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**Racial disparities in the sharing economy: Evidence from more than 100,000 Airbnb hosts
across 14 countries**

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Abstract

Sharing economy platforms like Airbnb often require (or strongly encourage) hosts to share personal information, such as names and profile photos. Previous research suggests that consumers rely on this information to discriminate against sellers from racial minorities. If there is a preference for White hosts, then they should be able to charge higher prices for qualitatively similar rentals. Here, we examine racial price disparities on Airbnb. An analysis of 96,150 listings across 24 cities and 14 countries showed that non-White hosts charge approximately 2.5-3% lower prices for similar listings (Study 1). A preregistered analysis of 12,648 listings across 14 cities in the United States showed that Black hosts charge approximately 5-7% lower prices and Asian hosts charge approximately 4-6% lower prices for similar listings (Study 2). These findings support the hypothesis that, all else being equal, consumers prefer to stay with White hosts, which allows them to charge higher prices.

Keywords: sharing economy; profile photo; racism; discrimination; privacy

Racial disparities in the sharing economy: Evidence from more than 100,000 Airbnb hosts across 14 countries

A central challenge for sharing economy platforms, such as Airbnb and Uber, is to establish trust between sellers and customers (Guttentag, 2013). Reputation systems, where previous customers rate their satisfaction with the seller, are a common solution to this problem. Many peer-to-peer platforms also display various personal characteristics of sellers to reduce anonymity and increase trust (Guttentag, 2013). Sellers are required, or strongly encouraged, to provide information such as names and profile photos. As Airbnb's CEO Brian Chesky put it in a press release in 2013 (Airbnb, 2013): "Access is built on trust, and trust is built on transparency. When you remove anonymity, it brings out the best in people."

However, the availability of personal information can also have negative consequences for sellers, as consumers can rely on this information to discriminate against individuals from certain social groups (Köbis et al., 2020). For example, research suggests that consumers favor White hosts on Airbnb, which affects the earning opportunities of hosts from racial minorities (Edelman & Luca, 2014; Nødtvedt et al., 2020). That is, in line with common definitions of discrimination, consumers seem to prefer the listings of certain hosts because of their racial background (Dovidio et al., 2010; Lee et al., 2021). Here, we test this hypothesis using data on actual Airbnb listings. We examine the prevalence and magnitude of racial disparities on Airbnb by analyzing more than 100,000 Airbnb hosts from 24 cities, 14 countries, and 3 continents (total $N = 108,798$).

Racial Discrimination in the Sharing Economy

In one of the earliest studies on racial discrimination in peer-to-peer markets, Doleac and Stein (2013) investigated how a subtle cue indicating the race of a seller influenced the demand for items posted in local online markets. The same item (an iPod Nano) attracted fewer responses, fewer offers, and lower average and maximum offers when it was held by a dark-skinned (vs. a light-skinned) hand. In a similar study, baseball cards held by dark-skinned hands attracted lower offers on eBay resulting in lower profits for sellers (Ayres et al., 2015). These results suggest that even subtle cues to a person's race can influence consumer decisions and sellers' earnings. Subsequent studies have demonstrated that consumers rely on various cues, such as names (Cui et al., 2020; Zussman, 2013) and profile photos (Edelman & Luca, 2014), to discriminate against sellers from racial minorities. Racial disparities have been observed in

various peer-to-peer markets, including eBay (Ayres et al., 2015), Uber (Ge et al., 2020), and online markets for used cars (Zussman, 2013).

Although racial discrimination seems to be pervasive in online markets, it may be particularly problematic for platforms that are part of the so-called sharing economy. While some markets involve little to no direct contact between sellers and buyers (e.g., eBay), sharing economy platforms like Airbnb require people to enter a stranger's home, which may be perceived as particularly risky (Guttentag, 2013). Indeed, results from a recent lab experiment suggest that people less willing to stay with hosts from racial minorities. Nødtvedt and colleagues (2020) showed a fictitious Airbnb listing to a sample of Norwegian participants and manipulated whether the profile photo showed a host belonging to participants' racial in-group or out-group. Participants liked the apartment less, indicated that they were less likely to rent it, and were willing to spend less money on it when the profile photo showed that it was rented out by "Abdi from Somalia" rather than "Martin from Norway".

Hedonic pricing models have also yielded evidence for racial biases on Airbnb (e.g., Edelman & Luca, 2014; Jaeger et al., 2019b; Marchenko, 2019). Hedonic pricing models test which attributes of a good or service are predictive of its price to infer which attributes are preferred by consumers (Malpezzi, 2008; Rosen, 1974). The main principle behind this analysis is that if a good or service has characteristics that are favored by consumers. Then this should translate to increased demand, which should lead to an increase in price, especially in cases where supply is inflexible. Imagine an artist who creates and sells ten oil paintings every year. If the artist experiences a lot of demand for the paintings she may increase the price, especially because she can only produce a limited number of paintings each year. Hedonic pricing models take advantage of this relationship between consumer preferences and prices to understand preferences, which are often difficult to measure directly, by analyzing prices, which are often easy to measure. In hedonic pricing models, the price of goods or services (e.g., paintings) is regressed on their individual characteristics (e.g., their style, color palette, or size). For example, if consumers generally value larger over smaller paintings, size should be positively related to price. Phrased differently, a positive relationship between the size of a painting and its price would suggest that consumers prefer larger paintings, all else being equal. For Airbnb hosts, supply is similarly inflexible. Irrespective of how popular their apartment is, they can only rent it out to one guest at a time and for a certain number of nights per year. There should be greater

demand for listings with more desirable characteristics and to capture this demand and increase profits, hosts can increase the price of their listings.

Hedonic pricing models are based on three key assumptions. Sellers should be (a) motivated to increase profits, (b) able to observe how much demand there is for their service, and (c) able to adjust the price of their service in response to varying demand. Airbnb markets seem to satisfy these conditions. Although hosts may also be driven by non-monetary motives when sharing their homes (e.g., social contact), the possibility to generate extra income is often mentioned as the central reason for hosting (Dillahunt & Malone, 2015). Hosts receive real-time information on the demand for their listing by observing the frequency of booking requests and Airbnb makes it easy for hosts to flexibly adjust the price of their listing. Previous findings also support the notion that higher prices of Airbnb listings reflect the presence of more desirable listing characteristics. Listings with characteristics that one would expect consumers to prefer (e.g., larger apartments, hosts with better review scores) are associated with higher asking prices (Edelman & Luca, 2014). In short, hedonic pricing models are a promising tool for studying which characteristics of Airbnb hosts or their apartments are valued by consumers.

Edelman and Luca (2014) estimated a hedonic pricing model with a sample of 3,752 Airbnb listings in New York City to examine which features (including the host's race) predict the price of listings. If consumers tend to avoid hosts from racial minorities, all else being equal, demand for their apartments should be lower and they might set lower prices for their apartments. Results showed that Black (vs. non-Black) hosts charged approximately 12% lower prices for similar apartments (i.e., when controlling for a host of features, such as apartment size and review scores). This effect was replicated by Jaeger and colleagues (2019), who found a price disparity of 10% in favor of White hosts in New York City. Similar racial price differences were found in San Francisco (comparing White with Asian, and Hispanic hosts; Kakar et al., 2018) and in Oakland and Berkeley (comparing White with Asian hosts; Wang et al., 2015). The most comprehensive analysis to-date was performed by Marchenko (2019), who examined more than 45,000 listings across seven large cities in the United States. Again, results showed price disparities that disfavored Black and Asian hosts compared to White hosts. In Table 1, we summarize key aspects of the study design and results of these investigations. We also include a description of the current studies to facilitate comparisons across studies.

Previous investigations have yielded consistent evidence for a racial price gap on Airbnb. However, several key questions remain unanswered. First, the exact size of the price gap is unclear. Observed disparities between Black and White hosts ranged from 2.3% (Kakar et al., 2018) to 12% (Edelman & Luca, 2014; see Table 1). This uncertainty may be due to the fact that analyses were based on a limited sample of listings in one or a few cities. Even though the number of Airbnb listings is vast, researchers are often forced to focus on a subset of the available data (e.g., Kakar et al., 2018). The race of hosts is usually classified by participants, which means that sample sizes are constrained by the size of participant pools or research budgets. In the present studies, we circumvent this problem by relying on an algorithm to code hosts' race based on their profile photo (as described in Jaeger et al., 2020). This allowed us to analyze a substantially larger sample of listings ($N = 108,798$), which should enable us to estimate the racial price gap with more precision.

Second, based on previous studies it is unclear whether racial price gaps are due to racial preferences of potential guests or due to other differences between the listings of White and non-White hosts, which may influence booking decisions of guests. Relationships between hosts' race and the price of their listings are only indicative of guests' racial preferences if other attributes that could (a) vary between White and non-White hosts and (b) influence the choices of guests are controlled for. For example, White hosts might live in places that are, on average, closer to key tourist attractions. Consequently, racial price disparities might emerge because guests take into account the listing's location, rather than the host's race, when making booking decisions. In the present studies, we improve on previous analyses by including a more comprehensive set of control variables (see Table 1). We control for a large set of attributes of the listing (e.g., number of bedrooms, review scores), the host (gender, age) and the booking process (e.g., cleaning fees, strictness of the cancelation policy). In Study 2, we also control for the poverty rate, unemployment rate, and average apartment price in a listing's neighborhood, which serve as proxies for the attractiveness of the listing's location. We also test the hypothesis that racial price gaps are indicative of discrimination by potential guests in an alternative way. If racial price disparities emerge because guests are avoiding hosts from racial minorities, then we should observe larger disparities when guests can expect to have more direct contact with the host (i.e., when renting a shared or private room as opposed to an entire listing).

Third, it is unclear how widespread racial price disparities are. Racial biases in hiring decisions, criminal sentencing, and many other domains have been observed in many countries (e.g., Quillian et al., 2019). Airbnb represents an ideal opportunity to study racial biases from a cross-cultural perspective because the company operates in many countries and provides consumers with a relatively standardized decision-making environment. Yet, previous studies that examined racial biases on Airbnb have overwhelmingly focused on a few cities in the United States (see Table 1). We address this shortcoming by analyzing 35 cities across 14 countries in Europe, Australia, and North America.

Table 1

Summary of the key methods and results of the current and previous hedonic pricing models that examined racial price disparities on Airbnb

Study	Sample size (# of hosts)	Listing locations	Price predictors ^a	Key findings
Edelman & Luca (2014)	3,752	New York City (US)	Host race (Black, non-Black), number accommodated, listing type (entire apartment vs. shared), number of bedrooms, location review score, accuracy review score, cleanliness review score, communication review score, picture quality, contact points (LinkedIn, Facebook, Phone Number, Twitter)	Black hosts charge 12% less than non-Black hosts, ^b
Wang et al. (2015)	101	Oakland (US) Berkeley (US)	Host race (Asian, White), number of bedrooms, number of bathrooms, number accommodated	Asian hosts charge 20% less than White hosts
Kakar et al. (2018)	715	San Francisco (US)	Host race (Black, Hispanic, Asian, White, other), host gender, host couple, host sexual orientation, superhost designation, number accommodated, number of bedrooms, number of bathrooms, location review score, cleanliness review score, value for money review score, location value (average cost of apartment per square foot)	Black hosts charge 2.3% less (non-significant), Hispanic hosts charge 9.6% less and Asian hosts charge 9.3% less compared to White hosts.
Jaeger et al. (2019)	1,017	New York City (US)	Host race (Black, Asian, White), host gender, perceived trustworthiness, perceived attractiveness, smile intensity, superhost designation, number of bedrooms, entire apartment (vs. private room), number of reviews, apartment attractiveness (rated based on a photo), location value (average cost of apartment per square foot)	Black hosts charge 10.1% less and Asian hosts charge 0.6% less (non-significant) compared to White hosts,
Marchenko (2019)	45,073	Los Angeles (US), New York City (US), Austin (US), Chicago (US), New Orleans (US), Washington D.C. (US), Nashville (US)	Host race (Black, Asian, Hispanic, White, unknown), host gender, host age, property type (apartment/loft, townhouse/condo, house, other), listing type (entire apartment, private room, shared), number accommodated, number of bedrooms, number of bathrooms, number of beds, cleaning fee, extra guest charge, minimum nights, availability, number of amenities, year of first review, strictness of cancellation policy	Black male hosts charge 3.5% less, Black female hosts charge 1.7% less (non-significant), Asian male hosts charge 4.5% less, Asian female hosts charge 4.0% less, Hispanic male hosts charge 2.0% less (non-significant), and Hispanic female hosts charge 2.0% less (non-significant) compared to White male hosts, ^c

Table 1 (continued)

Present Study 1	96,150	Amsterdam (NL), Barcelona (ES), Berlin (DE), Copenhagen (DK), Edinburgh (GB), Florence (IT), Hawaii (US), Lisbon (PT), London (GB), Los Angeles (US), Lyon (FR), Madrid (ES), Mallorca (ES), Melbourne (AU), Milan (IT), Montreal (CA), New York (US), Paris (FR), Prague (CZ), Rome (IT), San Diego (US), Sydney (AU), Toronto (CA), Vienna (AT)	Host race (Non-white, White), host gender, host age, superhost designation, verified identity, property type (apartment, house), listing type (entire apartment, private room, shared), number of bedrooms, number of bathrooms, number of beds, overall review score, review score - description accuracy, review score - cleanliness, review score - check-in, review score - communication with host, review score - location, review score - value for price, number of reviews, availability in last year, cleaning fee, instant booking possible, strictness of cancelation policy	Non-white hosts charge 2.90% less than White hosts. ^d
Present Study 2	12,648	Asheville (US), Austin (US), Boston (US), Chicago (US), Denver (US), Los Angeles (US), Nashville (US), New Orleans (US), New York City (US), Oakland (US), Portland (US), San Diego (US), San Francisco (US), Santa Cruz County (US), Seattle (US), Washington D.C. (US)	Host race (Black, Asian, White), host gender, host age, superhost designation, verified identity, property type (apartment, house), listing type (entire apartment, private room, shared), number of bedrooms, number of bathrooms, number of beds, overall review score, review score - description accuracy, review score - cleanliness, review score - check-in, review score - communication with host, review score - location, review score - value for price, number of reviews, availability in last year, cleaning fee, instant booking possible, strictness of cancelation policy, location value (average cost of apartment per square foot), neighborhood poverty rate, neighborhood unemployment rate	Black hosts charge 7.3% less and Asian hosts charge 4.0% less than White hosts. ^e

^aIn most studies, different models were estimated, which included different sets of control variables. Here, we list all control variables that were considered.

^bThis estimate reflects the results of models 5-7 which included the largest set of control variables.

^cThese estimate reflects the results of model 6 which included host race as a predictor.

^dThese estimate reflects the results of model 2 (Table 2) which included the largest set of control variables.

^eThese estimate reflects the results of model 4 (Table 5) which included the largest set of control variables.

The Current Studies

We report the results of two studies. In Study 1, we analyze 96,150 Airbnb listings across 24 cities and 14 countries. In Study 2, we conduct a preregistered analysis of 12,648 listings across 14 cities in the United States. In both studies, we test whether non-White hosts charge lower prices for qualitatively similar listings. We report how our sample sizes were determined, all data exclusions, and all measures. All data, analysis scripts, and preregistration documents are available at the Open Science Framework (<https://osf.io/7pfh3>).

Study 1

In Study 1, we examined the prevalence and magnitude of racial price disparities across a wide range of Airbnb markets. Previous work has overwhelmingly focused on Airbnb hosts in the United States (e.g., Edelman & Luca, 2014; Marchenko, 2019). Here, we focused on the largest Airbnb markets in countries with a predominantly White population. We analyzed 96,150 listings from 24 cities in 14 countries across Europe, Australia, and North America (see Table 1). Patterns of discrimination against specific racial minorities may differ substantially across these countries due to differences in racial composition and racial stereotypes. We therefore tested for price disparities between White and non-White hosts. That is, we tested whether non-White hosts charge significantly lower prices for qualitatively similar listings compared to White hosts.

Methods

Inside Airbnb (<http://insideairbnb.com>) provides a detailed documentation of all Airbnb listing that were available in a given city on a given day. We downloaded data on all listings from cities with at least 10,000 available listings on the day the data set was created (26 April 2019). Our goal was to test if prejudice against racial minorities leads to price disparities that disfavor non-White Airbnb hosts. We therefore focused on countries with a White majority where such prejudice is expected to exist, which lead to the exclusion of four cities from our sample (Beijing, Cape Town, Istanbul, and Rio de Janeiro). We used the Face++ algorithm (www.faceplusplus.com) to classify hosts' race (White, Black, Asian, Indian), sex, and age. After applying our exclusion criteria (for a detailed description, see the Supplemental Materials), the final sample contained 96,150 listings spanning 24 cities, 14 countries, and 3 continents. The sample size per city ranged from 647 (Mallorca) to 10,202 (Paris) with a median of 3,141 listings ($M = 4,006$, $SD = 2,461$). For each listing, we recorded the price per night and a host of control variables (see Table 1). Price and number of reviews were \log_{10} -transformed due to their skewed

distributions. Age, number of reviews, review scores, availability, and cleaning fee were z -standardized.

Results

Racial price disparities. We estimated multilevel regression models with random intercepts per city and random slopes for the effect of race. For our primary analysis of interest, we predicted price with a dummy variable indicating whether the host was classified as White (coded as 0) or non-White (i.e., Black, Asian, or Indian; coded as 1), controlling for a pre-defined set characteristics that may differ between White and non-White hosts and influence booking decisions. This revealed a negative effect of race, $\beta = -0.0120$, $SE = 0.0034$, $p = .002$, 95% CI [-0.0187, -0.0048] (see Table 2, Model 1). Non-White hosts charged 2.73% lower prices than White hosts for similar apartments. To put this effect in perspective, being designated a superhost was associated with a 1.70% price increase, a one standard deviation increase in review score was associated with a 4.09% price increase, and the presence of an additional bedroom (which can also be seen as a proxy for the apartment's size) was associated with a 33.89% price increase.

Variation across listing and cities. While our main goal was to estimate price differences as a function of hosts' race, we also conducted several exploratory analyses. First, we examined variation in price disparities across different types of listings. Specifically, we tested whether racial price disparities were larger when consumers could anticipate to have more direct contact with the host. Consumers might be particularly reluctant to stay with a non-White host if they know that they will share the listing with the host (i.e., when renting a shared or private room as opposed to an entire listing). The interaction effect between race (White vs. non-White) and a dummy variable indicating whether the entire listing was rented out or whether it was shared with the host was significant, $\beta = -0.0112$, $SE = 0.0028$, $p < .001$, 95% CI [-0.0168, -0.0055]. The price disparity was larger for shared listings (i.e., shared room and private room listings), $\beta = -0.0169$, $SE = 0.0045$, $p = .001$, 95% CI [-0.0257, -0.0081], compared to listings that are not shared (i.e., entire home listings), $\beta = -0.0118$, $SE = 0.0036$, $p = .003$, 95% CI [-0.0189, -0.0045]. Compared to White hosts, non-White hosts charged 3.83% lower prices when listings were shared and 2.70% lower prices when listings were not shared.

Table 2*The association between host race and the price of Airbnb listings*

	Model 1	Model 2
Non-White	-0.0120 **	-0.0128***
Female	-0.0106 ***	-0.0075***
Age	0.0019 **	0.0009
Superhost	0.0073 ***	0.0140***
Verified identity	0.0135 ***	0.0163***
Review score	0.0174 ***	
Number of reviews	-0.0082 ***	-0.0161***
House	-0.0270 ***	-0.0346***
Shared room	-0.1201 ***	-0.1149***
Entire apartment	0.2816 ***	0.2313***
Number of bedrooms	0.1268 ***	0.0575***
Number of beds		-0.0078***
Number of bathrooms		0.0809***
Accommodates		0.0313***
Availability in last year		0.0217***
Instant booking		-0.0050***
Flexible cancelation		-0.0197***
Cleaning fee		0.0221***
Review score: Accuracy		0.0015 [†]
Review score: Cleanliness		0.0177***
Review score: Check-in		-0.0011
Review score: Communication		-0.0019*
Review score: Location		0.0447***
Review score: Value for price		-0.0212***
Observations	96,150	82,808

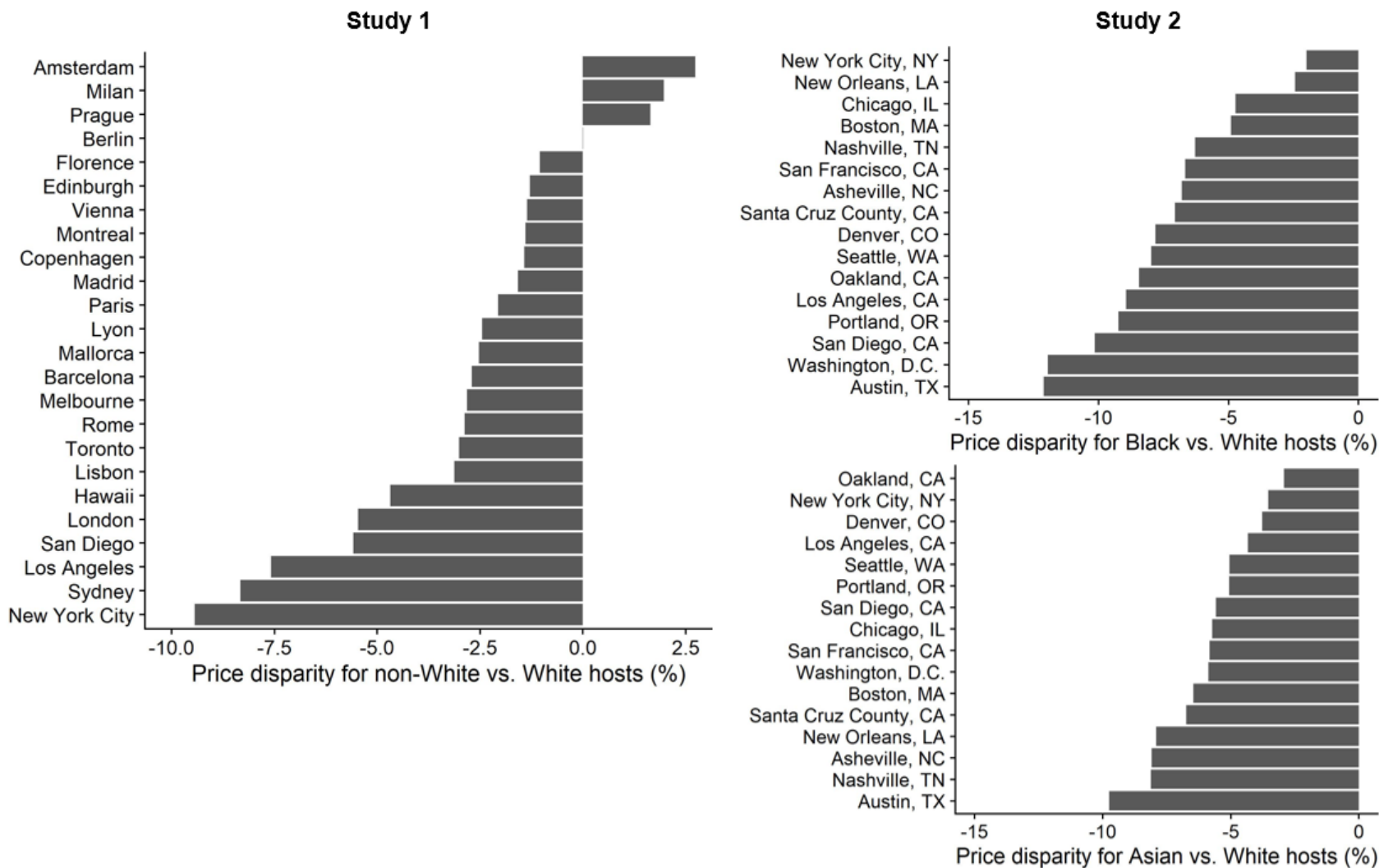
*** $p < .001$. ** $p < .01$. * $p < .05$. [†] $p < .10$.

Next, we explored variation in racial price disparities across cities (see Figure 1 left panel). Price disparities disfavoring non-White hosts were largest in New York City (-9.44%), Sydney (-8.33%), and Los Angeles (-7.58%). The sign of the disparity was reversed in four cities

(Amsterdam, Milan, Prague, and Berlin), where non-White hosts charged higher prices than White hosts. However, these price differences were much smaller, ranging from +0.01% in Berlin to +2.74% in Amsterdam. Overall, these results show that price disparities favoring White hosts are common in the sample of markets examined here.

Figure 1

Price disparities between non-White vs. White hosts across the cities analyzed in Study 1 and Study 2



Robustness checks. Finally, we explored the robustness of the estimated price disparity by adding more characteristics that may influence prices to our model. We added review scores for six separate dimensions (description accuracy, cleanliness, check-in, communication with host, location, value for price) instead of the overall review score, and several features of the listing (e.g., number of beds and bathrooms) and the booking process (e.g., cancellation policy, cleaning fee) to the model (see Table 2). Racial price disparities were still apparent with non-White hosts charging 2.90% lower prices than White hosts (see Table 2, Model 2).

Discussion

Study 1 showed evidence for a racial price gap on Airbnb: Compared to White hosts, non-White hosts charged lower prices for qualitatively similar listings. Although the size of the disparity varied across cities, it favored White hosts in 20 out of the 24 cities examined here. Price disparities were larger for listings that were shared with the host, rather than rented out completely. This may indicate that consumers are particularly reluctant to stay with a host from a racial minority when their stay involves direct contact with the host.

Study 2

In Study 1, we focused on a large set of countries to examine the prevalence of racial price disparities. This broad focus also introduced challenges due to the heterogeneity of racial groups and racial stereotypes across countries. For example, the algorithm we relied on to classify hosts' race provides a limited set of relatively broad labels (White, Black, Asian, Indian), which may sufficiently overlap with common labels of major racial groups in some countries (e.g., the United States), but less so in other countries (e.g., Germany or Australia). In Study 2, we therefore focused on a single country to estimate racial price disparities with more precision. We focused on the United States because it is the country with the largest number of Airbnb listings. Compared to previous investigations, which focused only on one (Edelman & Luca, 2014; Jaeger et al., 2019; Kakar et al., 2018) or a few cities (Marchenko, 2019; Wang et al., 2015), we examined a large number of Airbnb listings across 16 cities located in 11 different states and the District of Columbia.

Compared to Study 1, we implemented several methodological changes. We relied on the Kairos algorithm (Kairos AR, Inc., www.kairos.com) to classify the race of hosts. One advantage of Kairos is that it provides confidence estimates for each classification. Focusing on listings with hosts that could be classified with high levels confidence (i.e., at least 90%) allowed us to

estimate racial price disparities more reliably by minimizing noise due to misclassified hosts. We also examined the robustness of our results by varying the classification confidence threshold. Our analysis focused on White, Black, and Asian hosts, as these categories can be classified with high levels of accuracy (Jaeger et al., 2020).

We also controlled for additional features of Airbnb listings that might confound the relationship between hosts' race and the price of their listings. Guests prefer to stay in rentals that are located in desirable neighborhoods (Jaeger et al., 2019). Moreover, the racial composition of neighborhoods can vary substantially. We therefore control for the quality of a listing's location. Following previous investigations (Jaeger et al., 2019; Kakar et al., 2018), we use the average rental price in a given zip code as our measure of neighborhood desirability. We also explored how the inclusion of additional control variables, such as the neighborhood's poverty and crime rate, influenced our results.

Methods

This study was preregistered (<https://osf.io/7pfh3>). We downloaded data for 16 U.S. cities located in 11 different states and the District of Columbia (see Table 1) from the Inside Airbnb website (<http://insideairbnb.com>). After applying our preregistered exclusion criteria (see the Supplemental Materials for a detailed description), the final sample contained 12,648 listings. The sample size per city ranged from 92 (Santa Cruz County) to 3,925 (New York City) with a median of 507 listings ($M = 791$, $SD = 982$). For each listing, we recorded the price per night (which constituted our outcome variable) and a host of control variables (see Table 1). We used the Kairos algorithm (<https://kairos.com>) to classify hosts' race (White, Black, Asian), sex, and age. Rental data from Zillow (<https://www.zillow.com/>) was accessed with the Quandl API (<https://docs.quandl.com/>). For each listing, we extracted the zip code and recorded the average rent per square foot for an apartment in that zip code. This served as an indicator of how desirable the listing's location is. We also recorded the poverty and unemployment rates in a listing's zip code (taken from U.S. census data, <https://data.census.gov/>) as additional indicators of location desirability. Price, location value, and number of reviews were \log_{10} -transformed due to their skewed distributions. Age, number of reviews, review scores, availability, cleaning fee, and the three indicators of location desirability were z -standardized.

Results

Racial price disparities. We estimated multilevel regression models with random intercepts per city and random slopes for the effect of race. In line with our preregistered analysis plan, we focused on all hosts for whom Kairos provided a race classification with at least 90% confidence ($n = 12,648$). Regressing price on race (White vs. Black vs. Asian, with White being the reference category) and all control variables revealed negative effects for Black hosts, $\beta = -0.0333$, $SE = 0.0100$, $p = .008$, 95% CI [-0.0537, -0.0121], and Asian hosts, $\beta = -0.0266$, $SE = 0.0059$, $p < .001$, 95% CI [-0.0408, -0.0140] (see Table 3, Model 1). Compared to White hosts, Black host charged 7.39% lower prices and Asian hosts charged 5.94% lower prices for similar apartments. To put this effect in perspective, being designated a superhost was associated with a 3.23% price increase, a one standard deviation increase in review score was associated with a 3.30% price increase, and the presence of an additional bedroom was associated with a 37.53% price increase.

Table 3
The association between host race and the price of Airbnb listings

	Model 1	Model 2	Model 3	Model 4
Black	-0.0333 **	-0.0373 **	-0.0204 *	-0.0331 ***
Asian	-0.0266 ***	-0.0274 ***	-0.0230 ***	-0.0175 ***
Female	-0.0052 †	-0.0042 †	-0.0019	-0.0029
Age	0.0063 ***	0.0070 ***	0.0054 ***	0.0034*
Superhost	0.0138 ***	0.0109 **	0.0162 ***	0.0118**
Verified identity	0.0076 *	0.0073 *	0.0080 **	0.0103**
Review score	0.0141 ***	0.0143 ***	0.0123 ***	
Number of reviews	-0.0226 ***	-0.0227 ***	-0.0208 ***	-0.0188***
House	0.0452 ***	0.0436 ***	0.0441 ***	0.0255***
Shared room	-0.1550 ***	-0.1382 ***	-0.1477 ***	-0.1541***
Entire apartment	0.2463 ***	0.2414 ***	0.2492 ***	0.1874***
Number of bedrooms	0.1384 ***	0.1385 ***	0.1386 ***	0.0543***
Location value	0.1241 ***	0.1243 ***	0.1230 ***	0.0987***
Number of beds				-0.0102***
Number of bathrooms				0.0654***
Accommodates				0.0242***
Availability in last year				0.0205***
Instant booking				-0.0124***
Flexible cancelation				0.0042
Cleaning fee				0.0557***
Review score: Accuracy				0.0011
Review score: Cleanliness				0.0134***
Review score: Check-in				-0.0012
Review score: Communication				0.0063**
Review score: Location				0.0172***
Review score: Value for price				-0.0155***
Unemployment rate (zip code)				-0.0108†
Poverty rate (zip code)				-0.0005
Observations	12,648	16,939	19,651	9,782

*** $p < .001$. ** $p < .01$. * $p < .05$. † $p < .10$.

Variation across listings and cities. We again explored whether racial disparities were larger when consumers could expect to have more contact with hosts. The interaction effect between race and a dummy variable indicating whether the entire listing was rented out or whether it was shared with the host was not significant when comparing Black and White hosts, $\beta = 0.0149$, $SE = 0.0098$, $p = .129$, 95% CI [-0.0036, -0.0334], and when comparing Asian and White hosts, $\beta = -0.0153$, $SE = 0.0103$, $p = .137$, 95% CI [-0.03375, 0.0056].

We also examined variations in racial price disparities across cities (see Figure 1 right panel). Racial price gaps disfavoring Black hosts were largest in Austin (-12.11%), Washington D.C. (-11.95%), and San Diego (-10.15%) and smallest in New York City (-2.00%), New Orleans (-2.44%), and Chicago (-4.73%). Racial price gaps disfavoring Asian hosts were largest in Austin (-9.75%), Nashville (-8.12%), and Asheville (-8.09%) and smallest in Oakland (-2.93%), New York City (-3.54%), and Denver (-3.78%). Price disparities disfavoring Black and Asian hosts emerged in all 16 cities.

Robustness checks. We conducted three robustness checks. Rather than excluding listings with photos in which multiple faces were detected, we retained them and coded whether any Asian or any Black person was detected in the photo. Hosts with profile photos that included at least one Black person (vs. only White individuals) charged 8.22% lower prices (see Table 3, Model 2). Hosts with profile photos that included at least one Asian person charged 6.12% lower prices.

We also implemented less stringent exclusion criteria. Instead of focusing only on hosts whose race could be classified with at least 90% confidence, we assigned hosts the racial group that was detected with the highest level of confidence. Compared to White hosts, Black host charged 4.58% lower prices and Asian hosts charged 5.15% lower prices (see Table 3, Model 3).

Finally, we explored how our results change when additional control variables that may influence prices were included in our model. We added variables indicating the poverty and unemployment rates in the listing's zip code, review scores on six separate dimensions (e.g., cleanliness, location) instead of the overall review score, and several features of the listing (e.g., number of beds and bathrooms) and the booking process (e.g., cancelation policy, cleaning fee) to the model. Results showed that compared to White hosts, Black hosts charged 7.34% lower prices and Asian hosts charged 3.95% lower prices (see Table 3, Model 4). More detailed results are reported in the Supplemental Materials.

Discussion

Replicating the results of Study 1, we again found evidence for a racial price gap: Compared to White hosts, both Black and Asian hosts charged lower prices for similar listings. This disparity still emerged when employing different exclusion criteria, different confidence thresholds for the classification of hosts' race, and when controlling for a larger set of characteristics that may differ between White, Black, and Asian hosts. Although the size of the racial price disparity varied substantially across cities, we found disparities favoring White hosts in all 16 cities that were examined here.

General Discussion

Sellers in sharing economy markets are often required (or strongly encouraged) to display personal information, such as profile photos and names, in order to reduce anonymity and enhance trust between consumers and sellers (Guttentag, 2013). However, disclosing personal information may come at a cost for some sellers, as studies suggest that consumers use this information to discriminate against sellers from racial minorities (Köbis et al., 2020). For instance, a recent study found that participants had a lower willingness to pay for the same Airbnb apartment when it was advertised by a host from a racial minority (Nødtvedt et al., 2020). Lower demand for apartments of racial minorities should negatively influence their earning opportunities. In line with these idea, our analysis of more than 100,000 listings across 24 cities, 14 countries, and 3 continents consistently showed that non-White hosts charge significantly lower prices for qualitatively similar apartments compared to White hosts. Three key findings emerged from our studies.

First, price disparities disfavoring Airbnb hosts from racial minorities are widespread. In Study 2 ($n = 12,648$), we analyzed data from a wide range of cities across the United States (the country with the most Airbnb listings worldwide) and found price disparities of 7.39% and 5.94% for Black hosts and Asian hosts, respectively. Previous studies mostly focused on a few Airbnb markets (e.g., Edelman & Luca, 2014; Jaeger et al., 2019), which raised questions about the generalizability of the observed price disparities. Many parameters that plausibly influence racial disparities vary substantially across cities and regions, including the prevalence of hosts from racial minorities and the types of guests that visit the place. We analyzed a larger and more representative set of U.S. markets and found that racial price gaps were apparent in all 16 cities analyzed here.

Second, going beyond previous studies, our results show that racial price disparities are also apparent outside of the United States. In Study 1 ($n = 96,150$), we focused on the 24 largest Airbnb markets worldwide (in countries with a predominantly White population) and found that, on average, hosts from racial minorities charge 2.74% lower prices for qualitatively similar apartments. Racial price gaps were again common: We found price disparities favoring White hosts in 20 out of the 24 cities that were analyzed.

Third, although we consistently found price disparities in favor of White hosts, the exact size of the disparity varied. We were particularly interested in examining whether price disparities would vary depending on whether a listing is shared or not. If price disparities reflect consumers' reluctance to stay with a non-White host, then this disparity might be stronger when guests share the listing with the host, rather than rent it out entirely. In other words, potential guests might be particularly reluctant to stay with a host from a racial minority when they anticipate to have more direct contact with the host. Results of Study 1 showed evidence for this hypothesis: Racial price disparities were significantly larger for listings that were shared with hosts. It should be noted that similar effects were not observed in Study 2, which may have been due to the smaller sample size or the exclusive focus on listings in the United States.

Practical Implications

Sharing economy platforms often highlight that providing personal information is crucial to foster trust between consumers and sellers (Airbnb, 2013; Guttentag, 2013). However, a growing number of studies suggest that people rely on this information to discriminate against sellers from racial minorities. Given the prevalence of personal information on sellers' profiles across different sharing economy platforms, it is likely that racial price disparities not only exist on Airbnb, but across the sharing economy. In fact, while the majority of studies have focused on Airbnb, other work has found racial disparities on Uber (Ge et al., 2020), Lyft (Ge et al., 2020), and BlaBlaCar (Farajallah et al., 2016). This is particularly problematic because the relatively low barriers to becoming a seller make sharing economy markets attractive to economically disadvantaged groups (Dillahunt & Malone, 2015). In short, evidence is accumulating that racial discrimination is a common phenomenon across the sharing economy and that this may be exacerbated by common design features of sharing economy platforms.

Sharing personal information can have advantages and disadvantages for sellers. On the one hand, profile photos contain information that is perceived to be relevant by consumers

(Eckel & Petrie, 2011). Although more evidence is needed to test this question directly, providing profile photos may increase consumer trust and engagement. On the other hand, results of the current and previous studies suggest that profile photos and other forms of personal information enable discrimination. When deciding how to balance these concerns, the priorities of sellers and the platforms they are featured on may not be aligned (Buhalis et al., 2020). Sharing economy platforms have an incentive to provide as much personal information as possible if this increases consumer engagement (and, therefore, the company's revenue). It is individual sellers who will experience the negative externalities of this design feature. Sellers should be aware of this potential conflict between their own interests (e.g., anonymity, fair treatment) and the platform's interests (e.g., transparency, consumer trust).

To reduce the prevalence of discrimination in the sharing economy, more fundamental changes to the design of the platforms may be needed (Lee et al., 2021). Parallels can be drawn to changes in hiring procedures to mitigate discrimination. In many countries, it is now uncommon (or even prohibited) to ask applicants to include a photo or other personal information in their application. A similar intervention may be needed in the sharing economy. Again, it should be noted that these changes are unlikely to be initiated by the companies themselves if they face competing incentives. In the case of Airbnb, many hosts have already voiced their discontent by sharing their negative experiences on Twitter under the hashtag "airbnbwhileblack". Media coverage of the issue may help raise public awareness. Ultimately, legislation may be needed to ensure that the same level of protection from discrimination that is available to sellers and buyers in more traditional markets (e.g., the housing market) also extends to the sharing economy.

The current results should be seen as a snap shot of racial price disparities on Airbnb at the time the studies were conducted. Airbnb is continuously updating its booking procedures and web design, which may influence the extent to which racial biases emerge. In fact, Airbnb has been aware of these issues for more than five years (Murphy, 2016). Recently, Airbnb announced additional efforts to study and mitigate discrimination on its platform (Airbnb, 2020). It remains to be seen how these changes will impact racial disparities on the platform.

Limitations and Future Directions

Following previous investigations (e.g., Edelman & Luca, 2014), we investigated racial discrimination on Airbnb by testing whether hosts from racial minorities charge lower prices for qualitatively similar listings compared to White hosts. If consumers favor staying with White

hosts then they will have a lower willingness to pay for the apartments of hosts from racial minorities, all else being equal. As a consequence, hosts from racial minorities would be able to charge lower prices for similar apartments compared to White hosts. One advantage of this approach is that it does not rely on hypothetical choices in a lab task, but gives insights into consumers' *actual* choices on the platform. One disadvantage is that, due to the correlational nature of the approach, the cause of racial price differences remain somewhat ambiguous. It is possible that price disparities are not caused by racially biased preferences of consumers, but by other factors, such as differences in the quality of apartments between White and non-White hosts. For example, it is plausible that White hosts live in more attractive neighborhoods. As a consequence, White hosts may be able to attract more guests and charge higher prices not because guests are willing to pay more to stay with White hosts, but because they favor staying in attractive neighborhoods. To address this issue, we controlled for a large set of potential confounds in our analyses (see Table 1) that included attributes of the listing (e.g., number of bedrooms, review scores, the unemployment and poverty rate in the listing's zip code), the host (gender, age), and the booking process (e.g., cleaning fees, strictness of the cancelation policy). We find that many desirable characteristics are positively related to the price of listings, as predicted by hedonic pricing theory (Malpezzi, 2008; Rosen, 1974). For example, listings that were located in more desirable neighborhoods (as indicated by higher average rental prices in the listing's zip code) and listings that received more positive review scores for their location were more expensive, which suggests that hosts are taking advantage of guests' higher willingness to pay for apartments located in attractive locations. We also find that White hosts tend to live in more attractive locations. In our studies, we therefore controlled for location attractiveness and many other potential confounds. The fact that racial price disparities emerge even after controlling for a large set of potential confounds make it more likely that price disparities are caused by consumers' lower willingness to pay for listings of non-White hosts.

Two additional considerations support the idea that rental decisions on Airbnb are partly guided by racial preferences. In a recent lab study, Nødtvedt and colleagues (2020) manipulated the perceived race of Airbnb hosts by manipulating their profile photo and name. In line with the idea that hosts' race influences booking decisions, Norwegian participants showed stronger preferences for an apartment when it was rented out by "Abdi from Somalia" rather than "Martin from Norway". Moreover, if racial price disparities result from a disinclination to stay with hosts

from racial minorities, then disparities should be larger when consumers can expect to have more direct contact with hosts. Results from Study 1 supported this prediction. Racial price disparities were larger when listings were shared with hosts rather than rented out entirely.

These findings also speak against another alternative explanation of the present results. Racial price disparities may not be due to lower demand for apartments of non-White hosts by racially biased consumers, but due to White hosts setting higher prices irrespective of demand, for example, because of an increased sense of entitlement. In general, it is plausible that the prices that hosts set for their apartments are not perfectly calibrated to the demand that they experience, but also influenced by various other factors. However, this account would not predict that racial price disparities are larger when guests have more contact with the host, which we observed in Study 1, or that experimental manipulations of hosts' race would influence apartment choices, which was observed by Nødtvedt and colleagues (2020). Overall, the current findings support the interpretation that the observed price disparities reflect racially biased preferences of consumers.

Our large sample of cities and hosts and converging results from different analyses attest to the robustness of the price disparity in favor of White hosts. However, the exact size of the disparity should be interpreted with caution, as it may depend on several methodological and statistical choices such as which cities and hosts were included in the analysis and which potential confounds were statistically controlled for. A comparison of results for cities that were analyzed in Study 1 and Study 2 illustrates this point. The two studies used different inclusion criteria and control variables and, although results were similar for some cities (e.g., 5.6% vs. 8.0% lower prices for Asian hosts in San Diego), others showed larger differences (e.g., 13.7% vs. 2.0% lower prices for Black hosts in New York City).

The current analysis focused on a large set of countries in Europe, Australia, and North America. This allowed us to test how widespread racial price disparities are, but it also introduced substantial heterogeneity in the racial groups that were represented in our data set. Even though we focused on countries with a White majority, their exact racial compositions of countries differed substantially. Our data show that non-White hosts charge lower prices for qualitatively similar listings across various cities and countries, but more cross-cultural work is needed to map which racial groups are affected most in each country. Results of Study 2 provide first insights into this question. Although both Black and Asian hosts charged lower prices than

White hosts in all cities, the price gap for Black hosts was larger. Additional studies are also needed to test racial price differences in countries with a predominantly non-White population. On the one hand, we might observe price disparities that disfavor White hosts in these countries if consumers avoid staying with hosts from racial minorities. On the other hand, we might still find price disparities that favor White hosts because being White is a (true or perceived) indicator of status and wealth in some countries (e.g., South Africa, South East Asia) and hosts may therefore prefer to stay with White hosts even though they constitute a racial outgroup.

In general, the current analyses leave open the question of how the race of consumers and hosts interacts in shaping booking decisions. Some consumers may prefer to stay with a White host because they are (consciously or unconsciously) avoiding contact with a person from a racial outgroup. Alternatively, consumers may hold the (accurate or inaccurate) belief that stays with White hosts are somehow better. These views are in line with accounts of racially biased booking decisions as driven by taste-based or statistical discrimination, respectively (Becker, 2010). Future analyses that consider the race of consumers may help to shed light on the process underlying racially biased booking decisions. For example, if decisions are driven by the motivation to avoid racial outgroups, then Black hosts should be avoided by White, but not by Black guests. If decisions are driven by stereotypes that stays with White hosts are somehow better, then Black hosts may be avoided by both White and Black guests.

In the present investigation, we relied on face classification algorithms to code the race of Airbnb hosts based on their profile photo. Using automated procedures instead of human raters has several key advantages. For instance, coding a large number of hosts requires many participants and previous work often focused on a subset of all available listings in one or a few Airbnb markets due to limitations in participant pool size or research budget (Jaeger et al., 2019; Kakar et al., 2018). Relying on automated procedures circumvents this problem and allowed us to examine large samples of listings across many different markets. Yet, relying on algorithms also has disadvantages. The algorithm that was used in Study 1 classified hosts into four categories; White, Black, Asian, and Indian. This may not capture all racial groups in a given country. Moreover, race classification algorithms rely on perceptual cues that are easily detectable and discriminate between different racial groups (e.g., skin color). Previous studies found relatively high levels of accuracy in race classification, especially for Black and White targets (Jaeger et al., 2020; Rhue & Clark, 2016). However, accuracy may be lower for racial groups that are more

perceptually ambiguous (i.e., not characterized by unique and easily detectable facial characteristics). Given these limitations, we decided to focus on the broader distinction between White and non-White hosts in Study 1. Moreover, in Study 2, we only focused on hosts that were classified with high confidence to reduce measurement error.

Additional work is needed to better understand how racial preferences of consumers translate into lower prices (and, presumably, lower earnings) for hosts from racial minorities. Airbnb and other websites offer algorithms with which hosts can determine a reasonable price for their listing. Algorithm suggests a price by comparing the host's listing to similar listings, but the exact features that influence this recommendation are not clear. If prices algorithm's training set reflect racially biased preferences of consumers, then these biases may be reflected in (and propagated by) the algorithm's suggestions. Racial preferences could also be reflected in reviews of listings. A negative review of a host from a racial minority that was, at least partially, due to prejudice could deter future guests even if they are unbiased. Again, this mechanism would propagate racial price disparities.

Conclusion

Our analysis of more than 100,000 Airbnb listings across 24 cities, 14 countries, and 3 continents revealed widespread price disparities favoring White hosts who charged higher prices for qualitatively similar listings. We also find some evidence that racial price disparities were larger when listings were shared with hosts, that is, when consumers could anticipate to have more direct contact with their hosts. Although the exact size of the racial price gap varied substantially across different cities and countries, it emerged in 20 out of the 24 largest Airbnb markets worldwide and in 16 out of 16 U.S. cities examined here. Our findings are in line with experimental work showing that consumers prefer to stay with White hosts, which allows them to charge higher prices for their listings.

References

- Airbnb. (2013). *Airbnb announces “verified identification.”*
<https://www.airbnb.nl/press/news/airbnb-announces-verified-identification>
- Airbnb. (2020). *A new way we’re fighting discrimination on Airbnb.*
<https://www.airbnb.com/resources/hosting-homes/a/a-new-way-were-fighting-discrimination-on-airbnb-201>
- Ayres, I., Banaji, M., & Jolls, C. (2015). Race effects on eBay. *The RAND Journal of Economics*, 46(4), 891–917. <https://doi.org/10.1111/1756-2171.12115>
- Becker, G. S. (2010). *The economics of discrimination*. University of Chicago press.
- Buhalis, D., Andreu, L., & Gnoth, J. (2020). The dark side of the sharing economy: Balancing value co-creation and value co-destruction. *Psychology & Marketing*, 37, 689–704.
<https://doi.org/10.1002/mar.21344>
- 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. <https://doi.org/10.1287/mnsc.2018.3273>
- Dillahunt, T. R., & Malone, A. R. (2015). The promise of the sharing economy among disadvantaged communities. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2285–2294. <https://doi.org/10.1145/2702123.2702189>
- Doleac, J. L., & Stein, L. C. D. (2013). The visible hand: Race and online market outcomes. *The Economic Journal*, 123(572). <https://doi.org/10.1111/eoj.12082>
- Dovidio, J. F., Hewstone, M., Glick, P., & Esses, V. M. (2010). Prejudice, stereotyping and discrimination: Theoretical and empirical overview. In *The SAGE handbook of prejudice, stereotyping and discrimination* (pp. 3–29). Sage Publications.
- Eckel, C. C., & Petrie, R. (2011). Face value. *The American Economic Review*, 101(4), 1497–1513. <https://doi.org/10.1257/aer.101.4.1497>
- Edelman, B., & Luca, M. (2014). Digital Discrimination: The Case of Airbnb.com. In *Harvard Business School NOM Unit Working Paper No. 14-054*. <https://ssrn.com/abstract=2377353>
- Farajallah, M., Hammond, R. G., & Pénard, T. (2016). What drives pricing behavior in peer-to-peer Markets? Evidence from the carsharing platform BlaBlaCar. *Information Economics and Policy*, 48, 15–31. <https://doi.org/10.1016/j.infoecopol.2019.01.002>

- Ge, Y., Knittel, C. R., MacKenzie, D., & Zoepf, S. (2020). Racial and gender discrimination in transportation network companies. *Journal of Public Economics*, *190*, 104205. <http://www.nber.org/papers/w22776>
- Guttentag, D. (2013). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, 37–41. <https://doi.org/10.1080/13683500.2013.827159>
- Jaeger, B., Slegers, W. W. A., & Evans, A. M. (2020). Automated classification of demographics from face images: A tutorial and validation. *Social and Personality Psychology Compass*, e12520. <https://doi.org/10.1111/spc3.12520>
- Jaeger, B., Slegers, W. W. A., Evans, A. M., Stel, M., & van Beest, I. (2019). The effects of facial attractiveness and trustworthiness in online peer-to-peer markets. *Journal of Economic Psychology*, *75*. <https://doi.org/10.1016/j.joep.2018.11.004>
- Kakar, V., Franco, J., Voelz, J., & Wu, J. (2018). The visible host: Does race guide Airbnb rental rates in San Francisco? *Journal of Housing Economics*, *40*, 25–40. <https://doi.org/10.1016/j.jhe.2017.08.001>
- Köbis, N., Soraperra, I., & Shalvi, S. (2020). The consequences of participating in the sharing economy: A systematic literature review. *Journal of Management*. <https://doi.org/10.1177/0149206320967740>
- Lee, K., Hakstian, A. M., & Williams, J. D. (2021). Creating a world where anyone can belong anywhere: Consumer equality in the sharing economy. *Journal of Business Research*, *130*, 221–231. <https://doi.org/10.1016/j.jbusres.2021.03.036>
- Malpezzi, S. (2008). Hedonic pricing models: A selective and applied review. In T. O'Sullivan & K. Gibb (Eds.), *Housing Economics and Public Policy*. Sage Publications, Inc.
- Marchenko, A. (2019). The impact of host race and gender on prices on Airbnb. *Journal of Housing Economics*, *46*(July 2018). <https://doi.org/10.1016/j.jhe.2019.101635>
- Murphy, L. (2016). *Airbnb's work to fight discrimination and build inclusion: A report submitted to Airbnb*. http://blog.airbnb.com/wp-content/uploads/2016/09/REPORT_Airbnbs-Work-to-Fight-Discrimination-and-Build-Inclusion.pdf
- Nødtvedt, K. B., Sjøstad, H., Skard, S. R., Thorbjørnsen, H., & Van Bavel, J. (2020). *Racial bias in the sharing economy and the role of trust*. <https://ssrn.com/abstract=3434463>

- Quillian, L., Heath, A., Pager, D., Midtbøen, A. H., Fleischmann, F., & Hexela, O. (2019). Do some countries discriminate more than others? Evidence from 97 field experiments of racial discrimination in hiring. *Sociological Science*, 6, 467–496. <https://doi.org/10.15195/V6.A18>
- Rhue, L., & Clark, J. (2016). *Who gets started on Kickstarter? Racial disparities in crowdfunding success*. <http://www.ssrn.com/abstract=2837042>
- Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82(1), 34–55. <https://doi.org/10.1086/260169>
- Wang, D., Xi, S., & Gilheany, J. (2015). The model minority? Not on Airbnb.com: A hedonic pricing model to quantify racial bias against Asian Americans. *Technology Science*. <http://techscience.org/a/2015090104/#Suggestions>
- Zussman, A. (2013). Ethnic discrimination: Lessons from the Israeli online market for used cars. *Economic Journal*, 123(572), 433–468. <https://doi.org/10.1111/eoj.12059>