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The path of least resistance explaining tourist mobility patterns in destination areas using Airbnb data

Umut Türk [a,*], John Östh [b,e], Karima Kourtit [b,c,d,e,f,g,h], Peter Nijkamp [b,c,d,e,g,h]

[a] Abdullah Gül University, Kayseri, Turkey
[b] Open University, Heerlen, the Netherlands
[c] Alexandru Ioan Cuza University of Iasi, Iasi, Romania
[d] University of Technology, Benguérir, Morocco
[e] Uppsala University, Upsala, Sweden
[f] Center for the Future of Places, KTH Royal Institute of Technology, Stockholm, Sweden
[g] Polytecnic University, Ben Guerir, Morocco
[h] Adam Mickiewicz University, Poznan, Poland

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ABSTRACT

Destination attractiveness research has become an important research domain in leisure and tourism economics. But the mobility behaviour of visitors in relation to local public transport access in tourist places is not yet well understood. The present paper seeks to fill this research gap by studying the attractiveness profile of 25 major tourist destination places in the world by means of a 'big data' analysis of the drivers of visitors' mobility behaviour and the use of public transport in these tourist places. We introduce the principle of '*the path of least resistance*' to explain and model the spatial behaviour of visitors in these 25 global destination cities. We combine a spatial hedonic price model with geoscience techniques to better understand the place-based drivers of mobility patterns of tourists. In our empirical analysis, we use an extensive and rich database combining millions of Airbnb listings originating from the Airbnb platform, and complemented with TripAdvisor platform data and OpenStreetMap data. We first estimate the effect of the quality of the Airbnb listings, the surrounding tourist amenities, and the distance to specific urban amenities on the listed Airbnb prices. In a second step of the multilevel modelling procedure, we estimate the differential impact of accessibility to public transport on the quoted Airbnb prices of the tourist accommodations. The findings confirm the validity of our conceptual framework on 'the path of least resistance' for the spatial behaviour of tourists in destination places.

1. Setting the scene

The nexus of transportation and tourism is increasingly determined by digital technology. In our era of the 'third data revolution' (Kourtit et al., 2020), urban development patterns and geographical mobility processes – and related policy measures – are increasingly depicted, analysed and governed by the manifold opportunities offered by digital technology. The pervasive nature of modern information and communication systems is not only embodied in the radical transformation from analog to digital data systems (causing an unprecedented efficiency rise in data storage and management), but also in the rise of hitherto unknown digital big data platforms and interactive social media channels. The accompanying third data revolution has meant a drastic change in decision-making mechanisms of industries and governments, ranging from the banking sector to the hospitality sector, and from urban traffic management control to citizens' participation and empowerment. In particular, the tourism industry has been strongly influenced by the digital revolution (Mason, 2016). Electronic booking systems, online tourist services and customized digital guidance for visitors have drastically changed the operation of the tourist market. Digital information, e.g. based on big data extracted from social media outlets, is now extensively used to study the attractiveness of tourism destinations (see e.g. Ardito et al., 2019; Giglio et al., 2019; Del Vecchio et al. 2018).

In the present paper we will zoom in on the travel and leisure industry, as part of the hospitality business, in tourism destinations. Many cities all over the world (e.g., Barcelona, Paris, New York, Tokyo, Sydney) have increasingly turned to digital technology as a smart vehicle for attracting more tourists, through fast public transport, open-access

* Corresponding author.
E-mail address: umut.turk@agu.edu.tr (U. Türk).

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information and marketing systems, electronic booking systems, and the like (see e.g. Wang et al., 2018). Well informed visitors in tourist places are permanently 'on the move', not only in destination places in their own region or country of residence, but also increasingly in cities or tourist areas in foreign countries (see Romao, 2019). Next to conventional vacation visits of one or two weeks to favourite tourist areas, we have in the past decade seen a rapid rise in short-term city trips. Such short-term trips have the potential of generating substantial returns on tourism investments; Croes and Severt (2007) show that visitors spend considerable amounts on lodging services in destination cities. This new tourism behaviour is in particular facilitated by: (i) digital technology advances in the airline (and the railway) sector, so that digital bookings can be realized in an efficient and cost-saving manner; and (ii) an avalanche of local information systems in attractive tourist destination places (e.g., user-friendly apps), so that in a few days the most interesting highlights in a city can be visited. Consequently, due insight into geographical mobility of short-term visitors in a certain destination place has become a major research and policy challenge.

Clearly, the visitors' spatial behaviour in tourist places is not a random phenomenon. Usually, tourists want to visit many attractions in a short time period. We take for granted here that the spatial movements of visitors are driven by least cost determinants (in terms of time, money, psychological barriers etc.). We call this behavioural motive here the 'path of least resistance', which takes for granted that tourists are driven by the objective to reduce local mobility efforts in reaching a maximum number of desired attractions in a city. The local mobility behaviour of visitors to a given tourist place, especially the behaviour of peer-to-peer accommodation users (e.g. Airbnb) in relation to intra-city transport choices, is not well researched.

The capricious mobility patterns of visitors in a given locality are often extremely complex due to a great heterogeneity in visitors' motives, historical-cultural amenities, financial spending capacity, age and gender characteristics, travel preferences, socio-cultural interests etc. (see Loo, 2019; Kozak, 2002). We hypothesize that short-term tourist visits to a city are characterized by the drive to enjoy 'as much as possible' in a limited time, which prompts the use of efficient inner-city transport ('the path of least resistance'). Clearly, there is not a single database from which comprehensive information on the tourists' behaviour in destination areas can be extracted. In practice, we observe a multiplicity of databases, with often significant differences in spatial, temporal, socio-economic, ethnic-cultural and geo-demographic detail (see also Ruth and Franklin, 2014). Consequently, a coherent study of spatial behaviour of tourists in a destination place is fraught with many empirical information and research problems.

Our empirical model-based contribution seeks to explore 'roads less travelled' in tourism destination research by (i) resorting to an analytical framing inspired by Zipf's (1949) principle of least effort (coined here '*the path of least resistance*'); (ii) testing the validity of this principle through a merger of official statistical databases, global urban tourism indicators and social media platform data on tourists' mobility in destination cities; and (iii) designing and testing an appropriate multilevel model structure based on hedonic pricing for statistical inference from a 'big' data set.

The present study aims to examine the smart potential of modern 'digital geography or internet geography' (Malecki, 2002; Arribas-Bel et al., 2015; Ash et al., 2018; Wentrup et al., 2019) for analyzing and mapping out the complex space-time dynamics of mobile tourists in destination places, taking into account the distinct localized tourist attractions in these destination places. To explain their mobility behaviour from the perspective of 'the path of least resistance' (see Section 2), 'big data' extracted from global information and booking platforms (in particular, Airbnb data) will be used and complemented with publicly available and structured local information on tourists' movements (Section 3). We will use GIS modelling to depict and explain the complex spatial mobility pattern of visitors in tourist places (Section 4). Our study will use extensive data from a broad range of 25 important tourist places in the world. After a description of the databases and the methodology employed in our study, we will design a hedonic-pricing inspired visitors' mobility model, and next present and interpret the results from our tourist attraction and mobility study (Section 5), while the paper will conclude with some retrospective and prospective remarks (Section 6).

2. Literature

In this section, we will situate our study in the current literature focused on the intersection between tourism preferences in terms of choice of ackomodation, with particular focus on Airbnb) and the geographical patterns of both ackomodations and destination characteristics.

3. Location and price of Airbnb accomodations

There is a large and growing number of studies with a focus on Airbnb pricing and relationship to cost of housing, hotels and the effects of location (see Tussyadiah, 2016; Tran and Filimonau, 2020; Del Chiappa et al., 2021; Bang Nong and Ha, 2021). A comprehensive review on Airbnb research can be found in Guttentag (2019). A first class of studies focusses on the relationship between the regular housing demand in the city and urban Airbnb facilities. In the past years, Airbnb data have in particular been used to study in empirical research the impact of Airbnb on house prices in various cities. Traditionally, the research in this field employs usually standard hedonic price models on the housing market (see for a general description of hedonic price models among others, Basu and Thibodeau, 1998; Kain and Quigley, 1970; Wilkinson, 1973) in order to assess the monetary value of externalities on the rents or sales prices of dwellings in the local neighbourhood. In the past years, we witness a rising tide of hedonic Airbnb studies. Examples of recent applied modelling studies using Airbnb data on Los Angeles and Amsterdam can inter alia be found in Lee (2016) and Van der Bijl (2016). There are indeed several studies which have addressed the price determinants of Airbnb listings in a number of cities. For instance, Oskam et al. (2018) show that frequent price adjustments and the number of properties per host tend to increase the revenue for rooms and the daily average rate in Amsterdam. A few studies have also shown that the hosts' experience on Airbnb platform increases the ability of effective pricing. For instance, in a study on Airbnb listings in Verona, Magno et al. (2018) argue that hosts gain experience over time and improve their marketing and pricing strategies (see also Gibbons and Machin, 2005). Consumer reviews also have been integrated in these studies of Airbnb so as to analyse reputation management. The findings are usually counter to those of traditional hotelling services, where the number of reviews for a listing is shown to have a moderate but negative impact on Airbnb prices (Gibbs et al., 2018; Magno et al., 2018).

Complementary impact studies of Airbnb on the hotel industry and of Airbnb on the neighbourhood environment were respectively undertaken by Zervas et al. (2015) and Xu et al. (2020). The impact of hotels on the Airbnb market has also been examined. For example, Önder et al. (2019) show that the prices of Airbnb listings increase with the prices of hotel rooms and other Airbnb listings that are located within a radius of 650 m in Tallinn.

Another class of Airbnb studies is related to the geographical dimensions of these facilities in cities. It should be noted at the outset that Airbnb units are not randomly scattered over the urban area, but have, in general, specific locational characteristics and distributions that are often rather central (or close to public transport stations or bus stops) in the city. An interesting feature is that in various cities the goal of Airbnb rentals is no longer to share private housing facilities, but to rent dwellings on a fully commercial basis by developers (as some sort of quasi-hotels), which may lead to serious conflicts with prevailing urban housing policy (see e.g., Gutiérrez and Domènech, 2020; Ki and Lee, 2019).

In general, the few papers that model location as one of the Airbnb-price determinants show significant effects (Doran et al., 2015; Dudás et al., 2017a; Dudás et al., 2017b). In a study of the Airbnb market in Vienna, Gunter and Önder (2018) >find that distance from the city centre is a significant and negative determinant of demand for listings. Similarly, each 5-km increase in distance from the City Hall corresponds to a 4 to 20% price decrease in five metropolitan cities in Canada, as was shown by Gibbs et al. (2018). Another spatial hedonic price study on Airbnb listings and prices can be found in Deboosere et al. (2019), who addressed in particular the impacts of neighbourhood effects including transit accessibility on the price formation of Airbnb units. In a comprehensive investigation of price determinants in 33 cities, Wang and Nicolau (2017) measure 0.59% decrease in prices as a response to 1-km increase in distance from the city centre. Next, Gutiérrez et al. (2017) found similar results for Airbnb location patterns and related pricing systems in Barcelona. They also observed a locational pattern of Airbnb that reveals a proximity to the city's main tourist attractions. It is also noteworthy that the authors found that the locational factors of Airbnb differ from these in the hotel sector in Barcelona. And finally, another study on the locational pattern and geographical distribution of Airbnb facilities in urban areas was undertaken by Zhang and Chen (2019) for major American cities. They also found a tendency toward rather central locations of Airbnb units in the city, while especially attractive tourist points of interest may lead to a clustering of Airbnb. More recently, Gunter et al. (2020) studied the spatial relationship between Airbnb and the traditional hotel industry and found that hotels and neighbouring listings are substitutes to eachother.

4. Tourist preferences and choice of destination

Visitors to tourist places are heterogeneous in nature, in terms of place of origin, age, gender, education, income, length of stay or choice motivation. For instance, Tang et al. (2020) show that the length of visit, companion type (alone, with family, friend or group) and car ownership are significant determinants of destination choice in Hangzhou, China. Recent literature shows that visitors wish to identify themselves and their motivations different from typical tourists (Doran et al., 2015). Many popular tourist destinations offer a wide spectrum of attractions such as museums, theatres, cultural-historical heritage, entertainment places, urban parks, or, in general, urban ambiance. So, there is a broad portfolio of choice options; usually, tourists like to enjoy multiple attractions, as is evident from an inspection of the appreciation of cultural and recreational amenities by visitors who have expressed their perceptions or value judgments on the TripAdvisor platform (see for an application also Kourtit et al., 2019). In general, many tourist destinations derive their attractiveness from their abundance of cultural capital (see e.g. Amin and Thrift, 2007; Giaoutzi and Nijkamp, 2017; Grodach, 2013; Gravagnuolo et al., 2020; Kourtit and Nijkamp, 2019; Rodrigues and Franco, 2018; Scott, 2000, and Vanolo, 2008; Zamparini et al., 2016). Tourists have, in general, multiple motives to visit an attractive destination in a foreign country (Kozak, 2002). The choice possibilities are often numerous, and tourists know that 'you can't have them all'. Consequently, clear choices have to be made by the visitors (Uysal et al., 2012). The mobility of tourists at destination cities may change substantially based on the length of stay. Jin et al. (2018) show that, while during a one-day trip tourists flows are characterized by longer-distance mobilities between attractions, during a three or more days trip flows are relatively short-distance and more around the attractions. Given the limited time and money, they seek to maximize their utility ('enjoyment' or 'happiness') from visiting several tourist amenities. In other words, visitors desire to satisfy the need to enjoy many amenities during their visit, within a reasonable time span that is restricted by the total length of their stay in a destination place.

5. Path of least resistance, and the role of public transport

With reference to the literature on tourist behaviour in earlier section, it is with a minimum of effort the visitors aim to maximize their enjoyment. This principle is called here the '*path of least resistance*'. This behavioural paradigm leads essentially to constrained mobility behaviour of tourists in their choices in the destination place. The challenge is to find an optimal mix of attractions in a city that complies with their space-time-money constraints. This behavioural proposition of reducing the risk of human activity so as to create more space for alternative choice options is essentially similar to Zipf's (1949) '*principle of least effort*'. For a further exposition of Zipf's Law on hierarchical spatial network structures we refer to Reggiani and Nijkamp (2015). This social-science inspired principle is the dual formulation of the principle of 'highest enjoyment' and has been highly influential in various disciplines. For related travel and tourism contributions, the following studies are noteworthy: Chang (2016) for a review, Önder et al. (2020) for an application to tourism marketing, and Pinto et al. (2019) for an analysis of the choice behaviour of car-poolers.

In the context of the use of digital technology, we assume that there are two prominent mechanisms that help the visitors to find the 'path of least resistance', viz. digital booking systems at reasonable prices (in particular, the Airbnb search platform) and local apps guiding the visitors to find with a minimum effort the maximum number of tourist attractions. In our comparative research on the visitors' behaviour in tourist areas we will use a wealth of digital information to describe and analyse their choice and spatial behaviour.

Having that said, it should be noted at the outset that a uniform database on all tourist motives and movements in destination areas for testing the above mentioned proposition does not exist. There is a wide array of fragmented data systems originating from different sources, such as local statistical offices, surveys among visitors, TSA (Tourist Satellite Accounts) data, social media information (e.g. Twitter, Facebook) and global data (tourist) platforms (e.g. Tripadvisor, Airbnb). The data from "Smart Travel Cards" is another example of fragmented data systems, which has the potential of providing valuable information to improve public transport services at touristic destinations. For example, in a recent study on the tourists' use of public transport in Costa Daurada (Spain), Gutiérrez et al. (2020) show that personalized solutions such as multi-personal tickets guarantee a higher tourists' mobility in the region. Especially the use of 'big data' in travel and tourism research is gaining importance in recent years. Qian et al. (2021), for example, study tourism transportation demand in Shanghai by mobile phone data and show that-among other findings- tourists prefer transportation hubs in the city centre.

Clearly, there is a rising tide of Airbnb research in the hospitality sector. However, the role of local – mainly intra-urban public – transport in tourist destination places in Airbnb clients' choice decisions on tourist attractions are not yet fully understood (see also McNeill, 2016). The exisiting literature focus, for instance, on the strategies to promote tourism public transportation (Gronau and Kagermeier, 2007), the role of public transportation in countryside visits (Lumsdon et al., 2006), public transport as a factor for tourism satisfaction (see Virkar and Mallya, 2018 for a review) and also toursist' use of public transport for sustainable mobility (see Le-Klaehn and Hall, 2015 for a review). We refer to the work of Hall et al. (2017) for a comprehensive and global look on the relationship between publica transport and tourism. Departing from previous studies, in the present study, we will analyse the geographically-determined choices of tourists – using a hedonic pricing method – based on an integrated urban model constellation of the quality of the listing of Airbnb facilities, the tourist amenities in the vicinity of the Airbnb dwellings concerned, and the distance to specific tourist attractions in the city (including accessibility to public transport). This framework will then be instrumental in testing 'the path of least resistance' hypothesis with access to public transport. Before offering a specification of our hedonic price model, we will sketch out in Section 3 the extensive database on several large cities used in our study.

6. Database composition

Our analysis seeks to offer a broad coverage of the mobility drivers of tourists in different cities or urban areas. We study here these behavioural patterns in 25 global cities. These 25 cities were selected from the GPCI (Global Power Cities Index) database. This extensive database is since 2009 annually published by the Japanese Mori Memorial Foundation, Institute for Urban Strategies (Tokyo) and contains rich quantitative information on a multiplicity of systematically organised dimensions of cities related to urban development (e.g., innovation, economy, infrastructure, environmental quality, visitors etc.).

This database contains for many years the same 40 cities and provides also detailed and annually tested data on visitors to the cities concerned, cultural attractions, environmental quality, etc..[1] We have taken these GPCI cities as the starting point for our data collection and have made an attempt to collect for a given base year (2017) for the same cities all relevant Airbnb data. After a careful screening and scraping, it turned out that for 25 out of the 40 GPCI cities it was possible to compose a consistent and complete Airbnb database, so that for these 25 cities we have a complex data set on both Airbnb listings and GPCI indicators. The list of these 25 global cities can be found in Fig. 2. Thus, the choice of the 25 cities in our sample is determined by their presence in the GPCI list and the completeness of Airbnb data in these cities.

The Airbnb platform – often presented as one of the most successful digital manifestations of the sharing economy – is one of the largest global supply-demand platforms serving the accommodation and lodging sector. It is accessible, user-friendly and efficient, and hence it has gained much popularity over the past decade, despite also some negative externalities involved (see also Xu et al., 2018). Airbnb as a support tool for visitors to find accommodation in tourist destinations – outside of the official hotel facilities system – was created in 2008 and covers nowadays on a word-wide basis extensive location-based information on and booking facilities for temporary stay in private dwellings. It contains several millions of listings in a large set of countries in the world and is nowadays seen as the major competitor of the prevailing hotel industry. Airbnb units have now become an indispensable information and booking vehicle in the contemporaneous leisure and travel industry, with a wealth of tourist data. We will now briefly describe the contents and composition of our empirical database which finds its origin mainly in Airbnb platform data.

The Airbnb data used in our study were retrieved from one online data-repositories namely, Inside Airbnb.[2] We have restricted the scope of the data to encompass only listings from the year 2017 in order to ensure a comparative case between global cities. Detailed information about the price, the characteristics of the accommodation and its limitations in terms of size, availability, etc. are included for all listings in all cities in our data set. The list of variables and summary statistics is shown in Table 1. We made use of all listings having at least one review, which means that the facility has been successfully rented out at least once. The selection rule is based on two assumptions: (i) the review score (between 0 and 5) informs us about the overall quality of the facility in terms of value for money; (ii) being rented out at least once means that the price offer has been accepted by a renter, and therefore can be expected to be within a realistic price range for the client.

In light of the previous observations, it is possible to compare accommodation characteristics not only within the same urban area, but also between different regions all over the world. The following variables often included in hedonic price studies were created/used from the Airbnb data sets: **LogPrice** is the log of the price offer in Euros per night and per listing; **RoomType** describes the kind of accommodation and can be either part of a room (i.e., a bed in a shared room), a separate room (room in apartment, possibly with other guests), or an entire apartment (not shared). **Rating** is the average recorded score given by the guests who have used the Airbnb facility concerned. Each of the listings is geocoded, which means that an approximate geographic location is known. Using GIS, we were also able to retrieve the most central facility of the listing for each city; we used this location as a proxy for urban centrality. The distance from all listings to the central listing in each city is next stored in the variable **centre**. We note here that the accuracy of the position may slightly vary between listings due to some uncertainty in the renting-out settings where some noise is present in the geo-information on how close the shown location is to the factual location.[3]

Table 1
List of variables and summary statistics.

Variable	Mean	Standard Deviation	Definition
Room Type	0.432	0.561	Accommodation types: 0 = entire appartment, 1 = private room, 2 = shared room
Reviews	14.528	29.346	Number of reviews per year
Listing per Host	5.440	19.213	Total number of listings per host
Bedrooms	1.255	0.913	Number of bedrooms
Accommodations	3.141	2.000	Number of guests that can be accommodated
Distance to Bus	211.291	1219.436	Distance to nearest 10 bus-stops (meters)
Distance to Rail	886.738	2166.59	Distance to railway station (meters)
Distance to Centre	5351.83	5580.303	Distance to city centre (meters)
Distance to Attractions	3449.27	4180.933	Distance to the nearest 10 attractions (meters)
Distance to Water	645.058	595.279	Minimum distance to sea, lake etc. (meters)

The next step in our research is the analysis of tourist amenities (e.g., museums, galleries, theatres, historical sites etc.). In the context of our hypothesis on 'the path of least resistance', tourists are assumed to optimize their mobility pattern ('least cost routes') so as to visit many of these amenities. Admittedly, given a limited bias in the centrality indicators, this also means that all distances calculated between listings and amenities may also be slightly biased. However, since this error is uncorrelated with the amenity measures used in our study, we assume that this marginal error is random and does not cause any statistical problems with inferencing. Information on all amenities in a city is next geographically drawn from OpenStreetMap (OSM), since the maps material is available for all listed cities and with the same categorization settings regarding objects classified as water, park, railway station etc. Consequently, although there is a considerable user-2contribution element – meaning that a variation in activity between map-information-contributors might generate differences between cities –, the benefit from using the same set of classifications for definitions and resolutions makes the OSM data more favourable compared to all other available alternatives when comparing tourist amenities in a wide range of different cities.

Using the near function in ArcGIS Pro we calculated the nearest Cartesian metric distance to the following OSM-derived amenities: **Park**, **Water** (with manually added ocean water, where this was missing), **bus station**, **tram station** and **subway/railway station** (specifics regarding the OSM layers and the selection codes is contained in Appendix A). Thus, the OSM provides us with relevant locational and distance information that is comparable across all cities studied in our research. But OSM data are not very specific in terms of the nature of relevant tourist attractions (such as museums, historical sites etc.).

To cope with the need for more detailed information on tourist

[1] More information can be found throuh the following link: http://mori-m-foundation.or.jp/english/ius2/gpci2/index.shtml

[2] Credits to Dr. T. Slee (SAP SE).

[3] Information retrieved from (January 25/2020): https://www.Airbnb.com/help/article/2141/how-will-my-listings-location-be-shown-on-the-map

amenities in a city, we have, in addition to OSM data, also employed TripAdvisor data in order to better depict the spatial distribution of city-specific visitors' attractions. The TripAdvisor platform offers in a consistent and comparable way a wealth of detailed information on many tourist attractions in a city as well as on the individual judgments of visitors to these attractions (see also Kourtit et al., 2019). For each city we listed the 10 most popular **attractions** (using the traveller favourites sorting), and measured the Cartesian distance between each listing and the nearest attraction. The choice of 10 was motivated by our observations that the top attractions (often known worldwide) are always listed among the top attractions, together with several other attractions that deserve a visit. When we added more attractions to test the sensitivity for this number 10, the pattern became less uniform and more segmented in terms of the visitors' heterogeneous interests. The distances to the attractions in the city were calculated using the physical distance from the Airbnb units and the central-most coordinate of the location at hand.

We note here that some tourist attractions may have a large surface area (such as Central Park in New York or Vondel Park in Amsterdam). In that case, we distributed the coordinates representing the points of entrance or central parts of the area concerned, thereby assuring that the nearest distance was calculated to an entrance.[4] In Appendix B we have provided an example and some maps of the spatial distribution of the data generated and used in our analysis for an arbitrary particular city in our sample, viz. Sydney. Clearly, such maps can, in principle, be generated for all cities in our sample.

Clearly, in order to conduct an international comparative study, the data need to be as similar and consistent as possible for all of the studied metropolitan areas. It goes without saying that the composition of such an Airbnb database, including a great variety of complementary data, for all cities involved has been a painstaking effort.

7. Research methodology

The underlying idea behind 'the path of least resistance' is to capture the spatial choice mechanism of tourists when they act in ways that compensate for their lack of local knowledge, whilst aiming to find a balance between costs (or efforts) and unique tourist experiences. Generally, tourists lack time and resources to make a choice that optimizes their personal experience. In addition, the tourist is often dependent on external sources for information gathering and decision-making. The path of least resistance means in this case that the accommodation choices by visitors will favour Airbnb listings that are close to the urban core, to tourist attractions, and other favourable amenities, and that well-known areas or urban neighbourhoods will get a higher priority of visitors compared to more distant locations and less well-known neighbourhoods. Access to public transport will evidently affect Airbnb pricing, but the effect will be dependent on the distance to attractions and amenities. By designing a least-resistance model, we can depict user preferences, choices and price effects, and formulate a research hypothesis as illustrated in Fig. 1.

Our empirical research hypothesis is that the price effects of Airbnb listings will, apart from accommodation-specific characteristics (see the list of accommodation items in the Price column of Fig. 1), be affected by the least resistance principle. This means that the distance to the core area and to the amenities and attractions will have a strong impact on pricing, while access to public transport facilities (e.g., bus, tram, metro) will have a varying but second-order impact on Airbnb pricing, depending on the functionality and accessibility to public transport concerned. It also means that we hypothesize that the price effect from public transport will be different depending on whether the property is

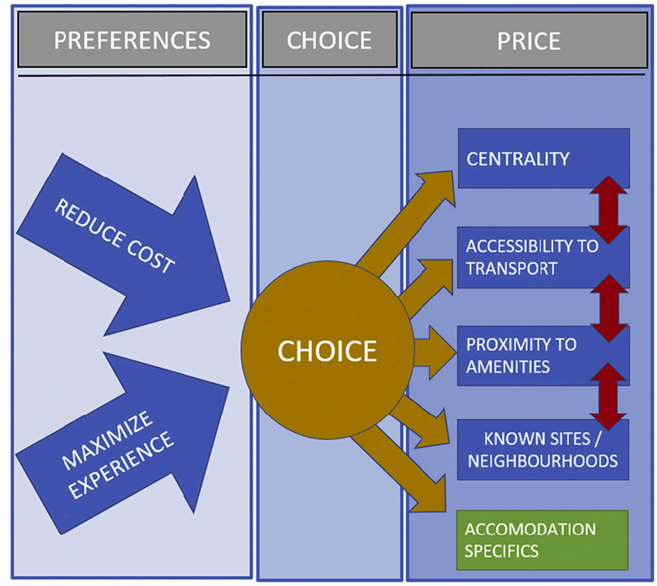

Fig. 1. Conceptual model of the 'path of least resistance' of tourists.

located in the urban core or outside, and that the price effect attributable to public transport accessibility can be related to the functionality of the local or regional public transport system. We also assume that there will be a substantial between-neighbourhood variation in pricing, also after controlling for proximity to attractions, amenities and the core area of the city.

Before we present in detail the analysis techniques and models used in our study, in particular the stepwise specification of the hedonic price function in a multilevel model, we will first outline why we use a multilevel hedonic pricing model that allows us to decompose the total variance into first-and second-level components. In contrast to previous works where hedonic price models are typically estimated by OLS regressions, we choose to adopt here a *multilevel modelling* approach. There are several reasons to justify our choice. Firstly, the prices of listings potentially show similarities among locations that are not fully accounted for by individual-level information. Multilevel models accommodate the spatial dependencies by differentiating within-level errors from between-level errors (see Snijders and Bosker, 2011), while the estimated standard errors of the regression slopes are corrected for spatial dependency. If these dependencies are not explicitly considered, the results might be biased, especially due to cumbersome spatial autocorrelation problems. Moreover, we are interested in spatial determinants of pricing in Airbnb listings, and by construction, multilevel models allow to decompose the total variance into fixed and random components, which in return allows us to determine how much of the total variation in prices is explained by the level-1 variables (variation between listings) or by the level-2 variables (variation between locations). Therefore, multilevel models have a great potential to examine the hedonic price model of Airbnb listings as a function of measurable and utility enhancing attributes, and their relative importance in predicting the observed prices.

We will now present our stepwise multilevel regression framework, starting with a two-level structure. The three-level multilevel model can immediately be constructed as an extension of the two-level model configuration. We start by constructing a so-called null model. The null model does not include any explanatory variables and serves as a benchmark model when variance decomposition is conducted. We fit thus only the grand mean with individual and random level effects as follows:

$$y_{ij} = \beta_0 + u_j + e_{ij} \tag{1}$$

[4] In a few cases such as for Moscow we disregarded such attractions as the subway system, since distance to the metro is already included in the subway/railway station variable.

where $y_{ij}$is the natural logarithm of listing i's price, $u_j$is the location-specific random effect and e_{ij} is the listing-specific error. The residuals are assumed to have a multivariate normal distribution and the variances sum up to the total variance as follows:

$$var(y_{ij}) = var(u_j) + var(e_{ij}) = {\tau_n}^2 + {\sigma_n}^2 \quad (2)$$

The subscript n indicates the null model, while the correlation between ${\tau_n}^2$and ${\sigma_n}^2$ gives the intraclass correlation coefficient (ICC). The ICC is a measure of the percentage of variance that is explained by the higher level (i.e., geographical locations), and is computed as:

$$ICC = \frac{{\tau_n}^2}{{\tau_n}^2 + {\sigma_n}^2} \quad (3)$$

ICC may take values from 0 (no dependency) to 1 (only spatial variation exits between locations), and higher values call for multilevel modelling applications. If the mobility patterns and choices in the tourist cities comply with the path of least resistance principle, we would expect Airbnb prices to vary by location (based on the distance from several points of interest) and, consequently, our multilevel model would register high ICC values. In eq. (3), we examine thus the extent to which neighbourhoods influence the prices of listings in the set of cities presented in the data section (Section 3). Then, by a stepwise regression strategy, we first include Airbnb property attributes in the first level as fixed effects. This allows us to determine how much of the total variance is explained by the listings' physical aspects. The equation that includes individual-level variables can now be written as:

$$y_{ij} = \beta_0 + \beta_{ij}x_{ij} + u_j + e_{ij} \quad (4)$$

where x_{ij} is a set of variables for listing i, located in j, and β_{ij} are associated coefficients. Eq. (4) contains two random components, u_j and e_{ij}, which share the same assumptions as Eq. (1) and with variances ${\tau_a}^2$and ${\sigma_a}^2$, respectively. Subscript a represents the variance of models with random intercepts and fixed slopes, where we have only variables at the first level.

Following Snijders and Bosker (1994), the total variance in eq. (4) can be decomposed in order to estimate the percentage variance explained by the first-level variables as follows:

$$\%\text{explained by predictors} = 1 - \frac{{\tau_a}^2 + {\sigma_a}^2}{{\tau_n}^2 + {\sigma_n}^2} \quad (5)$$

Adding more fixed-effect variables to the null model will change the variance at both the first level and the second level. The changes in the variance at the group level simply reflect the sorting of the similar types of listings to a given neighbourhood. For example, in low-cost neighbourhoods, most likely full apartments might be listed predominantly, while in neighbourhoods with higher property prices, shared apartments might be prevalent. We can compute the variance explained at the second level as follows:

$$\%\text{explained at group level} = 1 - \frac{\left({\tau_a}^2/n_j\right) + {\sigma_a}^2}{\left({\tau_n}^2/n_j\right) + {\sigma_n}^2} \quad (6)$$

where n_j is the average number of listings across neighbourhoods j.

After this hedonic-pricing inspired model on Airbnb facilities, we now address the core issue of the present study, namely to examine the contribution of the distance with respect to several modes of public transport to the total variance explained by the model. It is plausible that motorized transportation may to some extent be considered as a form of "effortless" mobility by the visitors. Therefore, tourists' attempts to minimize the distance to the nearest public transport mode become a relevant measure of the path of least resistance principle, which is reflected in the corresponding distance decay relationships. This step consists of adding variables of neighbourhood averages of distance to bus, tram and subway or railway (where applicable). This exercise signifies therefore, a first test of the 'path of least resistance' principle. The relevant model can then be written as:

$$y_{ij} = \beta_0 + \beta_{ij}x_{ij} + \beta_j transport_j + u_j + e_{ij} \quad (7)$$

where $\boldsymbol{transport_j}$ includes a set of variables that defines the average distance to public transport in each neighbourhood. We can now redefine the level-1 and level-2 variances as ${\tau_t}^2$and ${\sigma_t}^2$, respectively, where the subscript t denotes the variance of the models incorporating neighbourhood structure in relation to transport provisions. The relationship between the variances yielded from the first model (including level-1 variables) and eq. (7) allow us to determine how much of the second-level variation in prices is explained by transport-related features of neighbourhoods. It should be noted that in this way we can compute the proportional reduction in the mean squared prediction error for neighbourhood level averages with respect to eq. (4) so as to determine the importance of transport accessibility for tourists in destination cities:

$$\%\text{explained by transport} = 1 - \frac{\left({\tau_t}^2/n_j\right) + {\sigma_t}^2}{\left({\tau_a}^2/n_j\right) + {\sigma_a}^2} \quad (8)$$

Finally, we extend Eq. (7) to construct the full test model for the path of least resistance hypothesis, which includes a set of additional contextual variables at the neighbourhood level and then we define the location of listings in terms of distance to centre and tourist attractions. The full model can now be specified as follows:

$$y_{ij} = \beta_0 + \beta_{ij}x_{ij} + \beta_j neighbourhood_j + u_j + e_{ij} \quad (9)$$

The dependent variable and the individual level covariates are denoted as before, while $\boldsymbol{neighbourhood_j}$ includes neighbourhood-level variables. The level-1 and level-2 variances are ${\tau_f}^2$ and ${\sigma_f}^2$, respectively, whereas the subscript f denotes the variances of the full model. As before, the variances of the null model can be compared with that of the full model to quantify the added value of defining the neighbourhood structure of listings, when it comes to identifying the price differences. The following equation measures higher values in locations wherein the path of least resistance principle plays an important role in the spatial distribution of Airbnb listings, as defined by the explanatory power of accessibility to desired locations and public transport:

$$\%\text{explained by neighbourhood} = 1 - \frac{\left({\tau_f}^2/n_j\right) + {\sigma_f}^2}{\left({\tau_n}^2/n_j\right) + {\sigma_n}^2} \quad (10)$$

The equations from (1)–(10) allow us to study the price determinants of Airbnb listings in 25 cities from 16 different countries with a particular interest in testing the path of least resistance principle. In the following section, we present our results by starting from a global 3-level perspective wherein all cities (available in the data set) are pooled in the model described above. In order to cater both for the heterogeneity among neighbourhoods, but also across cities, we may specify here even a 3-level model, which adds the city of the listings as the highest hierarchical unit. This approach is a straightforward extension of the 2-level model and is used to demonstrate the effects of the variables on the prices of listings in a number of cities simultaneously (see Subsection 5.1). Next, the second part of the following section (Subsection 5.2) presents the price determinants of Airbnb listings for each city separately, where the analyses are conducted at two levels as described above. Due to space limitation, the regression outputs of the single cities (25 in total) are omitted, but variance decompositions are discussed explicitly. It is worth noting that to construct the 3-level multilevel framework, we need to run four regression models sequentially. Meanwhile, the broad city-level multilevel framework requires one hundred regressions to be run sequentially, while each regression is needed to obtain the estimates of: (i) null models that show the significance of the location; (ii) fixed effects of listing-level characteristics; (iii) transport-related attributes as a proxy of mobility opportunities of tourists in destination cities; and (iv) the full model of fixed effects and proximity to both transport stops and desired locations.

8. Empirical results

This section presents the results of the regression analyses when all listings are pooled in multilevel models (Subsection 5.1) and when also cities are considered separately (Subsection 5.2).

8.1. Global level of analysis

It seems plausible to expect prices to vary among neighbourhoods, and indeed previous studies have shown significant differences in prices of Airbnb listings among cities from different countries (Wang and Nicolau, 2017). Therefore, we specify here our multilevel model with three levels for the empirical analyses that address the full range of cities. The listings are defined at the first level, and neighbourhoods and cities at the second and third levels, respectively. We restrict the analyses to the year 2017; the dependent variable is the natural logarithm of the average price of an Airbnb listing across months. As mentioned, only the listings with at least one review are included in the model.

Table 2 summarizes the regression outputs from the models described in the previous section. The null model can be used to examine the variation at the neighbourhood and city levels with respect to the total variance in the distribution of prices. ICCs are listed below each column; they indicate for the null model that 71% of the total variation in pricing is explained by city-specific differences and 78% stems from heterogeneity among both cities and neighbourhoods. This means that a large portion of the variation in prices is attributable to contextual and listing specific factors. The price differences among cities reflect both heterogeneities between countries (and also continents), and may result from a number of factors including tax regimes, cost structures, and local market needs. Meanwhile, disparities between neighbourhoods in a city result from micro-scale characteristics such as centrality, transport systems, and proximity to desired locations and attractive amenities. We examine neighbourhood-scale variation in the subsequent analyses by extending the null model, first by including the listings' physical aspects (Model I), then transport-related variables (Model II) and, finally, a more comprehensive representation of spatial information about the neighbourhood where listings are located (Model III).

The second column in Table 2 examines the physical aspects of the listings (fixed slopes) with random intercepts. The model interprets the type of the listing as an entire apartment (reference category), private or shared room, while the variable *accommodates* is the number of guests the listing can accommodate. The number of bedrooms available in the apartment shows the capacity of the listing and differs from the variable *accommodates* in that it represents whether a given accommodation houses more people while offering separate bedrooms. Additionally, we use the number of listings belonging to the same host as a proxy of the hosts' expertise in the Airbnb platform (see also Gibbs et al., 2018; Magno et al., 2018).

The results of Model I show that private rooms are about 40% (exp(−0.513)-1), and shared rooms 63% (exp(−0.996)-1) less expensive than entire apartments after controlling for spatial dependencies at the city and neighbourhood levels. As in previous studies, we find a negative association between Airbnb prices and the number of online reviews (see also Wang and Nicolau, 2017; Oskam et al., 2018). The Airbnb marketplace can be defined as price-sensitive, which means that the cheaper listings receive higher demand and a potentially greater number of reviews are posted for affordable alternatives. In the traditional hotel industry, higher reviews usually associate with greater revenues (see for instance Ye et al., 2011). Therefore, the relationship between review counts and price is rather specific to sharing-based accommodation economies and, in this context, quantity does not imply quality.

Another difference observed between the hotel industry and Airbnb is that hotels and other commercial accommodation providers use marketing tools and staff expertise to make strategic pricing decisions. Airbnb hosts, on the other hand, are generally property owners who are sometimes not well informed, especially about the market value of their offerings. However, multiple offerings on an Airbnb platform may provide hosts with a better understanding of the marketing tools and strategies to differentiate their products. Our findings concerning the number of listings per host indicate that the variable shows a statistically significant and positive influence on prices. Assuming that hosts gain more experience with a higher number of listings in Airbnb, this suggests that experienced hosts show greater ability to use efficient pricing strategies.

The remaining two variables at the first level of the multilevel model show a positive and statistically significant and positive impact. The price increases with the number of bedrooms and the number of guests that the Airbnb unit concerned can host. In particular, one additional bedroom increases the price by 17% and extra space for an additional guest by 8%. Finally, the decomposition of variance indicates that listings-level variables explain a relevant portion of the residual variance. With respect to the null model, the variables in Model (I) explain 15% of the total variance in prices (see eq. (5)) for two-level models, which can be readily extended to a 3-level structure).

In Model (II), we introduce now neighbourhood-level predictors in the model. In particular, the first-level model is extended with transport-related variables to predict the neighbourhood intercept. Since some of the cities do not have tram networks, and in order to preserve the number of cities as in the previous model, we include average distance to bus and rail as two variables representing accessibility to transport systems and preserve the average distance to tram for later analysis, where we examine each city separately.

As shown in the third column of Table 2, the regression coefficients of the neighbourhood transport structure are significant and negative. This means that prices decline for the listings that are located in more distant neighbourhoods, far from public transportation access. Our findings indicate that 1% increase in distance to the nearest bus stops generates 2% decline in prices, and 1% increase in distance to railway stations decreases prices by 8%. These results are similar to previous studies on the relationship between housing and hotel room prices and transportation accessibility. For instance, Gibbons and Machin (2005) estimate a 9.3% higher rise in house prices in locations which experienced a transport improvement in access to the nearest rail station between the years 1997 and 2001 in London. Zhang et al. (2011) show that hotel room prices decline as the distance to the nearest transport hub increases in Beijing. We note that both London and Beijing are present among the cities we examine in the present paper. Therefore, we may argue that despite apparent differences between online accommodation sharing platforms and the traditional hospitality industry, transport accessibility affects prices in similar ways for both types of lodging services.

The analysis of the relationship between public transport accessibility and Airbnb prices provides a further test on the path of the least effort principle. Assuming supply- and demand- driven market prices, our results indicate that individuals who stay with Airbnb compare different alternatives and choose the locations which minimize the walking distances to nearest public transport places. We note that this finding is valid for varying distances from the centre and attraction points. As will be shown below, when two listings are located at the same distance from a desired location, this effect is different for distance-to-bus stops.

After the presentation of the results of the full model below, we will provide a detailed analysis of the variance decomposition which represents the variance of prices as a sum of transport factors and other inputs for each city in the dataset.

The final model in which cities are pooled in a single multilevel model is an extension of the previous model by centrality-related variables at the neighbourhood level. Since attractions are not necessarily located at the centre, average distances to attractions, water and parks are introduced to the model along with the variable distance-to-centre. The multilevel model outputs suggest that the further the listings are located from the centre and attractive amenities, the lower their prices

Table 2
Results from multilevel models in Airbnb listings in 25 cities.

	Multilevel Regression Analysis			
	Null Model	Model (I)	Model (II)	Model (III)
	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
_cons	4.500*** (0.209)	4.293*** (0.209)	4.946*** (0.219)	5.9235*** (0.226)
Listing's characteristics				
Private room (ref: Entire apartment)		−0.513*** (0.001)	−0.513*** (0.001)	−0.513*** (0.001)
Shared room (ref: Entire apartment)		−0.996*** (0.003)	−0.996*** (0.003)	−0.996*** (0.003)
Reviews		−0.004*** (0.000)	−0.004*** (0.015)	−0.004*** (0.015)
#Listings per Host		0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.001)
#Bedrooms		0.157*** (0.000)	0.157*** (0.000)	0.157*** (0.000
Accommodations		0.080*** (0.000)	0.079*** (0.000)	0.088*** (0.001)
Neighbourhood characteristics of transportation:				
Distance to Bus			−0.019** (0.009)	−0.015 (0.016)
Distance to Rail			−0.084*** (0.008)	−0.032*** (0.009)
Centrality:				
Distance to Centre				−0.076*** (0.010)
Distance to Attractions				−0.146*** (0.009)
Distance to Parks				0.002 (0.009)
Distance to Water				−0.049*** (0.008)
Variance (City level)	1.054 (0.305)	1.052 (0.304)	1.057 (0.305)	1.119 (0.008)
Variance (Neighbourhood level)	0.102 (0.003)	0.056 (0.002)	0.052 (0.001)	0.029 (0.001)
Variance (Residual)	0.326 (0.000)	0.160 (0.000)	0.160 (0.000)	0.160 (0.000)
Observations	705,776	705,776	705,776	705,776
Log likelihood	−524,724.8	−307,419.64	−307,351.8	−306,679.78
Number of Cities	25	25	25	25
Number of Neighbourhoods	2874	2874	2874	2874
Prob>Chibar2	0.000	0.000	0.000	0.000
Icc City	0.71	0.82	0.83	0.85
Icc City Neighbourhood	0.78	0.87	0.87	0.87
				[1]*

[1] Standard errors in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

get. Especially, the prices are higher for listings that are located in neighbourhoods with a more favourable access to attractions, where 1% increase in distance causes 13.5% decrease in observed prices. This final model is essentially the full test model for the path of least resistance hypothesis. The distance decay parameters in Table 2 support the hypothesis that the locations of Airbnb listings are chosen to minimize especially costs to access to attraction points and the city centre, while the prices respond negatively to deviations from this principle. The same finding can be also observed from the percentage of variance explained by the locational forces in the final model. The ICCs below Table 2 reinforce this finding; they indicate that 87% of the total variance is attributable to city and neighbourhood differences.

As a sensitivity analysis, we have run alternative models for listings located within a set of radii from the centre and distinct attractions.[5] The same results hold for the listings located within a 3-km or 2-km radius from the centre, with one exception. The effect of distance-to-centre becomes insignificant with a negative coefficient and distance to the nearest park becomes significant and negative. Meanwhile, when we repeat the analysis for the listings within a 3, 2 and 1-km radius from attractions, the results remain the same as in Model III. This finding can be interpreted as strong support for the path of least resistance principle for tourists' mobility behaviour. Several studies show that pedestrians do not always take the shortest route (Armeni and Chorianopoulos, 2013) to avoid, for instance, crowded and unsafe areas, and owing to other preferences (e.g. urban ambiance) that influence the selection of routes (Müller et al., 2017). However, tourists generally have limited information about the surroundings in destination cities. This lack of information might distinguish their mobility behaviour from locals (where the effort required for mobility is lower), even when choosing between accommodation alternatives within walking distances.

When we introduce new variables in the baseline model, the weight of the unexplained spatial influences in the total variability increases. The reason is that the first- and second-level variances respond to the variables included in the listings and the neighbourhood level, and clearly decrease, but a variance decomposition points to substantial price differences across cities. The city-scale differences should therefore, be further explored. We need thus to get a better comparative perspective and thus to repeat our analyses at a lower hierarchical level of individual cities. For this reason, we will conduct in Subsection 5.2 the analyses for the 25 cities separately. This approach allows us to examine distinct variance decompositions for cities included in the dataset and their relative price determinants in terms of transport accessibility and centrality. Additionally, as discussed above, the percentage of price variation explained by the location can be used as a test of the path of least resistance principle. If a large portion of Airbnb price differences is driven by the distance to several locations of tourist interest, we may argue that this principle plays an important role in the Airbnb market in these cities.

8.2. *Distinct analysis of cities*

Our subsequent analysis uses the same methods introduced in the previous section as distinct multilevel models for each city in the dataset. It is of course impossible to provide here all findings on all cities in our large sample. An example of the distinct analysis of cities is provided in Appendix C for London. We start by null models (eq. (1)) as baseline models. Fig. 2 summaries the intra-class correlation coefficients (ICCs) computed from the null models (eq. (3)). The ICCs represent the variance in the price explained by the second-level clustering variable:

[5] Regression tables are available from authors upon request.

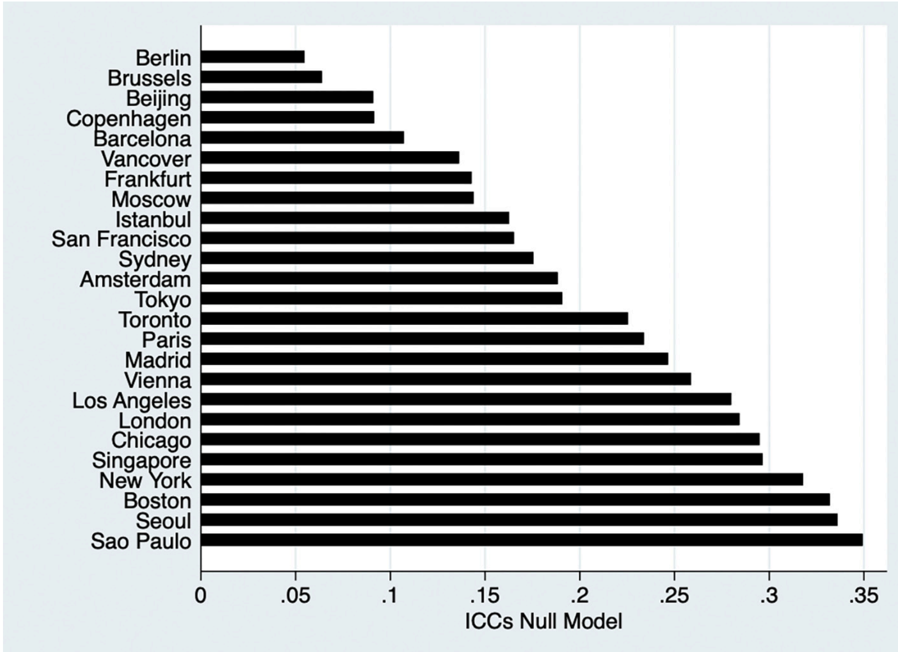

Fig. 2. Intraclass correlation coefficients (ICCs) based on the Null Models.
Legend: The ICCs show the share of variance accounted for by neighbourhood differences when there are no second-level or fixed effects in the model.

neighbourhoods. The results indicate strong neighbourhood effects for each city, which suggests that the multilevel modelling approach is relevant when examining price determinants of Airbnb listings. In particular, Fig. 2 lists Berlin (5,47%), Beijing (9,09%), Brussels (6,38%) and Copenhagen (9,14%) as the cities with the lowest neighbourhood heterogeneity, and Sao Paulo (34,93%), Seoul (33,61%), Boston (33,19%) and New York (31,79%) as the cities with the highest neighbourhood level variation in prices.

In the second step, we add level-1 variables to the models (eq. (4)) to determine the proportional decrease in unexplained variance in prices (eq. (5–6)). The level-1 variables are defined in the same way as the global measures, while explained variances at the first (grey bars) and second level (black bars) are reported in Fig. 3. The variance decomposition indicates that we are able to explain a relevant portion of variation in both levels by including fixed effects at the first level. In general, the results show that major drivers of price differences among listings are: the type of listings (full apartment, private or shared rooms), capacity (number of bedrooms and guest capacity), and the experience of the host. Moreover, the decline in the unexplained variance at the neighbourhood level reflects the sorting of similar types of listings in the same neighbourhoods. This trend is especially evident in Barcelona, Madrid, New York, São Paulo, Sydney and Toronto, as in these cities the

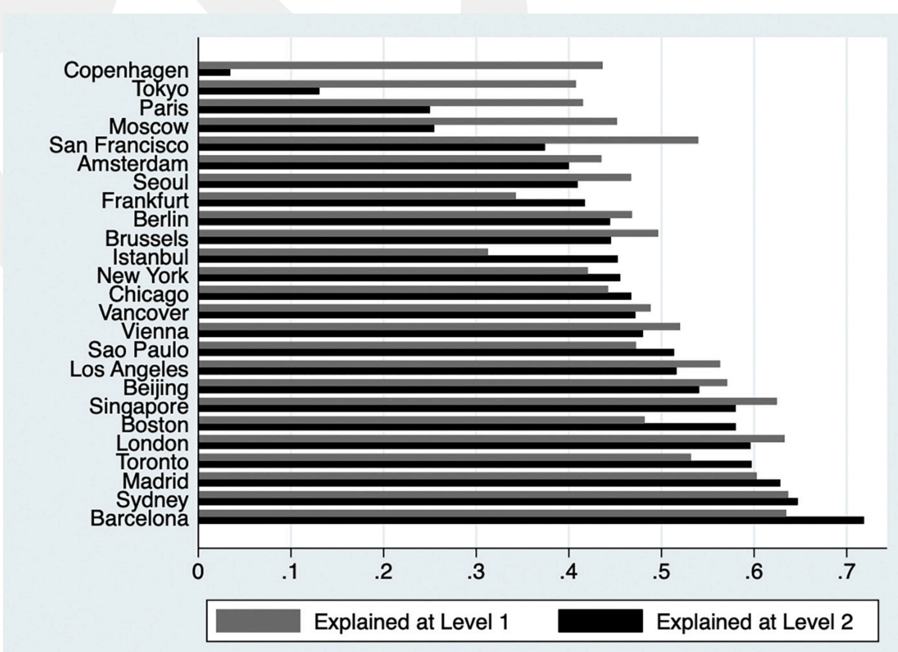

Fig. 3. Explained variance measures at level 1 and 2 from multilevel models with only the variables at the listings' level included.

level 1 variables explain the neighbourhood level variation as much as they explain the listings' level variation in prices. This means that in these cities, neighbourhoods contain listings with very similar features.

Neighbourhood sorting and the accommodation choice of tourists are driven by distinctive characteristics of neighbourhoods, and as the global analysis above suggests, by transport- related features that are similar to the traditional lodging industry. By incorporating next transport accessibility, we can examine the price differences among neighbourhoods and determine the degree to which the path of least resistance principle is reflected in the total variance. We include now neighbourhood-scale variables in relation to transport accessibility (eq. (7)) and compute the importance of public transport proximity (eq. (8)). Average distances to the nearest bus station and railway stations are modelled as proxies of transport systems access in neighbourhoods, and – except the cities Vancouver, Singapore, Seoul, New York and Chicago – the distance to the nearest tram station is also included in the models.

Fig. 4 displays interesting results about the transport related prices differences. In cities with highly developed transport systems, transport accessibility plays a minor role in determining the price of a listing (since good public transport is *ubiquitous*). The International Association of Public Transport (UITP, 2018) lists Tokyo, Moscow, Beijing, Seoul and New York among the top 10 cities with the busiest and longest metro systems. In our findings, these are the cities with the lowest influence of transport accessibility, where transport structure accounts for less than 10% for neighbourhood differences in Airbnb prices. Clearly, as Fig. 4 illustrates, starting from Berlin and Frankfurt, neighbourhood proximity to transport systems explains at least 30% of the price variation among neighbourhoods. The latter group of cities has very high taxi fares,[6] and high costs of taxi rides potentially decrease the price elasticity of demand for listings located in well-connected neighbourhoods by public transport. Having that said, it is clear that some urban areas such as Los Angeles where the lion share of transport is conducted using cars, access to public transport also plays a minor role in pricing.

Our findings are in several ways similar to earlier findings on the relationship between the use of public transport and tourism. For example, Le-Klaehn and Hall (2015) conclude in their review paper that there are many factors affecting the considerable geographical variation in tourists' usage of public transport, but among the more important ones are urban strategies for delivering relevant information directed to tourists, and the availability of- and access to public transport. In other words, urban or regional information strategies, urban design, and alternative transport alternatives such as private transport will affect the usage of public transport by visitors. Moreover, the cities with highly developed public transport systems appear to provide tourists with almost “effortless” mobility experience. Therefore, in these cities, the variation due to public transport, and thus due to, the path of least resistance principle, is minimized.

The global measures sketched out above show that the prices of Airbnb listings vary greatly in different cities or urban regions and even in the same city. As our theoretical framework (summarized in Fig. 1) suggests, the accommodation preferences and mobility of tourists can be understood by examining price variations between listings. Within the destination cities, the price variations occur at two levels, wherein the first level consists of the features of listings, the way they are rented and the host's experience in peer-to-peer services. The second-level variation in prices largely reflects the path of least resistance principle, in particular interpreted by the distance-decay relationships. In these models, we have specified transport accessibility as a driver of accommodation choice, while distance to public transport was considered as a barrier to mobility. Meanwhile, in the final full model, we incorporate distances to centre, attractions, parks and water as four additional variables representing locational attributes (eq. (9)), and compute how much variability we are able to explain at the listings' and neighbourhood levels. By minimizing the distance friction to desired locations, tourists minimize the effort needed for mobility. The second-level variation measures thus the extent to which the observed prices reflect the advantage for listings to be located in the neighbourhoods that minimize the effort for mobility. Fig. 5 summarizes the variance decomposition results. Cities are here ranked on the basis of the variance explained, from the least to the highest at the neighbourhood level (black bars in Fig. 5). The full model is successful in predicting the first-level variation. As shown by grey bars in Fig. 5, on average 55% of the variation between the prices of listings is attributed to the variables specified in our model. Moreover, overall neighbourhood-scale variables contribute to a large part of variation at the second level (at least 50%); in Barcelona, Boston and Sydney between-neighbourhood deviations in prices are almost fully captured by the combination of centrality and transport accessibility measures. This points to a strong effect of distance decay in determining the observed prices in Airbnb and a indicates a strong support for the path of least resistance hypothesis.

9. Conclusions

Airbnb has become a popular information and booking platform for sharing accommodations by tourists on a temporal basis. Despite various negative externalities, it has added to the flexibility and resilience on the urban accommodation market. Its large-scale use has also prompted several intriguing research and policy questions (see e.g. Dudás et al., 2017a; Dudás et al., 2017b; Gurran and Phibbs, 2017; Garcia-Ayllon, 2018a, 2018b; Huh and Noh, 2018; Romão et al., 2018). There is – as mentioned above - a rising tide of studies on Airbnb, in particular on housing market and related pricing developments, on the hospitality sector in cities, and on locational and transportation aspects of Airbnb in cities. Our study aims to map out specifically the local drivers and geographic and transport implications of Airbnb clients (or visitors). In doing so, the study seeks to test the novel principle of ‘the path of least resistance’.

Zipf's (1949) principle of least effort suggests that individuals tend to choose the path of least resistance and costs. In the context of tourist behaviour in destination places, the path of least resistance is reflected in the accommodation and travel choices of tourists who will favour Airbnb listings that are located in neighbourhoods close to the urban core, to prominent tourist attractions, and public transport. The present paper has tested this principle in relation to tourist mobility patterns in destination areas by means of Airbnb platform data in 25 global cities in the world. In contrast to previous studies in this field, we have constructed a multilevel model of hedonic price relationships. Multilevel models allow to disentangle the integral price impact of relevant factors in the individual Airbnb listings as well as at group level. The present paper has taken a novel approach in integrating local and global models in a multilevel framework. The approach has allowed analyzing the hierarchical relationship between listings, neighbourhoods and cities from both a global and local perspective. In the global multilevel model, the results indicated a degree of unexplained variation at the city level, which then led us to repeat the regression analysis distinctively for each location. Our analysis has thereafter tested whether the price variations at group levels -local and global- may be attributed to the ‘path of least resistance’ principle.

The main findings of the study point to strong dependencies between the price of Airbnb listings and their geographical location in the city, defined as travel distances to appealing locations and, hence, support the hypothesis. By the multilevel modelling approach, we have quantified the contribution of transport accessibility and centrality to the observed prices of Airbnb units in each city of the set of 25 cities, whereby a ranking of cities, in relation to locational determinants, is provided. An important finding from our results is that tourists prefer lodging alternatives that are located nearby public transportation. Especially, in cities like Berlin and Frankfurt, the availability of public

[6] https://www.priceoftravel.com/555/world-taxi-prices-what-a-3-kilometer-ride-costs-in-72-big-cities/

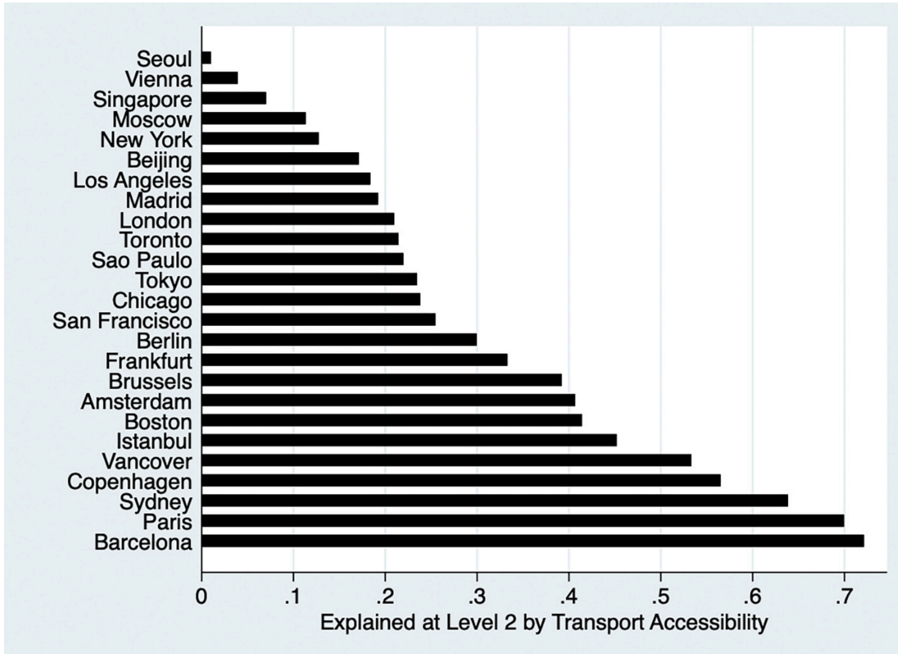

Fig. 4. The contribution of neighbourhood transport accessibility to Airbnb price differences. Legend: Explained variances are computed by comparing models with and without transport-related variables.

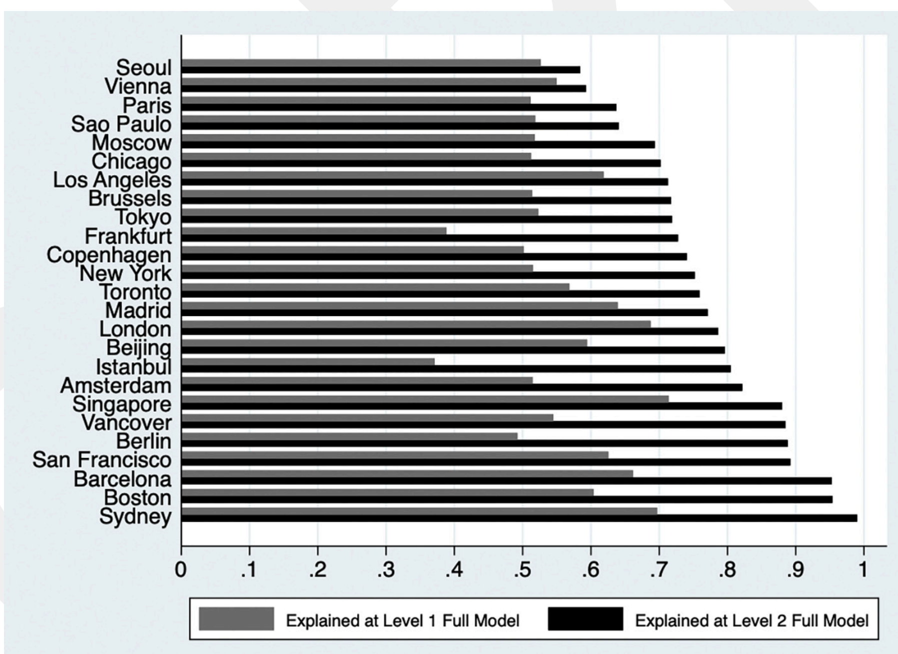

Fig. 5. Decomposition of price variance into level-1 and -2 components as predicted by the full model.

transport system explains the majority of the variation in listing prices. Connsequenntly, it seems that in urban areas with either poor or well-developed transit systems, public transport plays a minor role in determining Airbnb pricing (since change of location has a limited effect on access to public transport). This finding calls for urban policies ensuring efficient delivery of public transport information directed to tourists, and in general on local availability of public transport.

In our study we have used an enormous volume of 'big data' from the Airbnb platform, the TripAdvisor platform and the OpenStreetMap. This allowed us to make detailed place-based estimations of price impacts. Moreover, our analysis has offered a comprehensive investigation of how prices vary by specific accommodation features and host experience. From both an overall and city-specific perspective, we have shown the contribution of the listing's size, the experience of hosts and online reviews to the total variance in prices. Transport access appears to play always a significant role, especially light-rail transport systems (railway, metro, and tram), which means essentially a confirmation of our hypothesis on the 'least resistance' principle.

Our empirical findings have convincingly demonstrated that the 'path of least resistance' hypothesis for understanding the spatial mobility behaviour of tourists in destination cities is confirmed. Our findings also show the significance of different database combinations (OSM) data, statistical information, social media data) – supported by GIS methods – for mapping out the complex spatial mobility patterns of tourists in destination places. And finally, the use of advanced multi-level spatial modelling turned out to provide highly interesting results for the 25 global cities under consideration.

The analysis carried out in the present study does by no means provide the final answer to many intriguing questions related to the spatial behaviour of visitors in tourist places. The duration of stay, the experiences from previous visits to the same place (or to other comparable places), the 'herd' behaviour of tourists (rather than isolated decisions), the heterogeneity in tourists' preference profiles, and the frequency of tourist visits or city trips, all these factors may play a role in the spatial mobility patterns of tourists (see also Briassoulis, 2002). Further research on the mobility patterns and impacts of tourists – in particular, in crowded tourist cities – would also have to identify individual mobility motives. Consequently, in addition to the wealth of data from booking and social media platforms, there is also a need for individual survey-based research, in combination with traditional statistical indicators on the supply and demand side of tourist mobility in destination places. In particular, the merger of official statistical tourist data, survey data and 'big' social media data will provide a new departure for evidence-based modelling research on the spatial mobility of tourists world-wide. And finally, it is noteworthy that in the era of a pandemic, Airbnb use and access to – or use of – public transport are critically dependent on human health conditions in these facilities, as perceived risks of density in cities tend to have a major negative impact on the use of these facilities. Consequently, the path of least resistance is a proposition that calls for a broader interpretation than cost considerations alone; it captures also health risk elements.

Authorship statement

All persons who meet authorship criteria are listed as authors. All authors conceived of the presented idea. The authors developed the theory and performed the estimations. They verified the data, discussed the results, revised and contributed to the final manuscript. All authors contributed equally to this manuscript.

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Appendix A. OpenStreetMap information

Table A1
Identifiers of OSMTable A1.

Name	OSM-file	Numeric code in field: *code*
Park	Land-Use	7202
Water	Water	All selected
Bus-stop	transport	5221
Train-station, Subway station	transport	5201, 5202
Tram station	transport	5203

Appendix B. Illustrative GIS Representation of Geographical Distribution of Relevant Variables in Sydney

Fig. B1 shows the spatial distribution of the selected attractions in Sydney, with all parks and waterbodies recorded in distance measures (Fig. B1, A), the location of central Airbnb listings and a circle indicating a 30 km radius around the city centre (Fig. B1, B), and the full coverage of Airbnb listings (Fig. B1, C). Fig. B1, D shows the distribution of bus-stops and rail-stops, while finally Fig. B1, E shows a neighbourhood-specific color-coded map of all Airbnb listings. Similar data and maps were generated for all cities included in our sample, so that at the end we have a very rich data set.

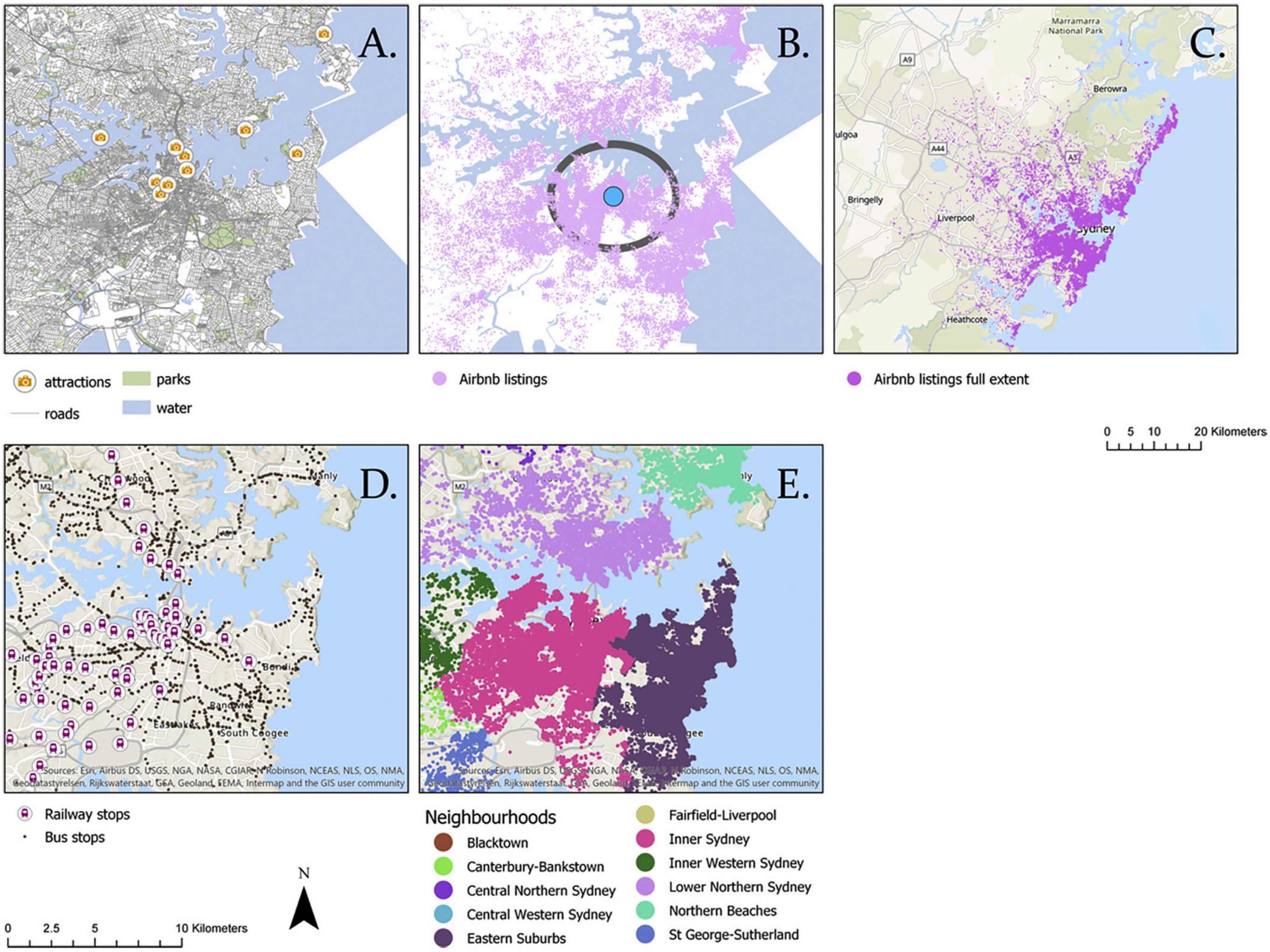

Fig. B1. Illustrative example of the distribution of Airbnb listings and spatial attributes in Sydney.

Appendix C. London as an example of distinct analysis of cities

	Multilevel Regressions Analysis			
	Null Model	Model (I)	Model (II)	Model (III)
	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
_cons	4.325*** (0.015)	4.337*** (0.010)	4.899*** (0.040)	6.7475*** (0.057)
Listing's characteristics				
Private room (ref: Entire appartment)		−0.634*** (0.001)	−0.634*** (0.002)	−0.630*** (0.002)
Shared room (ref: Entire appartment)		−1.120*** (0.006)	−1.120*** (0.006)	−1.113*** (0.007)
Reviews		−0.001*** (0.000)	−0.001*** (0.000)	−0.001*** (0.000)
#Listings per Host		0. 0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
#Bedrooms		0.220*** (0.001)	0.221*** (0.000)	0.223*** (0.001)
Accommodations		0.004*** (0.000)	0.004*** (0.000)	0.005*** (0.000)
Neighbourhood characteristics of transportation:				
Distance to Bus			0.005** (0.001)	0.004*** (0.001)
Distance to Rail			−0.018*** (0.001)	−0.015*** (0.009)
Distance to Tram			−0.051*** (0.004)	−0.057*** (0.004)
Centrality:				
Distance to Centre				−0.080*** (0.004)
Distance to Attractions				−0.100*** (0.004)
Distance to Parks				−0.004 (0.633)
Distance to Water				−0.027*** (0.001)
Variance (Neighbourhood level)	0.150 (0.002)	0.057 (0.002)	0.044 (0.001)	0.030 (0.001)
Variance (Residual)	0.393 (0.000)	0.153 (0.000)	0.153 (0.000)	0.151 (0.000)

(continued on next page)

(*continued*)

	Multilevel Regressions Analysis			
	Null Model	Model (I)	Model (II)	Model (III)
	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)	Coeff. (Std. Err.)
Observations	257,035	257,035	257,035	257,035
Log likelihood	−122,955.3	−130,033.41	−129,865.43	−122,955.3
Number of Neighbourhoods	586	586	586	586
Prob>Chibar2	0.000	0.000	0.000	0.000
Icc Neighbourhood	0.28	0.27	0.22	0.16

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