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**Racism during booking and what should platforms do? Evidence from face recognition
and a natural experiment**

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Racism during booking and what should platforms do? Evidence from face recognition and a natural experiment

Abstract: Research has shown that racial discrimination is detrimental to the ethnic minorities in accommodation and hospitality sectors. However, whether racial discrimination happens during the stage of online booking before check-in remains unclear. Leveraging a natural experiment of the anti-discrimination policy implemented on Airbnb and face recognition techniques to identify the racial information of hosts and guests, this study reveals that racism from hosts against ethnic guests indeed exists during the stage of online booking. The results indicate that the monthly proportion of ethnic guests increases 5% after the launch of anti-discrimination policy. We also find that discrimination exists between ethnic hosts and ethnic guests, which was not documented in previous studies. Moreover, the anti-discrimination policy in relieving racism plays a bigger role among hosts with severer racial discrimination. These findings are critical for online booking platforms to set anti-discrimination policies.

Keywords: racial discrimination, ethnic minorities, accommodation platform, face recognition, natural experiment

Introduction

Expanding diversity in tourists and employees is a trend in global tourism (Gursoy & Maier, 2023), even more so considering that providing equal accommodation opportunities and experiences for all tourists is the mission of the hospitality industry. However, racism seriously affects the experience of ethnic tourists (Torabian & Miller, 2017). Despite the legal and moral constraints to racial discrimination or prejudice, ethnic minorities are still facing unreasonable difficulties in their tourism related activities (Hudson et al., 2020). For example, the Black American traveler is often viewed as a new market segment that destination marketing organizations are keen to engage with. However, as shown by Tucker et al. (2023), this segment has constituted a strong market for more than a century. During this time, the establishment of organizations created for and managed by Black innovators played a crucial role in safeguarding against the detrimental impact of segregation laws.

In the context of peer-to-peer accommodation sharing, racial discrimination hurts both hosts and guests. Racism from guests will cause unnecessary loss to hosts of ethnic minorities. For example, leveraging the sharing listings in San Francisco on Airbnb, Kakar et al. (2018) found that the rental price of houses whose hosts are Asian or Hispanic is 8%–10% lower than those with similar conditions but the hosts are White. The authors explained that hosts of ethnic minorities foresee that they may be discriminated against by potential guests, thus they have to reduce the price to make up for the impact of racial discrimination. Similarly, using data collected from Airbnb in Chicago, Marchenko (2019) found that Asian hosts earn 4–5% and Black male hosts 3% less than White males for the same type of property. Racial discrimination from hosts would cancel or reject the reservations from guests of ethnic minorities without a specific reason. Using an experiment of Airbnb listings, Edelman et al. (2017) found that the possibility of booking order is 16% lower if one’s username is a common name used by African Americans in comparison with a common name used by White. By conducting randomized field experiments on Airbnb, Cui et al. (2020) found that the reservation requests using African American-sounding names are 19.2% less likely to be accepted than those using White-sounding names.

In October 2018, Airbnb took action to fight against discrimination. That is, “moving forward, rather than displaying a potential guest’s profile photo *before* the booking is accepted, hosts will receive a guest’s photo in the booking process only *after* they’ve accepted the booking request”. This action is expected to reduce racial discrimination on Airbnb (Cheng & Foley, 2018). Previous studies have employed various methods to detect racism in online communities, such as manual annotation, statistics, and natural language processing (NLP) technologies (Li et al., 2020), which mainly focus on review texts. This study employs image recognition models to detect specific ethnic information embedded in profile images. Image recognition models can extract valuable information from unstructured visual data (Ren et al., 2021). Therefore, by leveraging the anti-discrimination policy implemented on Airbnb and using the techniques of face recognition and deep learning, this study fills the research gap in detecting racial related information and potential racism during the booking process.

The research objectives of this study are straightforward. We first examine whether the anti-discrimination policy implemented on Airbnb works in fighting racism, that is, whether

guests of ethnic minorities increase after the anti-discrimination policy is implemented. Second, if the answer is yes, we can infer that racism indeed exists during online booking and then examine whether discrimination occurs when White hosts encounter ethnic guests and when ethnic hosts encounter ethnic guests. Finally, we further examine whether the anti-discrimination policy works better in alleviating racial discrimination among hosts with severer racial discrimination. The empirical findings reveal whether discrimination exists during the booking stage and provide new insights into the relationship between ethnic hosts and ethnic guests. The answers to the above research questions offer practical implications for accommodation platforms to fight against discrimination in different stages of consumption and in different groups of transaction.

Face recognition and race classification

The dependent variable in this study is the proportion of ethnic guests for a given host in a given month. We utilize a face recognition tool named `face_recognition` package (https://github.com/ageitgey/face_recognition) of Python to perform face detection for the profile image of each guest and host. Then the racial information is extracted from each profile image by employing the `MLPClassifier` module of Sklearn (<https://scikit-learn.org/stable/>). Trained on LFWA dataset (Liu et al., 2015), `MLPClassifier` is able to classify the race of each image into White, Black, Asian, and Indian (Li et al., 2023). Figure 1 reports the accuracy of identification, and the specific accuracy of each race is Black (0.976), Indian (0.973), Asian (0.959), and White (0.894). Table 1 presents some examples of image recognition, all photos employed are from the dataset LFWA (Labeled Faces in the Wild with Attributes).

For data collection, we first retrieved the number of Airbnb listings and guest reviews of top cities in the US, and Los Angeles was selected as it possesses the most guest reviews (more than twice as many as other big cities in the US). We then collected the profile photo of each guest and host, and the reviews each host received. Specifically, the profile photo of a guest can be reached next to his/her review and the profile photo of a host can be retrieved via the listing webpage. The profile photo employed in this paper need not be identifiable, or attributable to an individual guest or host.

The monthly distribution of guest reviews on Airbnb is quite scattered and sparse for most

of the hosts. For example, the monthly average (maximum) number of guest reviews is only about 3 (35) even for Los Angeles. This situation is even worse after race classification because the profile photo of some guests cannot be recognized. However, we should calculate the monthly proportion of ethnic guests in this study, which requires a sufficient monthly number of guest reviews. In practice, we only use the samples with ≥ 5 guest reviews in a month to perform the empirical analysis. As a result, a panel dataset consisting of 20,794 observations remains (covering 12 months before and after the anti-discrimination policy). Table 2 presents the detailed distribution of guest reviews. We observe that 30.3% (monthly average) of the reviews in our research sample were posted by guests from ethnic groups, including 5.8% posted by Black, 20.7% posted by Asian, and 3.8% posted by Indian.

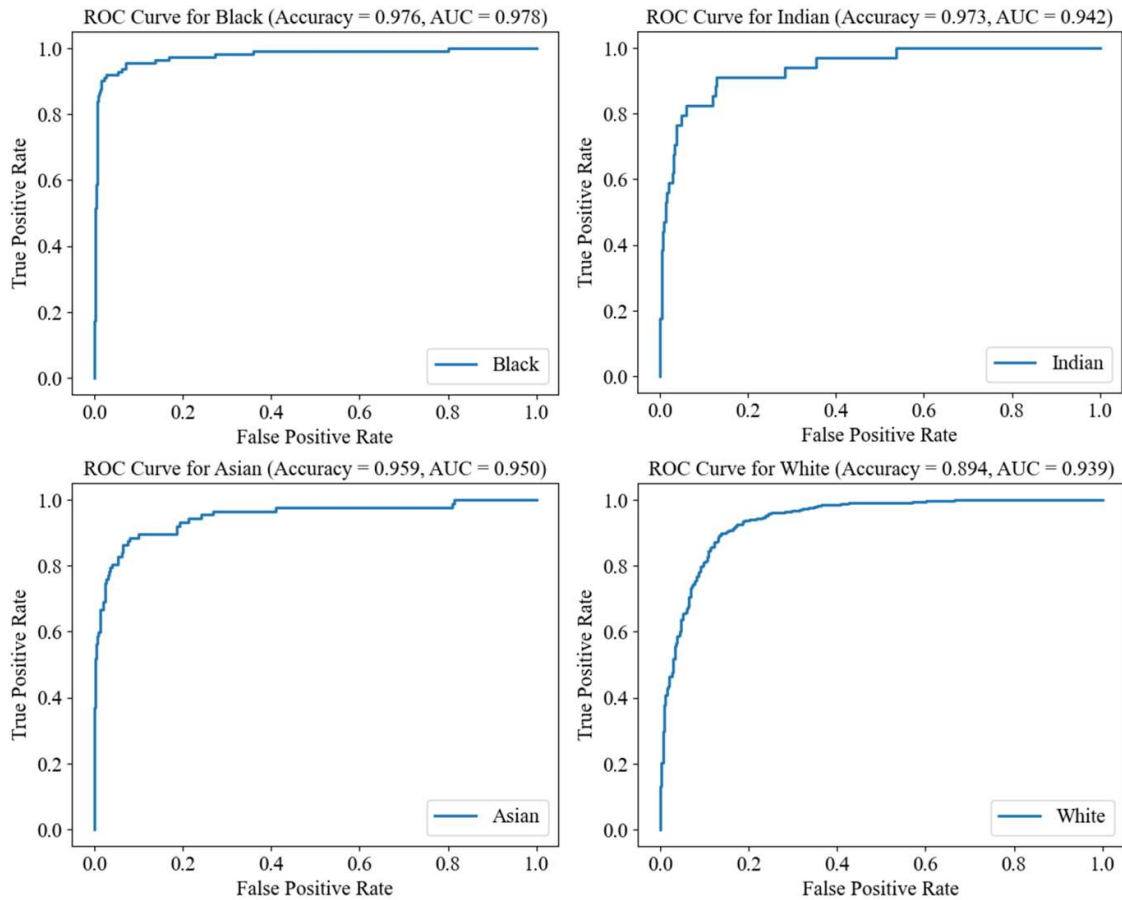


Figure 1. Performance of race recognition model.

Table 1. Examples of profile photo recognition.


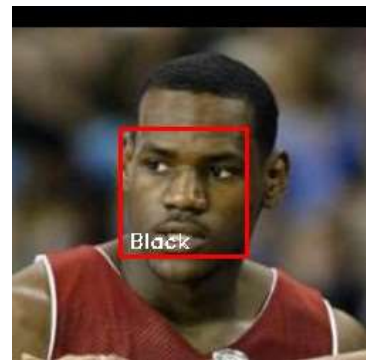

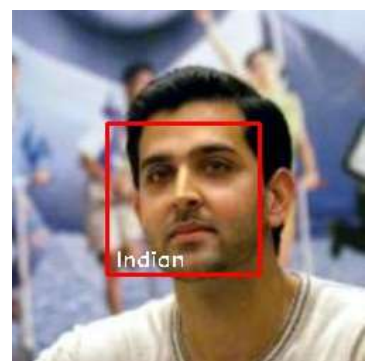

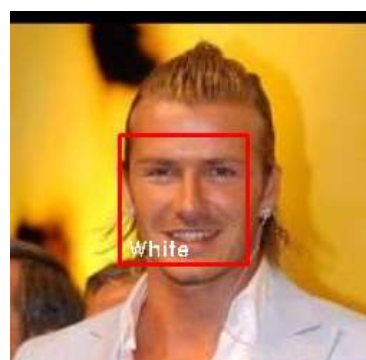


| Original image | Recognition result | Race |
|---|--|--------|
|  |  | Black |
|  |  | Indian |
|  |  | White |
|  |  | Asian |

Table 2. The distribution of guest reviews.

| Variable | Obs. | Mean | S.D. | Min. | Max. |
|---------------|--------|-------|-------|------|------|
| <i>White</i> | 20,794 | 0.697 | 0.223 | 0 | 1 |
| <i>Ethnic</i> | 20,794 | 0.303 | 0.223 | 0 | 1 |
| <i>Black</i> | 20,794 | 0.058 | 0.104 | 0 | 1 |
| <i>Asian</i> | 20,794 | 0.207 | 0.190 | 0 | 1 |
| <i>Indian</i> | 20,794 | 0.038 | 0.081 | 0 | 1 |

Research design

The anti-discrimination policy launched by Airbnb in October 2018 that hosts cannot observe a guest's profile photo before the booking is accepted functions as a natural experiment. We then use the following econometric model to examine whether the proportion of ethnic guests changes after the launch of the anti-discrimination policy:

$$Ethnic_{it} = \beta_0 + \beta_1 Policy_t + u_i + e_{it} \quad (1)$$

where $Ethnic_{it}$ is the proportion of ethnic guests of host i in month t , $Policy_t$ is a dummy variable to denote whether month t is after October 2018 or not (1=after, 0=before), u_i is host fixed effect and e_{it} is the idiosyncratic error term. To obtain robust empirical results, we employ three months ($Policy[-3,3]$), six months ($Policy[-6,6]$), nine months ($Policy[-9,9]$), and 12 months ($Policy[-12,12]$) before and after the anti-discrimination policy. β_1 captures the change of the proportion of ethnic guests for each host after the launch of the anti-discrimination policy. To further examine whether the discrimination against ethnic guests only exists among White hosts or universally exists, we divide the hosts into two groups (White hosts versus ethnic hosts) and replicate the results using Model 1.

We further argue that if the anti-discrimination policy launched by Airbnb alleviates racial discrimination, this effect should be greater among the hosts with severer racial discrimination. To validate this conjecture, we evaluate the degree of racial discrimination for each host by calculating the proportion of White guests each host received a year before the anti-discrimination policy was launched, this variable (*White*) measures the degree of racial discrimination for each host. We then extend Model 1 as follows:

$$Ethnic_{it} = \beta_0 + \beta_1 Policy_t + \beta_2 White_i * Policy_t + \beta_3 White_i + u_i + e_{it} \quad (2)$$

Results

Table 3 presents the regression results using Model 1. From the first four columns in Table 3, we can observe that the proportion of ethnic guests increases after the launch of the anti-discrimination policy. Compared with three months before the anti-discrimination policy, the proportion of ethnic guests increases by 5% after Airbnb launched the anti-discrimination policy. This result confirms the existence of racism at Airbnb and validates the effectiveness of launching the anti-discrimination policy that a host cannot observe the profile photo of a guest before booking. Columns 5 to 16 report the change of the proportion of Black, Asian, and Indian guests after the launch of the anti-discrimination policy, respectively. These results suggest that discrimination is not only limited to Black, Asian and Indian are no exception.

Table 4 (White hosts versus ethnic hosts) replicate the results in Table 3, separately. We observe that the discrimination against ethnic guests not only exists among White hosts but also among ethnic hosts. According to the magnitude of the coefficients in columns 1-4 versus 5-8, the discrimination against ethnic guests is even worse among ethnic hosts.

Table 5 reports the regression results using Model 2. The first (last) four columns are without (with) host fixed effect. The significant and positive coefficients of the interaction terms indicate that the positive effect of launching the anti-discrimination policy in relieving racism during booking is greater among the hosts with severer racial discrimination.

Table 3. The results of Model 1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|-----------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| VARIABLES | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Black</i> | <i>Black</i> | <i>Black</i> | <i>Black</i> | <i>Asian</i> | <i>Asian</i> | <i>Asian</i> | <i>Asian</i> | <i>Indian</i> | <i>Indian</i> | <i>Indian</i> | <i>Indian</i> |
| <i>Policy[-3,3]</i> | 0.050*** (0.006) | | | | 0.013*** (0.003) | | | | 0.029*** (0.005) | | | | 0.008*** (0.003) | | | |
| <i>Policy[-6,6]</i> | | 0.029*** (0.004) | | | | 0.009*** (0.002) | | | | 0.015*** (0.003) | | | | 0.005*** (0.002) | | |
| <i>Policy[-9,9]</i> | | | 0.024*** (0.003) | | | | 0.005*** (0.002) | | | | 0.015*** (0.003) | | | | 0.005*** (0.001) | |
| <i>Policy[-12,12]</i> | | | | 0.013*** (0.003) | | | | 0.003** (0.001) | | | | 0.007*** (0.002) | | | | 0.003*** (0.001) |
| Constant | 0.292*** (0.003) | 0.296*** (0.002) | 0.298*** (0.002) | 0.300*** (0.002) | 0.057*** (0.002) | 0.063*** (0.001) | 0.064*** (0.001) | 0.063*** (0.001) | 0.196*** (0.003) | 0.195*** (0.002) | 0.197*** (0.002) | 0.200*** (0.002) | 0.039*** (0.001) | 0.038*** (0.001) | 0.037*** (0.001) | 0.037*** (0.001) |
| Host FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 5,234 | 10,647 | 15,895 | 20,794 | 5,234 | 10,647 | 15,895 | 20,794 | 5,234 | 10,647 | 15,895 | 20,794 | 5,234 | 10,647 | 15,895 | 20,794 |
| R-squared | 0.622 | 0.538 | 0.496 | 0.470 | 0.488 | 0.412 | 0.360 | 0.322 | 0.581 | 0.489 | 0.446 | 0.418 | 0.406 | 0.268 | 0.216 | 0.191 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4. The results of Model 1 (White versus ethnic hosts).

| VARIABLES | White host | | | | Ethnic host | | | |
|------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> |
| <i>Policy</i> [-3,3] | 0.047*** (0.008) | | | | 0.065*** (0.018) | | | |
| <i>Policy</i> [-6,6] | | 0.025*** (0.005) | | | | 0.045*** (0.011) | | |
| <i>Policy</i> [-9,9] | | | 0.021*** (0.004) | | | | 0.032*** (0.009) | |
| <i>Policy</i> [-12,12] | | | | 0.012*** (0.004) | | | | 0.023*** (0.008) |
| Constant | 0.257*** (0.004) | 0.262*** (0.003) | 0.265*** (0.003) | 0.268*** (0.003) | 0.381*** (0.010) | 0.384*** (0.007) | 0.386*** (0.006) | 0.386*** (0.006) |
| Host FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,615 | 5,346 | 8,014 | 10,521 | 742 | 1,505 | 2,241 | 2,891 |
| R-squared | 0.604 | 0.494 | 0.447 | 0.421 | 0.565 | 0.514 | 0.482 | 0.470 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5. The results of Model 2.

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|--------------------------------------|----------------------|----------------------|----------------------|----------------------|---------------------|---------------------|---------------------|---------------------|
| | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> | <i>Ethnic</i> |
| <i>Policy</i> [-3,3] | 0.053*** (0.005) | | | | 0.053*** (0.006) | | | |
| <i>Policy</i> [-3,3]* <i>White</i> | 0.330*** (0.035) | | | | 0.149*** (0.042) | | | |
| <i>Policy</i> [-6,6] | | 0.030*** (0.003) | | | | 0.031*** (0.004) | | |
| <i>Policy</i> [-6,6]* <i>White</i> | | 0.375*** (0.024) | | | | 0.168*** (0.026) | | |
| <i>Policy</i> [-9,9] | | | 0.025*** (0.003) | | | | 0.026*** (0.003) | |
| <i>Policy</i> [-9,9]* <i>White</i> | | | 0.424*** (0.020) | | | | 0.179*** (0.021) | |
| <i>Policy</i> [-12,12] | | | | 0.014*** (0.002) | | | | 0.015*** (0.003) |
| <i>Policy</i> [-12,12]* <i>White</i> | | | | 0.482*** (0.017) | | | | 0.181*** (0.018) |
| <i>White</i> | -0.971*** (0.018) | -0.990*** (0.014) | -0.995*** (0.012) | -0.993*** (0.011) | - | - | - | - |
| Constant | 0.969*** (0.014) | 0.987*** (0.010) | 0.994*** (0.009) | 0.995*** (0.008) | 0.292*** (0.003) | 0.296*** (0.002) | 0.299*** (0.002) | 0.302*** (0.002) |
| Host FE | NO | NO | NO | NO | YES | YES | YES | YES |
| Observations | 5,231 | 10,635 | 15,861 | 20,712 | 5,231 | 10,635 | 15,861 | 20,712 |
| R-squared | 0.378 | 0.356 | 0.331 | 0.303 | 0.623 | 0.540 | 0.499 | 0.472 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Conclusion and discussion

Previous studies researching on racism in hospitality mainly focused on review texts. From the perspective of visual cues, this study utilizes a natural experiment of the anti-discrimination policy implemented on Airbnb and face recognition techniques. Compared with textual clues, the profile image provides a more direct and definitive signal for confirming racial related information. The results reveal the racism from hosts against ethnic guests on accommodation sharing platforms and indicate that discrimination also exists between ethnic hosts and ethnic guests. It is worth noting that anti-discrimination policy (guest profile photo hiding policy) did make a difference in improving the booking acceptance rate of the ethnic group. Moreover, the anti-discrimination policy in relieving racism during booking plays a bigger role among the hosts with severer racial discrimination.

The findings of this study offer important implications for the operation of accommodation platforms. First, in order to reduce any racial discrimination phenomenon, accommodation platforms, or other online booking platforms, should avoid racial information disclosure between buyers and sellers before a booking is confirmed. Related policies should strive to foster relationship-building that sorely relies on the reputation of both sides. Second, our results show that discrimination also exists between ethnic hosts and ethnic guests. Thus, we suggest that anti-discrimination policies should not only be designed to fight against discrimination from White individuals toward ethnic minorities, but should also consider discrimination among ethnic minorities themselves.

This study also has several limitations that warrant further exploration. First, the empirical findings of this study were derived from the research samples of Los Angeles, thus, future studies may expand to other cities or markets to generalize our results. Second, this study aimed to reveal the effect of visual information disclosure on host's racial discrimination behavior, other forms of discrimination behaviors (e.g., gender, age, and region) are also worth studying.

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