Navigating Racial Bias in the Sharing Economy: Heterogeneity and Mechanisms

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Abstract

How can racial-minority entrepreneurs close the performance gap in the sharing economy? While recent studies reveal discrimination against racial-minority customers, less attention has been paid to the disparities faced by racial-minority suppliers. More evidence is needed to identify the conditions and mechanisms that exacerbate or mitigate the biases these micro-entrepreneurs face in different markets. Analyzing all Airbnb listings across the United States from May 2015 to April 2023, I show that Black, Hispanic, and Asian entrepreneurs experience reduced consumer demand for similar offerings compared to White entrepreneurs, especially in more-conservative ZIP Code Tabulation Areas, leading to heightened exit rates. I also assess more than 90 million Airbnb reviews, identifying specific feedback that exacerbates or attenuates biases in the sharing economy. Good numerical ratings fail to bolster the relative performance of racial-minority hosts. To help mitigate the racial disparities I find, platforms should design mechanisms that encourage guests to leave more textual reviews.

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

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1 Introduction

Sharing economy platforms have revolutionized business by simplifying connections between suppliers and consumers (Markman et al., 2021). Rather than investing in physical assets, these platforms provide information and technology to connect the various sides of the platform, for example, hosts and guests on Airbnb, and drivers and passengers on Uber.

Contact between suppliers and buyers in the sharing economy is direct and frequent, thus their perceptions and evaluations of one another are critical for capturing value and accessing resources. However, bias on platforms, based on demographic backgrounds, has become a heated issue in recent years. Aside from its far-reaching social implications, such discrimination impedes business performance by hindering innovation (Cook et al., 2022) and displacing high-skilled racial-minority workers and entrepreneurs (Hsieh et al., 2019).

Suppliers in the sharing economy are often viewed as micro-entrepreneurs (Sundararajan, 2017)—they 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 how and why they join a given platform. Management research into the timely and salient issue of platform-based discrimination can improve the outcomes of these affected entrepreneurs.

While research generally finds some discrimination against racial-minority entrepreneurs and subsequent negative economic impacts, many important theoretical and policy puzzles require closer 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 having imperfect information (Arrow, 1971; Phelps, 1972; they defined this as "statistical discrimination") or because they prefer to interact with specific groups (Becker, 1971; he defined this as "taste-based discrimination"). Understanding such differences thus sheds light on the processes that connect discriminatory behaviors to entrepreneurial outcomes.

If statistical discrimination is the prevailing phenomenon, designing 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 to combat. Yet, the evidence on the efficacy of these platform-design choices is often inconclusive and sometimes contradictory. Disentangling these conundrums requires exploring the rich characteristics and beliefs of suppliers and buyers and identifying the mechanisms and attenuating factors that differentially affect supplier outcomes.

Specifically, biases in the sharing economy affect how suppliers can choose their market position or location when they consider entry. Especially with polarization in the United States on the rise 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). Also, location choices of firms and entrepreneurs are susceptible to the impact of ideology—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 at all, as well as their strategies once they choose to enter.

Another critical issue regarding discrimination in the sharing economy is the online-reviews feedback mechanism between suppliers and customers. In the context of the sharing economy, online feedback usually includes numerical ratings and textual reviews. However, their potential effects on entrepreneurial outcomes can be ambiguous. Researcher have shown that certain types of online feedback can attenuate the disparity between White and African

American customers (Cui et al., 2020); others have 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 value (Tadelis, 2016), further examination is needed to understand the conditions under which different types of online feedback might mitigate or exacerbate bias.

In this study, I aim 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 it. Analyzing all Airbnb listings across the United States 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 I find that the impact of race is greater in more-conservative ZIP Code Tabulation Areas. Finally, I investigate the impact of online feedback; I 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 that they could play a crucial role in fostering a more-equitable marketplace. My robustness checks corroborate the validity of these findings and address 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 United States over eight years on Airbnb, a prominent platform that has previously focused more on bias against customers than against suppliers. Second, it 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. My research fills this gap, providing insights into the implications for market entry and exit among racial-minority entrepreneurs. Third, it adds to the literature on online reputation systems, particularly focusing on the recent inquiry into 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 grown tremendously in recent years. One prominent example is Airbnb, an online marketplace that connects people looking to rent out their homes with those seeking lodging. As of December 2022, there were over 4 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 has grown, so have 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.[1] In a December 2022 press release, Airbnb claimed that, going forward, the booking success rates for guests would be more even across different races (Airbnb, 2022).

[1]Notable efforts include allowing hosts to see a guest's picture only after accepting a reservation, expanding the Instant Book feature eligibility to more users, making it easier for all guests to receive reviews after their stay, and auditing reservation rejections and banning certain host accounts.

Despite these changes, Airbnb has remained largely silent about potential disparities among their hosts. Meanwhile, the platform continues to expand, and more hosts continue to join the platform. Figure 1 plots all U.S. Airbnb listings as of April 2023 (orange dots) and displays the racial diversity index by state using color coding.[2] It is evident that Airbnb hosts list their properties not only in major and secondary cities but also in many suburban and rural areas, which tend to be 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). 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 growing 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 multisided nature of platforms calls for careful consideration of discrimination originating from different sides of the platforms. Academic studies in this domain have

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

focused mainly on discrimination experienced by customers—specifically, on discrimination against 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). Academic evidence on *supplier* discrimination on platforms is relatively nascent. 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 studies have revealed the lower prices 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 demand 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, the effect is likely to be uneven across locations. Considering the sources, responses, and heterogeneity of discrimination, the issue of ideological polarization also calls for further examination—research has documented that increasing enmity toward individuals with different *ideological* identities leads to a rise in *racial* hostility (Iyengar and Westwood, 2015). In the management literature, a nascent stream of research has examined nonmarket strategy stemming from ideological differences, ranging from the impact of polarization on consumer behavior (Hou and Poliquin, 2023; Neureiter and Bhattacharya, 2021), firm disclosures (Benton et al., 2022), and social activism (Mohliver et al., 2023).

More recently, scholars have begun theorizing about the potential consequences of ideological identity (mis)alignment for firm strategy regarding location decisions (Barber IV and Blake, 2024). Individuals increasingly trust and favor others who share their ideological identity while distrusting and avoiding those who do not. Meanwhile, 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 cannot choose where to operate (because they are limited by where their property is), ideological distance to their intended market can still affect their expected business performance and, implicitly, their entry and exit decisions. racial-minority suppliers might have a more challenging time finding consumer demand for their offerings in more ideologically distant locations, though it is unclear how they will respond. As such, I expect the following:

Hypothesis 3: *The disparities in consumer demand 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 Sources of Bias on Sharing Economy Platforms

Buyers often use demographic groups as proxies for unobservable attributes such as quality, a theory known as statistical discrimination (Arrow, 1971; Phelps, 1972). They might also make decisions based on personal prejudice or bias, a theory known as taste-based discrimination (Becker, 1971). The taste-based aversion is not rooted in rational considerations such as differences in qualifications or abilities, but rather in a deep-seated bias. Recent management scholarship leverages these two competing theories of bias to explain performance gaps in top management teams (Damaraju and Makhija, 2018; Tsolmon, 2024), disparities in hiring and promotion (Barrymore et al., 2022; Hegde et al., 2023), and differences in entrepreneurial outcomes (Yang and Kacperczyk, 2024).

Sharing economy platforms have been shown to reduce uncertainty about quality (Benson et al., 2020) and improve trust between the two sides of its market (Gu and Zhu, 2021). And yet, performance gaps between racial minorities and Whites persist in many contexts (see Subsection 2.2.1). Further, growing ideological misalignment can drive the avoidance of those with differing identities (see Subsection 2.2.2). Thus, I hypothesize that taste-based discrimination is the primary driver of performance disparities for racial-minority suppliers in the sharing economy.

Hypothesis 5: *racial-minority suppliers face taste-based discrimination in the sharing economy.*

2.2.4 Online Reviews as a Bias Attenuator and Amplifier

As I discuss in Subsection 2.2.3, in the sharing economy and, more broadly, platform settings, online reputation systems can be essential in shaping consumer perceptions of service suppliers (Bajari and Hortaçsu, 2003; Luca, 2016; Moreno and Terwiesch, 2014; Reimers and Waldfogel, 2021) and affecting the efficiency of platforms (Bolton et al., 2004). Some research suggests that these systems can help reduce racial bias on platforms because ethnic disadvantages are smaller for users with ratings than for users without ratings (Abrahao 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 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 investigation into the role of online feedback in either 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 leave bad online feedback, which usually includes numerical ratings and textual reviews, for a racial-minority supplier if they believe the benefits will outweigh the potential costs. From this viewpoint, leaving a bad numerical rating is relatively easy, but leaving a noxious textual review is much more costly, because of the extra effort and because they might expose their identity 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 easier.

In his model of labor-market discrimination, Becker (1971) further argues that taste-based discrimination is particularly reduced when the cost of discrimination is high. Recent empirical evidence in the context of patent examiners also supports this claim (Hegde et al., 2023). Therefore, consistent with cost-benefit analyses of leaving online reviews and the anticipated presence of taste-based discrimination, I hypothesize that:

Hypothesis 6: *racial-minority suppliers benefit less than White suppliers from online feedback consisting of numerical ratings.*

Hypothesis 7: *racial-minority suppliers benefit more than White suppliers from online feedback consisting of textual reviews.*

Research has shown consumers' tendency to seek out media that conform to their own beliefs, which has become easier in part due to the lower cost of production and dissemination of online information (Bimber and Davis, 2003). As a result, consumers of 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 that:

Hypothesis 8: *The impact of online feedback is more pronounced in ideologically conservative markets.*

3 Data and Empirical Approach

3.1 Airbnb Data

To test the aforementioned hypotheses, I obtain Airbnb data from Inside Airbnb, a nonprofit organization that has been scraping data from Airbnb's website since early 2015. The inside Airbnb data has been used for numerous academic studies, so far on a small scale (Cheung and Yiu, 2022; Gyódi, 2022; Lima, 2019; Luca et al., 2024). I use all Airbnb listings, reviews, and calendar information across the United States from May 2015 to April 2023. The data is scraped at roughly monthly intervals, with the caveat that some 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 30-day prices and 30-day bookings as the main outcome variables for my panel data analyses. To construct such measures, I take advantage of the calendar feature, which 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 price measure as the weighted average price for these days and the booking measure as the days a listing is unavailable. To measure the "time until exit," I calculate the interval between the time when a new listing first appears in the data and the time when the listing no longer appears in the data.

In addition, 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), the Instant Book feature, and other miscellaneous information. I can also see host-related information for the listing, including names (mostly first names), Superhost status, host tenures, whether they have multiple listings, location, descriptions, and response time. Lastly, I have essential review information: 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—the top 1,000 first names capture the majority of the U.S. population (Tzioumis, 2018). I use the (programming language) R's predictrace 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. Overall, the match rate between algorithmic prediction and manual verification is accurate for race and gender, confirming the validity of this name-based inference approach.[3]

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 that an Airbnb listing appears in the data. Overall, racial-minority hosts from all groups have lower listing prices and fewer bookings and operate on Airbnb for less time 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]

3.2 Baseline Estimates for the Impact of Race 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

[3] Details of the match rates are reported in the Appendix.

to estimate this effect:

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

where the outcome can be either 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 listing (entire home/apartment, private room, shared room, and hotel room), whether the listing allows instant booking, numerical ratings and textual review counts (in log), and days since the last review (in log). X_{it} also includes characteristics of the listing host, 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. α_i is the ZIP Code fixed effects, to control for unobserved location-specific heterogeneity. θ_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:

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

where $H_i(t)$ is the expected hazard at time t, and $H_0(t)$ is the baseline hazard, representing when all of the predictors are equal to zero (or at their base levels). In addition to the host's race, I include the same set of controls 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), which produces estimates of the average political ideology of every state, congressional district, state legislative district, county, medium-sized city, and ZCTA in the United States by building a 275,000-person super-survey of Americans. Data from the AIP provide estimates of the overall 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). 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):

$$\log(y_{it}) = \beta_1 Race_{it} + \beta_2 Conservative_{it} + \beta_3 Race_{it} \times Conservative_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (3)$$

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

$$H_i(t) = H_0(t) \times \exp(\beta_1 Race_i + \beta_2 Conservative_{it} + \beta_3 Race_{it} \times Conservative_{it} + \gamma' X_i) \quad (4)$$

4 Results and Alternative Explanations

4.1 Empirical 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. My results generally show that racial-minority Airbnb hosts charge lower prices and 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. Including the ZIP Code interaction with the month fixed effect (i.e., columns 3 and 6) does not change the results by much, suggesting that 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 nonparametrically estimate the survival probability for hosts from different racial backgrounds after any given month. 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. All coefficients are already log-transformed, representing the probability of exit. Column 2, for example, estimates that Asian, Black, and Hispanic hosts have an 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 than 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 whose hosts are from various racial backgrounds. Overall, while racial-minority hosts do not evidently charge lower prices in more conservative areas, they generally face significantly lower consumer demand 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—this is 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]

4.1.3 Entire Property vs. Private Room

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 the presence of taste-based discrimination against suppliers of racial minorities, 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). 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, presumably 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 highlighted in Hypothesis 5.

[Insert Table 7 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 ZCTAs 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 movement, can shape the performance of different racial groups. While I cannot account for all sources of endogeneity, I conduct a series of checks to address these concerns.

4.2.2 Racial Backgrounds of Guests

Racial homophily refers to the tendency of individuals to associate with others who share the same racial background. It can be found in online communities (Wimmer and Lewis, 2010); 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.

I do not directly observe the identities of all guests, but 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 left by non-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 my previous estimates of racial discrepancies.

[Insert Table 8 about here]

4.2.3 Host Gender

Recent research in organizational theory and social psychology 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.

$$\log(y_{it}) = \beta_1 Race_{it} + \beta_2 Gender_{it} + \beta_3 Race_{it} \times Gender_{it} + \gamma' X_{it} + \alpha_i + \theta_t + \varepsilon_{it} \quad (6)$$

Table 9 shows that Black male hosts tend to charge 6% lower prices than Black female hosts (column 1). Hispanic male hosts also charge lower prices, especially in conservative ZCTAs (columns 1 and 2). However, their booking performance does not seem to suffer relative to Hispanic 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]

4.2.4 Effect of the COVID-19 Shock

My sample spans an eight-year period, so changes in broader socioeconomic trends could possibly affect the performance of various racial groups in different ways. For example, the COVID-19 pandemic had a profound impact on society. On March 16, 2020, former President Donald Trump called the coronavirus the "Chinese virus" in a tweet, boosting anti-Asian sentiment. Then, in May 2020, the murder of George Floyd spurred campaigns against systemic racism and violence toward Black people. Researchers have used the events to examine the performance of racial-minority suppliers in different contexts (Aneja et al., 2023; Luca et al., 2024). To examine whether these events affect the interpretation of previous findings, I estimate the following model, where "After" indicates the time periods after April 2020:

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

Table 10 reports the findings, which show that racial-minority hosts did not charge lower prices than White hosts after the onset of COVID-19 (columns 1 and 2). Although they have received significantly fewer bookings since April 2020, the overall trend for the COVID-19 impact is consistent across all racial-minority groups. For example, Asian hosts had fewer bookings in the "Asian hate" period that only grew worse after the "Chinese virus" tweet, but Black hosts also had fewer bookings despite the broad support of the Black Lives Matter movement.

In addition, Black hosts already experienced far fewer bookings than White hosts before the pandemic (columns 3 and 4). Hence, while the impact of COVID-19 seemingly exacerbated conditions faced by racial-minority suppliers, the underlying disparities they faced throughout the sample period are unlikely to be primarily driven by these single events.

[Insert Table 10 about here]

4.2.5 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 two listings are within 100 feet (30 meters) of each other, and I model the effects through dyadic analyses:

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

where i and j are restricted to two Airbnb listings located within 100 feet of each other, in which listing i is operated by a White host and listing j is operated by a racial-minority host. In the analysis, due to the scarcity of such neighboring White and Black listings, I group all non-White hosts together and contrast the group to White hosts.

Table 11 reveals a significant gap in the average prices charged by neighboring listings when host races differ, even after controlling for differences in other conceivable property differences. Specifically, White hosts were able to charge $7.30 USD more per night than non-White hosts over each 30-day period without experiencing discernible differences in bookings (a total of 0.2 nights over the same period). This disparity highlights the persistence of price-setting advantages for White hosts, despite accounting for quality differences related to neighborhood and property conditions.

[Insert Table 11 about here]

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 12 reports the impact of numerical ratings by race. For White hosts, the reference category, a 1% increase in numerical ratings 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 1% increase in numerical ratings is smaller for racial-minority hosts, at 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 they benefit racial-minority hosts.

[Insert Table 12 about here]

Table 13 reports the impact of the numbers of textual reviews by race. Unlike the results from numerical ratings, there is little 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 than White hosts from the sheer number of textual reviews. Together with the results in Table 12, these findings broadly support Hypothesis 6 and do not contradict Hypothesis 7.

[Insert Table 13 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, my 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. (I discuss the specific NLP procedure 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 14 reports how net positive sentiments—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, the 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., a 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 8. Nevertheless, these positive sentiments do not discernibly 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 most susceptible to the emotions expressed by consumers in textual reviews.

[Insert Table 14 about here]

Delving further into consumers' sentiments toward Black suppliers, research has shown that biased individuals are more fearful of Black strangers than of 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 15 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, the specifics of which can either attenuate or exacerbate the biases they face, especially in ideologically conservative markets.

[Insert Table 15 about here]

6 Discussion and Conclusion

6.1 Summary of Findings

I study how race affects 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 U.S. Airbnb listings from May 2015 to April 2023, I find that racial-minority Airbnb hosts charge lower prices, get fewer bookings, and are more likely to exit the market. 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%, respectively, for Asian, Black, and Hispanic suppliers. These revenue losses, coupled with a higher likelihood of business failure compared to White suppliers, not only affect current racial-minority suppliers but also might discourage potential racial-minority suppliers from entering the market.

6.2 Conclusion

This study has important implications for research on discrimination and nonmarket strategy, entrepreneurship and innovation, and platform designs in the context of the sharing economy. While my empiric analyses focus on Airbnb, I anticipate that 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, it also has strong business implications: attracting latent suppliers from racial-minority backgrounds is crucial for market expansion and enhancing the quality of entrepreneurship (Conti et al., 2022).

This study has some limitations. First, inferring demographics from supplier and customer names can introduce measurement errors, but given that my manual inspection confirmed that the algorithmic results are mostly accurate, 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 readers to interpret the results with some caution. Third, the NLP procedure I use to analyze textual reviews relies on predefined lexicons to opinionmine customer reviews. With the recent developments in large language models, future research could 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 discrimination against suppliers. It also enriches the literature on nonmarket strategy for entrepreneurs by examining the impact of ideological identity on firm and entrepreneur performance. Finally, it sheds light on the role of online reputation systems in creating a fair marketplace and fostering entrepreneurship. In all, this study is a valuable step toward exploring numerous opportunities in management research related to entrepreneurship, discrimination and nonmarket strategy, and platform design in the sharing economy and beyond.

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Tables

Table 1: Summary Statistics by Race, All Listing-Time Pairs

		White			**Asian**			**Hispanic**			**Black**	
Variables	**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

Notes: Room types include entire proprty, private room, shared room, or hotel.

Table 2: Summary Statistics by Race at the Final Time of Operation

	White			Asian			Hispanic			Black		
Variables	**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

Notes: Room types include entire proprty, private room, shared room, or hotel.

Table 3: Baseline OLS Estimates of the Race Impact

	Log(30-day price)			Log(30-day bookings)		
Race (ref. White)						
Asian	-0.0887***	-0.0534***	-0.0522***	0.00828	-0.0216**	-0.0189*
	(0.0127)	(0.00545)	(0.00547)	(0.0122)	(0.00972)	(0.00975)
Black	-0.107***	-0.0147	-0.0159	-0.0971***	-0.0845***	-0.0808***
	(0.0146)	(0.0134)	(0.0134)	(0.0187)	(0.0238)	(0.0232)
Hispanic	-0.106***	-0.0354***	-0.0343***	-0.0227*	-0.0174***	-0.0155**
	(0.0157)	(0.00416)	(0.00413)	(0.0128)	(0.00640)	(0.00636)
Multiple race	-0.124***	-0.0395	-0.0416	-0.0725*	-0.0669	-0.0636
	(0.0394)	(0.0279)	(0.0277)	(0.0422)	(0.0494)	(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 × 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^2	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

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

Table 4: Log-transformed Cox Coefficients of Demographic Impacts on Exit

Outcome: Exit					
Race (ref. White)			Gender (ref. female)		
Asian	0.201***	0.0849***	Male	0.0349***	0.0229***
	(0.0208)	(0.0183)		(0.00770)	(0.00634)
Black	0.794***	0.119***			
	(0.0790)	(0.0367)			
Hispanic	0.137***	0.0560***			
	(0.0182)	(0.0165)			
Multiple race	0.388***	0.227			
	(0.130)	(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^2	371.9	8,560.7		20.61	9,077.1

Notes: Controls include room types (entire property, private room, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are 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***	-0.0548***	-0.0122	-0.0556***
	(0.00570)	(0.00891)	(0.0103)	(0.0132)
Black	-0.0132	-0.0360*	-0.0999***	-0.138***
	(0.0148)	(0.0193)	(0.0262)	(0.0358)
Hispanic	-0.0374***	-0.0408***	-0.0134*	-0.0296***
	(0.00447)	(0.00583)	(0.00716)	(0.00836)
Race × Conservative ZCTA (ref. liberal ZCTA)				
Asian × Conservative ZCTA (binary)	0.0122		-0.0879***	
	(0.0171)		(0.0256)	
Black × Conservative ZCTA (binary)	-0.0423		-0.0245	
	(0.0348)		(0.0648)	
Hispanic × Conservative ZCTA (binary)	-0.0101		-0.0388**	
	(0.0109)		(0.0156)	
Asian × Conservative ZCTA (continuous)		0.00757		-0.126***
		(0.0260)		(0.0375)
Black × Conservative ZCTA (continuous)		-0.0659		-0.140
		(0.0509)		(0.0988)
Hispanic × Conservative ZCTA (continuous)		-0.00797		-0.0444*
		(0.0167)		(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^2	0.659	0.659	0.138	0.138
F	3,876.1	3,876.6	640.1	650.7

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

Table 6: Log-transformed Cox Coefficients of Heterogeneity in ZIP Code-level Ideology

Outcome: Exit		
Race (ref. White)		
Asian	0.0972***	0.149***
	(0.0146)	(0.0207)
Black	0.126***	0.194***
	(0.0351)	(0.0457)
Hispanic	0.0710***	0.0912***
	(0.0141)	(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^2	15,436.6	14,519.8

Notes: Includes only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are 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***	-0.0335***	-0.0651***	-0.0503***
	(0.00730)	(0.00768)	(0.0109)	(0.0120)
Black	-0.00849	-0.00477	-0.0831***	-0.0860***
	(0.0151)	(0.0163)	(0.0248)	(0.0272)
Hispanic	-0.0241***	-0.0276***	-0.0142**	-0.00346
	(0.00496)	(0.00579)	(0.00701)	(0.00835)
Race × Room type (ref. entire property)				
Asian × Private room	-0.0734***	-0.0490***	0.0836***	0.0710***
	(0.0106)	(0.0112)	(0.0176)	(0.0188)
Black × Private room	-0.0396	-0.0298	-0.0255	-0.0196
	(0.0255)	(0.0281)	(0.0501)	(0.0547)
Hispanic × Private room	-0.0339***	-0.0199**	-0.0195*	-0.0234*
	(0.00765)	(0.00854)	(0.0116)	(0.0129)
Race × Room Type × Conservative ZCTA (ref. liberal ZCTA)				
Asian × Private room × Conservative ZCTA (binary)		-0.0801**		-0.0189
		(0.0319)		(0.0552)
Black × Private room × Conservative ZCTA (binary)		-0.0330		-0.0740
		(0.0673)		(0.137)
Hispanic × Private room × Conservative ZCTA (binary)		-0.0538***		-0.0221
		(0.0205)		(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^2	0.656	0.658	0.139	0.138
F	2,938.2	1,991.4	482.6	328.1

Notes: Includes 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, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: OLS Estimates for Subsamples Using Reviewer Backgrounds

	DV: Log(30-day price)			DV: Log(30-day bookings)		
# of White reviewers as a % of all reviewers	**100%**	**> 50%**	**< 50%**	**100%**	**> 50%**	**< 50%**
Host race (ref. non-White)						
White	0.0404***	0.0319***	0.0332***	0.0184***	0.000458	-0.0107
	(0.00355)	(0.00504)	(0.00451)	(0.00453)	(0.00556)	(0.00887)
Host race × Conservative ZCTA (ref. liberal ZCTA)						
White × Conservative ZCTA (binary)	-0.00903	-0.0169	-0.00515	0.0420***	0.0495***	0.0453*
	(0.00868)	(0.0138)	(0.0166)	(0.0101)	(0.0154)	(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^2	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

Notes: Includes only listings by hosts identified as Asian, Black, Hispanic, or White. Controls include room types (entire property, private room, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are in parentheses. * 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***	-0.0629***	-0.0453***	-0.0402**
	(0.00787)	(0.00850)	(0.0144)	(0.0158)
Black	0.0137	0.0194	-0.0895**	-0.0934**
	(0.0198)	(0.0219)	(0.0375)	(0.0420)
Hispanic	-0.0288***	-0.0315***	-0.0316***	-0.0205**
	(0.00563)	(0.00664)	(0.00788)	(0.00907)
Race × Gender (ref. female)				
Asian × male	0.00990	0.00733	0.0446**	0.0556***
	(0.0104)	(0.0111)	(0.0178)	(0.0193)
Black × male	-0.0591**	-0.0596**	-0.00405	-0.000362
	(0.0256)	(0.0283)	(0.0504)	(0.0559)
Hispanic × male	-0.0158**	-0.0120	0.0218**	0.0174
	(0.00702)	(0.00816)	(0.0110)	(0.0129)
Race × Gender × Conservative ZCTA (ref. liberal ZCTA)				
Asian × Male × Conservative ZCTA (binary)		0.0225		-0.0707
		(0.0329)		(0.0495)
Black × Male × Conservative ZCTA (binary)		0.00605		-0.0549
		(0.0678)		(0.131)
Hispanic × Male × Conservative ZCTA (binary)		-0.0399**		-0.0117
		(0.0187)		(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^2	0.656	0.657	0.139	0.138
F	3,536.0	2,571.4	594.7	429.4

Notes: Includes 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, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: OLS Estimates of the COVID-19 Shock of Race Effect

	DV: Log(30-day price)		DV: Log(30-day booking)	
Race (ref. White)				
Asian	-0.153***	-0.0566***	-0.0393***	-0.0105
	(0.00943)	(0.00545)	(0.0106)	(0.00968)
Black	-0.0175	-0.0207	-0.132***	-0.0870***
	(0.0197)	(0.0135)	(0.0238)	(0.0245)
Hispanic	-0.101***	-0.0367***	-0.0270***	-0.00633
	(0.00811)	(0.00402)	(0.00776)	(0.00653)
Asian × After COVID	-0.00902	0.00780	-0.197***	-0.184***
	(0.0103)	(0.00592)	(0.0211)	(0.0225)
Black × After COVID	0.0146	0.00315	-0.139***	-0.137***
	(0.0200)	(0.0130)	(0.0386)	(0.0443)
Hispanic × After COVID	-0.00796	-0.000221	-0.162***	-0.188***
	(0.00922)	(0.00436)	(0.0169)	(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^2	0.291	0.658	0.108	0.139
F	75.68	3,902.8	50.50	677.6

Notes: Includes 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, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: OLS Estimates of Dyadic Race Differences for Neighboring Listings

	30-day price differences	**30-day booking differences**
Neighboring host races (ref. both White)		
Listing i (White) - listing j (non-White)	7.296***	-0.200
	(2.014)	(0.159)
ZIP Code FE	Yes	Yes
Time FE	Yes	Yes
Controls	Yes	Yes
Observations	5,073,980	5,073,980
R^2	0.159	0.026
F	141.2	87.84

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

Table 12: OLS Estimates of the Impact of Numerical Ratings by Race

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

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

Table 13: 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***	-0.0210
	(0.0109)	(0.0188)
Black	0.00786	-0.119**
	(0.0268)	(0.0517)
Hispanic	-0.0516***	-0.0846***
	(0.0107)	(0.0135)
Log(textual review counts)	-0.0673***	0.0266***
	(0.00146)	(0.00175)
Asian × log(textual review counts)	0.0224***	-0.00125
	(0.00350)	(0.00592)
Black × log(textual review counts)	-0.0114	0.00918
	(0.00942)	(0.0163)
Hispanic × log(textual review counts)	0.00590*	0.0242***
	(0.00341)	(0.00417)
ZIP Code FE	Yes	Yes
Time FE	Yes	Yes
Controls	Yes	Yes
Observations	16,433,954	16,438,948
R^2	0.656	0.139
F	3,734.9	621.6

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

Table 14: 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	-0.00000222		-0.000158	
	(0.000207)		(0.000331)	
Black × Bing % of positive sentiment share	0.000181		-0.00102	
	(0.000521)		(0.000976)	
Hispanic × Bing % of positive sentiment share	0.0000236		-0.00127***	
	(0.000157)		(0.000232)	
Asian × NRC % of positive sentiment share		0.000474*		-0.000431
		(0.000258)		(0.000355)
Black × NRC % of positive sentiment share		-0.0000452		-0.00102
		(0.000517)		(0.00116)
Hispanic × NRC % of positive sentiment share		0.000115		-0.00107***
		(0.000155)		(0.000252)
Asian × Conservative ZCTA (binary) × Bing % of positive sentiment share	-0.000869		-0.00142	
	(0.000629)		(0.00108)	
Black × Conservative ZCTA (binary) × Bing % of positive sentiment share	0.00276**		0.00539**	
	(0.00116)		(0.00247)	
Hispanic × Conservative ZCTA (binary) × Bing % of positive sentiment share	0.000136		0.000763	
	(0.000367)		(0.000623)	
Asian × Conservative ZCTA (binary) × NRC % of positive sentiment share		-0.00104		0.000127
		(0.000667)		(0.00103)
Black × Conservative ZCTA (binary) × NRC % of positive sentiment share		0.00170		0.00561**
		(0.00113)		(0.00244)
Hispanic × Conservative ZCTA (binary) × NRC % of positive sentiment share		-0.000286		0.000389
		(0.000356)		(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^2	0.667	0.665	0.193	0.193
F	2,826.5	3,019.3	769.6	850.4

Notes: Includes 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, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: OLS Estimates of the Impact of "Fear" Textual Sentiment by Race

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

Notes: Includes 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, shared room, or hotel), bedroom and amenities counts, numerical ratings and text review counts, recency of the listing, Instant Book feature, Superhost status, host tenure, and host listing counts. Robust standard errors clustered at the ZIP Code level are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01

Figures

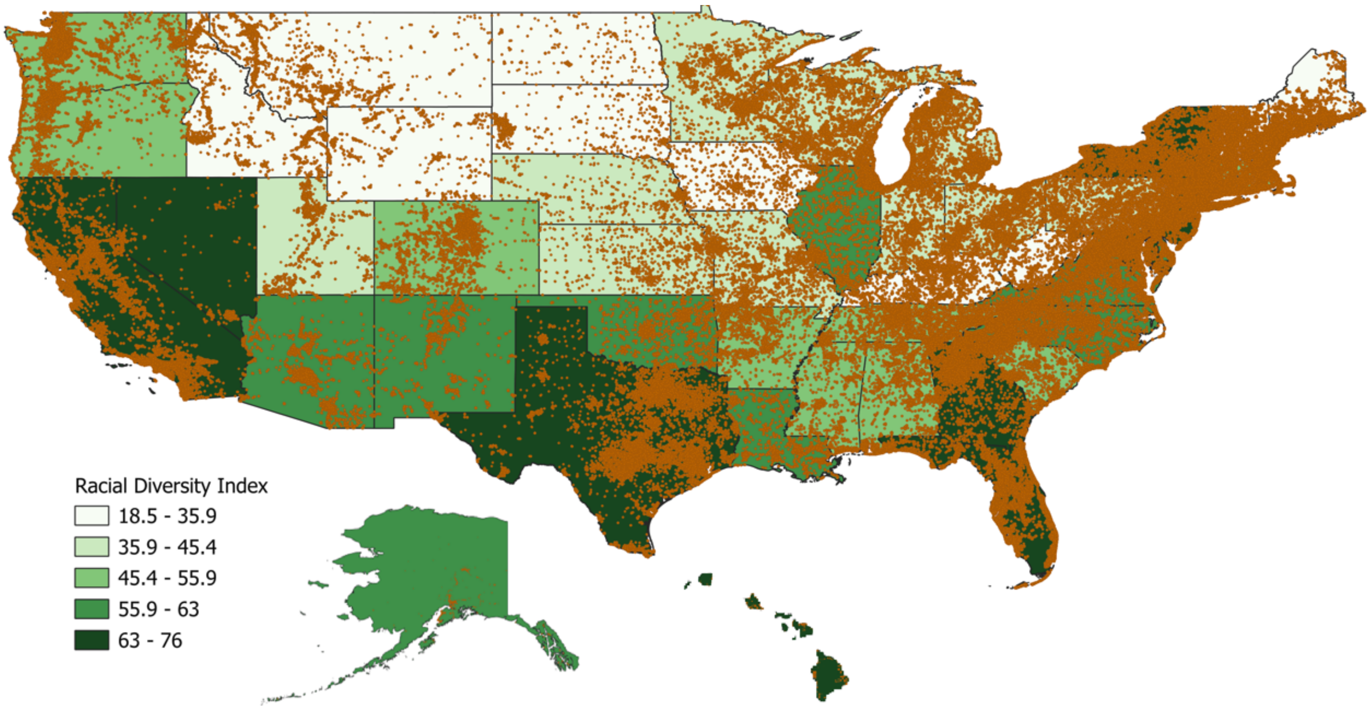

Figure 1: U.S. Airbnb Listings, as of April 2023

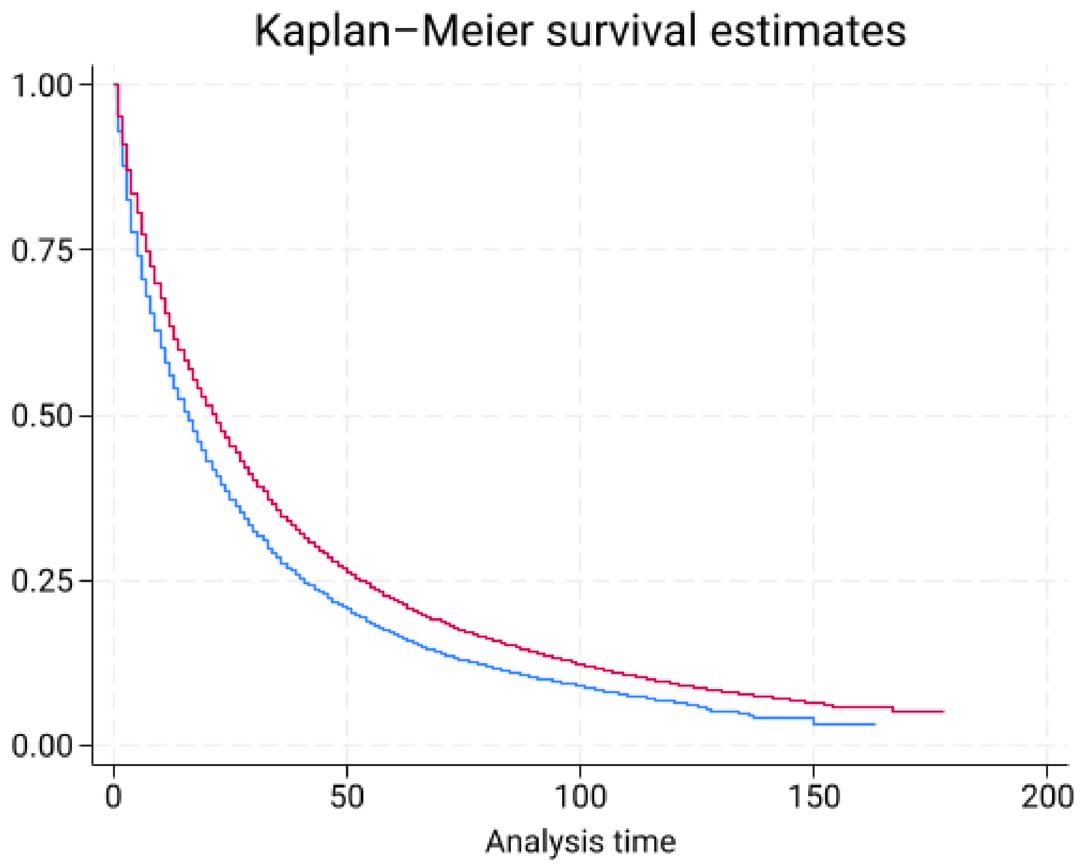

Figure 2: Nonparametric Estimates for Survival: White Hosts (red) vs. Non-White Hosts (blue)

Appendix A: NLP Procedure

To make use of the textual review data, I use Natural Language Processing (NLP), a machine-learning technique for analyzing 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 to remove special characters from the text, and I keep only reviews written in English. In addition, I convert contractions containing apostrophes into separate words. Next, I lemmatize all the words (e.g., "improve," "improves," "improved," "improving," "improvement," and "improver" all become "improve"). I further remove stop words that add little or no 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 that maps the words to a numerical value that measures some features of the text.

To analyze sentiment, I attach sentiment *values* to each word in a lexicon of predefined words, then I calculate these sentiment values using the lexicon. Various lexicons cater to different needs; I chose 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 customer reviews (Hu and Liu, 2004). Its classification is binary—a word is either positive or negative. It contains 6,786 words, 2,005 positive ones and 4,781 negative ones. The NRC Emotion lexicon, which was developed by crowdsourcing on Amazon Mechanical Turk (Mohammad and Turney, 2013), 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. Consumers can also drill down to find older reviews, but those 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 I handle the text sentiment scores, because consumers can observe only the cumulative numerical rating of a listing.

In both the NRC Emotion and Bing lexicons, a positive sentiment score can be measured by the percentage of positive words in the 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 then multiplied by 100). Similarly, the relative percentages 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 then multiplied by 100). Beyond positive and negative sentiments, other NRC-based sentiments can be calculated in a similar manner.

Appendix B: Match Rates by Gender and Race

Table A1: Match Rates Between Name Prediction and Manual Verification by Gender

Algorithmic prediction	Male (N = 466)	Female (N = 372)
Manual verification	419 males	357 females
Match rate	90%	96%

Table A2: Match Rates Between Name Prediction and Manual Verification by Race

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