Airbnb's reputation system and gender differences among guests: Evidence from large-scale data analysis and a controlled experiment

Eunseo Choi and Emőke-Ágnes Horvát

Northwestern University, Evanston IL 60208, USA
eunseochoi2019@u.northwestern.edu
a-horvat@northwestern.edu

Abstract. Sharing economy platforms are rapidly scaling up by reaching increasingly diverse demographics. However, this expansion comes with great difficulties in adequately identifying and responding to everyone's needs. In this paper, we study gender-related behaviors of guests on the currently most prominent home-sharing platform, Airbnb. While our results confirm the efficacy of Airbnb's reputation system, we also find that the level of trust and participation on the platform varies by gender. In particular, female solo travelers are more likely to be conscious of review sentiment and choose more often female hosts than male solo travelers. Our findings are obtained by combining exploratory data analysis with large-scale experiment and call for further studies on the usage of sharing economy platforms among subpopulations, informing and improving both policy and practice in these growing online environments.

Keywords: Sharing economy · Reputation systems · Trust · Gender bias.

1 Introduction

Airbnb provides both small entrepreneurs the chance to thrive and travelers to secure cost-efficient housing options. Despite the economic benefits that the platform presents, the interplay between guests making booking requests and hosts choosing to selectively accept requests might facilitate discrimination based on demographic characteristics. For instance, previous research has uncovered racial bias on Airbnb [12, 13]. To counter such biases, Airbnb provides a reputation system based on user reviews, has a damage protection and insurance program, publicizes anti-discrimination policies, and promotes an instant booking option that does not require hosts' approval. Recent research has shown that this reputation system is effectively mitigating some social biases [3, 21]. However, it remains unclear how in particular men and women use the information provided by the reputation system and how this influences their choices as guests to book with a host or not. This study addresses thus the question of *whether male and female travelers exhibit differential information processing and decision-making on Airbnb to increase and facilitate their usage of the platform.*

With an analysis of large-scale Airbnb data and human subject experiment, we focus on people who travel alone, as multiple travel websites have seen a surge of demand from this understudied market segment [4, 14, 19]. Our study makes the following contributions:

1. It identifies large-scale trends in the structural underpinnings of the reviewing process by studying patterns in host–guest networks built from Airbnb data.
2. It uncovers guests' safety-concerns on the platform using simple linguistic analyses of over 150,000 Airbnb reviews.
3. It studies experimentally the different role of review sentiment for men and women.
4. It examines the effect of the preference to interact with other users of one's own gender (i.e., homophily) on booking rates.

The results are aligned with and extend previous findings in social computing [25, 26, 33, 34, 16, 21, 3]. The paper is structured as follows: we summarize relevant work in Section 2, and detail the used methodologies and obtained findings in Sections 3 and 4. Finally, we discuss our results in light of existing literature proposing directions for further research in Section 5.

2 Related Work

Social biases Recent research has started to explore biases in online rental marketplaces and showed that hosts exhibit different acceptance rates for guests with certain racial characteristics. Specifically, Edelman, Luca, and Svirsky conducted a field experiment in which they created fictitious guest profiles with distinctively white or African-American names and sent booking requests to actual hosts on Airbnb. This experiment showed that African-American guests were 16% less likely to be accepted compared to white guests [13]. In a separate experiment that tested for digital discrimination against Airbnb hosts, Edelman and Luca found African-American hosts to be at a disadvantage as well, making less money than white hosts [12]. Based on this literature, *it is unclear whether and how gender bias would manifest itself on Airbnb*. More broadly, there is evidence that women are perceived as more trustworthy than men in an artificial investment setting [5], which suggests that female hosts could have an advantage over male hosts. Additionally, there is evidence that the preference for females is more pronounced among other females [30]. To accurately assess the implications of a potential preference for one's own gender on Airbnb, we need systematic comparisons about the participation rates of men and women. If there would be a strong imbalance in participation on top of a considerable in-group preference, the smaller group's growth could be limited.

Gender-based risk aversion Since participation rates may be closely associated with perceived risks, this research is also informed by previous literature on gender-based risk aversion. An extensive body of literature reported that women are in general more risk-averse than men (e.g., see [6]). In the context of the sharing economy, a study on online freelance work found that while workers of both genders considered crime and distance when accepting tasks to complete, female taskers were less likely to accept tasks than males in the presence of safety concerns [34]. The difference in willingness to perform tasks was close to 20%. Again, *it is not well understood how risk is perceived and dealt with on Airbnb*. If we were to find female users to be more concerned about their safety when using the platform and thus be more sensitive to negative signals about hosts than male users, this would have implications for policies imposing universal non-discrimination rules under the assumption of uniform attitudes towards risk.

Reputation systems Various studies have also investigated the effect of similar reputation systems. Favorable reputation and trust are positively correlated, and high trust can affect consumer decision-making [25, 23, 20, 26, 11, 15, 14]. A study involving field experiments found that both positive and negative reviews significantly increase the acceptance rate for Airbnb guests with an African-American-sounding name [8]. These results suggest that information provided by the reputation system about service quality reduces the risks perceived by consumers. Ert et al. compared specific features of the reputation system with evaluations of trustworthiness: After measuring the effect of star ratings and number of reviews, they showed that the latter has a stronger effect on engendering trust than average ratings [15]. None of these studies, however, have explicitly considered demographic characteristics of reviewers contributing to the reputation system nor how these reviews might be evaluated differently by guests from the same vs other demographic groups. *We are thus lacking an understanding of the potential differences between male and female guest's use of Airbnb's reputation system.*

3 Exploratory Data Analysis of User Activity on Airbnb

3.1 Data and Methods

To first gain a macro-level understanding of Airbnb users' behavior, we used large-scale data available on *InsideAirbnb.com* [17, 29]. To ensure representativeness and sample sizes that lend themselves to statistical analysis, we picked listings associated with three large cities from across the U.S.: New York City (25,636 listings recorded between March 12th, 2009 and March 4th, 2018), Los Angeles (18,405 listings recorded between January 10th, 2009 and May 10th, 2017), and Chicago (3,610 listings recorded between July 3rd, 2009 and May 10th, 2017). For each city, we manually picked 100 listings and verified that the available data is consistent with the real information provided on Airbnb's website. This sample contained details about 47,651 listings that accumulated in total 1,014,134 reviews.

We assigned gender to each unique host and reviewer using U.S. census data [2], applying a procedure similar to [18, 35]. Additionally, we validated each persons gender with the GenderChecker database [1]. In total, 84.2% of the reviewers and hosts were gender-identifiable. To restrict our sample to solo travelers, we filtered out reviews that used collective group words like "`us`", "`we`", and "`our`". We further limited the data to listings that are commonly chosen by individuals traveling alone, i.e., private or shared rooms. By doing so, we focus on the concerns of solo travelers who are unlikely to have had the resources to opt for a whole house or apartment and were thus only left with the option to share space with strangers on Airbnb. These data processing steps restricted our sample to 18,123 listings and 169,632 reviews.

To uncover systematic trends, we performed both structural and linguistic analyses. First, we explored preferences in choosing one gender over the other in the Airbnb context with a structural mapping of the reviewing process to a host–guest bipartite network [24]. Essentially, we built a network for every city by connecting each host having a listing in the considered region with every guest who left a review on their profile. Since we have extensive longitudinal data for over six years, the resulting networks can be assumed to reflect stable gender-related patterns. Second, we studied the content of the reviews. We used a common dictionary-based approach known as LIWC [31] to match stemmed words from the reviews with a large human-curated dictionary. LIWC was only used to annotate reviews with their overall sentiment. To also investigate user concerns about security, we identified and counted the occurrence of safety-related words (i.e, "`safe`", "`secure`", "`lock`", "`safety`", "`dangerous`", "`crime`"). Note that while not every Airbnb guest writes reviews, we used reviewers as a proxy for Airbnb guests throughout both types of analyses.

3.2 Results

Structural Analysis Table A.1 in Appendix shows the number of hosts and solo traveling guests of both genders in the three networks. Although in NYC and LA, female hosts outnumber male hosts, across the board there are less female guests who write reviews. In total, 44.0% of the 149,112 unique gender-identifiable reviewers were women. To enhance readers' understanding of the link between roles (guest vs host), gender, and prevalence of activity on Airbnb, we show the distribution of users with a given number of activities (i.e., having written a review as a guest and having had a review written for them as a host) in the studied time frame (see Fig. A.1 in Appendix). For each city, we found typical right-skewed distributions indicating that most activities are generated by a few users, while the majority of people utilize Airbnb only occasionally. While it is unsurprising that guests have systematically less activity than hosts, the gender differences are interesting. In terms of the number of reviews written, which is a proxy for the number of stays of a guest on Airbnb, male guests write significantly more reviews than female guests (Mann-Whitney U tests: $p < 0.001$ for all three cities). Male hosts also receive significantly more reviews (i.e., proxy for the number of visitors a host has) in NYC and Chicago (Mann-Whitney U tests: $p < 0.001$ and $p = 0.03$). The fact that male hosts receive more reviews in

NYC is especially noteworthy given that, in absolute numbers, there are fewer male hosts than female hosts.

In addition to differences between male and female users' presence and frequency of activity on the platform, we studied how gender-homophily could penetrate Airbnb's booking system. Homophily is the tendency to prefer others within one's own gender group, which is a fundamental and wide-spread social process in the formation of social ties [22]. We computed a homophily index [9] that captures the fraction of female reviewers (guests) among prior reviewers on a listing when the current reviewer (guest) chooses it. We found that female guests choose listings reviewed previously by more females than males, while male guests choose listings reviewed by more males. The difference between male and female guests is consistently significant (Chi-squared tests: $p < 0.001$) across all three cities (see Fig. 1).

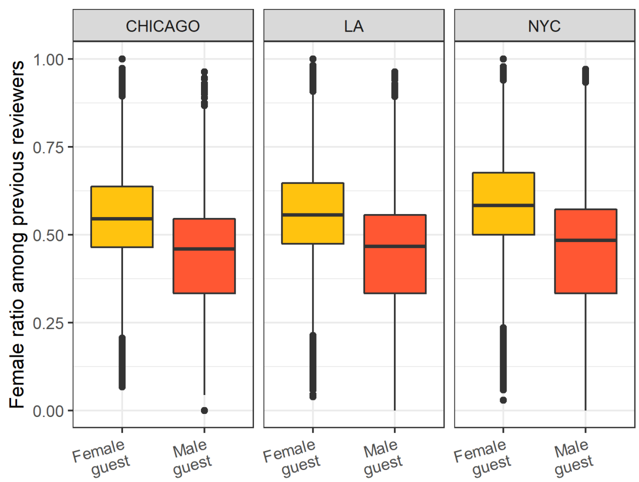

Fig. 1: The fraction of females among the reviewers seen by female vs male guests when considering a listing indicates that female guests choose listings reviewed by more females.

Linguistic Analysis The overall sentiment of review texts was strongly skewed towards positive reviews (98.6% positive). This wide-spread positivity is in agreement with trends identified on Airbnb five years ago [36]. We also explored basic differences in the text of male and female users' reviews. To examine whether safety concerns vary by gender, we compared female and male reviewers' explicit mentions of safety-related words. We listed the words that are generally associated with security. Then, we counted the instances in which female and male reviewers mentioned safety-related words to measure its frequency. Among female solo reviewers, 6.6% mentioned concerns or satisfactions related to safety, while only 5.3% of male solo reviewers talked about safety. This difference is statistically significant ($p < 0.001$).

Summary and Unanswered Questions Our analysis of large-scale Airbnb data resulted in four main findings. First, although there tend to be more female hosts, male hosts have more reviews and, by extension, more guests. Second, there are fewer female than male reviewers (guests) and they write less reviews. Third, female guests choose listings reviewed by more females. Finally, female guests' reviews mention safety-concerns more frequently. While the first two findings represent observations about patterns created over more than six years on Airbnb around the LA, Chicago, and NYC area, the last finding lends itself to experimental study. To strengthen thus the validity of these findings and further explore potential explanations behind them, in what followed we conducted an experiment that tackles the following questions:

1. *How effective are positive reviews?* Our analysis finds that essentially nearly all reviews on Airbnb are positive. It is unclear how potential guests would react to negative reviews. Understanding this would indicate whether the current Airbnb system has selected an efficient tool in the usage of positive reviews.
2. *Is there a preference for hosts of either gender and do reviewers of a specific gender have more weight?* On the one hand, literature about the link between trust and gender indicates more trust for females [5]. On the other hand, our empirical analysis shows that potential guests on Airbnb might be drawn to listings with reviews written by reviewers of their own gender. We tested this possibility with an appropriately designed experiment.
3. *Is the lower participation rate of female solo travelers explained by gendered response and sensitivity to review sentiment?* To exclude the possibility that this mode of travel is simply less desirable for female solo travelers, we created identical scenarios for men and women and explored which elements of the situation influence their decisions, this way increasing our understanding of a key factor behind observed behaviors.

4 Experimental Study

Given existing evidence for the effectiveness of Airbnb's reputation system [8, 3], we anticipated that reviews influence decision-making for both genders. However, literature on women's risk-aversion [6] suggests that they might be more sensitive to review sentiment than men. We thus tested whether review sentiment impacts guests differently based on their gender. To better understand differences in participation on Airbnb and to more directly address the different risk-attitudes in the face of safety concerns, we also tested whether guest gender itself is associated with booking decision after accounting for factors related to review sentiment, host and reviewer gender. Additionally, we considered insights from the large-scale data analysis related to gender-based homophily and different levels of concern about safety for men and women. To assess the effect of homophily, we first examined whether the gender of reviewers on a certain host's profile acts as a significant decision factor for guests, for instance as a strategy to better assess risk with the help of reviews from others of the same gender. Second, we investigated the possibility that guests have a preference with regard to host gender. To this end, we explicitly tested for an interaction effect between guest and host gender. Our hypotheses are as follows:

H1.1 *There is an interaction effect between the sentiment of review text and guest gender.*

H1.2 *Guest gender affects booking decision.*

H1.3 *Reviewer gender affects guests' booking decisions.*

H1.4 *There is an interaction effect between host and guest gender.*

For the experiment, we created a set of fictitious profiles such that each profile had a gender-revealing host name, reviewer name, and one review (either positive or negative). Reviews used in each profile were randomly drawn from *InsideAirbnb* data by sentiment category. Both positive and negative reviews had similar word counts. Reviews only discussed sentiment towards the host without mentioning any physical attributes of the listed property to avoid confounding. Additionally, we inserted star ratings into a random sample of profiles to better replicate the effects of the reputation system. Selected profiles with a negative review were given 3 stars, while profiles with a positive review were given 5 stars.

We recruited 1,041 Mechanical Turk workers who had completed more than 1,000 tasks, had above 97% acceptance rate, were residents of the U.S., and were current Airbnb users.Participants were shown one of sixteen randomly assigned host profiles that were simplified mock-ups of real Airbnb profiles. To avoid confounding, host profile photos were replaced with scenery images and fictitious hosts were assigned race-neutral names. Participants were then asked whether or not they would send a booking request if they were to travel alone and only had enough budget to book a shared/private room on Airbnb. One attention checker was included that asked participants halfway through the questions which type of room they were opting for in this study. We retained only those participants' answers who stated to be making decisions as solo travelers looking to book shared/private rooms. For each combination of variables, we measured the percentage of participants who decided to book with the host. The randomization of host profiles and participants acted as a valid instrument for the estimation of causal relationships.

4.1 Results

As shown in Fig. 2, we examined the difference in booking rate by review sentiment and guest gender using non-parametric proportion tests. We stratified the data by the sentiment of the review text. When one negative review was presented in a host's profile, female participants (guests) had a 1.3% probability of booking, while male participants (guests) booked in 6.2% of the cases; this difference is statistically significant ($p = 0.006$). However, the difference in the booking rate between male and female participants was *in*significant in the presence of a positive review ($p = 0.784$). Similarly, without further controls, the overall difference in the probability of deciding to book between male and female participants (i.e., 32.4% vs 27.3%) was not significant ($p = 0.08$). We also stratified the data by host gender. Female participants had a 33.3% probability of booking with female hosts and a 21.5% probability of booking with male hosts, a difference that is statistically significant ($p = 0.002$). In the absence of other controls, the difference in male participants' probability of booking with female vs male hosts was 28.6% vs 36.3%, $p = 0.09$. Finally, participants did not show statistically significant booking differences based on the gender of the reviewer when we stratified the data by the reviewer's gender.

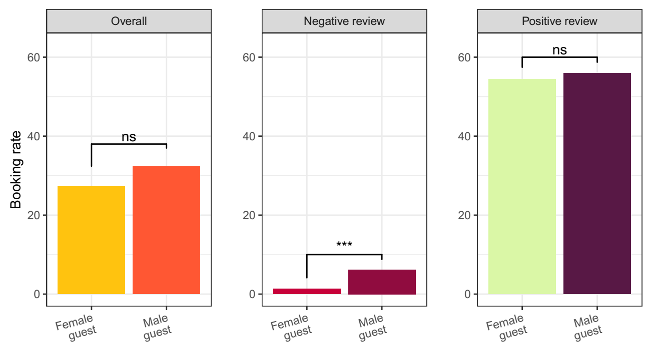

Fig. 2: Booking rates as percentages in the experimental study. The difference in the overall booking rate between male and female guests is insignificant, but it becomes significant in the presence of a negative review.

We formally tested these findings with a logistic regression model whose dependent variable was the decision to book or not. Key independent variables were guest gender, host gender, reviewer gender, and review sentiment (i.e., either positive or negative review about a host). Our model explicitly tested for interaction effects between these variables. Additionally, we controlled for guest age, income, frequency of activity on Airbnb, as well as star rating of the host. Table 1 shows the results. Positive reviews are a highly significant indicator of booking. One positive review played a significant role in increasing the chances that a female guest would book with a host of any gender. Holding other variables constant, the odds of a female guest choosing a host with a positive review was 115 times higher than the odds of a female participant choosing a host with a negative review. In a similar scenario, the odds of a male participant (guest) choosing a host with a positive review was 21 times higher than the odds of a male participant (guest) choosing a host with a negative review. Positive review sentiment plays thus a role among both genders, although female guests are more sensitive to the sentiment of review text than male guests, supporting hypothesis H1.1.

Although the lower overall booking rate for women was not significant in the direct comparison, the odds of female guests booking are 88% less than the

Variable	Coeff	SD
Female host	-0.28	0.24
Positive review	3.07***	0.31
Female guest	-2.12***	0.64
Female guest x Female host	1.03**	0.34
Female reviewer	0.10	0.24
Female guest x Female reviewer	-0.18	0.34
Female guest x Positive review	1.67**	0.61
Stars	0.40*	0.17
Constant	0.14	1.45
Deviance = 809.95		
Penalized Deviance = 781.76		
McFadden's pseudo $R^2 = 0.36$		

Table 1: Results of logistic regression models for our experimental study. The model emphasizes the role of positive reviews. Above and beyond that, the model also indicates that on the one hand there is a significant gender-homophily between guests and hosts with whom they book and on the other hand female guests book overall less. Note that guests in this table correspond to study participants, hosts and reviewers are deduced from the fictitious profiles.
Note: $^{*}\,p < 0.05$; $^{**}\,p < 0.01$;$^{***}\,p < 0.001$.

odds of male guests booking, confirming hypothesis H1.2. In contrast, hypothesis H1.3 is not supported: Reviewer gender and its interaction with guest gender are insignificant, suggesting that positive reviews are efficient regardless of the gender of the reviewer. Finally, we studied the effect of guest gender and its interaction with host gender. Both female and male participants (guests) in our experiment demonstrated a preference for hosts of their own gender. Holding other variables constant, the odds that a male guest booked a male host were 25% greater than the odds of them booking with a female host. Female guests displayed an even stronger homophily: The odds of a female guest booking with a female host were twice the odds of them booking with a male host. This finding supports hypothesis H1.4 and concludes our regression analysis.

To further unpack the finding that solo female guests were more sensitive to negative reviews than male participants, in a post-experiment questionnaire, we asked about accommodation preferences and safety-concerns. 1,275 study participants (631 females and 644 males) responded to this questionnaire. 70% of the participants indicated that they would rather stay at a hotel than book a room on Airbnb if they had to travel alone. 80% of the respondents who preferred hotels selected "`security`" as one of their reasons. Broken down by gender, 73.3% of females preferred hotels over Airbnb and 89.2% of them mentioned security as a reason. In contrast, only 65.9% of males preferred hotels over Airbnb, and a lower percentage of them (i.e., 69.6%) referred to security as a reason. The questionnaire encapsulated the perceived association between risk and staying at an Airbnb and implied that safety is a key involved risk. According to participants' responses, users (especially female solo travelers) opt for hotels instead of Airbnb listings because of the safety of hotels. This observation is aligned with previous research indicating that women are more risk-averse than men in the presence of safety concerns in the sharing economy and beyond [34, 6].

5 Discussion and Conclusion

This paper extends previous studies on the role of front-end features in signaling trustworthiness of a user [8] by initiating questions about gender-related differences in solo travelers' usage of Airbnb. Specifically, the paper studies the effect of the reputation system on male versus female guest's trust judgments. Our study creates new knowledge about how male and female solo travelers utilize Airbnb's reputation system and its (gender-related) features designed to give guests the opportunity to leave reviews and have more information about their choices. We examined whether and how informational elements available in this reputation system acted as a security blanket.

Given our finding that one positive review leads to a sizeable increase in booking rates for both male and female guests compared to one negative review, it is extremely important for new hosts with no prior hosting experience to receive positive reviews from their first guests. Our results also show gender-homophily among guests of both genders. This result explains why male hosts had a higher number of reviews in our structural analysis of *InsideAirbnb* data. *InsideAirbnb* data had a greater number of male than female reviewers (96,726 vs 72,906). Male guests preferring male hosts led to a greater number of bookings for male hosts. This effect was overcoming a larger absolute number of female hosts and a potentially higher trust in them. The result implies that simply having a high percentage of female hosts does not necessarily mean that Airbnb is a hospitable ecosystem for female hosts to thrive.

InsideAirbnb data indicated that female reviewers explicitly stated more safety-related words than male reviewers. Additionally, in our experiment, solo female guests were more sensitive to negative reviews than male participants. Given that Airbnb (a peer-to-peer platform) has a different business structure from, and provides different service than hotels (business-to-peer institutions), women traveling solo require stronger signals of safety. The lower number of female reviewers in *InsideAirbnb* data suggests that more risk-averse solo travelers had effectively opted out of using the platform. Participants in our study, especially females, appealed to gender-homophily as a strategy to deal with uncertainty [10]. While homophily is effective in this respect, it can also have considerable drawbacks. Most importantly, the imbalance in male vs female guests' participation on top of a considerable in-group preference can be assumed to further restrain the expansion of the platform's female user base.

With this dilemma in mind, Airbnb could potentially carefully leverage the features in its reputation system that enable homophily to lower the barrier to participation. For example, Airbnb could offer its users personalized recommendation of hosts with an eye for exposing guests to a variety of host options, but also encouraging connections within subpopulations when the risk-aversion of the guest is high. Airbnb can potentially provide (female) solo travelers with more equitable access to its sharing economy platform. For our specific recommendation to be valid, however, further research is required to test and measure its impact.

5.1 Limitations of Exploratory Data Analyses

InsideAirbnb data There are some intrinsic limitations to the dataset that utilized public information compiled from the Airbnb website. The group that verified, processed, and analyzed aggregate data is unaffiliated with Airbnb [17], so the accuracy and completeness of the entire information cannot be guaranteed. More importantly, while findings from real Airbnb profiles provided some insights about actual Airbnb hosts and guests who travel alone, the data comprised only the sample of guests who left reviews and did make the choice to book a shared/private room. Finally, we acknowledge that gender is not binary [28] and use in this study name-based gender assignment approaches to approximate salient categories that display gendered behavior.

Structural and linguistic analysis In the linguistic analysis, the frequency of safety-related words mentioned by female and male reviewers was measured by listing words that are generally associated with security and counting the instances. We did not consider reviews that are less explicit and more descriptive about safety-related situations during reviewers' stay. For example, we did not consider reviews such as "It was really dark at night and I heard someone knocking on my door multiple times" or "My host installed and hid a camera in my room."

We also did not consider or measure the distribution of key safety concerns expressed by reviewers on Airbnb. Although this does not significantly influence our current findings, in the future, we could expand on how guests connect Airbnb with safety issues and better specify their concerns, which could involve issues about hosts, location, electronic transaction process, and more. In addition to analyzing review content, future studies should explore the linguistic characteristics of the positive reviews and their relation with booking decisions. In other words, given that most reviews are positive, whether certain distinctive linguistic characteristics within positive reviews make readers convinced to book a place is still a question to be explored. Future studies could also explore how emotional tone and linguistic style differ by reviewer gender.

5.2 Limitations of the Experimental Study

Absence of host decision Inside Airbnb data, on which we conducted our EDA, accounts for successful transactions between guests and hosts. In our experiment, however, we take Airbnb hosts' decision making into account only indirectly. Female hosts having less reviews than male hosts may not solely be attributed to guests favoring the same gender host. If female hosts also exhibit gender-homophily favoring same gender guests, more so than male hosts, there will be a surplus of female hosts in the market given the relatively large number of female hosts and the small number of female guests. This may provide additional explanation as to why female hosts had less reviews and, by extension, less guests in our structural analysis.

Number of reviews In our experimental study, we only included one review for each of our fictitious host profiles to avoid confounding. We found that the host profile with a positive review attracts more booking. However, in reality, listings can have multiple reviews. It may be that the fraction, not the existence of positive reviews, matters the most in solo guests' decision making. The results of our study call for further investigations using multiple reviews in a host profile. Those studies could also verify the effect of the reviewer's gender on booking. In our exploratory data analysis, we saw that female guests book listings with greater fraction of females than males. In our experiment, however, we found reviewer gender to be statistically insignificant. If the reviewer gender only becomes significant after a certain number of reviewers, such discrepancy in results may be reconciled.

Atypical motivation Participants in our studies knew that they were put in a hypothetical situation and it is difficult to know whether each participant was fully engaged and made their truest possible decisions involving trust. If participants lacked the motivation to evaluate the provided host profiles, this could have affected our findings. Future studies should consider conducting a field experiment to explore solo guests' decision outcomes in real settings. For example, one possible study could collaborate with current Airbnb hosts in a specific geographic area (controlling for other attributes of hosts and listing characteristics) and analyze the booking requests they received to more accurately estimate the effect of variables explored in this study.

Altogether, our findings provide a better understanding of male vs female solo travelers' usage of Airbnb's reputation system. These results have implications for designing an open and safe space on the platform for the growing market segment of solo travelers. Above all, our study highlights the value of not assuming uniform attitudes towards risk, but breaking down the user population into subpopulations with differing behaviors and needs. We thus encourage future research examining Airbnb's reputation system and policies to consider perspectives across different subpopulations. Our approach relying on both insights from large-scale user activity data and controlled experiment produces knowledge that can potentially lead to a more personalized and thoughtful service experience that will ultimately embrace and satisfy a more diverse population on the platform.

Acknowledgement

The authors would like to thank Joshua Becker and Johannes Wachs for their feedback. We are also grateful to all the anonymous Mechanical Turk participants for their input to the presented experimental studies (IRB: STU00207726). This work was supported in part by a Northwestern Undergraduate Summer Research grant and the U.S. National Science Foundation (IIS-1755873).

References

1. Name checking database: Gender checker, https://www.genderchecker.com/
2. Baby names from social security card applications national level data (2016), https:catalog.data.gov/dataset/baby-names-from-social-security-card-applications-nationallevel-data
3. Abrahao, B., Parigi, P., Gupta, A., Cook, K.S.: Reputation offsets trust judgments based on social biases among airbnb users. Proceedings of the National Academy of Sciences **114**(37), 9848–9853 (2017). https://doi.org/10.1073/pnas.1604234114
4. Booking.com: Holidays with me, myself and I give women a self esteem boost (Aug 2014), https://news.booking.com/holidays-with-me-myself-and-i-give-women-a-self-esteem-boost
5. Buchan, N.R., Croson, R.T., Solnick, S.: Trust and gender: An examination of behavior and beliefs in the investment game. Journal of Economic Behavior Organization **68**(3), 466 – 476 (2008). https://doi.org/10.1016/j.jebo.2007.10.006
6. Byrnes, J.P., Miller, D.C., Schafer, W.D.: Gender differences in risk taking: A meta-analysis. Psychological Bulletin **125**(3), 367–383 (1999). https://doi.org/10.1037//0033-2909.125.3.367
7. Cheng, M., Foley, C.: The sharing economy and digital discrimination: The case of Airbnb. International Journal of Hospitality Management **70**, 95–98 (2018). https://doi.org/10.1016/j.ijhm.2017.11.002
8. Cui, R., Li, J., Zhang, D.: Discrimination with incomplete information in the sharing economy: Evidence from field experiments on Airbnb (2016). https://doi.org/10.2139/ssrn.2882982
9. Currarini, S., Jackson, M.O., Pin, P.: An economic model of friendship: Homophily, minorities, and segregation. Econometrica **77**(4), 1003–1045. https://doi.org/10.3982/ECTA7528
10. Currarini, S., Mengel, F.: Identity, homophily and in-group bias. European Economic Review **90**, 40 – 55 (2016), https://doi.org/10.1016/j.euroecorev.2016.02.015
11. Diekmann, A., Jann, B., Przepiorka, W., Wehrli, S.: Reputation formation and the evolution of cooperation in anonymous online markets. American Sociological Review **79**(1), 65–85 (2013). https://doi.org/10.1177/0003122413512316
12. Edelman, B., Luca, M.: Digital discrimination: The case of Airbnb.com. Harvard Business School Working Paper (14-054) (2014)
13. Edelman, B., Luca, M., Svirsky, D.: Racial discrimination in the sharing economy: Evidence from a field experiment. American Economic Journal: Applied Economics **9**(2), 1–22 (April 2017). https://doi.org/10.1257/app.20160213
14. Elliott, A.F.: Why are so many of us now choosing to travel alone? (May 2018), https://www.telegraph.co.uk/travel/comment/whats-behind-the-rise-in-solo-travel
15. Ert, E., Fleischer, A., Magen, N.: Trust and reputation in the sharing economy: The role of personal photos in airbnb. Tourism Management **55**, 62–73 (2016). https://doi.org/10.1016/j.tourman.2016.01.013
16. Hannák, A., Wagner, C., Garcia, D., Mislove, A., Strohmaier, M., Wilson, C.: Bias in online freelance marketplaces: Evidence from Taskrabbit and Fiverr. In: Proceedings of the 2017 ACM Conference on Computer

Supported Cooperative Work and Social Computing. pp. 1914–1933 (2017). https://doi.org/10.1145/2998181.2998327
17. InsideAirbnb: Get the data, http://insideairbnb.com/get-the-data.html
18. Karimi, F., Wagner, C., Lemmerich, F., Jadidi, M., Strohmaier, M.: Inferring gender from names on the web: A comparative evaluation of gender detection methods. In: Proceedings of the 25th International Conference Companion on World Wide Web. pp. 53–54. International World Wide Web Conferences Steering Committee (2016). https://doi.org/10.1145/2872518.2889385
19. Lazer, D., Kennedy, R., King, G., Vespignani, A.: The parable of google flu: Traps in big data analysis. American Association for the Advancement of Science **343**(6176), 1203–1205 (Mar 2014). https://doi.org/10.1126/science.1248506
20. Livingston, J.A.: How valuable is a good reputation? A sample selection model of internet auctions. Review of Economics and Statistics **87**(3), 453–465 (2005). https://doi.org/10.1162/0034653054638391
21. Ma, X., Hancock, J.T., Lim Mingjie, K., Naaman, M.: Self-disclosure and perceived trustworthiness of Airbnb host profiles. In: Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing. pp. 2397–2409. ACM, New York, NY, USA (2017). https://doi.org/10.1145/2998181.2998269
22. McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: Homophily in social networks. Annual Review of Sociology **27**(1), 415–444 (2001). https://doi.org/10.1146/annurev.soc.27.1.415
23. Melnik, M.I., Alm, J.: Does a seller's ecommerce reputation matter? Evidence from eBay auctions. The Journal of Industrial Economics **50**(3), 337–349 (2003). https://doi.org/10.1111/1467-6451.00180
24. Newman, M.: Networks: An Introduction. Oxford University Press, Inc., New York, NY, USA (2010)
25. Resnick, P., Zeckhauser, R.: Trust among strangers in internet transactions: Empirical analysis of eBay's reputation system. The Economics of the Internet and E-commerce Advances in Applied Microeconomics pp. 127–157 (2002). https://doi.org/10.1016/s0278-0984(02)11030-3
26. Resnick, P., Zeckhauser, R.J., Swanson, J., Lockwood, K.: The value of reputation on eBay: A controlled experiment. Experimental Economics **9**, 79–101 (2006). https://doi.org/10.1007/s10683-006-4309-2
27. Ridgeway, C.L.: Why status matters for inequality. American Sociological Review **79**(1), 1–16 (Feb 2014). https://doi.org/10.1177/0003122413515997
28. Rode, J.A.: A theoretical agenda for feminist hci. Interact. Comput. **23**(5), 393–400 (Sep 2011). https://doi.org/10.1016/j.intcom.2011.04.005, https://doi.org/10.1016/j.intcom.2011.04.005
29. Rosenbloom, S.: New tools and tours for solo travelers (Dec 2017), https://www.nytimes.com/2017/12/15/travel/getaway-solo-travel.html
30. Rudman, L.A., Goodwin, S.A.: Gender differences in automatic in-group bias: Why do women like women more than men like men? Journal of Personality and Social Psychology **87**(4), 494–509 (2004). https://doi.org/10.1037/0022-3514.87.4.494
31. Tausczik, Y.R., Pennebaker, J.W.: The psychological meaning of words: LIWC and computerized text analysis methods. Journal of Language and Social Psychology **29**(1), 24–54 (2010). https://doi.org/10.1177/0261927X09351676
32. Thebault-Spieker, J., Kluver, D., Klein, M.A., Halfaker, A., Hecht, B., Terveen, L., Konstan, J.A.: Simulation experiments on (the absence of) ratings bias in reputation systems. Proc. ACM Hum.-Comput. Interact. **1**, 101:1–101:25 (Dec 2017). https://doi.org/10.1145/3134736

33. Thebault-Spieker, J., Terveen, L.G., Hecht, B.: Avoiding the south side and the suburbs: The geography of mobile crowdsourcing markets. In: Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. pp. 265–275. CSCW '15, ACM, New York, NY, USA (2015). https://doi.org/10.1145/2675133.2675278
34. Thebault-Spieker, J., Terveen, L.G., Hecht, B.J.: Toward a geographic understanding of the sharing economy: Systemic biases in uberx and taskrabbit. ACM Trans. Comput.-Hum. Interact. **24**, 21:1–21:40 (2017)
35. Wachs, J., Hannák, A., Vörös, A., Daróczy, B.: Why Do Men Get More Attention? Exploring Factors Behind Success in an Online Design Community. arXiv e-prints arXiv:1705.02972 (May 2017)
36. Zervas, G., Proserpio, D., Byers, J.: A first look at online reputation on Airbnb, where every stay is above average. Social Science Research Network (2015)

A Appendix

Table A.1: Basic statistics of host–reviewer networks built for NYC, LA, and Chicago.

	NYC	LA	Chicago
Female hosts	5,445	3,483	627
Male hosts	4,898	2,908	690
Female reviewers	35,167	24,584	6,336
Male reviewers	43,706	31,749	8,884
Total reviews	87,241	65,339	16,271

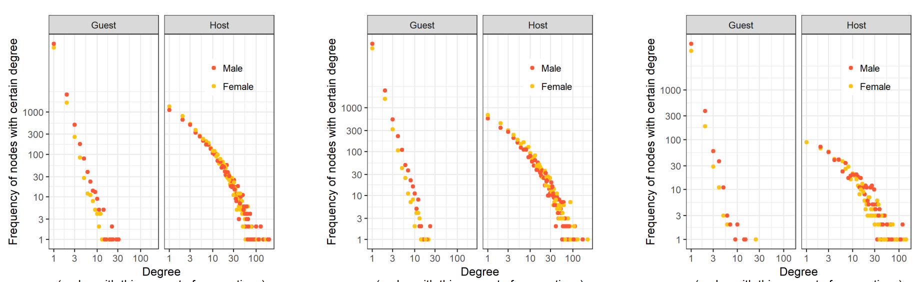

Fig. A.1: Degree distributions of networks built for NYC, LA, and Chicago. Bipartite networks connect each host having a listing in the considered region with every guest who left a review on their profile. The number of reviews written by guests and the number of reviews obtained by hosts show that, in all but one case, male guests write and male hosts receive significantly more reviews.