

# Navigating Racial Bias in the Sharing Economy: Heterogeneity and Mechanisms

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## Abstract

Recent studies reveal discrimination against racial minority customers, yet less attention is given to the performance disparities faced by racial minority suppliers in the sharing economy. Especially, more evidence is needed to identify the conditions and mechanisms that exacerbate or mitigate the biases faced by these micro-entrepreneurs. Analyzing all Airbnb listings across the U.S. from May 2015 to April 2023, I show that Black, Hispanic, and Asian entrepreneurs experience reduced consumer demands for similar offerings compared to White entrepreneurs, especially in more conservative ZIP Code Tabulation Areas, leading to heightened exit rates. Importantly, while quality signals from better numerical ratings fail to bolster their performance relative to White entrepreneurs, increased textual reviews present a potential pathway to mitigating these disparities. Using natural language processing, I further delve into over 90 million Airbnb reviews, identifying specific feedback that exacerbates or attenuates biases in the sharing economy.

**Keywords:** discrimination, sharing economy, platform, entrepreneurship, natural language processing

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# 1 Introduction

The proliferation of sharing economy platforms provides a new way to organize business by dramatically facilitating engagement between resource suppliers and consumers (Markman et al., 2021). These platforms typically do not invest in physical inputs but instead provide information and technology to connect different sides of the platform, such as hosts and guests for Airbnb and drivers and passengers for Uber. Consequently, direct contact between suppliers and buyers in the sharing economy is frequent, and their perceptions and evaluations of one another affect their relative success in capturing value and accessing resources. However, bias based on demographic backgrounds on platforms has become a heated issue in recent years. Aside from its far-reaching social implications, such discrimination significantly impedes business performance by hindering innovation (Cook et al., 2022) and displacing highly skilled racial minority workers and entrepreneurs (Hsieh et al., 2019).

Suppliers in the sharing economy are often viewed as micro-entrepreneurs (Sundararajan, 2017) and require skills such as managing projects, managing relationships with clients, and setting prices (Kane, 2016). The empowerment of these entrepreneurs crowds out some traditional jobs (Li et al., 2021) and entrepreneurial activities outside of the sharing economy (Burtch et al., 2018). However, their success depends on overcoming regulatory barriers (Paik et al., 2019) and gaining cognitive legitimacy among customers (Garud et al., 2022). Therefore, examining the obstacles faced by suppliers in the sharing economy deepens our understanding of the catalysts and impact of their entry and is of significant interest and importance to management research.

While research generally finds some discrimination against racial minority entrepreneurs and the subsequent negative economic impacts, many important theoretical and policy puzzles require careful examination. For example, it is not always clear whether investors and customers selectively reject minority suppliers because they attempt to infer quality from suppliers' backgrounds due to imperfect information (Phelps, 1972) or because they have

an actual taste for interacting with specific groups (Becker, [1971](#)). Understanding such differences thus sheds light on the processes that connect discriminatory behaviors to entrepreneurial outcomes. If statistical discrimination is the prevailing phenomenon, leveraging platform ecosystems that highlight merit through algorithms, rating systems, and reputation building should help mitigate disparities in entrepreneurial performance. However, such measures might be less effective in combating taste-based discrimination, which requires broader cultural and societal changes that are especially difficult in some socioeconomic contexts. Yet, the evidence on the efficacy of these platform design choices is often inconclusive and sometimes contradictory. To disentangle these conundrums, it is essential to explore the rich characteristics and beliefs of suppliers and buyers and identify the mechanisms and attenuating factors that differentially affect supplier outcomes.

Specifically, biases in the sharing economy have important implications regarding how suppliers can choose the market position or location when they consider entry. Especially with the increasing polarization in the U.S. in recent years, enmity toward individuals with different ideological identities has been found to increase racial hostility, traditionally the most profound divide in American society (Iyengar and Westwood, [2015](#)). Additionally, the location choices of firms and entrepreneurs are susceptible to the impact of ideology, as they can benefit more when their staff build connections, collaborate, and share resources across facilities in ideologically similar locations (Barber IV and Blake, [2024](#)). While suppliers in the sharing economy often have limited options about where to enter, they need to consider whether they should enter or not and their strategic undertakings once they choose to enter.

Another critical issue when we consider discrimination in the sharing economy is the feedback mechanism between suppliers and customers through online reviews. In the context of the sharing economy, online feedback usually includes numerical ratings and textual reviews. However, their potential roles in affecting entrepreneurial outcomes can be ambiguous. While research has shown that certain types of online feedback can attenuate the disparity between White and African American customers (Cui et al., [2020](#)), it has also been

argued that rating systems can lead to discriminatory spillovers and amplify discrimination (Teng et al., 2023). Since online feedback is crucial for platforms to build an ecosystem of high-quality users and increase their values (Tadelis, 2016), further examination is needed to understand the conditions under which different types of online feedback might mitigate or exacerbate bias.

Overall, this study aims to understand how racial backgrounds influence the business performance of suppliers in the sharing economy by examining where discrimination is more prevalent, why it occurs, and how racial minority entrepreneurs can mitigate discrimination. Analyzing all Airbnb listings across the U.S. from May 2015 to April 2023, I find that non-White Airbnb hosts charge lower prices, have fewer bookings, and experience higher exit rates compared to their White counterparts. To understand the impact of ideology on the success of racial minority entrepreneurs, I further examine zip code-level heterogeneity across the country and find that the impact of race is greater in more conservative ZIP Code Tabulation Areas. Finally, I investigate the impact of online feedback and find that White hosts benefit more from better numerical ratings than racial minority hosts, possibly because racial minorities face greater challenges in accumulating ratings. However, textual reviews help offset this relative disparity under specific conditions, suggesting they could play a crucial role in fostering a more equitable marketplace. A series of explorations into alternative explanations enhances the robustness of these findings and addresses several potential endogeneity concerns.

This paper makes several contributions to the management literature. First, it expands on existing research that examines racial bias in platform settings by addressing the critical issue of discrimination against suppliers. I use rich data to study the impact of race on supplier performance across the entire U.S. over eight years on Airbnb, a prominent platform that has previously focused more on bias against customers than suppliers. Second, this study contributes to a nascent stream of research on the implications of polarization and ideology for firm performance. While recent research has explored polarized

consumer behaviors and responses by established firms (Barber IV and Blake, 2024; Hou and Poliquin, 2023; Mohliver et al., 2023), limited evidence exists on how ideology affects the entrepreneurial outcomes of individual suppliers. This research fills this gap and provides insights into the implications for market entry and exit among racial minority entrepreneurs. Third, this study adds to the literature on online reputation systems, particularly focusing on the recent inquiry on suppliers’ performance improvements through responding to online reviews (Ananthakrishnan et al., 2023; Zeng and Sakakibara, 2024). Specifically, it examines how different feedback mechanisms can disproportionately benefit suppliers from different racial backgrounds. This analysis identifies conditions under which online reputation systems can mitigate or exacerbate biases, highlighting implications for enhancing equity and efficiency on platforms.

## 2 Motivation and Related Literature

### 2.1 Background and motivation

Sharing economy platforms have experienced tremendous growth in recent years. One prominent example is Airbnb, an online marketplace that connects people looking to rent out their homes with those seeking accommodations. As of December 2022, there were over four million Airbnb hosts worldwide, with active listings in more than 100,000 cities and towns. In the United States, a typical Airbnb host earned about \$14,000 in 2022 (Airbnb, 2023).

As Airbnb grows, so do claims of discrimination. Following high-profile coverage from media reports (Glusac, 2016) and academic research (Edelman et al., 2017) on discrimination experienced by African American guests, Airbnb conducted internal analyses (Basu et al., 2022) and implemented a series of measures to make reservations more accessible for all guests<sup>1</sup>. In December 2022, Airbnb released an update claiming that the booking success

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<sup>1</sup>Notable efforts include allowing hosts to see a guest’s picture only after accepting a reservation, expanding the Instant Book feature eligibility to more guests, making it easier for all guests to receive reviews when they travel, and auditing reservation rejections and banning certain host accounts.

rates for guests are more even across different races as a result of their efforts (Airbnb, 2022).

Despite these efforts, Airbnb has remained largely silent about the potential disparity among their hosts. Meanwhile, with its continuous expansion, more hosts have joined the platform than ever before. Figure 1 plots all Airbnb listings in the U.S. as of April 2023 using orange dots and displays the racial diversity index by state using color coding<sup>2</sup>. It is evident that Airbnb hosts list their properties not only in major and secondary cities but also in many suburban and rural areas, where populations are less racially diverse. The potential challenges faced by racial minority hosts and the variability of these challenges across the country thus hold great social and business implications.

[Insert Figure 1 about here]

## 2.2 Related literature and expected findings

### 2.2.1 Discrimination on platforms

There is a broad literature on racial discrimination across various settings. For example, discrimination is widely documented in the labor market, where several “resume studies” have shown that African-American-sounding names revealed in job applications generally receive fewer callbacks across occupations, industries, and employer sizes (Bertrand and Mullainathan, 2004; Kaas and Manger, 2012; Kessler et al., 2019; Nunley et al., 2015). Additionally, discrimination is also prevalent in pay and promotion for current employees (Bar and Zussman, 2017; Bodvarsson and Partridge, 2001; Brewster and Lynn, 2014; Hegde et al., 2023; Lynn and Sturman, 2011; Rider et al., 2023). With the increasing popularity of platforms, recent research has shown similar discrimination in hiring decisions and cancellation rates on labor platforms (Botelho and DeCelles, 2023; Teng et al., 2023).

The multi-sided nature of platforms necessitates more careful consideration of dis-

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<sup>2</sup>The diversity index indicates how likely it is that two randomly chosen people will be from different race and ethnicity groups. A value of 0 means everyone in the population shares the same racial and ethnic characteristics.

crimination originating from different sides of the platforms. Past academic studies in this domain mainly focus on the discrimination experienced by customers. Specifically, the body of work concentrates on discrimination experienced by Airbnb guests (Cui et al., 2020; Edelman et al., 2017), Uber passengers (Ge et al., 2020), mortgage applicants (Yinger, 1998), car buyers (Ayres and Siegelman, 1995), and small businesses (Blanchflower et al., 2003). Conversely, academic evidence on supplier discrimination on platforms is relatively scant. The most robust evidence comes from discrimination on eBay, where studies have shown that products sold by African American (Ayres et al., 2015) and female (Kricheli-Katz and Regev, 2016) sellers tend to fetch lower prices. Regarding Airbnb, some results have been shown on the lower price charged by African American hosts using cross-sectional data in selected cities (Edelman and Luca, 2014; Marchenko, 2019). More recently, Luca et al. (2024) find that Asian hosts in New York City received fewer reviews at the start of the COVID-19 pandemic. Although these studies often focus on discrimination against a specific racial group using a single performance metric, I anticipate that such discriminatory effects will be evident across the entrepreneurial outcomes of all racial minorities and throughout the country. Consequently, my baseline hypotheses are as follows:

**Hypothesis 1:** *On average, racial minority suppliers face worse market positions and consumer demands than White suppliers in the sharing economy.*

**Hypothesis 2:** *On average, racial minority suppliers are more likely to exit than White suppliers in the sharing economy.*

### 2.2.2 Heterogeneity in ideological distance

While I expect some discrimination against racial minority suppliers, such an effect is likely to be uneven across locations. Considering the sources, responses, and heterogeneity of discrimination, the issue of ideological polarization necessitates further examination, as research has found enmity toward different identities exacerbating racial hostility in the U.S. (Iyengar and Westwood, 2015). In the management literature, a nascent stream of research

has examined non-market strategy stemming from ideological differences, ranging from the impact of polarization on consumer behavior (Hou and Poliquin, 2023; Neureiter and Bhat-tacharya, 2021), firm disclosures (Benton et al., 2022), and social activism (Mohliver et al., 2023). More recently, scholars also theorize the potential consequences of ideological identity (mis)alignment for firm strategy regarding location decisions (Barber IV and Blake, 2024). Consequently, individuals increasingly trust and favor others who share their ideological identity while distrusting and avoiding those who do not. Additionally, research in other disciplines suggests correlations between political conservatism and racism, which are often moderated by political competition and voter redistribution (Lee and Roemer, 2006; Mas and Moretti, 2009; Sidanius et al., 1996; Whitehead, 2005). A review of several academic studies also highlights that racial minorities often hold more ideologically liberal views than their White peers (Kleinfeld, 2023). While suppliers in the sharing economy sometimes have limited location choices about where to operate, ideological distance to their intended market can still impact their expected business performance and, implicitly, their entry and exit decisions. In particular, while it is unclear how they will respond, racial minority suppliers might have a more challenging time finding consumer demands for their offerings in more ideologically distant locations. As such, I expect the following:

**Hypothesis 3:** *The disparities in consumer demands between racial minority and White suppliers are more pronounced in ideologically conservative markets.*

**Hypothesis 4:** *Racial minority suppliers are more likely to exit in ideologically conservative markets than in ideologically liberal markets.*

### 2.2.3 Online reviews as bias attenuator and amplifier

Finally, in the sharing economy and, more broadly, platform settings, online reputation systems can play an essential role in shaping consumer perceptions of service suppliers (Bajari and Hortaçsu, 2003; Luca, 2016; Moreno and Terwiesch, 2014; Reimers and Waldfogel, 2021) and affect the efficiency of platforms (Bolton et al., 2004). Some research thus suggests that



these systems can serve as a solution to racial bias on platforms because ethnic disadvantages are smaller for users with ratings than for users without ratings (Abraham et al., 2017; Alyakoob and Rahman, 2022; Cui et al., 2020; Robbins, 2017). However, other studies find that racial minorities have a harder time accumulating ratings on platforms (Kas et al., 2022) and that rating systems can lead to discriminatory spillovers because the initially unbiased customers can be sensitive to differences in ratings as indicators of quality (Teng et al., 2023). These subtle tensions in the literature thus warrant further empirical evidence on the role of different online feedback in mitigating or exacerbating discrimination.

I hypothesize the outcomes from the possible actions of suppliers and customers. On the customer side, discrimination is a costly action. Borrowing from Becker’s view on crime and punishment (Becker, 1968), a discriminatory customer will only leave bad online feedback, which usually includes numerical ratings and textual reviews, for a racial minority supplier if they see more benefits compared to the potential costs. From this view, leaving a bad numerical rating is relatively easy, but leaving a noxious textual review is much more costly because of the extra effort and the possibility of exposing their identities and opinions to the public. On the supplier side, one implicit implication is that it is harder for racial minority suppliers to garner and accumulate good ratings. However, acquiring unbiased feedback in an online reputation system that asks guests to leave textual reviews is relatively easier. Hence, I hypothesize:

**Hypothesis 5:** *Racial minority suppliers benefit less than White suppliers from online feedback consisting of numerical ratings.*

**Hypothesis 6:** *Racial minority suppliers benefit more than White suppliers from online feedback consisting of textual reviews.*

Additionally, research has shown consumers’ tendency to seek out media that conform to their own beliefs, which is facilitated by the lower cost of production and dissemination of online information (Bimber and Davis, 2003). As a result, consumers of Internet sources such as online news (Nie et al., 2010) and social media (Bond and Messing, 2015) often hold

stronger ideological views. It also takes longer for extreme conservatives to become providers of neutral content than extreme liberals in online crowd-sourced environments (Greenstein et al., 2021). Thus, the impact of online reviews is also likely to affect the ideological distance faced by racial minority entrepreneurs, who are often more liberal than their White peers (Kleinfeld, 2023). As a result, I expect:

**Hypothesis 7:** *The impact of online feedback is more pronounced in ideologically conservative markets.*

## 3 Data and Basic Empirical Approach

### 3.1 Airbnb Data

To test the aforementioned hypotheses in a sharing economy setting, I obtain Airbnb data from Inside Airbnb, a non-profit organization that has been scraping data from Airbnb’s website since early 2015. The inside Airbnb data has been used for numerous academic studies but on a much smaller scale (Cheung and Yiu, 2022; Gyódi, 2022; Lima, 2019; Luca et al., 2024). I use all Airbnb listings, reviews, and calendar information across the U.S. from May 2015 to April 2023. The data is scraped roughly at a monthly interval, with the caveat that scrapes are missing in a few particular months. The basic data structure is thus a listing-scraped date panel.

Given the approximate monthly frequency of the data, I use a 30-day price and 30-day bookings as the main outcome variables for panel data analyses. To construct such measures, I take advantage of the calendar feature that shows the number of days a listing is available 30 days into the future and the listing prices for these available days. I then calculate the weighted average price for these days for the price measure and the days a listing is unavailable for the booking measure. I also calculate the interval between the time when a new listing first appears in the data and the time the listing no longer appears in the data to measure the “time until exit” for survival analyses.

In addition to these measures, I observe the listing information for any particular Airbnb listing, including room types, bed types, number of bedrooms, amenities, listing recency and descriptions, location down to latitude and longitude, Instant Book feature, and other miscellaneous information. I can also see the host information for the listing, including names (mostly first names), Superhost status, host tenures, multiple listings, location, descriptions, response time, and so on. Lastly, I have essential review information, such as numerical ratings and textual reviews for all listings and the reviewer names (mostly first names) and profiles.

To identify the demographics of Airbnb hosts and reviewers, I first infer through first names as it is shown that the top 1,000 first names capture the majority of the U.S. population (Tzioumis, 2018). I use R’s `predictr` package, which is shown to be the best-performing algorithm among recent developments in name-based demographic inference (Lockhart et al., 2023). I then asked a research assistant to verify the accuracy of the prediction by looking at randomly sampled host profiles, which include host pictures, names, known languages, self-introductions, and location information. The match rate between algorithmic prediction and human verification is overall accurate for race and gender, confirming the validity of this name-based inference approach <sup>3</sup>.

Table 1 reports the summary statistics broken down by race for all listing-month pairs. Table 2 reports the summary statistics broken down by race in the final month when an Airbnb listing last appears in the data. Overall, racial minority hosts from all groups have lower listing prices and fewer bookings and operate on Airbnb for shorter time spans relative to White hosts. They also differ in some observable attributes in listing and host features, which reflects some potential quality differences of the offerings.

[Insert Table 1 about here]

[Insert Table 2 about here]

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<sup>3</sup>Details of the match rates are reported in the Appendix.

### 3.2 Baseline estimates for race impact on performance

The first part of the empirical analysis seeks to establish the baseline relationship between a host’s race and the listing’s performance. I use the following log-level fixed effects regression to estimate this effect:

$$\log(y_{it}) = \beta Race_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (1)$$

Where the outcome can either be the logarithm (hereinafter log) of the 30-day price or the 30-day booking measure for listing  $i$  in month  $t$ . The main independent variable is the race of the Airbnb host (relative to White).  $X_{it}$  is a set of controls including observable listing characteristics such as the number of bedrooms (in log), number of amenities (in log), the type of the room (entire home/apartment, private room, shared room, and hotel room), whether the listing allows instant booking, numerical ratings and textual reviews counts (in log), and days since the last review (in log).  $X_{it}$  also include characteristics of the host of the listings, such as whether the host qualifies as a Superhost (an elite status based on ratings, number of stays, cancellation rate, and response rate), days as a host (in log), and the number of simultaneous listings by the same host (in log), which may or may not be easily observable by guests.  $\alpha_i$  is the ZIP Code fixed effects to control for the unobserved, location-specific heterogeneity.  $\theta_t$  is the time fixed effect that controls for temporal shocks that apply to all listings. This log-level specification allows an interpretation of the effect of race on performance in elasticity terms (i.e.,  $100 \times \beta$ ).

In addition to OLS, I also use the Cox proportional hazard model to estimate the relationship between a host’s demographics and their probability of exit:

$$H_i(t) = H_0(t) \times \exp(\beta_1 Race_i + \gamma' X_i) \quad (2)$$

Where  $H_i(t)$  is the expected hazard at time  $t$ ,  $H_0(t)$  is the baseline hazard and represents

the hazard when all of the predictors are equal to zero (or at their base levels). In addition to the host race, I include the same set of control  $X_{it}$  as in the OLS regression. I report the results using regression coefficients rather than hazard ratios for ease of presenting the probability of exit.

### 3.3 Heterogeneity in political ideology

I explore differences in listing locations, down to the ZIP Code Tabulation Area (ZCTA), to examine whether the race effects for racial minority hosts are more potent in more ideologically distant locations. To measure conservativeness, I utilize the results from the American Ideology Project (AIP), a project that produces estimates of the average political ideology of every state, congressional district, state legislative district, county, medium-sized city, and ZIP Code Tabulation Area (ZCTA) in the United States by building a 275,000-person super-survey of Americans. Data from the AIP provide estimates of the mass public’s ideology in each geographic unit and time period based on a multilevel regression and post-stratification (MRP) model (Park et al., 2004; Tausanovitch and Warshaw, 2013). Importantly, these estimates adjust for race, education, and gender for each location-time unit and are shown to be reliable measures of public opinion (Caughey and Warshaw, 2019).

The MRP-based estimates of ideology are on a continuous scale. They are standardized so that one unit is one standard deviation in the raw individual scores. As such, they entail a within-comparison of how liberal or conservative the public is on policy. For example, someone at a “1” would be one standard deviation more conservative than the median person, who would have a value of zero. While these raw estimates provide granular estimates of public opinion, their interpretations in regressions are not straightforward. Therefore, I also create a binary MRP variable to categorize negative values of the estimates as liberal-leaning and positive values as conservative-leaning. To estimate the moderating effect of ideology, I thus include an interaction effect between the race of an Airbnb host and the political ideology of the ZCTA where a listing is located, using either the raw MRP

estimates (continuous) or the categorized MRP measure (binary):

$$\log(y_{it}) = \beta_1 \text{Race}_{it} + \beta_2 \text{Conservative}_{it} + \beta_3 \text{Race}_{it} \times \text{Conservative}_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (3)$$

Where the set of controls and fixed effects are the same as the baseline OLS model. Additionally, I also estimate the exit probability using a Cox proportional hazard model:

$$H_i(t) = H_0(t) \times \exp(\beta_1 \text{Race}_i + \beta_2 \text{Conservative}_{it} + \beta_3 \text{Race}_{it} \times \text{Conservative}_{it} + \gamma' X_i) \quad (4)$$

## 4 Basic results and Alternative Explanations

### 4.1 Basic results

#### 4.1.1 Baseline estimates for price, bookings, and survival

Table 3 reports the baseline OLS estimates for the impact of race on listing performance, measured in 30-day price or 30-day bookings. For both outcomes, I estimate models with fixed effects at various levels of geographic and temporal granularity. Results generally show that racial minority Airbnb hosts charge lower prices and also have fewer bookings compared to White hosts. Columns 2 and 5, for example, suggest that holding the observable listing and host characteristics constant, Asian, Black, and Hispanic hosts charge 5.3%, 1.5%, and 3.5% less and have 2.2%, 8.5%, and 1.7% fewer bookings than White hosts within the same ZCTA. These findings broadly support hypothesis 1. The inclusion of the Zip Code interaction with month fixed effect (i.e., columns 3 and 6) does not change the results by much, suggesting factors unique to ZCTA do not discernibly evolve over time. Thus, I primarily report the results of OLS models with ZCTA and month fixed effects in the tables that follow.

[Insert Table 3 about here]

Before showing the estimates for Cox models, I non-parametrically estimate the sur-

vival probability for hosts from different racial backgrounds after any given months. Figure 2 shows the results of putting all non-White hosts together and that they have a lower chance of continuous operation at any point in time compared to the White hosts.

[Insert Figure 2 about here]

Table 4 presents the Cox estimates of the demographic impact on hosts' exit decisions. Note that all coefficients are already log-transformed, representing the probability of exit. Column 2, for example, estimates that Asian, Black, and Hispanic hosts have 8.5%, 11.9%, and 5.6% higher probability of exit relative to White hosts, holding the observables constant. These results are in line with the prediction in hypothesis 2. In addition to the race impact, I estimate the gender impact on exit. The effect size is, however, much smaller compared to the race impact. For instance, column 4 shows that male hosts, on average, have a 2.3% higher chance of exit relative to female hosts.

[Insert Table 4 about here]

#### **4.1.2 Estimates for heterogeneity in ZCTA-level ideology**

Table 5 reports the OLS estimates for the differential effects of ZCTA-level ideology on Airbnb listings hosted by various racial backgrounds. Overall, while racial minority hosts do not evidently charge lower prices in more conservative areas, they generally face significantly lower consumer demands in those areas than racial minority hosts located in liberal areas. Using the binary measure of ZCTA ideology, column 3 shows that Asian hosts have 8.8% and Hispanic hosts have 3.9% fewer bookings in conservative ZCTAs than in liberal ZCTAs. Using the continuous measure of ZCTA ideology, column 4 shows that Asian hosts have 12.6% and Hispanic hosts have 4.4% fewer bookings in ZCTAs that are one standard deviation more conservative than the median ZCTA. Notably, Black hosts have a particularly hard time recruiting guests, even in more liberal areas. For example, column 3 shows that they have 10% fewer bookings compared to White hosts in liberal ZCTAs, highlighting the strongest

challenge faced across all racial minority groups. Table 6 presents the Cox estimates on hosts' exit decisions. The results generally show that racial minority hosts have higher exit probabilities, even in liberal ZCTAs. In addition, Asian and Black hosts are more likely to exit when operating in conservative ZCTAs when ideology is measured on a continuous scale. Taken together, these findings broadly support hypotheses 3 and 4.

[Insert Table 5 about here]

[Insert Table 6 about here]

## 4.2 Alternative explanations and robustness checks

### 4.2.1 Source of endogeneity

Although the specifications in Section 3 control for the most relevant listing and host characteristics, unobserved factors specific to ZCTA that are constant over time, and temporal shocks identical to all listings, the gap in performance between listings by racial minority hosts relative to White hosts can still be driven by unobservable quality differences. In addition, the backgrounds of the potential set of guests, and more generally, racial homophily, need to be examined. Last but not least, changes in broader socioeconomic trends, such as COVID-19 or the Black Lives Matter (BLM) movement, can shape the performance of different racial groups. While it is not feasible to account for all sources of endogeneity, I conduct a series of checks to address these concerns.

### 4.2.2 Entire property vs. private room

Customers are known to engage in using demographic groups as proxies for unobservable attributes, such as quality (Arrow, 1971; Phelps, 1972). They might also make decisions based on personal prejudice or biases against a particular group, which is known as taste-based discrimination (Becker, 1971). On Airbnb, hosts can rent out part or all of their properties. The type of room offered thus implies the need (or lack thereof) for hosts and



guests to share space (or not). Therefore, if racial minority hosts were to be passed over because of “taste,” they should have a harder time listing part of their property than listing the entire property. To investigate this race impact by room types, I include an interaction effect between the host race and the type of room a listing offers.

$$\log(y_{it}) = \beta_1 Race_{it} + \beta_2 Roomtype_{it} + \beta_3 Race_{it} \times Roomtype_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (5)$$

Table 7 shows that the price differentials between White and racial minority hosts when offering private rooms are generally larger than when offering the entire properties (column 1). The discrepancy is especially larger for Asian and Hispanic hosts in conservative ZCTAs (column 2). Additionally, Hispanic hosts also receive fewer bookings with private room listings on top of the reduced bookings they encounter when listing the entire properties (column 3). Asian hosts, however, receive more bookings with private rooms, presumable because of the aggressive pricing discounts they offer. Black hosts also generally have a harder time operating private room listings, although the coefficients are not statistically significant. Together, these results provide some support for the explanation of taste-based discrimination against racial minority suppliers.

[Insert Table 7 about here]

#### 4.2.3 Racial backgrounds of guests

Racial homophily, which can be found in online communities (Wimmer and Lewis, 2010), refers to the tendency of individuals to associate with others who share the same racial background. Hence, it is possible that guests on Airbnb might be more likely to seek out hosts with the same racial background. If so, the exacerbated disparities faced by racial minorities in conservative ZCTAs might be attributed to the lack of racial minorities living or traveling to those areas. To examine this possibility, I further investigate the racial backgrounds of guests. While I do not directly observe the identities of all guests, I am

able to infer the backgrounds of the guests who left reviews for their stays. To link guest backgrounds to the impact of race on listing performance, I reestimate specification (3) using White hosts as the base category on the following subsamples: (a) listings whose textual reviews are all left by White reviewers, (b) listings whose textual reviews are left mainly by White reviewers ( $> 50\%$ ), and (c) listings whose textual reviews are mostly not left by White reviewers ( $< 50\%$ ). Table 8 shows minimal differences in the estimates using these subsamples. For example, White hosts receive 4% to 5% more bookings when listing in conservative ZCTAs regardless of the racial compositions of guests who left reviews for their stays (columns 4 to 6). Therefore, racial homophily is unlikely to be the leading explanation for the previous estimates of racial discrepancies.

[Insert Table 8 about here]

#### 4.2.4 Genders of hosts

Recent research in organizational theory and social psychology also illuminates the importance of considering the ways in which multiple social categories intersect to shape outcomes (Rosette et al., 2018). In this context, host gender can be another facet that might moderate the race effect. To investigate the intersectionality of race and gender, I include an interaction term between the host race and host gender in the following specification.

$$\log(y_{it}) = \beta_1 \text{Race}_{it} + \beta_2 \text{Gender}_{it} + \beta_3 \text{Race}_{it} \times \text{Gender}_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (6)$$

Table 9 shows that Black males tend to charge 6% lower prices than Black females (column 1). Hispanic males also charge lower prices, especially in conservative ZCTAs (columns 1 and 2). However, their booking performance does not seem to suffer relative to female hosts (columns 3 and 4). Interestingly, Asian male hosts have 4.5% more bookings than Asian female hosts (column 3). While these results are worth exploring, they do not directly change the theory and empirical findings of discrimination against racial minority suppliers.

[Insert Table 9 about here]

#### 4.2.5 Effect of the COVID shock

As my sample spans an eight-year period, changes in broader socioeconomic trends can possibly affect the performance of various racial groups in different manners. For example, the COVID-19 pandemic had a profound impact on society. On March 16, 2020, former President Donald Trump described the coronavirus as the “Chinese virus” in a tweet, contributing to anti-Asian sentiment. Shortly after, in May 2020, the murder of George Floyd spurred campaigns against systemic racism and violence towards Black people. Research has used the events to examine the performance of minority suppliers in different contexts (Aneja et al., 2023; Luca et al., 2024). To examine if these events affect the interpretation of previous findings, I estimate the following model where “After” indicates the time periods after April 2020.

$$\log(y_{it}) = \beta_1 Race_{it} + \beta_2 After_{it} + \beta_3 Race_{it} \times After_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (7)$$

Table 10 reports the findings, which show that racial minority hosts do not charge lower prices than White hosts after COVID-19 (columns 1 and 2). Although they receive significantly fewer bookings in the post-COVID period, the overall trend for the COVID impact is consistent across all racial minority groups. For example, Asian hosts have fewer bookings in the “Asian hate” period, but Black hosts also have fewer bookings despite the broad support of the BLM movement at similar periods. Additionally, Black hosts already experience much fewer bookings than White hosts before COVID (columns 3 and 4). Hence, while the impact of COVID seemingly exacerbates conditions faced by racial minority suppliers, the underlying disparities they face throughout the sample period are unlikely to be primarily driven by these single events.

[Insert Table 10 about here]

#### 4.2.6 Matching and dyadic analyses

I perform several alternative specifications to demonstrate the robustness of the results. First, I implement coarsened exact matching (CEM) to create a matched sample to improve the estimation by reducing the imbalance in covariates among different racial groups. CEM offers many advantages over traditional matching methods, such as propensity score matching, in reducing covariate imbalance and effect bias because of its more accurate and less restrictive balance-checking procedures (Iacus et al., 2012). Results from CEM samples are largely consistent with the previous estimates. To improve the matched results, I further identify listing pairs where the distance between the two listings is within 100 ft (30 meters) to model the effects through dyadic analyses:<sup>4</sup>

$$\log(y_{it} - y_{jt}) = \beta(Race_{it} - Race_{jt}) + \gamma'(X_{it} - X_{jt}) + \alpha_{ij} + \theta_t + \varepsilon_{ijt} \quad (8)$$

## 5 Online Feedback and Sentiment Analyses

### 5.1 Effects of numerical ratings and textual reviews

As discussed in Section 2, while the efficacy of online reputation systems in mitigating racial discrimination is potentially ambiguous, I hypothesize that racial minority suppliers benefit less from numerical ratings but more from textual reviews than White suppliers. To empirically test these hypotheses, I first examine the moderating effects of numerical ratings and textual reviews on host performance by race using OLS.

Table 11 reports the impact of numerical rating by race, which shows that for White hosts, the reference category, a one-percent increase in numerical rating of their listing leads to a 0.27% increase in price (column 1) and a 0.62% increase in bookings. However, the impact of a one-percent increase in numerical rating is smaller for racial minority hosts, at

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<sup>4</sup>Note that the computational process is very intensive and still ongoing. Results to be reported.

0.21% (Asian), 0.21% (Black) and 0.14% (Hispanic) for price, and 0.39% (Asian), 0.59% (Black) and 0.55% (Hispanic) for bookings. Hence, better numerical ratings benefit White hosts more than racial minority hosts.

[Insert Table 11 about here]

Table 12 reports the impact of more textual reviews by race. Unlike the results from numerical ratings, there is hardly a major relative disparity between White hosts and racial minority hosts in terms of benefiting from textual reviews. If anything, certain racial minority groups, such as Hispanic hosts, benefit more from the sheer amount of textual reviews than White hosts. Together with the results in Table 11, these findings broadly support hypothesis 5 and do not contradict hypothesis 6.

[Insert Table 12 about here]

## 5.2 Sentiments of textual reviews

Unlike fixed-scale numerical ratings, textual reviews are much more qualitative and offer context and insights into particular listings. Hence, the use of review counts above is a relatively crude measure. To further delve into the nuances of textual reviews, I conduct natural language processing (NLP) on about 90 million Airbnb reviews left by guests. The specific NLP procedure is discussed in the Appendix. Broadly speaking, I use sentiment analysis to determine the emotional tone behind a body of textual reviews to examine how specific feedback from textual reviews shapes the performance of racial minority suppliers.

Table 13 reports how net positive sentiments, as measured by positive sentiments as a percentage of both positive and negative sentiments classified by the Bing (Hu and Liu, 2004) or NRC (Mohammad and Turney, 2013) lexicons in an Airbnb listing’s written reviews received in a given month, affect prices and bookings for racial minority hosts in liberal and conservative ZCTAs. Overall, results show that positive feedback from textual reviews improves the performance of Black hosts in conservative ZCTAs. For example,

columns 1 and 3 show that for a one-unit increase in Bing-based positive sentiments (i.e., 1% change), Black hosts are able to charge 0.3% (e.g.,  $100 \times 0.00276\%$ ) more and receive 0.5% (e.g.,  $100 \times 0.00539\%$ ) more bookings in conservative ZCTAs relative to the sentiment impact in liberal ZCTAs. This finding thus provides some support for hypothesis 7. Nevertheless, these positive sentiments do not discernible benefit Black hosts in liberal ZCTAs, nor do they affect other racial minority groups more in conservative ZCTAs. Hence, evidence suggests that Black suppliers in conservative areas are the group that is most susceptible to the emotions expressed by consumers in textual reviews.

[Insert Table 13 about here]

Delving further into consumers’ sentiments toward Black suppliers, it is shown that biased individuals are more fearful of Black strangers than any other racial groups (Bertrand et al., 2005; Quillian and Pager, 2001). Therefore, I examine the impact of the “fear” sentiment in guest reviews on listing performance. Table 14 shows that a 1% increase in fear expressed in textual reviews significantly reduces bookings for Black listings in conservative ZCTAs by 13.7% more than in liberal ZCTAs. This finding confirms that Black suppliers are sensitive to customer feedback in textual reviews, and the specifics of feedback can either attenuate or exacerbate the biases they face, especially in ideologically conservative markets.

[Insert Table 14 about here]

## 6 Discussion and Conclusion

### 6.1 Summary of findings

I study the role of race in determining business performance by focusing on suppliers in the sharing economy and exploring the underlying heterogeneity and mechanisms beyond the baseline investigations. Using data covering all Airbnb listings across the U.S. from May

2015 to April 2023, I find that racial minority Airbnb hosts charge lower prices, experience fewer bookings, and are more likely to cease their business operations. Using granular data on public opinion at the ZIP Code level, I show that the disparity is more severe in ideologically conservative markets. I further show that different online feedback can unevenly moderate such impacts. Specifically, racial minority suppliers benefit less than White suppliers from online feedback consisting of numerical ratings. This relative disparity, on average, disappears in online feedback consisting of textual reviews. However, depending on the sentiment expressed in these reviews, textual feedback can attenuate or exacerbate the bias, especially for Black suppliers operating in ideologically conservative markets.

While the existing suppliers on Airbnb are primarily White, racial bias can significantly hinder the entrepreneurial efforts of the 140,000 racial minority suppliers on the platform. For example, a back-of-the-envelope calculation suggests monthly revenue losses of 9.6%, 21%, and 7.1% for Asian, Black, and Hispanic suppliers, respectively. These revenue losses, coupled with a higher likelihood of business failure compared to White suppliers, not only affect current racial minority suppliers but might also discourage potential racial minority suppliers from entering the market.

## 6.2 Conclusion

This study has important implications for research on discrimination and non-market strategy, entrepreneurship and innovation, and platform designs in the context of the sharing economy. While my empiric analyses focus on Airbnb, I anticipate the findings will be relevant to other sharing economy platforms because of the increased direct contact among sharing economy participants and the similarity in online reputation systems. Beyond the sharing economy, many platform-based businesses can benefit from designing more equitable marketplaces. Not only is this socially important, but it also has strong business implications, as attracting latent suppliers from racial minority backgrounds is crucial for market expansion and enhancing the quality of entrepreneurship (Conti et al., [2022](#)).

There are some limitations to this study. First, inferring demographics from supplier and customer names can introduce measurement errors. Given that initial human verification shows mostly accurate results, the direction of my findings remains valid. In fact, the higher measurement errors in Black-sounding names likely result in more conservative estimates of race effects. Second, the performance gap between listings by racial minority hosts relative to White hosts may be partly influenced by unobservable quality differences and socioeconomic events. I control for all reasonable listing and host characteristics and conduct a series of robustness checks to rule out several alternative explanations for my findings. Nevertheless, it is not possible to account for all sources of endogeneity. I thus encourage the results to be interpreted with some caution. Lastly, the NLP procedure I use to analyze textual reviews relies on pre-defined lexicons to opinion-mine customer reviews. With the recent developments in large language models, future research can explore more context-specific consumer languages using techniques such as deep learning and neural networks.

Despite these limitations, this paper makes important contributions to several areas of literature. Specifically, it adds to the literature on discrimination by exploring the critical aspect of supplier discrimination. It also enriches the literature on non-market strategy for entrepreneurs by examining the impact of ideological identity on firm and entrepreneur performance. Additionally, it sheds light on the role of online reputation systems in creating a fair marketplace and fostering entrepreneurship. While there are issues that future research should address, this study is a valuable step toward exploring numerous opportunities in management research related to entrepreneurship, discrimination and non-market strategy, and platform design in the sharing economy and beyond.



## References

- Abrahao, B., Parigi, P., Gupta, A., & Cook, K. S. (2017). Reputation offsets trust judgments based on social biases among airbnb users. *Proceedings of the National Academy of Sciences*, 114(37), 9848–9853.
- Airbnb. (2022). A six-year update on Airbnb’s work to fight discrimination. <https://news.airbnb.com/sixyearadupdate/>
- Airbnb. (2023). The Airbnb story. <https://news.airbnb.com/about-us/>
- Alyakoob, M., & Rahman, M. S. (2022). Market design choices, racial discrimination, and equitable micro-entrepreneurship in digital marketplaces. *USC Marshall School of Business Research Paper Sponsored by iORB*.
- Ananthakrishnan, U., Proserpio, D., & Sharma, S. (2023). I hear you: Does quality improve with customer voice? *Marketing Science*, 42(6), 1143–1161.
- Aneja, A., Luca, M., & Reshef, O. (2023). *The benefits of revealing race: Evidence from minority-owned local businesses* (tech. rep.). National Bureau of Economic Research.
- Arrow, K. (1971). Some models of racial discrimination in the labor market. *RAND research memorandum*.
- Ayres, I., Banaji, M., & Jolls, C. (2015). Race effects on ebay. *The RAND Journal of Economics*, 46(4), 891–917.
- Ayres, I., & Siegelman, P. (1995). Race and gender discrimination in bargaining for a new car. *American Economic Review*, 304–321.
- Bajari, P., & Hortaçsu, A. (2003). The winner’s curse, reserve prices, and endogenous entry: Empirical insights from ebay auctions. *RAND Journal of Economics*, 329–355.
- Bar, R., & Zussman, A. (2017). Customer discrimination: Evidence from Israel. *Journal of Labor Economics*, 35(4), 1031–1059.
- Barber IV, B., & Blake, D. J. (2024). My kind of people: Political polarization, ideology, and firm location. *Strategic Management Journal*, 45(5), 849–874.

- Basu, S., Berman, R., Bloomston, A., Campbell, J., Diaz, A., Era, N., Evans, B., Palkar, S., & Wharton, S. (2022). Measuring discrepancies in airbnb guest acceptance rates using anonymized demographic data. *arXiv preprint arXiv:2204.12001*.
- Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76(2), 169–217.
- Becker, G. S. (1971). *The economics of discrimination*. University of Chicago press.
- Benton, R. A., Cobb, J. A., & Werner, T. (2022). Firm partisan positioning, polarization, and risk communication: Examining voluntary disclosures on covid-19. *Strategic Management Journal*, 43(4), 697–723.
- Bertrand, M., Chugh, D., & Mullainathan, S. (2005). Implicit discrimination. *American Economic Review*, 95(2), 94–98.
- Bertrand, M., & Mullainathan, S. (2004). Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination. *American Economic Review*, 94(4), 991–1013.
- Bimber, B., & Davis, R. (2003). *Campaigning online: The Internet in US elections*. Oxford University Press.
- Blanchflower, D. G., Levine, P. B., & Zimmerman, D. J. (2003). Discrimination in the small-business credit market. *Review of Economics and Statistics*, 85(4), 930–943.
- Bodvarsson, Ö. B., & Partridge, M. D. (2001). A supply and demand model of co-worker, employer and customer discrimination. *Labour Economics*, 8(3), 389–416.
- Bolton, G. E., Katok, E., & Ockenfels, A. (2004). How effective are electronic reputation mechanisms? an experimental investigation. *Management Science*, 50(11), 1587–1602.
- Bond, R., & Messing, S. (2015). Quantifying social media’s political space: Estimating ideology from publicly revealed preferences on facebook. *American Political Science Review*, 109(1), 62–78.
- Botelho, T., & DeCelles, K. (2023). *The customer cancellation gap: The drivers of racial/ethnic disparities in on-demand work* (tech. rep.). Working Paper.

- Brewster, Z. W., & Lynn, M. (2014). Black–white earnings gap among restaurant servers: A replication, extension, and exploration of consumer racial discrimination in tipping. *Sociological Inquiry*, 84(4), 545–569.
- Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? an empirical examination of the gig economy and entrepreneurial activity. *Management Science*, 64(12), 5497–5520.
- Caughey, D., & Warshaw, C. (2019). Public opinion in subnational politics. *Journal of Politics*, 81(1), 352–363.
- Cheung, K. S., & Yiu, C. Y. (2022). Touristification, airbnb and the tourism-led rent gap: Evidence from a revealed preference approach. *Tourism Management*, 92, 104567.
- Conti, R., Kacperczyk, O., & Valentini, G. (2022). Institutional protection of minority employees and entrepreneurship: Evidence from the lgbt employment non-discrimination acts. *Strategic Management Journal*, 43(4), 758–791.
- Cook, L. D., Gerson, J., & Kuan, J. (2022). Closing the innovation gap in pink and black. *Entrepreneurship and Innovation Policy and the Economy*, 1(1), 43–66.
- Cui, R., Li, J., & Zhang, D. J. (2020). Reducing discrimination with reviews in the sharing economy: Evidence from field experiments on airbnb. *Management Science*, 66(3), 1071–1094.
- Edelman & Luca, M. (2014). Digital discrimination: The case of airbnb. com. *Harvard Business School NOM Unit Working Paper*, (14-054).
- Edelman, Luca, M., & Svirsky, D. (2017). Racial discrimination in the sharing economy: Evidence from a field experiment. *American Economic Journal: Applied Economics*, 9(2), 1–22.
- Garud, R., Kumaraswamy, A., Roberts, A., & Xu, L. (2022). Liminal movement by digital platform-based sharing economy ventures: The case of uber technologies. *Strategic Management Journal*, 43(3), 447–475.

- Ge, Y., Knittel, C. R., MacKenzie, D., & Zoepf, S. (2020). Racial discrimination in transportation network companies. *Journal of Public Economics*, 190, 104205.
- Glusac, E. (2016). As Airbnb grows, so do claims of discrimination. *New York Times*. <https://www.nytimes.com/2016/06/26/travel/airbnb-discrimination-lawsuit.html>
- Greenstein, S., Gu, G., & Zhu, F. (2021). Ideology and composition among an online crowd: Evidence from wikipedians. *Management Science*, 67(5), 3067–3086.
- Gyódi, K. (2022). Airbnb and hotels during covid-19: Different strategies to survive. *International Journal of Culture, Tourism and Hospitality Research*, 16(1), 168–192.
- Hegde, D., Ljungqvist, A., & Raj, M. (2023). Race, glass ceilings, and lower pay for equal work. *Swedish House of Finance Research Paper*, (21-09).
- Hou, Y., & Poliquin, C. W. (2023). The effects of ceo activism: Partisan consumer behavior and its duration. *Strategic Management Journal*, 44(3), 672–703.
- Hsieh, C.-T., Hurst, E., Jones, C. I., & Klenow, P. J. (2019). The allocation of talent and us economic growth. *Econometrica*, 87(5), 1439–1474.
- Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, 168–177.
- Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1), 1–24.
- Iyengar, S., & Westwood, S. J. (2015). Fear and loathing across party lines: New evidence on group polarization. *American Journal of Political Science*, 59(3), 690–707.
- Kaas, L., & Manger, C. (2012). Ethnic discrimination in germany’s labour market: A field experiment. *German Economic Review*, 13(1), 1–20.
- Kane, G. C. (2016). Crowd-based capitalism? empowering entrepreneurs in the sharing economy. *MIT Sloan Management Review*, 57(3).
- Kas, J., Corten, R., & van de Rijt, A. (2022). The role of reputation systems in digital discrimination. *Socio-Economic Review*, 20(4), 1905–1932.

- Kessler, J. B., Low, C., & Sullivan, C. D. (2019). Incentivized resume rating: Eliciting employer preferences without deception. *American Economic Review*, 109(11), 3713–3744.
- Kleinfeld, R. (2023). Polarization, democracy, and political violence in the united states: What the research says.
- Kricheli-Katz, T., & Regev, T. (2016). How many cents on the dollar? women and men in product markets. *Science Advances*, 2(2), e1500599.
- Lee, W., & Roemer, J. E. (2006). Racism and redistribution in the united states: A solution to the problem of american exceptionalism. *Journal of Public Economics*, 90(6-7), 1027–1052.
- Li, Z., Hong, Y., & Zhang, Z. (2021). The empowering and competition effects of the platform-based sharing economy on the supply and demand sides of the labor market. *Journal of Management Information Systems*, 38(1), 140–165.
- Lima, V. (2019). Towards an understanding of the regional impact of airbnb in ireland. *Regional Studies, Regional Science*, 6(1), 78–91.
- Lockhart, J. W., King, M. M., & Munsch, C. (2023). Name-based demographic inference and the unequal distribution of misrecognition. *Nature Human Behaviour*, 7(7), 1084–1095.
- Luca, M. (2016). Reviews, reputation, and revenue: The case of yelp. com. *Com (March 15, 2016)*. *Harvard Business School NOM Unit Working Paper*, (12-016).
- Luca, M., Pronkina, E., & Rossi, M. (2024). The evolution of discrimination in online markets: How the rise in anti-asian bias affected airbnb during the pandemic. *Marketing Science*.
- Lynn, M., & Sturman, M. (2011). Is the customer always right? the potential for racial bias in customer evaluations of employee performance. *Journal of Applied Social Psychology*, 41(9), 2312–2324.

- Marchenko, A. (2019). The impact of host race and gender on prices on airbnb. *Journal of Housing Economics*, 46, 101635.
- Markman, G. D., Lieberman, M., Leiblein, M., Wei, L.-Q., & Wang, Y. (2021). The distinctive domain of the sharing economy: Definitions, value creation, and implications for research. *Journal of Management Studies*, 58(4), 927–948.
- Mas, A., & Moretti, E. (2009). Racial bias in the 2008 presidential election. *American Economic Review*, 99(2), 323–329.
- Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. *Computational Intelligence*, 29(3), 436–465.
- Mohliver, A., Crilly, D., & Kaul, A. (2023). Corporate social counterpositioning: How attributes of social issues influence competitive response. *Strategic Management Journal*, 44(5), 1199–1217.
- Moreno, A., & Terwiesch, C. (2014). Doing business with strangers: Reputation in online service marketplaces. *Information Systems Research*, 25(4), 865–886.
- Neureiter, M., & Bhattacharya, C. (2021). Why do boycotts sometimes increase sales? consumer activism in the age of political polarization. *Business Horizons*, 64(5), 611–620.
- Nie, N. H., Miller, D. W., III, Golde, S., Butler, D. M., & Winneg, K. (2010). The world wide web and the us political news market. *American Journal of Political Science*, 54(2), 428–439.
- Nunley, J. M., Pugh, A., Romero, N., & Seals, R. A. (2015). Racial discrimination in the labor market for recent college graduates: Evidence from a field experiment. *The BE Journal of Economic Analysis & Policy*, 15(3), 1093–1125.
- Paik, Y., Kang, S., & Seamans, R. (2019). Entrepreneurship, innovation, and political competition: How the public sector helps the sharing economy create value. *Strategic Management Journal*, 40(4), 503–532.

- Park, D. K., Gelman, A., & Bafumi, J. (2004). Bayesian multilevel estimation with post-stratification: State-level estimates from national polls. *Political Analysis*, 12(4), 375–385.
- Phelps, E. S. (1972). The statistical theory of racism and sexism. *The American Economic Review*, 62(4), 659–661.
- Quillian, L., & Pager, D. (2001). Black neighbors, higher crime? the role of racial stereotypes in evaluations of neighborhood crime. *American Journal of Sociology*, 107(3), 717–767.
- Reimers, I., & Waldfogel, J. (2021). Digitization and pre-purchase information: The causal and welfare impacts of reviews and crowd ratings. *American Economic Review*, 111(6), 1944–1971.
- Rider, C. I., Wade, J. B., Swaminathan, A., & Schwab, A. (2023). Racial disparity in leadership: Evidence of evaluative bias in the promotions of national football league coaches. *American Journal of Sociology*, 129(1), 227–275.
- Robbins, B. G. (2017). Status, identity, and ability in the formation of trust. *Rationality and Society*, 29(4), 408–448.
- Rosette, A. S., de Leon, R. P., Koval, C. Z., & Harrison, D. A. (2018). Intersectionality: Connecting experiences of gender with race at work. *Research in Organizational Behavior*, 38, 1–22.
- Sidanius, J., Pratto, F., & Bobo, L. (1996). Racism, conservatism, affirmative action, and intellectual sophistication: A matter of principled conservatism or group dominance? *Journal of Personality and Social Psychology*, 70(3), 476.
- Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Roy, P. K. (2017). Predicting the “helpfulness” of online consumer reviews. *Journal of Business Research*, 70, 346–355.
- Sundararajan, A. (2017). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. Cambridge: MIT Press.

- Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual Review of Economics*, 8, 321–340.
- Tausanovitch, C., & Warshaw, C. (2013). Measuring constituent policy preferences in congress, state legislatures, and cities. *The Journal of Politics*, 75(2), 330–342.
- Teng, F., Botelho, T., & Sudhir, K. (2023). *Can customer ratings be discrimination amplifiers? evidence from a gig economy platform* (tech. rep.). Working Paper.
- Tzioumis, K. (2018). Demographic aspects of first names. *Scientific Data*, 5(1), 1–9.
- Whitehead, J. (2005). Racial economic inequality and discrimination: Conservative and liberal paradigms revisited. *African Americans in the US Economy*, 83–93.
- Wimmer, A., & Lewis, K. (2010). Beyond and below racial homophily: ERG models of a friendship network documented on facebook. *American Journal of Sociology*, 116(2), 583–642.
- Yinger, J. (1998). Evidence on discrimination in consumer markets. *Journal of Economic Perspectives*, 12(2), 23–40.
- Zeng, Y., & Sakakibara, M. (2024). Learning from reviews: The role of text reviews in the sharing economy. *Academy of Management Proceedings*, 2024(1).



Tables

Table 1: Summary statistics by race, all listing-time pairs

Variables	White			Asian			Hispanic			Black		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
30-day price	190.53	125.00	454.90	150.74	95.00	516.65	154.77	100.00	411.64	143.00	95.00	783.15
30-day bookings	16.56	17.00	11.12	16.58	17.00	11.40	16.10	16.00	11.21	15.62	15.00	11.64
Numerical ratings	4.80	4.90	0.34	4.70	4.82	0.44	4.73	4.85	0.41	4.70	4.85	0.49
Textual review counts	33.40	14.00	54.02	30.47	12.00	49.74	30.25	13.00	47.60	25.29	10.00	38.50
Days since the last review	127.46	35.00	245.40	135.93	36.00	260.21	127.84	33.00	249.29	140.85	37.00	257.28
Bedroom counts	1.89	1.00	1.31	1.71	1.00	1.31	1.72	1.00	1.23	1.67	1.00	1.16
Amenity counts	27.78	25.00	13.01	26.35	24.00	12.43	26.53	24.00	12.92	27.27	25.00	13.14
Room type (1-4; 1=entire property)	1.55	1.00	0.91	1.94	1.00	1.02	1.69	1.00	0.98	1.83	1.00	1.01
Instant Book feature (Binary)	0.42	0.00	0.49	0.43	0.00	0.50	0.45	0.00	0.50	0.46	0.00	0.50
Superhost status (Binary)	0.41	0.00	0.49	0.32	0.00	0.47	0.33	0.00	0.47	0.30	0.00	0.46
Days as a host	1330.26	1212.00	838.32	1236.17	1108.00	830.11	1255.66	1126.00	835.45	1171.98	1014.00	830.10
Listing counts by the same host	12.12	2.00	83.15	6.28	2.00	20.77	8.66	2.00	32.30	4.09	1.00	24.20

**Table 2: Summary statistics by race at the final time of operation**

Variables	White			Asian			Hispanic			Black		
	Count	Median	SD	Count	Median	SD	Count	Median	SD	Count	Median	SD
30-day price	1,574,832	130.00	690.35	36,215	97.00	708.09	99,656	106.00	696.06	5,494	100.00	1362.55
30-day bookings	1,574,832	18.00	11.55	36,215	17.00	11.82	99,656	16.00	11.63	5,494	15.00	11.90
Survival months before exit	1,574,832	17.00	24.31	36,215	12.00	22.01	99,656	13.00	22.27	5,494	11.00	20.05
Numerical ratings	1,574,832	4.90	0.44	36,215	4.80	0.56	99,656	4.84	0.53	5,494	4.85	0.65
Textual review counts	1,574,832	12.00	60.00	36,215	9.00	52.15	99,656	11.00	51.08	5,494	8.00	39.99
Days since the last review	1,574,832	48.00	314.37	36,215	44.00	316.26	99,656	38.00	304.99	5,494	45.00	304.31
Bedroom counts	1,574,832	2.00	1.32	36,215	1.00	1.37	99,656	1.00	1.29	5,494	1.00	1.21
Amenity counts	1,574,832	31.00	16.73	36,215	27.00	15.68	99,656	28.00	16.18	5,494	28.00	16.31
Room type (1-4; 1=entire property)	1,574,832	1.00	0.91	36,215	1.00	1.04	99,656	1.00	0.98	5,494	1.00	1.00
Instant Book feature (Binary)	1,574,832	0.00	0.49	36,215	0.00	0.49	99,656	0.00	0.50	5,494	0.00	0.49
Superhost status (Binary)	1,574,832	0.00	0.49	36,215	0.00	0.45	99,656	0.00	0.46	5,494	0.00	0.44
Days as a host	1,574,832	1547.00	1029.81	36,215	1288.00	1013.25	99,656	1359.00	1004.55	5,494	1187.50	997.38
Listing counts by the same host	1,574,832	2.00	74.84	36,215	2.00	15.79	99,656	2.00	44.67	5,494	2.00	55.72

**Table 3: Baseline OLS estimates of the race impact**

	Log(30-day price)			Log(30-day bookings)		
Race (ref. White)						
Asian	-0.0887*** (0.0127)	-0.0534*** (0.00545)	-0.0522*** (0.00547)	0.00828 (0.0122)	-0.0216** (0.00972)	-0.0189* (0.00975)
Black	-0.107*** (0.0146)	-0.0147 (0.0134)	-0.0159 (0.0134)	-0.0971*** (0.0187)	-0.0845*** (0.0238)	-0.0808*** (0.0232)
Hispanic	-0.106*** (0.0157)	-0.0354*** (0.00416)	-0.0343*** (0.00413)	-0.0227* (0.0128)	-0.0174*** (0.00640)	-0.0155** (0.00636)
Multiple race	-0.124*** (0.0394)	-0.0395 (0.0279)	-0.0416 (0.0277)	-0.0725* (0.0422)	-0.0669 (0.0494)	-0.0636 (0.0499)
City FE	Yes	No	No	Yes	No	No
ZIP Code FE	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIP Code $\times$ Time FE	No	No	Yes	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,691,931	24,126,928	23,935,681	34,701,232	24,135,307	23,944,066
R <sup>2</sup>	0.526	0.648	0.659	0.074	0.130	0.229
F	972.9	3,971.0	3,933.9	220.1	756.5	856.0

Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at City or ZIP Code level in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 4: Log-transformed Cox coefficients of demographic impacts on exit**

<b>Outcome: Exit</b>				
Race (ref. White)			Gender (ref. female)	
Asian	0.201*** (0.0208)	0.0849*** (0.0183)	Male	0.0349*** (0.00770)      0.0229*** (0.00634)
Black	0.794*** (0.0790)	0.119*** (0.0367)		
Hispanic	0.137*** (0.0182)	0.0560*** (0.0165)		
Multiple race	0.388*** (0.130)	0.227 (0.138)		
Controls	No	Yes	No	Yes
Observations	39,480,402	29,556,753	29,318,039	22,595,963
Unique listings	3,366,837	2,410,048	2,514,484	1,857,099
Chi <sup>2</sup>	371.9	8,560.7	20.61	9,077.1

Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Cluster robust standard errors reported in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 5: OLS estimates for heterogeneity in ZIP Code-level ideology**

	Log(30-day price)		Log(30-day bookings)	
Race (ref. White)				
Asian	-0.0582*** (0.00570)	-0.0548*** (0.00891)	-0.0122 (0.0103)	-0.0556*** (0.0132)
Black	-0.0132 (0.0148)	-0.0360* (0.0193)	-0.0999*** (0.0262)	-0.138*** (0.0358)
Hispanic	-0.0374*** (0.00447)	-0.0408*** (0.00583)	-0.0134* (0.00716)	-0.0296*** (0.00836)
Race × Conservative ZCTA (ref. liberal ZCTA)				
Asian × Conservative ZCTA (binary)	0.0122 (0.0171)		-0.0879*** (0.0256)	
Black × Conservative ZCTA (binary)	-0.0423 (0.0348)		-0.0245 (0.0648)	
Hispanic × Conservative ZCTA (binary)	-0.0101 (0.0109)		-0.0388** (0.0156)	
Asian × Conservative ZCTA (continuous)		0.00757 (0.0260)		-0.126*** (0.0375)
Black × Conservative ZCTA (continuous)		-0.0659 (0.0509)		-0.140 (0.0988)
Hispanic × Conservative ZCTA (continuous)		-0.00797 (0.0167)		-0.0444* (0.0236)
ZIP Code FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	17,772,423	17,772,423	17,777,907	17,777,907
R <sup>2</sup>	0.659	0.659	0.138	0.138
F	3,876.1	3,876.6	640.1	650.7

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 6: Log-transformed Cox coefficients of heterogeneity in ZIP Code-level ideology**

<b>Outcome: Exit</b>		
Race (ref. White)		
Asian	0.0972*** (0.0146)	0.149*** (0.0207)
Black	0.126*** (0.0351)	0.194*** (0.0457)
Hispanic	0.0710*** (0.0141)	0.0912*** (0.0177)
Race × Conservative ZCTA (ref. liberal ZCTA)		
Asian × Conservative ZCTA (binary)	0.0628 (0.0427)	
Black × Conservative ZCTA (binary)	0.0556 (0.0870)	
Hispanic × Conservative ZCTA (binary)	-0.0198 (0.0296)	
Asian × Conservative ZCTA (continuous)		0.155*** (0.0563)
Black × Conservative ZCTA (continuous)		0.227* (0.128)
Hispanic × Conservative ZCTA (continuous)		0.0515 (0.0438)
Controls	Yes	Yes
Observations	15,460,446	15,460,446
Unique listings	1,075,973	1,075,973
Chi <sup>2</sup>	15,436.6	14,519.8

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust clustered standard errors reported in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 7: OLS estimates of heterogeneity in room types**

	DV: Log(30-day price)		DV: Log(30-day booking)	
Race (ref. White)				
Asian	-0.0233*** (0.00730)	-0.0335*** (0.00768)	-0.0651*** (0.0109)	-0.0503*** (0.0120)
Black	-0.00849 (0.0151)	-0.00477 (0.0163)	-0.0831*** (0.0248)	-0.0860*** (0.0272)
Hispanic	-0.0241*** (0.00496)	-0.0276*** (0.00579)	-0.0142** (0.00701)	-0.00346 (0.00835)
Race × Room type (ref. entire property)				
Asian × Private room	-0.0734*** (0.0106)	-0.0490*** (0.0112)	0.0836*** (0.0176)	0.0710*** (0.0188)
Black × Private room	-0.0396 (0.0255)	-0.0298 (0.0281)	-0.0255 (0.0501)	-0.0196 (0.0547)
Hispanic × Private room	-0.0339*** (0.00765)	-0.0199** (0.00854)	-0.0195* (0.0116)	-0.0234* (0.0129)
Race × Room Type × Conservative ZCTA (ref. liberal ZCTA)				
Asian × Private room × Conservative ZCTA (binary)		-0.0801** (0.0319)		-0.0189 (0.0552)
Black × Private room × Conservative ZCTA (binary)		-0.0330 (0.0673)		-0.0740 (0.137)
Hispanic × Private room × Conservative ZCTA (binary)		-0.0538*** (0.0205)		-0.0221 (0.0344)
ZIP Code FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	16,433,954	16,161,837	16,438,948	16,166,766
R <sup>2</sup>	0.656	0.658	0.139	0.138
F	2,938.2	1,991.4	482.6	328.1

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Coefficients for room type, conservative ZCTA, and some interaction terms are suppressed for ease of presentation. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

**Table 8: OLS estimates for subsamples using reviewer backgrounds**

# of White reviewers as a % of all reviewers	100%	DV: Log(30-day price)		100%	DV: Log(30-day bookings)	
		> 50%	< 50%		> 50%	< 50%
Host race (ref. non-White)						
White	0.0404*** (0.00355)	0.0319*** (0.00504)	0.0332*** (0.00451)	0.0184*** (0.00453)	0.000458 (0.00556)	-0.0107 (0.00887)
Host race × Conservative ZCTA (ref. liberal ZCTA)						
White × Conservative ZCTA (binary)	-0.00903 (0.00868)	-0.0169 (0.0138)	-0.00515 (0.0166)	0.0420*** (0.0101)	0.0495*** (0.0154)	0.0453* (0.0272)
ZIP Code FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,128,382	695,986	263,731	6,130,338	696,275	263,851
R <sup>2</sup>	0.666	0.685	0.725	0.169	0.206	0.182
F	6,003.2	3,264.9	4,873.7	1,672.3	582.0	286.2

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



**Table 9: OLS estimates of race effect by gender**

	DV: Log(30-day price)		DV: Log(30-day booking)	
Race (ref. White)				
Asian	-0.0633*** (0.00787)	-0.0629*** (0.00850)	-0.0453*** (0.0144)	-0.0402** (0.0158)
Black	0.0137 (0.0198)	0.0194 (0.0219)	-0.0895** (0.0375)	-0.0934** (0.0420)
Hispanic	-0.0288*** (0.00563)	-0.0315*** (0.00664)	-0.0316*** (0.00788)	-0.0205** (0.00907)
Race × Gender (ref. female)				
Asian × male	0.00990 (0.0104)	0.00733 (0.0111)	0.0446** (0.0178)	0.0556*** (0.0193)
Black × male	-0.0591** (0.0256)	-0.0596** (0.0283)	-0.00405 (0.0504)	-0.000362 (0.0559)
Hispanic × male	-0.0158** (0.00702)	-0.0120 (0.00816)	0.0218** (0.0110)	0.0174 (0.0129)
Race × Gender × Conservative ZCTA (ref. liberal ZCTA)				
Asian × Male × Conservative ZCTA (binary)		0.0225 (0.0329)		-0.0707 (0.0495)
Black × Male × Conservative ZCTA (binary)		0.00605 (0.0678)		-0.0549 (0.131)
Hispanic × Male × Conservative ZCTA (binary)		-0.0399** (0.0187)		-0.0117 (0.0288)
ZIP Code FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	16,419,007	1,6147,816	16,424,001	16,152,745
R <sup>2</sup>	0.656	0.657	0.139	0.138
F	3,536.0	2,571.4	594.7	429.4

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Coefficients of gender, conservative ZCTA, and some interaction terms are suppressed for ease of presentation. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

**Table 10: OLS estimates of COVID shock of race effect**

	DV: Log(30-day price)		DV: Log(30-day booking)	
Race (ref. White)				
Asian	-0.153*** (0.00943)	-0.0566*** (0.00545)	-0.0393*** (0.0106)	-0.0105 (0.00968)
Black	-0.0175 (0.0197)	-0.0207 (0.0135)	-0.132*** (0.0238)	-0.0870*** (0.0245)
Hispanic	-0.101*** (0.00811)	-0.0367*** (0.00402)	-0.0270*** (0.00776)	-0.00633 (0.00653)
Asian × After COVID	-0.00902 (0.0103)	0.00780 (0.00592)	-0.197*** (0.0211)	-0.184*** (0.0225)
Black × After COVID	0.0146 (0.0200)	0.00315 (0.0130)	-0.139*** (0.0386)	-0.137*** (0.0443)
Hispanic × After COVID	-0.00796 (0.00922)	-0.000221 (0.00436)	-0.162*** (0.0169)	-0.188*** (0.0188)
ZIP Code FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	23,531,227	18,080,468	23,539,307	18,086,023
R <sup>2</sup>	0.291	0.658	0.108	0.139
F	75.68	3,902.8	50.50	677.6

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Coefficients of after COVID is consumed by fixed effects. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 11: OLS estimates of the impact of numerical ratings by race**

	Log(30-day price)	Log(30-day booking)
Race (ref. white)		
Asian	0.0365 (0.0572)	0.341*** (0.114)
Black	0.0638 (0.125)	-0.0470 (0.253)
Hispanic	0.161*** (0.0371)	0.0890 (0.0785)
log(numerical ratings)	0.267*** (0.00833)	0.622*** (0.0156)
Asian $\times$ log(numerical ratings)	-0.0595 (0.0367)	-0.237*** (0.0720)
Black $\times$ log(numerical ratings)	-0.0541 (0.0808)	-0.0318 (0.162)
Hispanic $\times$ log(numerical ratings)	-0.127*** (0.0236)	-0.0720 (0.0499)
ZIP Code FE	Yes	Yes
Time FE	Yes	Yes
Controls	Yes	Yes
Observations	16,433,954	16,438,948
R <sup>2</sup>	0.656	0.139
F	3,724.6	623.4

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 12: OLS estimates of the impact of textual review count by race**

	Log(30-day price)	Log(30-day booking)
Race (ref. white)		
Asian	-0.113*** (0.0109)	-0.0210 (0.0188)
Black	0.00786 (0.0268)	-0.119** (0.0517)
Hispanic	-0.0516*** (0.0107)	-0.0846*** (0.0135)
Log(textual review counts)	-0.0673*** (0.00146)	0.0266*** (0.00175)
Asian $\times$ log(textual review counts)	0.0224*** (0.00350)	-0.00125 (0.00592)
Black $\times$ log(textual review counts)	-0.0114 (0.00942)	0.00918 (0.0163)
Hispanic $\times$ log(textual review counts)	0.00590* (0.00341)	0.0242*** (0.00417)
ZIP Code FE	Yes	Yes
Time FE	Yes	Yes
Controls	Yes	Yes
Observations	16,433,954	16,438,948
R <sup>2</sup>	0.656	0.139
F	3,734.9	621.6

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 13: OLS estimates of the impact of positive textual review sentiment shares by race**

	Log(30-day price)		Log(30-day booking)	
Race (ref. white)				
Asian × Bing % of positive sentiment share	-0.0000222 (0.000207)		-0.000158 (0.000331)	
Black × Bing % of positive sentiment share	0.000181 (0.000521)		-0.00102 (0.000976)	
Hispanic × Bing % of positive sentiment share	0.0000236 (0.000157)		-0.00127*** (0.000232)	
Asian × NRC % of positive sentiment share		0.000474* (0.000258)		-0.000431 (0.000355)
Black × NRC % of positive sentiment share		-0.0000452 (0.000517)		-0.00102 (0.00116)
Hispanic × NRC % of positive sentiment share		0.000115 (0.000155)		-0.00107*** (0.000252)
Asian × Conservative ZCTA (binary) × Bing % of positive sentiment share	-0.000869 (0.000629)		-0.00142 (0.00108)	
Black × Conservative ZCTA (binary) × Bing % of positive sentiment share	0.00276** (0.00116)		0.00539** (0.00247)	
Hispanic × Conservative ZCTA (binary) × Bing % of positive sentiment share	0.000136 (0.000367)		0.000763 (0.000623)	
Asian × Conservative ZCTA (binary) × NRC % of positive sentiment share		-0.00104 (0.000667)		0.000127 (0.00103)
Black × Conservative ZCTA (binary) × NRC % of positive sentiment share		0.00170 (0.00113)		0.00561** (0.00244)
Hispanic × Conservative ZCTA (binary) × NRC % of positive sentiment share		-0.000286 (0.000356)		0.000389 (0.000625)
ZIP Code FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,424,658	3,930,868	3,425,879	3,932,207
R <sup>2</sup>	0.667	0.665	0.193	0.193
F	2,826.5	3,019.3	769.6	850.4

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Some coefficients are suppressed for ease of presentation. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

**Table 14: OLS estimates of the impact of "fear" textual review sentiment by race**

	Log(30-day price)	Log(30-day booking)
Race (ref. White)		
Asian $\times$ % of NRC fear sentiment	-0.00152 (0.00234)	-0.00267 (0.00431)
Black $\times$ % of NRC fear sentiment	0.00691 (0.00692)	0.00427 (0.0125)
Hispanic $\times$ % of NRC fear sentiment	0.00425*** (0.00164)	-0.00450 (0.00313)
Asian $\times$ Conservative ZCTA (binary) $\times$ % of NRC fear sentiment	0.00411 (0.0110)	-0.00706 (0.0182)
Black $\times$ Conservative ZCTA (binary) $\times$ % of NRC fear sentiment	-0.0341 (0.0255)	-0.137** (0.0689)
Hispanic $\times$ Conservative ZCTA (binary) $\times$ % of NRC fear sentiment	-0.00596 (0.00541)	0.0127 (0.0105)
ZIP Code FE	Yes	Yes
Time FE	Yes	Yes
Controls	Yes	Yes
Observations	2,459,499	2,460,321
R <sup>2</sup>	0.667	0.198
F	2,800.2	721.9

Include only listings by hosts identified as Asian, Black, Hispanic, or White. Some coefficients are suppressed for ease of presentation. Controls include room types (entire property, private room, share room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instantbook feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at ZIP Code level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## Figures

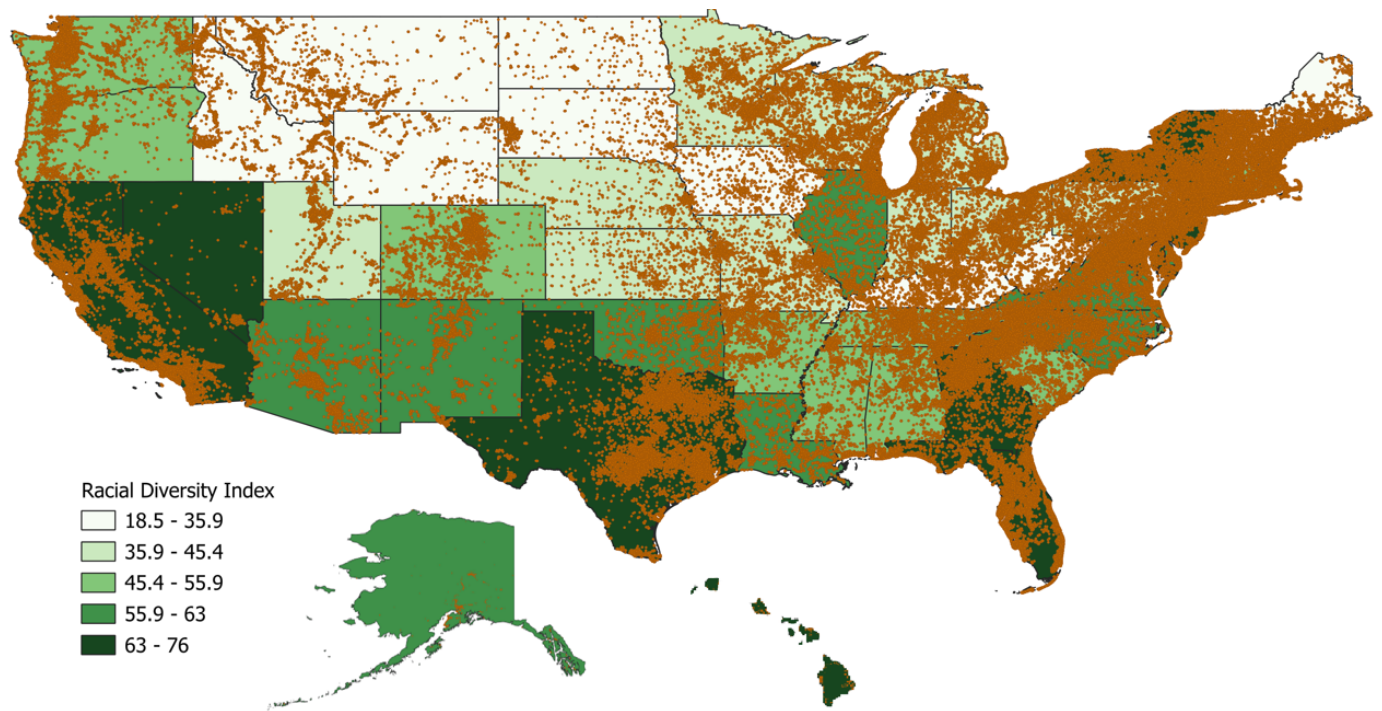


Figure 1: Airbnb listings across the U.S. as of April 2023

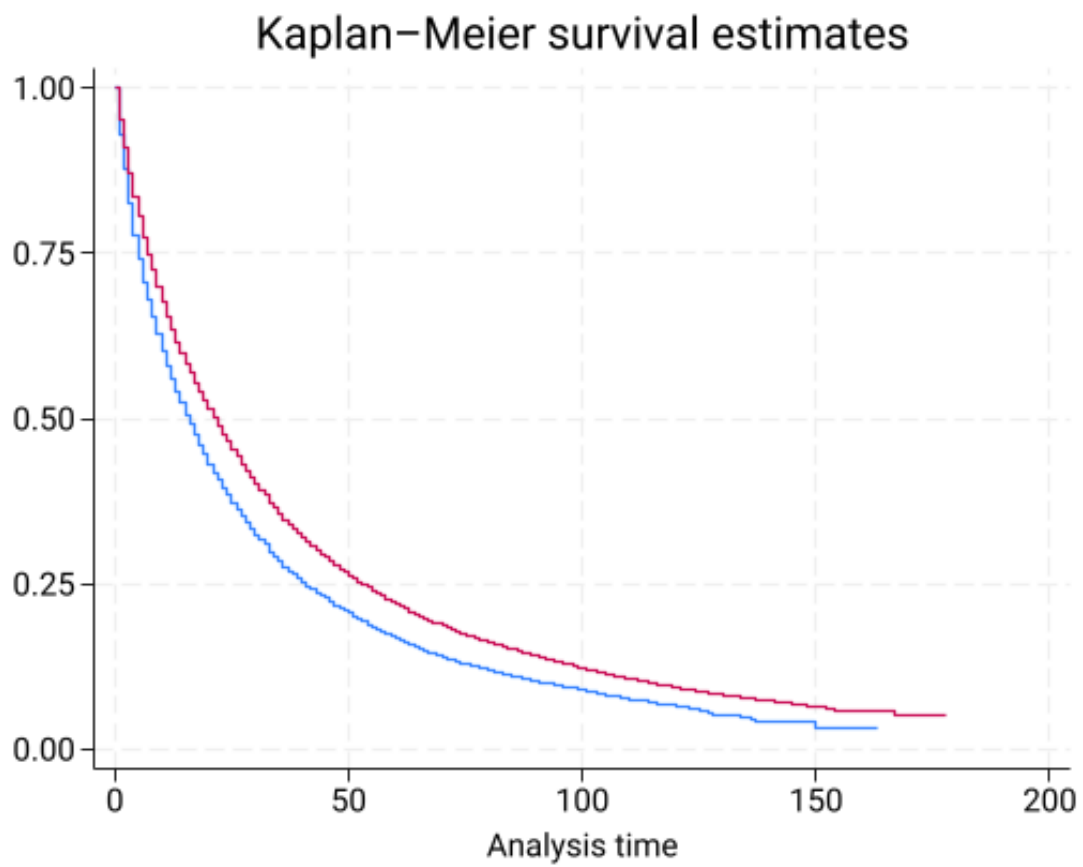


Figure 2: Non-parametric estimates for survival: white hosts (red) vs. non-white hosts (blue)



## Appendix A. NLP procedure

To make use of the textual review data, I use Natural Language Processing (NLP), a machine-learning technique to analyze human languages that developed naturally through use. First, for every single text review of a listing, I break it down (tokenize it) into words. I then clean all the review data so that there are no special characters in the text and only reviews in the English language are kept. In addition, I convert contractions containing apostrophes into separate words. Next, I lemmatize all the words into their lemma forms (e.g., “improve,” “improves,” “improved,” “improving,” “improvement,” and “improver” all as “improve”). I further remove stop words that do not add much meaning to a review (e.g., “a,” “of,” “is,”) to come up with the final sample of lemmatized words. I analyze these words primarily through sentiment analysis, a technique to provide mappings from words used to a numerical value that measures some feature of the text of interest.

In sentiment analysis, I need to attach sentiment values to each word in a lexicon of predefined words and then calculate the sentiment values of our lemmatized words using the lexicon. While various lexicons cater to different needs of text analysis, I choose to use the NRC Emotion lexicon and the Bing lexicon, which are suitable for analyzing customer reviews.

The Bing lexicon was developed with the goal of opinion mining of customer reviews (Hu and Liu, 2004). Its classification is binary, meaning a word is either positive or negative. It contains a total of 6,786 words, among which 2,005 are positive and 4,781 are negative. The NRC Emotion lexicon was manually developed by crowdsourcing on Amazon Mechanical Turk (Mohammad and Turney, 2013) and contains a list of 5,635 words and their association with two sentiments (positive and negative) and eight basic sentiments (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust).

Applying both lexicons, I obtain the sentiment scores for text reviews at a listing-month frequency, meaning a sentiment score is computed when a listing has informative

reviews in a particular month and is missing in months without reviews or, in rare cases, in months when reviews do not provide information based on the lexicons. I adopt this approach because reviews are sorted by recency on Airbnb, so only the most recent reviews are immediately available to potential guests. In addition, although consumers can also find older reviews, these reviews tend to carry less weight in influencing consumer decisions (Singh et al., 2017). Note that in the case of numerical ratings, I use the cumulative ratings but not the month-specific ratings. This is consistent with how we handle the text sentiment scores because consumers can only observe the cumulative numerical rating of a listing.

In both NRC Emotion and Bing lexicons, a positive sentiment score can be measured by the percentage of positive words in total words (e.g., the number of positive words according to the lexicons in a listing’s reviews in a particular month divided by the total number of words in a listing’s reviews in that month and multiplied by 100). Similarly, the relative percentage of positive and negative sentiments can also be calculated (e.g., the number of positive words divided by the sum of positive and negative words in a listing’s reviews in a month and then multiplied by 100). Beyond positive and negative sentiments, other NRC-based sentiments can be calculated in a similar manner.

## Appendix B. Match rates for gender and race

Table A1: Match rates between name prediction and human verification for gender

Algorithmic predictions	Male (N=466)	Female (N=372)
Human verifications	419 males	357 females
Match rate	90%	96%

Table A2: Match rates between name prediction and human verification for race

Algorithmic predictions	White (N=205)	Asian (N=211)	Black (N=167)	Hispanic (N=180)
Human verifications	185 White	178 Asian	116 Black	134 Hispanic
Match rate	90%	84%	69%	74%