A big data analysis of COVID-19 impacts on Airbnbs' bookings behavior applying construal level and signaling theories

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Abstract

This study investigates the impact of the COVID-19 pandemic on consumer booking behavior in the peer-to-peer accommodation sector. This study used a dataset composed of 2041,966 raws containing 69,727 properties located in all 21 Italian regions in the pre- and post-COVID-191. Results show that after the COVID-19 pandemic, consumers preferred P2P accommodations with price premiums and located in rural (versus urban) areas. Although the findings reveal a preference for entire apartments over shared accommodation (i.e., room, apartment), this preference did not change significantly after COVID-19 lockdowns. The contribution of this study lies in combining psychological distance theory and signaling theory to assess P2P performance in the pre- and post-COVID-19 periods.

Keywords – COVID-19; Airbnb host; occupancy; price premium; construal theory; signaling theory.

1. Introduction

The ubiquitous and rapid spread of the COVID-19 virus forced most countries in the world to close their borders, implementing lockdowns or various restrictions to travel and movement (Sigala, 2020). Since the tourism industry is based on the movement of people, the COVID-19 crisis has been causing unprecedented disruption for the tourism economy worldwide (Sigala, 2020). Social distancing measures launched by national governments to protect their citizens from the virus have affected all services that require proximity and social interactions.

Considering the high level of proximity between guests and hosts in Peer-to-Peer (P2P) short-term accommodation rentals, a well as the relevance of social interaction in choosing P2P over other accommodation types (i.e. hotels) (e.g., Tussyadiah and Pesonen, 2016; Liu and Mattila, 2017; Cheng and Jin, 2019), organizations like Airbnb have suffered the pandemic the most (Abril, 2020). The COVID-19 pandemic has severely hit Airbnb, the global leader for the sharing of accommodation between peers, with a decline of 72% of revenues compared to 2019 (Abril, 2020). According to AirDNA, Airbnb lost 5% of its total listings from January through June of 2020 (AirDNA, 2021).

The nature and the magnitude of the impacts of the COVID-19 may have had a profound impact on travellers' behavior. Although scholars hypothesize the pandemic would affect the sharing economy the most (Gerwe, 2021; Gossling et al., 2020), it is not yet clear if and how P2P traveller's behavior has evolved compared to the pre-pandemic situation.

In this study, we try to explain the impact of COVID-19 by combining signaling theory (Spence, 1974) and construal level theory (Liberman and Trope, 2008). First, signals are visible cues used to communicate the quality of products or services that are generally difficult to evaluate due to information asymmetries (Spence, 1974, 2002). This situation of information asymmetry motivates manufacturers and retailers to develop quality signals (Mavlanova et al., 2012; Kirmani and Rao, 2018) to help consumers assess the various products on offer. One of these signals is the

price (Wolinsky, 1983; Milgrom and Roberts, 1986). In this study, we argue that the high (*versus* low) price of P2P accommodation can send a signal of quality and create an expectation of professionalism and safety, which will affect consumers' booking decisions, affecting the occupancy of a P2P accommodation. Hence, we expect to see a significant difference in terms of bookings for premium-priced P2P accommodation in the post-COVID-19 periods compared to the pre-COVID-19.

Secondly, we draw upon the construal level theory of psychological distance (Trope and Liberman, 2010) to argue whether the impact of the COVID-19 pandemic on P2P revenues and occupancy depends on the dimensions of social and spatial distance. Construal level theory suggests that objects, events, and individuals can be perceived as being either psychologically near or distant from different dimensions of psychological distance (Trope and Liberman, 2010). The theory suggests that individuals use higher levels of construal to represent an object as the psychological distance from the object increases. Drawing on these theoretical underpinnings, we argue that the consumers' perception of the risk of getting contaminated with COVID-19 could be higher in situations of proximity with others versus distant ones. The geographical location of P2P accommodation and P2P accommodation types are likely to create higher or lower spatial distance, also affecting the perception of the risk of getting infected by other people. As such, we consider the rural *versus* the urban location of P2P accommodation as the two extremes of the geographical distance continuum. Moreover, we also argue that travellers will be more likely to book accommodation types enhancing high social distance such as entire apartments *versus* shared rooms or shared accommodation where the expected distance between hosts and guests is low or very low.

2. Literature review

Research on the sharing economy in hospitality has flourished in the last years (Mody et al., 2021). Existing studies have investigated various phenomena relating to consumer intention and behavior, focusing on users of leading P2P platforms (i.e., Airbnb). Scholars have initially tried to understand customers' motivation to choose (e.g., Chen and Xie, 2017; Mao and Lyu, 2017; Guttentag et al., 2018), or to continue to use Airbnb (Wang and Jeong, 2018), and more recently their discontinuance intention (Huang et al., 2020). In the Airbnb context, trust is particularly important because the service is delivered by peers, ordinary people and consumers who are not professional operators. Therefore, scholars have investigated the determinants of trust, focusing on self-presentation strategies, profile photos, personal reputation (e.g., Ert et al., 2016; Wu et al., 2017; Tussyadiah and Park, 2018; Mauri et al., 2018; Wang et al., 2020). Scholars have also studied the purchase and post-purchase stages of consumer decision-making, focusing on the determinants of purchase (Bae et al., 2017) and repurchase intention (Mao and Lyu, 2017; So et al., 2019), as well as the drivers of customer enjoyment (So et al., 2021), customer satisfaction and loyalty (Lee and Kim, 2018; Wang and Jeong, 2018; Ju et al., 2019).

Regarding pricing and the determinants of Airbnb host performance, which is the focus of our study, some research exists. Scholars investigated the relationships between listing attributes and price using the hedonic pricing approach (Chen and Xie, 2017). Other studies have proved the significant relationship between host attributes (i.e., superhost status, multiple listings, and verified identities) and higher prices (Wang and Nicolau, 2017). For instance, Xie and Mao (2017) studied the impact of host attributes (i.e., the number of listings per host, local, super host, responsiveness, years of experience, identity verification) on the performance of the listings (i.e., monthly reservation records) using a sample of 5,805 accommodation in Texas, US. Abrate and Viglia (2019) measured the impact of hosts' and products' reputation signals on revenues maximization using a sample of 981 listings in five European cities. Kwok and Xie (2019) used a sample of over 20 thousand Airbnb accommodation in the US over a period of 3 years (2014-2017). They found that price positioning (i.e. competitive pricing), dynamic pricing, and multi-listing hosts generate

higher revenues. Bresciani et al. (2021) reveal that travelers are less likely to reserve Airbnb shared accommodation for fear of social contacts. Filieri, Galati, and Raguseo (2022) investigate the effect of cancellation rate on Airbnbs' host occupancy rate and consider various source credibility signals to act as moderators.

Our study aims to explain how consumer booking behavior has changed after the COVID-19-induced lock-downs. We advance theory by using a large dataset and integrating construal level theory and signaling theory to explain the differential performance of Airbnb hosts before and after the COVID-19 pandemic.

3. Theoretical foundations and hypotheses development

3.1 Signalling theory, price signals, and host occupancy

Signaling theory suggests that signals are observable alterable attributes that can be used by individuals and organizations to communicate and to reduce information asymmetries (Spence, 1974; 2002). In online transactions, like online auctions or Airbnb transactions, consumers face high information asymmetry because of the limited amount of information about the reputation of the sellers and the quality of products being sold (Shen et al., 2011; Mavlanova et al., 2012; Kirmani and Rao, 2018). In situations of high uncertainty, signals seem to be very effective in reducing ambiguity and consumer risks (Biswas and Biswas, 2004). Information asymmetries are frequent in loosely-regulated marketplaces (Zervas et al., 2021), like Airbnb (Mao and Lyu, 2017), where buyers and sellers know little about each others' identity, motivation, attitude and behavior. Information asymmetries arise because buyers and sellers do not have the same information (Mao and Lyu, 2017; Zervas et al., 2021). Price is a type of signal that can reduce uncertainty and sends pre-purchase signals about products' unobservable quality (Wolinsky, 1983; Milgrom and Roberts, 1986). Price signals can help buyers distinguish high quality versus poor quality solutions to avoid deception (Milgrom and Roberts, 1986). Hence, at a certain price, consumers expect to find a certain quality (Wolinsky, 1983). In the P2P context, higher prices will send signals about the quality of the P2P accommodation, which would include considerations regarding the professionalism and preparedness of the host to make the stay safe and secure after the pandemic. Accordingly, the price may signal hosts would eventually use sanitization tools and hygiene measures to reduce the risk of contagion. Hence, we hypothesize:

H1: Compared to the pre-COVID-19, travellers will be more likely to pay a premium price for a P2P accommodation in the post-COVID-19.

3.2 Construal level theory, Social and spatial distance and P2P occupancy

Psychological distance is evaluated based on the construal level theory, according to which humans use mental constructs of different levels of abstraction to access objects (Trope and Liberman, 2010). Based on Trope and Liberman (2010), low-level and high-level construal may be differentiated from each other. Low-level construal is more concrete and detailed, as it is formed for rather close objects and events. High-level construal, on the other hand, is more abstract and refers to distant objects and events. Psychological distance is composed of four dimensions: geographical, temporal, social and hypothetical distance (Liberman and Trope, 2014). In this study, we focus on the social and spatial dimensions of psychological distance.

Spatial distance has been regarded as a vital parameter in understanding individuals' intentions and behavior (Trope et al., 2007). Spatial distance refers to the perceived geographical distance between the subject and an event or object. In this study, we assume that spatial psychological distance can explain the differential occupancy rate of P2P accommodation rentals before and after the COVID-19 pandemic. After an incessant campaign from public organizations on mass media, people have understood that maintaining safety distance between people would

reduce the possibility of contracting the COVID-19 virus. Thus, following this reasoning, people may think that the possibility to contract COVID-19 would be higher in crowded or densely populated areas. Research has shown that people residing in severely affected regions report high levels of anxiety and low levels of subjective well-being compared to individuals from more mildly affected regions (Kim, 2019; Lau et al., 2008; Wong et al., 2007). Therefore, given the detrimental effects of the COVID-19 pandemic on psychological outcomes, people may feel more anxious and less secure in specific geographical areas where the risk of contagion is higher. Urban areas are generally more densely populated and crowded than rural or suburban areas. Hence, we expect that travellers, in the post-COVID 19, will be looking for P2P accommodation located in peripheral geographical areas (i.e., rural or suburban areas), where they can minimize potential contacts with the crowds generally concentrated in urban areas. Hence, we hypothesize:

H2: Compared to pre-COVID-19, spatial distance (from urban areas) will affect the reservation likelihood of P2P accommodation in the post-COVID-19.

Airbnb hosts offer various types of accommodation, from shared rooms to shared flats to entire apartments (Zervas et al., 2017). Social distance refers to the perceived social distance between an individual and other people. In this study, we refer to social distance as the likelihood of interaction between host and guest in an Airbnb accommodation. The likelihood of social interaction between guests and hosts can change dramatically according to the P2P accommodation type, being minimal or absent in the case of the entire apartment to being moderate with the shared apartment and very high with the shared rooms type. In independent solutions like the entire apartment, travellers do not share common areas; hence they benefit from higher privacy, which creates the conditions for respecting social distancing.

In this study, we argue that in the aftermath of COVID-19 induced lockdowns, travellers will be more likely to choose solutions that guarantee higher social distance between guests and hosts (i.e. entire flats) to minimize the likelihood of social interaction and contagion of COVID-19. We assume that consumers will perceive high risks in situations of proximity from potential vectors of contagion, that is, other people living in a property. Therefore, we hypothesize:

H3: Compared to pre-COVID-19, the social distance will affect the reservation likelihood of P2P accommodation in the post-COVID-19.

4. Methodology

4.1. Sampling and data description

The data used in this study are from AirDNA, a world-leading provider of short-term rental data. To compare the pre- and post-pandemic periods, we used daily data of August 2019 and August 2020. Firstly, we choose August 2020 because in most countries, governments relaxed travel/movement restrictions in early July; therefore, August 2020 can be representative of the psychological impact of the COVID-19 pandemic soon after reopenings. Choosing this period also allowed us to minimize the presence of unrealized reservations (i.e., reservations declined because of last-minute changes in travel restrictions), which could have affected our estimates. Further, according to the number of arrivals, August 2020 is considered the best-performing month in 2020 (World Bank, 2021), enabling a more accurate comparison with the pre-pandemic period (i.e., August 2019).

Secondly, we have chosen the Italian market because it is one of the largest Airbnb markets in Europe (AllTheRooms.Analytics, 2021), as well as one of the major markets for tourism and leisure activities (The World Bank, 2021).

Thirdly, following previous studies (Gunter and Önder, 2018), we have restricted our datasets to only continuously active listings during the period considered. A listing is considered continuously active if its daily status is either *reserved* (i.e., booked) or *available* (i.e., not booked). The dataset used for the analysis was composed of 2,041,966 property-day data points (for both August 2019 and 2020) made of 69,727 properties (i.e., all the Italian properties on Airbnb in the considered period) owned by 47,312 different hosts. Furthermore, our dataset covers 3,462 Italian cities from all 21 Italian NUTS2 regions[1].

4.2. Variables' operationalization

The first independent variable is the price premium signal. We measured whether the occupation of accommodation with higher prices (i.e., *price premium*) changed between 2019 and 2020. We hypothesized that a higher price sends a signal of higher quality; hence we distinguished the Airbnb listings between *premium* and *non-premium* ones, following the algorithm proposed by Farronato and Fradkin (2018). The algorithm steps are synthesized as follows: i) we firstly run the hedonic panel regression in August 2019 using the logarithm of daily price per bed (i.e., the price normalized on the number of beds, because the larger the house, the higher the price) as the dependent variable, and property fixed effects ($\delta(i)$) and time fixed effects as independent ones; ii) we assume that each listing is associated to its quality measure q(i) such that the distribution of q(i) reflects the real distribution of quality within the Airbnb market; iii) since the real value of q(i) is unknown, we estimate from the hedonic panel regression an estimate of quality q(i)^ (that is the property fixed effect $\delta(i)$) such that $q(i) = q(i)^ + \eta(i)$; iv) to reduce the presence of biases due to the error term $\eta(i)$, we apply the Empirical Bayesian Shrinkage to shrink the estimated values q(i)^ toward the real value q(i)[2].

The result of this approach is a continuous variable measuring the price premium of each listing which follows an almost normal distribution with a mean zero (see Figure 1). According to the distribution, we have then categorized listings as *premium* if the price premium is in the upper quartile of the distribution (0.364). Given that a definition of *price premium* is not present in the literature and that the econometric analyses may provide different results according to the different cut-off thresholds for *premium* versus *non-premium* accommodations, we carried out two additional robustness checks testing different definitions of *premium* accommodations varying the cut-off thresholds. In particular, we tested our models identifying *premium* accommodations as those with a price premium in the top 20th percentile (0.450) or in the top 15th (0.580) percentile.

[**Insert Figure 1 here**]

We adopted the Degurba classification proposed by Eurostat to measure spatial distance. Degurba stands for *Degree of Urbanization*, and it is a classification indicating the population density of geographical areas, such as the Local Administrative Units (LAU), a subpart of a NUTS2 region. Based on a grid made of one squared kilometers cells covering the European territory, areas are classified as *Cities*, densely populated ones where at least 50% of the population lives in the urban center, *Town*, intermediately populated areas, and *Rural*, less populated areas where 50% of the population lives in rural cells.[3]. These three dimensions of distance were operationalized by creating a categorical value. For the sake of clarity, we label the Town areas as *Sub-Urban* in our analysis.

[1] A further detailed description of the distribution of properties within the NUTS2 regions is available upon request to the authors.

[2] For a more detailed description of the methodologies, see Farronato and Fradkin (2018), Morris (1983), while for the Stata see Nichols (2008) and Sacarny (2013).

[3] For further information and a deep dive on the DEGURBA classification methodological procedure, we provide the following link to Eurostat: https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/degurba.

We operationalize social distance according to the listing typology because some accommodation types present a higher (*versus* lower) likelihood of interaction between guests and hosts than others (i.e. shared room *versus* entire apartment). Our variable is categorical and assumes three different values: *Entire Apartment* (i.e., highest social distance and lowest interaction likelihood), *Private room* (i.e., moderate social distance and medium interaction likelihood) and *Shared room* (i.e., lowest social distance and highest interaction likelihood). A shared room has been considered a reference baseline in our econometric models.

A dummy variable was used to measure the occupancy of the listing (i.e., 1 versus 0 = reserved versus free, respectively), our dependent variable, following other scholars' approaches (e.g., Yao et al., 2019). We identified various control variables based on their likely impact on our dependent variable (see Mody et al., 2021 for a comprehensive review). All these variables are recorded twice, once in 2019 and once in 2020. Appendix A1 provides an overview of the controls employed in the models.

4.3. Estimation Technique

To test our hypotheses, we estimate the following equation, which describes the probability of observing a reservation for a listing *i* in a day (of August) *t* given a vector of parameters:

$$p(y_{i,t} = 1, x_i | d_t, \beta) = \frac{e^{d_t + x'_i \beta}}{(1 + e^{d_t + x'_i \beta})}$$

where $y_{i,t}$ is the dependent variable, as described in section 4.2, x_i is the vector containing either the control variables (reported in section 4.2 and A1) and the explanatory ones (as described in section 4.2), β is the vector of coefficients and d_t is the set of time-varying fixed effects accounting for the time-varying variation of the dependent variable over the month. We adopted a *logit* model with standard errors clustered at the individual (property) level, including, as previously reported, time and NUTS2 fixed effects of measuring the equation. The software Stata was used for this purpose. In order to compare the propensity to reservation according to the main explanatory variables in the *pre* and *post*-COVID era, we have estimated the model twice, in August 2019 and August 2020.

5. Results

5.1. Descriptive Statistics

Table 1 provides descriptive statistics of the whole variables employed in the model. Overall, we notice that within our sample of continuously active listings during August 2019 and 2020, the occupancy rate has declined from 57% to 42%, showing that demand, despite the COVID-19 pandemic, was still high in August 2020. Being the distribution of premium listings derived from the definition of the variable (i.e., the top 25th, 20th and 15th percentile), Table 1 provides the distribution of the Airbnbs according to the location and the listing type (proxying the expected level of social interactions). At a glance, 22.35% of listings are classified as *Rural*, 49.93% as *Urban* and the remaining 34.72% as *Sub-Urban*. The majority of Airbnb listings (72.50%) are classified as Entire Apartment, 27.06% as Private Room and the remaining 0.44% as Shared Room. No significant variations in the mean values of control variables emerge from Table 1, which shows that only 20% of properties switched from strict to moderate refund policies. Appendix A2 shows the correlation matrix of the variables employed in the models. No strong correlations (only a few values slightly greater than 0.3 or lower than -0.3) were found, such that no threat of multicollinearity is present within our independent variables.

[**Insert Table 1 here**]

Table 2 provides descriptive evidence of the Italian market comparing absolute and relative (in terms of market share within the respective classification) performances in August 2019 and

August 2020. Firstly, Table 1 confirms, in absolute numbers, that the market demand during August 2020 has been resilient, being only 25% lower than the previous year (the variation should be intended in comparison to the variation in the months before, see for reference Hu et al., 2020). On the other hand, the revenues have recorded a lower percentage decrease. Turning to revenues, Table 2 shows that premium accommodations (accounting for respectively the 22.67% and 24.51% of reserved nights in 2019 and 2020) generate more than 40% of total revenues. According to the distribution of demand per spatial area, we notice that, while in August 2019, the majority of reservations were for P2P located in urban areas (see Table 1), in 2020, rural and sub-urban areas recorded the highest shares in terms of both reservations and revenues (despite they account for a lower number of active properties). Conversely, urban areas face a significant decrease in both metrics. Finally, the distribution of demand according to the listing typology is similar to 2019 and 2020, with the entire apartment accounting for most reservations and revenues, followed by private and shared rooms.

[**Insert Table 2 here**]

5.2. Econometric Analyses

Table 3 provides results of the logit model estimating the equation in section 4.3. The models adopt clustered standard errors at the individual (listing) level and include geographical regions (i.e., NUTS2) and day of the month (1 to 31)'s fixed effects. The models of August 2019 and 2020 are based on the same set of continuously active listings, such that a comparison between the estimated effects on the logarithm of the odds ratio of being reserved (called *log-odds* hereafter) are directly comparable. With this purpose in mind, Figure 2 shows the estimated coefficients with the respective 95% confidence interval.

[**Insert Table 3 here**]

The models M2-2020, M2-2019, M5-2020 and M5-2019 show the marginal impact of *price premium* accommodation on the reservation likelihood before and after the COVID-19 pandemic. In August 2019, the models predicted that *ceteris paribus*, the impact on the log-odds of being reserved for *premium* listings (compared to *non-premium* ones) is negative, varying from -0.170 (M5-2019) to -0.179 (M2-2019), both significant at the 0.001 confidence level. In other words, *premium price* accommodation was less likely to be reserved in the pre-COVID-19 period (i.e., August 2019). Conversely, in August 2020, we reveal the opposite effect, *ceteris paribus*, the log-odds of being reserved of *premium-priced* accommodation increases from 0.081 (M5-2020) to 0.111 (M2-2020), significant at the 0.001.

Models M3-2020, M3-2019, M5-2020 and M5-2019 show the marginal effect of spatial distance. All coefficients must be interpreted as a change in the log-odds with respect to the reference baseline sub-urban areas. In August 2019, results showed a significant preference for rural areas while urban centers were less likely to be reserved by Airbnb customers. The results in August 2020 are rather similar but with a significantly different magnitude, as the comparison of the confidence intervals in Figure 2 confirms. Consistent with our hypothesis, we notice that as the marginal effects on the log-odds of being reserved for listings in rural areas increases to 0.196 (M5-2020) – 0.210 (M3-2020) after COVID-19 lockdowns (compared to the marginal effect of 0.056 (M5-2019) – 0.078 (M3-2019) in August 2019). Similarly, the marginal effects on the reservation likelihood for properties in urban areas significantly decrease to -1.013 (M5-2020) – -1.037 (M3-2020) after COVID-19 lockdowns (compared to the marginal effect of -0.515 (M5-2019) – -0.546 (M3-2019)). We interpret these results as a significant increase in the occupation of properties located in rural areas.

Model M4-2020, M4-2019, M5-2020 and M5-2019 show the predicted marginal effects on the log-odds of the listing typology, proxying the expected level of social distance. The comparison of the magnitude effects in August 2019 and August 2020 predicts that, while the average marginal effects

are larger in 2020 rather than in 2019 (0.902 (M5-2020) – 1.193 (M4-2020)) compared to 0.759 (M5-2019) – 0.884 (M4-2019) for entire apartments, and 0.316 (M5-2019) – 0.379 (M4-2019) compared to 0.614 (M5-2020) – 0.807 (M4-2020) for private rooms), the respective 95% confidence interval overlay (see Figure 2), suggesting that the marginal effects on the reservation likelihood are not significantly different comparing 2020 and 2019, but it is still positive.

5.3. Robustness Checks

We conducted robustness checks to test different cutoff thresholds defining premium listings according to the estimate of the price premium. Table 4 and Table 5 report the results of the models for the top 20th percentile (0.450) and the top 15th percentile (0.580) of the price premium.

[Insert Table 4 here]

[Insert Table 5 here]

Overall, the outcomes presented in Table 3 are confirmed in Table 4 and Table 5[4]. Particularly, the negative marginal effect of premium accommodation in 2019 is significant (at 0.001 confidence level), adopting both different definitions of premium. The impacts on the log-odds are respectively -0.190 (M8-2019) to -0.198 (M7-2019) for premium as top 20th percentile and -0.208 (M12-2019) to – 0.210 (M10-2019) for premium as top 15th percentile. Similarly, the robustness checks confirm the inversion of customers' preferences for higher-priced accommodation. Indeed, we find positive and significant marginal effects on the log-odds in August 2020, with coefficients varying from 0.063 (M11-2020, Table 5) to 0.107 (M10-2020, Table 5). Other than the variable premium, the results regarding the spatial distance and the interpersonal social distancing factors reported in Table 3 are fully confirmed in Table 4 and Table 5.

Finally, we have tested the robustness of our results with an alternative estimation methodology. First, we have generated a new unique dataset including all together the observations from 2019 and 2020, thus matching the properties in 2019 with those in 2020. Second, we have estimated a new model, where we have included two additional variables compared to the main equation in Section 4.3: a dummy variable, called *2020*, indicating whether the observation comes from 2020 (compared to 2019), and the interaction of this dummy with the variable *Price Premium*. To this end, this interaction shows the shift in the likelihood of a Premium listing comparing 2020 (i.e., the Pandemic year) with 2019. The results are reported in the Online Appendix A3 and are fully in line with the main outcomes in Table 3, being the shift due to pandemic to premium listings reservation propability positive and significant, and, consequently, resulting in a positive overall probability in the post-Covid phase.

6. Discussion

Drawing upon construal level theory (Liberman and Trope, 2008) and signaling theory (Spence, 1974; Spence, 2002), this study advances our understanding of the impact of COVID-19 pandemic on consumers' booking behavior of P2P short-term accommodation rental. Our results prove that the COVID-19 pandemic has affected consumer booking behavior of P2P accommodations but not necessarily in the direction that many scholars have hypothesized (i.e., Bresciani et al., 2021; Gerwe, 2021). The findings of this study reflect consumers' willingness to pay a premium price for P2P accommodation after the COVID-19, as well as their preference for listings located in peripheral areas enabling spatial distancing from crowded areas. Surprisingly, our

[4] Notice that for the sake of comparison, models M6(2019/2020) and M9(2019/2020) are identical to models M1(2019/2020) as they include control variables only.

results also show that they continued to book shared rooms and apartments (low/moderate social distance) the same way as they did in the pre-COVID-19 period.

Based on our analysis, the change in booking patterns on the Airbnb platform reveals that travelers are keener to reserve premium accommodation in the aftermath of COVID-19-induced lock-downs. High price conveys a signal of quality in the P2P service delivery, which could mean consumers were expecting higher safety and hygiene standards. Hence, our study confirms that price premiums signal quality and, in the context of health crises like COVID-19, they also signal safety and security. This result advances the literature on pricing in the P2P accommodation rental literature, which previously focused on the influence of host and listing attributes on the pricing of P2P accommodation (Chen and Xie, 2017; Wang and Nicolau, 2017; Xie and Mao, 2017; Kwok and Xie, 2017; Mauri et al., 2018; Sainaghi, 2021) or on the effect of Airbnb's price difference and dispersion on hotels' performance (Xie and Kwok, 2017). Irrespective of host and listing attributes - identified as important price determinants in past studies, in our study, Airbnb customers are more willing to pay premium prices in the aftermath of COVID-19 lock-downs.

Furthermore, our findings show consumers demonstrated a significantly higher preference for P2P accommodation located in peripheral (i.e., rural) and semi-peripheral (i.e., sub-urban) areas with higher spatial distance from the urban areas, which have been severely penalized by the COVID-19 pandemic. This result may imply travelers are looking more for accommodation located in peripheral rural or mountain destinations. This result contrasts with previous studies showing that proximity to city centers is a strong predictor of higher listing prices and revenues (Gibbs et al., 2018; Deboosere et al., 2019; Chica-Olmo et al., 2020). This result may also be explained by reducing collective group trips, opting for smaller accommodation (Sánchez-Pérez et al., 2021). The findings continue the discussion on the role of spatial distance, which, in a previous study (where it was measured in miles distance between the host and the guest), showed a positive impact on customer loyalty (So et al., 2019). In summary, the higher spatial distance in P2P accommodation was significantly and positively related to occupancy after COVID-19.

However, there was no support for the hypothesis relating to the influence of COVID-19 on the preference for accommodation with higher social distance, highlighted in previous studies using experiments (Bresciani et al., 2021). Thus, our results support the idea that the social aspect (i.e. social interaction with locals) is still important in the motivation to choose P2P (Tussyadiah and Pesonen, 2016; Liu and Mattila, 2017; Guttentag et al., 2018; Cheng and Jin, 2019) and COVID-19 has not changed it. Hence, this study reinforces the relevance of the social aspect of P2P accommodation even at a time where social interactions and gatherings are dangerous and discouraged. We thus support the role of social closeness, agreeing with the result of a recent study demonstrating that age closeness between guests and hosts (social distance) influenced guest loyalty toward the host, whereas increased age distance diminished their loyalty (So et al., 2019). Previous studies also reveal that the concept of home in Airbnb is constructed as a social dimension entailing the interaction and communication with the host (Zhu et al., 2019). In summary, in the aftermath of COVID-19 lockdowns travelers sought to minimize the risk of contagion by booking premium accommodation, they still prefer entire apartments located in rural areas.

6.1 Theoretical contribution

This study contributes to the emerging literature on the influence of social and spatial psychological distance dimensions on traveller behavior. Overall, the study contributes to advancing the application of psychological distance theory to explain the differences in consumer behavior between pre and post-pandemic times in the context of P2P accommodation rental. Specifically, this study applied construal level theory of psychological distance (Liberman and Trope, 2008; Trope and Liberman, 2010) and signaling theory (Spence, 1974; Spence, 2002) to

understand the impact of COVID-19 pandemic on Airbnb micro-entrepeneurs' performance. Previous studies measured spatial distance in terms of distance (calculated in miles) between the host and the guest and found it has a positive impact on loyalty (So et al., 2019). Our study conceptualized spatial distance as the distance from the densely populated areas, which corresponded to urban areas and revealed a positive effect on P2P occupancy. Furthermore, this study conceptualized P2P accommodation type (entire apartment *versus* shared apartment *versus* shared room) as a proxy for social distance. A previous study measured social distance in terms of age differences between hosts and guests (So et al., 2019).

This study also differs from previous studies that used perceptual approaches, such as experiments (Bresciani et al., 2021), and instead adopts a large database based on 2,041,966 property-day data points of actual booking behavior. This approach provides robust evidence of consumers' behavior in the pre- and post-COVID periods.

6.2 Practical Implications

The findings of this study are useful to provide recommendations to P2P organizations and for Airbnb hosts to navigate this health crisis. This study has shown that the social interaction advantage that P2P accommodation sharing had over other accommodation types (e.g. hotels) (e.g., Guttentag et al., 2018) has not vanished because of the COVID-19 pandemic whereas social distance did not affect consumers' decisions regarding shared or independent accommodation. However, it is important that this social interaction occurs in a safe and clean environment. Accordingly, our findings reveal that travelers are looking for premium-priced accommodation, expecting a higher quality of the P2P accommodation as well as higher safety and hygiene standards. This expectation means that Airbnb hosts should be (especially those offering shared accommodations) very careful and take extra care to make their environment safe and communicate this to their guests. Airbnb hosts should appropriately communicate the quality of their offering, sending hygiene level signals to guests, for example, in the title of the listing, in the amenities, and description. The higher price can have a double sword effect if Airbnb hosts are unprepared to deal with the new situation or show carelessness about the potential risks of contagion.

Furthermore, Airbnb can improve its competitive advantage over hotels by stimulating the creation of short-term rentals in rural areas, for which consumers are showing a preference in the post-COVID-19 era. Furthermore, Airbnbs' location matters when setting prices, but rural accommodation can benefit from higher revenues due to the increased demand (e.g., Gibbs et al., 2018).

Finally, this study has implications for policymakers. Specifically, results show a growing preference for entire apartment listings, which are the most likely category to be removed from the long-term housing rental market (e.g., Wachsmuth and Weisler, 2018). The fact that Airbnb customers are increasingly opting for rural areas indicates that after city centers, peripheral areas will be increasingly on-demand, leading to a rise in house prices. If this situation persists, policymakers would have to intervene to tighten the control over the number of entire apartments offered on the P2P market in order to avoid new protests and claims that the short-term rental is killing the long-term housing market.

6.3 Limitations and future research

This study has various limitations, which can pave the way for future research. First, the dataset adopted focused on Airbnb accommodation in Italy. Although Italy is one of the most important Airbnb markets, it is not the only one. Furthermore, contextual differences, such as the severity of the COVID-19 pandemic in different countries, may have affected the results of this

study. Italy has been severely hit by COVID-19; however, it is plausible to expect that the results may be different in contexts where the pandemic has made fewer victims. Moreover, culture could possibly affect the results of this study. Italy has a high score on uncertainty avoidance; the impact of COVID-19 on consumer behavior could be lower for consumers from countries that score low on uncertainty avoidance (i.e., UK). Hence, scholars could replicate the study in other cultural contexts to generalize the results.

Furthermore, the data of this study refers to a situation in which a vast part of the population was not vaccinated against COVID-19. Thus, we expect that higher vaccination levels could affect booking behavior in the future. Although this is far from the scope of our study, a comparison with August 2021 would be useful to consider the impact of COVID-19 vaccination on consumer behavior.

Finally, our study did not take into account the Airbnb customer segments or socio-demographic characteristics of guests. Different customer segments behave differently. For instance, younger consumers may be more likely to take risks compared to adult or elderly consumers, which face higher health risks. Hence, future research could investigate the moderating influence of socio-demographic factors. On the other hand, further research can also investigate other supply-side factors, which are not directly tackled by this research. Among the others, we identify two main directions to be investigated. First, in line with the results depicting rural areas growing as of Pandemic outbreak, we recognize the spatial location of properties as an important driver of customers' booking behavior. To this end, future research could investigate the role of other location factors, such the distance from the city centre (as often done in city-level studies, e.g., Deboosere et al., 2019), comparing periods before and after pandemic outbreak. Second, grounding on the increasing professionalization of Airbnb supply-side (Dogru et al., 2020), we suggest future research to investigate the role of the host in determining consumer behavior, which can have a significant impact as long as the preparedness of a host can be a crucial factor in determining customers' choices. Consistently, we suggest futher research to study the performances and the strategic choices adopted by professionals after the pandemic.

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Tables

Table 1 – Sample Descriptive Statistics (Panel A – 2019; Panel B – 2020)

Panel A - 2019

Variable Type	Variables	Mean	Std. Dev	Min	Max
Dependent Variable	Reserved	0.57	-	0	1
Price Premium	Premium (Top 25th Perc.)	0.24	-	0	1
	Premium (Top 20th Perc.)	0.19	-	0	1
	Premium (Top 15th Perc.)	0.14	-	0	1
Spatial Distance	Rural	0.22	-	0	1
	Sub-Urban	0.35	-	0	1
	Urban	0.43	-	0	1
Interpersonal Social Distancing	Entire Apartment	0.73	-	0	1
	Private Room	0.27	-	0	1
	Shared Room	0.004	-	0	1
Functional Attributes	Instantbook	0.54	-	0	1
	Strict Cancellation Policy	0.28	-	0	1
	Moderate Cancellation Policy	0.39	-	0	1
	Flexible Cancellation Policy	0.32	-	0	1
Host performance Signal	ln(Reviews)	2.29	1.47	0	6.75
	ln(Rating)	1.72	0.11	0.69	1.79
Host Trust Signal	ln(Photos)	3.01	0.67	0.69	5.65
Host reputation Signals	Superhost	0.23	-	0	1
Dual Attributes	Security Deposit	0.24	-	0	1
	Cleaning Fee	0.59	-	0	1
Host Responsiveness	ln(ResponseRate)	4.34	0.98	0	4.62
	Multiplatform	0.18	-	0	1

Panel B - 2020

Variable Type	Variables	Mean	Std. Dev.	Min	Max
Dependent Variable	Reserved	0.42	-	0	1
Price Premium	Premium (Top 25th Perc.)	0.24	-	0	1
	Premium (Top 20th Perc.)	0.19	-	0	1
	Premium (Top 15th Perc.)	0.14	-	0	1
Spatial Distance	Rural	0.22	-	0	1
	Sub-Urban	0.35	-	0	1
	Urban	0.43	-	0	1
Interpersonal Social Distancing	Entire Apartment	0.73	-	0	1
	Private Room	0.27	-	0	1
	Shared Room	0.004	-	0	1
Functional Attributes	Instantbook	0.55	-	0	1
	Strict Policy	0.06	-	0	1
	Moderate Policy	0.58	-	0	1
	Flexible Policy	0.36	-	0	1
Host performance Signal	ln(Reviews)	2.42	1.46	0	6.78
	ln(Rating)	1.72	0.11	0.69	1.79
Host Trust Signal	ln(Photos)	3.03	0.68	0.69	5.92
Host reputation Signals	Superhost	0.22	-	0	1
Dual Attributes	Security Deposit	0.25	-	0	1
	Cleaning Fee	0.60	-	0	1
Host Responsiveness	ln(ResponseRate)	4.14	1.28	0	4.62
Host performance Signal	Multiplatform	0.18	-	0	1

Note: Price Premium, Spatial Distance and Interpersonal Social Distancing are fixed and do not change between 2019 and 2020. All the other variables have been recorded in 2019 and 2020.

Table 2 – Market Performance Comparison (August 2019 versus August 2020). Market shares (calculated as the ratio of the absolute metric to the total over the Italian market in the respective year) are in parentheses. The variation 2019-2020 is computed according to the absolute value.

		Reserved Nights 2019	Reserved Nights 2020	Delta Reserved Nights 19-20	Revenues 2019	Revenues 2020	Delta Revenues 2019-2020
	Italy	1,221,375	907,453	-25.70%	$ 148,972,338	$ 123,036,122	-17.41%
Price	**Premium**	276,878 (22.67%)	222,383 (24.51%)	-19.68%	$ 59,953,445 (40.24%)	$ 50,190,548 (40.79%)	-16.28%
	Non-Premium	944,497 (77.33%)	685,070 (75.49%)	-27.47%	$ 89,018,893 (59.76%)	$ 72,845,574 (59.21%)	-18.17%
Spatial Distance	**Rural**	285,224 (23.35%)	244,351 (26.93%)	-14.33%	$ 41,285,894 (27.71%)	$ 38,769,868 (31.51%)	-6.09%
	Sub-Urban	444,273 (36.37%)	372,742 (41.08%)	-16.10%	$ 59,823,232 (40.16%)	$ 56,730,853 (46.11%)	-5.17%
	Urban	491,878 (40.27%)	290,360 (32.00%)	-40.97%	$ 47,863,212 (32.13%)	$ 27,535,401 (22.38%)	-42.47%
Interpersonal Social Distancing	**Entire Apartment**	959,747 (78.58%)	714,461 (78.73%)	-25.56%	$ 130,455,855 (87.57%)	$ 107,457,897 (87.34%)	-17.63%
	Private Room	258,817 (21.19%)	191,786 (21.13%)	-25.90%	$ 18,416,760 (12.36%)	$ 15,534,870 (12.63%)	-15.65%
	Shared Room	2,811 (0.23%)	1,206 (0.13%)	-57.10%	$ 99,723 (0.07%)	$ 43,355 (0.04%)	-56.52%

Table 3 – Regression Results. Dependent variable: reservation likelihood of property *i* at time *t*. (*** p<0.001, ** p<0.01, * p<0.05, # p<0.10). Robust Standard errors clustered at the individual level are reported in parentheses.

	M1 2020	**M1 2019**	**M2 2020**	**M2 2019**	**M3 2020**	**M3 2019**	**M4 2020**	**M4 2019**	**M5 2020**	**M5 2019**
Price Premium (Top 25th Perc.)	…	…	0.111***	-0.179***	…	…	…	…	0.081***	-0.170***
			(0.016)	(0.014)					(0.016)	(0.014)
Rural [vs Sub-Urban]	…	…	…	…	0.210***	0.078***	…	…	0.196***	0.056***
					(0.018)	(0.016)			(0.018)	(0.016)
Urban [vs Sub-Urban]	…	…	…	…	-1.037***	-0.546***	…	…	-1.013***	-0.515***
					(0.017)	(0.015)			(0.018)	(0.015)
Entire Apartment [vs Shared Room]	…	…	…	…	…	…	1.193***	0.884***	0.902***	0.759***
							(0.141)	(0.096)	(0.141)	(0.098)
Private Room [vs Shared Room]	…	…	…	…	…	…	0.807***	0.379***	0.614***	0.316**
							(0.141)	(0.096)	(0.141)	(0.098)
Instantbook	0.506***	0.606***	0.508***	0.600***	0.535***	0.629***	0.483***	0.566***	0.519***	0.587***
	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)
Moderate Cancellation Policy [vs Flexible]	0.112***	0.145***	0.107***	0.151***	0.057***	0.154***	0.097***	0.127***	0.043**	0.142***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
Strict Cancellation Policy [vs Flexible]	-0.743***	0.286***	-0.752***	0.306***	-0.958***	0.221***	-0.816***	0.236***	-1.013***	0.201***
	(0.037)	(0.015)	(0.037)	(0.016)	(0.037)	(0.015)	(0.038)	(0.015)	(0.038)	(0.016)
ln(Reviews)	0.206***	0.245***	0.210***	0.239***	0.326***	0.302***	0.204***	0.249***	0.325***	0.296***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
ln(Rating)	0.941***	0.453***	0.907***	0.503***	0.830***	0.393***	0.982***	0.510***	0.842***	0.495***
	(0.067)	(0.055)	(0.067)	(0.055)	(0.068)	(0.055)	(0.068)	(0.055)	(0.069)	(0.055)
ln(Photos)	0.297***	0.200***	0.295***	0.203***	0.247***	0.170***	0.245***	0.125***	0.209***	0.109***
	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
Superhost	0.347***	0.318***	0.341***	0.329***	0.339***	0.307***	0.352***	0.332***	0.339***	0.329***
	(0.017)	(0.014)	(0.017)	(0.014)	(0.017)	(0.013)	(0.017)	(0.014)	(0.017)	(0.014)
Security Deposit	-0.105***	-0.106***	-0.112***	-0.096***	-0.144***	-0.122***	-0.143***	-0.159***	-0.177***	-0.157***
	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
Cleaning Fee	0.013	0.103***	0.025#	0.085***	0.093***	0.147***	-0.078***	-0.015	0.031*	0.023#
	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)	(0.015)	(0.013)	(0.015)	(0.013)
ln(ResponseRate)	0.129***	0.108***	0.129***	0.107***	0.130***	0.113***	0.132***	0.114***	0.132***	0.118***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Multiplatform	0.086***	0.024	0.080***	0.034#	0.085***	0.019	0.007	-0.062***	0.022	-0.045*
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)
NUTS2 dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Day dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-3.540***	-3.266***	-3.606***	-3.306***	-3.443***	-2.837***	-4.548***	-3.742***	-4.260***	-3.302***
	(0.112)	(0.101)	(0.112)	(0.101)	(0.113)	(0.101)	(0.178)	(0.136)	(0.179)	(0.138)
N	2,023,060	1,974,731	2,023,060	1,974,731	2,023,060	1,974,731	2,023,060	1,974,731	2,023,060	1,974,731
Pseudo R2	0.120	0.103	0.120	0.104	0.151	0.112	0.124	0.110	0.153	0.118
AIC	2,439,522.56	2,412,441.34	2,438,638.22	2,410,162.78	2,354,400.61	2,389,374.68	2,429,298.22	2,395,125.94	2,348,756.88	2,373,914.80

Table 4 - Robustness Check #1 (Premium = top 20th percentile). The dependent variable is the probability of property *i* of being reserved at time *t*. (*** p<0.001, ** p<0.01, * p<0.05, # p<0.10). Robust Standard errors clustered at the individual level are reported in parentheses.

	M6 2020	**M6 2019**	**M7 2020**	**M7 2019**	**M8 2020**	**M8 2019**
Price Premium (Top 20th Perc.)	…	…	0.105***	-0.198***	0.070***	-0.190***
			(0.017)	(0.015)	(0.017)	(0.015)
Rural [vs Sub-Urban]	…	…	…	…	0.196***	0.056***
					(0.018)	(0.016)
Urban [vs Sub-Urban]	…	…	…	…	-1.013***	-0.515***
					(0.018)	(0.015)
Entire Apartment [vs Shared Room]	…	…	…	…	0.905***	0.757***
					(0.141)	(0.098)
Private Room [vs Shared Room]	…	…	…	…	0.618***	0.314**
					(0.141)	(0.098)
Instantbook	0.506***	0.606***	0.507***	0.600***	0.519***	0.587***
	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)
Moderate Cancellation Policy [vs Flexible]	0.112***	0.145***	0.107***	0.151***	0.043**	0.143***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
Strict Cancellation Policy [vs Flexible]	-0.743***	0.286***	-0.752***	0.307***	-1.012***	0.202***
	(0.037)	(0.015)	(0.037)	(0.016)	(0.038)	(0.016)
ln(Reviews)	0.206***	0.245***	0.209***	0.239***	0.324***	0.296***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
ln(Rating)	0.941***	0.453***	0.912***	0.502***	0.847***	0.494***
	(0.067)	(0.055)	(0.067)	(0.055)	(0.069)	(0.055)
ln(Photos)	0.297***	0.200***	0.295***	0.203***	0.209***	0.110***
	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
Superhost	0.347***	0.318***	0.342***	0.328***	0.340***	0.329***
	(0.017)	(0.014)	(0.017)	(0.014)	(0.017)	(0.014)
Security Deposit	-0.105***	-0.106***	-0.110***	-0.097***	-0.175***	-0.158***
	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
Cleaning Fee	0.013	0.103***	0.023	0.086***	0.030*	0.024#
	(0.014)	(0.012)	(0.014)	(0.012)	(0.015)	(0.013)
ln(ResponseRate)	0.129***	0.108***	0.129***	0.107***	0.132***	0.118***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Multiplatform	0.086***	0.024	0.081***	0.035#	0.024	-0.045*
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)
Constant	-3.540***	-3.266***	-3.606***	-3.312***	-4.259***	-3.306***
	(0.112)	(0.101)	(0.112)	(0.101)	(0.179)	(0.138)
NUTS2 dummies	yes	yes	yes	yes	yes	yes
Day dummies	yes	yes	yes	yes	yes	yes
N	2,023,060	1,974,731	2,023,060	1,974,731	2,023,060	1,974,731
Pseudo R2	0.120	0.103	0.120	0.104	0.153	0.118
AIC	2,439,522.56	2,412,441.34	2,438,855.71	2,410,085.84	2,348,920.67	2,373,789.56

Table 5 - Robustness Check #2 (Premium = top 15th percentile). The dependent variable is the probability of property *i* of being reserved at time *t*. (*** p<0.001, ** p<0.01, * p<0.05, # p<0.10). Robust Standard errors clustered at the individual level are reported in parentheses.

	M9 2020	**M9 2019**	**M10 2020**	**M10 2019**	**M11 2020**	**M11 2019**
Price Premium (Top 15th Perc.)	…	…	0.107***	-0.210***	0.063**	-0.208***
			(0.019)	(0.017)	(0.019)	(0.017)
Rural [vs Sub-Urban]	…	…	…	…	0.196***	0.057***
					(0.018)	(0.016)
Urban [vs Sub-Urban]	…	…	…	…	-1.014***	-0.514***
					(0.018)	(0.015)
Entire Apartment [vs Shared Room]	…	…	…	…	0.908***	0.753***
					(0.141)	(0.098)
Private Room [vs Shared Room]	…	…	…	…	0.622***	0.308**
					(0.141)	(0.098)
Instantbook	0.506***	0.606***	0.507***	0.602***	0.519***	0.589***
	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)
Moderate Cancellation Policy [vs Flexible]	0.112***	0.145***	0.108***	0.150***	0.044**	0.142***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)
Strict Cancellation Policy [vs Flexible]	-0.743***	0.286***	-0.752***	0.305***	-1.011***	0.200***
	(0.037)	(0.015)	(0.037)	(0.016)	(0.038)	(0.016)
ln(Reviews)	0.206***	0.245***	0.208***	0.240***	0.323***	0.297***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
ln(Rating)	0.941***	0.453***	0.918***	0.492***	0.853***	0.487***
	(0.067)	(0.055)	(0.067)	(0.055)	(0.069)	(0.055)
ln(Photos)	0.297***	0.200***	0.295***	0.204***	0.209***	0.109***
	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
Superhost	0.347***	0.318***	0.342***	0.326***	0.341***	0.327***
	(0.017)	(0.014)	(0.017)	(0.014)	(0.017)	(0.014)
Security Deposit	-0.105***	-0.106***	-0.110***	-0.097***	-0.174***	-0.158***
	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)
Cleaning Fee	0.013	0.103***	0.021	0.087***	0.028#	0.024#
	(0.014)	(0.012)	(0.014)	(0.012)	(0.015)	(0.013)
ln(ResponseRate)	0.129***	0.108***	0.129***	0.107***	0.132***	0.118***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Multiplatform	0.086***	0.024	0.082***	0.035#	0.025	-0.044*
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)
Constant	-3.540***	-3.266***	-3.615***	-3.306***	-4.262***	-3.297***
	(0.112)	(0.101)	(0.112)	(0.101)	(0.179)	(0.138)
NUTS2 dummies	yes	yes	yes	yes	yes	yes
Day dummies	yes	yes	yes	yes	yes	yes
N	2,023,060	1,974,731	2,023,060	1,974,731	2,023,060	1,974,731
Pseudo R2	0.120	0.103	0.120	0.104	0.153	0.118
AIC	2,439,522.56	2,412,441.34	2,438,972.54	2,410,348.94	2,349,025.61	2,373,891.24

Figures

Figure 1 – Distribution of Price Premium

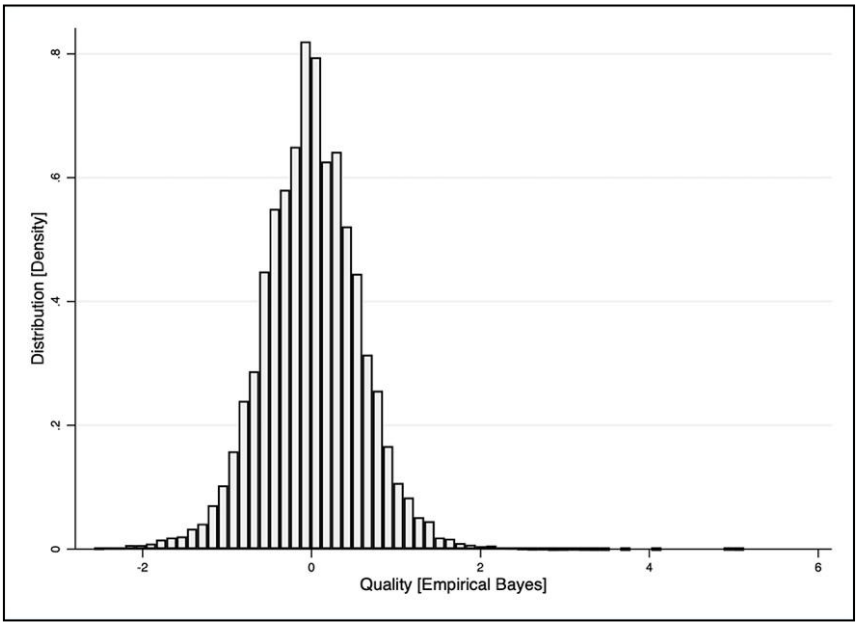

Figure 2 – Coefficients and Confidence Interval at 95%: 2020 compared to 2019