)	(0.009)	(0.014)	(0.005)**	(0.017)	(0.008)
Less than two years	-0.013	-0.006	0.003	-0.012	-0.005	0.011
in the area	(0.020)***	(0.019)***	(0.027)***	(0.022)	(0.031)	(0.016)***
Observations	3356	3338	3361	3357	3071	3286
F-Stat FS	211.3	204.0	210.5	207.1	99.9	201.7
Individual controls	X	X	X	X	X	X
Ward controls	X	X	X	X	X	X

Note: The sample includes individual responses from the Survey of Londoners 2018-19 (run by the Greater London Authority). *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km² times Airbnb Google Trend/100* in October 2018. All Columns include an interaction with a dummy equal to 1 if the respondent has lived in the local area for less than 2 years. The dependent variable in Column 1 is a dummy equal to 1 if the respondent feels they belong to the local area. In Column 2 is a dummy equal to 1 if the respondent feels they belong to London. In Column 3 is a dummy equal to 1 if the respondent never felt lonely. In Column 4 is a dummy equal to 1 if the respondent had any contact with their neighbours. In Column 5 is a dummy equal to 1 if the respondent feels that they can influence the local area. In Column 6 is a dummy equal to 1 if the life satisfaction index is less than or equal to 4 (on a scale from 0, Not at all satisfied, to 10, Completely Satisfied). Individual controls are: age band dummies, female dummy, homeownership dummy, dummy if completed a university degree, income score, years since in London, and whether the survey was conducted online. Ward controls are: 2001 share of workers by sector, 2001 log of house prices per square meter, distance from ward centroid to Charing Cross, distance from ward boundaries to the closest underground station. All Columns include local authority fixed effects. F-stat First Stage refers to the K-P F-stat for a weak instrument. Conley (1999) standard errors, parameters considered: 14 km. *** p<0.01; ** p<0.05; * p<0.1.

Table E.4: **Housing and Business Rents Market**

	Advertised rents				Sold properties		Business rents	
	ln(n. of ads)		ln(Median rent)		ln(n. of transactions)	ln(Median price per sqm)	Floorspace available	Rateable Value
	1-2 rooms	More 3 rooms	1-2 rooms	More 3 rooms				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: IV								
Cumulative Airbnb	-0.111	-0.083	0.024	0.020	0.035	0.001	0.008	-0.012
Penetration (x100)	(0.059)*	(0.052)	(0.011)**	(0.014)	(0.020)*	(0.008)	(0.007)	(0.021)
Panel B: OLS								
Cumulative Airbnb	0.035	0.046	0.000	-0.001	-0.008	0.005	0.023	-0.005
Penetration (x100)	(0.018)*	(0.017)***	(0.004)	(0.005)	(0.006)	(0.003)*	(0.004)***	(0.009)
Observations	27805	37351	43479	43563	84026	84026	8736	5418
F-Stat FS	74.7	40.7	61.7	61.7	68.8	68.8	58.6	56.7
Ward FE	X	X	X	X	X	X	X	X
LLA x Year-Month FE	X	X	X	X	X	X	X	X
Vars 2001 x Year-Month FE	X	X	X	X	X	X	X	X
Geo x Year-Month FE	X	X	X	X	X	X	X	X
Years	2011-2018	2011-2018	2011-2018	2011-2018	2006-2019	2006-2019	2006-2019	2006-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1-6 consider monthly data. Columns 7 and 8 consider yearly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. The dependent variable in Columns 1 and 2 is the log of the number of rents advertised on Zoopla (source: UBDC) for properties with 1 or 2 rooms (Column 1) and 3 rooms or more (Column 2). In Columns 3 and 4, the outcome variable is the log of the median monthly asking rent (source: Zoopla from UBDC) for properties with 1 or 2 rooms (Column 3) and 3 rooms or more (Column 4). In Column 5, I consider the log of the number of registered selling transactions (source: UK Land Registry). In Column 6, I consider the log of the median property price per square meter (transaction selling price; source: UK Land Registry). In Column 7, I consider the log of commercial floor space available, and in Column 8, I consider the log of Rateable Value (source: Valuation Office Agency). All Columns include ward fixed effect, local authority time trends and the interaction of year-month (or year) dummies with 2001 share of workers by sector, 2001 log of house prices per square meter and interaction of year-month (or year) dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 24 months (Columns 1 to 6) or 2 years (Columns 7 and 8). *** p<0.01; ** p<0.05; * p<0.1.

Table E.5: **Include bars and nightclubs density**

	N. Charitable Organizations	ln(N. Charitable Organizations)	ln(Population)	At least one complaint about Tourists	Rubbish	ln(Number of ASB incidents)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.046	-0.075	-0.008	0.015	0.006	0.045
Penetration (x100)	[-0.262;-0.007]	(0.022)***	(0.003)**	(0.008)*	(0.015)	(0.015)***
ln(Bars and Nightclubs)	0.161	0.089	0.053	0.000	-0.002	0.034
	[-0.047;0.329]	(0.068)	(0.021)**	(0.003)	(0.015)	(0.016)**
Panel B: OLS						
Cumulative Airbnb	-0.001	0.017	-0.003	0.009	0.012	0.013
Penetration (x100)	[-0.022;0.018]	(0.008)**	(0.002)*	(0.004)**	(0.005)***	(0.005)***
ln(Bars and Nightclubs)	0.155	0.060	0.051	0.001	-0.003	0.041
	[-0.044;0.324]	(0.068)	(0.012)***	(0.002)	(0.014)	(0.016)**
Observations	5616	4689	1248	67392	67392	67391
F-Stat FS	21.1	19.6	18.9	22.1	22.1	22.1
90% C.I. C.F.	[0.006;0.224]					
Ward FE	X	X	X	X	X	X
LLA x Time FE	X	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X	X
Geo x Time FE	X	X	X	X	X	X
Timing	Year	Year	Year	Year-Month	Year-Month	Year-Month
Years	2011-2019	2011-2019	2011-2021	2011-2019	2011-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1-2 consider yearly data; Column 3 considers data from the 2011 and 2021 Censuses, with all the explanatory variables measured in 2011 and 2019, respectively. Columns 4 to 6 consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. All specifications control for the log of the number of *Bars and Nightclubs*. Column 1 considers the count model presented in Section 3.1 where the dependent variable is the number of charitable organizations (source: Digimap). Columns 2 to 6 consider the 2SLS presented in Section 3. In Column 2, the dependent variable is the log of the number of charitable organizations. In Column 3 is the log of ward population. In Columns 4 and 5 dependent variables are dummies equal to 1 if at least one complaint about each category was reported in the ward i in month t. In Column 6 is the log of anti-social behaviour (ASB) crime (source: Police statistics). All Columns include ward fixed effect, local authority time trends and the interaction of year (or year-month) dummies with 2001 share of workers by sector, 2001 log of house prices per square meter and interaction of year (or year-month) dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for a weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 2 years (Columns 1 to 3) or 24 months (Columns 4 to 6). *** p<0.01; ** p<0.05; * p<0.1.

Table E.6: **Pre-Trends**

	ln(Population)	ln(n. of transactions)	ln(Median price per sqm)	ln(Business Floor Space)	ln(Rateable Value)	At least one complaint to the local authority about			ln(N. Charitable Organizations)	At least one Charitable Organization	ln(Number of ASB incidents)
						Tourists	Rubbish	Anything			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: IV											
Cumulative Airbnb	-0.005	-0.006	-0.002	0.001	0.026	0.000	-0.045	-0.021	0.024	-0.010	-0.003
Penetration (x100)	(0.004)	(0.026)	(0.006)	(0.007)	(0.024)	(0.010)	(0.047)	(0.039)	(0.041)	(0.016)	(0.013)
Panel B: OLS											
Cumulative Airbnb	0.000	-0.009	-0.001	0.004	0.005	-0.004	-0.007	-0.018	0.000	-0.006	0.004
Penetration (x100)	(0.001)	(0.009)	(0.003)	(0.002)	(0.006)	(0.006)	(0.020)	(0.014)	(0.012)	(0.008)	(0.005)
Observations	624	624	624	624	314	624	624	624	522	624	624
F-Stat FS	19.6	19.6	19.6	19.6	9.0	19.6	19.6	19.6	17.4	19.5	19.5
LLA FE	X	X	X	X	X	X	X	X	X	X	X
Vars 2001	X	X	X	X	X	X	X	X	X	X	X
Vars Geo	X	X	X	X	X	X	X	X	X	X	X
Years	2002-2005	2002-2005	2002-2005	2006-2008	2006-2008	2007-2008	2007-2008	2007-2008	2011-2012	2011-2012	2011-2012

Note: Note: this table regresses the change in outcomes (as reported in the last row) against the change in instrumented Airbnb penetration in the period 2009-2019 (in Columns 1 to 8) or 2013-2019 (in Columns 9 to 11). All regressions include local authority fixed effects, 2001 share of workers by sector, 2001 log of house prices per square meter, distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for a weak instrument. Standard errors clustered at the ward level. *** p<0.01; ** p<0.05; * <0.1.

Table E.7: **First Stage Robustness**

	Cumulative Airbnb Penetration		Airbnb Tourist Nights per resident	Cumulative Airbnb Tourist Nights	Airbnb penetration		Airbnb property over dwelling
					bed	visits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Historical Sites x	0.103	0.121	0.042	6241.473	0.077	0.298	0.117
Google Trend/100	(0.012)***	(0.018)***	(0.005)***	(823.559)***	(0.010)***	(0.037)***	(0.021)***
Observations	104832	104832	104832	104832	104832	104832	104832
F-Stat FS	71.9	46.4	59.7	57.4	55.5	64.0	30.1
Ward FE	X	X	X	X	X	X	X
LLA x Time FE	X	X	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X	X	X
Geo x Time FE	X	X	X	X	X	X	X
Instrument	Historic England	Airbnb London	Baseline	Baseline	Baseline	Baseline	Baseline
Years	2006-2019	2006-2019	2006-2019	2006-2019	2006-2019	2006-2019	2006-2019

Note: The sample includes a panel of 624 electoral wards in Greater London from 2006 to 2019 at the month level. The specification considered is the same as Column 6, Appendix Table E.1 unless otherwise specified. In Column 1, I consider Historical Buildings per square kilometre as a share. In Column 2, I consider Google Trends for "Airbnb London" as a shift. In Column 3, I consider the contemporaneous Airbnb penetration (not the cumulative). In Column 4, I consider just the numerator of expression 1. In Column 5, I consider in the numerator of Equation 1 the number of beds per listing instead of the number of people a listing can accommodate. In Column 6, I consider as the numerator of Equation 1 the number of Airbnb visits (*i.e.*, ignoring adjustment by number of guests the property can accommodate and minimum number of nights to consider) and as the denominator the 2007 residents. In Column 7, I consider the number of entire properties listed on Airbnb over the number of dwellings in 2011.

Table E.8: **Robustness: using beds in the flat**

	N. Charitable Organizations	ln(N. Charitable Organizations)	ln(Population)	At least one complaint about Tourists	Rubbish	ln(Number of ASB incidents)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.092	-0.147	-0.012	0.040	0.062	0.097
Penetration (x100)	[-0.521;-0.005]	(0.045)***	(0.006)**	(0.015)***	(0.032)*	(0.030)***
Panel B: OLS						
Cumulative Airbnb	0.006	0.042	-0.003	0.019	0.022	0.025
Penetration (x100)	[-0.035;0.044]	(0.016)***	(0.003)	(0.007)***	(0.009)***	(0.009)***
Observations	5616	4689	1248	97344	97344	67391
F-Stat FS	54.8	51.7	265.6	56.3	56.3	58.2
90% C.I. C.F.	[0.004;0.489]					
Ward FE	X	X	X	X	X	X
LLA x Time FE	X	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X	X
Geo x Time FE	X	X	X	X	X	X
Timing	Year	Year	Year	Year-Month	Year-Month	Year-Month
Years	2011-2019	2011-2019	2011-2019	2007-2019	2007-2019	2011-2019

Note: I replicate results presented in Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) replacing number of people a flat can accommodate with number of beds in the flat in the expression for *Airbnb tourists nights* in Equation 2.

Table E.9: **Restrict from 2013 onwards**

	N. Charitable Organizations	ln(N. Charitable Organizations)	At least one complaint about Tourists	Rubbish	ln(Number of ASB incidents)
	(1)	(2)	(3)	(4)	(5)
Panel A: IV					
Cumulative Airbnb	-0.027	-0.071	0.020	0.028	0.037
Penetration (x100)	[-0.131;0.097]	(0.019)***	(0.008)**	(0.017)*	(0.017)**
Panel B: OLS					
Cumulative Airbnb	0.009	0.022	0.011	0.014	0.008
Penetration (x100)	[-0.014;0.028]	(0.008)***	(0.004)**	(0.005)***	(0.005)*
Observations	4368	3605	52416	52416	52415
F-Stat FS	52.4	48.8	58.8	58.8	58.8
90% C.I. C.F.	[-0.134;0.157]				
Ward FE	X	X	X	X	X
LLA x Time FE	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X
Geo x Time FE	X	X	X	X	X
Timing	Year	Year	Year-Month	Year-Month	Year-Month
Years	2013-2019	2013-2019	2013-2019	2013-2019	2013-2019

Note: I replicate results presented in Tables 1 (Columns 2 and 4), 5 (Columns 1 and 2), and 6 (Column 1), restricting my sample from 2013 onwards.

Table E.10: **Alternative measure of Airbnb Penetration: dwellings**

	N. Charitable Organizations	ln(N. Charitable Organizations)	ln(Population)	At least one complaint about Tourists	Rubbish	ln(Number of ASB incidents)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: IV						
Cumulative Airbnb	-0.074	-0.122	-0.009	0.026	0.041	0.068
Penetration (x100)	[-0.749;0.032]	(0.037)***	(0.005)**	(0.010)***	(0.021)*	(0.021)***
Panel B: OLS						
Cumulative Airbnb	-0.007	0.007	-0.003	0.007	0.004	0.010
Penetration (x100)	[-0.031;0.014]	(0.012)	(0.002)*	(0.003)***	(0.003)	(0.004)***
Observations	5616	4689	1248	97344	97344	67391
F-Stat FS	33.7	29.2	197.0	30.3	30.3	27.4
90% C.I. C.F.	[-0.672;0.586]					
Ward FE	X	X	X	X	X	X
LLA x Time FE	X	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X	X
Geo x Time FE	X	X	X	X	X	X
Timing	Year	Year	Year	Year-Month	Year-Month	Year-Month
Years	2011-2019	2011-2019	2011-2019	2007-2019	2007-2019	2011-2019

Note: I replicate results presented in Tables 1 (Columns 2 and 4), 2 (Column 2), 5 (Columns 1 and 2), and 6 (Column 1) using as measure of Airbnb penetration the number of entire flats listed on Airbnb over the number of dwellings. This is described in Appendix Section B.2.1.

Table E.11: **Non linear effects**

	ln(N. Charitable Organizations)	ln(Population)	At least one complaint about Tourists	Rubbish	ln(Number of ASB incidents)
	(1)	(2)	(3)	(4)	(5)
Panel A: IV					
Cumulative Airbnb	-0.325	-0.097	0.019	-0.085	0.243
Penetration (x100)	(0.128)**	(0.049)**	(0.019)	(0.057)	(0.066)***
Cumulative Airbnb	0.018	0.005	0.000	0.010	-0.016
Penetration (x100) squared	0.008	0.003	0.002	0.005	0.005
Panel B: OLS					
Cumulative Airbnb	0.044	0.022	-0.006	0.013	0.035
Penetration (x100)	0.015	0.005	0.005	0.008	0.009
Cumulative Airbnb	-0.002	-0.002	0.002	0.000	-0.002
Penetration (x100) squared	0.001	0.000	0.001	0.001	0.001
Observations	4689	1248	97344	97344	67391
F-Stat FS	2.6	1.1	3.5	3.5	3.4
Ward FE	X	X	X	X	X
LLA x Time FE	X	X	X	X	X
Vars 2001 x Time FE	X	X	X	X	X
Geo x Time FE	X	X	X	X	X
Timing	Year	Year	Year-Month	Year-Month	Year-Month
Years	2011-2019	2011-2021	2007-2019	2007-2019	2011-2019

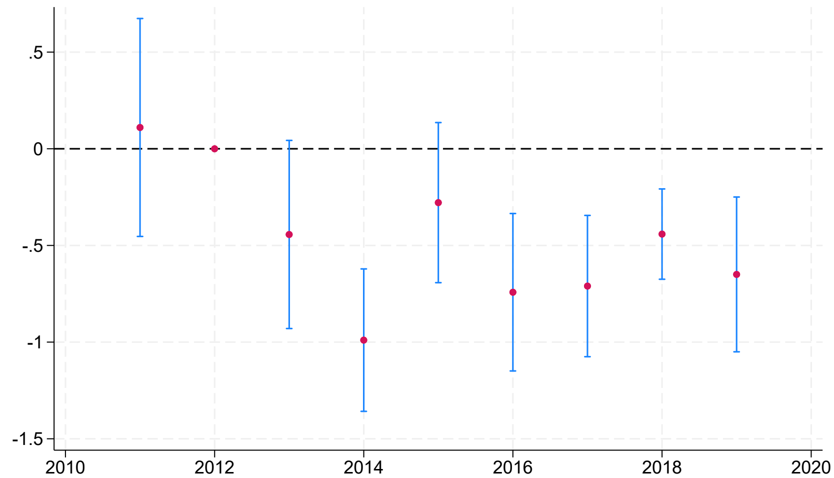
Note: The sample includes a panel of 624 electoral wards in Greater London. Columns 1-2 consider yearly data; Column 3 considers data from the 2011 and 2021 Censuses with all the explanatory variables measured in 2011 and 2019, respectively. Columns 4 to 7 consider monthly data. *Cumulative Airbnb penetration* represents the cumulative number of Airbnb tourists' nights over residents' nights. Instrument in Panel A is *Historical Sites per km^2 times Airbnb Google Trend/100*. Column 1 considers the count model presented in Section 3.1 where the dependent variable is the number of charitable organizations (source: Digimap). Columns 2 to 6 consider the 2SLS presented in Section 3. In Column 2 the dependent variable is the log of the number of charitable organizations. In Column 3 is the log of ward population. In Columns 4 and 5 dependent variables are dummies equal to 1 if at least one complaint about each category was reported in the ward i in month t. In Column 6 is the log of anti-social behaviour (ASB) crime (source: Police statistics). All Columns include ward fixed effect, local authority time trends and the interaction of year (or year-month) dummies with 2001 share of workers by sector, 2001 log of house prices per square meter and interaction of year (or year-month) dummies with distance ward centroid to Charing Cross, and distance ward to the closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument Conley (1999) standard errors, parameters considered: 14 km and 2 years (Columns 1 to 3) or 24 months (Columns 4 to 7). *** p<0.01; ** p<0.05; * p<0.1.

Table E.12: **Multiple hypothesis testing**

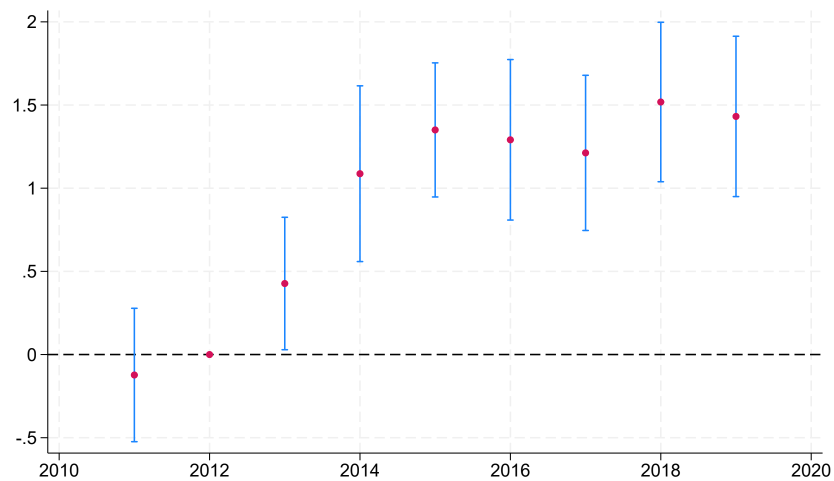
	Original p-value	Anderson (2008)	Westfall-Young (1993)
	(1)	(2)	(3)
Panel A: IV			
ln(N. of Charitable Organizations)	0.001	0.006	0.028
At least one Charitable Organization	0.758	0.464	0.180
ln(Population (Census))	0.038	0.074	0.247
ln(Total Domestic Electric Consumption)	0.402	0.333	0.499
ln(N. pupils enrolled in school)	0.497	0.360	0.263
Share of population 0-24 (Census)	0.046	0.078	0.172
Share of population 25-34 (Census)	0.314	0.274	0.086
Share of population 35-49 (Census)	0.774	0.466	0.331
Share of population 50-64 (Census)	0.000	0.001	0.002
Share of population 65+ (Census)	0.006	0.025	0.280
Share of population with at least a University Degree (Census)	0.382	0.332	0.130
Share of population born in the UK (Census)	0.000	0.001	0.000
Share of population living in the UK less than 2 years (Census)	0.000	0.001	0.000
Share of pupils entitled to freemeals	0.046	0.078	0.004
Share of pupils with English not as first language	0.521	0.360	0.125
Share of pupils with Special Educational Needs	0.011	0.035	0.050
At least one complain about tourists	0.138	0.159	0.060
At least one complain about rubbish	0.395	0.333	0.039
At least one complain about dog fouling	0.031	0.074	0.005
At least one complain about abandoned vehicle	0.364	0.321	0.004
At least one complain about car parking	0.632	0.426	0.107
At least one complain about road conditions	0.184	0.188	0.001
At least one complain about green areas	0.502	0.360	0.007
At least one complain	0.085	0.114	0.002
ln(N. Anti social behaviour crimes)	0.001	0.005	0.019
ln(N. Parking Charge Notice)	0.001	0.005	0.002
At least one flytipping incident	0.254	0.223	0.027
Complaints over incidents - Parking	0.940	0.533	0.372
Complaints over incidents - Rubbish	0.147	0.159	0.180
Panel B: OLS			
ln(N. of Charitable Organizations)	0.035	0.074	0.275
At least one Charitable Organization	0.228	0.208	0.547
ln(Population (Census))	0.150	0.159	0.529
ln(Total Domestic Electric Consumption)	0.645	0.426	0.805
ln(N. pupils enrolled in school)	0.410	0.333	0.707
Share of population 0-24 (Census)	0.272	0.236	0.586
Share of population 25-34 (Census)	0.066	0.107	0.095
Share of population 35-49 (Census)	0.792	0.470	0.926
Share of population 50-64 (Census)	0.180	0.188	0.208
Share of population 65+ (Census)	0.012	0.037	0.270
Share of population with at least a University Degree (Census)	0.222	0.208	0.660
Share of population born in the UK (Census)	0.000	0.001	0.000
Share of population living in the UK less than 2 years (Census)	0.000	0.001	0.000
Share of pupils entitled to freemeals	0.014	0.040	0.401
Share of pupils with English not as first language	0.000	0.001	0.049
Share of pupils with Special Educational Needs	0.000	0.001	0.001
At least one complain about tourists	0.005	0.022	0.018
At least one complain about rubbish	0.605	0.411	0.723
At least one complain about dog fouling	0.010	0.035	0.137
At least one complain about abandoned vehicle	0.420	0.334	0.262
At least one complain about car parking	0.533	0.360	0.497
At least one complain about road conditions	0.089	0.114	0.101
At least one complain about green areas	0.036	0.074	0.356
At least one complain	0.037	0.074	0.152
ln(N. Anti social behaviour crimes)	0.010	0.035	0.010
ln(N. Parking Charge Notice)	0.036	0.074	0.186
At least one flytipping incident	0.043	0.078	0.037
Complaints over incidents - Parking	0.218	0.208	0.513
Complaints over incidents - Rubbish	0.063	0.106	0.028

Note: Column 1 contains p-values computed using Conley (1999) as described in Section 3. Column 2 contains sharpened q-values following Anderson (2008). Column 3 stepdown adjusted p-values following Westfall and Young (1993). Details are described in Appendix Section D.6.

Figure E.1: **Dynamic: Charitable organizations and ASB incidents**



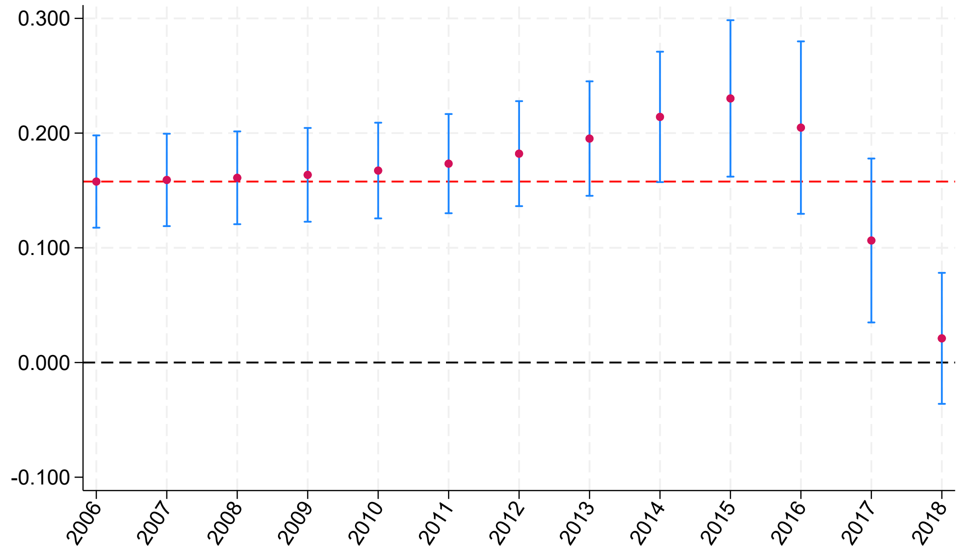
(a) ln(N. Charitable Organizations)



(b) ln(Number of ASB incidents)

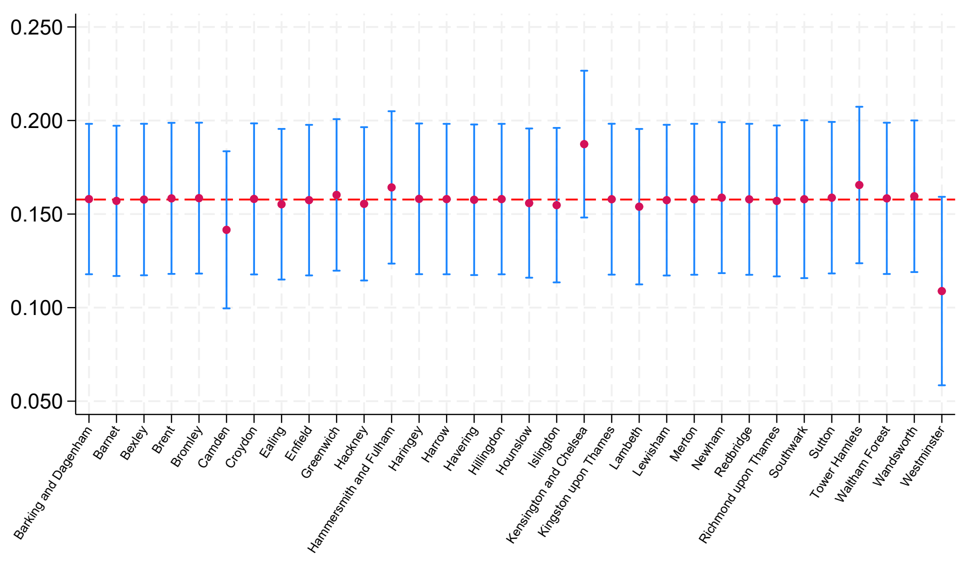
Note: Plotting the coefficients and the corresponding 95% confidence intervals of the interaction between year dummies and 2013 *Cumulative Airbnb penetration*. The dependent variable is the log of the number of charitable organizations (Panel A) and the log of the number of anti-social behaviour incidents (Panel B). All specifications include ward and year fixed effects. Conley (1999) standard errors, parameters considered: 14 km and 2 years.

Figure E.2: **First stage: modify starting year**



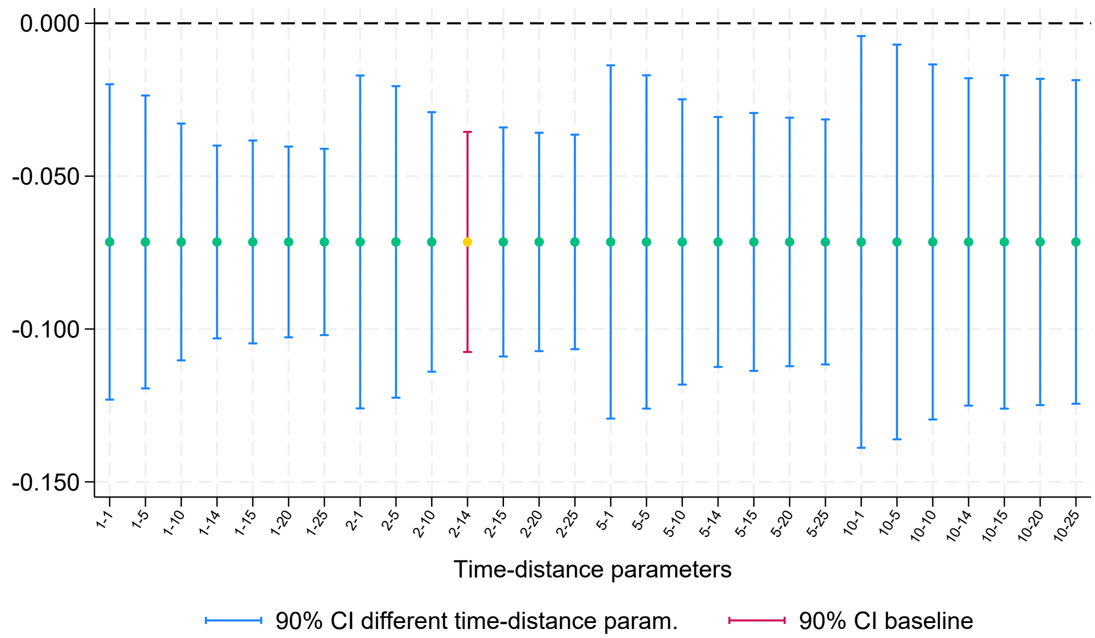
Note: Plotting coefficient of Column 6, Appendix Table E.1 where I modify the starting year of analysis. Starting years are reported on the x-axis. Baseline coefficient of Column 6, Appendix Table E.1 level reported by the dashed red line.

Figure E.3: **First stage: Removing one by one a local authority**



Note: Plotting coefficient of Column 6, Appendix Table E.1, where I exclude one by one a local authority from the analysis. Excluded local authorities are reported on the x-axis. Baseline coefficient of Column 6, Appendix Table E.1 level reported by the dashed red line.

Figure E.4: **Different Standard Errors parameters**



Note: Plotting 90% confidence intervals of Table 1, Panel A Column 4 specification. On the x-axis reporting the combination of time-distance parameters considered in Conley (1999) standard error correction.