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THE SPATIAL AND QUALITY DIMENSIONS OF AIRBNB MARKETS

ABSTRACT

Airbnb is now present in many tourist destinations worldwide. With the pricing power in the hands of the individual hosts, the assessment of competition is of great relevance. Despite the many studies on the drivers of Airbnb prices, there is no contribution yet on how quality affects the spatial dimensions of Airbnb markets. We aim to fill this gap with a case study of Bristol (UK). Using standard regression techniques, we find a quality-moderated spatial decay in the price effects of competition in local Airbnb markets. Thus, the price of a given listing is affected negatively by other listings within a set of radii that decrease with product differentiation. Beyond this local market boundary, the existence of other listings may increase prices, as demand is driven to the neighbourhood- or city-wide markets because of the diversity of tourism accommodation.

Keywords: Accommodation pricing; Airbnb; sharing economy; spatial economics.

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1. INTRODUCTION

The tourism sector was characterized by a market structure mainly formed by tour-operator, air carriers, travel agencies, and hotel brands. Since the 1970s, the successive air market liberalizations, the advent of the internet and, more recently, the development of peer-to-peer (P2P) sharing economy platforms (such as Airbnb) have transformed the sector by lowering entry barriers and facilitating the appearance of a new supplier: private owners (Zervas et al., 2017; or Blal et al., 2018). While Guttentag (2015) and Drogu et al. (2019) highlight the "disruptive" effect of sharing economy platforms in the hotel sector (particularly in the lowend segments of the market) (Zervas et al., 2017), other studies reduce the impact of P2P accommodation in hotel performance by emphasizing the different tourist profiles attracted by the former (Varma et al., 2016; STR, 2017). The impact can also be mitigated by the size and growth of the market, as well by incumbency advantages. For instance, the pricing power of US hoteliers has not been hit by Airbnb supply as demand has grown steadily since 1930 (STR, 2017). Also, Eugenio-Martín (2019) found that the penetration of Airbnb listings was higher in cities and small towns than in sun-and-beach areas in the Canary Islands, where hotel establishments hold a prevailing market position occupying the better locations.

Despite that, P2P platforms are usually regarded as unfair competition by incumbents that demand more oversight in terms of tax compliance and safety standards (Dickinson, 2018). Other areas of concern are the nuisance caused by visitors in residential areas (Gutiérrez et al., 2017), and the increase in rents and house prices that is pushing traditional tenants out of neighborhoods (Wachsmuth and Weisler, 2018). Despite the effects on the hotel and residential sectors, the entry of new P2P platforms has facilitated the boom of private accomodation supply in many cities, with an ever-increasing share of the market. These platforms allow hosts to establish a direct link with prospective guests by showing information about their properties, and allowing former guests to leave comments or rank the property. The availability of such amount of public information boosts competition, turning product differentiation into the cornerstone for attracting guests.

A key element of product differentiation is location, and its influence can be clearly seen in the spatial distribution on hotels and Airbnb listings in most cities worldwide, which tends to be concentrated in areas with better tourist attributes. As a result, *ceteris paribus,* prices are expected to be higher in these areas than in peripheral locations (Chamberlain, 1933). This effect has been confirmed by most studies that account for location as one of the drivers of

Airbnb prices (e.g. Wang and Nicolau, 2017; Magno et al., 2018; Önder et al., 2018; or Lorde et al., 2019). From studies on hotel prices, we also know another key aspect of location as a driver of price: the influence of competitors decays with distance and thus markets can be defined according to a geographical boundary (Lee, 2015). However, the distance relationship is moderated by quality differentiation, with competing hotels of similar quality exerting an influence over longer distances (Balaguer and Pernías, 2013; Lee, 2015; Soler and Gemar, 2018) so different market boundaries may exist. In view of that, it seems reasonable that Airbnb markets could also be defined from both spatial and quality dimensions, with the second having an impact on the first. Thus, we should be able to find different radii around a given listing within which the presence of competitors of varying levels of quality has an influence on its price. Despite the many contributions in the area, there is no study to date that provides an estimate of the geographical scope of Airbnb markets that considers quality differences.

This paper explores the role of location and competitor prices (proxy for quality) as drivers of the price of Airbnb listings in the city of Bristol, UK. To this end, we estimate a series of hedonic price equations using ordinary least squares (OLS) methods. The goal is to arrive at an optimal market definition (or definitions) in terms of distance and price difference among competing listings. The results can have implications for Airbnb hosts at the time of assessing their local level of competition: either a fixed-radii around the property or a city-wide approach may be misleading, with the real market definition lying somewhere in between (different radii based on quality differences).

The remainder of this paper is structured as follows: Section 2 provides a literature review of Airbnb price determinants and the spatial dimensions of local accommodation markets. Section 3 presents the Bristol case study, covers the process of data collection and processing, as well as the OLS regression approach. Section 4 presents the results and discusses their main implications. Section 5 concludes with a summary of the main findings.

2. LITERATURE REVIEW

2.1 Non-location price determinants

The relatively fixed capacity and perishable nature of the accommodation product makes price the main strategic variable in this sector (Yelkur and Dacosta, 2001). The broad literature on hotel room prices has employed regression methods to test the relevance of different categories of price determinants, such as 1) room characteristics and other amenities: room size, room service, internet access, LED TV, or having a fitness centre (Schamel, 2012; Chen and Rothschild, 2010); and 2) quality signals, such as the hotel star rating, being part of a branded chain, or online customer reviews (Becerra et al., 2013; Masiero et al., 2015; Schamel, 2012; Yang et al., 2016).

With pricing in the hands of the individual hosts, the question of which factors drive Airbnb rates has also received substantial attention in the recent literature. These studies employ a broader choice of price determinants than those in the hotel sector. All studies include variables related to room or property characteristics, such as the number of beds, bedrooms, or bathrooms, some or all of which have been found to be statistically significant drivers of price (e.g. Chen and Xie, 2017; Gibbs et al, 2018; Günter and Önder, 2018; Lorde el al., 2019). The characteristics of the host are common predictors as well, with studies focusing on reputation or “superhost” status (Chen and Xie, 2017; Magno et al., 2018) as well as on the positive impact of responsiveness (Günter and Önder, 2018), experience (Zhang et al., 2017), and multiple listings (Önder et al., 2018). According to Tussyadiah and Pesonen (2016) and Guttentag (2015), having direct contact with the host enriches the local experience of the clients, while

Ert et al. (2016) conclude that posting attractive photos of the property is more important that having high online ratings as a host. It was also found that hosts with multiple listings can better implement dynamic pricing (adjusting price according to seasonal demand fluctuations), leading to superior price positioning and revenue performance (Magno et al., 2018; Kwok and Xie, 2019). A third category of price drivers refers to rental rules, such as the check-in window (Lawani et al., 2019). Fourth, we can mention customer feedback, as prices can be influenced by customer reviews and ratings (Lawani et al., 2019; Kwok and Xie, 2019).

While all the variables above can be considered relevant drivers of demand for Airbnb properties, most studies on price determinants in the accommodation sector also recognize the pre-eminent role that location plays in influencing travellers' choices (Bull, 1994).

2.2 Location price determinants

The importance of location in hotel pricing is related to the fact that the proximity to tourism resources (such as tourism attractions, bus/train/metro stations, or even the airport) is a key differentiating characteristic of accommodation supply (see e.g. Urtasun & Gutierrez, 2006; Rigall-i-Torrent et al., 2011; Lee & Jang, 2012; Gutiérrez, et al, 2017; Benitez-Aurioles, 2018; or Gunter and Önder, 2018). The most commonly used location characteristic in hotel studies is proximity to city centre (or centres), which is generally expected to push prices up (Soler and Gemar, 2018). For example, Gutiérrez et al. (2017) and Benitez-Aurioles (2017) found that each additional kilometer of distance to the city center implies a 0.704% and 0.165% decrease in hotel prices in Barcelona and Madrid, respectively.

Most studies on Airbnb prices also include a measurement of distance to city centre (Günter and Önder, 2018). However, it is also common to evaluate proximity to alternative places, such as convention centres (Kwok and Xie, 2019), bus/train stations (Magno et al., 2018), coastline

(Perez-Sanchez et al., 2018) and/or other points of interest such as sightseeing, nightlife, shopping or eating hotspots (Magno et al., 2018; Perez-Sanchez et al., 2018). Indeed, Boros et al. (2018) and Dudás et al. (2017) noted how most of the Airbnb supply in Budapest is concentrated in few districts of the city center where prices vary according to the proximity to tourist attractions.

While a central location is usually an advantage for hotels and Airbnb hosts, Chen and Rothschild (2010) found the opposite effect in the Taipei market which the authors associate to increased competition. Thus, location can be a double-edged sword and well-situated accomodation providers may face severe constraints in their pricing power (Chung and Kalnins, 2001) that can even affect their ablity to survive (Baum and Mezias, 1992).

2.3 Spatial competition and market definition

In line with the idea of location being a key aspect of product differentiation in this sector, it is not surprising that competition occurs at a spatial level. This has important implications at the time of defining the relevant market for a given accomodation provider. Market definition can be linked to the concept of demand substitutability, which can have both product and spatial dimensions (Martin, 2010). The spatial element is brought in by recognizing that the influence of competitors decays with distance (due to e.g. transportation costs) until it disappears at the market boundary. Furthermore, past authors have also noted that the effect of distance on price competition is moderated by quality. In fact, quality can be an effective mechanism to limit competition among well-located lodgings, thus resulting in higher prices (Becerra et al., 2013; and Soler and Gemar, 2018). These results can be understood as an effort by hotel managers to escape from the damaging effects of aggressive price competition under a high degree of product homogeneity and excess capacity, as predicted by the well-known Bertrand oligopoly model (Lee, 2015). Thus, price competition can be mitigated by vertical differentiation (Shaked and Sutton, 1982) and, in the accomodation sector, it has been shown that hotels of higher quality have a lower price sensitivity to the presence of neighboring competitors (Balaguer and Pernías, 2013; Becerra et al., 2013; and Lee, 2015). Quality-moderated spatial competition can also occur between traditional accommodation services (e.g. hotels) and Airbnb listings, with past studies including average hotel prices as a driver of Airbnb prices (Önder et al., 2018; Magno et al., 2018).

In regards to the sign of the price effects of competition, the general finding in the accommodation sector is that a higher market supply has a negative impact on prices (Becerra et al., 2013; Önder et al., 2018; Lee, 2015; Balaguer and Pernías, 2013). However, when analysing the price effects amongst competing Airbnbs, Lawani et al., (2019) found some degree of price complementarity, with evidence of spillover effects across listings in the same area. This is a sign of agglomeration externalities that have also been documented in the past for the hotel sector (Baum and Haveman, 1997). The existence of neighbouring competitors can have a positive impact on prices as more visitors are drawn to the area, with Urtasun and Gutiérrez (2006) showing that the differentiated hotels are the ones for which the positive spillover effects offset the downward pressure of prices brought by competition. An alternative explanation for this price complementarity is that, in the absence of strong differentiation, tacit cooperation, rather than competition, could become the main driver of market behaviour (Gan and Hernández, 2013).

In this context of complex spatial competition, the literature on Airbnb prices is still to provide an estimate of the geographical scope of local Airbnb markets that is moderated by quality differences. Such estimates exist for hotel markets. For example, Lee (2015) regressed hotel prices against the price of competitors measured at varying levels of distance (10 and 20 miles) and quality. The results indicate that competing hotels of similar quality still exert a significant impact on price at a distance of 20 miles, while the influence of hotels of different quality is only statistically significant at 10 miles. A similar approach was employed by Balaguer and Pernías (2013), who defined three distance radii around hotels (200, 400, and 600 meters) and considered quality differentiation according to star category. They also concluded that the effect of the number of competitors on hotel prices is moderated by quality differentiation and spatial distance.

In Airbnb studies, there are a few implicit examples of geographical market definition. Xie and Kwok (2017) assumed that hotel prices were affected by the number of city-wide Airbnb listings, as well as the prices of listings within the same postal code. More recently, Eugenio-Martin et al. (2019) published a paper on the determinants of Airbnb location in the Canary Islands. Their implicit market definition is based on a radius of 7 km around Airbnb locations because it maximized spatial autocorrelation. However, neither of these two geographical references consider that the competitive pressure that Airbnb listings exert among themselves (and hotels) is affected by product differentiation. The same applies to the more local estimate (650 m) provided by Önder et al. (2018), which is the closest reference to our study. They estimated an optimal radius of 650 m in Vienna for hotel prices (regardless of category) to exert a significant influence on Airbnb prices. This was done by estimating a large number of price regressions with different distance radii and choosing the best model based on goodness-of-fit indicators (e.g. adjusted R-square). We aim to improve on their optimization method with the introduction of a quality dimension in similar fashion than past hotel studies. The combination of these two past approaches is at the core of our methodological contribution. A second novel aspect is that all studies in this area are centered around the competition between hotels and Airbnb but there is still a research gap in investigating the impact that Airbnb listings exert amongst themselves under different levels of distance and quality differences.

3. DATA AND METHODOLOGY

3.1. Case study and datasets

As one of the largest cities in the United Kingdom, Bristol is also one of the country's top tourist destinations. This has prompted the fast development of sharing economy platforms in the short-term property rental market that primarily target tourists and other visitors to the city. The most popular of those platforms is Airbnb, whose presence in the city can be traced back to 2011 (the date of the oldest extant listing). This has brought increased level of competition to the traditional tourism accommodation sector, and hotel companies have been very vocal about what they consider to be unfair competition that is not bound to the same tax regulations or safety standards (ITV, 2018). Airbnb usually responds by noting the positive impact on visitor arrivals to Bristol as a consequence of the expanded accommodation supply, as well as the fact that the use of peer-to-peer platforms enables locals (as hosts) to capture a higher portion of the benefits associated to tourism activity in detriment of international hotel chains. The supply of private properties in Airbnb and similar platforms has grown considerably since launch because short-term tourism rentals are usually more profitable than medium- or long-term residential contracts. Furthermore, Airbnb allows hosts to set their own prices and they retain the proceeds minus a fee.

We obtained a dataset with all Airbnb listings in Bristol dated April 14th, 2018. This data has been web-scraped and made freely available in www.insideairbnb.com. Past studies on Airbnb prices (e.g. Wang and Nicolau, 2017) have used this data. The file contains information on 2,056 listings featuring a wide variety of property and room types. For the purposes of this paper, we focus only on entire properties (as opposed to private or share rooms), since our exploratory analysis reveals that the prices for the latter are not sufficiently explained by the traditional determinants in the tourism accommodation sector. We also focus on the most common types of properties (Apartments and Houses). This leads to a subsample of 818 listings, which represent 39.8% of Bristol's Airbnb supply. The spatial distribution of our dataset is shown in Figure 1. The city centre concentrates most of the 534 apartments, while the 234 houses appear in different clusters around the city. In line with the past literature, we selected a number of variables from the raw dataset that relate to room prices, host characteristics, room features, and customer feedback. In addition, due to the well-documented link between Airbnb and the housing market (See e.g. Wachsmuth and Weisler, 2018) we also compiled information from the Office of National Statistics (ONS) about house values using the mean price paid for all houses sold in Bristol within the year ending June 2018. This data is available for the 55 Middle layer Super Output Areas (MSOA) defined in the City of Bristol[1]. House values act as a control variable that is expected to capture additional characteristics of the areas in which the listings are located that can affect short-term rental prices.

[Insert Figure 1]

Our dataset is completed with location factors for each individual listing, such as the distance to the Bristol city center (located in the "Bristol Castle"), as well as the distance to the nearest bus/train station. However, for the purposes of this paper, the most important location factors will have a variable radius around the listing (as in Önder et al., 2018): 1) the number of tourism attractions, 2) the average hotel price per person, and 3) the number of competing Airbnb listings of the same property type. All geospatial analysis was carried out in ArcGIS, and distances are computed "as the crow flies", based on the latitude and longitude of the listings, which is the same approach used by past authors. The location of all tourism attractions in

[1] This was sourced from the House Price Statistics for Small Areas (HPSSAs) dataset provided by the ONS.

Bristol was sourced from openstreetmap.com and the hotel data (location and prices) was scraped from the online platforms hotels.com and booking.com for the month of April 2019.

3.2 Methodology

In order to explore the spatial and quality dimensions of local Airbnb markets, we estimated a series of price equations using ordinary least squares (OLS) methods. The equations aim to explain the price of the individual listings in relation to the characteristics of the property and the host, local home values, and proximity to tourism attractions, hotels, and other listings. Each model will differ in relation to the proximity variables, which are measured with increasing distance radius and quality margin (measured as a price difference). The main conclusions of our paper will be derived from the analysis of our goodness-of-fit coefficient (adjusted R-square), as well as the values and signs of the proximity variables across all models.

The basic specification is log-linear and is shown in Equation 1. We use a similar set of variables than the paper by Önder et al. (2018) with the addition of house values.

(1) $$ln(listing\ price_i) = \beta_0 + \beta_1 house\_value + \beta_2 bedrooms_i + \beta_3 baths_i + \beta_4 rating_i + \beta_5 diststation_i + \beta_6 superhost_i + \beta_7 distcenter_i + \beta_8 POIS\_radius_i + \beta_9 price\_hotel\_radius + \beta_{10} n\_comp\_radius\_diff_i + \varepsilon_{it},$$

Where β is the vector of coefficients to be estimated and ε is the usual random error. The dependent variable is the natural logarithm of the listing price of the *i*-th property (*listing price$_i$*). The log-linear specification was chosen because it delivered a significantly higher goodness-of-fit. Alternative dependent variables, such as the price per guest were also explored but discarded due to worse performance. The number of bedrooms and bathrooms have been well established as drivers of price by past studies, as well as the average user rating of the property or the host having a "superhost" status. The *house_value* variable indicates the mean price paid for all houses sold in the MSOA that corresponds to the relevant listing. Then, we also included the distance to city center (*distcenter*) and to the nearest bus/train station (*diststation*), both measured in km.

POIS_radius refers to the number of points of interest (tourism attractions) within a given radius of the listing. We employ 34 different radii: between 350m and 2,000m in 50m steps. This range of distances is chosen as it includes the 650m reference, which is the optimal radius suggested by Önder et al. (2018), while also covering from an extremely local market definition to an (almost) city-wide level. *Price_hotel_radius* refers to the average hotel price (for a double-room) within a given radius. The strong spatial concentration of hotels in Bristol and the lack of direct comparability between hotel and Airbnb prices does not allow us to introduce quality differentiation in this variable. *N_comp_radius_diff* refers to the number of competing Airbnb listings of the same property type, within the same distance radii as defined above, and within a predetermined price difference (as a proxy for quality difference), expressed in percentage above and below the left-hand-side listing price. We consider ten price margins, from 10% to 100% in 10% steps. In total, the combination of distance radii and price margins leads to 340 OLS equations, which are estimated using STATA.

Table 1 provides some descriptive statistics of the selected variables, with the proximity factors (*POIS*, *price_hotel*, and *n_comp*) combining data from all radii and price differences. Listing prices vary between 15 and 800 GBP per night and properties range between 1 and 7 bathrooms, which gives an idea of the great diversity of tourism accommodation available in a city like Bristol. Depending on the property's location and distance radius considered it can face a minimum of 1 competitor up to 629 listings in its local market. Table 2 shows the pairwise linear correlation coefficients between the chosen variables. Despite high correlations between the distance variables, the analysis of the variance inflations factors[2] (VIF) post-estimation allows us to discard any problems associated with multicollinearity in the specifications. Due to the presence of heteroskedasticity, robust standard errors were employed.

[Insert Table 1]

[Insert Table 2]

4. RESULTS AND DISCUSSION

The adjusted r-squared coefficients across all estimated models are shown in Appendix A (Table A1). The best-fitting models for each level of price difference (highlighted in bold) indicate that the optimal market definition has a smaller radius when the heterogeneity among listings increases. For example, the existence of other listings up to a 10% price difference is the best predictor of a given listing's price when the competitors within a 1,700 m radius are considered. If the maximum allowable price difference is expanded to 20%, 30%, and 40%, the optimal radius for market definition is 1,050 m, 900 m, and 600 m, respectively. While the analysis of confidence intervals for the adjusted r-square coefficients does not allow us to establish that these models are statistically superior to the other specifications, we can conclude (similarly to Önder et al., 2018) that these are the "optimal" (i.e. best-fitting) spatial and price/quality dimensions of local Airbnb markets in Bristol.

Moreover, for the models above 60% in price difference, adjusted r-squared values increase with distance up to the 2,000 m radius, which is the limit of our calculations. This second trend

[2] VIF=1/(1-R^2), where R^2 refers to the R-squared coefficient of the linear regression of a given explanatory variable against all other predictors.

suggests that there could be two ways in which Airbnb markets can be defined: a local market with decreasing radii, and a city-wide market with a longer radius.

Table 3 shows the OLS regression results for the optimal "local" model (i.e. highest adjusted r-square) with a distance radius of 1,700 m and 10% price difference. The estimated coefficients indicate that the number of bedrooms and bathrooms are both key drivers of price, thus agreeing with most past studies, such as, e.g. Chen and Xie (2017). The rating and superhost coefficients have a positive sign, which agrees with Wang and Nicolau (2017), and Önder et al. (2018). The negative sign of the distance to city center is consistent with the view that accessibility affects price (Gibbs et al., 2018) but the coefficient (alongside the distance-to-station one) is far from statistical significance at 5% level. A possible reason for the lack of significance is the presence of the points of interest (POIs) variable, which is positive and significant, and already captures the impact of accessibility to tourism attractions on Airbnb prices. The number of local competitors has a negative and significant impact on listing prices, which agrees with the well-established notion that increased supply bring prices down due to stronger competition among local hosts (Lee, 2015). The average price of the local hotels has a positive coefficient yet not significant at 5% level. This links well with economic theory, as prices are usually considered strategic complements in oligopolistic settings (Martin, 2010). On one hand, this can be interpreted as a sign that an increase in the average price of hotels in the local area can be an opportunity for hosts to increase prices as well (spillover effects). On the other hand, a positive price correlation can also signal direct competition (Davis and Garcés, 2009). Any aggressive pricing strategies by nearby hotels are likely to decrease prices and profitability for Airbnb listings within the local area, as they are forced react by decreasing their prices as well. This is the behavior that one would normally expect from Bertrand oligopolies operating under excess capacity.

[Insert Table 3]

The central estimates for the "number of competitors" variable are shown in Table A2 (Appendix A), with the significant coefficients (at 5% level) highlighted in bold. This table confirms the interpretation from Table A1 about the two different markets. Results show that, with 95% confidence, the price of any given listing is affected negatively by the presence of other listings within a maximum 40% price difference. In these local markets, price competition is strong and exerts a downward pressure in prices. Figure 2 presents that information graphically in order to illustrate the quality-moderated spatial decay of the competitive effects among Airbnb listings, as predicted by past studies in the accommodation sector (Lee, 2015). The higher the level of product homogeneity, the stronger the substitutability between listings and, in turn, the negative impact on prices, which translates into a larger market boundary.

Beyond these levels of quality differentiation, however, the neighbourhood- or city-wide agglomeration effects take over. In fact, for price differences of 70% of above, the presence of other listings affects prices positively, which agrees with Lawani et al. (2019)'s finding of price spillovers. Furthermore, the strength of this impact decreases with distance, which supports the existence of agglomeration effects at a neighbourhood level as well, because demand is driven to the areas with high diversity of tourism accommodation. Statistically significant agglomeration effects also appear at a city-wide level but are much weaker than in the local market as they decrease with market radius.

[Insert Figure 2]

These results have few implications for Airbnb hosts. Given the agglomeration effects and price spillovers at a city and neighbourhood levels, hosts should be aware that any policies that restrict the overall supply of accommodation (e.g. limiting annual availability) can have a negative impact on their prices, particularly if their own local supply conditions are affected. Furthermore, hosts should also be aware of their local competition within the spatial and quality/price boundaries set in this paper. Given the wide availability of open data in relation to Airbnb supply, quantifying the number of competing listings should be relatively straightforward. In a context of oligopolistic price competition, the main threat would be new properties with unrestricted availability. In order to prevent falling into a Bertrand trap, hosts are advised to invest in further differentiation of their properties.

5. SUMMARY

This paper aims to give insights on the spatial and quality/price dimensions of Airbnb markets using a case study of 818 entire houses and apartment listings from Bristol (United Kingdom). With this data, we carry out at set of 340 regression models in which the location of the listing and its proximity to competitors are specified as drivers of price, but the radius and price margins to assess competition are variable within a range of 350 to 2,000 m and 10% to 100% price difference (as a proxy for quality differences), respectively.

The results indicate that the number of bedrooms and bathrooms is a key driver of price, as well as its proximity to tourism attractions. Evaluating the results across all estimated models, we see that the relevant “local” market is best defined with a set of radii that decrease with the level of price differentiation: an optimal radius of 1,700 m, 1,050 m, 900 m, and 600 m corresponds to a price difference 10%, 20%, 30%, and 40%, respectively. Within these boundaries, the presence of competing Airbnb listings exerts a negative impact on prices. For higher levels of quality differentiation, however, the proximity of competitors has a positive impact on prices, which can be clearly interpreted as an agglomeration effect both at neighbourhood and city-wide levels. These results hint at the existence of two alternative market definitions: the local market (with price competition and strong agglomeration effects, depending on quality differentiation) and the city market (with weaker agglomeration effects).

In a context of concern from public authorities in the UK about the potential impact that short-term accommodation rentals can have on local residential markets, hosts should be aware of any city-wide trends and policies that can restrict the overall accommodation supply because that can have a strong negative impact on their prices. Furthermore, hosts should be aware of their local competition within the spatial and quality/price boundaries set in this paper, particularly from those properties with unrestricted availability, which are more likely to compete aggressively in prices.

The conclusions from our paper should be taken with caution since the results from a city like Bristol cannot be immediately generalized to other major tourist destinations in the UK or other countries. Also, since we only have the listed price at the time of data collection (April), there is a lack of information on dynamic pricing strategies potentially employed by the hosts that would have made the analysis more detailed. Any potential seasonal variations in the spatial or price dimensions of Airbnb local markets have not been captured either. Further research can address these issues when more time-series data becomes available. Expanding this analysis to other cities can serve to validate these conclusions beyond the geographical and temporal boundaries imposed by our data.

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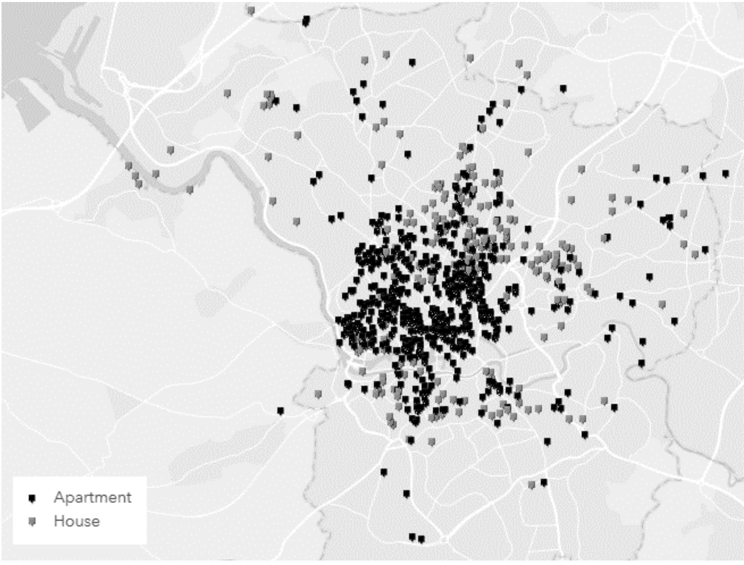

Figure 1. Sample dataset of Airbnb listings. *Source: www.insideairbnb.com*

Table 1. Descriptive statistics of the selected variables

Variable	*Unit*	*Mean*	*Std. Dev.*	*Min*	*Max*
listing_price	GBP	101.00	75.09	15.00	800.00
house_value	GBP	337,567	96,909	193,779	585,826
bedrooms		1.83	1.15	1.00	7.00
baths		1.31	0.59	1.00	5.00
rating	%	79.72	35.05	0.00	100.00
diststation	km	1.28	1.06	0.04	6.31
superhost		0.25	0.44	0.00	1.00
distcenter	km	1.91	1.25	0.07	7.13
POIS		90.14	90.92	0.00	498.00
price_hotel	GBP	68.16	62.50	53.00	242.00
n_comp		107.23	85.65	1.00	629.00

Note: The statistics of POIS, price_hotel, price_comp and n_comp combine the data for all radii and price differences. Sources: www.insideairbnb.com, www.openstreetmap.com, Own Elaboration.

Table 2. Pairwise linear correlation between the selected variables

	house_value	*bed rooms*	*baths*	*rating*	*dist_ station*	*super host*	*dist_ center*	*POIS*	*price_ hotel*	*n_ comp*
house_value	1.000									
bedrooms	0.133	1.000								
baths	0.140	0.636	1.000							
rating	0.069	-0.077	-0.022	1.000						
dist_station	-0.097	0.054	0.000	-0.051	1.000					
superhost	0.110	-0.002	0.057	0.240	0.024	1.000				
dist_center	0.095	0.213	0.072	-0.059	0.759	0.033	1.000			
POIS_450m	-0.070	-0.239	-0.023	0.015	-0.297	0.002	-0.631	1.000		
price_hotel_450m	0.073	-0.264	-0.090	-0.005	-0.205	0.032	-0.433	0.638	1.000	
n_comp_450m_10%	-0.019	-0.347	-0.246	0.075	-0.270	0.044	-0.465	0.532	0.443	1.000

Table 3. OLS coefficients for the best-fitting market definition (1,700 meters and 10% price difference).

	Coef.	*s.d.*	*Prob.*	*VIF*
house_value	0.0000	0.0000	0.2160	1.36
bedrooms	0.1957	0.0172	0.0000	1.95
baths	0.2029	0.0296	0.0000	1.80
rating	0.0002	0.0004	0.6580	1.08
dist_station	0.0011	0.0188	0.9540	2.99
superhost	0.0912	0.0239	0.0000	1.10
dist_center	-0.0092	0.0227	0.6850	5.48
POIS_450m	0.0014	0.0002	0.0000	2.77
price_hotel_450m	0.0002	0.0002	0.2690	1.68
n_comp_450m_10%	-0.0026	0.0005	0.0000	1.94
constant	3.7195	0.0832	0.0000	-
No. of obs.	818	Adjusted R-squared	0.5485	

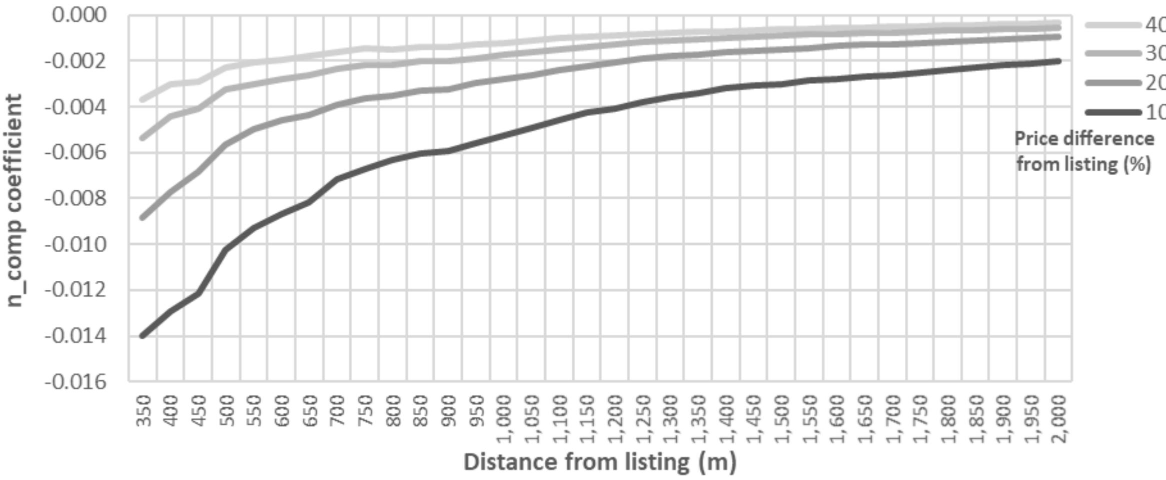

Figure 2. Quality-moderated spatial decay for the price impact of competition in local Airbnb markets

Appendix A. Estimation results

Table A1. Adjusted R-squared (left) and competing Airbnb price (right) coefficients for all models

Adj-R2	**Price difference from listing (%)**									
Distance radius from listing (m)	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
350	0.538	0.538	0.534	0.531	0.528	0.528	0.531	0.537	0.541	0.543
400	0.539	0.539	0.534	0.532	0.529	0.529	0.534	0.540	0.548	0.550
450	0.543	0.541	0.537	0.535	0.531	0.531	0.536	0.543	0.551	0.553
500	0.542	0.540	0.536	0.534	0.531	0.531	0.537	0.545	0.555	0.557
550	0.543	0.541	0.537	0.535	0.531	0.532	0.538	0.546	0.556	0.558
600	0.545	0.542	0.538	**0.535**	**0.531**	**0.532**	0.539	0.548	0.558	0.561
650	0.545	0.542	0.537	0.534	0.530	0.531	0.539	0.549	0.560	0.563
700	0.542	0.540	0.535	0.532	0.528	0.530	0.538	0.550	0.562	0.565
750	0.543	0.540	0.535	0.532	0.528	0.530	0.539	0.550	0.563	0.567
800	0.543	0.542	0.536	0.533	0.528	0.529	0.537	0.548	0.561	0.564
850	0.545	0.542	0.537	0.533	0.528	0.529	0.537	0.549	0.562	0.566
900	0.547	0.544	**0.538**	0.534	0.528	0.528	0.536	0.548	0.561	0.564
950	0.547	0.544	0.538	0.534	0.528	0.528	0.535	0.547	0.561	0.564
1,000	0.548	0.544	0.538	0.534	0.528	0.528	0.535	0.547	0.561	0.564
1,050	0.548	**0.544**	0.538	0.534	0.528	0.528	0.536	0.548	0.562	0.565
1,100	0.548	0.544	0.538	0.534	0.528	0.528	0.536	0.549	0.563	0.566
1,150	0.547	0.544	0.538	0.534	0.528	0.528	0.536	0.549	0.563	0.566
1,200	0.548	0.543	0.538	0.533	0.528	0.528	0.537	0.551	0.564	0.568
1,250	0.547	0.543	0.538	0.533	0.528	0.528	0.537	0.551	0.565	0.569
1,300	0.547	0.543	0.538	0.534	0.528	0.528	0.537	0.551	0.564	0.568
1,350	0.547	0.543	0.538	0.534	0.528	0.528	0.537	0.551	0.564	0.567
1,400	0.547	0.543	0.538	0.534	0.528	0.528	0.537	0.551	0.565	0.568
1,450	0.548	0.543	0.538	0.534	0.528	0.528	0.537	0.552	0.566	0.569
1,500	0.548	0.543	0.538	0.533	0.528	0.528	0.537	0.553	0.568	0.571
1,550	0.548	0.543	0.537	0.533	0.527	0.528	0.538	0.554	0.569	0.573
1,600	0.548	0.543	0.537	0.533	0.527	0.528	0.538	0.555	0.571	0.575
1,650	0.548	0.543	0.537	0.533	0.527	0.528	0.539	0.556	0.573	0.577
1,700	**0.548**	0.543	0.537	0.533	0.527	0.528	0.539	0.557	0.576	0.580
1,750	0.548	0.543	0.537	0.533	0.527	0.529	0.540	0.558	0.577	0.582
1,800	0.547	0.542	0.537	0.532	0.527	0.529	0.541	0.560	0.580	0.585
1,850	0.547	0.542	0.536	0.532	0.527	0.529	0.541	0.561	0.582	0.587
1,900	0.546	0.541	0.536	0.532	0.527	0.530	0.542	0.563	0.584	0.590
1,950	0.546	0.541	0.536	0.531	0.527	0.530	0.543	0.564	0.586	0.593
2,000	0.545	0.541	0.535	0.531	0.527	0.530	**0.543**	**0.566**	**0.590**	**0.596**

Note: Bold denotes best-fitting model per column.

Table A2. Estimated coefficients of the number of competitors for all models

n-comp	Price difference from listing (%)									
Distance radius from listing (m)	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
350	**-0.014**	**-0.009**	**-0.005**	**-0.004**	-0.001	0.001	**0.003**	**0.005**	**0.007**	**0.007**
400	**-0.013**	**-0.008**	**-0.004**	**-0.003**	-0.001	0.001	**0.003**	**0.005**	**0.007**	**0.007**
450	**-0.012**	**-0.007**	**-0.004**	**-0.003**	-0.001	0.001	**0.003**	**0.005**	**0.006**	**0.006**
500	**-0.010**	**-0.006**	**-0.003**	**-0.002**	-0.001	0.001	**0.003**	**0.004**	**0.006**	**0.006**
550	**-0.009**	**-0.005**	**-0.003**	**-0.002**	-0.001	0.001	**0.003**	**0.004**	**0.005**	**0.005**
600	**-0.009**	**-0.005**	**-0.003**	**-0.002**	-0.001	0.001	**0.002**	**0.004**	**0.005**	**0.005**
650	**-0.008**	**-0.004**	**-0.003**	**-0.002**	-0.001	0.001	**0.002**	**0.003**	**0.005**	**0.005**
700	**-0.007**	**-0.004**	**-0.002**	**-0.002**	0.000	0.001	**0.002**	**0.003**	**0.004**	**0.005**
750	**-0.007**	**-0.004**	**-0.002**	**-0.001**	0.000	0.001	**0.002**	**0.003**	**0.004**	**0.004**
800	**-0.006**	**-0.004**	**-0.002**	**-0.001**	0.000	0.001	**0.002**	**0.003**	**0.004**	**0.004**
850	**-0.006**	**-0.003**	**-0.002**	**-0.001**	0.000	0.001	**0.002**	**0.003**	**0.004**	**0.004**
900	**-0.006**	**-0.003**	**-0.002**	**-0.001**	-0.001	0.000	**0.002**	**0.002**	**0.003**	**0.003**
950	**-0.006**	**-0.003**	**-0.002**	**-0.001**	-0.001	0.000	**0.001**	**0.002**	**0.003**	**0.003**
1,000	**-0.005**	**-0.003**	**-0.002**	**-0.001**	-0.001	0.000	**0.001**	**0.002**	**0.003**	**0.003**
1,050	**-0.005**	**-0.003**	**-0.002**	**-0.001**	0.000	0.000	**0.001**	**0.002**	**0.003**	**0.003**
1,100	**-0.005**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.002**	**0.003**	**0.003**
1,150	**-0.004**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.002**	**0.002**	**0.002**
1,200	**-0.004**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.002**	**0.002**	**0.002**
1,250	**-0.004**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.002**	**0.002**	**0.002**
1,300	**-0.004**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,350	**-0.003**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,400	**-0.003**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,450	**-0.003**	**-0.002**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,500	**-0.003**	**-0.001**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,550	**-0.003**	**-0.001**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,600	**-0.003**	**-0.001**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,650	**-0.003**	**-0.001**	**-0.001**	**-0.001**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,700	**-0.003**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,750	**-0.002**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,800	**-0.002**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,850	**-0.002**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,900	**-0.002**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
1,950	**-0.002**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**
2,000	**-0.002**	**-0.001**	**-0.001**	**0.000**	0.000	0.000	**0.001**	**0.001**	**0.002**	**0.002**

Note: Bold denotes statistically significant coefficient at 5% level.