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The effects of location before and during COVID-19 Impacts on revenue of Airbnb listings in Milan (Italy)

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ABSTRACT

This article explores the ability of locational variables and spillover to influence Airbnb listing performance in Milan. The effects of different determinants are analyzed for the periods before and during the pandemic. The sample includes 7213 listings, is based on AirDNA data, and developed using two regression models. The findings confirm the hypotheses proposed. The revenue estimated for a standard apartment in 2020 was approximately double that estimated for 2021. The results showed some substantial changes during the pandemic, which considerably reduced the ability of well-known variables (such as size) to explain the listing performance variance. The role of host characteristics (superhost badge) increased during the pandemic, while some contractual terms were significantly changed, and the spatial spillover almost doubled.
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Introduction

The worldwide growth of peer-to-peer accommodation platforms, especially Airbnb properties (later simply called listings), has attracted the interest of researchers attempting to understand the determinants of listing performance (Sainaghi, 2020b). This is not surprising when considering that the main motivation to let an apartment is to earn additional income (Tussyadiah & Pesonen, 2016). A growing body of research has been concerned with explaining listings' results and measuring performance by using price, revenue, or more than one performance indicator (Oskam et al., 2018) as dependent variables. This study is part of this research stream (performance determinants) and has two objectives. First, it expands on the determinants of listing performance by introducing two partially novel locational variables (distance to commercial activities and availability of transportation systems near each Airbnb listing) and the existence of spatial spillover effects among peers. All these variables are presented later. Second, the current paper compares an extensive list of Airbnb performance determinants from the periods before and during the pandemic in order to reveal the effects generated by COVID-19.

Focusing on the locational variables, Airbnb guests are usually described as price-sensitive (Guttentag, 2015), more respectful toward environmental issues (Tussyadiah, 2016), and leisure-oriented. Therefore, they are interested in being located close to tourist attractions (Chen & Xie, 2017). Based on this profile, this study explores two locational gaps. First, many Airbnb listings offer a kitchen, allowing guests to cook their own food, thereby reducing restaurant costs. Surprisingly, few papers have explored the distance to commercial shops as a determinant of listing performance (Perez-Sanchez et al., 2018). Second, Airbnb guests use sustainable transportation more intensively, defined here as services able to reduce their carbon footprints, such as public trans-

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portation or renting a bicycle (Önder et al., 2019). While previous studies have analyzed the effects generated by being located close to public transportation (Deboosere et al., 2019), train stations, and subway stops (Boto-García et al., 2021), no study has considered the distance to rentable bicycles.

Moving on to the spatial spillover effect, Airbnb guests are mainly leisure clients (Tussyadiah & Pesonen, 2016) and search for listings located close to tourist attractions (Cai et al., 2019). Airbnb providers are therefore more densely located in some areas than in others (Gyódi & Nawaro, 2021; Sainaghi, 2020a). Airbnb listings located close to museums and monuments charge higher rates (Boto-García et al., 2021). These locational patterns have an impact on both competition levels and agglomeration economies between Airbnb providers (Xie et al., 2019). Furthermore, mimicking strategies can occur, and single-listing hosts tend to follow the pricing choices implemented by multi-listing hosts (Boto-García et al., 2021). However, few papers have explored the spatial spillover effect (Zhou et al., 2022), which largely remains an enigma. This article contributes to filling this gap by exploring the so-called spatial spillover effect, defined here as the ability of neighboring apartments to influence listing prices (Chica-Olmo et al., 2020). This idea is in line with previous studies that considered that a shock in one listing could affect other apartments, "even though they are not direct neighbors" (Boto-García et al., 2021, p. 4).

These locational variables and spatial spillover effects were analyzed for the periods before and during the COVID-19 pandemic. Based on these gaps, a list of hypotheses (see Hypotheses development section) was tested by exploring the ability of the two locational variables (commerce and transportation system) and the spatial spillover effect to positively affect the revenue per available room of Airbnb listings and the ability of COVID-19 to change the overall performance determinants. The study was carried out in the city of Milan, Italy, and compared 7213 listings from before (January 2020) and during the pandemic (March 2021). We selected January 2020 because it was the last "normal" month before the pandemic, while March 2021 represented the first "pandemic month" but without a lockdown. The sample was composed of the same Airbnb apartments in order to ensure full comparability. For each of the two periods, two models were compared: an ordinary least squares regression (OLS) model and a spatial autoregressive (SAR) model, which considered the spatial spillover effect. The main findings showed a strong reduction in the listings' performance during the pandemic. Before the pandemic, the group of non-locational variables (size, contractual terms, rules, host, and guests) illustrated results that largely converged with those of previous studies. The COVID-19 outbreak changed the relevance and intensity of these variables. The proposed hypotheses were confirmed, and the spatial spillover effect doubled its impact on Airbnb listing results. The spread of COVID-19 considerably reduced the city center's advantage and conversely decreased the disadvantage of being peripherally located. Finally, the hosts changed the contractual terms considerably during the pandemic, particularly the cancellation policy.

Literature review

Determinants of listing performance

This study adopted the groups of determinants identified in a recent literature review focused on Airbnb performance (Sainaghi, 2020b) and largely used in many previous studies (those cited here and in the following sections). The literature on Airbnb performance has employed different dependent variables, mainly price and, more rarely, occupancy, revenue, and revenue per available room (RevPAR). This last indicator (RevPAR) has risen in importance due to its ability to combine rates and occupancy. Some studies not considered in this section have used guest performance indicators, such as the number of reviews or the review score. Moving on to the independent variables, the first determinant used in this study was the listing's size, which was measured by considering the number of beds, bathrooms, and guests. Previous studies have confirmed a positive and significant relationship between size and listing results (Chen & Xie, 2017; Wang & Nicolau, 2017). The second group included contractual terms and focused on a broad set of rules that can influence the relationship between the host and the guests. Some explanatory variables were the cancellation policy, security deposit, cleaning fee, extra people fee, times for check-in and check-out, and minimum stay. Their relationship with host results (price, in particular) has usually been positive (Benítez-Aurioles, 2018; Oskam et al., 2018). The rules included the possibility to accommodate pets or smoking. The relationship with these was usually negative (Chica-Olmo et al., 2020; Wang & Nicolau, 2017). The host was operationalized using a comprehensive set of variables ranging from the status of "superhost," the response rate and response time, and the number of photos, to experience (number of years that the apartment had been rented). The effects of these variables on listing performance have been mainly positive (Cai et al., 2019; Deboosere et al., 2019). Guests typically focus on the number of reviews and the overall rating. The first variable (review number) has shown contradictory results (positive and negative) with a predominantly negative influence on rates (Proserpio et al., 2018) and a positive influence on revenue (Abrate & Viglia, 2019; Deboosere et al., 2019; Sainaghi et al., 2021). By contrast, review ratings are usually positively related to listing results (Gibbs et al., 2018; Xie et al., 2019; Xie & Mao, 2017). Finally, locational factors represent the main focus of this study, and for this reason, these variables are analyzed separately in the next section.

Locational variables

Location is a widely used characteristic in exploring real estate (Dubin, 1992) and is one of the most desired by Airbnb guests (Visser et al., 2017). Not surprisingly, in the existing research on listings' performance, locational patterns have been used more and more (Boto-García, 2022a; Benítez-Aurioles, 2018; Boto-García et al., 2021; Oskam et al., 2018; Türk et al., 2021; Xie & Mao, 2017; Yang & Mao, 2020). The location's effect can be measured using different groups of characteristics: environmental, social/

economic, and accessibility related. *Accessibility* is the most widely used locational characteristic and is usually operationalized by considering the Euclidean distance to the city center (Tong & Gunter, 2020). This polarizing effect of the city center over the *whole city* is known as a spatial trend (Chica-Olmo et al., 2013). Other accessibility variables are transportation (Deboosere et al., 2019), local points of interest (Önder et al., 2019), and nightlife (Perez-Sanchez et al., 2018). These variables are normally measured in terms of "distance to" and therefore tend to show a negative correlation with listing performance. *Environmental* variables, such as noise, have a negative influence on prices (Chica-Olmo et al., 2020). *Social and economic* variables include factors such as the ethnicity of the residents in the destination neighborhood (Chica-Olmo et al., 2020), household income (Deboosere et al., 2019), and population density (Tang et al., 2019).

In the following section, we review the specific literature on the two locational factors considered in the study: transport systems and commerce.

Transport systems

The effect of *transportation systems* on the hotel industry has been widely studied (Adam & Amuquandoh, 2014), and the Euclidean distance to transportation hubs is the classic specification in hedonic hotel price models (Soler & Gemar, 2018). However, transportation systems have seldom been addressed in the Airbnb industry and have shown contradictory results. In one study, mass transit was considered a strong predictor of Airbnb revenue (Deboosere et al., 2019). The authors included a binary variable for transport equal to one if the apartment was located within an 800-m radius of a metro station and concluded that apartments within this radius charged 2 % less. Another paper included the transport factor as the distance between an Airbnb accommodation and the closest public transport and found that it was not a significant variable of the Airbnb accommodation's price (Önder et al., 2019). However, another study analyzed a large data set of online review comments and concluded that public transport strongly influenced (7 %) the locational factor (Cheng & Jin, 2019). Moreover, accessibility to local public transportation provided a vital location advantage for guests because it could reduce travel costs and increase guest satisfaction (Yang & Mao, 2020). Recently, a study analyzed 25 cities and explored the effect that the distance to transportation generated. It concluded 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 %" (Türk et al., 2021, p. 7). In addition, public transport is a sustainable urban tourism mode (Le-Klähn et al., 2015) that has been scarcely studied in the Airbnb literature. Public transport is used most frequently by visitors to small areas, and the educational level of tourists and the price of public transport significantly influence the transport mode choice (Le-Klähn et al., 2015). Being located close to public transportation has a positive impact on listing rates (Türk et al., 2021).

Tourist buses are a type of public transport used specifically by tourists. A seminal study argued that transport is a key part of the tourist experience, and tourist buses should therefore be integrated into the design of cities' bus networks to promote a change in the mode of transport used by tourists (Lumsdon, 2006). Cycling tourism is another transport mode that is non-polluting and sustainable and therefore a healthy and attractive option for tourists. Because cycling is an active mode of transport that contributes to sustainable mobility by reducing car use, a growing number of cities are promoting bike-sharing systems, particularly large European tourist cities. Bike-sharing is a cheap and simple system that is easy for tourists and citizens to use. Other authors have studied tourists' interest in bike-sharing and found that 73 % are likely or very likely to use this system (Kaplan et al., 2015). This suggests that this mode of transport is of great interest to a large percentage of tourists, so they are likely to be interested in selecting accommodations close to bike-sharing services (Kaplan et al., 2015).

Commerce

A second important locational factor is *commerce*. As suggested in previous papers, shopping is an important activity for tourists (García-Milon et al., 2020) and results in satisfactory experiences. Street markets are some of the most important attractions in big cities and are visited by tourists who travel not only on foot but also by bicycle (Kaplan et al., 2015).

Two different types of commerce are analyzed in this study. The first includes food and beverage establishments. Although the presence of a kitchen has not been found to exert a particular effect on apartment price (Dudás et al., 2020), many Airbnb listings offer such facilities, and Airbnb clients staying in an apartment with a kitchen may purchase food and beverages during their stay. Therefore, the proximity to this type of commerce may exert some effects on listing performance. The second type of commerce is non-food shops (e.g., local crafts and fashion). While both types of commercial establishments may be of interest to Airbnb clients, it is reasonable to assume that non-food establishments are more important, at least in Milan, which is famous worldwide for its fashion and design. In fact, although food and beverages are a basic commodity, non-food shops can be tourist attractions. Surprisingly, commercial establishments have rarely been analyzed as independent variables in papers on listing performance, and the few exceptions have reported contradictory results. For example, one study found that proximity to a shopping area had a positive effect on listing price (Perez-Sanchez et al., 2018), while other studies found that this variable was not significant (Cai et al., 2019) and could even exert a negative effect (Yang & Mao, 2020).

Spatial spillover

The spatial spillover effect is based on two different theoretical backgrounds: the ability of neighboring companies to influence pricing decisions (discussed later) and the existence of agglomeration economies, especially in tourism destinations. In one way or another, all the above localizing variables can be directly measurable and included in classic regression models. However, there may be other spatial aspects, such as spatial spillovers or substantive spatial dependence (Anselin, 1988; Anselin & Rey, 1991; Boto-García, 2022a), which are difficult to measure and specify in the classic model, thus justifying the use of spatial econometric models.

Focusing on the first research stream, the spatial spillover effect refers to the ability of neighboring apartments to influence listing prices. This is based on the idea that nearby spatial data are related (Tobler, 1970), a process that a recent paper referred to as "contagion" (Chica-Olmo et al., 2020), which can be defined as economic externalities that "produce non-compensated or indirect impacts for a receiver situated nearby" (Zhou et al., 2022, p. 3). A recent literature review of tourism studies explored the spillover effect (Chang et al., 2020). In the field of Airbnb, this effect is mainly triggered by benchmarking and mimicking activity. Single-listing hosts are often described as amateurs and micro-entrepreneurs (Stabrowski, 2017) who frequently mimic the choices made by neighboring professional hosts (Boto-García et al., 2021).

Studies on agglomeration economies have a long tradition in tourism (Baum & Mezias, 1992). Neighboring companies exert an effect on the competition—significantly defined as "localized competition" (Baum & Mezias, 1992)—on the positioning of new hotels (Urtasun & Gutierrez, 2006), and, more generally, on the failure rate (Baum & Ingram, 1998). In the hotel industry, there is a tradeoff between positive agglomeration economies that push to be closely related to neighbor companies and competition perspectives that suggest the opposite (Baum & Haveman, 1997). Many studies have revealed a positive effect generated by agglomeration economies (Yang, 2012).

In the current paper, the spatial spillover overlaps these two determinants: agglomeration economies and the ability of neighboring listings to influence prices. A paper found that neighbors (other Airbnb apartments) had a positive effect on listing price (Chica-Olmo et al., 2020). Listing price and revenue are related (Sainaghi, 2020b); therefore, it is expected that listing revenue also presents a spatial spillover effect via prices. A study conducted in New York City showed that spatial spillover had a positive effect on Airbnb listing revenues, which was reinforced by host tenure and mitigated by host capacity (Xie et al., 2019).

COVID-19 and listing determinants

The pandemic has disrupted the tourism industry on a scale not seen since the Second World War (Yang et al., 2020). All travelers, companies, destinations, and countries have felt the impact of COVID-19 (Sharma & Nicolau, 2020), and Airbnb listings are no exception (Chen et al., 2020). A plethora of studies has agreed that contagion diffusion has raised the attention of lodging guests to cleaning standards (Pappas & Glyptou, 2021). The cleaning fee requested by the host is accounted for within the contractual terms (see Determinants of listing performance section). A positive relationship is expected between the cleaning fee and the listing results, and, reasonably, the relevance of cleaning improved during the pandemic period. During the pandemic, people preferred to travel to domestic and nearby destinations; the journey was mainly made with their personal cars, and the party sizes were usually lower than before (Ivanova et al., 2020; Pappas, 2021). Based on these travel behaviors, the relevance of size (see Determinants of listing performance section) during the pandemic should have been less than before in explaining Airbnb results. Travelers searched for less crowded places and selected more peripheral areas; therefore, centrality (the distance to the city center) should have been less relevant during the pandemic period. The uncertainty created by the pandemic and the sudden changes in travel restrictions dramatically increased the risk of cancellation (Peluso & Pichierri, 2020). Accordingly, the cancellation policy should have had higher importance during the pandemic than before. Finally, the overall uncertainty generated by the outbreak (Williams et al., 2022) could orient Airbnb guests more toward superhosts. In fact, this badge was usually perceived as the host's ability to manage problems (Liang et al., 2017; Roelofsen & Minca, 2018).

Hypotheses development

The hypotheses were structured into two groups. The first was based on the discussion provided in the previous sections. Focusing on two locational variables and the spatial spillover for the periods before and during the pandemic, the following hypotheses were tested (see Fig. 1):

H1. The accessibility to transport systems positively affects the RevPAR of Airbnb listings.

H2. The spatial distribution (the density of medium-to-large shops) of commercial establishments (food, non-food, and shopping centers) positively affects the RevPAR of Airbnb listings.

H3. The spatial spillover effect positively influences the RevPAR of Airbnb listings.

The second group compared the determinants—non-locational variables, including (i) size, (ii) contractual terms, (iii) rules, (iv) host, and (iv) guest (as previously analyzed in Determinants of listing performance section), locational determinants (transport and commerce), and the spatial spillover effect—from the periods before and during the pandemic. Based on the analysis carried out in COVID-19 and listing determinants section, the following hypotheses were tested:

H4. The positive effect of the cleaning fee on the RevPAR of Airbnb listings was greater during the COVID-19 pandemic than before.

H5. The positive effect of size on the RevPAR of Airbnb listings was less during the COVID-19 pandemic than before.

H6. The positive effect of centrality on the RevPAR of Airbnb listings was less during the COVID-19 pandemic than before.

H7. The positive effect of the cancellation policy on the RevPAR of Airbnb listings was greater during the COVID-19 pandemic than before.

H8. The positive effect of the superhost badge on the RevPAR of Airbnb listings was greater during the COVID-19 pandemic than before.

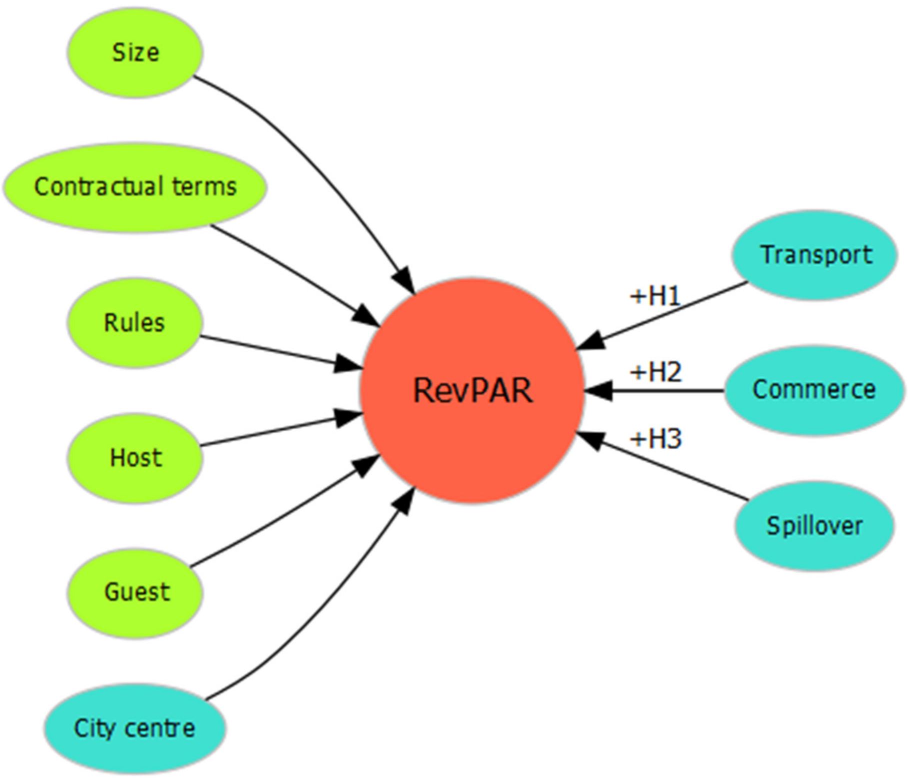

Fig. 1. Groups of characteristics and hypotheses for RevPAR. Non-locational (green) and locational factors, spatial spillover effects (turquoise), and controls are shown on the left, with interest factors and hypotheses (H) on the right.

Listing performance

Listing performance is traditionally measured using price and operationalized in various ways (Chen & Xie, 2017). In a recent review (Sainaghi, 2020b), roughly 60 % of the 33 papers focused on price. However, the hosts were more interested in maximizing revenue than they were in rates (Sainaghi et al., 2021). Several other studies have used the occupancy rate either alone (Xie & Mao, 2017) or integrated with other dependent variables, such as price or revenue (Gunter & Önder, 2018).

Each metric has its advantages. For example, when prices are used, the determinants that positively or negatively impact the listing rate are shown immediately. When the focus is on occupancy, which has rarely been used in previous studies, the ability of such determinants to attract new guests and saturate the fixed capacity is shown. In the lodging industry, the revenue per available room is usually the most relevant variable due to its ability to combine the rate and occupancy. Therefore, the factors related to the RevPAR may be more relevant than price determinants for the hosts (Yang & Mao, 2020).

Case study

Study area

Italy, an icon of international tourism, was ranked fifth by the World Tourism Organization (UNWTO) before the COVID-19 outbreak in terms of arrivals and sixth for receipts (UNWTO, 2020). As the third-largest national tourism destination in terms of overnights after Rome (30.9 million overnights) and Venice (12.9 million), Milan (12.4 million) is an interesting case for exploring listing determinants (ISTAT, 2020, p. 628). While the other large Italian cities (Rome, Florence, and Venice) are mainly focused on the leisure market segment, Milan is the national economic capital and the headquarters of the Italian stock market. The city has many attractions, including business firms and investors, the second-largest European trade fair center, and numerous points of interest, such as the Duomo and Leonardo da Vinci's *The Last Supper*. Other important attractions include the city's nightlife and the design and fashion industry. The city hosted the Expo in 2015, a mega-event that increased hotel RevPAR by 59 % (Sainaghi et al., 2019; Sainaghi & Mauri, 2018) and reduced demand seasonality (Sainaghi, Mauri, & d'Angella, 2018). The Milan Expo has partially changed the destination's image and increased the leisure market segment.

Table 1
Variables used in the empirical study.

Variable	Description
RevPAR	Revenue per available room (€)
Non-locational factors	
Size	
Bedrooms	Number of bedrooms
Bathrooms	Number of bathrooms
MaxGuests	Maximum number of guests allowed
Contractual terms	
CancePolic	1 if apartment has cancellation policy, 0 if other
Security	Security deposit (in hundreds of €)
Cleaning	Cleaning fee (€)
ExtPeopFee	Extra people fee (in hundreds of €)
Checkin	1 if check-in is after 7:00 p.m., 0 if other
Checkout	1 if check-out is 11:00 a.m., 0 if other
MinimumStay	Minimum stay (days)
Rules	
Pets	1 if pets are allowed, 0 if other
Host	
Superhost	1 if host is superhost, 0 if other
ResponR	Response rate
ResponT	1 if response time is within an hour, 0 if other
NPhotos	Number of photos
Experience	Number of years apartment has been in database
Guest	
Nreviews	Hundreds of reviews
OverRat	Overall rating
Locational factors	
Spatial trend	
DtCityCenter	Distance from Duomo (km)
Transport	
DtMetro	Distance from nearest metro station (km)
DtTuribus	Distance from nearest tourist bus stop (km)
DBikePark	Bike-share parking density (index)
Commerce	
DFood	Density of medium-to-large commercial food establishments (index)
DNon-Food	Density of medium-to-large commercial non-food establishments (index)
ShopCenters	Number of shopping centers in district
Spillover	
WRevPAR	Mean revenue per available room (€) of apartments within a radius of 3.3 km

Data and variables

Two sources of information were used in this work. The information regarding the RevPAR, control variables related to the apartments (size, contractual terms, rules, host, and guests), and their geographical locations was obtained from AirDNA. Previous studies have focused on Airbnb listings' performance using AirDNA data (Perez-Sanchez et al., 2018). Two periods of time were defined: before and during the COVID-19 pandemic. The period before the pandemic included the month of January 2020, while the period during the pandemic included March 2021. January 2020 was the last "regular" month before the outbreak. The first lockdown started in March 2020; however, some COVID-19 cases had already been found in February, and the tourism flow suddenly dropped significantly. For this reason, February 2020 cannot epitomize a regular pre-pandemic month. March 2021, by contrast, could represent a "good" pandemic month. In fact, on March 2, a new government law reduced mobility between Italian regions. The second lockdown (2021) was less restrictive than the first (2020); thus, it was chosen for this study. Only the rented listings during the two periods were included in the sample (7213 listings). Therefore, the two subsamples contained the same listings, improving the comparability between the two periods. The information related to the locational variables of interest (metro stations, tourist bus stops, bike-sharing stations, and commercial establishments) was obtained from the Comune di Milano.

With the help of a geographic information system (GIS), distances and spatial density indexes were obtained. Spatial kernel density indexes were calculated (Silverman, 2018), representing the densities of bike-share parking and commercial establishments. The search radius per unit area (km^2) used to obtain these indexes was 200 m for shared parking and 500 m for medium-to-large commercial establishments (food and non-food). In addition, to determine the spatial effect of large commercial establishments, we considered the number of shopping centers in each district. Table 1 explains the meaning of the variables used, while Table 2 shows the descriptive statistics of the variables and their descriptions.

Between January 2020 and March 2021, the mean RevPAR registered a 35 % decrease from €62 to €40. Of the 7213 apartments analyzed, there were 5755 (80 %) apartments for which the RevPAR decreased and only 1458 (20 %) for which it increased. The

Table 2
Descriptive statistics and descriptions of variables (N = 7213 listings).

Variable	Mean		Min.		Max.		SD		*t*-test
Year	2020	2021	2020	2021	2020	2021	2020	2021	
RevPAR	61,989	40,102	10,033	2368	570,372	347,707	37,252	37,617	
Non-locational factors									
Size									
Bedrooms	1310	1305	1	1	6	6	0.601	0.597	0.444
Bathrooms	1166	1170	0	0	6	6	0.427	0.431	−0.543
MaxGuests	3584	3558	1	1	16	16	1557	1558	1005
Contractual terms									
CancePolic	0.580	0.031	0	0	1	1	0.494	0.175	88.939***
Security	1027	1027	0	0	44	44	2263	2263	0
Cleaning	40,170	28,993	0	0	115	450	28,452	23,561	25.695***
ExtPeopFee	0.137	0.120	0	0	2810	2.5	0.169	0.149	6231
Checkin	0.0001	0.0001	0	0	1	1	0.012	0.012	−67.886***
Checkout	0.448	0.023	0	0	1	1	0.497	0.149	69.638***
MinimumStay	2602	3524	1	1	365	365	8091	13,719	−4.918***
Rules									
Pets	0.205	0.216	0	0	1	1	0.404	0.411	−1511
Host									
Superhost	0.260	0.260	0	0	1	1	0.438	0.438	0
ResponR	93,166	89,545	0	0	100	100	18,579	25,559	9.731***
ResponT	0.650	0.561	0	0	1	1	0.477	0.496	10.93***
NPhotos	22,166	23,022	1	1	200	372	12,721	15,327	−3.651***
Experience	2330	2120	0	0	10,668	9665	1836	1846	0.023
Guest									
Nreviews	0.445	0.590	0	0	7900	8830	0.703	0.839	−11.247***
OverRat	4670	4649	1	1	5	5	0.405	0.386	−970.65***
Locational factors									
Spatial trend									
DtCityCenter	3972		0.099		14,133		2116		0
Transport									
DtMetro	0.791		0.013		5156		0.627		0
DtTuribus	1682		0.025		7128		1152		0
DBikePark	2934		0.001		11,459		2373		0
Commerce									
DFood	0.0002		0		0.002		0.0002		0
DNon-Food	0.001		0		0.026		0.002		0
ShopCenters	2598		1		5		1460		0
Spillover									
WRevPAR	56,245	29,065	12,948	4264	101,567	52,595	9435	4264	241.03***

Note: Sig-level $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. The t-test is the test for the difference in means between 2020 and 2021.

listings of the two periods (2020 and 2021) were the same; therefore, it is reasonable to assume that the means of the number of bedrooms, bathrooms, and maximum guests were very similar, as were the locational variables. The cancellation policy decreased from 58.0 % (2020) to 3.1 % (2021). The mean of the cleaning service variable dropped from €40 to €29.

Regarding the *locational* factors, the distance to the city center has been classically considered, representing the spatial drift or trend (Chica-Olmo et al., 2013). In Fig. 2, the spatial distributions of the RevPAR in January 2020 and March 2021 are reported. This figure shows that the revenues of apartments close to each other were more similar and concentrated in 2020 than in 2021. However, according to the Global Moran's I test, there was a significant global spatial autocorrelation in both years. The values of this statistic were low in both years and particularly in 2021 (I = 0.129 [2020] and I = 0.038 [2021]), which indicated that the said autocorrelation was not very strong in either of the two years. In the maps, this can be seen in the confetti effect of the color of this variable. In 2020, high prices (red color) were concentrated in the city center and low prices (yellow color) in the outskirts of the city, as clearly shown in the spatial estimation of the RevPAR using Kriging. However, in 2021, the high and low prices were distributed more evenly over the entire city, which was reflected in the spatial estimation carried out with Kriging. These figures show that there was a strong spatial trend of increasing prices from the outskirts to the city center in 2020, but in 2021, this trend was very weak. Therefore, although there were spatial autocorrelations during the two years, the effect of the distance to the city center was much weaker in 2021 than it was in 2020. In addition, Fig. 2 shows the choropleth maps of the RevPAR in both years using the Kriging method. This method allows spatial interpolations to be made from the spatial autocorrelation structure observed through the variogram (Cressie, 1991; Matheron, 1970). The variogram shows that as the distance between apartments (h) increased, the variability in the RevPAR also increased (Gamma(h)); that is, the autocorrelation decreased. The range or distance from which the variability stabilized was approximately 3 km in 2020, while in 2021, it dropped to 2 km. The range indicated the radius of influence in the spatial autocorrelation structure. On the other hand, the relationship between the nugget effect and the sill, which represented the total variability, was very high in both models

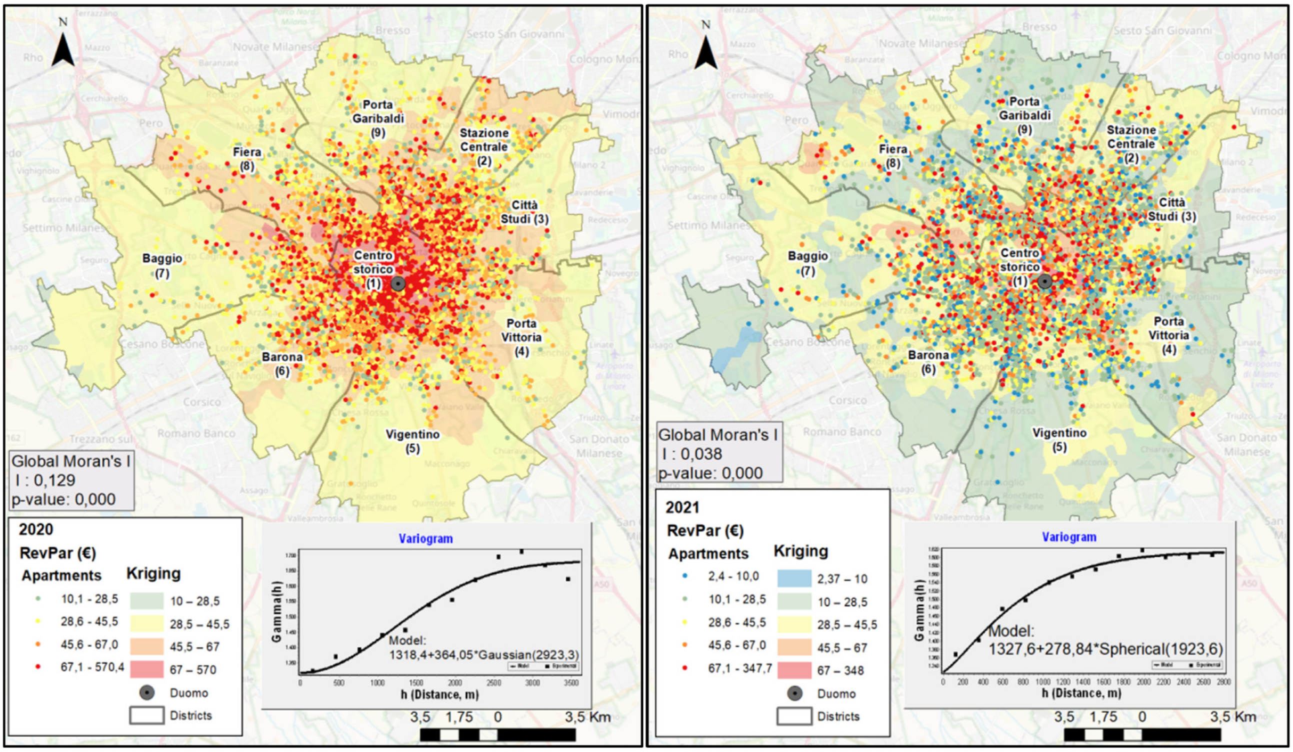

Fig. 2. Milan districts, city center (Duomo), revenue per available room in January 2020 and March 2021, and spatial estimation of RevPAR with Kriging.

(1318.4 / 1682.45 × 100 = 78 % [2020] and 1327.6 / 1606.4 × 100 = 83 % [2021]), indicating the strong spatial randomness already observed in the low values of the Moran's I tests. Part of this spatial random component may have been due to the apartments having different non-locational factors. Therefore, Fig. 2 not only shows that the RevPAR dropped from 2020 to 2021 but also the spatial distribution and spatial autocorrelation structure.

Methods

In line with the literature review (Yang & Mao, 2020), a semi-log model was estimated, where the dependent variable was the log of RevPAR. Although OLS is the classic method used to estimate this type of model, this method is inefficient when the perturbations are autocorrelated (Anselin, 1988). Moreover, classic models do not consider the spatial spillover effect. Two types of spatial models that allow controlling for spatial effects are the spatial autoregressive (SAR) model, which considers substantive spatial dependence, and the spatial error model (SEM) with spatial nuisance dependence (Anselin, 1988):

SAR:

$$y = \rho Wy + X\beta + e \tag{1}$$

SEM:

$$y = X\beta + u, \text{with } u = \lambda Wu + e \tag{2}$$

In our work, y represents the natural logarithm of revenue per available room (*lnRevPAR*); X and β are the explanatory variables and associated parameters, respectively; W is a spatial weights matrix row-normalized, which represents neighborhood structure; Wy (*WlnRevPAR*) is the spatially lagged dependent variable and can represent the mean of *lnRevPAR* of neighboring apartments; ρ represents global spatial spillover effect; Wu and λ represent the spatially lagged disturbances and their associated coefficient, respectively; and e represents a normal iid vector of disturbances. To determine the presence of spatial autocorrelation in the disturbances, Moran's I of the errors was used. To determine whether it is more appropriate to specify the SAR model or the SEM, Lagrange multiplier (LM) tests (LM-error and LM-lag) and their robust versions (RLM-error and RLM-lag) of the OLS models were performed (Anselin & Rey, 1991).

Table 3
OLS and SAR models for 2020 (Mod_20.ols and Mod_20.sar) and 2021 (Mod_21.ols and Mod_21.sar). Dependent variable: lnRevPAR. N = 7213.

Variable	OLS		SAR	
	2020	2021	2020	2021
Constant	3.005***	2.280***	1.798***	0.874**
Non-locational factors				
Size	$\overline{R}_1^2 = 0.234$	$\overline{R}_1^2 = 0.072$	–	–
Bedrooms	0.115***	0.103***	0.115***	0.102***
Bathrooms	0.190***	0.181***	0.188***	0.180***
MaxGuests	0.064***	0.050***	0.063***	0.050***
Contractual terms	$\overline{R}_2^2 = 0.277$ %Δ = 15.7	$\overline{R}_2^2 = 0.078$ %Δ = 8.5	–	–
CancePolic	0.034***	0.261***	0.034***	0.256***
Security	0.005**	0.0001	0.005**	0.0001
Cleaning	0.001***	0.002***	0.001***	0.002***
ExtPeopFee	−0.071**	−0.005	−0.071**	−0.004
Checkin	2.052***	2.051***	2.072***	2.085***
Checkout	0.072***	−0.025	0.072***	−0.022
MinimumStay	0.001*	−0.001	0.001*	−0.001
Rules	$\overline{R}_3^2 = 0.277$ %Δ = 0.0	$\overline{R}_3^2 = 0.078$ %Δ = 0.0	–	–
Pets	0.022*	0.036	0.021*	0.037
Host	$\overline{R}_4^2 = 0.303$ %Δ = 9.4	$\overline{R}_4^2 = 0.118$ %Δ = 50.0	–	–
Superhost	0.078***	0.108***	0.078***	0.107***
ResponR	0.001***	0.001***	0.001***	0.001***
ResponT	0.037***	0.154***	0.037***	0.153***
NPhotos	0.002***	0.002***	0.002***	0.002***
Experience	−0.016***	−0.053***	−0.016***	−0.053***
Guest	$\overline{R}_5^2 = 0.314$ %Δ = 3.5	$\overline{R}_5^2 = 0.121$ %Δ = 3.3	–	–
Nreviews	0.054***	0.042***	0.053***	0.042***
OverRat	0.044***	0.003**	0.044***	0.003**
Locational factors				
Spatial trend	$\overline{R}_6^2 = 0.428$ %Δ = 36.4	$\overline{R}_6^2 = 0.146$ %Δ = 20.2	–	–
DtCityCenter	−0.034***	−0.015*	−0.020***	−0.003
Transport	$\overline{R}_7^2 = 0.445$ %Δ = 4.0	$\overline{R}_7^2 = 0.152$ %Δ = 4.2	–	–
DtMetro	−0.056***	−0.053***	−0.046***	−0.040**
DtTuribus	−0.033***	−0.030**	−0.026***	−0.021*
DBikePark	0.020***	0.021***	0.017***	0.015**
Commerce	$\overline{R}_8^2 = 0.454$ %Δ = 1.9	$\overline{R}_8^2 = 0.156$ %Δ = 2.3	–	–
DFood	−0.954	−2268	−0.798	−2558
DNon-Food	15.995***	20.424***	15.603***	19.290***
ShopCenters	0.027***	0.025***	0.022***	0.016**
Spillover			–	–
WlnRevPAR	–	–	0.288***	0.411***
Spatial autocorrelation tests				
LM-error	11.826***	16.503***	1261	0.925
RLM-error	0.148	0.038	–	–
LM-lag	15.772***	19.944***	–	–
RLM-lag	4.095**	3.479*	–	–
Goodness-of-fit				
R^2	0.456	0.158	0.457	0.160
R^2-adj.	0.454	0.156	–	–
AIC	6466.8	17,031	6466.7	17,017

Note. Sig-level $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. R^2 in SAR models is Nagelkerke pseudo-R^2. %Δ is the percentage of increase of the R^2-adj. of group of variables i ($\overline{R}_i^2$).

It is important to note that the coefficients of the SAR model are not directly interpretable, so it is more convenient to obtain the direct and indirect effects and their sum or the total effects of the explanatory variables (Pace & LeSage, 2009). The total effect represents the effects of an explanatory variable on the RevPAR, both of the Airbnb apartment (direct effect) and the spatial spillover effects of the neighboring apartments (indirect effect).

In this work, W was specified considering the inverse distance with threshold according to the first law of geographers; that is, the closest data in space are more alike than the furthest (Tobler, 1970):

$$w_{ij} = \frac{1}{d_{ij}} \tag{3}$$

where d_{ij} is the distance between apartments i and j, with a threshold equal to 3.3 km, which represents the minimum distance in kilometres between apartments so that no apartment is isolated.

In the two OLS models (see Table 3 in Findings), a decomposition analysis of R2 was developed to understand the relevance of each block of independent variables. To calculate the R2 of each block, a restricted model was obtained, then new variables were added, and the R2 variance was considered. An alternative approach (not used in the present paper) is to apply the Shapley method (Sainaghi et al., 2021).

Findings

Table 3 depicts two nested classic models estimated using OLS and two SAR models. Both models (OLS and SAR) considered the two periods analyzed. Focusing on 2020 (pre-pandemic), the locational factors (transport and commerce), the spatial spillover effect, and the three underlying hypotheses were tested. The control variables comparing the variability between the periods before and during the pandemic to test the remaining hypotheses (4, 5, 6, 7, and 8) are discussed later.

Using the OLS models, the distance to the metro and the distance to the tourist bus showed a negative coefficient. Both variables were highly significant ($p < 0.01$ and $p < 0.05$). Not surprisingly, the metro was perceived to be more important than a tourist bus (absolute value of the coefficient and significance). The density of bike-sharing generated a positive impact on the RevPAR and was again highly significant ($p < 0.01$). The evidence fully supported the first hypothesis: accessibility to transport systems *positively* affects the RevPAR. The second locational variable explored the relevance of commerce. The density of food shops was not significant, while non-food stores and shop centers both yielded positive and highly significant results. The second hypothesis was accepted but only by focusing on non-food stores. Therefore, the spatial distribution of *non-food* commercial establishments *positively* affects the RevPAR of Airbnb listings. Food stores are likely perceived as a commodity, and as discussed in the literature review, the presence of a kitchen does not generate a positive effect on listing results. Finally, the spatial spillover effect in 2021 (0.411) was much greater than it was in 2020 (0.288), and both were highly significant ($p < 0.01$). The underlying hypothesis was therefore confirmed: the spatial spillover effect *positively* influences the RevPAR. Following Anselin and Rey (1991), the SAR specification was chosen over the SEM, since both the LM-lag and the RLM-lag statistics were greater than the LM-error and RLM-error in all the models.

Based on Table 3, the differences between the periods before and during COVID-19 were discussed by analyzing the control group (size, contractual terms, rules, host, guest, and spatial trend), the two locational determinants (transport and commerce), and the spatial spillover effect. We anticipated that in all the cases (control, locational groups, and spatial spillover), the intensity (value of the coefficient) and relevance (statistical significance) would be diverse. To compare the two periods, the OLS models were used to analyze the single variables and consider the overall effect, measured by R_i^2, which represented the change in R^2 with respect to the previous group of variables (nested models). Starting from the end of Table 3, the goodness-of-fit was greatly reduced (from 0.456 to 0.158). This was probably the most relevant premise in comparing the periods before and during the COVID-19 pandemic. The groups of variables used in this study were able to explain an important part of the RevPAR variance in 2020 (0.456), while during the pandemic, the fit of the OLS decreased dramatically (0.158).

Size can be considered an exception, as all three determinants remained very positive and highly significant, showing stability. However, R_1^2 revealed a strong decrease in size from 0.234 to 0.072. A possible explanation was the smaller party size during the pandemic, leading to an overall reduced significance of size. This possible explanation found partial support in the reduced significance of the extra people fee (included in the next block). These findings supported the fifth hypothesis.

Contractual terms showed a strong drop in the cumulated variance explained (R_2^2) from 0.277 to only 0.078. The increase (%Δ) was considerably lower (8.5 % in 2021 and 15.7 % in 2020). The cancellation policy increased its positive effect from 0.034 to 0.261. The high uncertainty generated by COVID-19 and the sudden travel restrictions approved by the government increased the selection of listings with clear cancellation policies, raising the positive effect on the RevPAR from 0.034 to 0.261, which supported the seventh hypothesis. Four variables (security, extra people fee, check-out, and minimum stay) that were significant in 2020 were not significant during the pandemic. These outputs clearly suggested considerable changes in travel behaviour. The non-significance of the extra people fee again epitomized a lower party size but also, more generally, a different relationship with the host. In fact, the security deposit, check-out, and minimum stay were not significant during the pandemic. In this group of variables, cleaning remained highly significant, and the coefficient doubled from 0.001 to 0.002 in both models (OLS and SAR). This result appeared congruent with the pandemic improving the awareness of cleanliness, thus confirming the fourth hypothesis.

The presence of pets (*rules*), which had a slightly positive and statistically significant effect in the pre-pandemic period, was not significant during the pandemic. A reduction in people traveling with pets was likely. However, as R_3^2 and the variation (%Δ) illustrated, the rules had a marginal effect on the RevPAR in the pre-pandemic period.

Host was the second strongest variable during the pandemic (after size). In fact, R_4^2 increased from 0.078 (R_3^2 rules) in 2020 to 0.118 (R_4^2 host) in 2021, an increase of 50 %. Generally speaking, this increase was favored by coefficients that remained positive and significant. During the pandemic, the host remained important or became more important than before (+50 %). This overall

Table 4
Direct, indirect, and total effects.

Variable	2020			2021		
	Direct	Indirect	Total	Direct	Indirect	Total
Bedrooms	0.114***	0.046***	0.161***	0.101***	0.070**	0.172***
Bathrooms	0.188***	0.076***	0.264***	0.180***	0.125**	0.305***
MaxGuests	0.063***	0.025	0.089***	0.049***	0.034**	0.084***
CancePolic	0.033***	0.013**	0.047***	0.256***	0.178**	0.435***
Security	0.005***	0.002*	0.007***	−0.0004	−0.0002	−0.0002
Cleaning	0.001***	0.001**	0.001***	0.002***	0.001**	0.003***
ExtPeopFee	−0.070**	−0.028	−0.099**	−0.003	−0.002	−0.006
Checkin	2.071***	0.838**	2.910***	2.085***	1.451*	3.536**
Checkoutb	0.071***	0.029**	0.100***	−0.021	−0.015	−0.036
MinimuStay	0.001*	0.0004	0.001**	−0.0026*	−0.0008	−0.0018
Pets	0.021*	0.008	0.030***	0.036*	0.025	0.062
Superhost	0.077***	0.031**	0.109***	0.107***	0.074**	0.181***
ResponR	0.001***	0.0004**	0.001***	0.001***	0.001**	0.002***
ResponT	0.036***	0.014**	0.051***	0.153***	0.106**	0.259***
NPhotos	0.001***	0.001**	0.002***	0.002***	0.001**	0.003***
Experience	−0.015***	−0.006**	−0.022***	−0.052***	−0.036**	−0.089***
Nreviews	0.053***	0.021**	0.074***	0.041***	0.029*	0.070***
OverRat	0.043***	0.017**	0.061***	0.003**	0.002	0.005**
DtCityCentre	−0.020***	−0.008***	−0.028***	−0.003	−0.002	−0.005
DtMetro	−0.045***	−0.018***	−0.064***	−0.039**	−0.027*	−0.067**
DtTuribus	−0.025***	−0.010**	−0.036***	−0.021	−0.014	−0.036
DBikePark	0.017***	0.006**	0.023***	0.015**	0.010*	0.026**
DFood	−0.798	−0.323	−1121	−2560	−1782	−4342
DNonFood	15.609***	6.319**	21.929***	19.280***	13.420**	32.701***
ShopCentres	0.022***	0.008***	0.030***	0.016**	0.011*	0.027**

Note: Sig-level $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

effect could be explained by the rising positive impact generated by the superhost badge (from 0.078 to 0.108). During the pandemic, guests appeared to be more appreciative of skilled hosts, thus confirming the eighth hypothesis. While the response rate remained stable, the response time quadrupled its positive effect from 0.037 to 0.154. A reasonable explanation is that the fall in demand and hosts consequently responding more quickly to guests improved their RevPAR. A future study can add the professionalization degree to the independent variables to understand whether professional hosts were more efficient than single-listing hosts during the pandemic, which has emerged in some studies (Boto-García, 2022b; Farmaki et al., 2020). The number of photos remained stable. Finally, experience (the number of years the apartment had been in the database) showed a negative correlation with performance. This was in line with previous studies using revenue (such as the current article) and not price (Abrate & Viglia, 2019).

Guest remained very similar in 2020 and 2021; for example, in terms of increase in variance explained (%Δ). This result focusing on the two indicators used appeared reasonable. In fact, both the number of reviews and overall rating were stock variables mainly influenced by the past. During the pandemic, the number of guests decreased dramatically; therefore, the number of reviews for a listing was largely related to the past. This was also the case for the overall rating. As past-oriented determinants, they did not show particular changes, confirming the robustness of the sample used.

The last control variable was DtCityCenter (*spatial trend*). As anticipated and shown in Fig. 2, the relevance of centrality diminished during the pandemic. Therefore, hypothesis six was confirmed. This was strongly confirmed by the increase in R_6^2 in absolute and percentage terms. In absolute terms, before the pandemic, the increase was strong and equal to 0.114 (from 0.314 to 0.428), resulting in 36.4 %Δ. During the pandemic, the rise was considerably smaller at 0.025 (from 0.121 to 0.146), which was 20.2 %Δ. The coefficient in 2020 was also highly significant and double that of 2021, which had an insignificant coefficient. Moving on to the SAR model, the distance to the city center was not significant during COVID-19. One possible explanation was that during the pandemic, travelers were less interested in central tourism attractions because many of them were closed (e.g., museums). Furthermore, the city center was usually more crowded than the peripheral areas. Finally, during the pandemic, travelers may have been interested in non-leisure attractions that were more spread out around the city.

The two locational variables characterizing this study are now discussed. The percentage increase in the variance explained (%Δ) by *transport* remained stable in 2020 (4.0 %) and 2021 (4.2 %). The distances to the metro and tourist buses were very similar in the two periods, registering a marginal (third decimal) reduction. The tourist bus variable was less significant (from three stars to two), which was reasonable considering the COVID-19 restrictions. The density of bike-sharing was the only transport variable that simultaneously remained highly significant ($p < 0.01$) and showed a marginal (third decimal) increase. Overall, these results showed slightly reduced interest in public transportation during the pandemic period (due to the risk of contagion) but also a marginal rising interest in outdoor transportation (e.g., bicycles).

Commerce marginally increased the percentage variance (%Δ) from 1.9 % to 2.3 %. This effect was triggered by the rising coefficient achieved by the density of non-food shops. The coefficient, in fact, remained largely significant (three stars), and the value moved from 15.995 to 20.424. Two possible alternative explanations were proposed. The first simply considered that the density

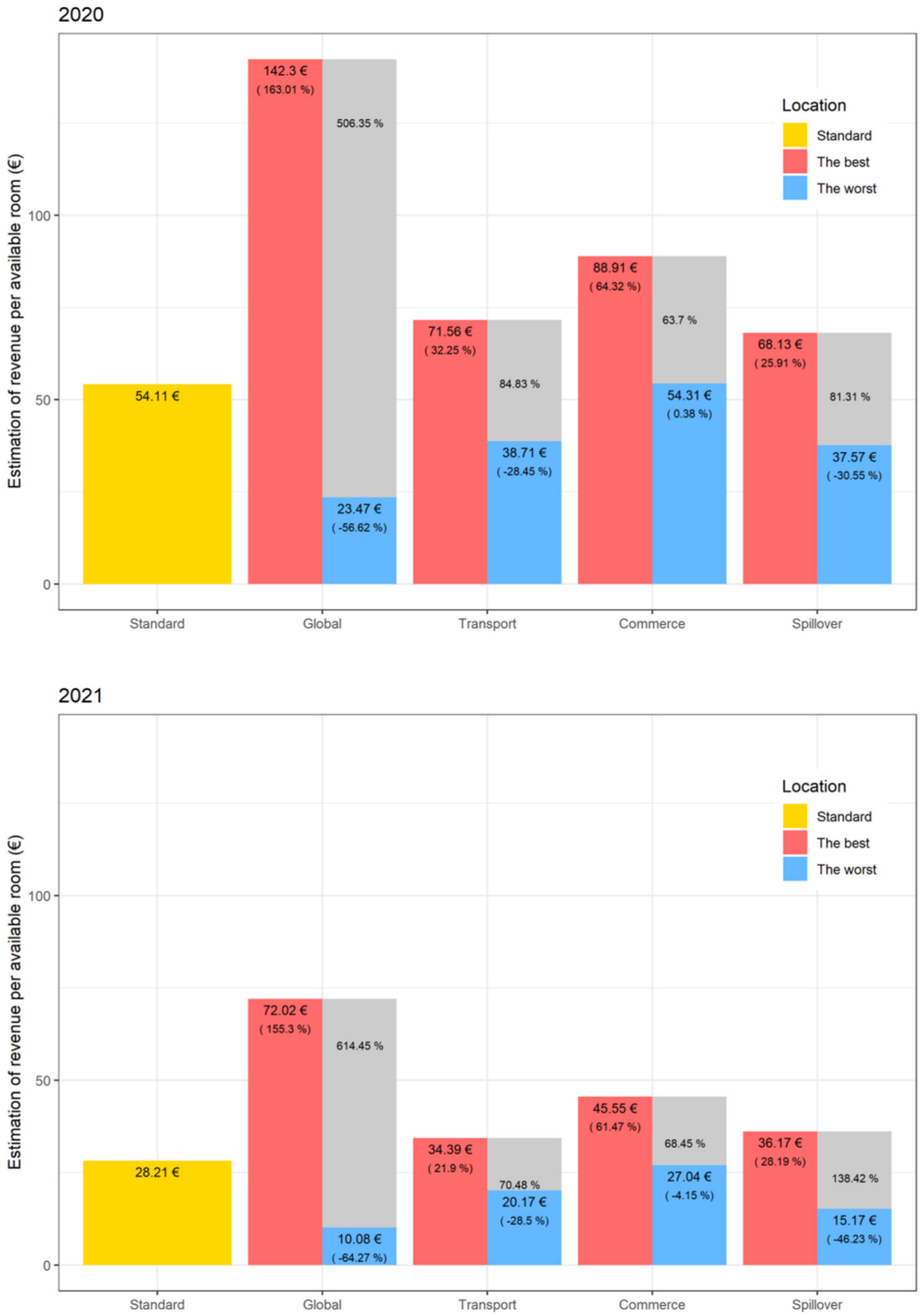

Fig. 3. Estimation of RevPAR for different groups of locational factors.

of non-food shops was higher in non-central areas. During the pandemic, as previously discussed, many Airbnb guests reserved an apartment in the peripheral areas; therefore, the density coefficient of non-food shops automatically increased. This explanation was reasonable because many shops were closed during the pandemic. A second explanation considered the importance that non-shop stores had for Airbnb guests during the pandemic (even when many of the stores were closed) in a city famous worldwide for design and fashion. Finally, the shop center variable showed very similar results.

The spatial *spillover* effect was measured using the two SAR models. In both cases, the effect was positive, relevant, and highly significant. During the pandemic (Mod_21), the spatial spillover coefficient increased significantly from 0.289 to 0.411. Both results (2020 and 2021) confirmed the positive effects of neighboring listings, which was in line with previous studies (Xie et al., 2019). This localization variable was the one that had the greatest proportional increase between 2020 and 2021, so it could

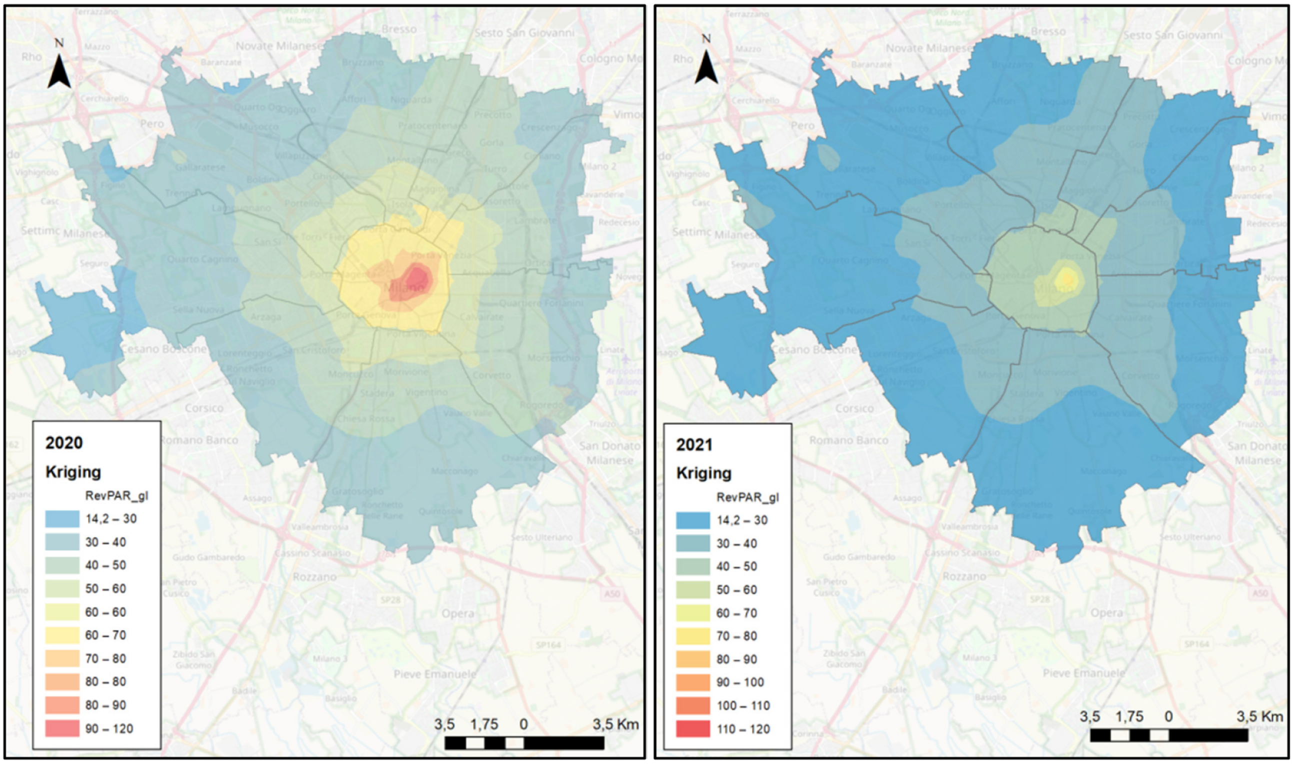

Fig. 4. Estimation of all locational characteristics (RevPAR_gl).

be said that the greatest spatial effect that the pandemic had was the increase in the spatial contagion effect. The coefficients of the SAR model were not directly interpretable, so it was more convenient to obtain the direct and indirect effects and their sum or the total effects of the explanatory variables (Pace & LeSage, 2009). The total effect represented the effect of the explanatory variables on the revenue per available room of the apartment (direct effect) and the spatial spillover effect of the neighboring apartments (indirect effect). Table 4 shows these effects. For instance, the total effect of shopping in 2020 was 0.030—the sum of 0.022 (direct) and 0.008 (indirect)—which could be interpreted as semi-elastic. A unit increase in the number of shopping centers in a district corresponded to a rise in revenue of 3 %, ceteris paribus. This 3 % represented both the effects of the listing (2.2 % or direct) and those of the neighboring apartments (0.8 % or indirect).

By separately analyzing the locational variables and the spatial spillover effect, an overall vision is provided in Figs. 3 and 4. From the SAR models, different estimates of the RevPAR of fictitious apartments were made (see Fig. 3). The standard (RevPAR_sd) was an average apartment with all the characteristics; the best and the worst were the two apartments with mean values in non-locational characteristics and maximum or minimum values in all locational characteristics (global location), or only in transport, commerce, or spillover characteristics. Fig. 3 depicts a comparison between the best (red) and the worst (blue) locations and a calculation of the variation in percentage. The variations (written in brackets) closest to the best and the worst scenarios were calculated assuming the RevPAR_sd. For example, in 2020, the RevPAR_sd (yellow) was €54.11. Globally, the best-located listings registered a RevPAR of €142.3, which was 163.01 % higher than the RevPAR_sd. By contrast, the worst locational scenario generated a drop in the RevPAR of 56.62 %. Finally, the gray area compares the best and worst scenarios by calculating how the best outweighs the worst in terms of percentage.

The pandemic approximately halved the RevPAR_sd: the value was reduced from €54.11 (yellow, 2020) to €28.21 (yellow, 2021). However, it is interesting to note that the global effect of the location between the best and the worst locations remained (as a percentage) very similar in 2020 and 2021. The best (red) increased by roughly 150 % (163.01 % in 2020 and 155.3 % in 2021), while the worst (blue) decreased by roughly 60 % (−56.62 % in 2020 and −64.27 % in 2021). Being in the best location generated a strong (but similar) rise in RevPAR (gray), which was equal to 506.35 % in 2020 and 614.45 % in 2021.

Moving on from the global effect to the two locational factors, *transport* showed a strong reduction in the percentage gap in 2021 compared with 2020. This was reasonable, as the pandemic increased the use of personal transportation modes and, more generally, the presence of domestic guests. For this reason, the gray area moved from 84.83 % (2020) to 70.48 % (2021). Similarly, being in the best location (red) generated a RevPAR increase of 21.92 % (2021), lower than that of 2020 (32.25 %). The opposite was true for the worst-located listings. In the case of *commerce*, the gray area illustrates similar values in 2020 (63.7 %) and 2021 (68.45 %). Finally, the *spatial spillover* effect substantially increased the so-called contagious impact, registering a rise in the gray percentage from 81.31 % (2020) to 138.42 % (2021).

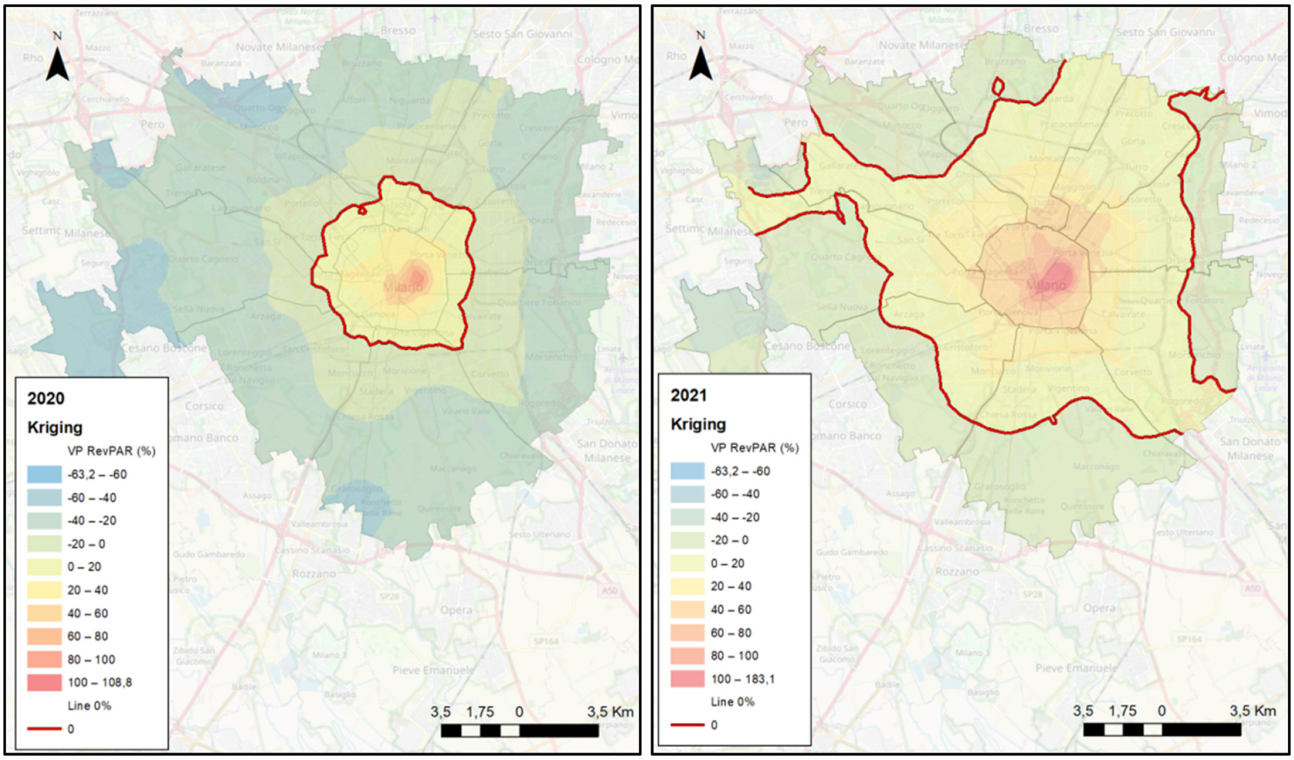

Fig. 5. Estimation of variation in percentage of RevPAR_gl (VP RevPAR).

Figs. 4 and 5 show the choropleth maps using the Kriging method of the estimates of the 7213 apartments by fixing their non-locational characteristics to the mean values (RevPAR_gl) and their variations as percentages with respect to the standard apartment (VP RevPAR). These maps show how locational factors affect revenue; that is, how the value of the location on the map varies and how it varies with respect to that of a standard apartment. In 2020, the value of the location was much higher than it was in 2021. However, the area that covered the positive variations with respect to the standard listing area—that is, inside the 0 % line (red line)—was much larger in the year 2021 than it was in the year 2020. Therefore, in the year 2021, the values of the locations of the apartments were not as concentrated in the central area as they were in 2020, indicating that the possible effect of the pandemic on the value of the location of an apartment not only consisted of reducing the value but also expanded the area where a standard apartment could manage to improve its revenue. This was probably due to the decrease in the effect of the distance to the center and the increase in the spatial spillover effect.

Discussion and conclusions

Beginning with the fourth hypothesis, the first *theoretical* conclusion focused on the effect generated by the pandemic on listings' performance. First, the group of non-locational variables (size, contractual terms, rules, host, and guests) has been widely used in different empirical settings (presented in the second section) and showed largely convergent results. However, the pandemic changed the relevance and intensity of these variables. In particular, the overall ability of these determinants to explain variances decreased considerably, as shown by size. Second, transportation and commercial (non-food) services were predictors of the RevPAR. The relevance of public transportation (the metro in this study) and bike-sharing suggested that a more sustainable approach was desired by Airbnb guests. During the pandemic, the explanatory power of these two locational variables slightly decreased. Third, neighboring listings (spatial spillover) exerted a positive effect, confirming the presence of positive agglomeration economies before and during the pandemic, the impact of which doubled during the outbreak. Fourth, the spread of COVID-19 considerably reduced the city center advantage (the spatial trend in this study) and conversely reduced the disadvantage of being peripherally located. In 2021, the area that covered positive revenue variations compared with a standard listing increased dramatically. Thus, we can conclude that during the outbreak, the location advantage (centrality) both reduced the value and expanded the area where a standard listing could raise its sales.

As for the *practical conclusions*, the hosts substantially changed their contractual terms to accommodate the pandemic, specifically the cancellation policies. Being a superhost also appeared to be more relevant during uncertain periods, and the response time played a crucial role. The reduction in party size generated a strong decrease in size. Furthermore, during the pandemic, guests were less sensitive to centrality. The new locational variables introduced in this study suggested the relevance of non-food shops and transport facilities. Being closely located to other listings generated a strong spatial spillover effect. Another important practical conclusion was that the RevPAR estimated for a standard apartment decreased by half (from €57.19 to €28.45).

Based on the findings, some *policy implications* are proposed. While the non-locational factors (size, contractual terms, rules, host, and guest) are strategic levers managed by the hosts, destination managers can support the development of Airbnb listings by working on transport and commerce facilities. The ability of city managers to create efficient subway connections can favor the rise of listings in peripheral urban areas. A similar effect is produced by non-food and shopping services. The effects of these policies can exert a greater effect in the post-COVID-19 period. In fact, as discussed in the Findings section, during the pandemic, the negative coefficient "distance to city center" decreased by more than half.

The main study *limitations* are related to the use of a single case study, although the sample size was robust (>7000 listings). Milan is a city famous worldwide for fashion and design, and this may have an impact on the relevance of non-food shops. The pandemic was analyzed by focusing only on one pandemic wave (the second in 2021), and the study considered only one pandemic month. In the R2 decomposition, the Shapley method can be used instead of the restricted model (as explained at the end of Methods section). In the host group, the distinction between professional and single-listing hosts can be explored. Based on these limitations, several *new research avenues* are proposed. First, new empirical settings should be considered in order to provide additional evidence. Second, in this study, the focus was on the second pandemic wave (2021). It may be useful to compare the different waves (2020, 2021, and early 2022) and consider more than one month for each period. Third, a multiple case study approach may reveal differences in the relevance of locational variables, such as non-food shops and other additional features. To calculate the relevance of each block, the Shapley method can be used. Finally, the distinction between professional and single-listing hosts can be considered.

CRediT authorship contribution statement

Ruggero Sainaghi: Conceptualization, Funding acquisition, Methodology, Validation, Investigation, Writing - original draft, Writing - review & editing. Sainaghi has written the following sections: 1, 2, 3.1, 6.

Jorge Chica-Olmo: Conceptualization, Data curation, Methodology, Visualization, Writing - original draft, Writing - review & editing. Chica-Olmo has written the following sections: 3.2, 4, 5 and has revised the sections 2.2 and 2.3.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.annals.2022.103464.

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