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Airbnb and COVID-19: SPACE-TIME vulnerability effects in six world-cities

Karima Kourtit [a], Peter Nijkamp [a,*], John Östh [b], Umut Turk [c,d]

[a] Open University, Heerlen, the Netherlands, Smedestraat 2, 6411, CR Heerlen
[b] Uppsala University, Upsala, Sweden
[c] Abdullah Gul University, Kayseri, Turkey
[d] Barbaros, Sümer Kampüsü, Erkilet Blv, 38080, Kocasinan/Kayseri, Turkey

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ABSTRACT

This study examines the COVID-19 vulnerability and subsequent market dynamics in the volatile hospitality market worldwide, by focusing in particular on individual Airbnb bookings-data for six world-cities in various continents over the period January 2020–August 2021. This research was done by: (i) looking into factual survival rates of Airbnb accommodations in the period concerned; (ii) examining place-based impacts of intra-city location on the economic performance of Airbnb facilities; (iii) estimating the price responses to the pandemic by means of a hedonic price model. In our statistical analyses based on large volumes of time- and space-varying data, multilevel logistic regression models are used to trace 'corona survivability footprints' and to estimate a hedonic price-elasticity-of-demand model. The results reveal hardships for the Airbnb market as a whole as well as a high volatility in prices in most cities. Our study highlights the vulnerability and 'corona echo-effects' on Airbnb markets for specific accommodation segments in several large cities in the world. It adds to the tourism literature by testing the geographic distributional impacts of the corona pandemic on customers' choices regarding type and intra-urban location of Airbnb accommodations.

1. Setting the scene

The worldwide COVID-19 pandemic has left everywhere visible footprints. One of the sectors most affected by the current corona crisis is the hospitality industry. The seemingly unlimited rise in spatial leisure and business mobility over the past decades has suddenly turned into a steep decline (see, e.g., Gössling et al., 2020; Hall et al., 2020; Huang et al., 2020; Qiu et al., 2020; Kim & Lee, 2020; Gussoy & Chi, 2021; Liang et al. 2020; Benitez-Aurioles, 2021). This was accompanied by an equally steep decline in the entire tourism, recreation and cultural industry. The number of visitors to hotels, accommodations, cultural amenities and entertainment facilities has dramatically declined and this has cast serious doubt on the assumed resilience and adaptive capacities of the entire sector (see, e.g., Adger, 2000, 2006; Brown et al., 2017; Hartman, 2020). Clearly, cities in particular – as the main recipients of travellers – have been severely affected. In addition, exposure to high urban density and geographic concentration of tourist amenities became in the view of visitors suddenly a health risk due to the COVID-19 pandemic.

There is a wealth of literature on disruption impact studies ranging from economic shocks to natural disasters (Okuyama & Rose, 2019; Yigitcanlar and Inkinen, 2019). Such studies show a great variety in methodological framing and level of aggregation. Several contributions to the 'economics of shocks' address the question of distributional effects ('spatial echo effects') of disruptions in an economic system (see e.g., Banica et al. 2020). In the present study we test the proposition that the COVID-19 pandemic has significant equity implications (both economic and spatial) for the Airbnb market, viz. an unequal demand effect for Airbnb facilities by specific user groups (business versus low-income customers), which leads to a distinct spatial-economic market segmentation of actual bookings (luxury versus economy-class apartments). This proposition on a selective 'corona echo-effect' originates from the

* Corresponding author.
E-mail addresses: k_kourtit@hotmail.com (K. Kourtit), pnijkamp@hotmail.com, peter.nijkamp@ou.nl (P. Nijkamp), John.Osth@kultgeog.uu.se (J. Östh), umut.turk@agu.edu.tr (U. Turk).

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plausible distributional assumption that well-to-do customers of accommodation facilities tend to book – for health risk reasons – more individualised – and hence more expensive – forms of Airbnb accommodation.

A useful point of departure for describing the changing state of peer-to-peer accommodation services is the concept of resilience, originally designed to capture the dynamic state of ecosystems that either withstand or adapt to a shock (see for instance Holling, 1973,1996; Pimm, 1984). In current corona times, resilience is also a useful framework for understanding how the pandemic (as a shock) affects agents in the hospitality sector. We note that a decade ago the establishment of the "sharing economy" in the hospitality sector was described as a strong disruptive event challenging the resilience of the hospitality market; currently the rapid and adaptive peer-to-peer system underlying the Airbnb business model may imply that the echo-effects of a shock such as the COVID-19 pandemic are likely to be profound (Belk, 2014; Dolnicar & Zare, 2020; Sharma et al., 2020; Gyódi, 2021; Hesse Lianeza & Raya Vilchez, 2021; Hidalgo, Riccaboni, Rungi, & Velazquez, 2021; Jang & Kim, 2022). It is too early to establish to what near-equilibrium state peer-to-peer accommodation services will bounce back after the pandemic, but from an engineering resilience perspective it is challenging to trace the localized qualities and contextual attributes that facilitate Airbnb survival in different parts and in different cities of the world.

The Airbnb platfrom is one of the most successful examples of a peer-to-peer business model. It has been growing steadily since it was founded in 2008, and now the platform offers more accommodation services than many well-known hotel chains (Hartman, 2020). The platfrom has been so successful that it effectively integreated itself into many residential areas and changed even the residential market (Gil and Sequera 2020). Clearly, Airbnb represents a large share of the hospitality market, at least regarding the number of rooms it has to offer. Therefore, it becomes pertinent to study the Airbnb market under the corona disruption not only for the purpose of analysing the resilience of the peer-to-peer business model against the current shocks, but also for a focussed discussion on how the hospitality market responded to an unprecedented decrease in human mobility. Admittedly, our choice of zooming in on the Airbnb sector and not on the entire hospitality market – is mainly driven by the rich and accessible dataset the platfrom offers for many major cities so that a comparative analysis can be pursued.

In many countries we observe multiple and fluctuating corona waves. This capricious pattern resembles a roller-coaster, with unexpected outliers in different periods and places; this pattern is by no means uniform in space and time (Couclelis, 2020; Florida, Rodriguez,-Pose, & Storper, 2021). The question is not whether the Airbnb market has been hit by COVID-19, but how much, where and why. Although there are in the meantime several case studies that focus on the Airbnb market during the pandemic (Bresciani et al., 2021; Dolnicar & Zare, 2020), the present literature does not yet offer a comprehensive quantitative study of the recent crisis from the perspective of large cities all over the world. A notable exception is a study by Liang et al. (2021) who analysed vacation rentals in various big cities and changing tourist sentiments during the pandemic, but did not develop an econometric model of the underlying forces and impacts. In this paper, we try to fill this gap in spatial-econometric modelling. We seek to examine the space-time dynamics and economic consequences for the worldwide Airbnb sector in six selected global cities. Our research aim is to trace and explain the heterogeneous space-time footprints of the COVID-19 pandemic on the Airbnb sector among and within six large cities of the world. To understand the detailed – monthly – dynamics in this space-time pattern of Airbnb bookings and prices, four subsequent empirical research questions are formulated:

- Is the worldwide curve of the pandemic over continents and cities showing a global space-time distance-decay curve (starting from Wuhan, China) for the entire Airbnb sector in different parts of the world in a way similar to spatial innovation diffusion models (see e.g. Brown, 1981)?
- If lockdown measures are imposed in an uncoordinated way in different countries/places and if the clients' response is not predictable, has the Airbnb sector been able to address these unforeseen and spatially differentiated shocks in a stable way?
- If clients of Airbnb amenities are sensitive to crowding and health conditions, would then the urban Airbnb market be uniformly hit by the pandemic? In particular, do Airbnb bookings in cities follow a reverse-distance distributional gradient pattern from the dense city center outward?
- If during lockdown periods the accommodation market has largely collapsed in several cities, how has the price of Airbnb settings responded to extremely high vacancy rates? And have all segments of the urban Airbnb market been hit equally or is the principle of a 'selective echo-effect' also reflected in the Airbnb market?

In addressing these questions the present paper contributes to the tourism literature in several respects, both theoretically and methodologically:

- It is to our knowledge one of the first studies documenting COVID-19 related shocks in peer-to-peer accommodation services from a global model-based perspective covering many world-cities (with Liang et al., 2021 as a noteworthy exception).
- It conducts a survival analysis of Airbnb listings in corona times by a detailed investigation of remaining or exiting listings from the platform using a novel multi-level approach to both the supply and demand side. The results show that hosts offering multiple apartments, or have multiple listings on Airbnb, tend to be more resilient. In addition, the intra-urban location of a given Airbnb facility affects clearly the survival rate.
- It employs massive Airbnb data and improves previous econometric approaches by incorporating a Spatial Durbin Model for estimating price elasticities in both the pre-corona and the actual corona periods.

The paper is organised as follows. Section 2 provides a background of recent studies on impacts of the pandemic on the hospitality market. Section 3 is devoted to data and relevant databases used here. In Section 4 the space-time dynamics ('*roller-coaster*') of Airbnb is presented by comparing outcomes on a monthly basis for subsequent periods for six large cities. The survival analysis and hedonic price elasticities are presented in Section 5, while Section 6 provides the empirical results. In Section 7 several retrospective and prospective observations and strategic policy comments are made.

2. Literature review

2.1. Airbnb as a global player in the hospitality market

Airbnb has become one of the most successful examples of a peer-to-peer accommodation business model. We refer to Dolnicar (2019) for an extensive discussion on the business model of Airbnb and how it differs from general sharing economies. There were as many as over six million Airbnb listings around the world in 2019.[1] This means that the platform now represents a significant share of the hospitality market (see for more information Zervas et al., 2017; Nieuwland & Melik, 2020). Furthermore, the 'big' potential data regarding the daily operations on the Airbnb home-sharing platform has attracted much attention in tourism research. For example, Wang and Nicolau (2017) study the effects of host attributes, site and property attributes, amenities and services,

[1] https://news.airbnb.com/airbnb-hosts-share-more-than-six-million-listings-around-the-world/.

rental rules, and online review rankings on the pricing of Airbnb listings in 33 cities. They find that while centrally located listings and entire apartments are listed at higher prices, each additional review per year decreases prices. Similarly, Teruel-Gurierrez and Sanchez-Val (2021) examine the locational determinants of listing prices in Barcelona, and find significant and positive effects of proximity to Instagram tourist spots and to the nearest underground stations (see also Cócola Gant, 2016; Guttentag, 2015; Guttentag et al., 2017; Gyódi & Nawaro, 2021; Oskam & Boswijk, 2016; Sheppard & Udell, 2016; Stors & Kagermeier, 2015). Therefore, the importance of geography seems to offer a meaningful proposition for Airbnb locations.

The volume and extent of the Airbnb data allows testing several theories. For instance, Türk et al. (2021) show the validity of "*the path of least resistance*" principle for explaining the spatial behaviour of tourists in 25 major tourist destination cities by Airbnb data. Research topics also include the analysis of the relationship between the traditional hotel industry and Airbnb, and also the implications of Airbnb for the regular housing market. In this respect, Önder et al. (2018) find a significant and positive correlation between the prices of traditional hotels and that of Airbnb listings in the same areas in Tallin, using hedonic price regression models (see also Sainaghi & Baggio, 2020; Dogru et al., 2020a,b). On the relationship between the presence of Airbnb listings and the prices of rents in Boston, Horn and Merante (2017) illustrate that the asking rents increase with the number of available Airbnb listings in the area (see also Guttentag, 2015; Edelman & Geradin, 2016, pp. 293–328; Oskam & Boswijk, 2016; Nieuwland & Melik, 2020; Romano, 2021). Consequently, spatial price and rent mechanisms are another key characteristic of the Airbnb sector.

Previous literature includes also several contributions on the Airbnb demand side (Gunter & Onder, 2018; Volgger et al., 2019); the principles of sharing economic goods (Hamari et al., 2016); the effect of online reviews on hotel and Airbnb accommodation (Bridges & Vásquez, 2018; Lawani et al., 2019; Ye et al., 2009; Zhang et al., 2019). Prayag and Ozanne (2018) and Dolnicar (2019) published reviews of many studies conducted with Airbnb data. Thus, listing information and client evaluation is critical for the functioning of the Airbnb market (see also Teruel-Gutierrez & Maté-Sánchez-Val, 2021). Despite the above propositions on corona echo effects for Airbnb accomodations, the research on the effect of the COVID-19 outbreak on Airbnb market is still limited.

Recently, Bresciani et al. (2021) and Dolnicar and Zare (2020) discussed the potential effects of COVID-19 on the Airbnb market. Dolnicar and Zare (2020) hypothesized that in the post-COVID period the market would not return to its pre-COVID level, as capitalist hosts would turn to long-term rental markets due to current and potentially more frequent economic shocks in the future. Meanwhile, using experimental studies, Bresciani et al. (2021) posited that the need for social distancing would drive the hosts' choice of the type of lodging; this would in particular lead to an increased demand for entire apartments. We may conclude that Airbnb research is on a rising edge, due to its economic position and its 'big data' availability, while recently also several studies on COVID-19 effects have been published. This will be highlighted in Sub-section 2.2.

2.2. Vulnerability in the hospitality market: the corona shock

The hospitality market has had a steady growth over recent decades. Even the recent recession (2008–2012) has not led globally to a dramatic disruption. However, since the beginning of the pandemic a need to address the vulnerability of the tourism market has arisen (Alonso et al., 2020; Bartik et al., 2020; Farzanegan et al. 2020; Gössling et al., 2020; Menegaki, 2020; OECD, 2020; World Bank, 2020; Yang et al., 2020). Clearly, there is plenty of literature on sustainable tourism development (Adamiak, 2019, 2021; Adongo et al., 2018; Gössling, 2009) and vulnerability after shocks (see, e.g., Sarewitz et al., 2003; Borsekova & Nijkamp, 2019; Modica et al., 2019; Ritchie and Jiang, 2019). Obviously, the worldwide COVID-19 pandemic shows that this disruption has brought to light a less stable growth and a high vulnerability of tourism markets (Adongo et al., 2018; Centeno and Marquez, 2020; Bakar and Rosbi, 2020; Asmelash & Cooper, 2020; Guan et al., 2020; Madani et al., 2020; Sharifi and Khaverian-Garmsir 2020; Miao et al., 2021).

Clearly, the current corona crisis is not the first time the hospitality sector has been affected by an unexpected shock (see, e.g., Hystad & Keller, 2006; Brown et al., 2017; Shao & Xu, 2017; Ord & Getis, 2018; Xu & Shao, 2019; Chang et al., 2020). Many of these perturbations have severely influenced the revenues and socio-economic performance in the hospitality markets. Revenue management in the hospitality market under uncertain external conditions is a usual business challenge (see, e.g., Strauss et al., 2018; Pulina & Santoni, 2018; Wangui et al., 2018), where the critical parameter is the accommodation price which determines both the profitability of accommodation offered and the willingness to accept an offer by the customers (Ioannides et al., 2018).

In our study we do not address the functioning of the entire accommodation market in corona times, but only the Airbnb segment in various large cities in the world. The main reason that detailed information on hotel prices, bookings and cancellations is not available, whereas for the Airbnb sector this information can to a large extent be distilled from the platform. Clearly, this analysis leads to a massive data-analytic experiment, which even cannot be handled by one single computer.

It is noteworthy that the supply of Airbnb is a function of several macro factors, such as gross domestic product, wages and unemployment as well as tourism demand (Dogru et al., 2020). Therefore, it is plausible that the Airbnb market has been one of the most affected sectors after the sudden reduction in travelling and economic activity. Most Airbnb accommodations are found in cities, but in the past period cities have also been the main geographical sources of the spread of the pandemic. In addition, the corona spread pattern shows clear heterogeneous and unpredictable fluctuations (see e.g. Nijkamp & Kourtit, 2022). Consequently, it is pertinent to examine the spatial corona echo-effects, including price elasticities of Airbnb facilities, in various cities. It should be noted that, although the shock in the Airbnb market was instantaneous at the beginning of 2020, subsequently it showed different phases of intensity of perturbations over the subsequent months of 2020 and 2021, depending on both sudden changes in customers' travel behaviour, and in time-varying anti-corona and lockdown regulations.

This study starts from the proposition – often found in the literature on disaster impact assessment (see e.g. Buckle et al., 2001; Benson & Twigg, 2006; Dekens, 2007; UNDP, 2004; UNISDR, 2009; Mercer et al., 2009) – that shocks or disruptions do not uniformly affect all actors involved. Natural disasters, economic shocks, technological disruptions, or political turmoils appear to be unequally distributed over the economy and tend to have serious equity effects. In our analysis we add to the literature on spatial-economic equity in two ways, by: (i) investigating whether specific types of Airbnb accomodations are more affected by the corona crisis than others (by making a distinction between Luxury and Budget types); (ii) identifying spatial patterns (depending on an analysis of the distance decay of Airbnb amenities to concentrated urban tourism attractions) in the tourist cities under investigation. We postulate that the more luxury Airbnb facilities in less densely populated urban areas (often at the fringe of the city) are least affected.

3. Databases

The extensive data on individual Airbnb listings in our study originate from the Inside Airbnb website,[2] which includes listed prices, characteristics of the accommodation, client reviews, and daily availability. We have collected data from various world cities that are also key tourism destinations. We selected six large cities which can also be

[2] http://insideairbnb.com/get-the-data.html.

found in relevant databases, viz. GaWC (see Derudder & Taylor, 2021) and GPCI (see Institute for Urban Strategies, 2021). The following six major cities are included: Barcelona, Beijing, London, Milan, New York, and Paris. These cities are selected based on both their initial exposure level to the shocks and the intensity of Airbnb activities. Beijing was the first global tourism city where the pandemic was recognised, while Milan was the first city in Europe heavily affected and with strict mobility restrictions and lockdown measures (close to the pandemic epi-center Bergamo). The virus – and its awareness – then gradually spread to Paris, Barcelona and London, and finally reached New York. Additionally, these are the cities where the Airbnb market place is highly appreciated, with high occupancy rates and activity.[3] Admittedly, we have a few missing data points in our dataset. While the data for May was unavailable for all cities in 2021, the analysis in Milan and London lacks the month July in 2020, and in Beijing the months of July and August in 2020 and June in 2021 are missing. Since the analysis are conducted separately by city and month, we believe missing data do not impose any serious biases in our findings, which are derived from a dataset of over 200 gigabyte of daily information about Airbnb listings in the six cities under examination.

In our data-analytic research we use also data from the pre-pandemic year (2019) in order to perform a proper contrast analysis. The Airbnb data enable us to track changes in prices, entry-exit patterns and booking rates during the period January 2019 until August 2021. This means that – following the four research questions in Section 1 – we can analyse: (i) the space-time patterns of Airbnb listings and bookings for all six cities; (ii) the Airbnb market responses to COVID-19-related shocks from both a demand and a supply perspective, including the survival rates; (iii) the physical and locational characteristics of Airbnb listings in cities in relation to the survival probabilities on the platform; (iv) the price elasticity of demand in a comparative inter-urban framework between pre- and post-crisis periods.

As mentioned in Section 1, we aim to test the proposition that the COVID-19 pandemic has unequal distributional echo effects, both between cities and within cities. We use therefore both supply (e.g. presence of listings) and demand (e.g. acceptance decisions data) in our geographical and socioeconomic footprint analysis.

In the survival model, we use the continuous presence on the platform (for 6 months during the pandemic) as our dependent variable, while the monthly demand per listing is used as the dependent variable in the model for the price elasticity of demand (see descriptive statistics in Appendix Table A1). In line with previous literature, both models control for listing-levels and locational characteristics. Several contributions show that professional hosts have a greater ability to charge higher prices for their listings (Wang & Nicolau, 2017; Gunter & Onder, 2018; Gyódi, 2021). We include the number of listings per host as a proxy of proficiency at the platform to control whether professional hosts could use and mobilise financial resources and also strategic management practices better than non-professional hosts during the pandemic.

The privacy and health concerns of Airbnb clients in this period has likely favoured non-shared entire apartments and private rooms. We control for this by the variable room type. The variable includes hotel-type listings in addition to entire apartments, private rooms and shared rooms. It should be noted that the hotel-type does not include all hotels in given locations, but only those which rent their rooms also on the Airbnb platform.

The visitors during this period may have sought as much information as possible about the short-term rentals before their travels. In this respect, information flows might have become a significant determinant of both prices and also survival rates. We include then the number of reviews as a control variable. Similarly, the visitors might have preferred to avoid restriction policies regarding the minimum number of nights they can rent a listing. Our model controls for this by the variable minimum nights. The literature on Airbnb shows that centrally located listings and those near tourist attractions are valued high in the hospitality market. We model next location by a set of proximity variables including distances to center, hotels or touristic attractions, to predict locational influences during the pandemic. While several studies indicate centrality and proximity to attractions as predictors for high prices and demand (Wang & Nicolau, 2017; Gunter & Onder, 2018; Nicola et al., 2020; Teruel-Gurierrez and Sanchez-Val 2021), we expect alterations in preferences during the pandemic. We define the center as the location of the central train station in all cities. In addition, distances to the nearest ten hotels and touristic attractions are calculated in urban GIS environments.

Airbnb operates generally with a minimum of controls and regulations on prices and supply decisions. Prospective hosts list their properties, indicate available nights and establish nightly prices in a calendar. Each month in the calendar sets out a daily plan of pricing and availability. From the platform information, we can also retrieve the total number of listings posted on the platform each day.

Calendar information can be used to extract both the expectations of hosts in terms of the upcoming prices (used as signalling mechanisms to optimize occupancy rates) and also guests' travelling plans for the following months. However, quantifying supply and demand is challenging, since the available data does not allow this information to be derived directly, and imposes noise due to "stale vacancies". According to a study by Fradkin (2015), 21%–32% of the booking requests are rejected, because hosts forget or neglect to unlist their properties, even though they are no longer active on the platform. To ensure that the host is still active on the platform and the data capture actual booking events, in our study only those listings are considered that received at least one review in the last three months.

Another challenge relates to quantifying bookings and occupancy rates of Airbnb facilities. Even though the information about the daily availability is updated each month, it is hard to tell whether the hosts are not renting out their properties for an unavailable day or whether the property has actually been booked. To cope with this, we adopted the following strategy to derive actual booking rates. On the Airbnb platform, both the booked and unavailable nights are coded as "unavailable" in the Airbnb calendar data. For each month in the calendar data, we are able to track the daily availability information for the same listings over the period concerned (in 2019, 2020 and 2021). The days in which the listing shows an "unavailable" status systematically (every week and in each month, for at least 7 months) are counted in our analysis as "apparently unavailable". The remaining unavailable days are then considered as bookings.

Although COVID-19 became a global pandemic, we expect a clear degree of within-city variation in the impact of the virus, while different price segments might show different responses to the shocks. Most likely, Airbnb accommodations located in dense inner-cities are less attractive in corona times. The spatial heterogeneity in cities may in particular prevail between central and peripheral locations due to population density or the presence of isolated accommodations in the periphery. It is noteworthy that Airbnb data is geocoded. This information is used to compute the distance of each listing to the inner-city center, the shops, touristic attractions, hotels, and nature, thus allowing to capture spatial patterns in the vulnerability of Airbnb locations to shocks. In our analysis, we also use OpenStreetMap (OSM) information to retrieve the relevant geo-data on these locations.

Airbnb accommodation differs, of course, in quality (size, facilities etc.). To investigate the demand for lower and higher segments, we compute the quartiles of prices (determined for each month) to create an Airbnb segmentation similar to the standard hotel market segments of Budget, Economy, Midprice, and Luxury. We focus here on the changes in price elasticity of demand for the two extreme Airbnb segments, viz. Budget and Luxury listings, since the lowest and the highest quintiles

[3] https://www.usatoday.com/picture-gallery/travel/destinations/2019/09/05/airbnb-capitals-world-cities-with-most-rentals-top-20/2208730001/.

attract potentially diverse income groups and may have a higher explanatory and discriminating power. In Section 4, we will analyse the space-time supply and demand shocks as a response to COVID-19 in the six major cities under consideration.

4Global roller-coaster analysis of six cities: supply and demand shocks

This section presents the global analysis of the pandemic shocks by comparing the supply and demand dynamics in six global cities, on the basis of a comparison of current monthly shocks (2020–2021) with respect to the same period in a year before the pandemic (2019). In Figs. 1–3, we compare the changes in the volume of listings on the Airbnb platform, the cancelled bookings, and the occupancy rates from January to August, in both 2019 and 2020–2021.

Volume indicates the percentage change in the number of the listings posted on the platform in each cited month in both 2019 and 2020. Volume changes occur when accommodation listings are deleted from or added to the Airbnb platform.

Next, we identify cancellations by tracking the listings that were booked in a given month for a future date, but became available again in the subsequent data cohort. To ensure that the booking was indeed cancelled by the guest, we excluded the listings that became "apparently unavailable" by the above-mentioned method.

Monthly average *occupancy* rates are computed as the ratio of the total number of unavailable days to the total number of available days, excluding the apparently unavailable days for each listing.

It is plausible that the trends in supply and demand over the same months in 2019 would relatively have been rather similar to those in 2020–2021, if the pandemic had not hit the industry. Therefore, Figs. 1–4 reveal the potentially devastating hardships for the Airbnb market and related hosts. Figs. 1 and 2 show the year-on-year monthly changes in booking cancellations, where the difference in the rate of cancellations in two subsequent months in 2020 and 2021, respectively, is compared with the difference in the rate of cancellations in the same months in 2019. In Barcelona, New York and Paris, the percentage change in cancellations in 2020 appears to peak between the months March and April (50–60% more cancellations compared with 2019), while in March the cities of Milan and Beijing saw lower cancellations compared with the previous year owing to inactivity of the Airbnb hosts on the platform. Many of the guests had to cancel their bookings, mainly because of forced travel restrictions and lockdowns. Fig. 2 for the year 2021 shows that the cancellations in 2021 continued to be higher than their level in 2019. Clearly, the contagious disease model is present here, but apparently in a less regular manner as predicted by geographical dispersion models (Brown, 1981).

Legend: Positive values indicate the percentage increase in cancellations in 2020 with respect to the same month in 2019.

Legend: Positive values indicate the percentage increase in cancellations in 2021 with respect to the same month in 2019.

Mirroring the first policy response of the hotel industry, Airbnb even overruled its own cancellation policy and provided guests with free cancellation rights. This policy – in fact encouraging cancellations – accelerated revenue losses for the hosts. Fig. 3 shows that 30–50% of the hosts had already deleted their listings in March 2020, while by 2021 around 70% of the hosts had removed their listings from the platform compared to the same month in 2019. This certainly indicates great supply shocks in addition to cancellations. The hypothesis put forth by Dolnicar and Zare (2020), in an early study on the current crisis, posits that professional types of host who often possesses many Airbnb listings, might turn to long-term rental markets, which would mean Airbnb would turn back to its original business model as a peer-to-peer sharing place on a more structural basis. However, among the six cities included in our analysis, only in New York the average number of listings per host decreased during the crisis. This means that we observe a general decrease in supply by ordinary and professional hosts alike in most of the cities.[4]

In addition to the supply shocks that slightly recovered in the holiday season, the Airbnb market place recorded considerably lower new bookings rates compared with the previous year. Fig. 4 quantifies this decline in new demand. The average booking rates appear to drop by 40% to almost 100%! The results shown for the cities of Milan and Beijing largely reflect the dramatic consequences of travel bans and lockdowns, where the Airbnb activities grind to a halt by March 2020. Even though, we already see a degree of first recovery in Beijing in May and June 2020, which is a similar finding to that of DuBois (2020), while the supply shock accelerates in 2021 as shown in Fig. 5. This means that while hosts were inclined to return to the marketplace after the first shock, especially in Beijing and London and in other cities during the summer, the majority of them left the platfrom due to the prolonged COVID-19 pandemic in 2021 (see Fig. 6).

Legend: Negative values indicate a lower effective demand in 2020 compared with the same period in 2019.

Legend: Negative values indicate a lower effective demand in 2021 compared with the same period in 2019.

This space-time roller-coaster phenomenon shows wildly fluctuating corona perturbations. Now the question is: how many hosts did step out of business and why? In the following section, we analyse the survival probabilities of Airbnb listings, while we then estimate a hedonic price elasticity of demand model to investigate the changes in consumer behaviour on the Airbnb platform during the COVID-19 crisis.

5. Modelling framework: survival probabilities, intra-city characteristics, and price elasticity of demand

In this section, we develop a comprehensive two-step methodology for the analysis of *vulnerability* in the Airbnb market. The first step involves defining a model of survival probability in the face of the pandemic. The core of the Airbnb business model builds essentially on the supply side, with hosts and their supply decisions. The pattern of the supply shocks sketched in Section 4 shows that the hosts had a high degree of exit behaviour as a response to the pandemic (in relation to lockdown measures and consumer responses). This means that a careful analysis of the common attributes of those Airbnb listings with greater chances of survival is critical in an ex-post assessment of their dynamics, particularly from a resilience perspective. Moreover, Airbnb targets a similar market as hotels, and there are several similarities between the two. Both hotels and Airbnb listings receive higher revenues in central locations, which also has led to a rise in equity values (Sheppard & Udell, 2016; Wang et al., 2019; Wang & Nicolau, 2017).

One of the current challenges faced by the hospitality market is to understand drastic changes in consumer behaviour in the short run, including also the choice of inner-city Airbnb locations. And therefore, we develop a hedonic price elasticity of demand model, which aims to analyse the changes in consumer behaviour during the various phases of the pandemic.

5.1. Modelling survival of airbnb listings

The survival probability of Airbnb suppliers during the pandemic is defined here by a binary response to whether a listing stayed or did not stay on the platform until the month of August in 2020 and similarly until the month of August in 2021 (we refer to Biggs, 2011 for a similar approach to the vulnerability of reef tourism in Australia). It is worth noting that the analysis in the present section does not imply a survival analysis in the traditional sense where the duration until a given event is

[4] Tables on volume changes by host type are available on request.

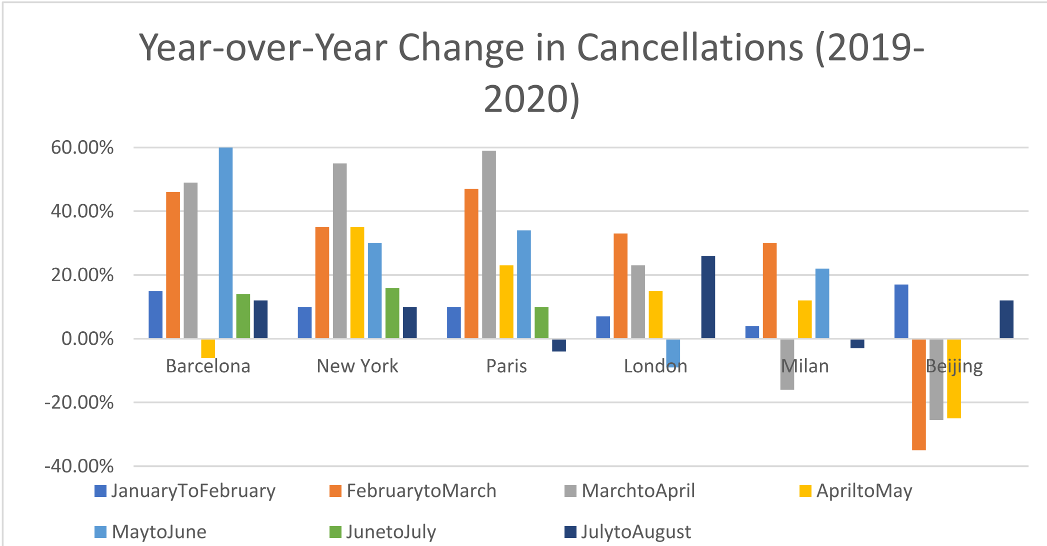

Fig. 1. Year-on-year change in cancellation rates (2019–2020).

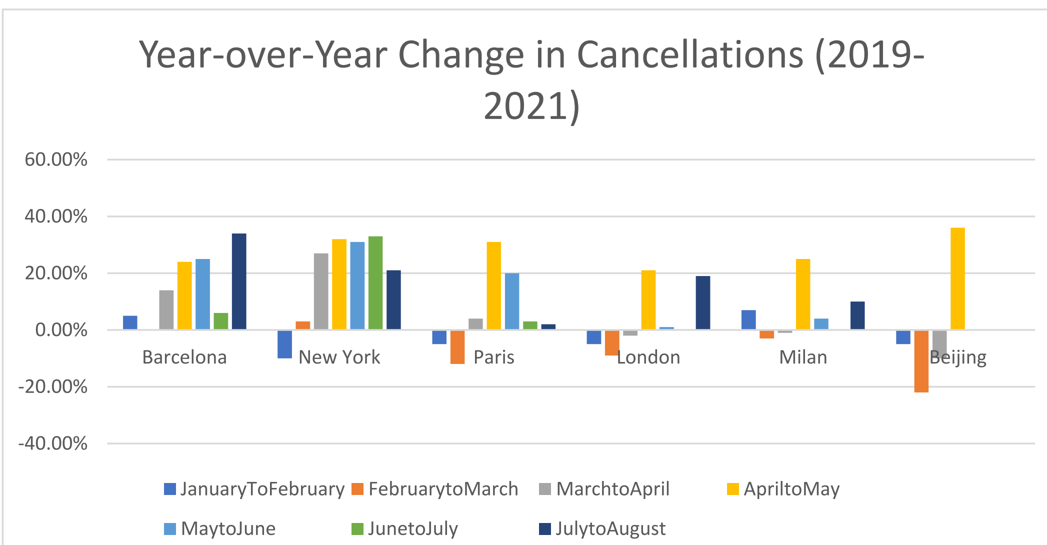

Fig. 2. Year-on-year change in cancellation rates (2019–2021).

recorded and examined by hazard ratios. We are interested in the listings' probability of being active on the platform during the six months (in 2020 and 2021) under the pandemic. The alternative is dropping out from the platform during the pandemic and showing no presence for six months. The reason for the approach is that hosts can enter to or exit from the platform costlessly, therefore, a listing might be deleted from the platform in a given month, but might turn back to activity in the following month (see Leoni, 2020 for an alternative approach). If the listing has not returned to the platform for six months, there is enough evidence to think that the host has turned to, for instance, long-term rentals.[5] We conduct separate analyses for the year 2020 and 2021. The reason is that we consider 2020 as the period of first response to the pandemic by the Airbnb marketplace, while the year 2021 may be considered as an indicator of quasi-long term implications of the pandemic on the platform.

The survival in a vulnerability condition depends on several factors, such as the listings' physical characteristics, but also on their location in the city. By using distance-based measures of accessibility, we are able to estimate locational influences on the demand for Airbnb accommodation. However, such intra-urban areas or neighbourhoods where the listing is located might incorporate place-based effects that are not directly observable. To structure a 'grand model' of survival, we use a multilevel logistic model, which simultaneously estimates the variation at both the listings and the neighbourhood level:

$$Logit\left(\Pr\left(M_{ij}=1\right)\right)=\beta_0+\beta_{ij}x+u_j, \tag{1}$$

where M_{ij} is the binary response variable, with $M_{ij}=1$ denoting survival until August 2020 or August 2021 (the alternative is failure to do so, i.e. $M_{ij}=0$) of a listing located in neighbourhood j; $\Pr(M_{ij}=1)$ is the probability of survival; β_0 is the overall mean probability expressed on a logistic scale; x is a vector including all listing-specific covariates, such as rental type, number of listings per host, and distance to amenities; and β_{ij} represents the set of associated coefficients. Finally, u_j are neighbourhood-specific residuals. All data used in model (1) originate

[5] https://www.cnbc.com/2020/03/25/airbnb-hosts-turn-to-long-term-rentals-competitors-due-to-coronavirus.html.

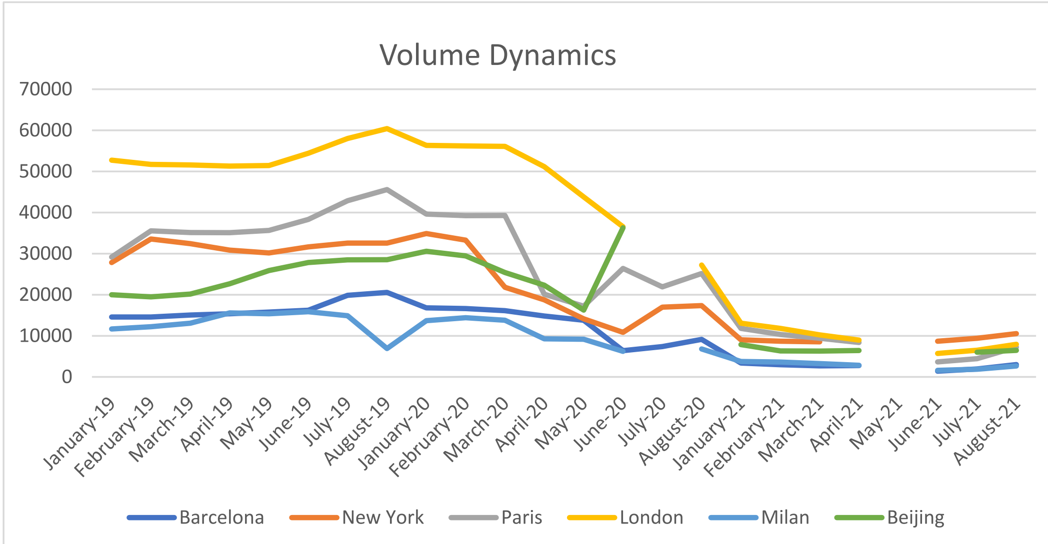

Fig. 3. Change in volume dynamics (number of active listings) on Airbnb platforms in 6 major cities from 2019 to 2021 (January, February, March and April).

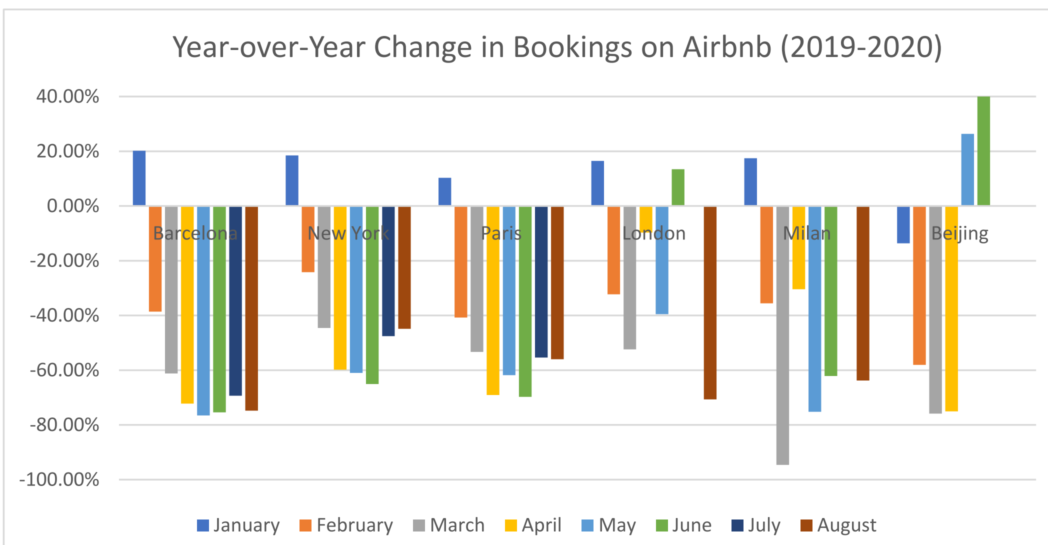

Fig. 4. Year-on-year change in monthly bookings.

from the Airbnb platform database and the OSM database pertaining to these cities.

5.2. Price elasticity of demand model

Next, we estimate the price elasticity of demand. In the theoretical demand function, the quantity demanded for a listing (in a given period) is co-determined by the accommodation price and other characteristics of lodging which influence the demand of new urban tourists (see for instance Damonte et al., 1998; Holmgren & McCracken, 2014; Russo & Quaglieri, 2016; Belarmino et al., 2017; Vives & Jacob, 2019; Gunter et al., 2020). As underlined in the literature, several spatial factors – including neighbourhood characteristics – influence the relationship between demand and price (Anselin, 2008; Gutiérrez et al., 2017; Tong & Gunter, 2020). In a study on estimation methods in Airbnb research, Faye (2021) suggests to incorporate potential spatial autocorrelations to improve the technical-statistical aspects of the employed models. Following these spatial-econometric suggestions, we estimate the following Spatial Durbin Model (SDM) (Anselin, 2013; Gyódi & Nawaro, 2021) by a maximum likelihood estimator to derive the price elasticity of demand for listings in six major cities and in different months before and during the pandemic:

$$\log(demand_{ist}) = \rho W \log(demand_{ist}) + \beta_{ist} \log(price_{ist}) + \partial W \log(price_{ist}) + x_{is} + e_{its} \tag{2}$$

where the dependent variable is the log of monthly demand for listing i,

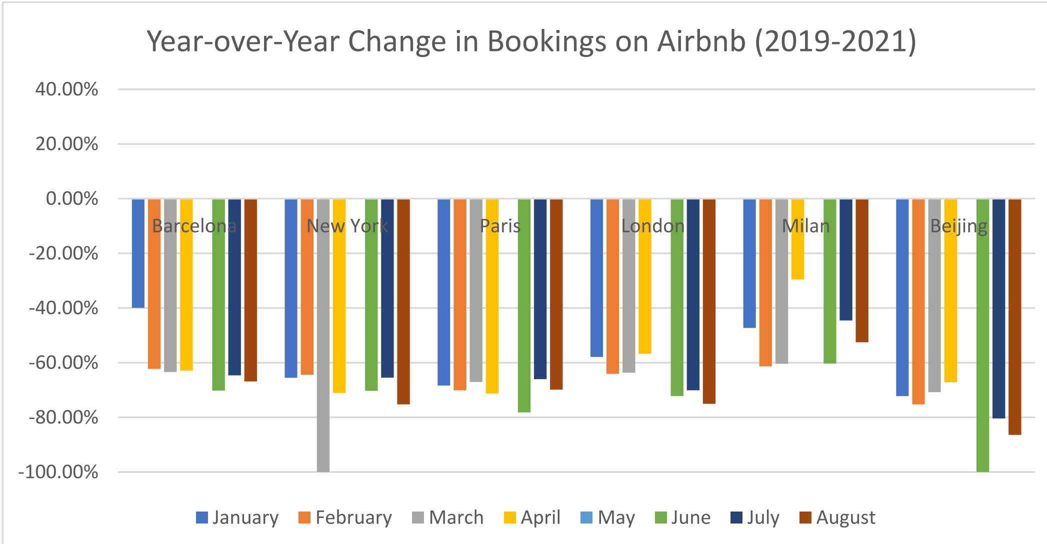

Fig. 5. Year-on-year change in monthly bookings.

belonging to accommodation segment s and in month t; β_{ist} is the price elasticity of demand; to be estimated x_{is} are listings fixed effects, including the distance to the city-center ; W is the row-standardised, inverse-distance spatial weights matrix. Eq. (2) models the demand and price for listing i's neighbour listings. Spatially lagged demand and price control for spatial autocorrelation in residuals and cross-price elasticity of demand, respectively. The parameters ρ and ∂ are expected to show a positive direction. The assumption is that as the nearby prices increase, demand should shift to the listing i, and the demand should increase with high demand for neighbouring listings owing to advantages regarding to the location. Eq. (2) is the core spatial lag model for price elasticity to be estimated.

6Empirical results

In this section, the estimated outcomes from the multilevel logistic regressions described in Section 5 are summarised. The analysis provides not only a comprehensive view on the survival probabilities of Airbnb listings, but offers also insights into the hospitality market under the COVID-19 related shocks. The present section concludes with a discussion on the price elasticity of demand, as estimated by Eq. (2).

We first present the global findings from our survival analysis. The estimation results from Table 1 show that the number of Airbnb listings per host is positively and significantly related to whether the listing remains on the platform in 2020. This variable represents the proficiency and experience of hosts on Airbnb. Several studies have argued that what are called 'professional' Airbnb hosts (hosts with multiple listings) use more effective pricing strategies and generate more significant revenues per room (Gibbs et al., 2018; Guo et al., 2013; Magno et al., 2018; Moro et al., 2017). A more recent analysis shows that professional hosts are likely to exit from the platform first (Dolnicar & Zare, 2020). However, our empirical results appear to show the opposite trend except for Barcelona in 2021 (Table 2). It is noteworthy that only in Beijing and London the variable number of listings per host appear to be not significant. A plausible explanation may be found in the subsequent variable, which represents the room type. Different from other cities, in London and Beijing the hotel type of lodgings has been more vulnerable to the corona shocks compared with entire apartments. This means that in these two cities professional hosts (and hotels) might have failed to incorporate strategic marketing tools such as advertisement on hygiene or health conditions through targeted messaging and search engine optimization in 2020 .[6] On the other hand, in New York and Paris hotel type listings have been more resilient to closure compared to regular Airbnb listings. The trend we see in these two cities is somewhat expected. As argued above, professional hosts and hotels might have been more successful in mobilizing financial resources and also in promoting their rooms according to health-related consumer preferences. Table 2 supports the argument regarding professional hosts in 2021, when -despite high exit rates-hosts with multiple listings were still more resilient to closure. However, Table 2 also illustrates that the hotel type listings have shown a shorter presence on the platform in 2021. While we consider the hosts of hotel type listings as professionals, their exit behaviour might have been driven mainly by declining popularity of the Airbnb platform (as indicated by the volume change) and not due to a general lack of strategic conduct. Not surprisingly, the results regarding the room type indicate higher chances of survival for entire apartments as compared with shared and private rooms in both 2020 and 2021 (see Abrate et al., 2012, 2016).). This finding provides empirical support to recent experimental studies by Bresciani et al. (2021). Only in Paris, the room type does not apper to be a significant determinant of survival in 2021. This might be driven by new local restrictions on all apartment listings put forth in 2021, when primary residences (entire apartments) could be rented for a maximum of 120 nights[7] in a year. Our findings suggest that the restriction regarding the use of the property as an Airbnb listing exhausted the advantages of marketing entire apartments in Paris. We also note that some of the shared and private rooms in the Airbnb sector were rented out as entire apartments during the pandemic. In our analysis we have also considered the updated room types.

Legend: The regression outputs summarise the factors that influence the probability of survival in the Airbnb platform from January 2021 until the month of August 2021 for six major cities. Standard errors are

[6] The UN Tourism Minister Nigel Huddleston warns Airbnb hosts to offer accommodation only for essential travel and to key workers, and is against hygiene-related advertisements that encourage leisure travel. Source: https://www.bbc.com/news/technology-52184497.

[7] https://www.airbnb.com/help/article/2108/night-limits-in-france-frequently-asked-questions#:%7E:text=Starting%20January%201%2C%202021%2C%20in,Aix%2Den%2DProvence

Fig. 6. Price elasticity of demand results of Airbnb listings in 6 major cities, January–August 2019, 2020 and 2021.

Table 1
Multilevel logistic model results of vulnerability in 2020.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Barcelona 2020	Beijing 2020	London 2020	Milan 2020	New York 2020	Paris 2020
#Listing Per Host	0.039*	−0.084	0.014	0.264***	0.255***	0.218***
	(0.019)	(0.062)	(0.015)	(0.019)	(0.021)	(0.013)
Hotels (ref. Entire Apart.)	0.132	−0.064	−0.353*	0.414	0.334*	0.404***
	(0.151)	(0.154)	(0.185)	(0.302)	(0.180)	(0.101)
Private Rooms	−0.868***		−0.631***	−0.781***	−0.692***	−0.457***
	(0.060)		(0.040)	(0.090)	(0.040)	(0.056)
Shared Rooms	−1.574***		−1.209***	−0.405	−1.144***	−1.432***
	(0.470)		(0.313)	(0.318)	(0.148)	(0.285)
# Reviews	0.352***	0.360 ***	0.393***	0.426***	0.328***	0.444***
	(0.018)	(0.054)	(0.014)	(0.020)	(0.013)	(0.012)
Minimum Nights	−0.089***	−0.845**	−0.258***	−0.368***	−0.118***	−0.260***
	(0.032)	(0.419)	(0.023)	(0.060)	(0.023)	(0.025)
Distance to Center	0.086	0.794 ***	0.225***	0.213***	0.245***	0.062**
	(0.070)	(0.201)	(0.031)	(0.056)	(0.056)	(0.031)
Distance to Hotels	−0.015	0.700***	−0.025	0.063	0.113***	0.008
	(0.034)	(0.111)	(0.023)	(0.050)	(0.036)	(0.021)
Distance to Touristic Attractions	−0.071*	0.231***	−0.018	−0.085**	0.108***	0.036*
	(0.040)	(0.066)	(0.024)	(0.33)	(0.027)	(0.023)
var ([neighbourhood])	0.028	1.152	0.089	0.000	0.211	0.004
	(0.015)	(0.521)	(0.028)	(0.000)	(0.043)	(0.002)
Constant	−2.411***	−13.780***	−4.522***	−4.199***	−4.880***	−3.227***
	(0.522)	(2.000)	(0.405)	(0.421)	(0.524)	(0.285)
Observations	11,412	13,459	36,041	9,500	23,360	26,297
Number of groups	68	16	33	85	216	20

Legend: The regression outputs summarise the factors that influence the probability of survival in the Airbnb platform from January 2020 until the month of August 2020 for six major cities. Standard errors are in parentheses.

Table 2
Multilevel logistic model results of vulnerability in 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Barcelona 2021	Beijing 2021	London 2021	Milan 2021	New York 2021	Paris 2021
#Listing Per Host	−0.156***	0.057**	0.012	0.057**	0.126***	0.110***
	(0.031)	(0.025)	(0.017)	(0.024)	(0.023)	(0.014)
Hotels (ref. Entire Apt.)	−0.151		−0.325	−1.394**	−1.314***	−0.199
	(0.313)		(0.268)	(0.626)	(0.265)	(0.135)
Private Rooms	−0.715***	−0.211***	−0.138***	−0.476***	−0.736***	−0.020
	(0.097)	(0.065)	(0.050)	(0.124)	(0.053)	(0.078)
Shared Rooms	−2.156**	0.077	−0.762*	−0.722	−0.874***	−0.502
	(1.049)	(0.176)	(0.408)	(0.497)	(0.192)	(0.335)
# Reviews	0.281***	0.217***	0.072***	0.318***	0.410***	0.439***
	(0.047)	(0.031)	(0.026)	(0.038)	(0.026)	(0.026)
Minimum Nights	−0.248***	−0.351***	−0.193***	−0.182***	−0.362***	−0.126***
	(0.046)	(0.068)	(0.030)	(0.059)	(0.019)	(0.030)
Distance to Center	0.043	1.284***	0.107	−0.108*	0.027	−0.110
	(0.078)	(0.399)	(0.070)	(0.058)	(0.064)	(0.070)
Distance to Hotels	−0.125***	−0.009	−0.193***	−0.059	−0.160**	−0.052*
	(0.046)	(0.032)	(0.066)	(0.044)	(0.068)	(0.027)
Distance to Touristic Attractions	−0.379***	0.061*	0.152**	−0.255***	0.302***	−0.038
	(0.101)	(0.037)	(0.068)	(0.044)	(0.071)	(0.031)
var (_cons [neighbourhood])	0.028	0.251	0.037	0.000	0.116	0.071
	0.028	(0.101)	(0.019)	(0.000)	(0.029)	(0.027)
Constant	1.978**	−15.386***	−2.122***	1.510***	−0.132	−0.005
	(0.856)	(4.062)	(0.656)	(0.448)	(0.537)	(0.556)
Observations	3,381	7,872	13,082	3,738	9,039	11,799
Number of groups	66	16	33	79	208	20

in parentheses.

The variable number of reviews per room may be regarded as a proxy for the value information from guests. It suggests frequent visits and might be used as a proxy of efficiency. This variable too shows a significant positive association with survival probabilities in all six cities (for a study on the effect of reviews on online room sales, see Ai et al., 2019). We also find that another critical determinant of survival probability is the frequent use of hosts' restrictions regarding the minimum nights of stay. The likelihood of staying on the home-sharing platform during the pandemic decreases with the minimum number of nights guests need to stay in order to book the listing (see also Riasi et al., 2017; Zhang et al., 2011). Given the uncertainty posed by the corona virus, this finding indicates that guests have not been willing to take a financial risk by committing to a listing for a longer period.

We now turn to location-specific or place-based impacts on the demand for Airbnb accommodation. Our vulnerability analysis shows a different pattern from earlier findings on the relationship between location and, for instance, the price and demand determinants of Airbnb listings, especially in 2020, hence during the first period of crisis. Previous studies have shown that centrality and proximity to desired amenities contribute to higher prices and demand (Wang & Nicolau, 2017; Gunter & Onder, 2018). However, our results indicate that centrally located listings have had lower chances of survival in all six cities due to a perceived or actual lower level of health safety or environmental quality in 2020 (see Cole et al., 2020). We find that locations far from the center of the cities have had higher chances of survival, as indicated by the positive correlation between the variable distance-to-center and the probability of survival in Table 1. Meanwhile, in Table 2, we observe that centrality is not a significant determinant of survival anymore in 2021, except in Milan and Beijing. Similar to early responses in 2020, in Beijing, the listings located in remote locations from the center have had lower chances of activity in 2021. On the contrary, centrally located listings in Milan have had higher survival rates. As Fig. 3 shows, we do not observe any trend to return to the platfrom in 2021, and our empirical model suggests that for the remaining listings centrality does not play the favourable role it played in the pre-COVID period, except for Milan.

Meanwhile, the variable *distance to hotels* does not render significant effects for 2020, except for Beijing. It is plausible that the competition between the two lodging services has not played a significant role in survival probabilities for Airbnb listings during the first months of the pandemic. Table 2 shows that in 2021, the listings benefitted from spatial agglomeration effects, in that listings located in hotel areas appeared to have higher chances of activity in all cities. Moreover, the proximity of touristic attractions has made Airbnb listings more vulnerable in New York, Beijing and Paris in 2020, while the opposite has taken place in Milan and Barcelona. We observe the same trend also in 2021. Note that the spatial distribution of touristic attractions varies substantially in different cities. For example, the majority of the attractions in Beijing is located outside of the city center. However, in Milan, touristic places are centrally located. This means that, while the results regarding proximity to touristic attraction may reflect a rural shift in the Airbnb market in Beijing, in Milan hosts might have remained on the platform owing to expectations of high revenues in the future, based on pre-COVID experiences and despite the current decrease in activities.

It is noteworthy that, even though the model includes individual-level, distance-based measures, the variances at the neighbourhood level indicate a significant second-level variation. This supports the choice for a *multi-level modelling* framework for our analysis. The urban fabric and historical development of the cities varies substantially, so that path dependence of each urban area affects the survivability. As mentioned above, in some cities the attractions and amenities are centrally located, whilst in other urban areas, such as Beijing, many attractions (often connected to the Great Wall) are located far from the core. However, we can conclude that our overall results indicate that centrality reduced the survival opportunities in all cities in the first months of the pandemic, but became less relevant in the long run. Another finding from our analysis points out that, while the spatial competition between Airbnb listings and hotel rooms did not affect the survival probability on the Airbnb platfrom in 2020, the listings located in close proximity to hotels had a longer presence on the platform in 2021. The latter finding suggests that residential locations are becoming less preferred by the Airbnb clients. This is an interesting finding as the ability of Airbnb listings to locate in residential areas has been its competetive advantage over hotels. The analysis of the price elasticity of demand below will illustrate the implication of this spatial competition between Airbnb listings and hotel rooms, especially for the luxury segment.

The analysis above highlights the existence of several common physical and spatial determinants, although there are also differences for Airbnb listings in the six major cities. It seems plausible that, if density is an important driver of the visitors' choice behaviour during the pandemic, our findings also apply to traditional hospitality industries, whose survival is demand driven.

Finally, we present the estimates (for each city) of the *price elasticity* of demand for the surviving listings and investigate how the elasticities compare with the previous year. The aim to examine these elasticities is useful in order: (i) to understand the changing consumer behaviour in the hospitality market during the pandemic; and (ii) to get an operational insight into the market forces faced by Airbnb hosts.

The results of the estimates are summarised in Fig. 4 (and also in Table A2, A3 and A4). Elasticities for Budget and Luxury segments are plotted for each city from January to August in 2019, 2020 and 2021. In 2019 and for each of the six cities, the related coefficients (β_i) are statistically significant and negative, suggesting a plausible inverse relationship between price and demand. The Budget and Luxury segments reflect similar seasonal variation trends in elasticities in 2019. We find that Airbnb demand is inelastic in all six cities (see also Gunter & Onder, 2018; Gunter et al., 2020). The listings under the Budget segmentation have higher elasticities than those under the Luxury segments in all cities.

The findings for 2019 represent the "normal" (reference) elasticities for comparative purposes, while the elasticities for the year 2020 represent the first monthly responses to the pandemic. These results show considerable variation. For example, elasticities are, for obvious reasons, zero for the month of March 20 in Milan and Beijing, as then Airbnb activities were discontinued. In other cities, except for New York, the results indicate a lower price elasticity of demand compared with the year before, and for both Airbnb segments. The most elastic demands in 2020 appear to show up in the months of January and February, where elasticities still tend to follow the trend of 2019.

The results above are plausible, as the real awareness of the corona virus started in March 2020. In Beijing, the decline in elasticities was evident from January 2020, which suggests that the market was quick to respond to shocks. Elasticities for the Budget segment in 2020, starting in late spring, are somewhat similar to their levels in 2019. This coincides with the period when countermeasures were more relaxed. Only New York appears to exhibit a different pattern, where demand becomes substantially more elastic in comparison to 2019. It is noteworthy that in 2021, the estimates exibit higher standar errors in comparision to both 2019 and 2020; and we observe a general increase in elasticity for the Budget segment. On the one hand, this implies that the market for the Budget segment moves to a more elastic state in 2021 as already signalled in New York during the first summer of the pandemic, while Airbnb guests for this segment become more sensitive to pricing. The analysis also suggests that the estimates of elasticities have become less precise for all six cities in 2021 and that, even though the budget segment adjusts towards a more elastic state, the market becomes confused by the prolonged pandemic, as indicated by high standard errors.

Interestingly, the usual inverse relationship between demand and price appears not to hold in 2020 for the Luxury segments. The coefficients show either a positive and statistically significant direction, or they become insignificant. How can this anomaly be explained?

The upward-sloping demand, curve for the Airbnb Luxury segment accords with both a Veblen and Giffen goods interpretation, but with a different signalling mechanism. Higher prices in the Luxury segment might be a sign of more corona-specific hygiene and health safety resulting in a greater demand despite higher prices during the corona crisis. On the other hand, with regard to this segment visitors may have started to consider, in general, hotel services as an inferior alternative to

Airbnb, given the lack of health safety due to high density of guests in a regular hotel. This means that the other reason for decreasing elasticities and an upward-sloping demand curve may be the result of the substitution effect. That is, Airbnb services might have become a stronger substitute for hotel stays owing to more privacy in an entire house type of accommodation. This interpretation is in line with the findings of Bresciani et al. (2021) on the increasing demand for social distancing and consequently for renting entire apartments in the post-COVID-19 period. It also confirms the study of Sainaghi and Baggio (2020), that shows that Airbnb listings may become substitutes of the traditional hotels during weekends and holidays. Our findings suggest that the substitution between Airbnb listings and traditional hotels might become more pronounced in a later stage of the COVID-19 period.

In New York, the Giffen and Veblen type transformation appears to occur only in March 2021 and April 2020, while in the rest of the months, the market relations remain largely the same. In other cities, the price elasticities appear to converge to their levels in the regular holiday season, when the number of the listings starts to increase again in 2020, as shown in Fig. 2. We assume that competition increases the efficiency of the market and leaves less room for strategic anti-corona recommendations and signalling tools. The observed heterogeneity in price elasticities among the six cities and in their differential timing of the convergence to normal (pre-corona) levels indicates a policy-related response in consumer behaviour and market power. Fig. 4 shows that the price elasticities in Barcelona returned to normal levels in July, but displayed the previous upward trend again in August when the Catalonian government took new strict measures.[8] In Milan, price elasticities have remained insignificant also during the summer when restrictions and lockdowns were still in place. As for the Budget segment, we estimate high standard errors for the Luxury segment in 2021, with positive or insignificant elasticities especially in Milan and Barcelona. Paris appers as a different case than the remaning cities; this again might be related to the new restrictions put forth in 2021 regarding Airbnb activities in the city.

7. Conclusion

7.1. General

This study has addressed four research questions. They can be answered as follows:

- The space-time curve of the pandemic – and its implications for the Airbnb market segment – is showing an irregular roller-coaster pattern from a global dynamic perspective.
- The heterogeneity in lockdown measures among cities has meant a disruption in a standard space-time 'medical-disease spread' model, with great and unforeseen implications for the Airbnb sector.
- The perceived health consequences of the location of Airbnb amenities in cities has led to a 'flight' to less densely occupied urban areas, leading to unequal spatial impacts in cities.
- Policy interventions and restrictions have temporarely prevented or restricted access to tourist amenities that traditionally attract visitors in the central parts of the urban areas; this has decreased the attractiveness of dense central urban areas; the elasticity of demand of Airbnb facilities in corona times has been very sensitive to both customer behaviour and public health measures.

Our study confirms the selectivity in the customers' choice of type of Airbnb accomodaton in terms of health safety (internal condition) and geographical location (external condition) in the city. Apparently, the Airbnb market is faced with a difficult tradeoff between high-potential but high-risk locations in a city versus low-potential but low-risk locations in areas close to the urban fringe.

7.2. Policy lessons

The unprecedented shock in the hospitality sector is in sharp contrast to previous shocks in the past few decades. These earlier events did not lead to a significantly negative development of the hospitality sector. The effects of the present pandemic are different and call for a deep insight into the forces at work.

Although our price elasticity analysis indicates that active listings have kept some degree of market power in the first eight months of the corona crisis, off-season fluctuations and general volatility in consumer behaviour make the market clearly vulnerable. The market power for all segments increases with the fewer the number of active listings on the platform, which lessens the competition and hence price elasticities. Mobility restriction policies increase the market power of, in particular, the Luxury segment. Our analysis does not suggest a "new normal" equilibrium, where hosts gain higher market power. Instead, we observe a dynamic market arena, which responds quickly to changes. Given the heterogeneity in customer responses regarding type of accommodation and location of Airbnb facility, it seems a wise future policy in cities to strive for a broad and spatially dispersed package of accommodation options so as to be more robust against future shocks. However, the more client-oriented and resilient types of accomodations can also be perceived as healthier and safer. These findings have important implications for Airbnb management strategies. The public measures to limit the spread of the pandemic also had strong geographical effects. Most public attractions were closed or had restricted access during the pandemic, and a majority of these locations were centrally located. Restricting access to public attractions quicky affects businesses (accomodation businesses, in particular) concentrated in the area of attractions, meaning that the economic effects can not be estimated on an aggregated level but more on a specific local level. This means that awareness of the economic geography needs to be integrated in risk management in the hospitality sector.

7.3. Empirical findings

Our empirical findings reveal a significant difference between the Luxury and Budget segments. The Luxury segment tends to turn back to normal elasticities when restrictive policies are lifted (or relaxed). The elasticities for the Budget segment appear to become more elastic compared with the previous year in New York, Milan, Barcelona, and Paris in the months June and July. In Barcelona, when restrictions were announced again in August, the Budget segment records lower price elasticities, as in the first months of the pandemic. In 2021, the estimates of elasticities become less precise due to fluctuations in the market. Large volumes of exits from the platform and uncertainties imposed by the prolonged pandemic might have confused the market, which is still far from adjusting to a new equilibrium in 2021, as indicated by our estimates of high standard errors.

Considering the results of the survival analysis and the price

[8] https://www.eldiario.es/catalunya/barcelona-restricciones-confinamiento-medidas-contagios_1_6110720.html.

elasticity of the demand model together, we may infer the predominant presence of Luxury segment listings often located further from the center. Inner-city Airbnb accomodations tend to be more vulnerable to pandemic effects. Our findings suggest that entire apartments and Luxury segments have been more resilient to the ongoing shocks, suggesting 'selective echo-effects' for both the Airbnb market segments and their intra-urban locations. As highlighted by Thu et al. (2020), COVID-19 is not just a single medical health phenomenon; it affects the entire spectrum of human life, in particular liveability in large cities. It is therefore, pertinent that in strategic urban planning and design due attention is paid to the relationship between urban amenities, density and proximity of citizens and visitors, and health care considerations.

Credit Author statement

Karima Kourtit: Original draft preparation, Conceptualization, Methodology, Writing, Reviewing, Editing, Data Collection, Data Analytics, Investigation, Review. **Peter Nijkamp**: Original draft preparation, Conceptualization, Methodology, Writing, Reviewing, Editing, Data Collection, Data Analytics, Investigation, Review. **John Östh**: Software, Visualization, Methodology, Writing, Reviewing, Editing, Data. Transformation, Data Analytics, Review. **Umut Türk**: Software, Visualization, Methodology, Writing, Reviewing, Editing, Data. Transformation, Data Analytics, Review.

Impact statement

The hospitality market has been deeply affected by the corona crisis. This study provides quantitative and strategic information on the local survival conditions for Airbnb facilities in the wake of COVID-19, and the far-reaching consequences of COVID-19, with particular emphasis on the space-time dynamics in the Airbnb accommodation market in six world-cities in various continents. The research in this paper is based on a wealth of online Airbnb platform data on listings and bookings of individual Airbnb facilities since the beginning of the pandemic. It seeks to identify the vulnerability in the Airbnb market as a result of COVID-19 by estimating a hedonic model that captures volumes of detailed local information in the cities under consideration. The study highlights three unknown strategic parameters of recent change: customers' health motives, locational density considerations, and degree of privacy/safety in (luxury) Airbnb facilities.

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Appendix

Table A1
Descriptive statistics of the variables used in survival analysis.

	#LIstIngsperHost (2019)		#LIstIngsperHost (2020–2021)		Room Type (2019)		Room Type (2020–2021)		#RevIewsPerMonth		MInImum NIghts (2019)		MInImum NIghts (2020–2021)	
	Median	Std.	Median	Std.	Median	Std.	Median	Std.	Median	Std.	Median	Std.	Median	Std.
Barcelona	2	17.813	3	19.279	1	0.521	1	1	1.6	1.633	2	17.761	2	21.431
BeIjIng	5	13.113	5	14.474	1	0.596	1	0.561	1.15	1.657	1	14.734	1	18.917
London	1	13.984	2	14.613	1	0.517	1	0.999	1.12	1.516	2	16.878	2	16.685
MIlan	1	13.015	1	14.589	1	0.483	1	0.827	1.18	2.044	2	12.979	2	12.035
New York	1	10.865	1	10.128	1	0.548	1	1.0255	1.67	1.744	2	18.38	3	19.762
Paris	1	11.165	1	12.64	1	0.378	1	0.664	1.3	1.565	2	15.335	2	20.09

Barcelona	**DistanceToCenter** (2019)		**DistanceToCenter** 2020–2021)		**DistanceToHotels** (2019)		**DistanceToHotels** (2020–2021)		**DistanceToAttractions** (2019)		**DistanceToAttractions** (2020–2021)	
BeIjIng	Median	Std.	Median	Std.	Median	Std.	Median	Std.	Median	Std.	Median	Std.
London	2495	1113	3703	1514	308	383	294	316	310	136	303	125
MIlan	10,999	25,394	26,864	22,615	2027	9011	1969	9193	1256	3143	2837	3942
New York	6164	4457	13,212	6072	672	433	580	506	617	560	613	544
Paris	2907	1483	3150	1787	457	427	558	723	446	437	533	458
	6880	4484	5853	4594	1150	376	699	738	659	703	749	768
	4686	1868	2613	1767	1205	350	286	215	192	127	277	164

Table A2
Price elasticity of demand for Airbnb listings in London and Beijing.

	Paris						Barcelona						Milan					
	2019		2020		2021		2019		2020		2021		2019		2020		2021	
	Budget	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**
January	−0.398***	−0.243***	−0.445***	−0.208***	−0.0522	−0.100*	−0.439***	−0.141***	−0.402***	−0.177***	−0.805*	0.0105	−0.544***	−0.158***	−0.885***	−0.210**	−1.025**	0.162
	(0.121)	(0.0320)	(0.131)	(0.0290)	(0.244)	(0.0523)	(0.111)	(0.0432)	(0.112)	(0.0358)	(0.416)	(0.0762)	(0.119)	(0.0580)	(0.140)	(0.0835)	(0.440)	(0.129)
February	−0.613***	−0.379***	−0.310***	−0.164***	−0.405*	0.0298	−0.933***	−0.337***	−0.373***	−0.0501*	0.500	0.191***	−0.587***	−0.265***	−0.573***	−0.223***	−0.914**	0.253**
	(0.139)	(0.0341)	(0.108)	(0.0239)	(0.241)	(0.0512)	(0.109)	(0.0300)	(0.0913)	(0.0263)	(0.393)	(0.0505)	(0.107)	(0.0570)	(0.0840)	(0.0521)	(0.414)	(0.115)
March	−0.0423	−0.0277	−0.183	−0.00382	−0.814***	0.0725	−0.285***	−0.230***	−0.106	−0.0525	−0.818**	0.280***	−0.546***	−0.356***	0	0.00284	−1.363***	0.338**
	(0.181)	(0.0426)	(0.126)	(0.0293)	(0.265)	(0.0529)	(0.0825)	(0.0251)	(0.109)	(0.0339)	(0.396)	(0.0476)	(0.119)	(0.0761)	(0)	(0.00364)	(0.431)	(0.148)
AprIl	−0.267***	−0.216***	−0.319***	0.0948**	−0.418	0.0340	−0.368***	−0.305***	−0.215**	0.106***	−0.200	0.363***	−0.547***	−0.139***	−0.440***	−0.02	−1.126**	0.153
	(0.0972)	(0.0211)	(0.123)	(0.0434)	(0.275)	(0.0610)	(0.0659)	(0.0243)	(0.0980)	(0.0364)	(0.339)	(0.0407)	(0.0765)	(0.0505)	(0.145)	(0.138)	(0.439)	(0.138)
May	−0.283***	−0.165***	−0.536***	0.162***			−0.380***	−0.227***	−0.192	0.158***			−0.750***	−0.249***	−0.937***	−0.028		
	(0.0929)	(0.0231)	(0.136)	(0.0534)			(0.0603)	(0.0237)	(0.140)	(0.0401)			(0.0880)	(0.0472)	(0.170)	(0.128)		
June	−0.196***	−0.0455***	−0.649***	−0.0397	−0.914**	−0.231***	−0.421***	−0.181***	−0.518***	−0.0638	−0.364	0.0398	−0.647***	−0.324***	−0.882***	−0.0670	−1.573**	−0.343**
	(0.0716)	(0.0144)	(0.0925)	(0.0330)	(0.357)	(0.0883)	(0.0606)	(0.0200)	(0.130)	(0.0755)	(0.400)	(0.0806)	(0.0743)	(0.0457)	(0.127)	(0.0734)	(0.730)	(0.162)
July	−0.161***	0.0267	−0.326***	−0.0722***	−0.945**	−0.238***	−0.278***	−0.267***	−0.376***	−0.171***	−0.435	−0.00285	−0.566***	−0.204***			−0.529	−0.0750
	(0.0581)	(0.0182)	(0.0593)	(0.0279)	(0.366)	(0.0829)	(0.0591)	(0.0220)	(0.0895)	(0.0511)	(0.363)	(0.0771)	(0.0797)	(0.0461)			(0.391)	(0.138)
August	−0.314***	−0.145***	−0.351***	−0.0457**	−1.334***	−0.263***	−0.375***	−0.196***	−0.201***	0.00467	−0.656**	0.0602	−0.442***	0.0311	−0.724***	0.0963	−0.838***	−0.234**
	(0.0306)	(0.0175)	(0.0317)	(0.0213)	(0.303)	(0.0661)	(0.0477)	(0.0202)	(0.0581)	(0.0431)	(0.303)	(0.0679)	(0.0677)	(0.0457)	(0.101)	(0.0614)	(0.281)	(0.118)

	London						Beijing					
	2019		2020		2021		2019		2020		2021	
	Budget	Luxury	Budget	Luxury	**Budget**	**Luxury**	Budget	Luxury	Budget	Luxury	**Budget**	**Luxury**
January	−0.719***	−0.304***	−0.666***	−0.195***	−0.895***	0.006	−0.293***	−0.0671*	−0.202***	−0.164***	−0.174	−0.112
	(0.0661)	(0.0340)	(0.0663)	(0.0304)	(0.214)	(0.072)	(0.110)	(0.0403)	(0.0929)	(0.0385)	(0.217)	(0.103)
February	−0.966***	−0.371***	−0.576***	−0.360***	−0.725***	0.004	−0.270***	−0.128***	−0.211*	−0.197***	−0.731***	−0.258**
	(0.0709)	(0.0313)	(0.0493)	(0.0275)	(0.224)	(0.070)	(0.101)	(0.0359)	(0.126)	(0.0594)	(0.255)	(0.120)
March	−0.821***	−0.246***	−0.355***	−0.192***	−0.304	0.105	−0.288***	−0.151***	0	0	−0.103	−0.158*
	(0.0649)	(0.0320)	(0.0584)	(0.0345)	(0.243)	(0.064)	(0.0712)	(0.0310)	(0)	(0)	(0.207)	(0.095)
April	−0.717***	−0.279***	−0.130***	−0.00203	−0.881***	0.090	−0.275***	−0.0247	−0.001	0.0192	0.050	0.019
	(0.0505)	(0.0213)	(0.0356)	(0.0194)	(0.238)	(0.061)	(0.0753)	(0.0293)	(0.0055)	(0.0188)	(0.156)	(0.080)
May	−0.639***	−0.310***	−0.241***	−0.0176			−0.132**	−0.125***	0.00962	0.00894		
	(0.0558)	(0.0243)	(0.0361)	(0.0112)			(0.0585)	(0.0208)	(0.00802)	(0.00696)		
June	−0.594***	−0.113***	0.0301***	0.0126***	−0.478	0.107	−0.0600	−0.112***	−0.00858	−0.0702***		
	(0.0443)	(0.0161)	(0.00842)	(0.00382)	(0.296)	(0.078)	(0.0470)	(0.0181)	(0.0295)	(0.0162)		
July	−0.482***	−0.0889***			−0.731***	0.078	−0.160***	−0.151***			−0.025	−0.066
	(0.0369)	(0.0138)			(0.253)	(0.073)	(0.0431)	(0.0216)			(0.165)	(0.092)
August	−0.719***	−0.476***	−0.321***	−0.0488***	−0.640***	−0.053	−0.360***	−0.0813***			−0.071	0.234***
	(0.0661)	(0.0282)	(0.0330)	(0.0180)	(0.229)	(0.065)	(0.0396)	(0.0198)			(0.212)	(0.088)

Table A3
Price elasticity of demand for Airbnb listings in Paris and Barcelona.

	Paris						Barcelona					
	2019		2020		2021		2019		2020		2021	
	Budget	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**
January	−0.398***	−0.243***	−0.445***	−0.208***	−0.0522	−0.100*	−0.439***	−0.141***	−0.402***	−0.177***	−0.805*	0.0105
	(0.121)	(0.0320)	(0.131)	(0.0290)	(0.244)	(0.0523)	(0.111)	(0.0432)	(0.112)	(0.0358)	(0.416)	(0.0762)
February	−0.613***	−0.379***	−0.310***	−0.164***	−0.405*	0.0298	−0.933***	−0.337***	−0.373***	−0.0501*	0.500	0.191***
	(0.139)	(0.0341)	(0.108)	(0.0239)	(0.241)	(0.0512)	(0.109)	(0.0300)	(0.0913)	(0.0263)	(0.393)	(0.0505)
March	−0.0423	−0.0277	−0.183	−0.00382	−0.814***	0.0725	−0.285***	−0.230***	−0.106	−0.0525	−0.818**	0.280***
	(0.181)	(0.0426)	(0.126)	(0.0293)	(0.265)	(0.0529)	(0.0825)	(0.0251)	(0.109)	(0.0339)	(0.396)	(0.0476)
Aprll	−0.267***	−0.216***	−0.319***	0.0948**	−0.418	0.0340	−0.368***	−0.305***	−0.215**	0.106***	−0.200	0.363***
	(0.0972)	(0.0211)	(0.123)	(0.0434)	(0.275)	(0.0610)	(0.0659)	(0.0243)	(0.0980)	(0.0364)	(0.339)	(0.0407)
May	−0.283***	−0.165***	−0.536***	0.162***			−0.380***	−0.227***	−0.192	0.158***		
	(0.0929)	(0.0231)	(0.136)	(0.0534)			(0.0603)	(0.0237)	(0.140)	(0.0401)		
June	−0.196***	−0.0455***	−0.649***	−0.0397	−0.914**	−0.231***	−0.421***	−0.181***	−0.518***	−0.0638	−0.364	0.0398
	(0.0716)	(0.0144)	(0.0925)	(0.0330)	(0.357)	(0.0883)	(0.0606)	(0.0200)	(0.130)	(0.0755)	(0.400)	(0.0806)
July	−0.161***	0.0267	−0.326***	−0.0722***	−0.945**	−0.238***	−0.278***	−0.267***	−0.376***	−0.171***	−0.435	−0.00285
	(0.0581)	(0.0182)	(0.0593)	(0.0279)	(0.366)	(0.0829)	(0.0591)	(0.0220)	(0.0895)	(0.0511)	(0.363)	(0.0771)
August	−0.314***	−0.145***	−0.351***	−0.0457**	−1.334***	−0.263***	−0.375***	−0.196***	−0.201***	0.00467	−0.656**	0.0602
	(0.0306)	(0.0175)	(0.0317)	(0.0213)	(0.303)	(0.0661)	(0.0477)	(0.0202)	(0.0581)	(0.0431)	(0.303)	(0.0679)

Table A4
Price elasticity of demand for Airbnb listings in Paris and Barcelona.

	New York						Milan					
	2019		2020		2021		2019		2020		2021	
	Budget	Luxury	Budget	Luxury	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**	**Budget**	**Luxury**
January	−0.590***	−0.0536	−0.672***	−0.0958	−0.880***	−0.001	−0.544***	−0.158***	−0.885***	−0.210**	−1.025**	0.162
	(0.107)	(0.0560)	(0.106)	(0.0626)	(0.265)	(0.101)	(0.119)	(0.0580)	(0.140)	(0.0835)	(0.440)	(0.129)
February	−0.461***	−0.109**	−0.528***	−0.0634	−1.189***	−0.151	−0.587***	−0.265***	−0.573***	−0.223***	−0.914**	0.253**
	(0.0943)	(0.0487)	(0.0940)	(0.0521)	(0.267)	(0.095)	(0.107)	(0.0570)	(0.0840)	(0.0521)	(0.414)	(0.115)
March	−0.750***	−0.0687	−0.376***	−0.0782**			−0.546***	−0.356***	0	0.00284	−1.363***	0.338**
	(0.0784)	(0.0452)	(0.0873)	(0.0310)			(0.119)	(0.0761)	(0)	(0.00364)	(0.431)	(0.148)
April	−0.429***	−0.145***	−0.222**	0.0824**	−1.009***	−0.097	−0.547***	−0.139***	−0.440***	−0.02	−1.126**	0.153
	(0.0742)	(0.0286)	(0.104)	(0.0397)	(0.254)	(0.079)	(0.0765)	(0.0505)	(0.145)	(0.138)	(0.439)	(0.138)
May	−0.756***	−0.218***	−0.502***	−0.261***			−0.750***	−0.249***	−0.937***	−0.028		
	(0.0753)	(0.0276)	(0.133)	(0.0831)			(0.0880)	(0.0472)	(0.170)	(0.128)		
June	−0.573***	−0.186***	−0.786***	−0.198**	−1.041***	−0.129**	−0.647***	−0.324***	−0.882***	−0.0670	−1.573**	−0.343**
	(0.0597)	(0.0250)	(0.118)	(0.0874)	(0.214)	(0.066)	(0.0743)	(0.0457)	(0.127)	(0.0734)	(0.730)	(0.162)
July	−0.520***	−0.111***	−0.935***	−0.142***	−1.165***	−0.138**	−0.566***	−0.204***			−0.529	−0.0750
	(0.0566)	(0.0248)	(0.0979)	(0.0485)	(0.193)	(0.067)	(0.0797)	(0.0461)			(0.391)	(0.138)
August	−0.437***	−0.202***	−0.633***	−0.0595**	−1.392***	−0.092	−0.442***	0.0311	−0.724***	0.0963	−0.838***	−0.234**
	(0.0331)	(0.0203)	(0.0548)	(0.0289)	(0.166)	(0.066)	(0.0677)	(0.0457)	(0.101)	(0.0614)	(0.281)	(0.118)

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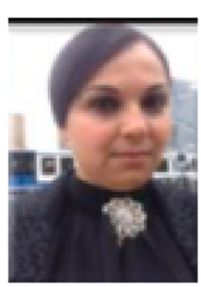
Peter Nijkamp is emeritus Professor in regional and urban economics and in economic geography at the VU University, and associated with The Open University of the Netherlands (OU), Heerlen (The Netherlands), and the Alexandru Ioan Cuza University of Iasi, Iasi (Romania). He has published more than 2000 articles and books in the field of regional development, urban growth, transport and the environment. He is a fellow of the Royal Netherlands Academy of Sciences (KNAW). He has served as president of the governing board of the Netherlands Research Council (NWO). In 1996, he was awarded the most prestigious scientific prize in the Netherlands, the Spinoza award. He is vice-president of *The Regional Science Academy* (TRSA) and involved in many international research activities.



Karima Kourtit is at the Open University, Heerlen, The Netherlands. Her main scientific research is in the field of creative industries, urban development, cultural heritage, digital technology, and strategic performance management. Her academic profile is characterized by a profound involvement in evidence-based urban and spatial research on smart city policy and data metrics, by a strong commitment to educational support to young researchers and by an active role in many international scientific and managerial activities. Furthermore, she has been an editor of several books and guest editor for many international journals, and has published a wide array of scientific articles, papers, special issues of journals and edited volumes in the field of geography and the spatial sciences. She is also managing director of *The Regional Science Academy* (TRSA).

Umut Türk is currently working at the Department of Economics, Abdullah Gül University, Turkey. He has extensively worked on the topics of (i) spatial economics (ii) regional science (iii) inequality of opportunity (iv) accessibility (v) social mobility and vi) tourism. He is particularly interested in geographical influences in distributional concerns.

John Östh is a professor in Human Geography at Uppsala University and in Urban Analysis at Oslo Metropolitan University. His research is oriented towards the study of accessibility, spatial analytics and geocoded computation.