Biased Reputations: Using Cross-Listed Properties to Identify the Negative Effects of Race on Users' Reputations on Airbnb

1. INTRODUCTION

The last two decades have witnessed a series of technological developments enabling the emergence of the "sharing economy"—online platforms that promote the sharing, through the Internet, of goods, services, resources, and talents among users (Schor et al 2015). Because transactions in the sharing economy tend to be more personal and intimate than other e-commerce transactions, oftentimes involving access to people's homes or the use of their possessions, transactions in the sharing economy demand a higher level of trust between users. As a result, social demographic characteristics, such as race and gender, tend to become more salient and users tend to rely more on stereotypes and biases in their sharing economy interactions (Abrahao et al. 2017).

Indeed, an emerging body of literature suggests that disparities in the sharing economy are significant, in magnitude and in implications. In one research project focusing on the short-term accommodation platform Airbnb, it was shown that non-Black hosts charge approximately 12% more than Black hosts for an equivalent rental, and that rental inquiries from guests with distinctively Black names are 16% less likely to be accepted, compared to identical guests with distinctively White names (Edelman and Luca 2014, Edelman et al. 2017). One study, of the Uber ride-sharing platform, found that in some locations, passengers with Black sounding names were subject to longer waiting times and more frequent cancellations (Ga et al. 2016). Finally, studies focusing on the online product marketplace eBay have documented disparities on the basis of race. In one field experiment involving baseball card auctions on the platform, it was shown that cards held by a dark-skinned hand sold for about 20% less than cards held by a light-skinned hand (Ayres et al. 2015).

Recently, scholars have suggested that reputation systems that provide concrete information about users (Bolton et al. 2004, Chevalier and Mayzlin 2006) may decrease the tendency to rely on stereotypes, and thus reduce racial disparities in the sharing economy (Cui 2020, Abrahao et al. 2017, Tjaden et al. 2018, Nunley 2011, Laouénan and Rathelot 2020). In one study, it was shown that prospective guests on Airbnb with Black sounding names are less likely to be accepted as guests compared to guests with White sounding names. Yet, when guests have a reputation on the platform, this tendency disappears (Cui 2020). In one experiment, it was shown that reputation tends to partly offset the tendency of users to trust other users who are more similar to them (Abrahao 2017).

In this project we ask whether the evaluations given by users in the sharing economy (ratings) are themselves racially biased, and thus cannot fulfill the promise of eliminating discrimination in the sharing economy. We wish to investigate whether otherwise identical users who vary by their race, would not receive similar reviews and not develop similar reputations in the online platform of Airbnb.

Why would reviews and reputations be biased? Studies in social psychology suggest that stereotypes tend to color people's expectations, perceptions, and evaluations of the performance of others. Thus, the same task performance might be evaluated more positively when produced by Whites rather than minorities, or by men rather than women (Bohren 2015, Swim 1989, Wynn and Correll 2018). In the context of the labor force, various studies have shown that race and sex stereotypes affect the evaluations of workers. As a result, minorities and women experience manifold disadvantages at work, including biases in hiring, salary setting, evaluation, and promotion decisions (Wynn and Correll 2018, Castilla 2008, Bertrand and Mullainathan 2007, Ridgeway 2011). In one field experiment on an online Q&A mathematics forum—on which users evaluate content posted by other users—it was found that with no prior evaluations, women's posts were evaluated more negatively than men's. It was further demonstrated that prior evaluations have a lingering effect: following a sequence of positive evaluations, women's posts were evaluated more positively than men's (Bohren, et al 2019).

Taking this reasoning and body of evidence into account, we propose that ratings and reviews in online marketplaces are racially biased.

To explore our prediction, we employ a quasi-experimental research design: we analyze a dataset of vacation rentals that are cross-listed on two sharing economy platforms: Airbnb and HomeAway. Whereas on Airbnb hosts are required to post their photographs and additional information, on HomeAway they are not required to do so. Thus, whereas on Airbnb the race of hosts is usually known, on HomeAway it is often unknown.[1] Formally, we hypothesize the following:

H1: Black hosts receive lower ratings on Airbnb compared to on HomeAway (for the same exact vacation rentals; net of the differences in ratings on Airbnb compared to on HomeAway for non-Black hosts).

[1] Note that although we predict that reputations are racially biased, we only compare the reviews of Black hosts and non-Black hosts (White, Asian and Latinx hosts). Unfortunately, the small number of Asian hosts and Latinx hosts in the sample does not allow us to test for differences between Asian host and White–hosts, nor between Latinx hosts and white hosts. We do however show that it is the differences between Black hosts and White hosts that drive the results we observe.

Note that we limit our prediction to ratings and do not address discrimination in the tendency to book rentals from Black hosts compared to from other hosts. In doing so, we build on studies in social psychology that have distinguished between implicit biases that might affect expectations and evaluations and between discriminatory behaviors.

Stereotypes and cultural beliefs tend to implicitly bias people's expectations of others as well as the evaluations of others' performance (Nelson 2009). Yet not all implicit biases lead to discriminatory behaviors. Crandall and Eshleman (2003) propose a justification-suppression model of the expression of discrimination by which the expression of every bias is restrained by beliefs, values, and social norms that indicate the inappropriateness of such expressions. Discrimination is therefore generated via a two-stage process: First, people categorize others, and stereotypes and cultural beliefs are automatically evoked. Second, prejudice is expressed in the form of discrimination only if there is no motivation to restrain it. In other words, whereas stereotypes and cultural beliefs are automatically and implicitly evoked to affect expectations and evaluations, the expression of discrimination is sometimes restrained by beliefs, values, and social norms. In the context of the sharing economy, previous studies have suggested that reputation systems that provide concrete information about users (Cui 2020, Bolton et al. 2004, Chevalier and Mayzlin 2006) tend to decrease the expression of discrimination. Put another way, concrete information about users provides motivation to restrain the expression of prejudice.

The focus of this project however is not on the expression of discrimination but rather on implicit biases and on their effects on expectations and evaluations. Because both on Airbnb and on HomeAway reputation systems provide concrete information about hosts, we do not hypothesize that users will discriminate against Black hosts. Therefore, we do not predict that in our sample, the number of bookings on Airbnb is affected by the race of hosts.

2. RACIAL BIASES IN REPUTATIONS ON AIRBNB

To test for racial biases in reputations on Airbnb, we generated a unique dataset incorporating data on vacation rentals cross-listed on two short-term accommodation platforms: Airbnb and HomeAway. Although both platforms are online marketplaces for short-term accommodation, they vary in terms of whether, and to what extent, the social demographic characteristics of users are salient in transactions between hosts and guests. In an effort to facilitate trust, Airbnb requires hosts to provide personal photographs as well as first names, which are then presented to potential guests. At the time the data was collected, hosts' photographs were presented on the front page of the relevant listing. Unlike Airbnb however, HomeAway did not (at the time the data was collected) require hosts to provide photographs; in most cases, personal photos of hosts were not used on the platform at all.[2] Oftentimes with such vacation rentals, guests do not meet the hosts at all during their stay. Thus, whereas guests on Airbnb usually know (or can infer) their host's race and gender before commencing their stay, on HomeAway race and gender is generally unknown at the time of booking, and oftentimes throughout the stay. We utilize the differences between the platforms to test whether the same exact vacation rental is evaluated differently by guests when the race of the host is known and if the host is a Black host (on Airbnb), compared to when the race of the host is unknown (on HomeAway).

Rating scores on both platforms are collected at the end of the guests' stay: guests can review their hosts, and vice versa. Neither party can see each other's ratings until both have submitted

[2] Since the data collection, both platforms have changed their policies regarding hosts' personal photographs. Airbnb decreased the size of photographs on the platform; HomeAway changed its policy, and hosts who wish to present their personal photograph(s) on the listing's front page may now do so.

their review or the submission period has ended. The platforms often send review reminder notifications to both guests and hosts after the visit has been completed. On Airbnb, guests rate hosts on the following 5-point scale factors: cleanliness, communication, check-in, location, and value. The ratings score that is presented on the front page of the listing (and which we use in our analyses) is the average score for all factors and all reviews. On HomeAway, ratings are also on a 5-point scales, and averages are presented on the listing's front page.

2.1 Materials and Methods

Data for the main analysis was collected during February 2019 by AirDNA, a company that provides data of short-term vacation rentals on online platforms. The original dataset included all the cross-listed rentals on Airbnb and HomeAway, in the US cities of New York, Los Angeles, Houston, and Chicago. Properties cross-listed on the two platforms were matched by the company by photos, texts, and geographical locations. A research assistant then coded the perceived race and gender of the Airbnb hosts (by evaluating the photographs and first names of the hosts). Both authors reviewed the coding independently. When there was no agreement among the co-authors regarding the race and gender of hosts, they were coded as missing. After cleaning the dataset and removing all observations with missing variables, the dataset consisted of 1084 observations of 542 rentals (each rental cross-listed on both platforms).

Recall that the dataset includes only vacation rentals cross-listed on both platforms: Airbnb and HomeAway; and that whereas the race of hosts is known on Airbnb, it is unknown on HomeAway. Thus, for each vacation rental in the dataset, we have two observations: the ratings on Airbnb and the ratings on HomeAway.

Our analysis considers the differential effects of identifiable race (Airbnb) on Black hosts versus non-Black hosts. We calculate the effect of the Airbnb platform on the ratings received by Black hosts, by comparing the average rating gap between the platforms (Airbnb and HomeAway) for Black hosts to the average rating gap between the platforms (Airbnb and HomeAway) for non-Black hosts. This is to say, we capture the effects of identifiable race (Airbnb) for Black hosts net of the effects of the platform (Airbnb) for non-Black hosts.

Note that whereas on Airbnb hosts may offer different types of listings, including private homes, private rooms, and shared rooms, rentals on HomeAway tend to be vacation homes. Thus, rentals that are cross listed on the two platforms (and are included in our data) tend to be vacation homes. Other than the usage of user photographs on Airbnb, two important differences between the platforms are relevant to our analyses. First, on Airbnb, hosts have the option of charging extra fees for additional guests, whereas on HomeAway there is no such option. Second, Airbnb only charges host fees per booking (no annual fees), whereas HomeAway hosts can choose to be charged per booking or per annum.

We estimate property fixed effects OLS regression models predicting the effect of the Airbnb platform on a Black host ('Black Host' X Airbnb), controlling for the platform effect ('Airbnb'), the published nightly rate, the extra-people fees, and the response rate. For property i and platform p, we estimate the following model:

$$Rating_{ip} = \beta_0 Airbnb_p + \beta_1 Black\ host_i * Airbnb_p + \gamma X_{ip} + \delta_i + \varepsilon_{ip}$$

Because we estimate property fixed effects, we do not estimate the direct effects of the race of hosts (which does not vary between platforms) and only include an interaction effect between the race of the host and the platform ('Black Host X Airbnb').

In order to detect the effects of identifiable race on ratings, we must assume that all the other differences between the two platforms affect the ratings of Black and non-Black hosts similarly. Our identifying assumption is that Airbnb and HomeAway guests do not differentially value the vacation rentals owned by Black hosts (compared to non-Black hosts). Whereas the clientele of Airbnb may be different than that of HomeAway, the selection of clients across the two platforms is a concern only if the preferences of clients for the types of rentals offered by Black hosts relative to those offered by non-Black hosts are different across the two platforms. We address this selection concern and provide evidence to support our identifying assumption in a few ways. Most notably, we show that including all the observed characteristics of vacation rentals in a regression model predicting ratings (such as the ‘number of bedrooms X Airbnb’ and the ‘number of bathrooms X Airbnb’) produces a *larger* coefficient on being a Black host on Airbnb (‘Black host’ X Airbnb). We assume that preferences for observed characteristics of vacation rentals are correlated with preferences for unobserved characteristics of vacation rentals. We thus conclude that the differences in the valuation of the characteristics of rentals across the two platforms do not drive the differences we document between the ratings of Black hosts and non-Black hosts (for a similar strategy, see: Chevalier and Mayzlin 2006, Mayzlin, Dover, and Chevalier 2014). In addition, we complement the analysis with an experimental study (Experiment 1) conducted on a sample of clients of Airbnb and Homeaway. We show that clients of Airbnb and HomeAway do not differ in their evaluations of otherwise identical vacation rentals.

2.2 Results

2.2.1 Biased Ratings. In Table 1, we present the descriptive statistics of the variables used in the analyses. The perceived race categories we use are "Black host" and "non-Black host." The non-Black category includes profiles of White (54%), Asian (7%) and Latinx (2%) hosts, as well as of people whose race could not be determined by their photograph/name (18.5%), and professional property managers (18.5%). The perceived gender categories we use are "female" and "non-female." The "non-female" category includes males, couples, families, and professional property managers. The data contains 542 properties that are each listed twice, once on Airbnb and once on HomeAway. Thus, the sample contains 1084 listings.

[TABLE 1 about here]

We estimate property fixed effects OLS regression models predicting the effect of race on hosts' ratings (a dummy per vacation rental). We use fixed effect regression models in order to estimate the effects of race on hosts' ratings *within* each vacation rental. The coefficient "Airbnb" captures the effects of being evaluated on Airbnb compared to being evaluated on HomeAway. The interaction term "Black Host X Airbnb" captures the additional effects of race (Black host) on Airbnb (where hosts' photographs are presented). The reference category in the models is "non-Black" on HomeAway. Because the models include property fixed effects, all the fixed traits of properties like the race and gender of hosts (that do not vary between platforms) are held constant. Because nightly rates, 'extra people fees', response rates, and the number of photos sometimes vary across the two platforms—even for the same vacation rental—we do control for them in our regression models (the 'extra people fees' on all HomeAway listings is equal to zero). Note that on both platforms, nightly rates are determined by hosts.

[TABLE 2 about here]

Our estimation results are presented in Table 2. We find that all hosts receive better ratings on Airbnb than on HomeAway. However, Black hosts are penalized in the ratings they receive on Airbnb. They receive lower ratings on Airbnb compared to the ratings that non-Black hosts would have received for the same exact vacation rental. In other words, the premiums hosts receive on Airbnb are lower for Black hosts compared to White hosts. On average, the ratings of Black hosts on Airbnb are 0.20 point lower than the ratings that non-Black hosts would have received for the same exact vacation rental property on Airbnb (Model 1, N=1084, p=0.059).

Model 2 additionally controls for the number of bookings and the number of reviews that tend to vary across the two platforms. Note that unlike the controls that were included in model 1, the number of bookings and the number of reviews might themselves be affected by the ratings of hosts (and not only affect the ratings). After including these two controls, the results remain similar in magnitude and significance (Model 2, N=1084, p= 0.041). Finally, in Model 3, we test whether the effects of race on Airbnb vary by the price of the rental (the interaction terms: "nightly rate X Black host X Airbnb"). We find that for Black hosts, penalties are similar across rentals regardless of their price.

Female hosts are also penalized in the ratings they receive on Airbnb (Models 1 and 2), specifically when they host more expensive rentals (model 3). Our original research hypotheses did not address gender. Yet, these findings suggests that reputations are also stereotypically framed by the gender of hosts (Ridgeway, 2011) and support our general claims about the potential biases in reputation systems in the sharing economy.

Note that differences between White and Asian hosts and between White and Latinx hosts are statistically non-significant, and that none of these drive the differences between non-Black hosts and Black hosts (Table A1 in the appendix, models 1-2). To ensure that the results are not driven by guest evaluations of listings managed by professional property managers, we replicate the analysis on a sample including only listings managed by private hosts (N=900).[3] Effects for Black hosts remain similar in magnitude and significance to the effects we report in Table 2 (Table A1 in the appendix, models 3-4). To account for the fact that two listings of the same property in the two platforms are related, we replicate the regression models with clustered standard errors. The effects obtained remain similar in magnitude and statistical significance (Table A1 in the appendix, models 5-6)**.** Finally, we replicate our analysis *between* vacation rentals. We estimate additional regression models predicting the ratings of hosts without property fixed effects . The effects we observe are similar in magnitude and statistical significance to the effects observed when using fixed-effects regression models (Table A1 in the appendix, models 7-8). Because this specification does not include property fixed effects, we can also separately estimate the effect of being a Black host. We find that between properties, Black hosts receive better ratings than White hosts. This could be either because Black hosts in our cross-listed sample list more desirable properties or because they perform better as hosts compared to the White hosts in the sample.

2.2.2 Selection Bias Concerns. The interpretation of the 'Airbnb X Black host' coefficient as a racial bias rests on the assumption that the two platforms attract similar clientele with respect to their preferences for the characteristics of vacation rentals listed by Black hosts and non-Black hosts. Yet, there is a concern that the clients who choose Airbnb tend to systematically value more the types of properties and services offered by non-Black hosts, compared to guests on HomeAway. In this section, we discuss the validity of our identifying strategy and present empirical evidence to support it.

[3] We include professional managers in the main analysis because in many cases they appear to be professional managers only on HomeAway and therefore users on Airbnb do not identify them as such.

To investigate the possible selection bias, we first compare a no-control specification to a full-control specification that includes all the observable characteristics of vacation rentals available in our dataset interacted with 'Airbnb' (such as the ‘number of bedrooms X Airbnb’ and the ‘number of bathrooms X Airbnb’). We assume that the selection on the observed traits of vacation rentals is associated with the selection on the unobservable traits of vacation rentals (Altonji et al 2005). Thus, if the inclusion of the observed characteristics of vacation rentals to the model predicting ratings attenuates the coefficient on our variable of interest – 'Airbnb X Black Host' – we can expect that the inclusion of additional unobserved characteristics of rentals would further attenuate the effects. This would imply a selection on the preferences of guests. However, comparing the no-control specification with the full control specification (Table A2), we find that including all the observed characteristics of vacation rentals produces a *larger* coefficient on our variable of interest. Specifically, including the gender of hosts, the nightly rates, the ‘extra people fees’, the response rate, the number of photos, the number of bookings, the number of reviews, the number of bedrooms, the number of bathrooms, the minimum stay, and the city (all interacted with the Airbnb indicator) produces a larger coefficient on our variable of interest. This suggests that the differences in the valuation of the characteristics of rentals across the two platforms do not drive the differences we document in the ratings between Black hosts and non-Black hosts (for a similar strategy see: Chevalier and Mayzlin 2006, Mayzlin, Dover, and Chevalier 2014).

To further support the claim that in our dataset guests on Airbnb do not tend to systematically value more the types of properties and observable services offered by non-Black hosts, we explore the differences in the tendency to book a listing between the two platforms. Note that both platforms present photos of the properties and provide very detailed lists of the amenities available, as well as information about the locations and neighborhoods. Additionally, both platforms provide ratings and written reviews to potential guests. Thus, any feature of the property that tends to be devalued by guests on Airbnb should come up either in the listing or in the reviews and discourage guests from booking the property.

We use the same within vacation-rental design to predict differences in the number of bookings by the race of hosts and the platform. In Table 3, we report the results of an OLS regression model predicting the number of bookings, by the race of hosts and the platform. We use fixed effect regression models in order to estimate the effects of race on the number of bookings *within* each vacation rental. Note that the 'number of bookings' captures the number of reservations made on the platform (and not the number of nights booked on the platform).

If clients on Airbnb tended to value more the types of properties hosted by non-Black hosts, we would expect the 'Airbnb X Black host' coefficient to be negative and statistically significant. In our analysis however, the 'Airbnb X Black host' coefficient is statistically insignificant. In other words, we do not find that properties hosted by Black hosts tend to be booked less on Airbnb compared to on HomeAway (and net of the general effect of using the Airbnb platform). This suggests that on average, guests on Airbnb are not more racially biased than guests on HomeAway, nor do they systematically value more the types of properties and observable services offered by non-Black hosts. Our discussion and the empirical evidence provided therefore alleviate concerns of a selection bias on the basis of all the factors that are observable to prospective guests and that are correlated with the race of hosts (location, neighborhood, amenities, photos, past guests' ratings and reviews on both platforms, as well as the race and gender on Airbnb). Assuming that the amount of selection on the observed explanatory variables provides a guide to the amount of selection on the unobservable variables (Altonji et al 2005), we conclude that our identification strategy is not compromised.

[TABLE 3 about here]

2.2.3 Economic Disadvantages. Finally, we turn to estimate the economic value of hosts' rating scores. We wish to establish that biased reputations generate economic disadvantages for Black hosts on Airbnb. Previous empirical studies have shown that users' rating scores on sharing economy platforms—like Airbnb and eBay—are associated with economic value (Resnick et al. 2006, Teubner et al. 2017).

Here, using our within vacation-rental design, we find that for the exact same rental, higher rating scores generate a greater annual revenue for hosts.

[TABLE 4 about here]

The results presented in Table 4 suggest that hosts with rating scores that are one point higher generate about $3000 more in annual revenues for the exact same vacation rentals (Models 1 and 2). Based on our estimates that on average Black hosts receive ratings that are lower by 0.22 points (Table 2), we estimate that in our data, the reputational penalty associated with being perceived as a Black host is of about $660 per year.

The results in Model 2 further suggest that female hosts are directly penalized on Airbnb (in addition to the penalty through their rating scores). On average, female hosts on Airbnb generate about $6600 less revenue per year, compared to the revenue that a non-female host would have generated for the exact same vacation rental. Note that annual revenues are determined by the nightly rates and the number of nights booked. Because nightly rates are determined by hosts, it is impossible to determine whether discrimination by users (number of bookings/nights booked) or the tendency to ask for lower nightly rates generate the gender differences we observe.

3. SUPPLEMENTARY EXPERIMENT I: BIASED RUPETATIONS AND CLIENTLE DIFFERENCES

To further address the abovementioned selection bias concerns and to provide additional evidence for a causal relationship between the race of hosts and the ratings they receive, we supplement the main analysis with an additional survey experiment. The purpose of the survey experiment is twofold: (i) to explore whether the reviews that Black hosts receive are worse than the reviews that White hosts receive for the same exact vacation rental (ii) to explore differences in the review related behaviors of clients of Airbnb compared to clients of HomeAway.

Following our findings in the main analysis we formally hypothesized that:[4]

H2: The ratings of Black male hosts will be lower than the ratings of White male hosts.

3.1 Materials and Methods

The experiment was conducted during January 2022. American participants on AMTurk were first asked to report whether they had used Airbnb, HomeAway or other vacation platforms in the past and about their tendency to leave reviews. They were then asked to imagine that they just rented a vacation rental through an online marketplace. In the listing, the host had written:

[4] Hypotheses for the experiment were preregistered at: "Biased Reputations." Anonymized OSF. September 22. https://osf.io/fh8cs/?view_only=cba1b36ba9184e95b10754c107905a5f

"Enjoy your stay in this cozy, newly remodeled studio! This studio is centrally located, and it is only a short drive from downtown and the beaches. Wifi and parking are included." Yet, participants were instructed to imagine that their overall experience was mixed. The location was great. The studio was not well cleaned. Although it was well equipped, amenities were only in a working condition.

Hosts were presented to the participants by their first names, varied by whether the names were White or Black male sounding names. More specifically, participants were randomly assigned to one of seven possible hosts: Darnell, Tyrone, Darius, Rasheed, Ethan, Edwin, Tayler, and Greg (for our selection of names, see Gaddis 2017). Thus, participants were randomly assigned to one of two possible hosts: a Black male host or a White male host. Participants were then asked to review their experience on the following 5-point scale factors: cleanliness, accuracy, communication, check-in, location, and value (the same factors and scales used by Airbnb's rating system). Because the cleanliness of the vacation renal was described to the participants as 'not well cleaned' and the overall experience as 'mixed', we predicted that that reviews of the cleanliness of the rental and of its value will reflect the greatest biases against Black hosts.

Altogether, 497 people participated in the experiment (see Appendix Table A3 for the sample characteristics). Balancing tests were performed. No statistically significant differences in participants' demographic characteristics across the two experimental conditions were found (White vs. Black host), except for finding that Asian participants were overrepresented in one of the experimental conditions (p=0.069). We therefore verify that the results are robust to both controlling for the race of participants and for the exclusion of Asian participants from the sample. Of all participants, 358 participants (72%) have used Airbnb in the past, 185 participants (37%) have used HomeAway; and 95 participants (19%) have used both. Fifty-one participants (10%) have not used vacation rentals in the past. (see Appendix Table A4 for the descriptive statistics of the variables we use in the analysis).

3.2 Results

In Figure 1, we present the ratings of participants (all five components and average), by hosts' race.

[FIGURE 1 about here]

Whereas the average ratings of White hosts in the experiment is 3.39, the average ratings of Black hosts is 3.26 (p=0.056 for a t-test comparing the ratings of Black hosts and White hosts).

To better understand the patterns in our results, we ran OLS regression models predicting the average ratings as well as each one of its components (Appendix Table A5): As predicted, we find that the overall ratings of Black hosts as well as their ratings with regard to cleanliness and value components are lower than the ratings of White men. Finally, to explore whether the ratings clients of Airbnb provide are different than the ratings clients of HomeAway provide - and thus address the selection biased concerns raised in the main analysis - we now turn to compare the responses of participants who are clients of Airbnb and the responses of clients of HomeAway.

We therefore ran additional OLS regression models predicting the average ratings as well as each one of its components by the race of the host, on a sub-sample of participants that includes only clients of Airbnb and of HomeAway (Appendix Table A6; N=445). These models include a variable capturing being a client of Airbnb (client of Airbnb) and interaction terms between the race of host and users' experience (Black Host X Client of Airbnb). In all models being a client of Airbnb has a statistically non-significant effect on the ratings. Relatedly, in all models the coefficients for the interaction terms between the race of host and users' experience are statistically non-significant. Taken together, these findings suggest that in the experiment the negative ratings of Black hosts are not generated by differences between users of Airbnb and users of HomeAway.

In sum, the results of the experiment replicate the findings of the online market analysis in a controlled setting and thus provide evidence for a causal relation between the race of hosts and the ratings they receive. Additionally, in the experiment, effects are not driven by differences in the ratings that clients of Airbnb and clients of HomeAway provide.

4. SUPPLEMENTARY EXPERIMENT II: RACIAL STEREOTYPES AND BIASED EXPECTATIONS

Finally, to better understand the mechanism that drives the biased reputations we observe, we now turn to experimentally investigate the racial stereotypes that people hold in the context of vacation rentals. More specifically, we wish to explore the content of people's beliefs and expectations about Black hosts and White hosts of vacation rentals.

The content of people's beliefs and expectations is important because people's perceptions and evaluations of the performance of others tend to be framed by their beliefs and expectations (Nelson 2009). Thus for example, if people expect Black hosts to perform worse than White hosts, their expectations will frame their evaluations of the performance of Black hosts and lead to biased reviews.

Following the literature and the results of our main analyses, we hypothesize that:

H3: Expectations of Black male hosts will be lower than expectations of White male hosts.

In our main analyses, the effects of being a Black female host on the rating scores (compared to being a Black male host or a White female host) were positive but statistically non-significant, possibly due to the relatively small sample size of female hosts (the sample included only 21 White female hosts and 25 Black female hosts).

Yet, the literature in social psychology on intersectionality suggests that some of the stereotypes about Black women tend to be different both from the stereotypes about White women and from the stereotypes about Black men. Additionally, this body of literature has shown that in some (but not all) contexts Black women are viewed more positively than Black men and White women. More specifically, Black women tend to be viewed as more agentic than White women and warmer than Black men (Ridgeway and Kricheli-Katz 2013, Livingston et al. 2012, Richardson et al. 2011).

Building on this literature, we hypothesize that in the context of vacation rentals:

H4: Expectations of Black female hosts are higher than expectations of Black male hosts or of White female hosts.

4.1 Materials and Methods

The experiment was conducted during April 2020. American participants on AMTurk were asked to imagine that they were planning a vacation and were considering renting a vacation rental property through an online marketplace. They were then told that the host was describing the rental as a “cozy, newly remodeled studio,” that is “centrally located” and is only "a short drive from downtown and the beaches.” “Wifi and parking are included." Hosts were presented to the participants by their first names, varied by whether the names were White, Black, female, or male sounding names. More specifically, participants were randomly assigned to one of eight possible hosts: Ann, Brad, Darnell, Greg, Keisha, LaToya, Tyrone (for our selection of names, see Gaddis 2017). Thus, participants were randomly assigned to one of four possible hosts: a Black male host, a Black female host, a White male host, or a White female host.

We also varied the description of the vacation rentals, so that half of the participants were told that the vacation rentals they were considering were luxurious. Participants were then asked to report their expectations on the following 5-point scale factors: cleanliness, accuracy, communication, check-in, location, and value (the same factors and scales used by Airbnb’s rating system).

Altogether, 646 people participated in the experiment. We excluded from the sample 45 participants who did not pass the attention test, and 7 participants who reported understanding that the experiment was testing for the effects of race on expectations. The final sample for the analysis includes 592 participants (see Appendix Table A7 for the sample characteristics).

4.2 Results

In Figure 2, we present the expectations of participants (average of all five factors), by hosts' race and gender (see Appendix Table A8 for the descriptive statistics).

[FIGURE 2 about here]

Whereas the average expectations scores of White male hosts in the experiment is 4.05, the average expectations score of White female hosts is 3.83 ($p<0.01$ for a t-test comparing the expectations of female and male White hosts). The average expectation score of Black male hosts is 3.82 ($p<0.05$ for a t-test comparing the expectations of Black and White male hosts). Finally, the average expectation score of Black female hosts is 3.96 ($p<0.1$ for a t-test comparing the expectations of female and male Black hosts; $p<0.1$ for a t-test comparing the expectations of Black and White female hosts). To better understand the patterns in our results, we ran OLS regression models predicting the average expectations scores as well as each one of its components (Appendix Table A9): We find that expectations of White women hosts with regard to the cleanliness, accuracy, communication, and location components are lower than expectations of White men. In addition, expectations of Black men hosts are lower with regard to the communication, location, check-in, and value components than expectations of White men. Expectations of Black female hosts are higher in all dimensions, other than cleanliness, than of White female hosts and of Black male hosts. Interestingly, even on some of the seemingly feminine traits (like cleanliness), the expectations of female (White) hosts were lower than the expectations of male (White) hosts. This may be because vacation rentals are perceived more as businesses and less as private homes. Relatedly, research has found that men's wage advantages in the labor force tend to be similar across male-dominated, female-dominated, and gender-balanced jobs (Budig 2002).[5]

5. *GENERAL DISCUSSION*

Our findings suggest that the reviews given on Airbnb, and by extension on sharing-economy platforms, are racially biased. When the race of Black hosts is known, they receive lower rating scores compared to the rating scores that non-Black hosts would have received for the exact same vacation rental. Biased reputations are linked to biased expectations and generate economic disadvantages for Black hosts.

5.1 Contribution

Our research design allows us to provide novel *market-based* evidence for the existence of racial biases in evaluations on the online vacation platform of Airbnb. Our findings thus contribute to the literature on racial discrimination, which has predominately relied on field experiments to show causality (Bertrand and Duflo 2016).

Our findings additionally contribute to the burgeoning literature on reputation systems. Our findings suggest that although reputation systems might decrease the direct race discrimination on online platforms (Cui 2020, Abrahao et al. 2017, Tjaden et al. 2018, Nunley 2011, Laouénan

[5] We do not find significant differences in the expectations from Black hosts by the race of participants. Nonetheless, we do find the expectations of female participants of female hosts are lower than the expectations of male hosts.

and Rathelot 2020) because reputations are themselves biased, they lead to systematic indirect discrimination on the basis of race.

5.2 Practical Implications

Because evaluations can be racially biased only if the race of the host is known, masking the race of Airbnb hosts (and by extension of users of all sharing economy platforms) would reduce racial biases in the evaluations hosts receive. We do not know nonetheless whether learning the race of hosts after expectations are already formed, would reduce racial biases (for example, learning the race of the host only upon arriving at the vacation rental). The results of studies about the effects of masking individual information at the first stages of an interaction on hiring discrimination are mixed (Goldin and Rouse 2000, Lumb and Vail 2000, Åslund and Nordströum Skans 2012, Bøg and Kranendonk 2011). In one seminal study it was found that female musicians who performed in 'blind' auditions (behind a screen), were more likely to pass the audition and to be hired than female candidates who performed in full view (Goldin and Rouse 2000). In another study that was conducted in Sweden (Åslund and Nordströum Skans 2012), it was found that anonymous applications were effective in eliminating the effects of both ethnic and gender biases on the probability of being invited to an interview; Yet, the initial positive effects of masking persisted at the final hiring stage, only with regard to gender, but not to ethnicity. In another study conducted in the Netherlands (Bøg and Kranendonk 2011), it was shown that masking ethnicity positively affected the probability of being invited to an interview but had no effect on the final hiring decisions.

5.3 Limitations and Future Research

Our study has some important limitations. Most notably, we limit our analysis only to properties that are cross listed on the two platforms. Thus, the dataset includes only high-end vacation rentals whose hosts chose to cross-list them. Relatedly, we only have information on the aggregated reputations of hosts and not specific ratings made by individual guests. We therefore cannot account for the traits of guests nor for the dynamics of biased reputations.

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TABLES

Table 1: Descriptive Statistics								
Fixed across Platforms:	mean	sd	min	max				
Black Host	0.08	0.28						
Female Host	0.32	0.46						
Bedrooms	2.1	1.1	0	7				
Bathrooms	1.61	0.87	1	7				
Chicago	0.27	0.44						
Houston	0.1	0.3						
Los Angeles	0.32	0.47						
New York	0.31	0.46						
Varying across Platforms:	Airbnb				Home Away			
Rating	4.76	0.26	2	5	4.6	0.74	1	5
Annual Revenue	39921	33570	0	290411	29597	28074	0	282817
Number of Bookings	44.88	26.31	0	150	21.42	13.45	0	66
Nightly Rate	320.01	235.87	55	2345	252.76	221.54	46	2135
Response Rate	97.95	5.55	50	100	94.2	11.19	0	100
Extra People Fee	27.73	28.79	5	300	0			
Number of Photos	25.16	13.32	5	106	19.28	10.05	3	50
Number of Reviews	59.93	55.41	2	465	12.49	19.29	1	128
Observations	542				542			

Table 2: OLS Regression Models Predicting Ratings

	(1)	(2)	(3)
Airbnb	1.783**	1.544**	1.591**
	(0.562)	(0.559)	(0.563)
Black Host X Airbnb	-0.203+	-0.218*	-0.556*
	(0.107)	(0.106)	(0.277)
Female Host X Airbnb	-0.167*	-0.165*	0.070
	(0.065)	(0.065)	(0.104)
Nightly Rate/100	0.005	0.025	0.006
	(0.029)	(0.029)	(0.029)
Nightly Rate/100 X Airbnb	-0.040*	-0.048**	-0.017
	(0.016)	(0.016)	(0.018)
Extra People Fee (USD)	0.002	0.002+	0.002
	(0.001)	(0.001)	(0.001)
Response Rate	0.006*	0.006*	0.006*
	(0.003)	(0.003)	(0.003)
Responserate X Airbnb	-0.013*	-0.011+	-0.012*
	(0.006)	(0.006)	(0.006)
Number of Photos	0.010**	0.009*	0.009**
	(0.004)	(0.004)	(0.004)
Number of Photos X Airbnb	-0.012***	-0.010**	-0.012***
	(0.003)	(0.003)	(0.003)
Number of Bookings		-0.001	
		(0.003)	
Number of Bookings X Airbnb		0.002	
		(0.002)	
Number of Reviews		0.006**	
		(0.002)	
Number of Reviews X Airbnb		-0.007***	
		(0.002)	
Nightly Rate/100 X Black Host X Airbnb			0.137
			(0.102)
Nightly Rate/100 X Female Host X Airbnb			-0.077**
			(0.026)
Constant	3.824***	3.765***	3.807***
	(0.263)	(0.261)	(0.261)
R-squared	0.645	0.658	0.651
Adjusted R-squared	0.277	0.298	0.287
Observations	1084	1084	1084

Standard errors in parentheses; All regressions include property fixed effects.M46
+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 3: OLS Regression Models Predicting the Number of Bookings		
	(1)	(2)
Airbnb	63.204*	63.719**
	(25.969)	(21.383)
Black Host X Airbnb	-2.222	-2.832
	(3.505)	(2.875)
Female Host X Airbnb	-6.147**	-4.749**
	(2.122)	(1.743)
Nightly Rate/100	-3.029**	-1.237
	(0.950)	(0.791)
Nightly Rate/100 X Airbnb	-0.991+	-0.148
	(0.531)	(0.442)
Extra People Fee (USD)	-0.072+	-0.093**
	(0.038)	(0.031)
Response Rate	0.094	0.093
	(0.086)	(0.070)
Responserate X Airbnb	0.164	-0.063
	(0.188)	(0.156)
Ratings	1.703	1.218
	(1.409)	(1.173)
Ratings X Airbnb	-9.702*	-8.434**
	(3.761)	(3.088)
Number of Photos	0.421***	0.087
	(0.117)	(0.098)
Number of Photos X Airbnb	-0.134	0.033
	(0.105)	(0.088)
Number of Reviews		0.426***
		(0.046)
Number of Reviews X Airbnb		-0.173***
		(0.042)
Constant	4.328	3.230
	(10.109)	(8.293)
R-squared	0.794	0.862
Adjusted R-squared	0.578	0.717
Observations	1084	1084

Standard errors in parentheses; All models include property fixed effects.

+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table 4: OLS Regression Models Predicting Annual Revenue		
	(1)	(2)
Airbnb	-18377.94	-14760.55
	(18876.219)	(18818.949)
Rating	3292.158*	2848.889*
	(1437.948)	(1444.499)
Rating X Airbnb	5421.505	5052.311
	(3917.092)	(3893.983)
Nightly Rate	-41.028***	-38.101***
	(9.750)	(9.780)
Nightly Rate X Airbnb	19.544***	17.803***
	(5.110)	(5.188)
Extra People Fee	-40.378	-28.534
	(39.223)	(39.401)
Black Host X Airbnb		3754.752
		(3626.055)
Female Host X Airbnb		-6581.849**
		(2201.006)
Constant	24824.819***	26123.781***
	(7088.151)	(7069.574)
R-squared	0.865	0.867
Adjusted R-squared	0.727	0.730
Observations	1084	1084

Standard errors in parentheses; All regressions include property fixed effects.
+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

FIGURES

Figure 1: Ratings, by Race of Hosts

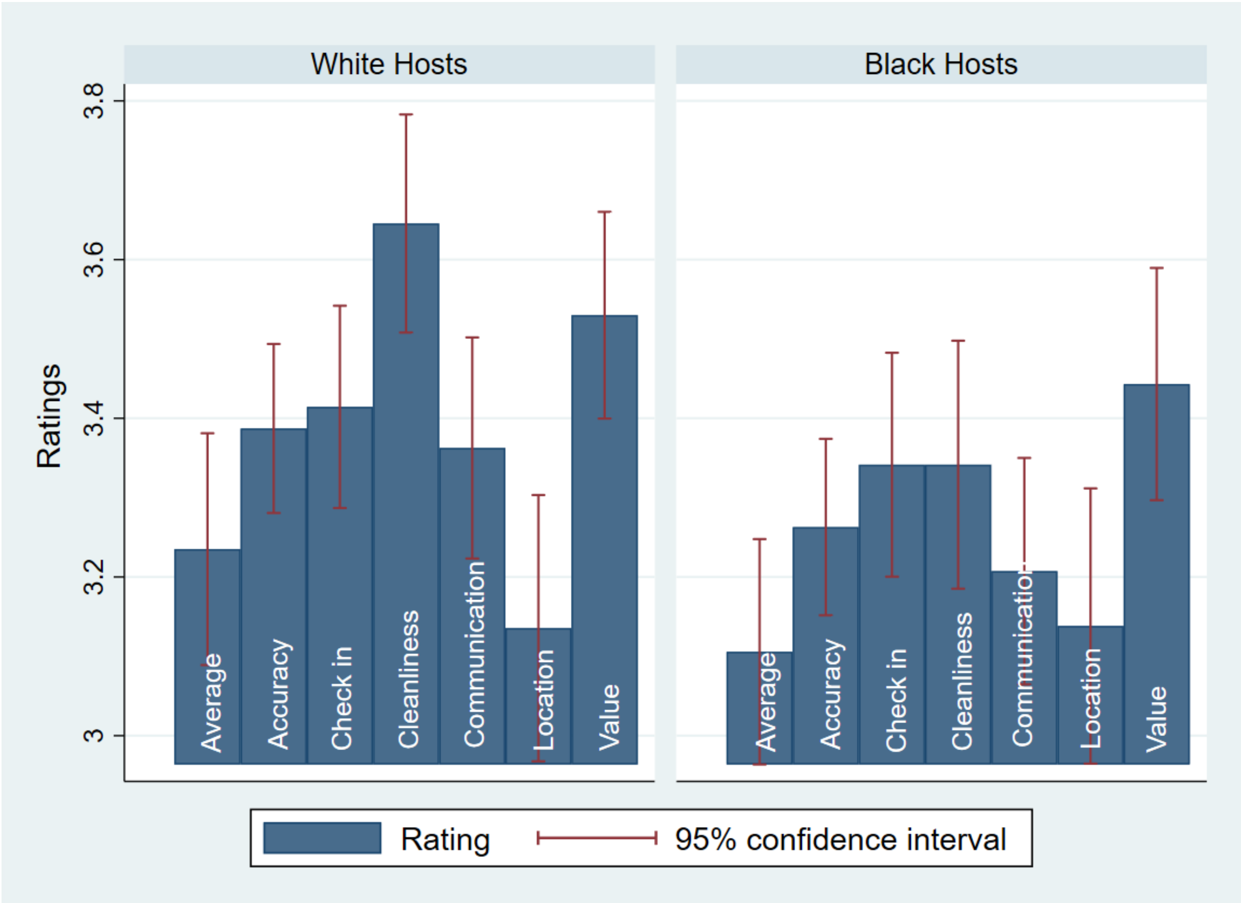
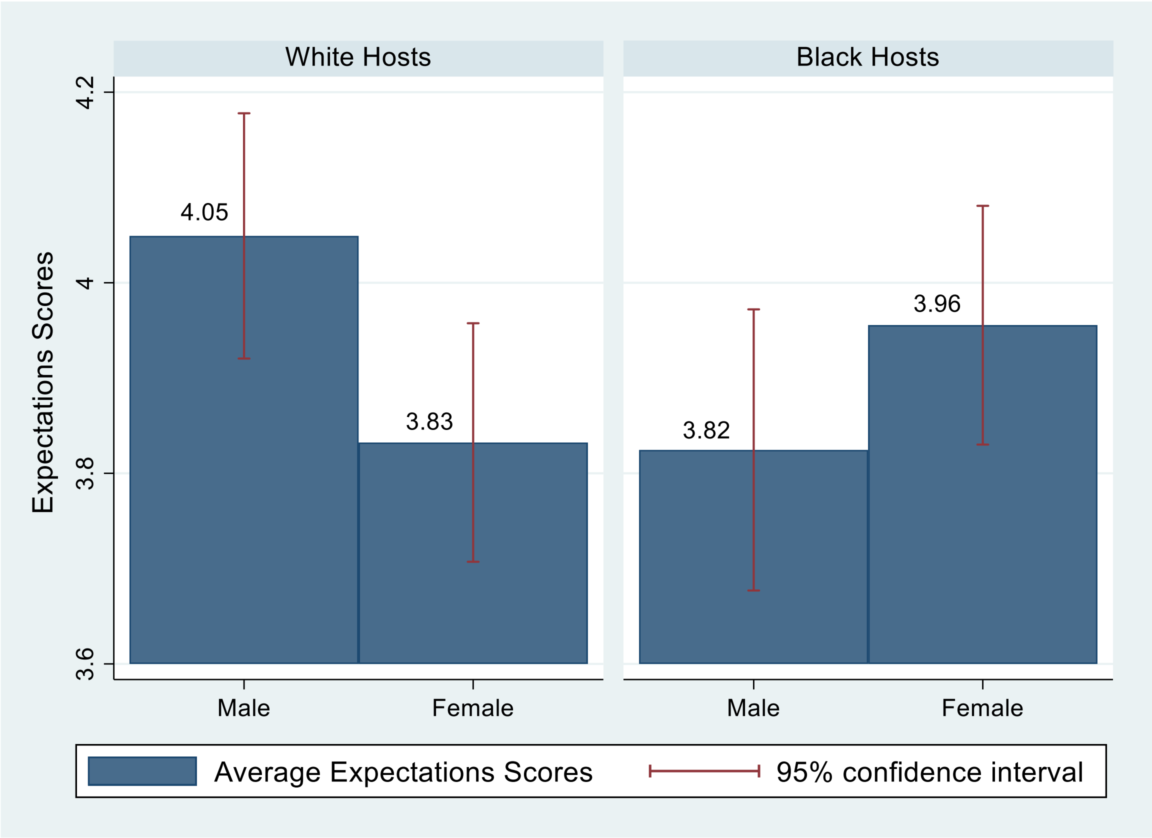


Figure 2: Expectations, by Race and Gender of Hosts



APPENDIX

Table A1: OLS Regression Models Predicting Ratings, Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Airbnb	1.696**	1.481**	1.530**	1.375*	1.783	1.544	1.118*	1.146*
	(0.576)	(0.570)	(0.576)	(0.568)	(1.090)	(1.048)	(0.470)	(0.463)
Black Host X Airbnb	-0.186+	-0.206+	-0.193+	-0.213*	-0.203+	-0.218+	-0.203+	-0.227+
	(0.111)	(0.109)	(0.106)	(0.104)	(0.120)	(0.118)	(0.121)	(0.119)
Female Host X Airbnb	-0.158*	-0.158*	-0.160*	-0.170**	-0.167*	-0.165+	-0.177*	-0.183*
	(0.066)	(0.066)	(0.065)	(0.065)	(0.083)	(0.084)	(0.073)	(0.072)
Latinx Host X Airbnb	-0.139	-0.268						
	(0.247)	(0.246)						
Asian Host X Airbnb	0.052	0.078						
	(0.122)	(0.120)						
Other Race Host X Airbnb	0.052	0.034						
	(0.069)	(0.069)						
Black Host							0.180*	0.200*
							(0.086)	(0.084)
Female Host							0.160**	0.157**
							(0.051)	(0.050)
Number of Bookings, Number of Reviews (and their interactions with Airbnb)		Y		Y		Y		Y
Constant	3.802***	3.749***	4.124***	4.072***	3.824***	3.765***	3.683***	3.694***
	(0.265)	(0.262)	(0.272)	(0.268)	(0.406)	(0.382)	(0.204)	(0.201)
R-squared	0.645	0.659	0.654	0.669	0.645	0.658	0.075	0.114
Adjusted R-squared	0.274	0.296	0.294	0.318	0.277	0.298	0.065	0.101
Observations	1084	1084	900	900	1084	1084	1084	1084

Standard errors in parentheses; All regression models control for Nightly Rate, Extra People Fee, Response Rate and Number of Photos, "and their interactions with an indicator for the Airbnb platform."

+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001

Table A2: OLS Regression Models Predicting Ratings		
	(1)	(2)
Airbnb	0.174***	1.546**
	(0.031)	(0.576)
Black Host X Airbnb	-0.172	-0.216*
	(0.108)	(0.107)
Female Host X Airbnb		-0.165*
		(0.065)
Nightly Rate		0.025
		(0.030)
Nightly Rate X Airbnb		-0.050*
		(0.020)
Extra People Fee		0.002+
		(0.001)
Response Rate		0.006*
		(0.003)
Response Rate X Airbnb		-0.011+
		(0.006)
Number of Photos		0.009*
		(0.004)
Number of Photos X Airbnb		-0.010**
		(0.003)
Number of Bookings		-0.001
		(0.003)
Number of Bookings X Airbnb		0.002
		(0.003)
Number of Reviews		0.006**
		(0.002)
Number of Reviews X Airbnb		-0.007***
		(0.002)
Number of Bedrooms X Airbnb		-0.006
		(0.042)
Number of Bathrooms X Airbnb		0.014
		(0.058)
Minimum Stay X Airbnb		-0.001
		(0.005)
Houston X Airbnb		-0.070
		(0.119)
Los Angeles X Airbnb		0.260**
		(0.087)
New York X Airbnb		0.154+
		(0.089)
Constant	4.600***	3.795***
	(0.021)	(0.266)
R-squared	0.615	0.666
Adjusted R-squared	0.228	0.308
Observations	1084	1084
Standard errors in parentheses;		
+ p<0.1 * p<0.05 ** p<0.01 *** p<0.001		

Table A3: Experiment I: Sample Characteristics

	All (1)	Clients of Airbnb (2)	Clients of HomeAway (3)
Respondents:			
Female Respondent	0.34	0.32	0.39
Black Respondent	0.14	0.15	0.17
White Respondent	0.6	0.58	0.57
Asian Respondent	0.05	0.05	0.05
High Income	0.29	0.3	0.3
High School	0.07	0.07	0.02
College	0.71	0.75	0.68
Tertiary	0.22	0.18	0.3
Usually leaves review	0.41	0.47	0.41
Clients of Airbnb	0.72		0.51
Clients of HomeAway	0.37	0.27	
Observations	497	358	185

Table A4: Experiment I: Descriptive Statistics				
	mean	sd	min	max
Black Host	0.49			
Average Rating	3.33	0.87	0.5	5
Cleanliness	3.49	1.18	0	5
Accuracy	3.17	1.15	0	5
Communication	3.29	1.13	0	5
Location	3.14	1.36	0	5
Check-in	3.38	1.07	0	5
Value	3.49	1.11	0	5
Observations	497			

Table A5: Experiment I: OLS Regression Models Predicting Ratings							
	Average Ratings	Cleanliness	Accuracy	Communication	Location	Check-in	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black Host	-0.128+	-0.321**	-0.127	0.027	-0.081	-0.096	-0.169+
	(0.077)	(0.106)	(0.103)	(0.120)	(0.097)	(0.097)	(0.100)
Female Respondent	0.162*	0.239*	0.089	0.134	0.081	0.211*	0.215*
	(0.082)	(0.112)	(0.109)	(0.128)	(0.103)	(0.102)	(0.106)
Black Respondent	0.126	0.072	0.260	0.181	0.082	-0.016	0.176
	(0.135)	(0.186)	(0.180)	(0.211)	(0.170)	(0.169)	(0.175)
White Respondent	-0.010	0.070	0.017	0.004	-0.102	-0.002	-0.045
	(0.098)	(0.135)	(0.131)	(0.153)	(0.124)	(0.123)	(0.127)
Asian Respondent	-0.173	-0.020	-0.263	-0.683*	-0.185	0.054	0.060
	(0.193)	(0.265)	(0.257)	(0.300)	(0.243)	(0.241)	(0.249)
High Income	0.008	0.050	-0.005	-0.042	0.124	0.046	-0.123
	(0.087)	(0.120)	(0.116)	(0.136)	(0.110)	(0.109)	(0.113)
High School	-0.465**	0.397+	-0.638**	-1.048***	-0.832***	-0.149	-0.521*
	(0.162)	(0.223)	(0.216)	(0.253)	(0.204)	(0.203)	(0.210)
Tertiary	0.178+	0.068	0.228+	0.234	0.197	0.016	0.325**
	(0.096)	(0.132)	(0.128)	(0.150)	(0.121)	(0.120)	(0.124)
Constant	3.318***	3.457***	3.161***	3.115***	3.532***	3.345***	3.295***
	(0.101)	(0.139)	(0.135)	(0.158)	(0.127)	(0.127)	(0.131)
R-squared	493	493	493	493	493	493	493
Adjusted R-squared	0.049	0.034	0.043	0.059	0.059	0.013	0.053
Observations	0.033	0.018	0.027	0.043	0.044	-0.003	0.037
Standard errors in parentheses; + p<0.1 * p<0.05 ** p<0.01 *** p<0.001							

Table A6: Experiment I: OLS Regression Models Predicting Ratings, by platform clientele							
	Average Ratings	Cleanliness	Accuracy	Communication	Location	Check-in	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black Host	-0.127	-0.513*	-0.098	0.040	0.092	-0.170	-0.115
	(0.183)	(0.245)	(0.247)	(0.280)	(0.226)	(0.229)	(0.237)
Client of Airbnb	-0.105	-0.086	0.063	-0.071	-0.125	-0.234	-0.178
	(0.150)	(0.201)	(0.202)	(0.229)	(0.185)	(0.188)	(0.194)
Black Host X Client of Airbnb	0.040	0.368	0.000	-0.020	-0.197	0.090	-0.004
	(0.204)	(0.274)	(0.276)	(0.313)	(0.252)	(0.256)	(0.265)
Female Respondent	0.165+	0.261*	0.057	0.130	0.078	0.254*	0.208+
	(0.087)	(0.117)	(0.118)	(0.133)	(0.107)	(0.109)	(0.113)
Black Respondent	0.094	0.086	0.244	0.102	0.047	-0.060	0.147
	(0.140)	(0.188)	(0.189)	(0.215)	(0.173)	(0.176)	(0.181)
White Respondent	0.012	0.102	0.077	-0.010	-0.061	-0.015	-0.018
	(0.103)	(0.138)	(0.139)	(0.158)	(0.127)	(0.129)	(0.134)
Asian Respondent	-0.188	0.094	-0.298	-0.817**	-0.220	0.041	0.070
	(0.198)	(0.266)	(0.268)	(0.304)	(0.245)	(0.249)	(0.257)
High Income	0.006	0.048	-0.037	-0.062	0.120	0.100	-0.133
	(0.093)	(0.124)	(0.125)	(0.142)	(0.114)	(0.116)	(0.120)
High School	-0.372*	0.439+	-0.591*	-0.946***	-0.648**	-0.057	-0.426+
	(0.185)	(0.248)	(0.249)	(0.283)	(0.228)	(0.232)	(0.239)
Tertiary	0.182+	0.100	0.258+	0.257	0.185	0.024	0.268*
	(0.103)	(0.139)	(0.140)	(0.159)	(0.128)	(0.130)	(0.134)
Constant	3.410***	3.434***	3.120***	3.236***	3.665***	3.541***	3.466***
	(0.163)	(0.218)	(0.220)	(0.250)	(0.201)	(0.204)	(0.211)
R-squared	445	445	445	445	445	445	445
Adjusted R-squared	0.041	0.032	0.034	0.057	0.051	0.023	0.044
Observations	0.019	0.010	0.012	0.035	0.029	0.001	0.022
Standard errors in parentheses; + p<0.1 * p<0.05 ** p<0.01 *** p<0.001							

Table A7: Experiment II: Sample Characteristics (by Experimental Condition)				
	White Male Host	White Female Host	Black Male Host	Black Female Host
	(1)	(2)	(4)	(5)
Respondents:				
Female Respondent	0.47	0.46	0.39	0.41
	(0.5)	(0.5)	(0.49)	(0.49)
Black Respondent	0.06	0.06	0.08	0.04
	(0.23)	(0.23)	(0.26)	(0.19)
White Respondent	0.79	0.77	0.72	0.71
	(0.41)	(0.42)	(0.45)	(0.46)
Asian Respondent	0.04	0.06	0.08	0.12
	(0.21)	(0.25)	(0.28)	(0.33)
High Income	0.36	0.38	0.26	0.44
	(0.48)	(0.49)	(0.44)	(0.5)
High School	0.06	0.08	0.1	0.06
	(0.25)	(0.27)	(0.3)	(0.24)
College	0.7	0.68	0.73	0.68
	(0.46)	(0.47)	(0.45)	(0.47)
Tertiary	0.24	0.24	0.17	0.26
	(0.43)	(0.43)	(0.38)	(0.44)
Observations	156	172	133	131

Table A8: Experiment II: Descriptive Statistics				
	mean	sd	min	max
Average Expectations Scores	3.91	0.81	0	5
Cleanliness	4.13	1.01	0	5
Accuracy	4.01	0.99	0	5
Communication	3.81	1.02	0	5
Location	4.02	1.02	0	5
Check-in	3.7	1.13	0	5
Value	3.83	1.05	0	5
Observations	592			

Table A9: Experiment II: OLS Regression Models Predicting Expectations Scores							
	Average Expecations	Cleanliness	Accuracy	Communication	Location	Check-in	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black Host	-0.229*	-0.061	-0.178	-0.303*	-0.286*	-0.225+	-0.319**
	(0.096)	(0.118)	(0.117)	(0.120)	(0.120)	(0.134)	(0.122)
Female Host	-0.210*	-0.215+	-0.267*	-0.283*	-0.223*	-0.151	-0.121
	(0.090)	(0.111)	(0.110)	(0.113)	(0.112)	(0.125)	(0.114)
Black Host X Female Host	0.349**	0.228	0.309+	0.425*	0.459**	0.327+	0.348*
	(0.134)	(0.165)	(0.164)	(0.168)	(0.168)	(0.187)	(0.171)
Luxury Rental	-0.107	-0.234**	-0.044	-0.018	0.090	-0.091	-0.345***
	(0.067)	(0.082)	(0.082)	(0.084)	(0.084)	(0.093)	(0.085)
Constant	4.100***	4.329***	4.174***	4.002***	4.111***	3.851***	4.132***
	(0.072)	(0.089)	(0.088)	(0.091)	(0.090)	(0.101)	(0.092)
R-squared	0.018	0.022	0.011	0.015	0.015	0.007	0.038
Adjusted R-squared	0.011	0.015	0.004	0.008	0.009	0.001	0.031
Observations	592	592	592	592	592	592	592
Standard errors in parentheses; + p<0.1 * p<0.05 ** p<0.01 *** p<0.001							