Sellers' behavior and online rating bias: A sentiment analysis on Airbnb reviews

Sellers' behavior and online rating bias: A sentiment analysis on Airbnb reviews*

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Abstract

We investigate the bias of online ratings stemming from the personal interaction between sellers and buyers, and quantify its effect on ratings and consumer demand. Using data and text reviews from Airbnb in Barcelona, we develop a text analytic algorithm and semantic analysis to measure host kindness. To expose the bias, we exploit the rating of the listing's location, which should not be influenced by host behavior. We find that kindness is positively related to the location's rating and to the listing's demand. Moreover, host kindness mitigates the negative impact of an inconvenient position on both the location score and the listing demand. We address endogeneity concerns by exploiting the shock to tourism caused by COVID-19.

Keywords: Online reviews, kindness, consumer bias, sentiment analysis, Airbnb

JEL codes: D90, L83

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1. Introduction

Performance evaluations, online reviews, and customer recommendations are increasingly used by consumers and firms, influencing purchasing, business, and working decisions. Review systems - rating scores and textual comments - are especially relevant for digital marketplaces, providing essential reputational signals to compensate for the intrinsic information asymmetry in online transactions. Unfortunately, the reliability of rating systems is often questioned due to a substantial bias towards high ratings (Zervas et al., 2021; Dellarocas and Wood, 2008). A considerable effort has been devoted to understanding the drivers of these skewed distributions, pointing to psychological factors as partly to blame (Magnani, 2020). Regret-aversion, the desire to validate purchasing decisions, or the need to reciprocate the seller's helpfulness may significantly bias ratings. These biases are likely amplified when personal relationships are established, leading to deeper psychological involvement. For example, in the home-sharing industry, positive social interactions between hosts and guests can improve the probability of positive reviews (Makkar and Yap, 2022; Fradkin et al., 2021).

In this paper, we investigate whether kind and warm personal interactions bias online ratings and whether these biases generate consumer demand. We exploit data from the Airbnb platform, focusing on reviews posted by visitors of Barcelona (Spain) in 2019. Airbnb guests rate their sojourn on seven dimensions, including the location of the house or apartment.[1] The possibility for guests to rate the location allows us to analyse the bias of the rating system. The location has three convenient characteristics: it can be objectively measured through latitude and longitude coordinates, the rating should be independent of the host's manners if unbiased, and location is an exogenous feature that cannot be modified by the host.[2]

To answer our research question, we develop a text analytic algorithm and semantic analysis based on neural networks to extract from each comment the sentences that refer to the host, inferring the quality of the host's attitude – i.e., "kindness" – towards guests. We then use regression analysis to test whether "kindness" may bias the rating of the listing's location, leveraging its actual distance from main tourist attractions. We control for omitted variables by including a large set of controls

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[1] Airbnb guests evaluate their stay according to the following categories: accuracy of the information provided by the website, apartment's cleanliness, location, check-in procedures, communication with the host, value for money, and an "overall" rating of the stay.

[2] An unbiased guest should give a low rating to a poorly located listing, even if the host provides a private transport service. A high rating given because the guest does not suffer any inconvenience from distance implies a biased rating given under the spell of kindness.

describing the listing, the host, and the contract's terms. To address simultaneity and reverse causality concerns, we exploit the shock to tourism caused by the COVID-19 pandemic.[3]

We find that the host's kinder attitude is associated with higher ratings of location and it moderates the negative effect of distance on the location score. These findings suggest that the host's behavior generates a bias, with guests feeling indebted to reciprocate the host's kindness with an overly generous valuation. This bias is stronger for listings in worse geographical positions.

The host's kindness might influence not only reviewers but also potential guests who read past reviews. We find that kinder behaviour is associated with significantly higher listing demand. When kindness increases from the 25th to the 50th percentile, demand grows from 5.7% to 8%, suggesting that text reviews convey information that the rating system does not cover. Interestingly, host kindness mitigates the negative impact of an inconvenient location on demand, indicating that the bias operates on prospective guests via past reviews, disproportionately raising demand for poorly located listings.

Several studies have identified host-guest interactions as key factors for a positive Airbnb experience (Sthapit and Jimenez-Barreto, 2018; Alsudais, 2017; Cheng and Jin, 2019), but none have previously measured how they may bias online ratings. The main challenge in measuring the bias of online ratings is that an objective measure of the attribute that is being rated is often unavailable, and research has to rely on subjective, self-reported measures (Bertrand and Mullainathan, 2001). Our first contribution to the literature is to propose an approach to identify the bias by comparing the location rating with an objective measure of its quality based on geolocation. Our second contribution is to quantify the impact of hosts' behavior on ratings and on listing demand. Kindness is an essential intangible asset in competitive markets (Tillquist, 2008).[4] Our third contribution is to shed light on the reasons for the bias of the rating system, highlighting the role of personal interactions. We show that host kindness not only biases location ratings but also influences consumer demand, raising the demand for listings in less convenient locations. Understanding these biases can help promote trust and transparency in online transactions, enhancing the efficiency of the review system.

The rest of the paper is organized as follows. Section 2 presents the pertinent literature and our hypotheses. Section 3 describes the data and variables used for the empirical analysis. Section 4 outlines our empirical strategy. The main results are presented in Section 5. Section 6 includes robustness checks and extensions. Section 7 concludes.

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[3] The impact of Covid-19 on the short-term rental industry has been studied from many perspectives, using different econometric methodologies to identify the effect. For example, Llaneza Hesse and Raya Vìlchez (2022) apply an extended diff-in-diff approach, the Synthetic Control Method (SCM), to estimate the effect for the city of Barcelona; Skare, Soriano and Porada-Ronchon (2021) use panel structural auto regressions (PSVAR) and system dynamic modelling to link the effect with past pandemics for a large group of countries, from 1995. On the consequence of the pandemic on the tourism industry see also the Special Issue in *Tourism Economics*, "Post-COVID-19 Tourism Economics and Economic Geography Research" (2022).

[4] "Be nice. Might airlines consider kindness as a business strategy?" The Economist, March 22nd, 2012.

2. Related literature and hypotheses

The efficient functioning of digital platforms depends on the possibility for consumers to review suppliers based on the level of satisfaction achieved after the purchase, both through predefined rating systems and by posting a detailed feedback that reviews various aspects of the product or service. This system is essential both on the demand side, reducing the information asymmetry for consumers, and on the supply side, allowing firms to reap the benefit of reputation (Goldfarb and Tucker, 2019; Chen and Xie, 2008) and improve the quality of their offering (Ananthakrishnan et al., 2023).

What in theory is an efficient system, in practice is vulnerable to psychological biases that may skew ratings on the high-end tail of the distribution (Zervas et al., 2021). Regret-aversion, for example, makes consumers more likely to remember the positive aspects after the purchase, thus minimizing negative aspects (Lind et al., 2017). Likewise, the desire to validate the purchasing decision once it is sunk may explain the higher propensity to leave a positive review (Hu et al., 2009). The dimension of informality characterizing the service provided by Airbnb contributes to making users more tolerant and understanding. Therefore, guests using the platform are more likely to feel satisfaction from the experience, have their expectations surpassed, and leave a positive review (Bridges and Vasquez, 2018).

These behavioral biases are likely exacerbated when a personal relationship is established between hosts and guests, causing a deeper psychological involvement of the reviewer. The Airbnb platform particularly leverages intrapersonal authenticity in creating brand-loving customers (Mody and Hanks, 2019), and hosts' personal profiles with social-oriented self-presentations have been shown to increase the seller's revenues (Nieto Garcıa et al., 2020). The interaction with the host is indeed crucial for guests evaluating their experience (Sthapit and Jimenez-Barreto, 2018; Cheng and Jin, 2019; Cavique et al., 2022), and most reviews mention the host (Alsudais, 2017). If a personal relationship is established, the guest might be reluctant to reveal his true opinion, when it comes to "giving bad news" (Dellarocas and Wood, 2008). Furthermore, the personal relationship exacerbates the reciprocity bias, which involves the tacit expectation of mutually positive evaluations and leads to omitting information that may be unpleasant (Fradkin et al., 2021; Proserpio et al., 2018). This phenomenon is aggravated by the lack of anonymity of review systems, as reviews are linked to the user profile – else they would be considered unreliable. These results support our conjecture that a more satisfactory personal interaction between hosts and guests may bias the ratings upwards, even on those dimensions – such as the score given to the location– that should not be related to the quality of the relationship with the host. This "halo effect" (Leuthesser et al., 1995) - an individual's tendency to bias his responses about an attribute by his predisposition toward another attribute - has been already detected in the hospitality industry for hotel stays (Nicolau et al., 2020) and might also influence guests on Airbnb platform, where the personal interactions might induce a psychological bias on reviewers and their ratings. Accordingly, we make the following hypothesis:

Hypothesis 1 *The rating of location is positively related to the host's kindness, regardless of the location of the listing.*

The guest's unwillingness to give "bad news" is likely to be stronger, the worse is the news, as the host is not responsible for the listing's bad location (Dellarocas and Wood, 2008). Hence, the behavioral bias induced by the host's kindness on the location rating is likely higher, the more decentralized the listing, thus resulting in a higher skewness of the rating. Thus, we suppose the following:

Hypothesis 2 *The host's kindness moderates the negative impact of the listing's distance from the city's points of interest on the location score.*

By observing the impact of the host's kindness on ratings, Hypotheses 1 and 2 focus on the potential bias induced on reviewers, i.e. past guests. However, host attitude might have an effect also on prospective guests, who could be influenced to book an apartment by reading about the host's behavior in past reviews (Bae et al., 2017). Recent literature has highlighted the demand-expansion effect of higher ratings (Magnusson, 2022). Moreover, the literature studying the role of textual reviews on demand suggests that consumers respond to the content of online reviews, in addition to customer ratings (Lawani et al., 2019; Lee et al., 2022) while Archak et al. (2011) find that textual comments influence consumer decisions even when a star rating system is available. This evidence suggests that the host's behavior might produce a direct effect on demand, beyond the effect passing via the rating channel. We therefore formulate the following hypothesis:

Hypothesis 3 *The host's kind attitude has a positive effect on the listing's demand, con- trolling for its overall rating.*

Hypothesis 3 suggests that potential guests rely not only on the information summarized by the rating scores, but also on the textual reviews left by previous guests. Such comments provide information on the hosts' attitude which influences their decision to book an apartment (e.g. Wu et al., 2021, on hotel demand forecast). As prior work reported decreasing returns to kindness (e.g. Becker et al., 2012 on tipping behavior), in the empirical analysis we assume a quadratic effect of kindness on demand.

The finding that host kindness raises the demand for their listing could be attributed to the fact that prospective guests consider the host's attitude revealed by past reviews as a dimension of quality, whereby "kindness" is an additional service provided by the host. Indeed, kind and welcoming hosts promote a home-like feeling by guests (Lv et al., 2021). Since host kindness and listing location can be considered as two independent dimensions of quality, unbiased guests should value the service provided by the host's kindness consistently across differently located listings, and vice-versa. What if, instead, future guests place a disproportionate value to the host's kindness when the listing is more inconveniently located? This would imply that host kindness biases guests' preferences about the location dimension. Therefore, also prospective guests are subject to a halo effect, whereby their valuation of the host's attitude spills over their preference for the listing's location. In such case, the effect of kindness would depend on the listing's location, leading to the following hypothesis:

Hypothesis 4. *The host's kindness mitigates the negative effect of a more decentralized location on listing demand, controlling for its overall rating.*

3. Data

We chose Airbnb data for our empirical analysis due to several advantages. Airbnb data offer an objective measure of quality to compare with ratings and provide an ideal research case for investigating personal relationships in online services. Firstly, there is no intermediary between parties to influence ratings. Secondly, Airbnb uses a double-blind rating system, where hosts and guests submit reviews before seeing each other's comments, ensuring unbiased feedback (Fradkin et al., 2021). Thirdly, personal interactions are intrinsic to Airbnb, as hosts and guests often meet or live nearby. The platform embodies the sharing economy philosophy, fostering a community where people share spaces and experiences, highlighting its social aspect (Guttentag et al., 2018; Zervas et al., 2017).

The Dataset

We collected data from 8,758 Airbnb listings in Barcelona in 2019, along with 257,477 guest reviews. Barcelona was chosen because it ranks among the top ten most visited cities in the world in 2022 according to Euromonitor. The unit of observation in our analysis is the listing, managed by a host. For each listing/host, we measured the average kindness conveyed by online reviews left by guests in 2019. We constructed three alternative measures of kindness using semantic analysis and machine-learning techniques. Our multi-method approach combines text analysis with econometric analysis, triangulating data and reviews from the publicly available Inside Airbnb database (http://insideairbnb.com) and AirDNA, a data analytics company providing information about Airbnb properties (https://www.airdna.com/). The next section details how we apply machine learning to measure kindness.

Measuring Kindness: A Machine Learning Approach

We analysed the text of 257,477 Airbnb reviews from Inside Airbnb using semantic analysis tools. After processing the reviews for consistent formatting and translating them into English, we extracted sentences commenting on the host's behaviour during the stay[5], which we used to construct three different measures of kindness.

First-name is the percentage of reviews where the host is mentioned by first name, indicating a familiar and friendly relationship. This is an unsophisticated but direct indication of the host-guest interaction.

Polarity is obtained by using the Textblob package, a currently available tool of Sentiment Analysis which analyses the words contained in each review basedon the specific dictionary and returns a value between -1 and 1 as the output.This value represents the level of positivity of the sentiment of the review. We averaged the polarity scores for each host and normalized them on a scale from 1 to 10. This measure evaluates the positivity of the reviews. For instance, "The hosts were very helpful and communicative" received a score of 0.7, while "Ana is a great host and communicative" got 0.6. A comment like "After our initial host cancelled our trip on the day, Monica was very quick to say we could stay from that night" received just 0.07, barely positive.

Finally, we developed a tailored measure, *Rank*, using a six-layer neural network to classify reviews into four categories: negative, neutral, positive, and excellent.[6] Neutral reviews are those that do not mention the host. We trained our algorithm on 5,000 reviews and validated it on another sample. The variable Rank is obtained as a weighted average of the relative frequencies of the four classes for every listing. For example, "After our initial host cancelled our trip on the day, Monica was very quick to say we could stay from that night" was classified as positive. Similarly, "although we never met Eduardo because the check-in and check-out were self-made, he was always available by phone for any eventuality" was also classified as positive despite the negative incipit. To calculate the host's kindness, each class is converted into a grade (10 for excellent, 7.5 for positive, 5 for neutral, and 0 for negative), and the host's kindness score (Rank) is the weighted average of these grades. Figure 1 reports an example for the host Jordi. The algorithm is described in detail in Appendix A.1

Figure 2 compares the output of the First-name, Score Polarity and Rank class for a small sample of reviews, illustrating how they distinguish between positive and negative review, and

[5] We identified sentences discussing host behaviour based on words associated exclusively to humans, e.g., personal pronouns, "host", "owner", "staff", "questions", "helpful", "help", "recommendation", "communication", "service", "friendly", "responsive".

[6] Sentiment analysis typically classifies reviews as negative, neutral, or positive. However, due to the rarity of negative reviews and the great heterogeneity of positive ones, we preferred a more nuanced classification.

highlighting that Rank identifies positive sentiments even when they are nuanced. Figure 3 reports the distribution of the rating and kindness measures used in the econometric analysis, showing that kindness measures exhibit a more balanced distribution compared to traditional rating systems which are biased upwards.

--- Figure 1, Figure 2 and Figure 3 around here ---

Other variables

Our research questions focus on the relationship of kindness with the listing's location rating the guests assign at the end of their stay, the listing's demand in 2019, and the actual distance of the apartment from the city's point of interest.

Location score is the average of the location scores assigned by guests in 2019, normalized by *Insideairbnb* on a scale from 1 (low) to 10 (high) and visible on the listing's website. It is one of the six characteristics rated by guests, in addition to an overall rating. Individual scores in the Airbnb rating system are highly correlated, but the location score shows the lowest cross-correlations (Appendix Table A.2).

We use the logarithm of the total number of reviews posted by guests on Airbnb for each accommodation in 2019 and the occupancy rate in 2019 to measure the listing's demand. The (log) number of reservations is used for a robustness test. Although leaving a review is not obligatory, Airbnb estimates that at least 70% of guests leave a review, and Fradkin et al. (2021) report that at least 67% of reservations result in a review. The platform's social vocation, frequent reminders, and reciprocity rule, whereby guests and hosts can see each other's reviews only if both leave one (Proserpio et al., 2018), reduce potential bias from non-compulsory reviews.[7]

The listing's average distance from the 14 most popular tourist places in Barcelona[8] indicates the location's convenience (Figure 4). We identified Barcelona's attractions identified using tourist guidebooks and blogs (Tripadvisor, Lonely Planet, Skyscanner, Barcellona.org) and then calculated the distances from each listing the 14 attractions. Because Barcelona's attractions are spread out over a wide area the average distance from all 14 sites provides a comprehensive indicator of how well-positioned a listing is with respect to points of interest.

--- Figure 4 around here ---

Control variables include a large set of host and property attributes, service, and contractual terms widely used in short-term rental literature (Liang et al., 2020), ensuring that the analysis accounts for potential confounding factors that might influence the outcomes. The *overall rating*

[7] Fradkin and Holz (2023) find that a policy incentivizing reviews does not change the impact of ratings on listing demand, and conclude that selection problem is not severe.

[8] Specifically, we consider the following 14 touristic attractions: Placa d'Espanya, Placa de Catalunya, Sagrada Familia, La Rambla, Casa Battlo, Casa Mil`a, Barcelonetta Beach, Boqueria, Park Guell, Historia Museum, Castell de Montjuic, Mir`o Foundation, Gracia district, Music Palace.

captures the guest's overall satisfaction and is thought to influence future bookings (e.g., Gunter and Önder, 2018). Including it ensures our kindness index has a separate role and is not conflated with general satisfaction. It is based on a ten-level scale from 1 (lowest) to 100 (highest).

Host attributes include inexperience, proxied by the year the listing first appeared on the platform, and whether the host manages multiple listings (*Multiproperty*), indicating a more professional approach. Superhost status, awarded by Airbnb, indicates proficiency and reliability, reflecting hosts who consistently provide excellent experiences (Ert and Fleischer, 2019). We also control for variables related to the host's social behavior, such as *Host response rate* - the share of inquiries and bookings replied by the host within 24 hours; host acceptance rate and *Verified identity*, indicating if the host's identity is verified. These attributes collectively describe the host's responsiveness (Gunter and Önder, 2018), reliability, and professionalism (Boto-García, 2024), all of which can influence guest satisfaction and the likelihood of positive reviews.

Property attributes include the number of bathrooms, bedrooms, and the size of the listing, measured by the number of guests it can accommodate. We also control for the number of photos on the listing's webpage, as a host with a more attractive property is expected to post more pictures. Quality amenities, such as air conditioning, microwave, dishwasher, washing machine, and complimentary parking space, indicate the apartment's quality and the host's investment in comfort. Luxury amenities, such as a garden, swimming pool, sauna, or terrace, imply an even larger investment and higher-end accommodations and are rare occurrences. Amenities enhance the overall appeal and comfort of the property, potentially increasing its demand and guest satisfaction.

Service terms can significantly impact the booking decision and the overall experience, influencing demand and reviews. They include the average price in 2019, a critical factor affecting demand; the stringency of cancellation policy; the request of the guest's phone number and of security deposit. Appendix Table A.2 details definitions and sources of all variables used.

Our empirical analysis focuses on 4,150 entire apartments, excluding single rooms to maintain a consistent host-guest relationship basis. This approach ensures comparability across listings, as entire apartments provide a more uniform setting for assessing the factors under study. In the robustness section, we re-estimate our regressions on shared and single rooms, ensuring that our findings are not driven by the type of accommodation. Tables 1 and 2 show descriptive statistics for the sample of entire apartments. The average location score and overall rating are high (9.7 and 91.28, respectively), with high minimum values, in line with the literature suggesting a bias towards high ratings in the review system.

--- Table 1 and Table 2 around here ---

Appendix Table A.4 reports the matrix of cross-correlations, to understand the relationships between different variables.

4. Empirical strategy

The first step of the empirical analysis relies on the guest's rating of the listing's location to reveal the bias generated by the host's kindness. This variable is useful for several reasons: the location cannot be altered by the host, its distance from attractions is objectively measured in kilometres by cross-referencing more sources, and it is a distinct physical characteristic rated separately within a system covering six aspects (of which, three rate personal interactions) and an overall evaluation. Therefore, the location rating should reflect only the guest's valuation of the listing's position. If not, the guest's evaluation is biased by the host behaviour, implying that guests are reluctant to give bad news to a kind but poorly located host suggesting that. Appendix Table A.3 shows the correlation between the location rating and other scores is the lowest.

To test whether host kindness moderates the negative impact of an inconvenient location on its rating, we regress the location score of each listing on the host's kindness and interact the kindness index with the listing's average distance from city points of interest:

$$LocationScore_i = \beta_0 + \beta_1 Kindness_i + \beta_2 Distance_i + \beta_3 Kindness_i * Distance_i + Controls_i + \epsilon_i. \tag{1}$$

The second step focuses on the effect of the bias on consumer demand. We test whether host kindness, by influencing past guests' reviews, affects the listing's demand by potential guests who read the reviews. To do so, we assume that an inconvenient location negatively affects guest decisions to rent the apartment and test whether host kindness, perceived through reviews, mitigates this negative effect, thereby suggesting that a bias exists, and reduces the negative impact of a poor location on demand. We account for decreasing returns to kindness (Becker et al., 2012) using use a quadratic specification, as follows:[9]

$$\begin{aligned} ListingDemand_i = {} & \beta_0 + \beta_1 Kindness_i + \beta_2 Kindness_i^2 + \beta_3 Distance_i + \qquad (2) \\ + \quad & \beta_4 Kindness_i * Distance_i + \beta_5 Kindness_i^2 * Distance_i + Controls_i + \nu_i. \end{aligned}$$

We recognize the challenge in identifying the causal effect of kindness on the quantity sold due to omitted variables, simultaneity, and reverse causality. To address the omitted variable problem, we include extensive controls for apartment and host characteristics, website informativeness, and

[9] Tables report tests of joint significance of the linear and quadratic terms. Estimation results with a cubic specification are in the Appendix.

contract terms, all sourced from InsideAirbnb. However, as Proserpio et al. (2018) noted, unobserved improvements in the listing's quality could influence ratings and reviews. To mitigate this, we compute kindness indexes based only on sentences describing the host's attitude, control for apartment quality with Quality and Luxury amenities, and include the Overall rating to absorb the residual positive effect of quality shocks.

Reverse causality, where hosts of poorly located apartments might adjust their behavior to obtain better reviews, is another threat. Data inspection suggests this is unlikely. Appendix Table A.4 shows low correlation between kindness and distance from tourist attractions. Multivariate analysis in Appendix Table A.5 indicates kindness relates to many apartment and host characteristics but not distance.

We further address reverse causality and simultaneity using an econometric strategy that exploits the COVID-19 lockdown. The lockdown froze tourism for several months in 2020, halting Airbnb activity and review postings. When the lockdown lifted, new demand was based on pre-COVID reviews, providing a unique opportunity to test the impact of pre-existing kindness on demand. This strategy, by lagging kindness by nearly six months, insulates it from reverse causality or simultaneity. Tourists in Summer 2020 made decisions based on old reviews, allowing us to identify the effect of host kindness on the decision to rent the apartment.[10]

We also account for a potential sample-selection problem, as some hosts active in 2019 may have left the market during the COVID period in 2020. We use a two-step Heckman model: the first step estimates the probability of a listing being posted and rented in 2020, and the second step assesses the impact of pre-COVID host kindness on post-lockdown listing demand in Summer 2020 for active listings.

5 Results

5.1 Does kindness bias the reviewer's rating of the apartment?

To determine if a bias exists, we estimate the relationship between host average kindness and the average rating of the listing's location. Our regressions control for the listing's average distance from 14 tourist attractions, its demand (number of reviews or occupancy rate) and average price. Moreover, as rating scores may be cross-correlated, we include a large set of potential confounding

[10] For other studies exploiting the pandemic as an opportunity to instrument otherwise endogenous variables see for example, Milone, Gunter and Zekan (2023), who rely on a two-way fixed effects (TWFE) difference-in-difference design with continuous country-level treatment to identify the pricing responses of Airbnb listings to demand variations, and Boto-Garcia and Leoni (2023), who study traveling behaviour (distance and choice of location) by employing an endogenous switching regression that exploits the variation in the distance travelled before and after the COVID 19 pandemic.

factors, i.e., characteristics of the accommodation and the host that should affect other scores but not the rating of location. A “bias” exists if the host, through a kinder attitude, sways the guest to assign an implausible location score, given the actual positioning. Under the alternative of unbiased reviewers, the rating of location should not be related to host kindness (Table 3).

Columns (1)-(3) show that location rating is negatively related to average distance and positively related to kindness, even though an unbiased reviewer should not be affected by host’s kindness when evaluating an objective characteristic such as the apartment’s distance from city attractions. Notably, a high rating of location given because the host alters the perception of distance by giving a ride, reducing the inconvenience, would indeed show that the bias exists, as the rating is assigned under the spell of the host’s kindness. This evidence is consistent with our Hypothesis 1.

— Table 3 around here —

In Columns (4)-(6), we add interactions between kindness and average distance to test whether the bias increases as the location of the apartment becomes more inconvenient (Hypothesis 2). Results show that both kindness and distance remain significant while the multiplicative term is positive and highly significant. The evidence suggests that the host’s kind attitude can assuage the guest’s judgment of a physical attribute like distance from focal points and that his reluctance to give “bad news” is stronger the worse is the news, i.e., the greater the distance. Our tests show that the effect of kindness on the location score at the median of the average distance from focal points (2.14 km) is positive and significant. Moreover, kindness mitigates the negative impact of distance as we find that, evaluated at the median values of kindness, the impact turns significantly positive.

Turning to control variables, we find that the location score is higher when the host is more experienced, is a Superhost, is not a professional operator and has a lower response rate, the smaller the house and the higher the quality of amenities. These features should not affect the rating of location, and the fact that they do may derive from its cross-correlation with the other scores, justifying our strategy to include them all to cleanse the confounding effects.

5.2 Host behaviour, listing demand, and the kindness bias

We now test how host kindness affects listing demand, leveraging on the listing location and controlling for the average price in 2019 and the overall rating, a key control variable that has been found to exert a strong influence on consumer demand (Magnusson, 2022). Accounting for the overall rating allows us to test whether kindness has an independent effect on demand. We also control for the usual set of host attributes and listing characteristics included in Table 3. Results are in Tables 4 and 5.

— Table 4 around here —

Results show that listing demand is positively related to kindness and overall rating and negatively related to distance. To quantify the economic significance, we calculate the magnitude of the effect by using the estimated coefficients. We find that an increase in host kindness from the 25th to the 50th percentiles of the distributions of Score POL, Rank, and First-Name - defining a shift from a not-too-kind to an average friendly host - leads to an increase in listing demand of 8%, 5.7%, and 12%, respectively.[11] The evidence supports our Hypothesis 3.

The listing's demand is positively related to host experience, number of photos, quality of furnishing, response and acceptance rates, and host's verification, and negatively related to the listing's price, request of security deposit and to multiproperty, suggesting that our measures of kindness are not picking up the artificial social skills of hired professionals but the actual quality of personal interactions. Indeed, as shown by Appendix Table A.4, multiproperty is negatively related also to host kindness indicating that guests discriminate between a genuine, welcoming attitude and the affected solicitude of a professional, and only the former increases listing demand (Lv et al., 2021).

In Table 5, we add the interactions between kindness and average distance to test whether host kindness mitigates the negative effect of a listing's poor location on its demand (Hypothesis 4), and in Table 6 we repeat the analysis with the occupancy rate (the number of booked nights divided by the sum of the available and booked nights) to measure listing demand, as a robustness test.[12] Results show that the kindness scores and their interactions are always statistically significant, in line with our predictions. This evidence suggests that the halo effect generated by host behaviour has a tangible effect on the listing's demand, as tourists, at the margin, seem to place more importance on the host's reviewed kindness than on location, depending on the distance of the apartments. Altogether our results imply that host kindness can bias not only past guests' judgment when they rate the apartment's position but also future guests' decisions to book an apartment.

— Tables 5 and Table 6 around here —

To allow better interpretation of results, we calculate the elasticity of demand to distance (in km) and how elasticity changes at increasing levels of kindness. If kindness moderates the negative impact of distance, we should find that the sensitivity of demand to distance gradually decreases as kindness increases. In Figures 5, 6, and 7 we used regression results from Table 5 and plotted the

[11] The magnitude of the impact of First-Name depends on its skewed distribution, as many reviews do not mention the host's name.

[12] We have also used the log of the number of reservation days (Airdna), and found that all results (available on request) hold.

elasticity as a function of distance at the 50th, the 90th, and 95th percentile of the distributions of kindness measures. We find that demand becomes more elastic (i.e., decreases), as the distance from the city's points of interest grows. Notably, as average kindness increases, the slopes flatten, suggesting that host kindness reduces the sensitivity of guest's demand to a bad location, which implies that kindness moderates the negative impact of an adverse characteristic of the listing.

— Figures 5, 6, and 7 around here —

6. Robustness and extensions

6.1 A quasi-natural experiment exploiting COVID restrictions on tourism

We address reverse causality and simultaneity concerns in the relationship between listing demand and kindness by estimating the effect of pre-COVID kindness in 2019 on the demand by guests renting the apartment in the summer of 2020, after the travel ban was lifted. We re-estimate the relationship between listing demand and kindness using the post-lockdown listing demand in late spring-summer 2020 and a six-month lagged measure of kindness based on 2019 reviews. Due to the freeze on tourism in early 2020, listing demand after the lockdown was based on "old" reviews from 2019, reducing causality concerns.

A further identification issue might derive from sample-selection bias since some hosts withdrew their apartments from the market due to the pandemic, making the dependent variable (demand) unobservable for these listings. To address this, we use the two-stage Heckman selection model. In the first stage, the dependent variable is a binary indicator of whether each listing available in 2019 received at least one review in 2020 (indicating it was rented). In the second stage, the dependent variable is the demand for listings available in 2020 after the lockdown was lifted. Attributes explaining the probability of a listing being active in 2020 are dated at 2019, while all regressors in the second step refer to 2020, except Host Kindness and Overall Rating, which date back to 2019.

Results are reported in Tables 7 and 8. In the first stage, the probability of posting a listing in 2020 is positively related to the host's kindness, acceptance rate, overall rating score, and quality of furnishings. The multi-property dummy is positive, suggesting business agencies were more willing to participate the market than private hosts. Other control variables enter with the same signs as in Table 4.

— Table 7 and Table 8 around here —

The second stage estimates the relationship between host kindness and the demand for active listings in 2020, accounting for the sample-selection problem. Our results show that the three kindness indicators are positive and significant, showing that visitors choose their accommodation driven by the host's attitude as reflected in reviews that were the last available with personal content before the lockdown. Our findings hold to concerns about reverse causality and sample-selection and support Hypothesis 3, suggesting that host behaviour is an independent attribute affecting Airbnb demand.

6.2 Other robustness and extensions

The robustness test concerns the functional form of the demand-kindness relationship, which we have hypothesized as quadratic to express diminishing returns of kindness. However, the inverted U-shape form implies that the effect of kindness becomes negative after reaching the maximum value. Therefore, we experimented with a cubic form, to capture whether returns to kindness remain positive after deceleration. Results in Appendix B Table B.1 confirm the significance of kindness, while Appendix Figure B.1 shows the positive effect of kindness first climbs steeply, slows down, then flattens but stays positive.

Next, we extend the analysis to hosts renting single and shared rooms. Guests sharing their living space with hosts or other guests might be more eager for personal interactions and sensitive to host behaviour. We repeat the full set of regressions on the sample of single and shared rooms. Results in Appendix C Tables C.1, C.2, and C.3 show that evidence holds for Hypotheses 1 and 2 (kindness leads to biased ratings of location) and Hypothesis 3 (kindness positively affects demand), but not Hypothesis 4 (kindness mitigates the negative effect of distance on demand). This suggests kindness might be less relevant for guests in shared and single rooms, despite the greater "sharing" content of the accommodation. This may be because Airbnb users choosing single rooms are more sensitive to price than to host manners. Indeed, comparing the signs of control variables for single rooms and entire apartments shows "quality" is no longer significant, "luxury" is negatively signed, and host identity verification is insignificant. Demand elasticity calculations from log-log regressions show a 1 percent price increase results in a 0.18 percent demand drop in single rooms and 0.09 percent (or less) in entire apartments. Higher demand elasticity in single rooms indicates guests are more sensitive to price than to host behaviour.

7. Conclusions

Rating systems provide invaluable information about the quality of online transactions, and yet they are well-known for their substantial bias (Zervas et al., 2021), undermining the reliability of the mechanism. In this paper, we shed light on one possible cause of distortion by investigating whether host behaviour biases ratings left by guests on Airbnb platform and affects listing demand. We perform semantic analysis on reviews left in 2019 on Airbnb platform in Barcelona and derive three alternative measures of host's kindness. To uncover the bias, we focus on the rating of the listing's location, an attribute that can be objectively measured, should be orthogonal to the host's behavior if unbiased, and cannot be altered in response to bad reviews.

Our results show that the kindness shown by the host to the guest during her stay can induce an upward bias on the ratings left by reviewers. We find that the bias on location rating is stronger, the worse is the listing's location with respect to the main touristic attractions, suggesting that reviewers may find it difficult to rate objectively when the host has been kind and the bad feature of the listing is not his fault. Hence, host kindness mitigates the guest's evaluation when he has to rate the listing's location. Turning to market performance, we find that kindness positively affects listing demand, as expected. However, our results also show that higher evaluations of kindness by previous guests reduce the negative impact of a poor location, especially for more inconveniently located listings.

Overall, our results have several theoretical and practical implications.

From a theoretical perspective, our findings contribute to our understanding of the review system and its impact on demand, emphasizing the independent role of kindness as a distinct attribute influencing review behavior. At a broader level, these results enrich the understanding of how intangible factors shape online review systems. Furthermore, this research can shed light on the mechanisms of information revelation in online services, highlighting the interaction between personal behavior and rating inflation (Filippas et al., 2022).

From a managerial perspective, our findings underline the strategic importance of kindness as an intangible asset in modern competitive markets (Tillquist, 2008). Hosts who exhibit kindness not only mitigate negative evaluations of objective shortcomings, such as poor location, but also enhance overall demand for their listings. This insight suggests that platforms and hosts should prioritize personal interactions and foster positive guest experiences to remain competitive. Additionally, the findings point to the potential for leveraging "guests' comments in their own words" as a tool to counteract rating inflation, thereby enhancing the credibility of review systems.

Nonetheless, the study has several limitations that suggest opportunities for future research. First, the analysis focuses on Airbnb listings in Barcelona. By concentrating on a single city, we do not need to account for location-specific factors like differences in the urbanistic structure, touristic attractiveness or cultural context. However, exploring different geographic environments could shed further light on the role of personal interactions in review systems. Second, because Airbnb reviews are not mandatory, there is a potential selection bias, as those who leave reviews may not reflect the broader guest population. Further research is needed to better understand review behavior and identify patterns among non-reviewing guests, possibly extending the analysis to other platforms with mandatory review systems. The analysis could also be extended also on the temporal dimension, to understand the long-term impact of host behavior and the role of external factors like local or global travel trends and competitor reviews. Addressing these limitations would deepen our understanding of online review systems and their implications for digital marketplaces.

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Figure 1: Example of construction of *Rank*

Host	**Review**	**Class**
Jordi	The host is superb, very helpful, from showing us map and places to visit and organizing safe taxis for us.	Excellent
Jordi	Hosts are great and make check in and check out easy.	Positive
Jordi	Everything was great!	Neutral
Jordi	Check in regularly which is appreciable.	Neutral

Rank				
Host	Frequency negative	Frequency neutral	Frequency positive	Frequency excellent
Jordi	0%	50%	25%	25%

Figure 2: Reviews and ML-based kindness variables

Text of the review	**First-name**	**Score Pol. [-1,1]**	**Rank class**
Roland was great he gave us a lot of tips of Barcelona and cautioned us on things that we may not be used to m. j he let us use anything and everything in the apartment and provided a lock for our room when we would leave for safety.	1	0.8	Excellent
I am very grateful for the availability of margarita, I have rarely been lucky enough to find a host like that !	1	0.2569	Excellent
The hosts were very helpful and responsive.	0	0.2	Positive
Ana is a great host and communicative	1	0.8	Positive
Many thanks to the host.	0	0.35	Positive
After our initial host cancelled our trip on the day, Monica was very quick to say we could stay from that night!	1	0.2708	Positive
Although we never met Eduardo because the check-in and check-out were self-made, he was always available by phone for any eventuality.	1	0.4	Positive
Regrettably, the host called me at 4,30pm on the check-out day and accused me of locking the room and not leaving the place, making him unable to accommodate the next guest and wanted compensations from me. I was reachable via ¡hidden by airbnb¿ the whole day, and so if he asked me earlier, I could have explained and helped, but instead he called at 4,30pm and accused me of lying about it.	0	-0.0933	Negative
We were extremely disappointed that Eduard refused to cancel and give us a refund due to the violent street protests.	1	-0.1159	Negative
When we turned up at 12pm (earliest time stated on post to enter room) we could not get hold of host for 30 mins and we were then told the room was not ready for us. Once it was not in contact with us he did do everything he could to help but unfortunately the lack of communication prior to the stay meant that the start of our stay wasn't as imagined.	1	-0.2	Negative
Very bad service not clear announcement.	0	-0.48	Negative

Figure 3: Distribution of ratings and kindness indicators

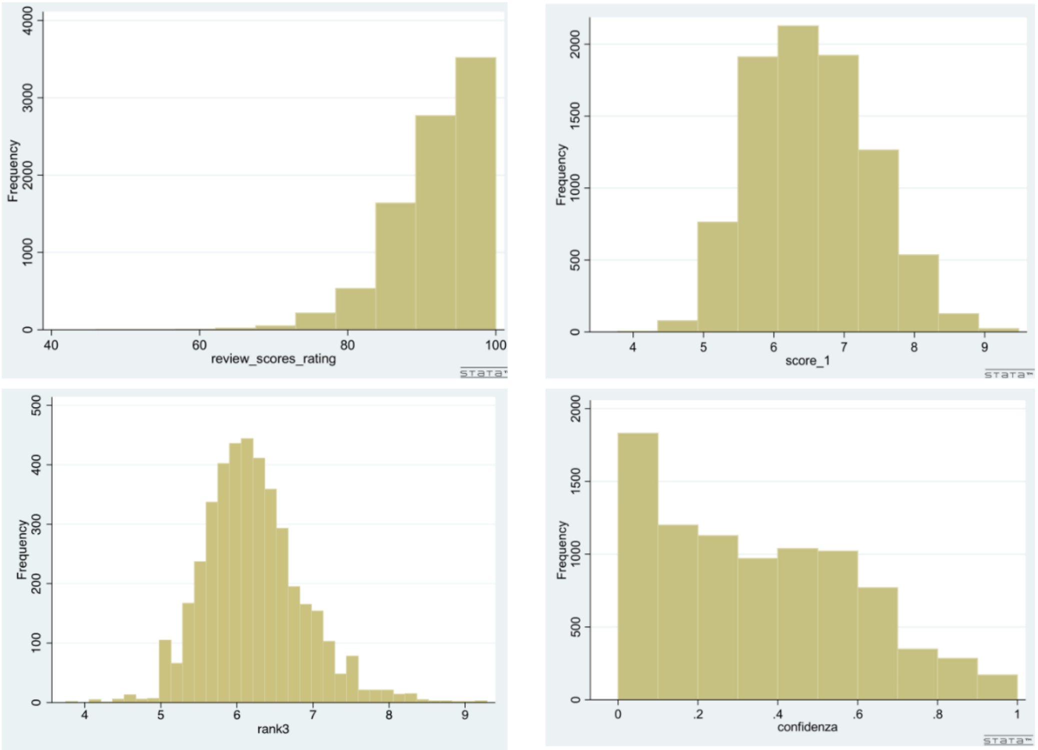


Figure 4: Map of the 14 most popular places for tourists in Barcelona

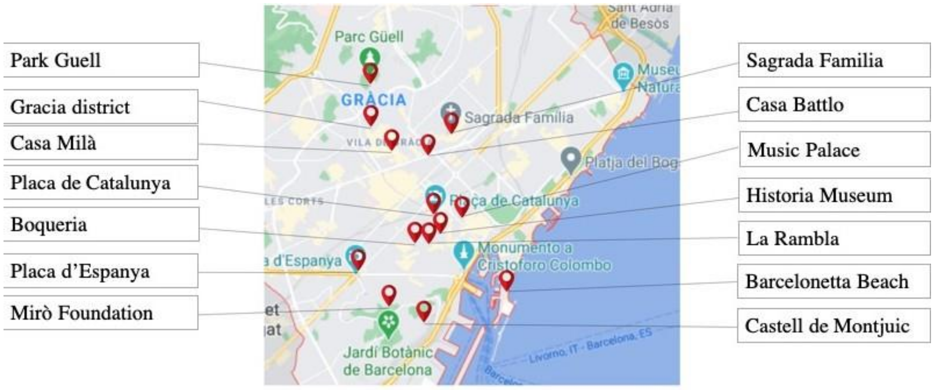
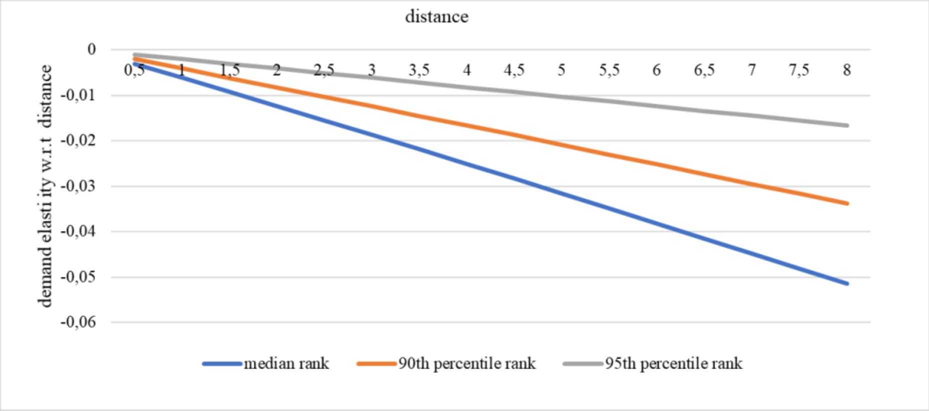
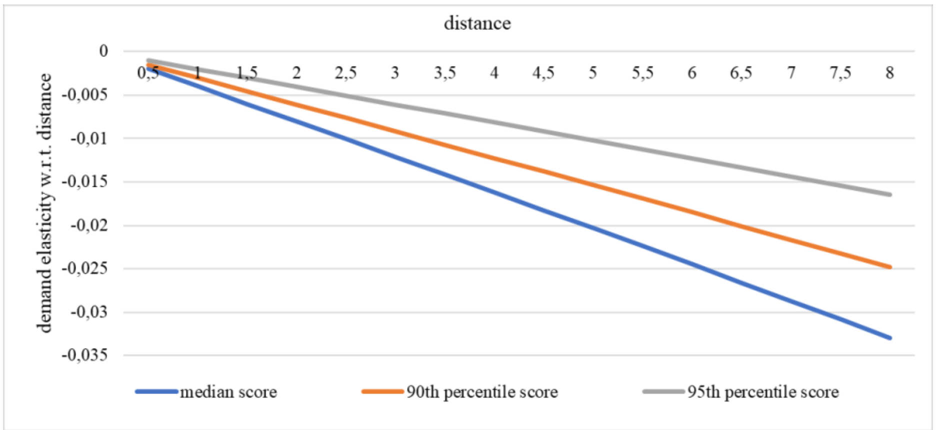


Figure 5: Marginal effect of average distance on listing demand moderated by kindness (Rank).



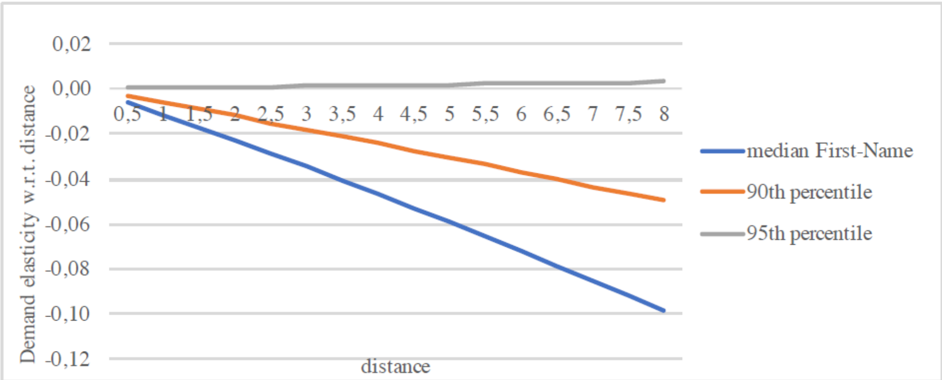
Note: Elasticity of demand in function of average distance, for different levels of Rank.

Figure 6: Marginal effect of average distance on listing demand moderated by kindness (Score)



Note: Elasticity of demand in function of average distance, for different levels of Score Polarity.

Figure 7: Marginal effect of average distance on listing demand moderated by kindness (First-Name)



Note: Elasticity of demand in function of average distance, for different levels of First-Name.

Table 1: Summary statistics - kindness measures

	mean	sd	min	median	max	count
Rank	6.212	0.649	3.75	6.15	9.29	4,150
Polarity	5.844	0.503	4.06	5.79	8.45	4,150
First-name	0.276	0.254	0.00	0.21	1.00	4,150

Table 2: Summary statistics - other variables

	Mean	Sd	min	max	count
Location score	9.701	0.500	7.00	10.00	4,149
Number of reviews – log	2.902	0.743	1.39	5.67	4,150
Number of reviews	23.434	16.799	4.00	290.00	4,150
Average distance (km)	2.386	0.782	1.50	7.93	4,150
Overall rating	91.280	6.097	46.00	100.00	4,150
Host inexperience	2016.288	2.130	2010	2020	4,150
Host response rate	0.937	0.123	0.00	1.00	4,068
Host acceptance rate	0.959	0.090	0.16	1.00	4,147
Verified host identity	0.363	0.481	0.00	1.00	4,150
Superhost	0.289	0.454	0.00	1.00	4,150
Price	139.303	109.870	16.00	1001.00	4,150
Multiproperty	0.755	0.430	0.00	1.00	4,150
Accommodates	5.211	2.161	1.00	20.00	4,150
Bathrooms	1.456	0.652	0.00	7.50	4,149
Bedrooms	2.251	1.115	0.00	9.00	4,148
Number of photos	24.303	11.667	3.00	115.00	4,143
Luxury amenities	0.146	0.430	0.00	4.00	4,081
Quality amenities	3.118	0.951	0.00	5.00	4,074
Strict cancellation	0.523	0.500	0.00	1.00	4,150
Guest phone number	0.057	0.232	0.00	1.00	4,150
Security deposit	227.966	216.505	0.00	4050.00	3,988

Table 3: Kindness, ”halo effect” and the location score

Kindness is: Dep.Var.: Location score	Polarity (1)	Rank (2)	First name (3)	Polarity (4)	Rank (5)	First name (6)
Kindness	0.107***	0.0681***	0.153***	-0.143***	-0.103**	-0.329***
	(0.0166)	(0.0130)	(0.0293)	(0.0522)	(0.0439)	(0.102)
Average distance	-0.238***	-0.238***	-0.237***	-0.845***	-0.681***	-0.292***
	(0.0124)	(0.0124)	(0.0124)	(0.135)	(0.124)	(0.0186)
Kindness*Average distance				0.103***	0.0708***	0.204***
				(0.0223)	(0.0191)	(0.0451)
Control variables						
Number of reviews	0.00367***	0.00377***	0.00354***	0.00370***	0.00380***	0.00354***
	(0.000644)	(0.000652)	(0.000624)	(0.000644)	(0.000652)	(0.000628)
Price	0.000149	0.000143	0.000123	0.000149	0.000147	0.000143
	(0.000106)	(0.000109)	(0.000108)	(0.000110)	(0.000111)	(0.000110)
Superhost	0.147***	0.156***	0.164***	0.145***	0.154***	0.164***
	(0.0164)	(0.0164)	(0.0154)	(0.0165)	(0.0165)	(0.0155)
Multiproperty	-0.0807***	-0.0851***	-0.0868***	-0.0767***	-0.0826***	-0.0811***
	(0.0168)	(0.0169)	(0.0168)	(0.0167)	(0.0168)	(0.0168)
Bedrooms	0.00264	0.00309	0.00136	0.00255	0.00194	0.000195
	(0.0110)	(0.0110)	(0.0111)	(0.0109)	(0.0109)	(0.0110)
Bathrooms	0.116	0.104	0.0984	0.161	0.158	0.0600
	(0.119)	(0.118)	(0.120)	(0.123)	(0.109)	(0.151)
Accommodates	-0.0148**	-0.0145**	-0.0139**	-0.0149**	-0.0142**	-0.0139**
	(0.00587)	(0.00591)	(0.00594)	(0.00582)	(0.00586)	(0.00590)
Guest phone number	0.0411	0.0378	0.0409	0.0400	0.0383	0.0399
	(0.0274)	(0.0273)	(0.0272)	(0.0271)	(0.0271)	(0.0271)
Host response rate	-0.160**	-0.137**	-0.0926	-0.128**	-0.115*	-0.0760
	(0.0621)	(0.0612)	(0.0603)	(0.0623)	(0.0615)	(0.0604)
Host Acceptance Rate	0.0276	0.00924	-0.00908	0.000138	-0.00382	-0.00991
	(0.0876)	(0.0880)	(0.0871)	(0.0874)	(0.0892)	(0.0870)
Verified host identity	-0.000129	0.00262	0.00356	0.00392	0.00572	0.00553
	(0.0157)	(0.0157)	(0.0156)	(0.0156)	(0.0155)	(0.0155)
Strict cancellation	-0.000471	-0.000861	0.00251	-0.00113	-0.000965	0.00339
	(0.0145)	(0.0145)	(0.0145)	(0.0144)	(0.0144)	(0.0144)
Security deposit	-6.30e-06	-3.94e-06	3.05e-06	-1.14e-05	-6.95e-06	-2.43e-07
	(3.28e-05)	(3.25e-05)	(3.24e-05)	(3.40e-05)	(3.32e-05)	(3.28e-05)
Luxury amenities	-0.00254	-0.000190	-0.00300	-0.00505	-0.00328	-0.00305
	(0.0276)	(0.0277)	(0.0279)	(0.0274)	(0.0276)	(0.0278)
Quality amenities	0.0598***	0.0573***	0.0558***	0.0614***	0.0577***	0.0530**
	(0.0217)	(0.0217)	(0.0217)	(0.0216)	(0.0216)	(0.0217)
Number of photos	0.000314	0.000261	0.000469	0.000327	0.000230	0.000567
	(0.000666)	(0.000667)	(0.000661)	(0.000657)	(0.000657)	(0.000657)
Host inexperience	-0.00466	-0.00555	-0.00600	-0.00307	-0.00450	-0.00550
	(0.00380)	(0.00380)	(0.00379)	(0.00379)	(0.00379)	(0.00378)
Constant	18.94**	20.96***	22.24***	17.15**	19.85***	21.36***
	(7.666)	(7.672)	(7.639)	(7.638)	(7.643)	(7.630)
H0: Kind.+(Kind.*avg.dist.)* *median Avg.dist.= 0						
F-Statistic (p-value)				23.78(0.00)	14.84 (0.00)	24(0.00)
H0:Avg.dist.+(Kind.*avg.dist.)* *median Kind.= 0						
F-Statistic (p-value)				357.31	363.43(0.00)	14.24(0.00)
R-squared	0.234	0.232	0.231	0.241	0.237	0.237
Observations	3,812	3,812	3,812	3,812	3,812	3,812

Robust standard errors in parentheses. $***p < 0.01$, $**p < 0.05$, $*p < 0.10$.

Table 4: Effect of Kindness on the listing's demand

Dep. Var.: Number of reviews (log) Kindness is:	Polarity (1)	Rank (2)	First name (3)
Kindness	5.246***	3.307***	1.280***
	(0.410)	(0.200)	(0.143)
Kindness squared	-0.441***	-0.266***	-1.325***
	(0.0342)	(0.0158)	(0.169)
Average distance	-0.0681***	-0.0649***	-0.0704***
	(0.0135)	(0.0135)	(0.0140)
Control variables			
Overall rating	0.0231***	0.0244***	0.0226***
	(0.00220)	(0.00212)	(0.00220)
Price	-0.000645***	-0.000591***	-0.000618***
	(0.000158)	(0.000155)	(0.000166)
Superhost	0.0925***	0.110***	0.0360
	(0.0303)	(0.0301)	(0.0308)
Multiproperty	-0.214***	-0.215***	-0.170***
	(0.0272)	(0.0273)	(0.0283)
Bedrooms	-0.00835	-0.00920	-0.0170
	(0.0161)	(0.0157)	(0.0163)
Bathrooms	0.420*	0.424*	0.399*
	(0.246)	(0.235)	(0.219)
Accommodates	0.0198**	0.0164**	0.0269***
	(0.00846)	(0.00823)	(0.00840)
Guest phone number	-0.0892**	-0.0953**	-0.0976**
	(0.0440)	(0.0438)	(0.0456)
Host response rate	0.196**	0.231**	0.187*
	(0.0959)	(0.0955)	(0.0983)
Host acceptance rate	1.104***	1.110***	1.313***
	(0.164)	(0.160)	(0.164)
Verified host identity	0.0583**	0.0633***	0.0540**
	(0.0229)	(0.0227)	(0.0233)
Strict cancellation	0.0244	0.0278	0.0171
	(0.0216)	(0.0214)	(0.0222)
Security deposit	-0.000532***	-0.000543***	-0.000618***
	(6.94e-05)	(6.58e-05)	(7.20e-05)
Luxury amenities	0.0175	0.0187	0.0112
	(0.0394)	(0.0387)	(0.0396)
Quality amenities	0.0679**	0.0755**	0.0756**
	(0.0318)	(0.0322)	(0.0326)
Number of photos	0.00603***	0.00657***	0.00586***
	(0.00102)	(0.00100)	(0.00106)
Host inexperience	-0.0367***	-0.0374***	-0.0350***
	(0.00549)	(0.00542)	(0.00563)
Constant	57.91***	64.49***	69.59***
	(11.21)	(11.00)	(11.37)
H0: Kindness, Kindness squared= 0 (F-statistic)	83.23	145.54	41.42
(p-value)	(0.00)	(0.00)	(0.00)
R-squared	0.265	0.278	0.230
Observations	3,813	3,813	3,813

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 5: Does Kindness mitigate the negative effect of distance on demand?

Dep. Var.: Number of reviews (log)Kindness is:	Polarity	Rank	First name
	(1)	(2)	(3)
Kindness	7.664***	4.815***	2.160***
	(1.079)	(0.550)	(0.404)
Kindness squared	-0.644***	-0.387***	-2.558***
	(0.0904)	(0.0431)	(0.511)
Average distance	2.919**	1.885***	-0.0391
	(1.222)	(0.668)	(0.0251)
Kindness * average distance	-1.012**	-0.632***	-0.367**
	(0.411)	(0.209)	(0.154)
Kindness squared *average distance	0.0850**	0.0505***	0.515***
	(0.0345)	(0.0163)	(0.193)
Control variables	YES	YES	YES
H0: Kindness, Kindness*average distance = 0 (F-statistic)	3.04	5.08	3.59
(p-value)	(0.048)	(0.00)	(0.028)
Observations	3,813	3,813	3,813
R-squared	0.266	0.280	0.232

Note: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6: Effect of kindness on occupancy rate

Dep. Var.: Occupancy rate Kindness is:	Polarity	Rank	First-name	Polarity	Rank	First-name
	(1)	(2)	(3)	(4)	(5)	(6)
Kindness	0.998***	0.586***	0.300***	1.863***	1.135***	0.550***
	(0.121)	(0.0646)	(0.0415)	(0.404)	(0.190)	(0.121)
Kindness squared	-0.0811***	-0.0456***	-0.231***	-0.150***	-0.0873***	-0.513***
	(0.00999)	(0.00504)	(0.0485)	(0.0339)	(0.0148)	(0.149)
Average distance	-0.0194***	-0.0189***	-0.0193***	1.099**	0.734***	-0.00664
	(0.00436)	(0.00437)	(0.00435)	(0.479)	(0.250)	(0.00805)
Avg dist.* Kindness Avg				-0.363**	-0.232***	-0.104**
				(0.161)	(0.0782)	(0.0471)
dist.*Kindness sq.				0.0292**	0.0176***	0.118**
				(0.0135)	(0.00608)	(0.0578)
Overall rating	0.00227***	0.00288***	0.00238***	0.00229***	0.00288***	0.00240***
	(0.000734)	(0.000722)	(0.000726)	(0.000733)	(0.000723)	(0.000730)
Price	-0.0000283	-0.0000232	-0.0000377	-0.0000324	-0.0000254	-0.0000354
	(0.0000400)	(0.0000376)	(0.0000403)	(0.0000407)	(0.0000383)	(0.0000407)
Superhost	-0.0291***	-0.0250***	-0.0399***	-0.0292***	-0.0249***	-0.0395***
	(0.00846)	(0.00853)	(0.00852)	(0.00846)	(0.00850)	(0.00854)
Other Control variables	Yes	Yes	Yes	Yes	Yes	Yes
F-all (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.177	0.177	0.175	0.179	0.180	0.177
Observations	3813	3813	3813	3813	3813	3813

Note: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7: Host kindness, travel restrictions and listing demand in the timeof COVID-19. (2nd step of Heckman's sample-selection model)

Dep. Var.: Number of reviews in 2020 (log) Kindness is:	Polarity (1)	Rank (2)	First name (3)
Kindness (2019)	2.388***	1.219*	0.363
	(0.838)	(0.624)	(0.318)
Kindness (2019) squared	-0.212***	-0.105**	-0.821**
	(0.0693)	(0.0494)	(0.357)
Average distance (2019)	-0.0553*	-0.0531	-0.0621*
	(0.0330)	(0.0330)	(0.0332)
Control variables dated at 2020			
Wald test (all var = 0): p-value	0.00	0.00	0.00
Wald test of independent equations (ρ=0): p-value	0.785	0.891	0.561
H0: Kindness, Kindness squared= 0 (F-statistic: p-value)	0.00	0.01	0.00
Observations	3,865	3,865	3,865

Notes. The full set of results for the control variables is in the Appendix in Table A.5. Maximum likelihood estimates.Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 8: Host kindness, travel restrictions and listing demand inthe time of COVID-19. (First step of the Heckman's sample-selection model)

Binary Dep. Var.: Number of reviews in 2020>=1 Kindness is:	Polarity (1)	Rank (2)	First name (3)
Kindness (2019)	1.555**	1.172***	0.541**
	(0.710)	(0.399)	(0.263)
Kindness (2019) squared	-0.133**	-0.0988***	-0.567*
	(0.0590)	(0.0313)	(0.302)
Average distance (2019)	-0.00460	-0.00281	-0.00636
	(0.0276)	(0.0277)	(0.0276)
Control variables dated at 2019			
Selected observations	2,100	2,100	2,100
Non-selected observations	1,765	1,765	1,765
Observations	3,865	3,865	3,865

Notes. Full set of results for control variables in the Appendix in Table A.6. Maximum likelihood estimates. Robust standarderrors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.