Backlash against Airbnb: Evidence from London *

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Abstract

Anti-globalization sentiments have been on the rise in recent years. In urban contexts, these attitudes may take the form of backlash against tourism. In this paper, I examine the role of Airbnb, a major short-term rental platform, in explaining the rising discontent against tourists. To do so, I construct a rich and spatially disaggregated dataset to study the consequences of Airbnb penetration in London. First, I document that 1 additional Airbnb tourist per 1000 residents increases complaints against tourists by 2.2 per cent. Secondly, I explore the roots – pecuniary and non-pecuniary – of these reactions. I find that higher Airbnb penetration is associated with a decrease in neighbourhood quality, while the housing market is only marginally affected. These negative externalities can be explained by a lack of monitoring and coordination by hosts, which are key differences between short-term renting and traditional hotel accommodations. Finally, I provide evidence that the deterioration of neighbourhood quality markedly reduces social capital, as measured by the number of charitable organizations, and worsens attitudes towards globalization, leading to higher support for Brexit.

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1 Introduction

A vast literature has studied the rising backlash against globalization, suggesting that opposition to international trade (Colantone and Stanig, 2018; Autor et al., 2020) and to immigration (Becker and Fetzer, 2016; Halla et al., 2017; Dustmann et al., 2019) have played a key role in fueling these views.[1] Some recent studies suggest that these grievances have economic but also social roots (Abramitzky and Boustan, 2017; Tabellini, 2020). In this paper, I examine the backlash against tourists, a phenomenon which has increased dramatically across European cities in recent years (Peeters et al., 2018), and I interpret it as a form of urban backlash against globalization.

To the extent that anti-globalization attitudes are linked to populism, these dynamics may suggest that also large cities, which have so far largely resisted populist waves (Rodden, 2019; Broz et al., 2020), may eventually undergo political shifts similar to those already experienced by rural areas.[2]

The growing backlash against tourism has coincided with extraordinary growth in visitors numbers. Based on the latest official statistics (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. This has been driven by a rising middle class across the world and by the significant reduction in airfares triggered by low-cost carriers. However, the key factor has been the rise of short-term renting, facilitated by digital platforms such as Airbnb, which represents the first and largest platform on the market.[3] By substantially reducing transaction costs, the emergence of these intermediation services allow existing housing units to be rent to short-term visitors, rapidly increasing the capacity for overnight stays. Even so, the rise in tourism has been a powerful engine of economic growth, with a direct GDP contribution growing yearly at 3.6 per cent rate (WTTC, 2019). 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).

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.[4] 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 cost of living, with locals "crowd out" from touristic neighbourhoods. Moreover, residents may

[1] Mudde and Kaltwasser (2017), Margalit (2019) and Guriev and Papaioannou (2020) provide thorough reviews of the existing literature on these phenomena.

[2] Highlighted in the media, *e.g.* The Guardian, January 2020, *Overtourism in Europe's historic cities sparks backlash*; The Economist, October 2018, *The backlash against overtourism*.

[3] From 2008 to 2019 in London the number of rooms available on Airbnb grew from 0 to 135,000, almost matching the number of hotel rooms at 159,000. See Quattrone et al. (2016) for a discussion on Airbnb spread in London.

[4] Highlighted in the media, *e.g.* The Guardian, January 2020, *Overtourism in Europe's historic cities sparks backlash*; The Economist, October 2018, *The backlash against overtourism*.

find that pavements, roads and public transports are clogged by tourists and they may deal with more and more common late-night misbehaviours.[5]

Motivated by these facts, in the first part of this paper, I investigate the relationship between rising backlash against tourists and Airbnb penetration in London. 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 from worsening of quality of life in the neighbourhoods. Finally, I ask whether the deteriorating quality of neighbourhoods reduces social capital and residents' support for globalization.

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 three novel features. First, the main proxy of backlash against tourists is the number of 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 measure allows me to exactly capture the "voice of losers" and 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 more standard measures typically used in political economy or urban economics to explore analogous questions.

Second, I introduce a new measure of Airbnb penetration that accounts for the "intensity" of Airbnb tourists presence by considering the length of stay and the number of guests in each listing. Notably, this measure does not suffer from the problem, recurring in the literature, of inactive listings not removed from the Airbnb website, as it uses actual reviews to infer the number of guests in the area. Moreover, I distinguish between types of Airbnb tourists (families *vs.* non-families), by ethnicity (following Tzioumis, 2018) and by type of accommodation (room *vs.* entire property).

Third, I complement the dataset with a rich set of neighbourhood quality measures (complaints about negative behaviours, anti-social behaviour crime rates, and proxies for congestions of local services), proxies for social capital (number of charitable, youth and political organizations) and anti-globalization views (Brexit vote share). These measures allow me to shed light on non-pecuniary mechanisms and social implications, so far unexplored by the existing literature.

The empirical analysis is performed at the electoral ward-year level, controlling for ward fixed characteristics as well as flexible time effects for each local authority within London.[6] In the baseline specification I also include a wide range of pre-determined and geographic characteristics

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

[6]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).

interacted with year fixed effects to control for different evolution depending on initial and fixed characteristics. 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 spatial variation of historical point 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 industry 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, the instrument proposed does not predict hotel penetration. Fourth, adding hotel penetration as a regressor alters neither the significance nor the magnitude of my results.

I begin my analysis by documenting a positive relationship between Airbnb penetration and backlash against tourists. For each additional tourist every 1000 residents, which represents the median impact in London, complaints against tourists increase by 2.2%.[7] 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., 2019), Amsterdam (Almagro and Domínguez-Iino, 2020), Los Angeles (Koster et al., 2019), Berlin (Duso et al., 2020) 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. However, in the context of London, I find limited evidence of this channel.

I explore the second channel documenting how neighbourhood quality is impacted by Airbnb presence. I do this in several ways. First, I show that public transports congestion, proxied by underground entries and exits flows, increases across London in areas with higher Airbnb penetration. Secondly, I document a rise in crime rates for anti-social behaviours. The estimated effects are sizeable: anti-social behaviour crime rates increase by 2.6 per cent in a ward with median Airbnb penetration. Third, complaints against rubbish in the streets increase due to Airbnb pen-

[7] However, the magnitude of the effect can vary widely given the extreme heterogeneity of Airbnb presence across London. As an example, Airbnb penetration in central London is, on average, ten times larger than in the median ward.

etration. However, it is important to underline that not all complaints are increasing, suggesting that i) residents are not complaining more in general or that, ii) local authorities are still investing in areas with high Airbnb penetration.[8] 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 to capture such heterogeneity and to unveil new patterns. To 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 rationalize these results, I highlight the differences between short-term renting and traditional accommodations in hotels. First, 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). Second, 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).[9]

Consistently with the hypotheses described, I provide evidence that negative externalities are triggered by a lack of control from Airbnb hosts. I observe fewer complaints where more families are present among Airbnb tourists, as well as in areas where most guests rent just one room and share the property with the host, rather than renting the entire property. The former result confirms that less disruptive tourists induce fewer complaints, and the latter suggests that monitoring through the presence of hosts mitigates negative behaviours from Airbnb guests. In a heterogeneity analysis, I provide evidence that complaints are decreasing when integration between tourists and residents is more likely, suggesting that more cosmopolitan areas are more prone to welcome tourists. Noticeably, I do not observe a decrease in population linked to Airbnb penetration but only minor changes in composition, reassuring that my results are not driven by specific dynamics of residents' sorting.

Finally, I provide suggestive evidence that deteriorating quality of neighbourhoods, through short-term renting, reduces social capital and residents' support for globalization. Following Guiso et al. (2016), I measure social capital by the number of charitable, youth and political organization. Using these proxies, I document that social capital and civic engagement decrease when Airbnb penetration rises. Moreover, I show that higher Airbnb penetration increases support for Brexit, suggesting a rising anti-globalization sentiment. This result provides another potential channel, on

[8]Complaints about roads' or green areas' status are not affected by Airbnb penetration.

[9]Hotel industry has an almost constant supply in the period studied and it is often heavily regulated.

top of the one already discussed in the literature (Broz et al., 2020; Eichengreen, 2018), that may fuel anti-cosmopolitan and populists sentiments. It is also consistent with Colantone and Stanig (2018), that shows how support for the Leave option in the Brexit referendum was systematically higher in regions hit harder by economic globalization.

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. (2019), Koster et al. (2019), Duso et al. (2020) 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.[10] Calder-Wang (2020) uses a structural model of residential choice to estimate the effect of the increased opportunity for landlords to rent short term for 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 presence negatively affected hotel revenues (Zervas et al., 2017; Farronato and Fradkin, 2018; Schaefer and Tran, 2020). The paper closest to mine is Rondon (2019), which focuses on electoral consequences of Airbnb penetration in Barcelona, and shows how areas with more Airbnb experience higher abstention and are more likely to vote for the party that campaigned in favour of home-sharing regulations.

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 political views. 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 guests nights over residents 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, 2020) to school quality (Bayer et al., 2007), several explanations have been advanced.[11] My contribution

[10] Differently from other studies, Koster et al. (2019) takes advantage of discontinuous regulation between Los Angles county and neighbourhood areas. Duso et al. (2020) takes advantage of policy changes in Berlin.

[11] Almagro and Domínguez-Iino (2020) uses a structural approach to study the endogenous link between amenities

is to highlight the role played by 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[12]. Not only tourists will misbehave, but their misbehaviour may induce similar responses by residents.

Finally, my work is related to the growing literature explaining how anti-globalization sentiments and social capital are shaped. Dustmann et al. (2019) shows that a larger share of refugees leads to an increase in the vote share for right-leaning parties with an anti-immigration agenda, but that this is not true in large urban municipalities. Autor et al. (2020) finds that trade-exposed electoral districts simultaneously exhibit stronger support for both radical-left and radical-right views. The results in my paper shed light on the additional channel of short-term tourism, which may shape social capital and political views, in particular looking at anti-globalization sentiments using Brexit votes. Cities have largely resisted these trends and, for this reason, results presented in this project may complement immigration and trade literature that explained these phenomenons.

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 studies the impact of Airbnb penetration on the backlash against residents and on pecuniary and non-pecuniary roots. Section 5 investigates the mechanisms behind the externalities generated by Airbnb penetration. Section 6 documents the consequences in terms of social capital and anti-globalization support. Section 7 summarizes the main robustness checks, which are then described in detail in the Appendix. Section 8 concludes.

2 Data

My analysis relies on a panel of 624 London electoral wards for years between 2002 and 2019, where each ward is uniquely assigned to a local authority (or "borough").[13] I exclude from the sample City of London local authority due to its unique characteristics. 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 presented in this Section.

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.

[12] This has been shown by comparing homeowners and long-term rentals, and it becomes even more salient if short-term renters are present (Putnam, 1993; Sims, 2007).

[13] I fix the boundaries at 2011 electoral wards. See Appendix Section A.1 for details on London administrative structure.

2.1 Airbnb Penetration

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

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

It represents the average number of tourists using Airbnb that a resident would meet in a random day in ward i and year t. The numerator in Equation (1) is computed in the following way:

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

where $Reviews_{jit}$ is the number of reviews received in year t by listing j in ward i.[14] 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 ($Nights_j$). This measure of Airbnb tourists nights produces an overall figure for 2018 that is very similar to official statistics in Airbnb (2018), 6.88 million vs 6.82 million. The denominator in Equation (1) is the number of residents in 2007 in ward i times 350, where I assume each resident spends 15 days outside London.[15]

Airbnb penetration before 2008 is set to zero, as the platform was founded in 2008 in San Francisco. Web scraped data start in 2013, which is the first year Airbnb presence become relevant in London and in most of the popular destinations (see *e.g.* Garcia-López et al., 2019). 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. (2019), Barron et al. (2020), Almagro and Domínguez-Iino (2020), Duso et al. (2020) or Koster et al. (2019), which studies

[14] I assign each listing based on latitude and longitude. Even if 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 neglectable. Since guests have 14 days maximum to fill a review, whose time of filling is, therefore, representative of the period of the visit.

[15] 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).

housing market outcomes using the number of properties listed on Airbnb website. This approach has two main advantages: i) since it considers only actual reviews, it automatically excludes listings present on 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 mechanisms and heterogeneity of my results, I identify families using Airbnb using keywords (*e.g.* ”children”, ”wife”, etc.) in the review content. Moreover, I distinguish among guests renting a room or renting an entire property. Finally, following Tzioumis (2018) I assign an ethnicity based on first name guests' ethnicity using the first name of the reviewer.

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 2018 quintiles. Exposure is decreasing with distance from the city centre, except for a cluster at the extreme west denoting Heathrow Airport area. In 2013 (see Appendix Figure C.2) Airbnb was more concentrated in the city centre and surrounding areas were overall less exposed.[16] Conversely, an analogous measure of hotel penetration for 2019 (Appendix Figure C.4) shows a higher concentration in fewer locations, mainly in Centre-West London (Westminster and Chelsea area).[17]

2.2 Outcomes of interests

Complaints against tourists I measure backlash against tourism with the number of complaints against tourists per resident. I web scrape “FixMyStreet”, an online service where residents can submit geolocalized complaints which are forwarded to the local authority in charge. Users can comment on each complaint, and I count each comment as a separate complaint when building my measure. Data collected span the period 2007-2019 and contain around 1.3 millions complaints (included comments) in 17 categories.[18] I identify complaints against tourists from the description associated with each complaint if specific keywords were used (*e.g.* ”tourist”, ”Airbnb”, etc.).

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 can capture the “voice of losers” and 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

[16]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.

[17]In Appendix Section B.2.2 I provide a detailed description on how I recover the number of hotel tourists nights.

[18]In Appendix Table C.3 I report the 17 categories. Top 4: Rubbish (23.0%), Road Status (21.4%), Fly-tipping (18.0%), Green Area Status (8.8%). FixMyStreet was founded in 2007, see Appendix Figure C.5 for aggregate take-up rates.

sentiment analysis to infer a negative attitude towards tourists.

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

Data on house prices are from UK Land Registry, which reports the details of the universe of transactions from 1995 to 2020. I match each transaction with Energy Performance Certificates to recover the size of the property, which enables me to compute the median price per square meter in ward i and year t. To guarantee representativeness, I exclude ward-year observations with less than 10 transactions.

Rent data come from Urban Big Data Centre (UBDC), with primary source being Zoopla, a popular UK property comparison-online platform. I construct the median long-term rent price for ward i in year t from 2011 to 2016.[19] Both house and long-term rental prices are adjusted using CPIH index (2015=100, source: Office for National Statistics).

Neighbourhood quality An alternative channel that may explain the observed backlash against tourists is represented by a drop of neighbourhood quality. I consider three measures of neighbourhood quality: i) a proxy for congestion, ii) the number of complaints from residents, and iii) anti-social behaviour crime rates.

I build the proxy for congestion by using Transport for London (TFL) data on all entries and exits from underground stations in each ward-year by resident population as-of 2007.[20]

As for complaints, I start from the measure described above, looking at complaints related to the local area quality, instead of that on tourists. Complaints are divided into 17 categories, and I construct the number of complaints by the resident population in 2007 in ward i in year t for each category. I further distinguish among three main types. First, complaints *susceptible to the presence of tourists and to a change in residents' behaviour* (complaints about rubbish, fly-tipping or flyposting). Second, complaints *susceptible to change in residents' behaviour* but not to the presence of tourists (complaints about car parking or dog fouling) would act as a proxy of civic engagement. Third, I consider complaints about the roads' status and green areas' status. I use this category of complaints as a *placebo group*, 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 consider the number of anti-social behaviour crimes per 2007 residents at the ward-year level. Anti-social behaviour is defined by the police as "behaviour by a person which causes,

[19] Zoopla reports advertised, not realized, rent prices. Original data are reported at MSOA-quarter level. Mapping from MSOA, an alternative geographic classification, to wards is described in B.1.2. I compute the average within year of quarterly data.

[20] For wards not containing a station but with stations within 500 meters I consider the distance squared weighted average number of entries/exits for all stations within 500 meters from ward boundaries.

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). The key difference with the previously-described complaints 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.[21]

Social capital Deteriorating quality of local amenities may reduce social capital and reduce residents' support for globalization. Following Guiso et al. (2016), I measure social capital as the number of charitable organizations per resident population in 2007.[22] Similarly, to capture how local networks within the neighbourhood evolve, I consider the number of youth and political organizations per 2007 residents. 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.[23]

Political outcomes To capture anti-globalization sentiments I leverage on the 2016 EU "Brexit" Referendum. The Brexit Referendum has been widely associated with globalization sentiments (Colantone and Stanig, 2018) and political dissatisfaction (Fetzer, 2019). BBC manually collected results at ward level, as official sources report data only at local authority level.[24] Even though a subset of local authorities is represented (14 over 33), the data feature a satisfactory level of geographic representation (see Appendix Figure C.7).

2.3 Demographic and geographic variables

I complement my dataset with various demographic variables. I collect the share of workers by sector and the share of workers by occupation (2001 Census); the share of residents by ethnicity, the share of residents by nationality, the share of residents by educational attainment, the share of homeowners (2011 Census). All variables are collected at Output Area level, which maps uniquely into wards. I also collect data on population by age group at the ward-year level from 2002 to 2018 (Office National Statistics). Caveats on 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 no-Census years). To mitigate these concerns I also collected information on the median electricity consumption at ward level as

[21] Original data are provided at the month-MSOA level. I thank CEP Community - Crime group for sharing the data with me. Appendix Section B.3.1 presents detailed definitions of anti-social behaviours.

[22] Another natural variable to consider as a proxy of social capital would be voter turnout. Three issues prevent me to use it. First, national elections 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 5 general elections from 2002 onwards, I suffer from small sample biases. Second, local elections (for which we have results at ward level) are not representative. Third, 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.

[23] There are 620 sectors and 9 categories. I thank Dr Lindsay Relihan, Nick Groome and Ordinance Survey team for their support with this data.

[24] BBC (2017), *Local voting figures shed new light on EU referendum*

an alternative proxy of population (source: UK Government, Department for Business, Energy & Industrial Strategy; 2013-2018).

Moreover, 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; the distance from each ward centroid to London 2012 Olympic Games venues, as London 2012 Olympic Games involved major renewing of certain areas; 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.

Finally, I collect public data on schools to check whether ward population composition is changing over time. At the school level, I collect data on the share of pupils in ward i and year t for which English is not the first language and the share of pupils entitled to free meals. Both variables are provided by the UK Government and 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.

3 Empirical Strategy

To study the social and economic effects of Airbnb penetration, I estimate the following model:

$$Y_{ibt} = \beta Airbnb\,Penetration_{ibt} + X_{it}\gamma + \eta_i + \delta_{bt} + \epsilon_{ibt} \qquad (3)$$

where Y_{ibt} represents the outcome of interest in ward i, local authority b and year t, and *Airbnb Penetration* is the measure described in section 2.1. X_{it} is a rich set of interactions between year dummies and 2001 share of workers by sector, 2001 share of workers by occupation, 2001 log of house prices per square meter, distance from ward centroid to Charing Cross, distance from ward centroid to the closest London 2012 venue, 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 and compared to wards with similar pre-determined and geographical characteristic in a given year.

Standard error computation follows Conley (1999), Conley (2010) and Hsiang (2010). I consider a spatial correlation parameter of 14 km and a serial correlation parameter of 10 years.[25]

[25] 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 3 complete local authorities from each ward centroid. For the autocorrelation parameter, I consider 10 years as Airbnb started in London in 2009.

Two opposite forces may be at force to 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 (3).

To address these concerns, I instrument Airbnb penetration following a shift-share IV strategy as in Garcia-López et al. (2019), Barron et al. (2020) or Almagro and Domínguez-Iino (2020). The "share" part of the IV exploits spatial variation from the spatial distribution of historical monuments and buildings per square kilometres, 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".[26]

$$Airbnb\,Penetration_{it} = Historical\,Sites_i \times Google\,Trend\,Airbnb_t \tag{4}$$

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 (see also Goldsmith-Pinkham et al., 2020 and Borusyak et al., 2020). This assumption can be violated if the characteristics of wards with the higher number of historical monuments had persistent confounding effects on tourism patters as well as on changes in the outcomes of interest.

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 dummies and several 2001 wards characteristics and proxies of "centrality" that might be linked to a higher number of historical monuments and may have had a time-varying

Note that Greene (2018) recommends at least $T^{0.25}$, even considering the longest panel (2002-2019) I am being more conservative. Results are similar by changing parameters value and by considering clustering at local authority level as described in Appendix Section D.7 and reported in Appendix Figure E.5.

[26] In Appendix Figure C.8, I plot the geographical distributions of historical monuments and buildings, notably they are not only concentrated in the city centre. In Appendix Figure C.9, I plot the time evolution of trend for the word "Airbnb" according to Google, denoting a stable growth over time.

effect on economic and social conditions across wards.

In terms of instrument relevance, in all my specifications, I obtain a strong first stage relation. Table 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 only ward and year FE. In column 2 I introduce local authority flexible time trends while, in Columns 3 and 4, I progressively include the set of controls interacted with year fixed effects. Column 4 reports my baseline specification. 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.

4 Impact of Airbnb on the neighbourhood

This Section outlines the first set of contributions of this paper. First, Airbnb penetration is associated with backlash from residents (Section 4.1). Second, I study what the causes of observed backlash against tourists are in relation to Airbnb penetration, in particular looking at pecuniary and non-pecuniary channels. While house and long-term prices react only marginally in the London context (Section 4.2), Airbnb penetration is associated with a decrease in neighbourhood quality (Section 4.3).

4.1 Backlash against Tourism

Abundant anecdotal evidence suggests that the increase in short-term renting in London has fueled residents' discontent. Airbnb, as one of the earliest and most widespread players, has been often accused to foster "touristification" and "killing" city centres.[27] Motivated by this discussion, in Table 2, I study the effect of Airbnb penetration on the number of complaints against tourists per person received by local authorities. Throughout the paper, Panels A and B always present, respectively, OLS and IV estimates. I also report the KP F-stat for weak instruments and years considered for each specific outcome variable.

Column 1 and 2 of Table 2 report the effect on the baseline measure of complaints against tourists, the log of complaints per 2007 residents. The coefficient in Column 2, Panel B, implies that an increase of one Airbnb tourist every 1000 residents increases complaints against tourists by 2.2%, while over the 2013-2019 period complaints against tourists grew on average by 7%. The positive relation between Airbnb penetration and complaints against tourists is invariant to the exclusion of the rich set controls interacted with year fixed effects described in Section 3 (Column 1), to the use of a logarithm version of the penetration measure (Column 3), and the result still holds

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

when looking at i) a dichotomous dependent variable taking value one if there has been at least one complaint against tourists in the ward i in year t (Column 4), or ii) including in the complaints measure only the original complaint and not all the subsequent comments to it (Column 5).

I consider an increase of one more tourist using Airbnb every 1000 residents which represents the median growth the period 2013-2019. The growth of Airbnb has been a common phenomenon across all wards (see Figure 1) but with substantial heterogeneity, with central London experiencing a growth ten times larger than the median ward. An increase of one tourist every 1000 residents can also be interpreted as one more tourists within 150 meters when taking into account London density.

This result confirms 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 more standard measures typically used in the political economy (*e.g* vote shares) or in the urban economics (*e.g* house prices) literature, as they would capture just a net effect. My outcome variable, on the contrary, can capture the "voice of losers" and those unhappy with the status quo, even when these groups represent a minority, whose discontent would not be captured by previously cited measures.

Finally, it is worth commenting on the fact that IV estimates are stronger in magnitude than OLS. The downward bias of OLS can be rationalized by i) omitted factors are negatively related to the number of complaints, and ii) locations of rising Airbnb are positively selected. The most likely omitted factor is a positive trend experienced by certain neighbourhoods, which is likely to reduce overall complaints. I provide suggestive evidence on positive selection of popular Airbnb neighbourhoods by showing that average 2013 amenities are higher in areas in the top quartile of 2019 Airbnb penetration than in the bottom quartile (Appendix Table E.3).[28]

Motivated by this evidence I proceed in my analysis and study the roots of such backlash. There exist at least two explanations for this finding. First, discontent might arise from the impact that a permanent shift in housing supply from long- to short-term rent has on prices, which is a channel I explore in the next Section. Second, the high turnout of tourists in residential areas might affect the quality of the neighbourhood, which I discuss in Section 4.3.

4.2 Housing market

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

[28]Similar results holds if I consider 2007. The choice of setting 2013 as "initial period" is based on the fact that before 2013 Airbnb penetration was limited, as reported also in Garcia-López et al. (2019), and on data available as outcomes of interest.

outcomes. Results are presented in Table 3. Interestingly, when looking at the IV specification with full controls (Panel B), I find no statistically significant effects of Airbnb penetration on both house prices and long-term rents.

In Column 1, I consider the impact of Airbnb penetration on the log of the median house price per square meter. OLS estimate implies a statistically significant increase in house priced by 0.2% for every additional tourist by 1000 residents, but the effect becomes statistically not different from 0 when looking at IV specification. Over 2013-2019 the median ward experienced a 30% growth rate in house prices, suggesting that Airbnb has only a limited impact, if any, on house prices in London. In column 3, I study the effect of Airbnb penetration on house prices without any rescaling by house size. Results are fully consistent. This also confirms the fact that previous evidence is not driven by the fact that, when presenting results for price-per-square-meter, I am just focusing on properties for which I can retrieve property size matching transaction data with energy certificates.[29]

Similarly, I find no effect of Airbnb penetration on long-term rents ask prices, which I measure in Column 4 by the median rent at the ward level. This is very interesting considering that the median ward experienced an 8 per cent growth rate in long-term rents over 2013-2016.

These results depart from previous literature, which found a positive and significant effect of Airbnb penetration on house prices and rents. However, my findings are robust to using alternative measures of Airbnb penetration closer to the ones proposed by the literature. In column 2 and 5, I look at the impact of the number of entire Airbnb properties over the number of dwellings in 2011 (see Appendix Section B.2.1 for details on how I construct this measure) on house prices and rents, respectively. Consistently with the literature, the magnitude of the coefficients using this alternative measure is bigger, but estimates remain not statistically different from 0. This suggests that an additional explanation for this discrepancy may rely on how standard errors are computed, as I explicitly allow for correlation over space and time. As described in Appendix Section D.7, just clustering at ward or local authority level may deliver standard errors too narrow.

Just looking at house prices in London, and assuming house prices internalize all benefits and costs for residents, we may be tempted to conclude that Airbnb has no effect on the welfare of residents or, looking at previous studies, that Airbnb has a positive effect. Heterogeneity of the impact of Airbnb across population subgroups is key to reconcile such zero effect 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

[29]Consistent with above discussion when looking at house prices, OLS suffers from an upward bias. A positive trend in neighbourhood quality in certain neighbourhoods is positively correlated with both house prices and Airbnb penetration, which positively biases my estimates for β. This was not the case for recent evidence for Amsterdam in Almagro and Domínguez-Iino (2020) or for the entire US in Barron et al. (2020), which find downward biased OLS estimates.

average effect: while few homeowners benefit from the rise in house prices values, many long-term renters are paying the cost.

Moreover, among Airbnb hosts in London, only half are reporting to live in London and around 3 per cent controls 43 per cent of all Airbnb listings in 2019, suggesting a high level of professionalism which may contribute to a rising inequality not captured by measures such house prices.[30]

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

4.3 Neighbourhood quality

In this Section, I explore the impact of Airbnb on neighbourhood quality as a source of backlash against tourists. This effect may arise for two key distinctive characteristics that differentiate short-term renting from hotel accommodations.

First, Airbnb supply can adjust almost immediately to market demand (Farronato and Fradkin, 2018).[31] 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 to a *quantity* externality.

Second, neither hosts nor Airbnb monitors guests during their visits.[32] 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 when in the property but also in the local area due to the lack of any verification procedures.[33] I call this a *quality* externality.

Congestion In Column 1 of Table 4, I provide evidence regarding the first type of externality. An increase of 1 tourist per 1000 residents increases the number of entries and exits per resident by 0.6 per cent, which is sizable given the almost constant average usage of underground services over the last decade. This result is particularly interesting in London, where underground represents the major system of transportation, with 4 millions of passenger journeys every day (Larcom et al., 2017).

Entries and exits may not be representative of actual congestion if the supply of trains increases. However, using aggregated data from TFL (Appendix Table C.6) I show that this is not the case,

[30] I define "professional" every host that manages more than 5 listings.

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

[32] Airbnb advertise its service saying that guests can "live like a local" and "feels like at home".

[33] "Airbnb Party flats" are a well know 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 by damages. Moreover consider that in a hotel an ID and a payment card is immediately registered, in Airbnb everything is carried online posing a question of traceability.

i.e. supply does not change, with more than half of the lines not increasing operated kilometres in 2006-2019 period, and the ones that increased their supply doing so in relation to the opening of new portions of the network, or to the start of night service.

Complaints about local area To document the *quality* externality, I report the impact on the number of complaints related to the local area quality per resident in Table 4. In Column 2 I consider my preferred measure: the log of the number of complaints about rubbish per resident. The IV specification shows that an increase in Airbnb penetration is associated with a 2.8 per cent increase in complaints, confirming a decline in neighbourhood quality. In Columns 3 and 4 I consider alternative measures, complaints regarding fly-tipping and flyposting, respectively, with similar results.

As discussed in Section 2, these measures are susceptible to both tourists and residents negative behaviours and in Section 6 I explicitly discuss how the presence of short-term tourists may reduce civic engagement by local citizens.

Finally, to be able to claim that these complaints are linked with a lower quality of local area I rule out that: i) local authorities, which are in charge of waste collection, do not have stopped investing in these areas, or ii) residents are generally complaining more. This is what I do in Table 4, where I try to look at the effect of Airbnb penetration on complaints about road status (Column 5) and green area status (Column 6), which are 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. Consistently with my prior, I find no effects.

Anti-social behaviours crime rates To further document the *quality* externality, in Column 7 of Table 4, I document how an increase in Airbnb penetration is associated with a 2.6 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.

Comparing this result to the magnitudes usually uncovered by the crime literature, I find this is a sizable 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 1.5 tourists per 1000 residents, which is close to the 60$^{\text{th}}$ percentile in the Airbnb penetration measure in 2019.

5 Mechanisms and heterogeneity of backlash

Once established that i) Airbnb penetration is associated with more complaints regarding tourists and ii) negative externalities on congestion and neighbourhood quality are a potential root of this backlash, I provide evidence on why the absence of monitoring causes rising backlash (Section 5.1), as discussed in Section 4.3. In addition, in Section 5.2, I document how Airbnb does not affect the population in London wards, ruling out the possibility that residents' movements drive my results (Section 5.2). Finally, in Section 5.3, I provide evidence about the heterogeneity of the results depending on the ethnic composition of the neighbourhood.

5.1 Monitoring

To back the intuition that lack of monitoring 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 present two results. First, complaints are reduced when monitoring is less important as tourists are less disruptive (families). Second, the same happens when monitoring is easier because hosts are present (room renting). I consider the following specification:

$$Y_{ibt} = \beta_1 Airbnb\, Pen_{ibt} + \beta_2 Airbnb\, Pen_{ibt} * HD_{ibt} + \beta_3 HD_{ibt} + \gamma X_{it} + \eta_i + \delta_{bt} + \epsilon_{ibt} \quad (5)$$

where $Airbnb\, Pen$ represents the Airbnb penetration measure described in Section 2 and and HD is a dummy variable capturing the heterogeneous effects of either i) families or ii) room renting. The definition of such dummy for the two cases is specifically described below. As in the main specification, I instrument Airbnb penetration with the usual shift-share instrument described in Section 3 and the interaction $Airbnb\, Pen * HD$ with the interaction between the instrument and the HD dummy.[34]

Families In Table 5 Column 1, I interact Airbnb penetration with a dummy equal to one when 15 per cent or more tourists are part of a family. Consistent with the idea that monitoring is an issue in the Airbnb context, and assuming families are more prone to behave properly, I find that when more families are present, Airbnb penetration is associated with 1.2 per cent fewer complaints.[35]

This result also dampens an alternative explanation of my results. One could argue that the

[34] Equation (5) is generic. In some of results described below HD will be constant, and it will be then absorbed by ward fixed effects. This specification is extremely demanding and 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 10 years.

[35] See Section 2 for how I defined families. The average share of families tourists-nights present in my sample in 2017-2018 is 12 per cent, while according to Airbnb (2018) families represent 14 per cent of total guests. Sample size drops because, by definition, I need Airbnb tourists to be present in the area and this may not be the case in the first years of Airbnb presence in London.

observed misbehaviours arise due to a lack of repeated interactions among neighbours and lack of knowledge of local rules due to the high turnout of residents. However, if that was the case, we should find no differences when comparing more or less disruptive types of tourists, as what would drive the results is this lack of cohesion rather than a negatively selection. The fact that when tourists are not negative selected, assuming families properly behave, suggests, however, that this alternative explanation of lack of cohesion is less likely to hold.

Room renting On Airbnb a guest can either rent an entire property or just a room. In Table 5 Column 2, the heterogeneity dummy equals one if the share of guests-nights renting just a room is greater than 50% of the total Airbnb tourists-nights. Results show that the number of complaints in the area decreases by 1.2 per cent 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. Average price per night per room in an Airbnb accommodation is 70 £ 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 (55 *vs.* 96 when considering per room prices). If negative selection is simply 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 2, Table 5 suggests that, when most tourists in the area are renting just rooms, there are fewer complaints in the area.

5.2 Exit or complain?

A natural consequence of the decline in neighbourhood quality may be that residents decide to leave the area. These movements may drive my results if not orthogonal to Airbnb penetration, as in a "vote with your feet" framework (Tiebout, 1956). This would be certainly true in a frictionless city, however, constraints as homeownership and school enrollment may limit movements and increase complaints (Hirschman, 1970). In the data, I observe no change in ward population, as reported in Column 1 of Table 6. In Columns 2 to 5, I check whether the age composition of ward population is affected. I just observe minor changes in the age structure, with fewer residents below 18 (Column 2), and few more aged 25-34 (Column 4).[36]

[36]Results are confirmed when using, as an alternative proxy, the median electricity consumption in the ward. This is important as population estimated measures from ONS may suffer from profound forecast biases, see Suárez Serrato and Wingender (2016) as an example in the US context.

Pupils composition To further verify whether neighbourhood composition is affected, I consider the impact of Airbnb penetration on i) the ward-specific share of pupils for which English is not the primary language, and ii) the ward-specific share of pupils entitled to a free meal registered in a school. In both cases, I find no statistically significant results, as reported by Columns 6 and 7 of Table 6. This is also consistent with the idea that residents with higher constraints are less likely to move. School admission is a relevant constraint to movings given that most schools in London run admission locally with small catchment areas.

Homeowners Consistent with the idea that more constrained individuals are less likely to move and file a complaint instead, I find more complaints in areas with higher homeownership. In Column 8 of Table 6, I interact, in Equation (5), Airbnb penetration with a dummy equal to 1 if the share of residents owning a flat according to 2011 Census is above the median London value. I find that, in wards where homeownership is above the median, each additional Airbnb tourist per 1000 residents increases complaints against tourists by 2% more than in wards below the median.

5.3 Cosmopolitan areas

Diversity is a recognized driver of social divisions (Easterly and Levine, 1997; Alesina et al., 1999). We may expect, in parallel with migration literature (Dahlberg et al., 2012; Tabellini, 2020), fewer complaints against tourists if i) local areas are more cosmopolitan, and ii) ethnic distance between tourists and residents is lower.

First, in Column 3 of Table 5, I show that the number of complaints is lower in areas with higher ethnic diversity. I show this by interacting Airbnb penetration with a dummy equal to one if the 2011 ward ethnic fractionation index is above the median value for London.[37] The coefficient on the interaction term is negative, and it suggests that more cosmopolitan areas are more prone to welcome tourists. The result holds also when the fractionalization index is based on the share of 2011 nationality composition of the local area (Column 4).

Second, I study the heterogeneity driven by the ethnic distance between Airbnb tourists and resident. I construct a dummy that equals one if, in a given ward-year, most of the residents are of ethnicity j and most of the Airbnb tourists are from an ethnicity different from j, for a given j.[38] Therefore the dummy takes value one when the ethnic distance is wider. Table 5 Column 5 shows that diversity in composition between tourists and residents drives up the complaints as well.

An alternative explanation for the above results is that residents may be complaining about

[37] Following a vast literate (Alesina and La Ferrara (2005)), I consider as an index of ethnic fractionalization: $ELF_i = 1 - \sum_j sh_i^j$ where sh_i^j is the share of the ethnic group j over total population according to 2011 Census in ward i.

[38] Consider for example black as ethnicity. This ethnic distance dummy is equal to 1 if the ward i is above median when looking at 2011 share of black residents and when the ward-year is above median when looking at the share of non-black Airbnb tourists visiting.

the influx of certain ethnicities, rather than about the presence and negative behaviours of tourists. Studying properly this hypothesis is appealing but goes beyond the purpose of this paper and it is an interesting avenue for future research. Literature has focused on peer-to-peer discrimination from the user perspective. Both black male hosts (Edelman and Luca, 2014) and black male guests (Edelman et al., 2017) are discriminated in the Airbnb platform. Similar results have been found regarding Uber and Lyft (Ge et al., 2020). Still very little is know on how peer economies may be related to local discrimination.

6 Consequences of Airbnb penetration

I have studied the roots and mechanisms of backlash of Airbnb penetration. In this Section, I study how the deterioration of local neighbourhoods due to Airbnb can have profound effects on social capital (Section 6.1) and attitudes towards globalization (Section 6.2).

Social capital has been used to explain an impressive range of phenomena (economic growth Knack and Keefer, 1997; institution's design and performance Djankov et al., 2003, etc.). Similarly, recent waves of populism have profound consequences in our societies and cities, when compared to rural areas, have largely resisted this trend (Broz et al., 2020; Rodden, 2019). It is then particularly important to shed light on the social and political consequences that the inflow of tourism through short-term renting may trigger in cities.

Evidence presented in this Section confirms the concerns of the many who oppose this new wave of tourism (the media even refer that to that as "overtourism"): such a high turnout of temporary residents is harmful for social capital formation, local networks formation, civic engagement and may favour anti-cosmopolitan sentiments.[39]

6.1 Social Capital

In Table 7 I study the impact of Airbnb penetration on social capital measures. In Column 1, I document the effect of Airbnb penetration on the number of charitable organizations (Guiso et al., 2016) following Airbnb penetration. Looking at Panel B, an increase of 1 Airbnb tourist per 1000 residents is associated with a drop of 2.1 per cent in the number of charitable organization per resident. Moreover, as shown by Columns 2 and 3, the number of youth organization per resident and the number of political organizations, proxies for local networks formation and civic engagement, drop by 0.6% and 0.5% respectively, when looking at full IV specification.

Residents' behaviour Consistently 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 4 and 5 of Table 7, I report the impact of Airbnb penetration on

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

complaints on car parking and dog fouling, which are two types of misbehaviour intimately linked to residents and unaffected by the presence of tourists.

In both cases I observe an increase of misbehaviour by residents: Airbnb penetration not only has a direct impact on neighbourhood quality due to the presence of tourists but it 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).

6.2 Brexit

Finally, I directly explore the political consequences or Airbnb penetration. In Table 7, I study its impact on the share of citizens supporting Brexit at the 2016 EU Referendum. Given the nature of the referendum, I cannot exploit the panel structure of my data but the empirical strategy remains similar. I estimate the following equation:

$$Y_{ib} = \beta Airbnb\, Penetration_{ib} + \gamma X_i + \delta_b + \epsilon_{ib} \tag{6}$$

where Y_{ib} is the vote share of leave option in 2016 Brexit EU referendum, $Airbnb\, Penetration_{ib}$ represents the Airbnb penetration in 2016, X_i is a set of ward level characteristics, and δ_b are local authority fixed effects. I instrument $Airbnb\, Penetration_{ib}$ with the shift-share IV described in Section 3 and I progressively increase the set of controls.

In Column 6, I include local authority fixed effects, the distance from the ward centroids to Charing Cross, and the distance from ward polygon to the closest underground station. Moreover, I control for the 2011 share of residents with a university degree, and the 2011 share of the population over 65, as these two factors have been shown to be determinant in predicting Brexit support. I find a positive and significant coefficient on both OLS and IV specifications.

In Column 7, I include the 2011 share of residents from the United Kingdom, 2011 share of residents from the European Union, and 2011 share of residents from the Commonwealth countries and the 2011 share of white residents. Looking at Column 7, an increase of 1 Airbnb tourist per 1000 residents is associated with an increase of 0.59 percentage points for Brexit support. The magnitude of this effect is quantitatively very relevant: it is equivalent to the impact of an increase by 1 percentage point of the share of university graduates, which is commonly recognized as a key factor in determining Brexit support.

A potential concern of this result is that, given its cross-sectional nature, I cannot control for fixed characteristics of the neighbourhood. Nevertheless, I control for all the major factors that the literature has described to be relevant for Brexit support: ethnic, age, and education composition (Colantone and Stanig, 2018; Fetzer, 2019), which takes care of most of the identification constraints.

Future research should take advantage of individual or household level surveys to study in even greater depth the impact of Airbnb penetration on perceptions over local neighbourhoods, trust in people, civic engagement, and political views.

7 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.

In Appendix Section D.1 I discuss the robustness of first stage results reported in Column 4 of Table 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 trend for "Airbnb London". Second, I test alternative specifications for the first stage. Third, I construct alternative measures of Airbnb presence. Appendix Table E.2 shows that results are robust in each of these cases. Finally, I verify the robustness of Column 4, Table 1 by i) modifying the starting year of analysis and ii) excluding one local authority at the time.

In Appendix Section D.2, D.3 and D.4, I replicate the OLS and IV specifications of Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (Column 1) using measures of Airbnb penetration built in different ways. Results are robust. 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.4).

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 for results on underground congestion, for which, however, I have a very short panel dataset (Appendix Table D.3).

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., 2019); Barron et al., 2020). My results do not change (Appendix Table E.6).

In Appendix Section D.5, I discuss whether my identification strategies (both OLS and IV) captures waves of hotel tourism rather than Airbnb tourism. I provide various evidence to show that it is not the case. First, hotel industry penetration is almost constant, therefore, fully 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, the instrument proposed does not predict hotel tourism penetration (see Appendix Section B.2.2 for details on how I construct this measure). Fourth, adding hotel tourism penetration as a regressor alters neither the significance nor the magnitude of my results (Appendix Table E.7).

In Appendix Section D.6, I explicitly take into account the seasonality of tourism flows by considering a monthly version of Equation (3). Results for complaints measures and anti-social behaviour crime rates - the only outcome for which I can credibly estimate a monthly regression - are presented in Appendix Table E.8. All results are in line with the baseline yearly specification, suggesting that even when taking into account monthly trends, Airbnb penetration is still associated with more complaints and a drop in neighbourhood quality.

In Appendix Section D.7 I discuss parameter choice (14 km and 10 years) for standard errors correction following Conley (1999), Conley (2010) and Hsiang (2010). Results are similar by changing parameter values and by considering clustering at ward or local authority level. However, not taking into account flexible spatial and time correlation (*i.e.* just clustering) may deliver standard errors too narrow, with the consequence of not significantly different from zero estimates being wrongly interpreted (Appendix Figure E.5).

Finally, in Appendix D.8, I discuss multiple hypothesis testing procedures that I run to ensure that my results are not false rejections of the null of no statistical significance. Results are presented in Appendix Table E.9. 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.

8 Conclusions

In this paper, I examine the backlash against tourists, a phenomenon which has increased dramatically across European cities in recent years, and I interpret as a form of urban backlash against globalization.

Before Covid19 pandemic, tourism flows management was at the forefront of the political debate, and tourists met increasing opposition on both economic and social grounds in many popular locations, especially in Europe. In this paper, I exploit variation in the number of Airbnb tourists received by London neighbourhoods between 2002 and 2019 to jointly study the consequences of mass short-term tourism inflow.

Using a panel dataset with unique features in terms of information richness and spatial disaggregation, and demanding OLS and IV specifications, I find that Airbnb tourism triggered hostile reactions. Exploring the causes of such backlash, I provide evidence that resident backlash is unlikely to have only pecuniary roots, as the impact of Airbnb penetration on the housing market and long-term rents is, on average, limited.

The main driver of backlash is, instead, declining neighbourhood quality. I find that Airbnb penetration increases congestion of the underground system, complaints by residents on the local area, and anti-social behaviour crime rates. Exploiting variation in the type of tourists and type of accommodations chosen, I document that residents' backlash is lower if tourists are less "disruptive" (*i.e.* families) or more monitored (*i.e.* hosts are present as they rent just a room), suggesting that lack of control as a potential key difference between Airbnb and hotel tourism.

In terms of long-term consequences, findings show how a higher Airbnb penetration is associated with decreasing social capital, lower civic engagement, and larger support for anti-globalization views. These results are particularly important given the urban context studied, with cities that have largely resisted populist trends (Broz et al., 2020; Rodden, 2019), and open up the way for a new avenue of research.

These set of results reconcile with the vast literature that has studied the rising backlash against globalization (see Mudde and Kaltwasser, 2017; Margalit, 2019 and Guriev and Papaioannou, 2020 provide thorough reviews of the existing literature). 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 and foster anti-globalization sentiments confirms that it can have profound effects on social dynamics and political views.

My results suggest that monitoring is crucial to guarantee future sustainable development of the touristic industry and to avoid disruptive consequences for residents.

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. The cross-cities comparison becomes particularly relevant to get a deeper understanding of the link between tourism, populism 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 Covid19 era, it will be important to regulate tourists 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 costs flights allow high flexibility in location choices and this is why these are important phenomena to monitor.

Tables and Graphs

Table 1: **First Stage**

	Airbnb Penetration (x1000)			
	(1)	(2)	(3)	(4)
Historical Sites x	1.331	0.712	0.538	0.527
Google Trend/100	(0.142)***	(0.085)***	(0.076)***	(0.075)***
Observations	11232	11232	11232	11232
R-Squared	0.553	0.762	0.804	0.808
F-Stat FS	88.0	70.0	50.1	49.3
Ward FE	X	X	X	X
Year FE	X			
LLA x Year FE		X	X	X
Vars 2001 x Year FE			X	X
Geo x Year FE				X
Years	2002-2019	2002-2019	2002-2019	2002-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. *Airbnb penetration* represents the 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 I include year and ward fixed effects. In Column 2 I include ward fixed effect and local authority time trends. Column 3 adds to Column 2 the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter. Column 4 adds to Column 3 the interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue 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 10 years. *** p<0.01; ** p<0.05; * p<0.1.

Table 2: **Backlash against tourists**

	ln(Complaints against tourists per resident (x1000))		Complaints against tourists per resident (x1000)	At least one complaint against tourists per resident	ln(Complaints against tourists per resident (x1000)) - No comments
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
Airbnb Penetration (x1000)	0.008	0.008	0.022	0.006	0.006
	(0.004)**	(0.004)**	(0.011)*	(0.002)***	(0.003)**
Panel B: IV					
Airbnb Penetration (x1000)	0.017	0.022	0.074	0.021	0.017
	(0.009)*	(0.012)*	(0.039)*	(0.010)**	(0.009)*
Observations	8112	8112	8112	8112	8112
F-Stat FS	66.8	43.7	43.7	43.7	43.7
Ward FE	X	X	X	X	X
LLA x Year FE	X	X	X	X	X
Vars 2001 x Year FE		X	X	X	X
Geo x Year FE		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. *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Instrument in Panel B is *Historical Sites per km*^{2} *times Airbnb Google Trend/100*. *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Dependent variable in Columns 1 and 2 is the log of complaints against tourists per 2007 residents. In Column 3 I consider the complaints against tourists per 2007 residents. In Column 4 a dummy equal to 1 if at least one complaint was lifted against tourists in the ward-year. In Column 5 I exclude from the number of complaints the comments received by the original complaint. To avoid taking the log of a zero, one is added to the number of complaints before taking logs in Columns 1, 2 and 5. In Column 1 I include ward fixed effect and local authority time trends. Columns 2 to 5 add the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter and interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to 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 10 years. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 3: **Housing Market**

	ln(Median house price per sqm)		ln(Median house price)	ln(Median rent)	
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
Airbnb Penetration (x1000)	0.002		0.009	0.004	
	(0.001)**		(0.001)***	(0.002)*	
Entire properties		0.008			0.014
over dwellings (x100)		(0.002)***			(0.008)*
Panel B: IV					
Airbnb Penetration (x1000)	-0.003		0.006	0.003	
	(0.002)		(0.006)	(0.005)	
Entire properties		-0.014			0.018
over dwellings (x100)		(0.009)			(0.032)
Observations	11231	11231	11231	11231	3514
F-Stat FS	46.1	19.5	47.5	47.5	18.0
Ward FE	X	X	X	X	X
LLA x Year FE	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X
Geo x Year FE	X	X	X	X	X
Years	2002-2019	2002-2019	2002-2019	2011-2016	2011-2016

Note: The sample includes a panel of 624 electoral wards in Greater London. *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Columns 2 and 5 consider as a measure of Airbnb presence the number of entire properties listed on Airbnb over the number of dwellings in 2007. Instrument in Panel B is *Historical Sites per km*^{2} *times Airbnb Google Trend/100*. Dependent variable in Columns 1 and 2 is the log of median house prices per m^2 (transaction price, source: UK Land Registry). In Column 3 I consider log of median house prices. In Columns 4 and 5, I consider the average of the quarterly median monthly asking rents (source: Zoopla from UBDC). In all columns, I include ward fixed effect and local authority time trends, the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter and interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to the closest London 2012 venue and distance ward to 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 10 years. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 4: **neighbourhood quality**

	ln(Entry and exit in tube per resident)	ln(Complaints per resident (x1000)) Rubbish	Fly-tipping	Flyposting	Road status	Green area status	ln(Anti Social behaviour per resident (x1000))
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Airbnb Penetration (x1000)	0.003	0.014	0.007	0.007	0.006	0.000	0.004
	(0.001)***	(0.004)***	(0.005)	(0.004)	(0.004)	(0.002)	(0.001)***
Panel B: IV							
Airbnb Penetration (x1000)	0.006	0.029	0.028	0.048	0.010	-0.004	0.026
	(0.003)*	(0.015)**	(0.014)**	(0.020)**	(0.014)	(0.005)	(0.007)***
Observations	3640	8112	8112	8112	8112	8112	5616
F-Stat FS	24.7	43.7	43.7	43.7	43.7	43.7	36.9
Ward FE	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X
Years	2007-2017	2007-2019	2007-2019	2007-2019	2007-2019	2007-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Instrument in Panel B is *Historical Sites per km^2 times Airbnb Google Trend/100*. Dependent variable in Column 1 is the log of entry and exit from underground stations in the ward per 2007 resident (source: TFL). In Columns 2 to 6, I consider the log of complaints per 2007 residents by category (source: FixMyStreet). In Column 7 I consider the log of anti-social behaviour crime per 2007 residents (source: Police statistics). All columns include ward fixed effect, local authority time trends and the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter and interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to the closest underground station. To avoid taking the log of a zero, one is added to the dependent variables before taking logs in Columns 2 to 6. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 10 years. *** p<0.01; ** p<0.05; * <0.1.

Table 5: **Mechanism - Monitoring and Inclusion**

	ln(Complain against tourists per person (x1000))				
	(1)	(2)	(3)	(4)	(5)
Panel A: IV					
Airbnb Penetration x	-0.003	-0.008	-0.006	-0.032	0.006
Heterogeneity dummy	(0.002)	(0.002)***	(0.003)**	(0.018)*	(0.004)
Airbnb Penetration (x1000)	0.008	0.008	0.011	0.049	0.003
	(0.004)**	(0.004)**	(0.005)**	(0.025)*	(0.000)***
Heterogeneity dummy	0.002	0.011			0.002
	(0.004)	(0.004)***			(0.004)
Panel B: IV					
Airbnb Penetration x	-0.012	-0.012	-0.012	-0.041	0.017
Heterogeneity dummy	(0.005)**	(0.003)***	(0.005)**	(0.022)*	(0.007)**
Airbnb Penetration (x1000)	0.018	0.021	0.020	0.064	0.007
	(0.014)	(0.016)	(0.011)*	(0.032)**	(0.007)
Heterogeneity dummy	0.011	0.011			-0.010
	(0.005)**	(0.004)***			(0.006)
Heterogeneity considered	More 15 pct families	More 50 pct no flat	ELF - ethnicity	ELF - nationality	Discrepancy ethnicity
Observations	4531	4531	8112	8112	4531
F-Stat FS	6.9	9.0	9.9	9.4	9.1
Ward FE	X	X	X	X	X
LLA x Year FE	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X
Geo x Year FE	X	X	X	X	X
Years	2010-2019	2010-2019	2007-2019	2007-2019	2010-2019

Note: The sample includes a panel of 624 electoral wards in Greater London. *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Instrument in Panel B is *Historical Sites per km*^{2} *times Airbnb Google Trend/100* and its interaction with the heterogeneity dummy. Dependent variable is the log of complaints against tourists per 2007 residents. *More 15 pct families* is a dummy equal to 1 if more than 15% of tourists-nights recorded in the ward-year are assigned to a family. *More 50 pct non-entire property* is a dummy equal to 1 if more than 50% of tourists-nights recorded in the ward-year are spent not in entire property. *ELF - ethnicity* is a dummy equal to 1 if, in 2011, the ward has an ELF index (based on ethnicity) above the median. *ELF - nationality* is a dummy equal to 1 if, in 2011, the ward has an ELF index (based on nationality) above the median. *Discrepancy ethnicity* is a dummy equal to 1 if the ward i is above median when looking at 2011 share of ethnicity j residents and when the ward-year is above median when looking at the share of non j ethnicity Airbnb tourists visiting. All Columns include ward fixed effect, local authority time trends, the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter and interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to the closest underground station. To avoid taking the log of a zero, one is added to the number of complaints before taking logs. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 10 years. *** p<0.01; ** p<0.05; * p<0.1.

Table 6: **Population and composition**

	ln(Total Population)	Share of population 0-18	19-34	35-64	65+	Share of pupils first lang. not English	free meals	ln(Complain against tourists per person (x1000))
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
Airbnb Penetration (x1000)	0.002	-0.072	0.103	-0.025	-0.006	0.168	0.010	0.008
	(0.001)**	(0.031)**	(0.043)**	(0.027)	(0.012)	(0.071)**	(0.031)	(0.004)**
Airbnb Penetration x								0.001
Share homeowners above median								(0.001)
Panel B: IV								
Airbnb Penetration (x1000)	0.009	-0.113	-0.100	0.211	0.001	-0.126	0.318	0.022
	(0.006)	(0.054)**	(0.155)	(0.111)*	(0.056)	(0.367)	(0.220)	(0.012)*
Airbnb Penetration x								0.020
Share homeowners above median								(0.012)*
Observations	10608	10608	10608	10608	10608	5595	5595	8112
F-Stat FS	39.9	39.9	39.9	39.9	39.9	34.2	34.2	7.2
Ward FE	X	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X	X
Years	2002-2018	2002-2018	2002-2018	2002-2018	2002-2018	2011-2019	2011-2019	2007-2019

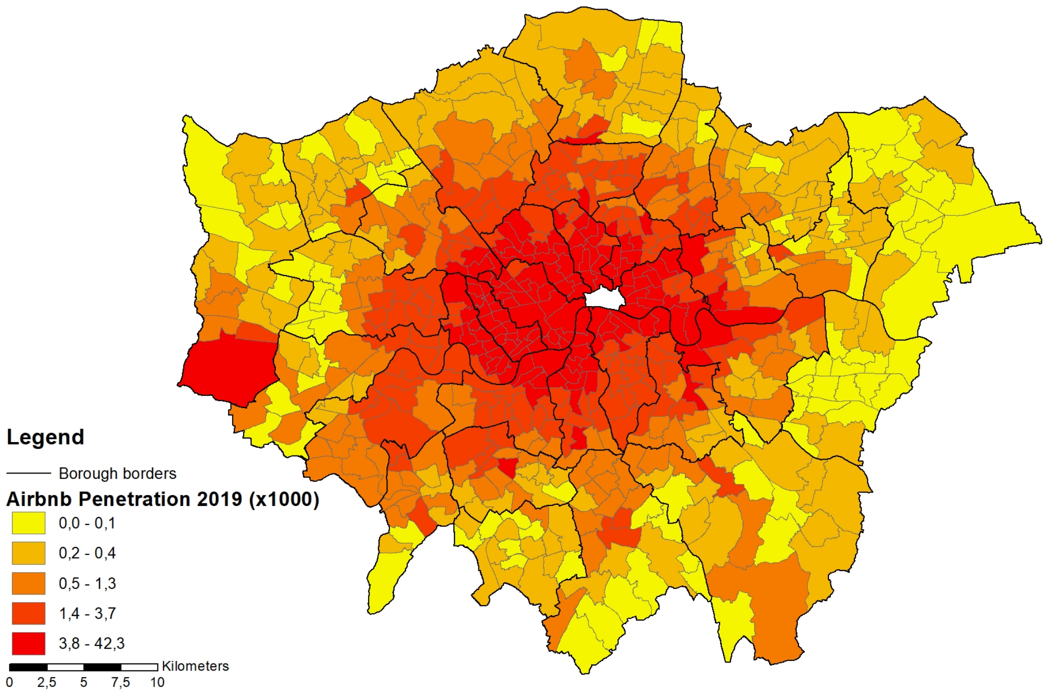
Note: The sample includes a panel of 624 electoral wards in Greater London. *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Instrument in Panel B is *Historical Sites per km^2 times Airbnb Google Trend/100* and its interaction with the heterogeneity dummy. Dependent variable in Column 1 is the log of ward population. In Column 2 to 5, it is the share of population by age group. In Column 6 and 7, it is the share of pupils (over total pupils enrolled in the ward) for which English is not their first language and entitled for free meals. Dependent variable in Column 8 is the log of complaints against tourists per 2007 residents. To avoid taking the log of a zero, one is added to the number of complaints before taking logs in Column 8. *Share homeowners above median* is a dummy equal to 1 if, in 2011, the ward has a share of homeowners above the median. All Columns include ward fixed effect, local authority time trends, the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter and interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to the closest underground station. To avoid taking the log of a zero, one is added to the number of complaints before taking logs. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 10 years. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 7: **Social Capital and Brexit**

	ln(Organizations per person (x1000)			ln(Complaints per resident (x1000))		Share of people voting	
	Charitable	Youth	Political	Car Parking	Dog fouling	Leave Brexit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Airbnb Penetration (x1000)	0.000	-0.001	0.000	0.015	0.025	0.697	0.567
	(0.002)	(0.001)*	(0.000)	(0.006)**	(0.011)**	(0.079)***	(0.069)***
Panel B: IV							
Airbnb Penetration (x1000)	-0.021	-0.006	-0.005	0.004	0.006	0.605	0.589
	(0.009)**	(0.003)*	(0.002)**	(0.002)**	(0.002)***	(0.336)*	(0.303)*
Observations	5616	5616	5616	8112	8112	280	280
F-Stat FS	36.9	36.9	36.9	43.7	43.7	15.4	14.1
Ward FE	X	X	X	X	X		
LLA x Year FE	X	X	X	X	X		
Vars 2001 x Year FE	X	X	X	X	X		
Geo x Year FE	X	X	X	X	X		
Geo Controls						X	X
Educ and age Controls						X	X
Ethnicity, Nationality							X
Years	2011-2019	2011-2019	2011-2019	2007-2019	2007-2019	2016	2016

Note: *Airbnb penetration* represents the number of Airbnb tourists nights over residents nights. Instrument in Panel B is *Historical Sites per km*^{2} *times Airbnb Google Trend/100*. Dependent variable in Column 1 to 3 is the log of the number of organizations per 2007 residents (source: Digimap). In Columns 4 and 5 I consider the log of complaints per 2007 residents by category (source: FixMyStreet). In Columns 6 and 7, I consider the share of votes in favour of Leave in 2016 EU referendum. In Columns 1 to 5 I include ward fixed effect, local authority time trends and the interaction of year dummies with 2001 share of workers by sector, 2001 share of workers by occupation and 2001 log of house prices per square meter and interaction of year dummies with distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to the closest underground station. Columns 6 and 7 control for geographical variables (local authority fixed effects, distance ward centroid to Charing Cross, distance ward to the closest underground station), the share of the population over 65 in 2011 and the share of the population with a university degree (or higher). Column 7 add share of white population in 2011, share of UK citizen in 2011, share of EU citizen in 2011 and share of Commonwealth citizen in 2011. To avoid taking the log of a zero, one is added to the dependent variables before taking logs in Columns 1 to 3. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameters considered: 14 km and 10 years in Columns 1 to 3, 14 km in Columns 4 and 5. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Figure 1: **Airbnb Penetration in 2019**



Note: Airbnb penetration (equation 1) in 2019 x 1000 at ward level. Bins are represented by 2018 quintiles of Airbnb penetration.

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A 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.[40] 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 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 ceremonial 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.

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 and each is represented by three councillors.

B Appendix – Data Sources and Description

B.1 Data management

Unit of analysis is the electoral ward. Each ward is fully contained in a borough.

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 OA geography level the mapping is straightforward. OAs are further aggregated at lower layer super output areas (LSOA) and then into the

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

middle layer super output areas (MSOA).

B.1.2 Mapping different geographies

Thanks to specific mapping provided by the Office for National Statistics (ONS) it has been possible to map:[41]

- 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 rented properties) I compute the share of the area in which each LSOA or MSOA is split across different wards and I assign proportionally data to the corresponding ward. When looking at relative numbers (*e.g. average rent*) I compute the shares of the ward represented by each specific LSOA or MSOA forming the ward and used them to compute a weighted average of the index of interest. Data originally reported at MSOA level: crime rates and rents data.
- Postcodes into Output areas 2011 Census. Data originally reported at postcode level: house prices.
- Electoral wards of any calendar year into 2011 electoral wards. When a ward is split across multiple wards I assigned its data proportionally to the area split. When two wards form a new ward I combine their data with a weighted average based on the areas of the two old wards.

B.2 Airbnb Penetration

InsideAirbnb is a source more reliable than Tomslee. In Appendix Table C.2 I report the dates and sources of each web scraped as reported by InsideAirbnb.com and Tomslee.net. Each web scrape can be thought 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 were available I used InsideAirbnb. If two "snapshots" from the same source are available for the same month I kept the one closer to the 15 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 it is the year in which the series of snapshots started.

[41] 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 enquirers regarding mapping and boundaries of different geography levels.

Thanks to these data I am able to compute the following measure of Airbnb penetration:

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

It represents the average number of tourists using Airbnb a resident would meet in a random day in ward i and year t. The numerator 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 year t.[42] Each listing is assigned to a ward i given its latitude and longitude.[43] 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 and host submit a review or 14 days had 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. 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.[44] Results are similar if considering the number of beds in the property, as explained in Appendix Section D.2. My measure of Airbnb tourists nights reports very similar figures when compared to official statistics reported in Airbnb (2018) for 2018 (6.88 million vs 6.82 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. (2019), Barron et al. (2020), Almagro and Domínguez-Iino (2020), Duso et al. (2020) or Koster et al. (2019) has mainly focused on the number of properties listed on Airbnb website. To replicate their results I consider:

$$Airbnb\,penetration = \frac{Entire\,Properties\,on\,Airbnb}{Number\,Dwellings_{2011}} \tag{7}$$

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

[43] 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 neglectable.

[44] These informations have been fixed at the last available date

where at the nominator I am considering the number of entire properties listed on Airbnb website in ward i and year 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 consider a measure that measures 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 7 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 on 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 on 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 7.

As robustness I replicate my analysis with this measure, results are unchanged, see Appendix Section D.4.

B.2.2 Hotel penetration

Data on number of tourists in hotels are not available at the unit of analysis used in this paper. More generally they are usually provided from professional data providers that take advantage of detailed surveys. In order to estimate the number of tourists using "standard" accommodation industry I proceed in the following way. Similarly to Airbnb penetration (equation 1) I define hotel penetration as:

$$Hotel\,penetration_{it} = \frac{Hotel\,Tourists\,nights_{it}}{Residents\,nights_{i2007}} \tag{8}$$

It represents the average number of tourists using hotels a resident would meet in a random day in ward i and year t.[45] The numerator is computed in the following way:

$$\begin{aligned} &Hotel\,Tourists\,nights_{it} = \\ &= N.\,London\,rooms_t \times \frac{N.\,Hotels_{it}}{Tot.Hotels_t} \times 3 \times 365 \times Occupation\,rate_t \end{aligned} \tag{9}$$

[45] For hotels I considered any "serviced" room, which include both hotel rooms as well as bed and breakfast and hostels

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 year t.[46] 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 Appendix Figure C.3 and C.4 I plot the geographical distribution of hotel penetration measure in 2013 and 2019 respectively. 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 when comparing the two years.

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.

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

B.4 Other variables

B.5 Demographic and geographic variables

As a control in baseline specification, I consider the share of workers by sector and by occupation. Sectors considered are: i) Agriculture, hunting and forestry (A), Fishing (B), Mining and quarrying (C), Electricity, gas and water supply (E), Construction (F); ii) Manufacturing (D) iii) Wholesale and retail trade, repairs of motor vehicles, motorcycles and personal and households goods (G), Hotels and restaurants (H), Transport, storage and communications (I); iv) Financial intermediation (J), Real estate, renting and business activities (K); v) Public administration and defense; 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).[47] Occupations considered are: i) managers and senior officials, ii) professional occupations and associate professionals/technical occupations, iii) administrative and secretarial occupations and skilled trades occupations, iv) personal services occupations and sales and customer services occupations v) process, pant and machine operatives and elementary occupations.

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

C Appendix – Additional Tables and Figures

Table C.1: **Summary Statistics**

	Mean	Sd	Min	Max	Obs	Sample
Panel A: Airbnb variables						
Airbnb listing	29.3	85.2	0.0	1,392	11,232	2002-2019
Airbnb tourists nights	2,513	9,574	0	194,643	11,232	2002-2019
Airbnb tourists nights per resident	0.61	2.38	0.00	42.26	11,232	2002-2019
Entire properties on Airbnb over 2011 (x100)	0.28	0.92	0.00	15.94	11,232	2002-2019
Panel B: Housing variables						
Median house price per square meter	5,024	2,413	1,853	24,889	11,231	2002-2019
Median rent price	1,488	480	664	6,963	3,519	2011-2016
Panel C: Complaints and neighborhood quality variables						
Complaints against tourists per resident	0.01	0.15	0.00	6.97	8,112	2007-2019
Complaints about rubbish per resident	2.85	15.91	0.00	282.59	8,112	2007-2019
Complaints about fly-tipping per resident	2.08	13.05	0.00	275.24	8,112	2007-2019
Complaints about flyposting per resident	0.44	2.78	0.00	86.07	8,112	2007-2019
Complaints about park status per resident	1.04	6.41	0.00	108.71	8,112	2007-2019
Complain about road status per resident	2.60	11.53	0.00	303.51	8,112	2007-2019
Entry/exit underground stations per resident	2.51	3.23	0.17	35.64	3,657	2007-2017
Anti social behaviour crimes per resident	40.52	28.52	7.31	470.60	5,616	2011-2019
Panel D: Social capital and political variables						
Charitable organizations per resident	0.31	0.56	0.00	12.09	5,616	2011-2019
Youth organizations per resident	0.06	0.08	0.00	0.83	5,616	2011-2019
Political organizations per resident	0.01	0.06	0.00	1.59	5,616	2011-2019
Share of votes supporting Brexit	40.5	14.5	15.0	79.0	280	2016-2016
Panel E: Ward characteristics						
Total population	12,948	2,586	4,608	35,210	10,608	2002-2018
Area (km^2)	2.55	2.58	0.39	29.03	624	

Note: Column Sample reports the year for which a variable is available. *Airbnb tourists nights over 2007 resident (x1000)* represents the main measure of Airbnb presence, called *Airbnb Penetration* and described in Section 2. All variables in Panel C and Panel D (with the exception of *Entry/exit underground stations per resident* and *Share of votes supporting Brexit* are multiplied by 1000. In all variables reporting data per resident the reference population is 2007 resident population.

Table C.2: **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		

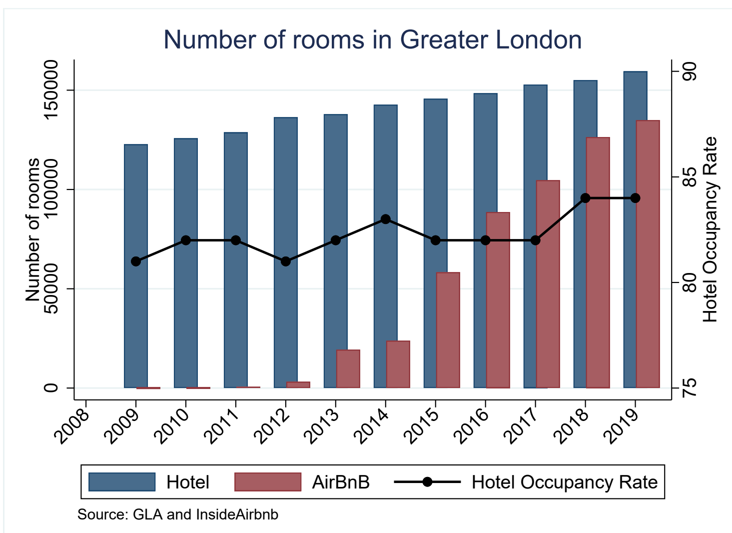
Note: Dates of webscrapes carried on by InsideAirbnb.com and Tomslee.net.

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

Complaints about	Share over total	Complaints about	Share over total
Rubbish	24.6%	Drain	1.8%
Road status	21.4%	Car parking	1.3%
Flytipping	18.0%	Dead animal	1.1%
Green area status	8.8%	Dog foul	0.8%
Street lights	6.8%	Admin	0.7%
Abandoned vehicle	6.6%	Street furniture	0.2%
Flyposting	3.8%	Dangerous structure	0.1%
Traffic sign	2.2%	Public toilet	0.0%
Other	1.8%		

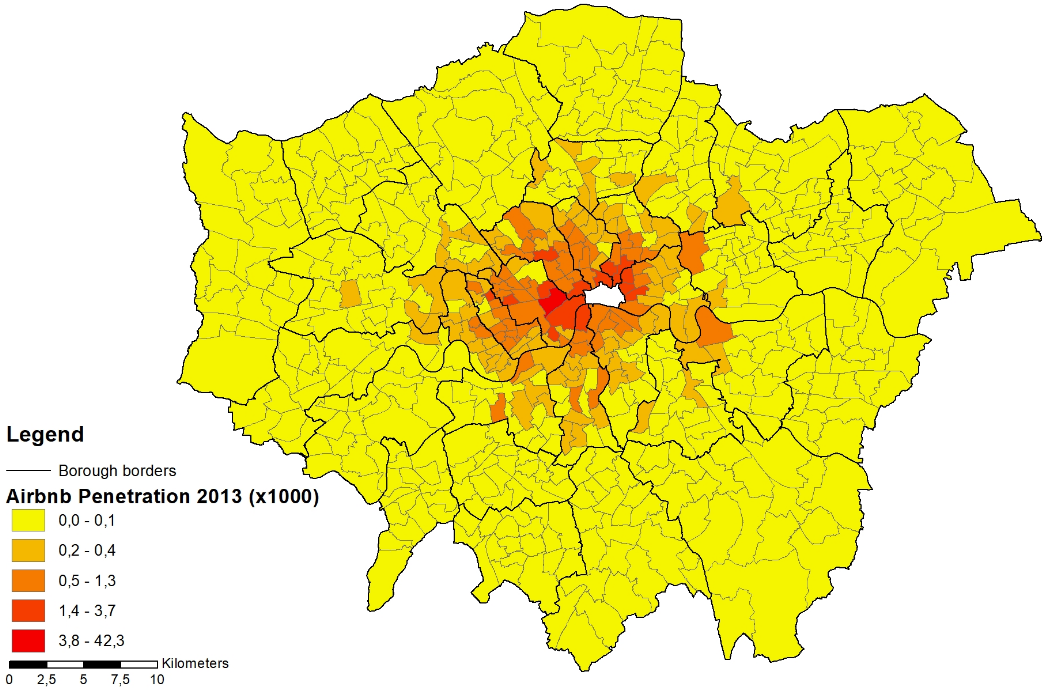
Note: Categories in FixMySteet after aggregating similar ones and share of complaints over total number of complaints (2007-2019)

Figure C.1: **Evolution hotel and Airbnb rooms in London**



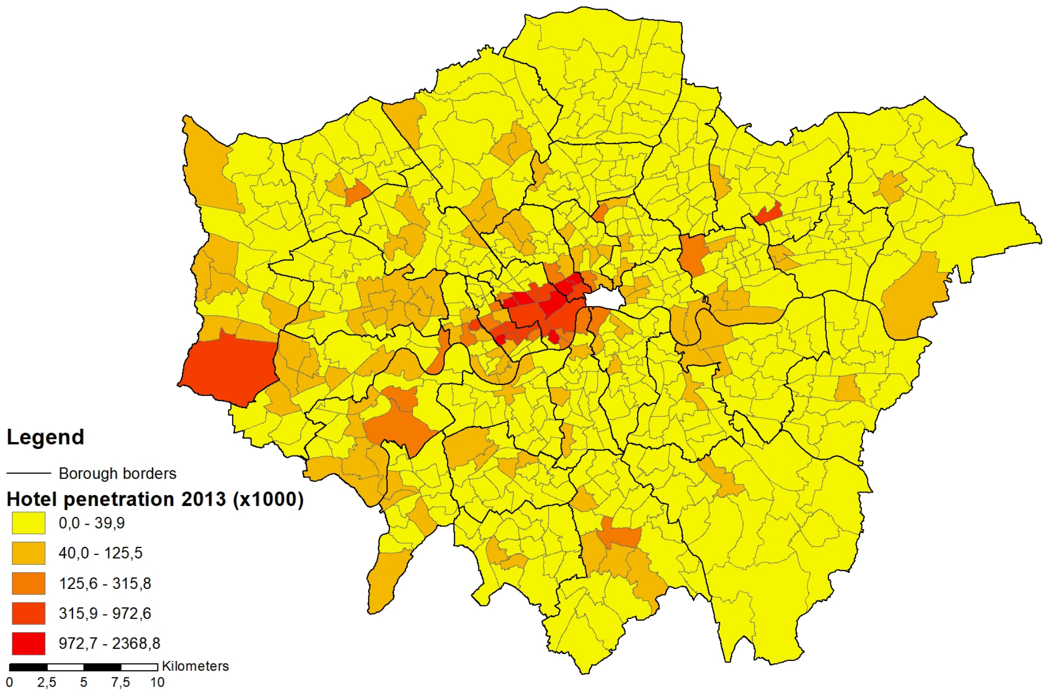
Note: Plotting number of hotel rooms in London (blue, source: Greater London Authority and PwC) and number of Airbnb rooms (red, source: Tomslee.net and InsideAirbnb.com) on the left axis. Plotting hotel occupancy rate (black line, source: PwC) on the right axis.

Figure C.2: **Airbnb Penetration in 2013**



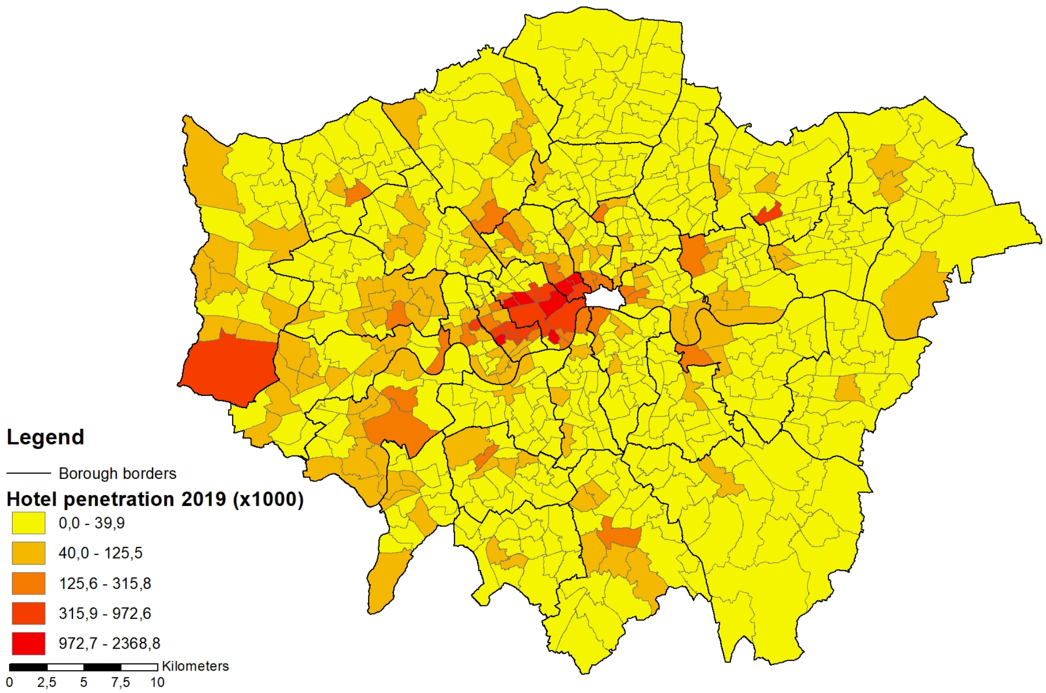
Note: Airbnb penetration (equation 1) in 2013 x 1000 at ward level. Bins represent 2019 quintiles of Airbnb penetration.

Figure C.3: **Hotel Penetration in 2013**



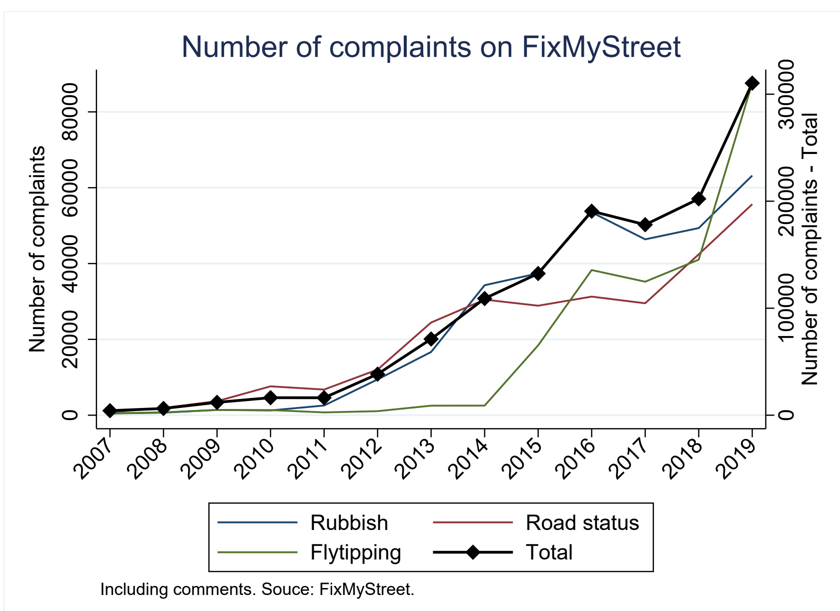
Note: Hotel penetration (equation 8) in 2013 x 1000 at ward level.

Figure C.4: **Hotel Penetration in 2019**



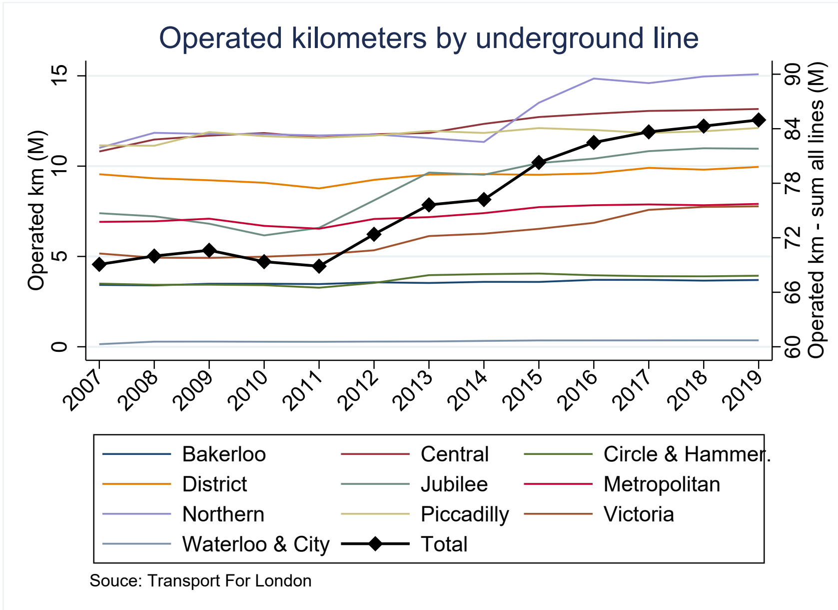
Note: Hotel penetration (equation 8) in 2019 x 1000 at ward level.

Figure C.5: **Number of complaints on FixMySteet**



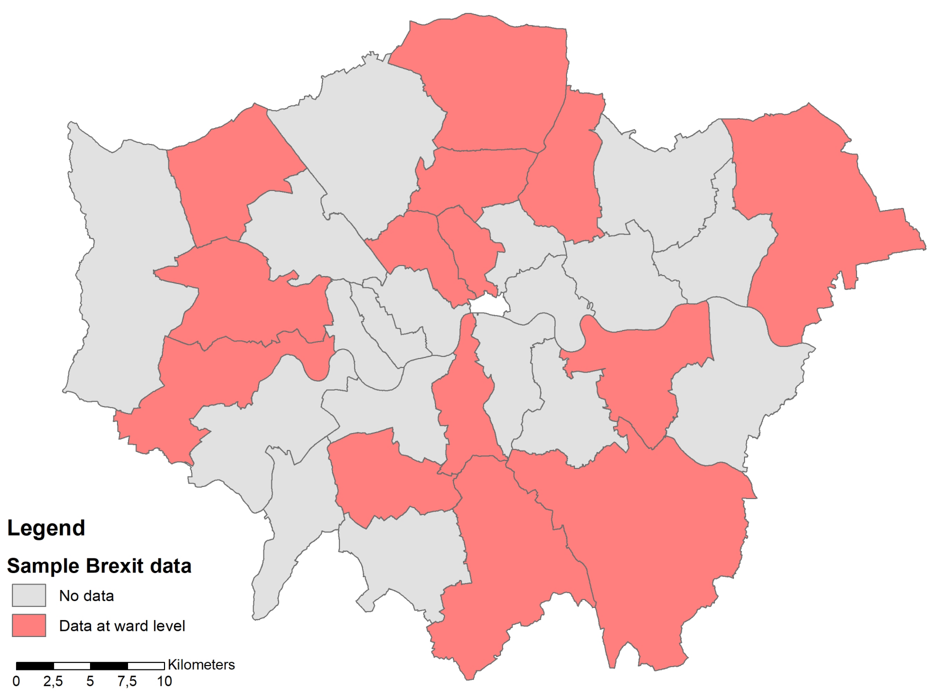
Note: Plotting total number of complaints and number of complaints for the three major categories. Including number of complaints and subsequent comments. Source: FixMyStreet (founded in 2007).

Figure C.6: **Operated kilometers by underground line**



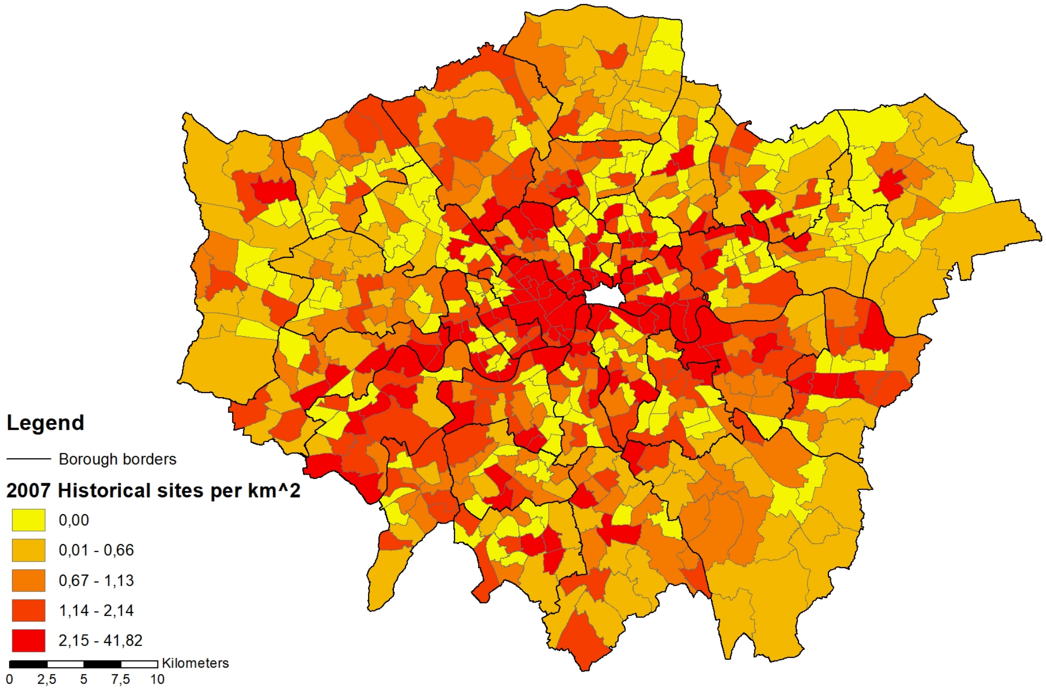
Note: Plotting operated kilometers by line. Central, Jubilee, Northern, Piccadilly and Victoria line since August 2016 are running Night services. Source: Trasport for London.

Figure C.7: **BBC Brexit Sample at ward level**



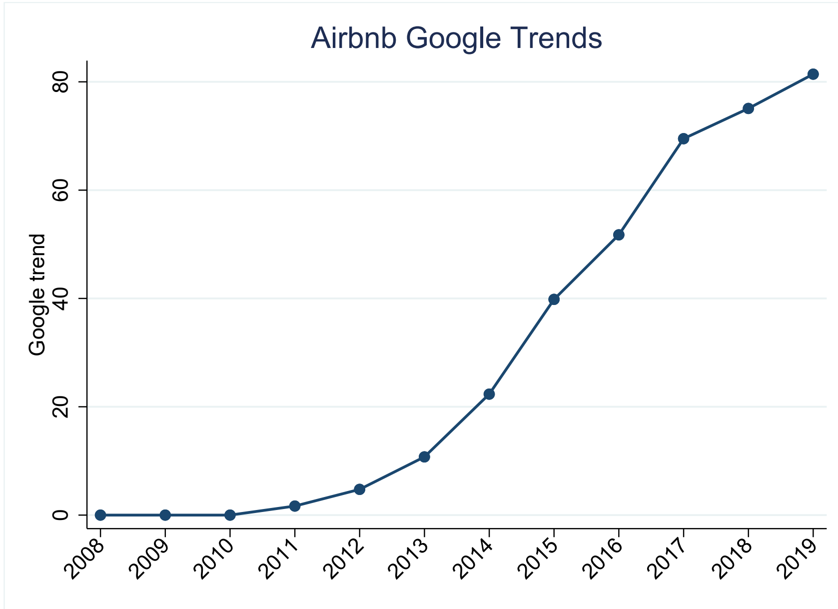
Note: Plotting local authority that reports data at ward level (source: BBC)

Figure C.8: **Geographical distribution of point of historical touristic interest**



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

Figure C.9: **Geographical distribution of point of historical touristic interest**



Note: Plotting time evolution of worldwide search volume for the word “Airbnb” (source: Google Trend). Google reports an index at the month level, that represents the search volume with respect to the month with maximum search volume. The index then ranges from 0 (no searches for the word “Airbnb”) to 100 (maximum search volume ever recorded for the word “Airbnb”). I consider the yearly average of these monthly indexes.

D 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 4 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.1 I test for pre-trends, regressing the pre-period (2002-2007) change in the outcomes of interest against the 2008-2019 change in Airbnb penetration predicted by the instrument. The estimated equation controls for local authority fixed effects, 2001 share of workers by sector, 2001 share of workers by occupation, 2001 log of house prices per square meter, distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to the closest underground station:

$$Y_{ib}^{2007} - Y_{ib}^{2002} = \beta(Airbnb_{ib}^{2019} - Airbnb_{ib}^{2008}) + \gamma X_i + \delta_b + \epsilon_{ib} \tag{10}$$

Unfortunately, among my outcomes, I can only consider median house prices and population. Reassuringly, coefficients (reported in Panel B) are never statistically significant. Also, and importantly, they are quantitatively different from the baseline IV estimates, reported in Panel A. These results indicate that historical sites are not in wards that were already undergoing economic or political changes.[48]

In the remaining on the section I described various modifications to the baseline specification of the first stage presented in 1.

Alternative shift and shares As first robustness, I consider alternative measures both for the shares and the shifts of equation 4. I consider a different source for the "share" component in Column 1 of Appendix Table E.2 using the number of historical buildings of grade I and II star reported by Historic England. In Column 2, I modify the "shift" component and consider the Google Trend for "Airbnb London". In both cases, results are robust to these modifications. I will present robustness only for the specification of Column 4 of Table 1 with the full set of controls.[49]

Alternative specifications Second, I consider instead of *Airbnb Penetration* alternative specifications. In Column 3 of Appendix Table E.2, I consider the log of Airbnb Penetration (to avoid taking the log of a zero, one is added to the number of Airbnb Penetration before taking logs). In Column 4 I consider just the numerator of equation 1.

[48] In Panel B I am considering standard errors clustered at ward level as Hsiang (2010) procedures fails to deliver spatially corrected standard errors

[49] Also the other specifications are robust to the modification proposed, results available upon request

Alternative measures of Airbnb presence Third, to verify that my results do not depend strictly on the assumptions made in constructing my measure of Airbnb penetration I consider alternative measures of Airbnb presence. In Column 5 of Appendix Table E.2, 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 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 in Column 8 I consider the number of Accommodation establishments per 2007 residents. 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 2002 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 the one of Column 4, Table 1. Results are presented in Appendix Figure E.1 where I am reporting the coefficient of each regression where I am changing the starting year of thr 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 2016 (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 from the baseline specification.

Exclude one by one a local authority In Appendix Figure E.2 I report estimates of Column 4, Table 1 where I am excluding, one by one a local authority. Only when excluding Westminster the first stage results is not robust anymore. This is not surprising given the prominent role in the tourism industry played by the Westminster borough as within its boundary we can find many popular destinations like Buckingham Palace or Hyde Park.

D.2 Data quality robustness: beds

As described in Appendix Section B.2 I take advantage of the information of 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 on sofas, etc. To make sure that this is not a problem in Appendix Table E.4 I replicate OLS and IV specifications of Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (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 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 prior 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.5 I replicate OLS and IV specifications of Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (Column 1) restricting my sample from 2013 onwards. All results are robust with the exception of results on underground congestion, for which, however, I have a very short panel dataset.

D.4 Alternative measure of Airbnb penetration

I replicate OLS and IV specifications of Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (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.6 and they are unchanged.

D.5 Airbnb or Hotel tourists?

A potential concern is that the effects described are not due to the presence of short-term tourists 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 Appendix Section B.2.2 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. Similarly, when looking at the total number of hotels rooms they increase only by 16,000 from 2013 to 2019 while Airbnb number of rooms increased by almost 87,000, see Appendix Figure C.1. In E.3 I plot the median ward, 25$^{\text{th}}$ percentile ward and 75$^{\text{th}}$ percentile ward from the distribution of number of hotels per square kilometre. It confirms that the number of establishment is relatively fixed. Even more important the geographic distribution of hotels is almost constant with the clustered identified in Appendix Figure C.4 in which I am plotting hotel tourists distribution for 2019. This appears evident when compared to the same figure in 2013 in Appendix Figure C.3. 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, as described in Appendix Section D.1 the instrument proposed in Section 3 does not predict the hotel presence nor the number of guests in hotel accommodations. This reassures that the variation used in the IV strategy is orthogonal to hotel presence.

Third, when adding as a regressor the predicted number of hotel tourists per residents as described in Appendix Section B.2.2 the significance of my estimates is not affected. In Appendix Table E.7 I am reporting the OLS and IV specifications of Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (Column 1) adding Hotel Penetration measure described in Appendix Section B.2.2. No results are affected. Moreover, increasing by one standard deviation the number of hotel tourists per resident (1.5) delivers much smaller results than an increase in one standard deviation in Airbnb penetration (2.4) suggesting that i) the impact from Airbnb tourism penetration is robust to the inclusion of hotel tourism penetration and ii) it is more relevant in explaining the dynamics documented in this paper.[50]

D.6 Monthly results

Tourism, and Airbnb tourism as well, is subject to a high degree of seasonality with the peak season from June to September (and a second small peak in December). In Appendix Figure E.4 I present quarterly aggregated data for international visitors and Airbnb visitors nights. Aggregating data at year level is a necessary step because i) most of the variables are available only at year level and ii) many variables contain meaningful variation only looking at relatively long time intervals.

Nevertheless, for some outcomes it is possible to credible estimate the model presented in Equation 3 at the month level, meaning that I will consider month-year specific time local authority trends as well as interacting pre-determined and geographic characteristics with month-year dummies.[51] Specifically, I can do it for: complaints against tourists, complaints about rubbish, road status and car parking and social behaviour crime rates.[52]

Results are presented in Appendix Table E.8. Results are all in line with baseline year specification suggesting that even with a demanding specification that takes into account monthly trends Airbnb penetration is associated with more complaints and a drop in neighbourhood quality.

[50] Standard deviations reported are for the measures multiplied by 1000 and 10 as reported in the Appendix Table E.7. Various concerns with respect to this regression apply: i) it is hard to think a credible instrumental strategy for hotel penetration, for this reason, I considered only the OLS, with all the common caveats; ii) hotel penetration may be a bad control if Airbnb penetration heavily affects also hotel presence and businesses as suggested by Farronato and Fradkin (2018)

[51] Standard errors consider a 120 time parameter and the usual 14km geographic correlation.

[52] I report results for each category of complaints, namely: susceptible to the presence of tourists and negative behaviours by residents, placebo and susceptible to negative behaviours by residents. All other measures display similar patterns, results available upon request

D.7 Standard Errors

As described in Section 3 throughout the paper I consider standard errors corrected following Conley (1999), Conley (2010) and Hsiang (2010) with the following parameter choice: 14 km and 10 years. 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 10 years as Airbnb started its presence in London in 2009, note that Greene (2018) recommends at least $T^0.25$, even considering the longest panel (2002-2019) I am being more conservative.

To validate my choice I report in E.5 the 10% confidence intervals of Table 2, Panel B Column 2 specification when changing the parameters of interest. In particular, I report all the combinations with time parameter equal to 2, 5, 10, 15, 20 and distance parameter equal to: 1, 5, 10, 14, 15, 20, 25. For completeness, I also report the confidence interval clustering at local authority and level. Notably, the clustered standard errors are the smallest, this reinforces our concerns in not considering explicitly autocorrelation and spatial correlation. When turning our attention to parameters combination it is evident how the "time" parameter does not alter confidence intervals while it is the distance parameters determining how wide the confidence intervals will be. Around the parameter choice (14 km and 10 years) results remain significant and confidence intervals almost identical. Wider standard errors appear when considering very limited time parameters jointly with a high distance parameter. Given that this is happening from parameter choices far from the baseline specification I am reassured over my choice.

D.8 Multiple hypothesis testing

Given the numerous outcomes considered under the same treatment, a concern is that we may falsely reject at least some null hypothesis 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.[53] 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 easily consider pvalues 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.[54]

[53]Code is available from Anderson's website

[54]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

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 amongst p-values.[55]. 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 amongst p-values I consider standard errors clustered at ward level[56]

Joint test that no treatment has any effect A third approach, suggested in Young (2018), rather than adjusting each individual 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.[57] Also here, given the added complexity imposed by the fact I am now controlling for dependence amongst 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 0.0017 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 0.0035. We can then reject the hypothesis that no treatment has any effect.

In Appendix Table E.9 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. In table footnote I report the Young (2018) pvalue of the joint test of the hypothesis that no treatment has any effect. I tested all the main specifications, namely Panel A and B of Table 2, Column 2; Table 3, Columns 1 and 4; Table 4; Table 6, Columns 1 to 5, 7 and 8; Table 7, Columns 1 to 3.

Comparing Columns 1 and 2 p-values and sharpened q-values following Anderson (2008) are similar. Only in one case original p-values wrongly reported a significant result, *i.e.* when looking at log median rent in the OLS regression. Also in columns 1 and 3 differences are limited. In only 4 cases a significant result is not significant anymore when considering corrected p-values: when looking at log median house price, log population, share of pupils for which English is not the first language and log number of political organizations per residents, in all cases in the OLS regressions.

false discovery rate low.

[55]Stata code available as `randcmd`

[56]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

[57]Stata code available as `randcmd`

E Appendix – Robustness Tables and Figures

Table E.1: **Pre-Trends**

	ln(Median house price per sqm)		ln(population)	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Panel A: baseline				
Airbnb Penetration (x1000)	0.002	-0.003	0.002	0.009
	(0.001)**	(0.002)	(0.001)**	(0.006)
Panel B: pretrend				
Airbnb Penetration (x1000)	0.001	0.003	0.000	0.001
2019-2008	(0.001)	(0.003)	(0.001)	(0.002)
Years Dep. Var.	2002-2007	2002-2007	2002-2007	2002-2007

Note: Note: this table reports baseline IV estimates in Panel A as in Table 3, Column 1 and 6, Column 1. Panel B regresses the 2002-2007 change in outcomes against the 2008-2019 change in instrumented Airbnb penetration. All regressions include borough fixed effects, 2001 share of workers by sector, 2001 share of workers by occupation, 2001 log of house prices per square meter, distance ward centroid to Charing Cross, distance ward centroid to closest London 2012 venue and distance ward to closest underground station. F-stat First Stage refers to the K-P F-stat for weak instrument. Conley (1999) standard errors, parameter considered: 14 km and 10 years in Panel A. Standard errors clustered at ward level in Panel B. *** p<0.01; ** p<0.05; * <0.1.

Table E.2: **First Stage Robustness**

	Airbnb Penetration (x1000)		ln(Airbnb Penetration (x1000))	Airbnb Tourist Nights	Airbnb penetration bed	Airbnb visits per resident	Airbnb property over dwelling	Accommodation per resident
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Historical Sites x Google Trend/100	0.361 (0.041)***	0.422 (0.062)***	0.030 (0.008)***	2131.325 (307.542)***	0.260 (0.038)***	0.094 (0.013)***	0.120 (0.025)***	0.004 (0.006)
Observations	11232	11232	11232	11232	11232	11232	11232	5616
R-Squared	0.827	0.808	0.938	0.794	0.812	0.812	0.874	0.974
F-Stat FS	79.4	47.0	14.7	48.9	46.0	54.2	22.2	0.4
Ward FE	X	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X	X
Instrument	Historic England	Airbnb London	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Years	2002-2019	2002-2019	2002-2019	2002-2019	2002-2019	2002-2019	2002-2019	2011-2019

Note: The sample includes a panel of 624 electoral wards in Greater London from 2002 to 2019. The specification considered is the same as Column 4, Table 1 unless differently specified. In Column 1 I consider Historical Buildings per square kilometers as share. In Column 2 I consider Google Trend for "Airbnb London" as shift. In Column 3 I consider the log of Airbnb Penetration (to avoid taking the log of a zero, one is added to the number of Airbnb Penetration before taking logs). 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 number of people a listing can accommodate. In Column 6 I consider as numerator of equation 1 the number of Airbnb visits (*i.e.* ignoring adjustment by number of guests the property can accomodate and minimum number of nights to consider) and as denominator the 2007 residents. In Column 7 I consider the number of entire properties listed on Airbnb over number of dwellings in 2011. In Column 8 I consider the number of Accommodation establishments per 2007 residents

Table E.3: **Selection**

	Top quartile	Bottom quartile	Difference
Median house price per square meter	6235.624	3276.900	2958.724
	(2307.165)	(2307.165)	0.000
Complaitns about rubbish per resident (x1000)	0.249	0.282	-0.033
	(0.635)	(0.635)	0.608
Charitable organizations per resident (x1000)	0.990	0.147	0.843
	(1.356)	(1.356)	0.000
Population	12121.709	12049.653	72.056
	(2245.219)	(2245.219)	0.322

Note: Quartiles are defined based on 2019 Airbnb Penetration. First two columns report the average and standard deviation (in parenthesis) of top and bottom quartile for all wards-year before 2013. Last column reports the difference of average values and the pvalue of a two side test for the difference being equal to 0.

Table E.4: **Robustness: using beds in the flat**

	ln(Complaints against tourists per resident (x1000))	ln(Median house price per sqm)	ln(Median rent)	ln(Tube entry/exit per resident)	ln(Complaints Rubbish per resident (x1000))	ln(ASB per resident (x1000))	ln(Charitable Organizations per resident (x1000))
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Airbnb Penetration (x1000)	0.014	0.003	0.008	0.006	0.025	0.007	0.000
	(0.007)**	(0.001)**	(0.005)	(0.001)***	(0.007)***	(0.002)***	(0.004)
Panel B: IV							
Airbnb Penetration (x1000)	0.044	-0.006	0.006	0.012	0.059	0.053	-0.043
	(0.024)*	(0.004)	(0.010)	(0.006)*	(0.030)**	(0.013)***	(0.017)**
Observations	8112	11231	3514	3640	8112	5616	5616
F-Stat FS	40.7	43.2	45.1	26.3	40.7	33.8	33.8
Ward FE	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X
Years	2007-2019	2002-2019	2011-2016	2007-2017	2011-2019	2007-2019	2011-2019

Note: I replicate results presented in Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (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 expression 2.

Table E.5: **Restrict from 2013 onwards**

	ln(Complaints against tourists per resident (x1000))	ln(Median house price per sqm)	ln(Median rent)	ln(Tube entry/exit per resident)	ln(ASB per resident (x1000))	ln(Complaints Rubbish per resident (x1000))	ln(Charitable Organizations per resident (x1000))
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Entire properties	0.008	-0.001	0.002	0.000	0.003	0.017	0.004
over dwellings (x100)	(0.004)**	(0.000)	(0.002)	(0.000)	(0.001)**	(0.004)***	(0.001)***
Panel B: IV							
Entire properties	0.035	-0.004	-0.001	0.002	0.028	0.040	-0.002
over dwellings (x100)	(0.018)*	(0.004)	(0.003)	(0.003)	(0.010)***	(0.021)*	(0.007)
Observations	4368	4367	2330	1654	4368	4368	4368
F-Stat FS	33.7	33.7	52.0	12.3	33.7	33.7	33.7
Ward FE	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X
Years	2013-2019	2013-2019	2013-2016	2013-2017	2013-2019	2013-2019	2013-2019

Note: I replicate results presented in Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (Column 1) restricting my sample from 2013 onwards.

Table E.6: **Alternative measure of Airbnb Penetration: dwellings**

	ln(Complaints against tourists per resident (x1000))	ln(Median house price per sqm)	ln(Median rent)	ln(Tube entry/exit per resident)	ln(ASB per resident (x1000))	ln(Complaints Rubbish per resident (x1000))	ln(Charitable Organizations per resident (x1000))
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Entire properties	0.026	0.008	0.014	0.006	0.009	0.040	-0.004
over dwellings (x100)	(0.015)*	(0.002)***	(0.008)*	(0.004)	(0.004)**	(0.018)**	(0.009)
Panel B: IV							
Entire properties	0.096	-0.014	0.018	0.034	0.114	0.129	-0.091
over dwellings (x100)	(0.052)*	(0.009)	(0.032)	(0.018)*	(0.029)***	(0.065)**	(0.037)**
Observations	8112	11231	3514	3640	5616	8112	5616
F-Stat FS	18.6	19.5	18.0	17.9	15.6	18.6	15.6
Ward FE	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X
Years	2007-2019	2002-2019	2011-2016	2007-2017	2011-2019	2007-2019	2011-2019

Note: I replicate results presented in Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (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

Table E.7: **Include Hotel Penetration**

	ln(Complaints against tourists per resident (x1000))	ln(Median house price per sqm)	ln(Median rent)	ln(Tube entry/exit per resident)	ln(Complaints Rubbish per resident (x1000))	ln(ASB per resident (x1000))	ln(Charitable Organizations per resident (x1000))
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Airbnb Penetration (x1000)	0.007	0.002	0.003	0.002	0.013	0.004	0.000
	(0.003)**	(0.001)**	(0.002)*	(0.001)***	(0.004)***	(0.001)***	(0.002)
Hotel Penetration (x10)	0.016	-0.003	0.013	0.010	0.021	0.004	-0.016
	(0.009)*	(0.003)	(0.012)	(0.004)**	(0.013)*	(0.011)	(0.011)
Panel B: IV							
Airbnb Penetration (x1000)	0.023	-0.004	0.001	0.005	0.030	0.034	-0.025
	(0.012)*	(0.002)*	(0.004)	(0.004)	(0.017)*	(0.009)***	(0.010)**
Hotel Penetration (x10)	-0.009	0.006	0.016	0.008	-0.005	-0.046	0.027
	(0.012)	(0.005)	(0.010)	(0.005)	(0.022)	(0.019)**	(0.015)*
Observations	8112	11231	3514	3640	11231	5616	5616
F-Stat FS	15.6	16.0	34.2	22.1	15.6	14.6	14.6
Ward FE	X	X	X	X	X	X	X
LLA x Year FE	X	X	X	X	X	X	X
Vars 2001 x Year FE	X	X	X	X	X	X	X
Geo x Year FE	X	X	X	X	X	X	X
Years	2007-2019	2002-2019	2011-2016	2007-2017	2007-2019	2011-2019	2011-2019

Note: I replicate results presented in Tables 2 (Column 2), 3 (Columns 1 and 4), 4 (Columns 1, 2 and 7) and 7 (Column 1) adding Hotel Penetration measure described in Appendix Section B.2.2.

Table E.8: **Month level regressions**

	ln(Complaints against tourists per resident (x1000))	ln(Complaints per resident (x1000)) Rubbish	Road status	Car Parking	ln(ASB per resident (x1000))
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS					
Entire properties	0.006	0.025	0.013	0.003	0.019
over dwellings (x100)	(0.003)**	(0.009)***	(0.005)***	(0.002)	(0.008)**
Panel B: IV					
Entire properties	0.036	0.137	0.041	0.022	0.264
over dwellings (x100)	(0.015)**	(0.039)***	(0.038)	(0.009)**	(0.072)***
Observations	97344	97344	97344	97344	67391
F-Stat FS	39.3	39.3	39.3	39.3	31.4
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	2011-2019

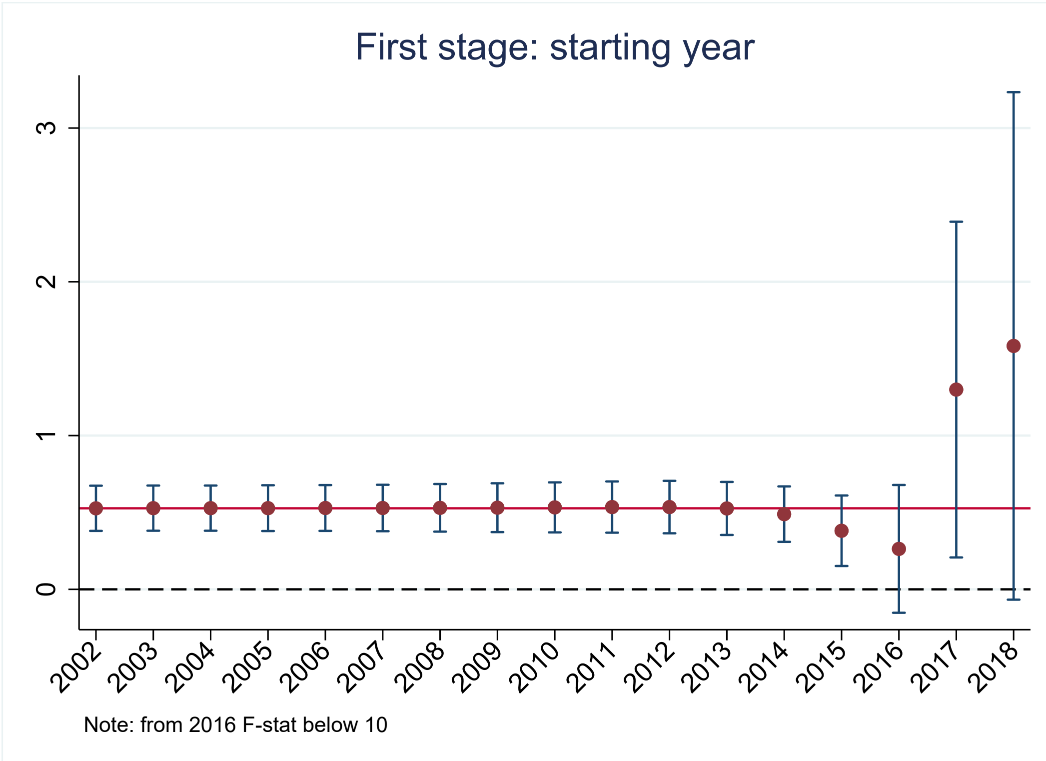
Note: I replicate results presented in Tables 2 (Column 2), 4 (Columns 2, 5 and 7) and 7 (Column 4) considering month level data.

Table E.9: **Multiple hypothesis testing**

	Original p-value	Anderson (2008)	Westfall-Young (1993)
	(1)	(2)	(3)
Panel A: OLS			
ln(complaints against tourists per resident (x1000))	0.038	0.087	0.001
ln(median house price per sqm)	0.015	0.067	0.105
ln(median rent)	0.089	0.123	0.053
ln(entry and exit in tube per resident)	0.000	0.003	0.067
ln(complaints per resident (x1000) Rubbish)	0.001	0.016	0.000
ln(complaints per resident (x1000) Fly-tipping)	0.149	0.138	0.122
ln(complaints per resident (x1000) Flyposting)	0.129	0.137	0.050
ln(complaints per resident (x1000) Road status)	0.108	0.133	0.129
ln(complaints per resident (x1000) Green area status)	0.800	0.339	0.844
ln(anti social behaviour per resident (x1000))	0.004	0.035	0.018
ln(Population)	0.045	0.096	0.247
Share population 0-18	0.020	0.070	0.003
Share population 19-34	0.016	0.067	0.039
Share population 35-64	0.355	0.227	0.562
Share population 65+	0.623	0.272	0.767
Share of pupils first language not English	0.019	0.070	0.111
Share of pupils with free meals	0.757	0.326	0.885
ln(Organizations per resident (x1000) - Charitable)	0.845	0.352	0.763
ln(Organizations per resident (x1000) - Youth)	0.058	0.097	0.108
ln(Organizations per resident (x1000) - Political)	0.590	0.270	0.709
Panel B: IV			
ln(complaints against tourists per resident (x1000))	0.064	0.097	0.000
ln(median house price per sqm)	0.103	0.133	0.038
ln(median rent)	0.562	0.270	0.055
ln(entry and exit in tube per resident)	0.056	0.097	0.027
ln(complaints per resident (x1000) Rubbish)	0.048	0.096	0.003
ln(complaints per resident (x1000) Fly-tipping)	0.037	0.087	0.006
ln(complaints per resident (x1000) Flyposting)	0.016	0.067	0.001
ln(complaints per resident (x1000) Road status)	0.484	0.270	0.001
ln(complaints per resident (x1000) Green area status)	0.490	0.270	0.219
ln(anti social behaviour per resident (x1000))	0.000	0.003	0.007
ln(Population)	0.115	0.137	0.167
Share population 0-18	0.036	0.087	0.000
Share population 19-34	0.519	0.270	0.119
Share population 35-64	0.056	0.097	0.049
Share population 65+	0.981	0.417	0.308
Share of pupils first language not English	0.732	0.323	0.118
Share of pupils with free meals	0.149	0.138	0.046
ln(Organizations per resident (x1000) - Charitable)	0.013	0.067	0.006
ln(Organizations per resident (x1000) - Youth)	0.064	0.097	0.053
ln(Organizations per resident (x1000) - Political)	0.012	0.067	0.021

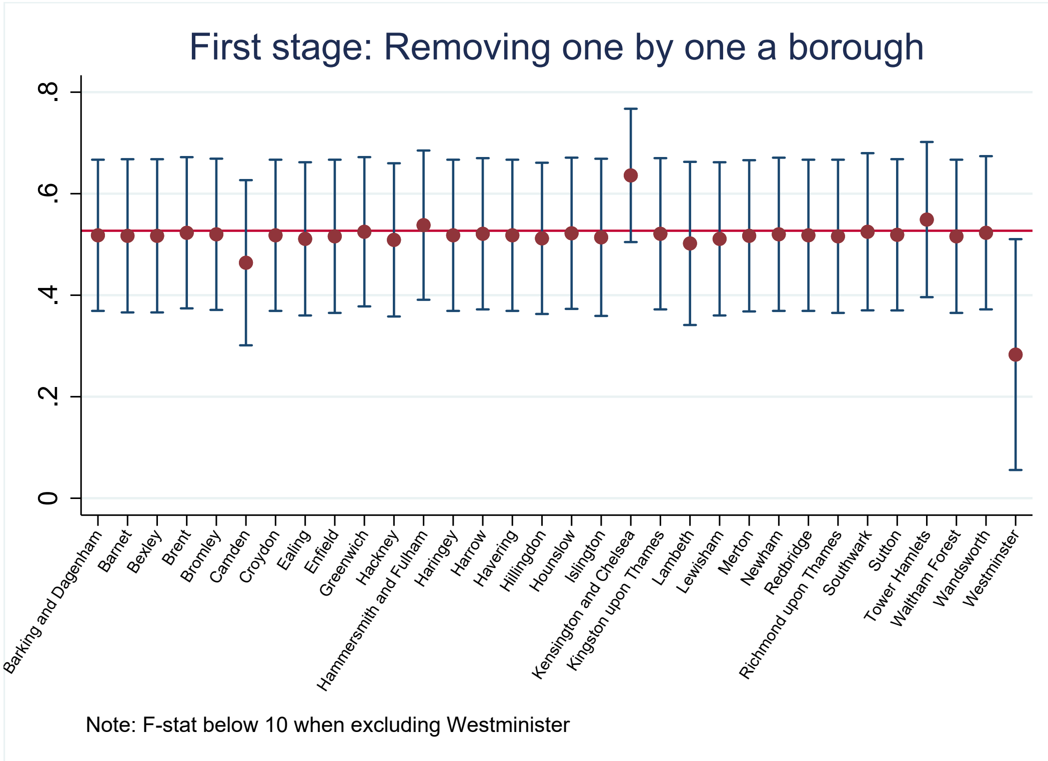
Note: Column 1 contains pvalues computed using Conley (1999) as described in Section 3. Column 2 contains sharpened q-values following Anderson (2008). Column 3 stepdown adjusted p-values following Westfall and Young (1993). Randomization-t p-value for the Westfall-Young multiple testing test of the significance of any treatment measure in each equation as a whole is 0.0035 following Young (2018)

Figure E.1: **First stage: modify starting year**



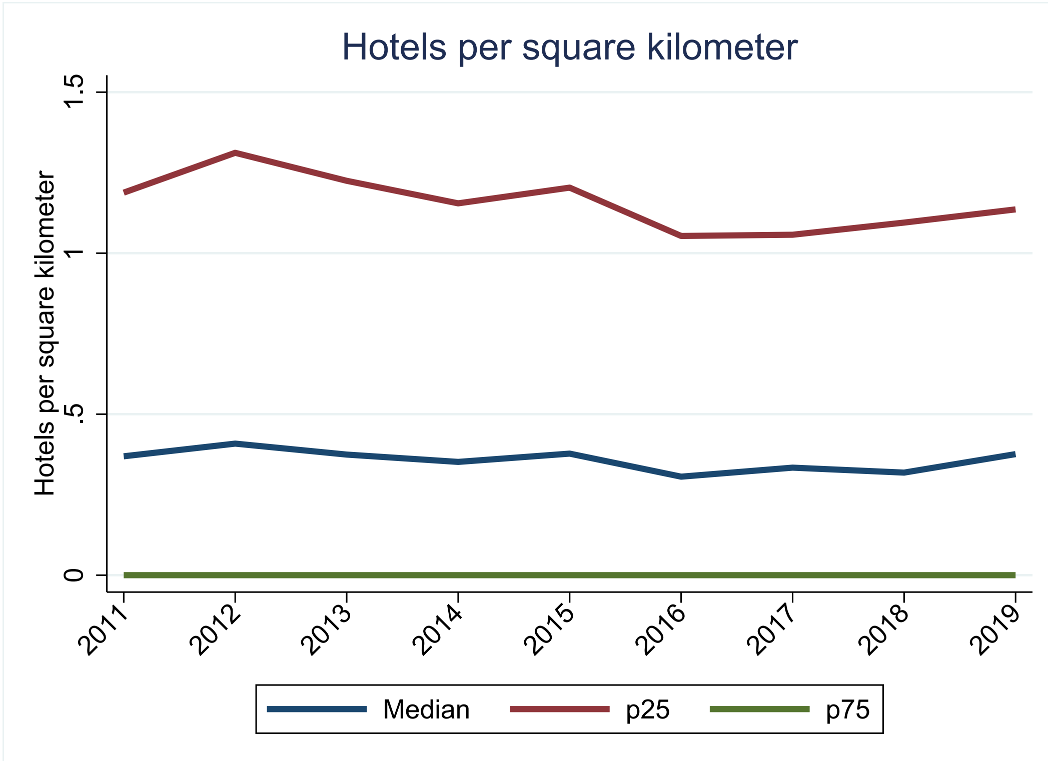
Note: Plotting coefficients of Column 4, Table 1 where I modify the starting year of analysis. Starting years are reported on the x-axis.

Figure E.2: **First stage: Removing one by one a local authority**



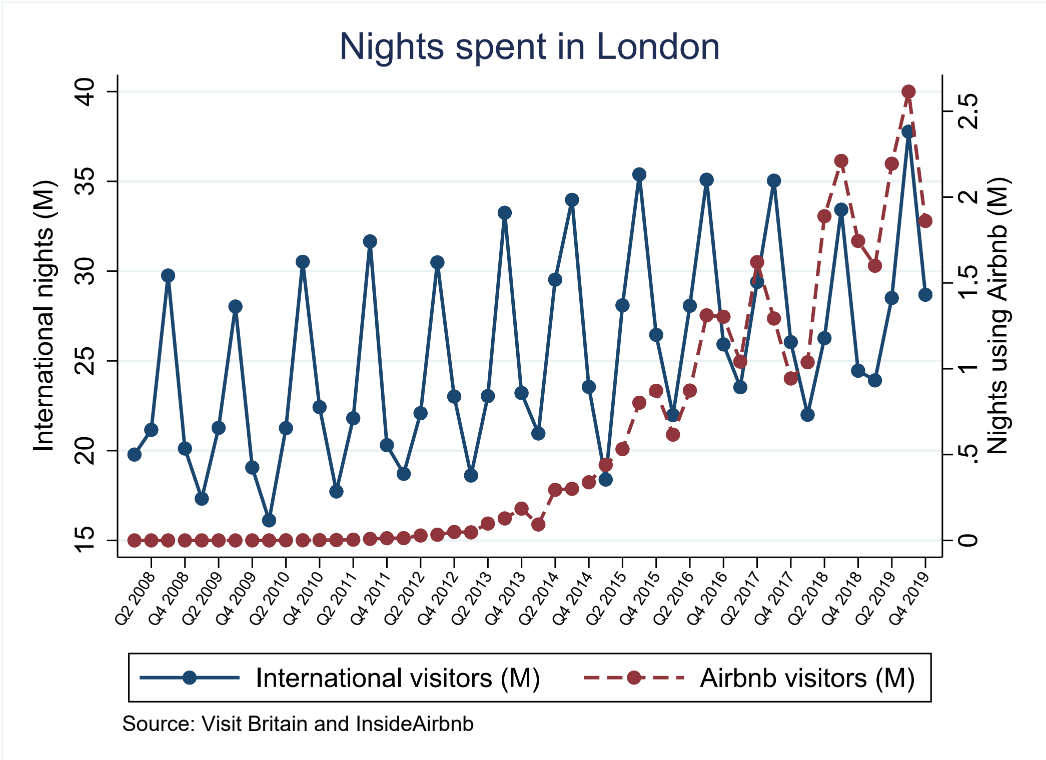
Note: Plotting coefficients of Column 4, Table 1 where I exclude one by one a local authority from the analysis. Excluded local authorities are reported on the x-axis.

Figure E.3: **Seasonal variation in tourists nights**



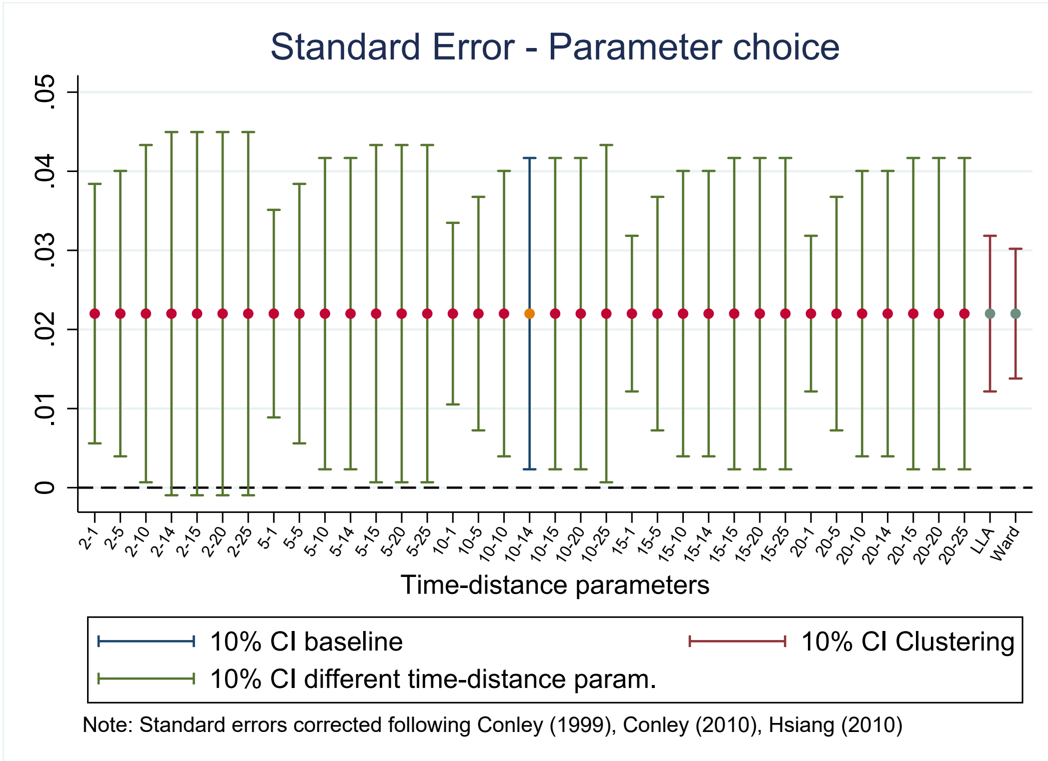
Note: Plotting median ward, 25th percentile ward and 75th percentile ward from the distribution of number of hotels per square kilometre.

Figure E.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.

Figure E.5: **Different Standard Errors computation**



Note: Plotting 10% confidence intervals of Table 2, Panel B Column 2 specification. On the x-axis reporting the combination of time-distance parameters considered in Conley (1999) standard error correction. Last two data points report standard errors clustering at Local Authority and ward level respectively.