RESEARCH ARTICLE

Understanding patterns and competitions of short- and long-term rental markets: Evidence from London

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Abstract

In this article, we compare short-term rental (STR) and long-term rental (LTR) price patterns in London using one of the most popular STR platforms, Airbnb, and the LTR platform, Zoopla property website. This research aims to enhance our understanding of both LTR and STR price patterns; as well as STR dynamics specifically, using predictive modeling to analyze how the patterns might evolve. We used the coefficient of variation and correlation analysis to examine the rental price patterns of both short- and long-term markets. Then we developed a rent-based gravity model to predict STR price pattern that is sensitive to the changes in visits to tourist destinations. Based on our analysis, we concluded that: (1) STR prices tend to be higher overall with an indication of higher volatility (less stability) compared to LTR; (2) there is statistical evidence supporting the arguments that STR and LTR markets are indeed in competition; and (3) the proposed gravity model provides a robust prediction of the STR pattern with a characteristic that higher-priced short-term properties are found to be geographically concentrated in the core city areas and those surrounding residential areas with easy access to popular tourist attractions.

1 | INTRODUCTION

In recent decades, there has been a rapid development of short-term rental (STR) platforms, including Airbnb. As a digital platform, Airbnb offers short-term accommodations by providing means to connect *hosts*, those with entire apartments, private or shared rooms to rent, and *guests*, travelers who would like to rent a place. Airbnb is an example of a phenomenon that has been emerging for the last decades, known as the online platform economy. This refers to the open-access approach of utilizing assets and services (Richardson, 2015; Rifkin, 2001), mostly for-profit (Belk, 2014), and generally mediated by Internet technology (McLaren & Agyeman, 2015; Schor, 2014). Airbnb as a hospitality online platform offers two main benefits to those who participate: (1) economic incentives for hosts from renting rooms or properties; and (2) choices of short-term accommodation with extra amenities often not available at traditional accommodation such as hotels for guests.

As a topic of contemporary interest, various research has focused on examining the implications of Airbnb. This includes the impact on traditional accommodation sectors where Airbnb are argued to have a profound impact on hotel revenues (Zervas et al., 2017) as well as the long-term housing market (Ayouba et al., 2020; Barron et al., 2017; Shabrina et al., 2022; Shokoohyar et al., 2020). Shokoohyar et al. (2020) found that certain neighborhood characteristics contribute to a higher rate of return when properties are being rented as STR. Ayouba et al. (2020) pointed out that Airbnb rentals put outward pressure on rents in several French cities and Shabrina et al. (2022) presented an analysis concluding that Airbnb misuse in London (in which entire home property listings do not follow the local regulations) can be associated with disruptions toward the traditional long-term housing market. Various studies emerge within the same themes, highlighting the challenges from the emergence of Airbnb, especially in relation to the housing market (Benitez-Aurioles et al., 2020) and examining the competing supply between long-term rental (LTR; for residents) and STR (for visitors) (Barron et al., 2017).

This article contributes to providing insights into the relationship between STR and LTR price patterns in London, and the dynamics of STR specifically through the use of predictive modeling. We propose several research questions (RQs) as follows:

1. *RQ1*: Are there any differences in the rental price patterns of STR and LTR in London?
2. *RQ2*: Is there any overlap between the two rental markets, indicating competition between STR and LTR?
3. *RQ3*: Can we predict STR price patterns in London using the gravity model to help understand its dynamics?

In our study, we use the assumption that STR are marketed to tourists while LTR are targeted at residents who live and work in London. Using both exploratory analysis and predictive modeling, we provide insights into STR and LTR simultaneously. For the latter analysis, we develop a gravity-based model using location attributes such as proximity to tourist locations based on the ease of accessing those locations which is an important factor for successful Airbnb listings (Tussyadiah & Zach, 2017).

The article is organized as follows. In Section 2, we explore the theoretical contexts and previous studies related the STR and LTR. In Section 3, we introduce the data used for the analysis and prediction including the method used for building the doubly constrained gravity model. Section 4 presents the results of the exploratory analysis and the predictive model along with a critical discussion of the implications of our analysis. Lastly, we conclude by synthesizing the theoretical and practical implications of our analysis and presenting the limitation of the study. We have also included a methodological annex in the appendix to provide the details of our gravity model.

2 | STR AND THE DISPLACEMENT OF HOUSING FOR LONG-TERM RESIDENTS

The rapid emergence of STR globally has sparked a heated debate with the Airbnb platform placed at the center of these discussions. In the last years, various studies have analyzed the spatial distribution of Airbnb locations

(Eugenio-Martin et al., 2019; Gutiérrez et al., 2017; Sans & Quaglieri, 2016). Airbnb has been mentioned to have a profound impact on the communities where the properties are located (Gutiérrez et al., 2017), associated with housing disruption (Barron et al., 2017; Shabrina et al., 2021) as well as disruption to other competing tourist accommodation (Zervas et al., 2017).

It is challenging to separate the discussion between STR and LTR as they come from the same supply, residential housing. Traditionally, tourists are heavily concentrated in areas where hotels are located. This could be in central areas (monocentric) or agglomerated around certain geographical points such as tourist destinations, airports, hospitals, etc. (Egan & Nield, 2000; Yang et al., 2014). However, Airbnb locations are more dispersed and geographically uneven as the listings are not just concentrated in prime urban cores, but also in other residential areas especially those in close proximity to restaurants and other amenities (Coles et al., 2017; Shabrina et al., 2021). These listings are located in highly desirable residential areas that otherwise would be available for long-term tenants (Lee, 2016; Shabrina et al., 2021; Wachsmuth & Weisler, 2017).

It has been pointed out further that Airbnb has been creating pressures, especially on housing and neighborhood in urban centers where long-term housing provision is already stressed (Cocola-Gant, 2020). Highly accessible neighborhoods, like those in the city center, are more desirable as Airbnb locations since Airbnb offers a high revenue premium (Deboosere et al., 2019). A study by Wachsmuth and Weisler (2017) shows that Airbnb allows a STR gap. Unlike the central argument proposed by Clark (1995) stating that there is a long life cycle explaining the property rent gap, Airbnb has made it possible to capitalize on the rental gap without major investment or redevelopment, only by the simple but controversial step of removing the existing tenant (Wachsmuth & Weisler, 2017). This is especially prominent in cities with high tourism activities such as Barcelona, where the consequence of Airbnb toward house prices is apparent (Garcia-López et al., 2020).

STR platforms such as Airbnb have created flexibility for property owners, making it easy to follow the existing demands, adjust prices, and avoid lease-related laws; thus, STR are less likely to return to the long-term residential markets (Cocola-Gant, 2020). This could create extra challenges, especially in cities that rely heavily on rental property markets such as those in the United Kingdom and other European cities.

3 | DATA AND METHODS

In this study, we use various datasets to support our exploratory data analysis of STR and LTR and build our predictive model of short-term rents using a doubly constraints gravity–spatial interaction model.

3.1 | Data

We use four main datasets including Airbnb data for STR, Zoopla property data for LTR, number of visits to tourist attractions, and travel time data. The details of the datasets are shown in Table 1. Both Airbnb and Zoopla data have been aggregated into lower layer super output areas (LSOAs), a geographic hierarchy of smaller area statistic in England with average population of approximately 1500 people.

3.2 | Methods

To answer the proposed RQs, we conducted a series of statistical investigations and applied predictive modeling to examine the relationship between STR and LTR (RQ1 and RQ2) and enhance our understanding of STR price specifically (RQ3). We use the coefficient of variation (CV) and correlation analysis to examine the patterns of STR and LTR

TABLE 1 Data sources and variables used in the study

No	Data[a]	Year	Source	Variables
1	Airbnb supply	2015–2019	Inside Airbnb (insideairbnb.com)	Listings price, number of beds, number of bedrooms, listings locations, number of reviews
2	Zoopla	2015–2017	Zoopla from Urban Big Data Centre	Property location (cross-checked with the Doogal (https://www.doogal.co.uk/) postcode data to obtain the spatial attributes), marketed rental price, number of bedrooms.
3	Visits to tourist attractions	2019	Visit Britain	Location of tourist destinations (88 most popular tourist attractions in London. This is a self-reported survey by the attractions and does not contain all the tourist attractions. The data are limited to those who are willing to provide the information), the data also includes the number of annual visits to these attractions.
4	Travel time	2018	Generated using Open Trip Planner	Travel time from LSOA centroids to tourist destinations. Data generated using Open Street Map Network and the public transit schedule.

Abbreviation: LSOA, lower layer super output area.

[a]All of the publicly available data and codes are available in https://github.com/robinmorphet/gravity-rent-calibration.
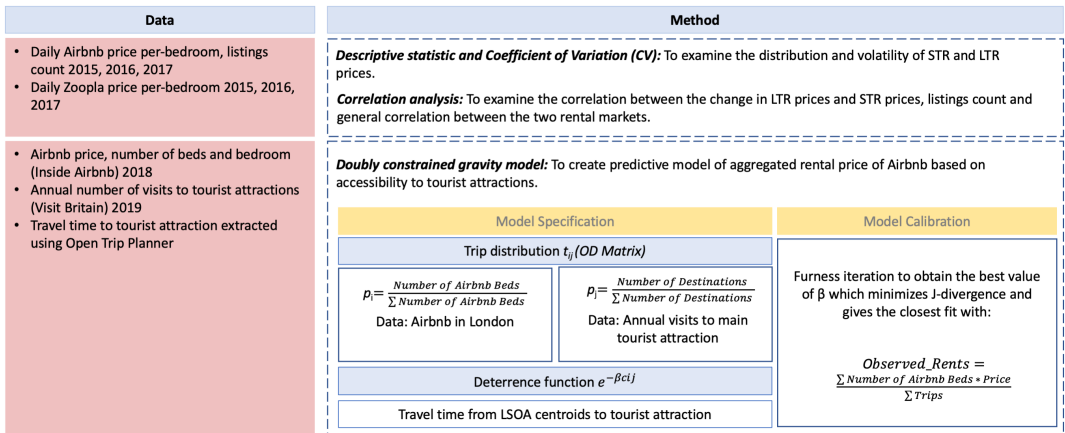

FIGURE 1 Flowchart of the methodology used

prices. We also use the gravity–spatial interaction model to calculate the predicted rental price pattern of Airbnb. The complete methodological flow used in this article is presented in Figure 1.

Through this research, we apply an exploration of the gravity model in tourism studies describing the interaction flow (or tourism flow) between two regions, areas, or locations. The interaction is influenced by the push factors associated with the flow leaving region *i* for tourism reasons (outflows) and the pull factors associated with the flow going to region *j* for tourism reasons (inflows) (Patuelli et al., 2013). In this article, we expand this basic concept and propose a novel form of gravity model for tourism analysis, by deriving the rental prices for given origin areas.

We have investigated relevant research in building the model specification. Tussyadiah and Zach (2017) suggest that proximity to points of interest and the characteristics of the neighborhood are two of the most important contributing factors to a successful Airbnb location. This is supported by the finding by Volgger et al. (2018) stating that Airbnb and non-Airbnb guests have a similar preference in terms of staying in areas with good access to well-known and iconic touristic highlights. This is strengthened by a study based on the sentiment analysis of Airbnb

reviews, which found that one of the key attributes of an Airbnb experience is location, followed by amenities and hosts (Cheng & Jin, 2019).

Thus, the main elements in our doubly constrained gravity model are: (1) the constraint on destination trip ends (i.e., the number of visitors to a given attraction); (2) the cost of deterrence function $f(c_{ij})$, which is the travel time data; and (3) a constraint on origin trip ends, which is the historic Airbnb supply. The model shows the relation of different locations by examining the degree of spatial interaction reflecting Tobler's First Law of Geography which states that 'everything is related to everything else but near things are more related than distant things' (Tobler, 1970). The measure of spatial separation is given by the deterrence function. Flows can be modeled where T_{ij} is the flow from origin i to destination j, K is a scaling constant, O_i is attraction at the origins i, D_j is attraction at the destinations j, and c_{ij} is the deterrence factor, following the equation:

$$T_{ij} = KO_iD_jf\left(c_{ij}\right) \text{ where } f\left(c_{ij}\right) = e^{-\beta c_{ij}} \tag{1}$$

c_{ij} represents the cost, which can be a generalized cost or weighted sum of distance d_{ij} and travel time t_{ij} costs. The negative exponential cost function $e^{-\beta c_{ij}}$ arises from the maximizing of entropy with a constraint on mean trip cost. A detailed description of the gravity model method used in this article is provided in the Methodological Annex.

4 | RESULTS AND DISCUSSION

4.1 | Exploration of STR and LTR price pattern

Using Zoopla property website data, we examine areas that have been experiencing major rental price changes in London. Figure 2 visualizes the percent rent changes in London LSOAs based on Zoopla data from 2010 to 2017 showcasing an East–West section view of the difference between the rental prices in the two time points. We observe sharp spikes appearing around East and Central London with some variations in the South and West parts of London near Heathrow Airport. The high and increasing rental value in central London further emphasizes London's monocentric trend, where the employment centers, retails, and many urban activities are concentrated in the core city areas. On the other hand, East and South London are areas that have been experiencing fast developments of new residential developments that might contribute to the rapid rental price changes.

Just like the British housing system, housing in London is dominated by private ownership, many of which are rented out to private tenants. According to official government data, the median monthly rental price in London is £1425 which is 190% higher than the median monthly rental prices of England (£755) between October 2020 and
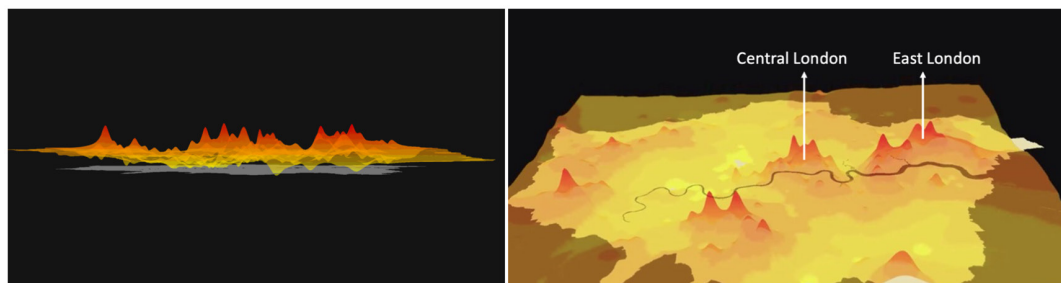

FIGURE 2 3D visualization of percent rent changes in London 2010–2017. Left: East–West snapshot of rental price changes in London showcasing higher variations in Central and Eastern part of London. Right: Bird-eye snapshot of rental prices changes in London. The color represents the percentage changes according to its intensity from yellow (low changes) to red (high percentage rental price changes)

September 2021 (ONS, 2021). This price difference is also apparent locally as the median rental price of Inner London areas is £1600 compared to £1300 in Outer London areas (ONS, 2021). Considering the LTR market trajectory especially with the stark housing price difference in London compared with the remainder of the UK, it is useful to investigate how the rapid influx of STR might also contribute to the overall LTR price changes.

Table 2 shows the descriptive statistics for the Airbnb and Zoopla datasets in London representing the supply of STR and LTR, respectively. Our first exploration is aspatial, meaning that we examine all the available Airbnb and Zoopla listings regardless of their location. For our initial analysis, we only include STR data with at least one review as a proxy of active listings. Airbnb has grown exponentially between 2015 and 2017 while properties being marketed on the Zoopla property website are quite steady. The annual Zoopla data sample is up to around seven times larger than active Airbnb listings as the LTR market is generally larger overall.

We can see that the mean Airbnb prices in London are consistently much higher compared with the mean Zoopla price per bedroom. In 2017, the mean price per bedroom of Airbnb is 246% higher when compared with the Zoopla mean prices. For example, based on a recent market study in the United States by AlltheRooms website (https://www. alltherooms.com) that analyses STR markets, the average occupancy rate of Airbnb is around 48%. Despite Airbnb occupancy might be lower than those for long-term properties, Airbnb often has a higher rental value in total. To create a comparable measurement, we also calculate the CV for the STR and LTR prices from 2015 to 2017. CV is also known as the coefficient of dispersion and is often used as a measure of volatility (Brown, 1998). Based on the CV calculation, we found that Airbnb consistently yields a higher CV of up to 0.6 indicating that prices disperse from the mean. An explanation would be that Airbnb prices can be easily adjusted following the increase and decrease in demand, seasonality, and even personal preferences. Airbnb and other known STR markets are using dynamic pricing for the purpose of achieving demand equilibrium with high-demand hosts using larger price variations as a strategy to optimize their revenue (Gibbs et al., 2018; Shokoohyar et al., 2020).

Figure 3 further shows the distribution of the rental price patterns based on STR and LTR in London where the yellow color indicates areas with the highest rental prices range. Figure 3a–c shows the distribution of Airbnb mean price per-bedroom in each London LSOA. We can see that Airbnb listings are concentrated in Central London and have expanded quite extensively over the years. Airbnb pattern concentrates in Central London areas spanning from West to East London including areas such as Westminster, Kensington and Chelsea, City of London, Hackney, and Tower Hamlet. According to a 2016 study, Tower Hamlets is considered the most gentrified borough with Hackney placed third in London (Almeida, 2021). Further investigation is needed to examine the implication of highly gentrified places that are populated by some of the highest priced Airbnb supply. Previous studies have highlighted that Airbnb thrives in central and touristic areas (Gutiérrez et al., 2017) which is apparent from our maps. This aligns with Gibbs et al.'s (2018) finding that physical locations matter greatly and yield high revenue.

TABLE 2 Descriptive statistics of historical Airbnb (STR) and Zoopla (LTR) data

Year	Listings count	Listings count (>1 review)[a]	Min	Max	Mean (μ)	SD (σ)	CV (σ/μ)
Airbnb price per-bedroom (daily) in London LSOAs							
2015	25,361	17,694	$5.00	$1000.00	$72.66	38.87	0.53
2016	42,646	28,398	$5.00	$1000	$65.54	36.86	0.56
2017	53,904	37,438	$3.33	$1150.00	$65.89	39.55	0.60
Zoopla price per-bedroom (daily) in London LSOAs							
2015	137,184	NA	$8.25	$117.00	$25.57	10.58	0.42
2016	148,897	NA	$9.33	$152.38	$26.84	10.09	0.39
2017	134,149	NA	$3.71	$140.49	$26.77	10.05	0.40

Abbreviations: CV, coefficient of variation; LSOAs, lower layer super output areas; SD, standard deviation.
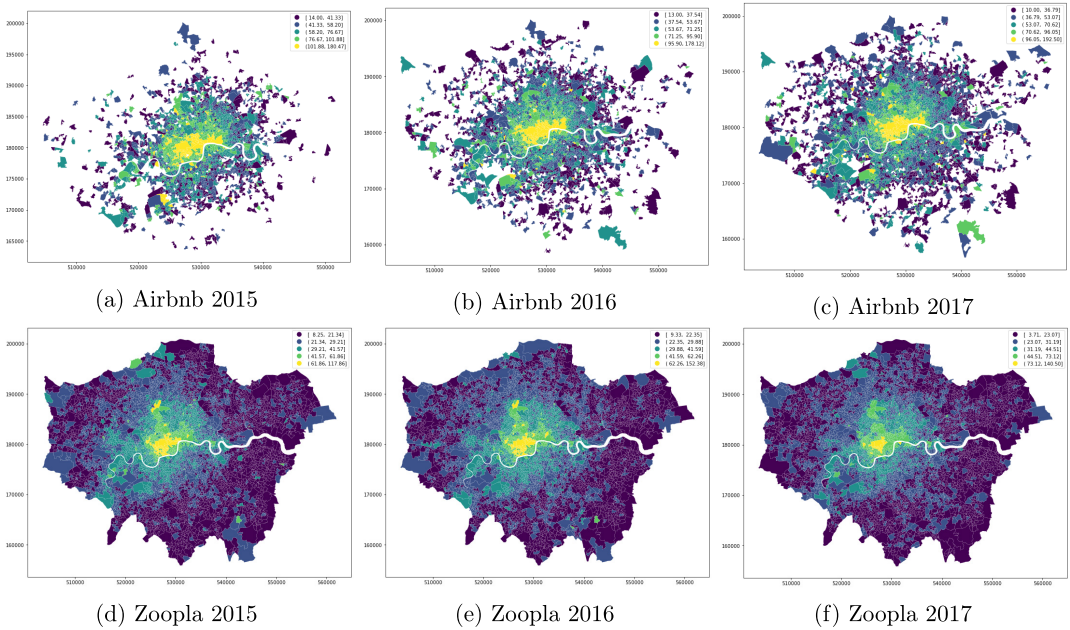[a]Only applies to Airbnb data.

(a) Airbnb 2015　　　　(b) Airbnb 2016　　　　(c) Airbnb 2017

(d) Zoopla 2015　　　　(e) Zoopla 2016　　　　(f) Zoopla 2017

FIGURE 3　Daily mean price per-bedroom for (top) Airbnb and (bottom) Zoopla in London lower layer super output areas (LSOAs)

	A2015	A2017	L2015	L2017	Z2015	Z2017	A2015_2017	L2015_2017	Z2015_2017
A2015	1.000000	0.978270	0.625645	0.625103	0.862615	0.946355	0.062448	0.503333	0.612977
A2017	0.978270	1.000000	0.579909	0.573624	0.872631	0.957994	0.016524	0.417843	0.602623
L2015	0.625645	0.579909	1.000000	0.986468	0.660216	0.693151	0.129815	0.760386	0.360117
L2017	0.625103	0.573624	0.986468	1.000000	0.681052	0.691195	0.062550	0.840965	0.364185
Z2015	0.862615	0.872631	0.660216	0.681052	1.000000	0.932198	-0.140242	0.569044	0.422577
Z2017	0.946355	0.957994	0.693151	0.691195	0.932198	1.000000	-0.038140	0.527530	0.580574
A2015_2017	0.062448	0.016524	0.129815	0.062550	-0.140242	-0.038140	1.000000	-0.219933	0.036831
L2015_2017	0.503333	0.417843	0.760386	0.840965	0.569044	0.527530	-0.219933	1.000000	0.293842
Z2015_2017	0.612977	0.602623	0.360117	0.364185	0.422577	0.580574	0.036831	0.293842	1.000000

FIGURE 4　Correlation analysis between annual changes of short- and long-term aggregate rental prices at the borough level. A, Airbnb mean price per-bedrooms per-night; L, number of listings; Z, Airbnb mean price per-bedrooms per-night

Zoopla price distribution, on the other hand, is concentrated in Central London spanning the high-priced western part of London such as Kensington and Chelsea, Westminster, Hammersmith and Fulham, and Richmond upon Thames. These West London areas were historically planned as residential areas and have now developed into upmarket areas with one of the most highly priced rentals.

We further investigate whether the annual rental changes of STR can be associated with the changes in the LTR market. The analysis is done at the borough level as the Zoopla data are quite sparse at the LSOA level (we do not have enough sample data for each LSOA even though LTR are obviously present), thus aggregation is needed. Figure 4 shows a correlation matrix between the changes in Zoopla rental prices (Z2015_2017), changes in Airbnb listings count (L2015_2017), and changes in Airbnb rental prices (A2015_2017) in London boroughs. These changes are presented in their logarithmic form to account for the non-normal distribution of the data. The matrix provides the information on correlation coefficient r that represents the linear association between variables.

The result shows that the mean rental price per bedroom of both Airbnb and Zoopla are highly correlated (r of 0.86 between A2015 and Z2015 and r of 0.96 between A2017 and Z2017). We also observe a positive linear correlation between the number of Airbnb listings and LTR price (r of 0.70). This indicates that areas with a high Airbnb supply are mostly located in highly priced residential areas. In terms of the rental changes, there is almost no correlation between the changes in Zoopla and Airbnb rental price per bedroom in 2015 and 2017, as the correlation coefficient is very small with an r of 0.04. However, the annual changes in Zoopla rental price-per bedroom in 2015–2017 are positively correlated with the changes in the number of Airbnb listings in 2015–2017 (r of 0.30). This indicates that LTR price increases linearly with the increase in the number of active Airbnb listings. These findings can provide an indication that the STR and LTR prices are competing in places with similar price patterns. These results relate to previous studies that have indicated Airbnb could be associated with a rental price increase for long-term residents (Barron et al., 2017; Lee, 2016; Shabrina et al., 2022; Todd et al., 2021) and even contributed to Airbnb-induced gentrification (Wachsmuth & Weisler, 2017).

We have explored the difference and overlaps in patterns of STR and LTR and provided an indication of how these two markets are in competition. For the next section, we shift the focus to modeling the STR price pattern.

4.2 | Predicting Airbnb price pattern using doubly constrained gravity–spatial interaction model

In this section, we focus on the STR price pattern and create a model to predict the Airbnb price pattern in 2019 based on the historical Airbnb attributes in 2018, the number of annual visits to tourist attractions in 2019 and easiness to reach those destinations. We implement the gravity model which provides a reasonable computation on where Airbnb locations are desirable based on the supply of Airbnb data in relation to access to various touristic destinations. Through the model, we have created a tool for predicting future Airbnb price patterns that consider the destinations' data. We use Greater London as our study area.

The gravity model simulates spatial interaction which refers to any movement as a result of human processes over space (Haynes et al., 1984). The idea is that the spatial interaction between places increases with improved accessibility to destinations, stressing the importance of accessibility as a key concept within spatial interaction models (Condeço-Melhorado et al., 2014). Bhat et al. (2000) emphasized accessibility as the ease of pursuing any kind of activities in any given location using a desired mode of travel. This type of concept uses the location perspective, in terms of how land use and transport influence access to destinations using several combinations of transport modes (Geurs & Van Wee, 2004), where locations are then assessed based on the number of activities that can be reached and weighted using travel time to destinations (Bertolini et al., 2005).

We construct our accessibility measure using the gravity–spatial interaction model. The model consists of three important components: (1) the origins (locations of Airbnb rentals in the previous year aggregated into LSOA level); (2) destinations (the points of interest that can be reached); and (3) the cost of traveling from origins to destinations given by the spatial separation. Underlying our spatial interaction model is the premise that Airbnb rental prices can be predicted based on the historical Airbnb data and external factors with assumptions that Airbnb will locate in places with high accessibility to tourist attractions (as measured by the number of visits), and those locations relate to well-sought-after neighborhoods, as indicated by their rents. It is worth noting that we filter our Airbnb data to only include those that have received at least 10 reviews to account for the listings that have been booked repeatedly.

We incorporate the number of visits to tourist attractions in London's central areas as the pull factor of our model. Attractions in urban tourism are often used to boost the image and economy of a city and provide destinations for tourists (Ashworth & Page, 2011; Judd & Fainstein, 1999; Law et al., 1993; Papadimitriou et al., 2015). Figure 5 shows the distribution of the main tourist attractions in London each according to the number of visits to the attraction represented by a set of graduated symbols. According to data by Visit Britain, as shown in Figure 5, the highest number of annual visits in 2019 is to the British Museum with more than 6 million annual visits, followed by
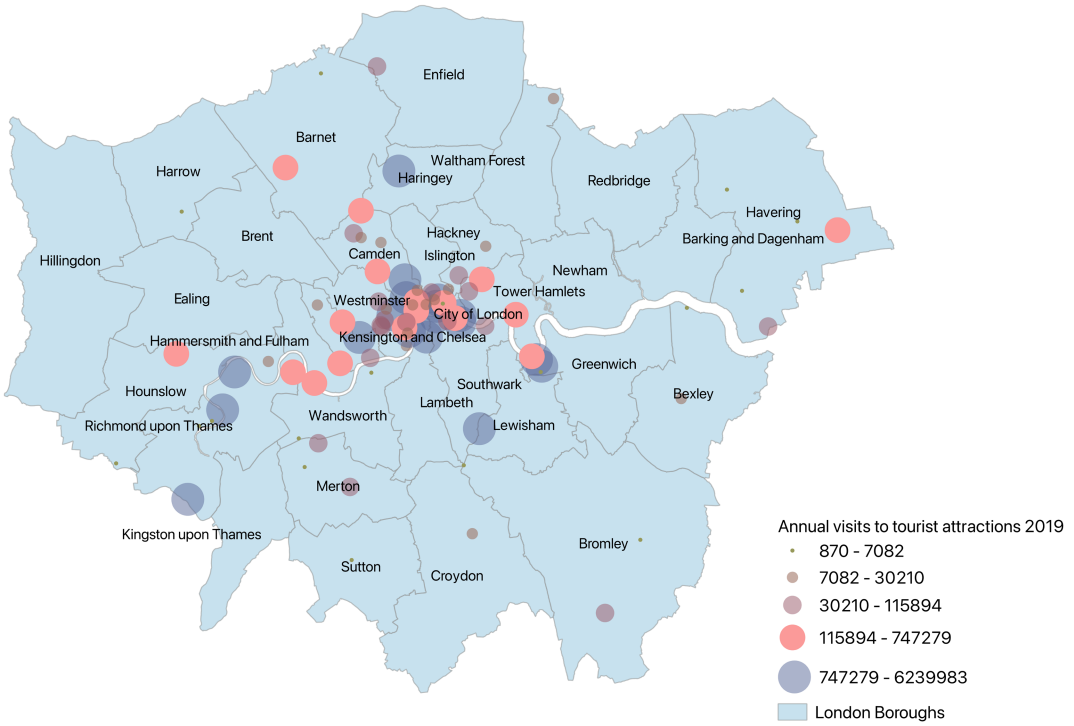
FIGURE 5 Annual number of visits to main tourists attractions in London 2019

the Victoria and Albert Museum with almost 4 million visits and St Paul Cathedral with almost 3 million visits. Most of the highly visited attractions are located in the central areas with some located in the north and south of London, although these receive fewer annual visits.

Another important element in our model is the use of travel time as the cost function. An assumption in spatial interaction is that ceteris paribus, travel flow declines with the difficulty of travel. Our cost function is expressed as $e^{-\beta t_{ij}}$, as in Equation 1 but with time t_{ij} replacing cost c_{ij}. We then derive the centroids of the 4835 LSOAs in London as our origin points and calculate the travel time to the 88 tourist destinations as our destination points using the Open Trip Planner (OTP) tool. OTP uses contraction mapping and the A* heuristic algorithm (Russell & Norvig, 2003) to find the optimal path and provide travel times between two geographical points based on the user's desired criteria (Hillsman & Barbeau, 2011). Travel times provide a more accurate representation of deterrence function compared to distance as it captures the actual time spent to travel between places as some destinations might be further apart in distance but can be reached relatively quickly using public transport.

The Furness (1965) iteration is used to iterate the base matrix, that is, $e^{-\beta c_{ij}}$ to the given row and column totals. For any given value of β, we solve the model iteratively and we calibrate the model by choosing the value of β which gives a mean trip cost sufficiently close to the mean. This value of β is chosen as that value that minimizes the J-divergence between the distributions (Rohde, 2016). The β values with the lowest J for our model is $\beta = 0.008$.

Based on the model calibration, we derive the predicted rents of Airbnb in London. Figure 6a shows the predicted rent distribution of Airbnb and this can be compared with the actual Airbnb rental pattern in 2019 as shown in Figure 6b. The model can explain 45% of Airbnb rental price variance (adjusted R^2 of 0.455) based on the level of attractiveness (shorter time to reach touristic destinations) as well as the historical data of Airbnb in the previous year. Based on Figure 6, we can see that the prediction presents a good depiction of the observed rental pattern with higher rental prices spanning across the south-western to north-eastern axis.
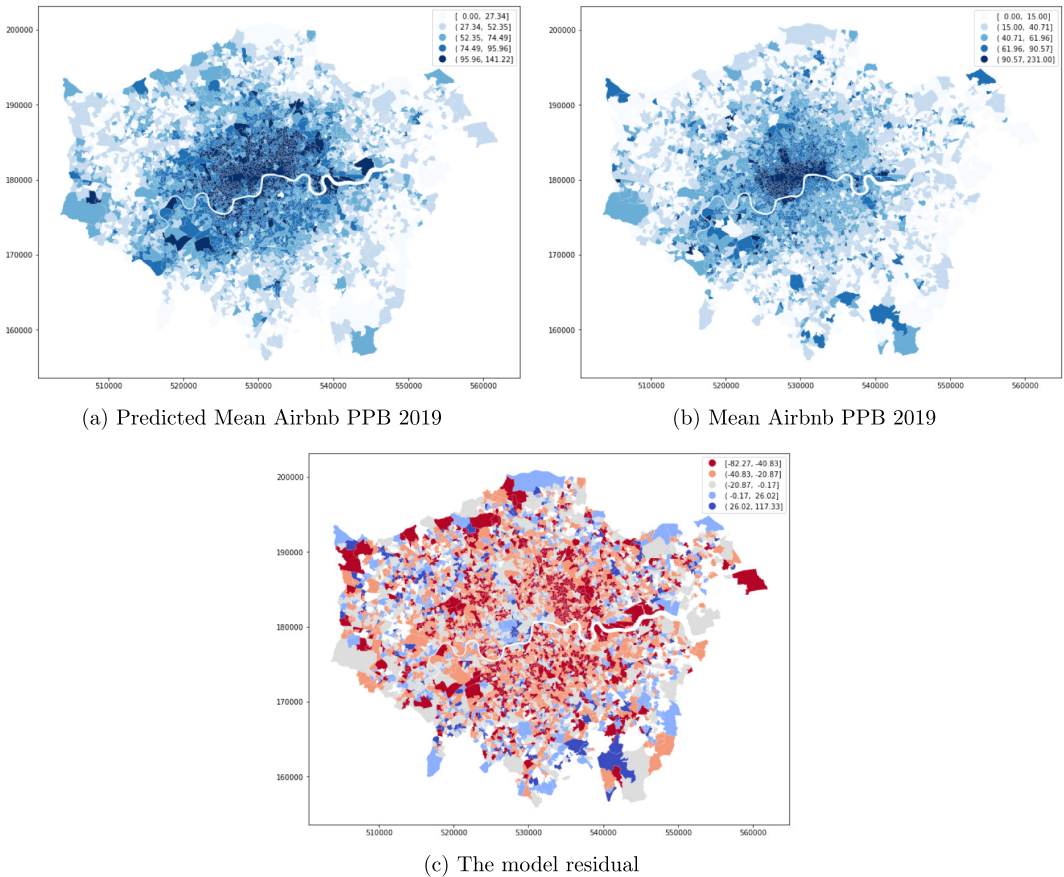
(a) Predicted Mean Airbnb PPB 2019

(b) Mean Airbnb PPB 2019

(c) The model residual

FIGURE 6 The result of doubly constrained gravity–spatial interaction model

The Airbnb gravity approach models the Airbnb market that computes accessibility of areas desirable for Airbnb locations. These areas are locations where tourists can reach a set of popular touristic destinations using public transport services. This computation is translated into rents, with the assumption that desirable Airbnb locations would have higher price premiums. As the model is computed in an aggregate form, the model does not take into account that with Airbnb's supply becoming saturated, listings will eventually compete with each other, and prices might go down due to the competing supply to reach equilibrium.

This seems to be the case as shown in Figure 6c computed by subtracting the observed Airbnb mean rental price 2019 from the predicted rental price 2019. Examining the model residual is useful to investigate areas where the model is under- and over-performing (represented as blues and reds respectively). The model seems to be over-performing in some areas, especially in the East, Northeast, and some areas in South London. There is a cluster of areas where the model is over-performing meaning that the observed rents are smaller than the predicted rents. This seems to be particularly apparent in areas with high listing counts such as those in East London. Further investigation is needed to examine this.

Considering the volatility of the Airbnb market, we have shown that it is possible to predict changes to the system such as those due to the closure of tourist destinations during the pandemic as well as development although this is beyond the scope of our article. The gravity model can be used to identify the impact of changes in accessibility on rents and as such is a useful policy tool for impact analysis if the possible driver of the impact is specified either in network changes or in trip ends (or their proxies).

5 | CONCLUSION

To summarize, our study provides insights into the competition and patterns of STR and LTR. Examining the supply of both Airbnb and Zoopla data over the years can help our understanding of the overlaps between the two markets. This study has practical and theoretical implications that contribute to the discourse on STR and their association with long-term housing.

5.1 | Theoretical implications

This study has used a series of quantitative approaches to investigate STR and LTR patterns using statistical analysis and gravity–spatial interaction modeling. We have incorporated a total of more than 200,000 Airbnb and around 500,000 Zoopla data points to create a robust analysis for examining the STR and LTR rental patterns and this can contribute to the understanding of the spatial patterns of these markets. We also propose a model that can take into account the dynamics of STR in relation to visits to tourist destinations. By incorporating the rent-based gravity model, we expand the use of the gravity model in tourism studies that will be useful to capture a dynamically changing tourism market.

5.2 | Practical implications

The result of this study can assist planners and policymakers to understand the competition from STR in relation to LTR. We have used a historical dataset of Airbnb supply from 2015 to 2017 in our analysis and found that Airbnb price tends to be higher and more volatile compared with LTR. By closely looking at the patterns of the two markets, policymakers can use a data-driven approach to be able to keep an eye on specific areas in which Airbnb premiums are high and many properties have been transformed into STR. As the correlation analysis shows that STR and LTR prices are highly correlated, with some of the highest priced long-term properties located in areas populated with Airbnb, further exploration is needed at the local level to account for the competing needs between properties for residents and those available for tourists. Regarding the model, it can be used as a tool to simulate future aggregate Airbnb price patterns that can take into account various possible changes in the tourism sector.

5.3 | Limitations and merits

It is important to note that the results of this study should be approached with consideration of the study's limitations. First, most of the analysis is done at an aggregate level, including the borough and LSOA levels. We need to acknowledge that analysis at an aggregate level might suffer from the Modifiable Areal Unit Problem (see Wong (2004) for details on MAUP). Despite this limitation, this study has showcased analysis using different spatial scales, including at point (the statistical analysis and CV) and aggregated levels. The approach of using a different spatial scales is necessary to provide effective analysis considering the nature of the data, such as Zoopla data that are not distributed equally.

Second, for both Airbnb and Zoopla data, we have used listed price data which can be used to showcase the prices for STR and LTR that are available and visible for renters. As they are not transaction prices, we are analyzing supply data instead of demand data. For the gravity model, we have not included competition between Airbnb listings themselves, by assuming that popular Airbnb locations would be utilized by tourists regardless of what is being offered. We acknowledge that the model might suffer from biases as we have not incorporated other possible elements that might influence the price of Airbnb listings, such as competing listings and the intrinsic elements of the

property itself including the amenities provided, building quality, host responsiveness, etc., as the model restricts this toward the location aspect of Airbnb. However, the model is useful in providing a way to simulate price patterns that is sensitive to changes in destinations as external factors repeatedly mentioned as being an important determinant for Airbnb (Deboosere et al., 2019; Tussyadiah & Zach, 2017).

Third, our analysis does not take into account the existing policies that might restrict Airbnb locations. The deregulation of short-term lettings in London (Ferreri & Sanyal, 2018) still provides some restrictions for hosts, while other granular level restrictions such as building associations, etc., have also made an effort to control where Airbnb can be located. This might somewhat affect STR rental distribution, perhaps even more than the LTR market. For further studies, these various factors as mentioned above should be considered.

In summary, our study contributes to providing rigorous geographical and quantitative analysis of the possible economic disparities between STR and LTR prices. We have provided an investigation of STR and LTR in one of the most heated housing markets in the world where the growth of Airbnb supply is very fast and might put pressure on the long-term markets. We also presented evidence of overlaps between STR and LTR markets which could indicate competition between them. Lastly, we provide the first predictive analysis of Airbnb prices using a novel form of gravity–spatial interaction model, expanding the application of the traditional gravity model to tourism-related studies.

DATA AVAILABILITY STATEMENT

Zoopla data is subject to third party restrictions (Glasgow Urban Big Data Centre).

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METHODOLOGICAL ANNEX: THE GRAVITY–SPATIAL INTERACTION MODEL A

A.1 | Antecedents

The gravity model we use in this research is based on the entropy maximizing derivation (Wilson, 1971). There are, however, many precursors including in transportation studies such as the work of Desart in the 1840s (Odlyzko, 2015) and migration (Ravenstein, 1889). In the 20th century, applications were developed in trade theory (Tinbergen, 1962) and retailing (Reilly, 1929), while its modern use dates from its application to retail planning (Lakshmanan & Hansen, 1965). Its current use in transport planning (Ortuzar & Willumsen, 2011) forms the basis of land-use transportation interaction models to the present day (Martinez, 2018). The gravity model has also been used in a variety of tourist analyses (Khadaroo & Seetanah, 2008; Morley et al., 2014; Patuelli et al., 2013), although its use in this context is still quite limited (Hall, 2006).

A.2 | Derivation

The derivation of the model follows that of Wilson (1970) with the difference that we use trip probabilities (p_{ij}) rather than trips (T_{ij}) and we include an extra constraint to ensure the probabilities sum to unity. This allows us to use the standard thermodynamic formalism of Gibbs (Cowan, 2005) and to include the partition function Z. We set up the Lagrangian multiplier Equation A1 which on differentiating $\mathcal{L}$ with respect to p_{ij} and setting the result equal to zero, which gives the model Equation A2.

$$\mathcal{L} = -\sum_{i=1}^{n}\sum_{j=1}^{n} p_{ij}\ln p_{ij} - \sum_{i=1}^{n}\lambda_i\sum_{j=1}^{n}p_{ij} - p_i - \sum_{j=1}^{n}\lambda_j\sum_{i=1}^{n}p_{ij} - p_j - \beta\sum_{i=1}^{n}\sum_{j=1}^{n}p_{ij}c_{ij} - U - \lambda_0\sum_{i=1}^{n}\sum_{j=1}^{n}p_{ij} - 1 \tag{A1}$$

$$p_{ij} = e^{-\lambda_i}e^{-\lambda_j}e^{-\beta c_{ij}}e^{-\lambda_0} = \frac{e^{-\beta c_{ij}-\lambda_i-\lambda_j}}{Z} \tag{A2}$$

where $Z = \sum_{i=1}^{n}\sum_{j=1}^{n}e^{-\beta c_{ij}-\lambda_i-\lambda_j}$.

A.3 | Estimation using mean trip cost

Knowing the origins p_i and the destinations p_j together with the trip costs c_{ij} and a given value of β, the expected trips may be calculated using a Furness iteration (Furness 1965). Conventionally, the value of β is chosen to equate the modeled and observed trip costs as this corresponds to a maximum likelihood estimate. The value is found using the method of Hyman (1969). In our case, however, we recognize that β is not the only parameter in the model.

A.4 | Estimation using rent

The terms $e^{-\lambda_i}$ and $e^{-\lambda_j}$ in Equation A2 are the balancing factors which are also parameters of the model and which ensure that row and column trip totals are equal to the exogenously determined origins and destinations. The terms $-\frac{1}{\beta}\ln\lambda_i$ and $-\frac{1}{\beta}\ln\lambda_j$ can be identified with von Thünen location rents (Morphet, 2013). The model is estimated as above using a Furness iteration which gives the estimated trips and the balancing factors from which we calculate the estimated rents for each zone. These are then compared with the observed rents and a value of β is found which minimizes the J-divergence between observed and modeled rents (Rohde, 2016). In our model, this is done solely for origin zones that correspond to residential rents. The rents are rents per trip, which, knowing the number of origins, can be converted to total rent per zone. The zonal rents can be converted into rent rates per unit area, per household or whatever denominator is required for the study at hand.

A.5 | Accessibility

The logarithmic terms for rent have also been identified as accessibility measures (Martinez, 1995) in comparison with more conventional measures of accessibility such as by Hansen (1959) which are additive rather than multiplicative. The argument for considering them as rents, apart from their links to von Thünen, is that they have dimensions of cost, as an inspection of Equation A.2 readily shows. Consideration of rents may also be more familiar and graspable for decision-makers than are the various definitions of accessibility (Geurs & Van Wee, 2004).

A.6 | Application to London's Airbnb rent market

The model requires data on origins, destinations, and travel costs between a set of zones. Travel time is used as the measure of the trip cost and is obtained from OTP, open-source software for multi-modal route planning using a combination of the Open Street Map network and public transit schedules in the General Transit Feed Specification format (https://gtfs.org/) for multi-modal application development (Antrim et al., 2013).

Travel times using both rail and bus datasets as public transport modes were obtained from Association of Train Operating Companies. The London bus and tube data were obtained from Transport for London. Travel time data were computed for three different days, mixing weekends and weekdays. The shortest time was chosen so as to mitigate the possibility of longer travel times due to disruptions or planned engineering work on those days. Also incorporated were walking times, transit times (time spent waiting in between modes), and boarding times (number of transfers between transit modes) to increase the relevance of our travel time data. Thus, the time calculated is time spent for the whole journey from an origin to a destination. The resulting cost data matrix is of travel times to the 88 main London tourist attractions from 4835 origins based on the centroid of each London LSOA. Around 450,000 travel time records were used from which were computed 81% of the system's travel time data. The remaining travel time data is beyond the 100 min maximum threshold set for the analysis on the assumption that tourists would not make trips of greater duration.

In the absence of observed origins and destinations, we use proxies. Destinations are proxied by the annual reported visitors at each of the attractions. Origins are proxied by the number of Airbnb beds in each LSOA (Table A1). This gives us the definition of p_i and p_j as shown in Equations A3 and A4 below:

$$p_i = \frac{\text{Number\_of\_Airbnb\_Beds}}{\sum_i \text{Number\_of\_Airbnb\_Beds}} \tag{A3}$$

TABLE A1 The sample O-D matrix from origins (LSOA) to tourist destinations. The summation of each row needs to equate to O_i while the summation of each column needs to equate to D_j

LSOA11CD	Barnet museum	British library	British museum	
E01000001	3325	1247	1208	= O_i
E01000002	3371	1460	1857	
E01000003	3239	1217	1377	
E01000005	3293	1349	1720	
E01000006	6000	4625	4077	
	= D_j			

$$p_j = \frac{\text{Number\_of\_Destinations}}{\sum_j \text{Number\_of\_Destinations}} \tag{A4}$$

In calibrating the model, we find the best value of β by running the model with different values of β and using the value which gives the closest fit of the predicted rents to the observed. The Furness iteration allows us to obtain the balancing factors for both origins $(e^{-\lambda_i})$ and the destinations $(e^{-\lambda_j})$ (see Equation A2) from which the predicted rents per trip, $\frac{\lambda_i}{\beta}$, are calculated. We estimate the observed rents as follows:

$$\text{Observed\_Rents} = \frac{\sum \text{Airbnb\_Beds*Price}}{\sum \text{Trips}} \tag{A5}$$

The best value of β is taken to be that which minimizes the J-divergence (Rohde, 2016). The J-divergence measures the divergence between two discrete probability distributions. In our model, p_i is the distribution of predicted rents for each origin zone (derived from the balancing factors of the model) and q_i is the observed rent distribution in Equation A5. J is calculated using Equation A6 below:

$$J = \sum_i (p_i - q_i) \left(\log \frac{p_i}{q_i} \right) \tag{A6}$$

Figure A1 plots the trial values of the β parameter against the J values. The β values with the lowest J give the best fit which for our model means $\beta = 0.008$.

A.7 | Competition

The gravity model as used in journey to work studies is an equilibrium model of imperfect competition in a labor market. It models competition between workers for jobs and employers for employees. Similarly, the Airbnb gravity model models the Airbnb market in which tourist destinations compete for visitors from Airbnb locations which themselves compete for tenants. The iterative method used to compute the model resembles a negotiation in which the balancing factors (i.e., the rents) for the origins (destinations) are modified by the destinations (origins) and vice versa. The computed rents are rents per trip hence rents per residential unit in an LSOA are estimated by calculating the total rent for the area (i.e., trip rent × no. of trips) and dividing this by the relevant number of residential units. This illustrates that when the supply of residential units increases so the unit price will decrease ceteris paribus. The demand in the model derives from the number and distribution of destinations and is mediated by the trip cost.
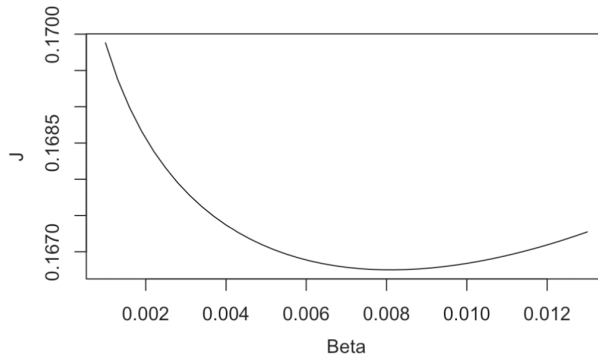
FIGURE A1 J-divergence for different values of beta

The resulting model supports the analysis of the effects on the Airbnb market of differential changes in travel cost and changes in the size and spatial distribution of tourist attractions. Such changes are fed into the model which is run assuming either β or the mean trip cost stays constant. The economic interpretation of the balancing factors has been discussed in the literature following the work of Hansen (1959). Wilson (1967) identified them as measures of accessibility and Neuburger (1971) as consumer surplus. They were subsequently identified as rents (Williams and Senior, 1978). The gravity model itself was shown to be consistent with utility-based discrete choice models by Anas (1983).