Discrimination in the Market for Short Term Rentals: Evidence from Airbnb

by

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We acknowledge with respect the Lekwungen peoples on whose traditional territory the university stands and the Songhees, Esquimalt and WSÁNEĆ peoples whose historical relationships with the land continue to this day.

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ABSTRACT

Discrimination against people of colour in the hospitality, labour, and housing markets has been causing harm throughout the history of the United States. Examining the discrepancy in outcomes for marginalized Airbnb hosts allows me to assess whether even those considered economically successful are harmed by racial and gender bias. Using an Ordinary Least Squares and a Propensity Score Matching approach, I find Airbnb hosts who are of Asian or Hispanic origin face both price and quantity penalties, having nightly prices on average 4% lower and receiving 3 percentage points fewer booked nights in a month than listings managed by white hosts. Black Airbnb hosts face higher nightly prices and a lower quantity of bookings; however, without holding neighbourhood constant, they charge approximately 12% less per night, indicating that Black hosts disproportionately own properties in low-price neighbourhoods. I also observe an intersectional discrimination penalty wherein women of colour face even higher price and quantity penalties.

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1 Introduction

Racial discrimination against people of colour in the hospitality, housing, and labour markets causes significant discrepancies in economic outcomes (Pager and Shepherd, 2008; Ondrich et al., 1998). This discrimination translates to Black Americans being twice as likely to be unemployed and to earn on average 15% less than white Americans, holding parental background, education, work experience, and job tenure constant (Cancio et al., 1996). Despite improvements brought about by the civil rights movement and the Civil Rights Act of 1964, and "despite gains made in the past 50 years, [the United States is] still a nation driven by inequality and racial division" (Bunch, 2020). Historically, discrimination has been particularly notable in the hospitality industry, where Black people have been unable to stay in most hotels, eat at most restaurants, or even stay out of their homes after sunset (Loewen, 2005).

This legacy of discrimination and racism still exists today; it is especially prevalent in the labour market where in 2015, Black people made on average 73.9% of the earnings of their white counterparts controlling for education, age, gender, and region (Cheng et al., 2019; U.S. Bureau of Labor Statistics, 2016). Multiple researchers have hypothesized that these differential outcomes are due to differences in parental education, familial wealth, and rates of parental self-employment (Long, 1999; Fairlie, 1999), but these group differences do not explain the entire differential in outcomes, and thus it is likely that the disparity is due at least in part to discrimination.

While anti-discrimination laws have been designed to attempt to level the playing field between white and Black people in the United States, there are limited protections against discrimination for small business owners including Airbnb hosts. Businesses owned by Black people have lower revenue and profit, are more likely to shut down, and hire fewer employees than businesses owned by white people (Fairlie and Robb, 2007). In this paper, I assess the relationship between an Airbnb host's race and gender and the nightly price they charge and the average percentage of a month that their property is booked. There is a large body of literature examining racial discrimination in the context of labour and housing markets, both of which apply to the market for short-term rentals (e.g. Airbnb). Individuals seeking rental housing assess the quality of the product both in physical characteristics of the home as well as the level of service they expect. Because renters choose a home based not only on its objective characteristics, but also their perception of the quality of the host, discrimination may occur. If renters believe that there is some undesirable and unobservable property attribute correlated with the host's race or gender, then hosts of a particular race or gender may have lower prices or book fewer nights per month because the quantity demanded for their units is lower. According to Wallace (2018), the average annual profit for an American Airbnb host is $20,619, thus if there are notable racial or gender differences in this profit (through either a price or quantity mechanism), then there can be large effects on minority hosts' yearly income.

Much of the literature assessing racial discrimination in the housing market evaluates landlords' discrimination against tenants or real estate agents' discrimination toward racialized clients, and little has been done to evaluate the role of tenants' discrimination against landlords.[1] In the context of short term rentals, Edelman et al. (2017) find that potential Airbnb renters with distinctly African-American names are 16 percent more likely to be rejected when making booking requests in comparison with identical potential renters with white sounding names. Observing discrimination has led researchers to examine its cause. Yinger (1986) suggests that racial discrimination in housing markets occurs because real estate agents cater to the racial prejudice of current or potential white customers, and thus are less likely to show units owned by white homeowners to Black tenants. This hypothesis suggests that the actions taken by real estate agents (and potentially Airbnb hosts) are partially responsible for differential outcomes in terms of housing access and quality between Black and white tenants (Hanson and Hawley, 2011).

Few researchers have studied tenants discriminating against landlords. However, this question may partially parallel discrimination in the labour market, as in the case of Airbnb, tenants are not only paying for the attributes of the housing unit itself, but also the level of service provided by the

[1] Turner et al. (2013) find that property managers and owners show white potential tenants more rental units than equally qualified Black, Hispanic, and Asian tenants. Ondrich et al. (1998) and Yelnosky (1998) find that real estate agents discriminate against Black and Hispanic customers by providing lower levels of service, and white prospective tenants are more likely to be given a showing when requested in comparison with equally qualified Black potential tenants.

landlord. This may be similar to the relationship between an employer and employee.

Both in examining discrimination in the labour market and in the housing market, researchers frequently use correspondence studies. This method has been used to assess homophobia, racism, and gender discrimination in the rental market (Carlsson and Eriksson, 2014; Hellyer, 2021; Flage, 2018). Recently there has also been a focus on the role of intersectionality in housing discrimination, and Flage (2018) finds that from a series of correspondence tests conducted between 2006 and 2017, gender discrimination is greater for minority rental applicants than for those in the majority.

In addition to correspondence studies, which may be costly, researchers frequently use different data collection and sample selection methods to quantify measures of discrimination. In particular, rather than creating a pairing of fictitious job applicants that only differ by race and sending job applications to observe the outcome, it is possible to pair otherwise identical Airbnb hosts, and evaluate in isolation the relationship between the host's race and the number of bookings they receive and the price they are able to charge. Techniques such as this are known as "matching models" and they are typically used to evaluate causal effects when a randomized control trial is not possible. In some cases, these techniques are used for non-causal questions including assessing racial disparities in an economic outcome of interest (Stuart, 2010).

Outside of empirical correspondence studies, the discrimination literature has a large theoretical base, beginning with Becker's (1971) book discussing his theory of "taste-based" discrimination as well as Phelps' (1972) and Arrow's (1973) discussions of "statistical discrimination". In the context of this paper, the presence of "taste-based" discrimination would imply that Airbnb renters may choose a listing with a White host over an identical listing owned by a Black host because they dislike Black people. On the other hand, the presence of "statistical discrimination" would imply that renters choose their hosts based on an observable characteristic (race) that they suspect to be correlated with an unobservable characteristic (for example the quality of the property's neighbourhood). While these theories imply the same result, their policy implications may differ. For example, if only taste-based discrimination is at play, simply removing host names and profile photos from listings should prevent discrimination entirely. However, if statistical discrimination exists, and there are unobservable factors correlated with race that affect the quality of the renter's stay, then more complicated policy solutions may be required. For example, if people of colour tend to own property in poorer neighbourhoods as observed by Firebaugh and Farrell (2015), and if low-income neighbourhoods are less desirable for short-term tenants, then systemic change in racial segregation in property ownership would be required to reduce the discrimination faced by people of colour who own short-term rental accommodations. Regardless of the motivation behind the discrimination, both forms are equally harmful and neither form should be considered acceptable or justifiable.

In this paper, I evaluate whether the race and gender of an Airbnb host is related to differentials in nightly price and the number of nights a host's property is booked. I use an Ordinary Least Squares approach along with Propensity Score Matching to estimate these differential effects. The empirical methodologies control for all characteristics of the Airbnb listing that a potential renter can observe, which allows me to estimate the differential impacts on demand for short-term accommodations managed by women and people of colour. I first estimate a simple OLS model where I separately regress the logarithm of nightly price and the percent of the month that a property is booked on numerous characteristics of the home, listing, and host.

In my preferred specification, I find a negative effect on price (approximately 4%) and quantity (approximately 3 percentage points) associated with being Hispanic, Asian, Native Hawaiian, or other Pacific Islander. Given that the average nightly price in my sample is $162.41 and the average number of booked nights per month is 21.3 (for average monthly earnings equal to $3.456.90), this translates to an approximately $3,343 differential in average yearly revenue. In my preferred specification, I also find a small negative effect on quantity and a small positive effect on price associated with being Black. The sign of the coefficient from the regression on price flips from negative to positive after including location controls, indicating that location drives the overall effect of Black hosts having a lower mean nightly price, but within the same neighbourhood and zip code, Black hosts charge more than their otherwise identical white counterparts and have a lower percentage of the month booked, indicating a movement along the demand curve, rather than a shift in demand. Additionally, when split by gender, this positive effect on price is only observed for Black male hosts. I also use a propensity score matching approach, through which I similarly estimate a negative average treatment effect on the treated (ATET) on nightly price associated with being a member of each of the marginalised "treatment" groups aside from the comparison between Black male and Black female hosts, where the effect is not statistically different from zero.

The remainder of the paper is organized as follows: first, I discuss the administrative details of Airbnb and price/quantity mechanism; second, I discuss the data used in my analysis and present summary statistics; third, I lay out my empirical methodologies; fourth, I present the results of my OLS and propensity score matching models; and finally, I conclude.

2 Administrative Details

Airbnb is an online platform that is part of the sharing economy, a business model wherein a corporation manages an online platform though which individuals who own idle assets temporarily rent them to other individuals. In the case of Airbnb, this means that individuals who own unused residential properties can rent them to others seeking typically short-term accommodations. When listing their property on Airbnb, hosts begin by submitting general attributes of their home including the property type (house, apartment, boat, etc.), the number of guests permitted, and the location. Then they add photos of their home and supplemental information including their name, availability, photo, and in some cases, social media handles. Next, prospective hosts add booking requirements including cleaning fees, minimum and maximum stay lengths, how far in advance their property can be booked, and check-in guidelines. At this stage, they can also book off specific dates for personal use, though these dates are not visible to consumers on the platform.

Next, the host determines the pricing information. Airbnb offers a built in "Smart Pricing Tool" with the option of automatically adjusting the nightly price according to demand for similar properties. They then request that the host selects a base price around which the Smart Pricing Tool will vary the nightly price. When selecting the base price, Airbnb provides a suggested value based on the current prices of similar units nearby. Finally, the host selects a minimum and maximum price, so the Smart Pricing Tool is restricted to a particular range of prices. Hosts can also decide to set weekly or monthly discounts at this stage.

While Airbnb offers comprehensive price-setting tools, hosts are not obligated to choose the prices suggested by the platform. There are other online tools that hosts can use to assess average prices in their area, and additionally, hosts may also search the Airbnb website and manually observe prices of properties they deem to be similar to their own; however, because it is simplest to use Airbnb's built-in pricing tools, it is likely that most hosts select their prices using the Smart Pricing Tool and suggested base price.

After listing their property, hosts can choose to enable "Instant Book," a function that allows tenants to book the property instantly without being vetted by the host. If they do not enable this option, when a tenant submits a request to book the property, the host is notified and can choose to accept or decline the request based off the tenant's profile and past reviews from other hosts. Finally, after a host has received multiple bookings, they may be eligible to become a "Superhost," which is a designation applied to their host profile that indicates a host has managed at least ten bookings in the past year, responds to at least 90% of booking requests, has at least 80% five-star reviews, and has not cancelled an accepted booking without extenuating circumstances. This designation aims to increase a tenant's trust in the host, and increase the number of booking requests for the property.

3 Data

The primary dataset I use in my analysis was compiled by Inside Airbnb[2] through monthly web-scraping of the information publicly available on the Airbnb website. It includes information on each Airbnb unit listing that consists of all home characteristics that are visible to a renter. This includes concrete statistics such as the number of bedrooms and bathrooms, as well as subjective descriptors including the host-defined neighbourhood name, and their description of amenities and the dwelling unit itself. Additionally, the dataset includes host attributes including their typical speed in responding to booking requests, the percentage of requests to which they respond, the number of listings that they manage, and their first name. Each listing also includes the host's profile photo. For my analysis, I use monthly data from January 1 2019 to December 31 2019.

Inside Airbnb additionally keeps a record of each unit's calendar for the 365 days after the data was scraped, indicating which days are booked and which are not at the time of data collection. This allows me to count the number of booked nights per month, which is one of my outcome variables of interest. From this data, I aggregate the monthly calendars for each listing, to obtain a total of the number of nights it is booked in each month of 2019. It is important to note, however, that the calendar data does not indicate unique bookings, only nights booked. A unit being booked for a week by one guest appears identically to seven individual one-night bookings by different guests. Thus, I am unable to examine whether there are systematic racial or gender-based differences between the average booking lengths, which may reflect that one demographic group is required to provide more work hours per dollar earned (as high turnover indicates a higher amount of work).

In addition to the information on individual Airbnb listings, calendars, and hosts, I also incorporate data that links host first names to the probability that they are a member of each of six distinct racial and ethnic groups. This dataset was compiled by Tzioumis (2018) from mortgage applications in the United States, and it indicates the percentage of mortgage applicants with a par-

[2]Inside Airbnb is an independent organization that compiles publicly-available web-scraped data from Airbnb including listing and calendar information. They also provide data visualization tools.

ticular first name who self-identify as each of six racial and Hispanic origin groups[3]. While there are datasets available that use the United States Census to obtain similar conditional probabilities, it is likely that the chosen dataset more accurately covers the range of first names of Airbnb hosts, as the majority of Airbnb owners likely applied for a mortgage. As a robustness check, I additionally conduct my analysis using the United States Census first name database, and there is no notable difference in the coefficient estimates.

Because intersectionality has been increasingly recognized as an important consideration in the discrimination literature (Kim, 2020; Ruwanpura, 2008; Schulz and Mullings, 2006), I also incorporate a dataset to approximate whether a host is male or female. In this context, intersectionality refers to the case where an individual identifies as a member of more than one marginalized group and is therefore more likely to experience discrimination based on more than one identifying characteristic. For example, a Black woman may be more likely to experience discrimination because she is both a member of a racialized group and female. I obtained this dataset from the United States Social Security Administration (2018). It lists the number of all Americans who applied for social security numbers in 2018 by first name and gender, which allows me to obtain a measure of the percentage of all applicants with a given first name who are men and the percentage who are women. From this, I construct a conditional probability that an individual with a given first name is a man or a woman. The Social Security Administration (SSA) dataset does not allow for individuals to identify as neither male nor female, so every host with a first name included in the SSA dataset is either classified as expected to be male or female.

Using the conditional probabilities on race from the mortgage applications data and the conditional probabilities on gender from the United States Social Security Administration, I construct dummy variables indicating whether a person is expected to be white, Black, or a person of colour[4] as well as whether given their first name, I expect the individual to be male or female. For the race classifications, I define the indicator variable for a particular race to be equal to one if the con-

[3]Racial and Hispanic origin groups: Hispanic or Latino; non-Hispanic White; Black or African American; Asian, Native Hawaiian, or Other Pacific Islander; American Indian or Alaska Native; and two or more races

[4]Hispanic or Latino; Black or African American; Asian, Native Hawaiian, or Other Pacific Islander; American Indian or Alaska Native

ditional probability that the host is a member of that racial group is larger than the conditional probabilities of being in any of the other five groups[5,6]:

$$\text{Race Indicator}_j = \begin{cases} 1 & P(\text{Race}_j|\text{First Name}) > P(\text{Race}_k|\text{First Name}) \quad \forall k \neq j \\ 0 & \text{Otherwise} \end{cases} \qquad j,k \in (1,6)$$

Because the distinction between male and female names is much more precise than that of name race or ethnic group, the dummy variable indicating if a host is expected to be female is equal to one if the conditional probability of an individual with the host's first name being female is greater than fifty percent:

$$\text{Gender Indicator}_j = \begin{cases} 1 & P(\text{Gender}_j|\text{First Name}) \geq 0.5 \\ 0 & P(\text{Gender}_j|\text{First Name}) < 0.5 \end{cases} \qquad j \in Male,\ Female$$

See Tables 1 and 2 for summary statistics. The first notable feature of the descriptive statistics is the racial composition of my sample. Approximately 91.5% of my sample is classified as white, 0.3% is classified as Black, and 8.4% is classified as a person of colour (including Black). While this is clearly not representative of the American population as a whole, which is 60.1% white (non Hispanic or Latino), 13.4% Black, and 39.3% people of colour[7] (United States Census Bureau, 2019), given the historic and ongoing wealth gap between white people and people of colour (R. B. Williams, 2017), it is unsurprising that the racial distribution of individuals with sufficient wealth to purchase and maintain an Airbnb is disproportionately skewed away from people of colour.

Second, there is a notable difference in both the mean and median nightly price charged by hosts of colour in comparison with white hosts. See Figure 1 for difference in means tests. Because

[5]There are 274 hosts for whom the highest probabilities are tied between two racial or ethnic group categories. This translates to 0.016% of the sample. There are only three first names that fall into this category: Magdalena, which I classify as white; Rico, which I classify as Hispanic; and Salim, which I classify as Asian, as there is no category for Arabic or Middle Eastern.

[6]As a robustness check, I redefine these indicator variables as equal to 1 if the conditional probability of being in that group is greater than 75%

[7]Includes Black or African American; American Indian or Alaska Native; Asian; Native Hawaiian and Other Pacific Islander; and Hispanic or Latino

Table 1: Sample Composition by Imputed Race and Sex

Group		Northeast	Midwest	West	South	All
		Region				
Both Sexes	Black	549	77	391	293	1,310
	White	107,276	33,776	120,577	77,530	339,159
	Hispanic	9,940	1,660	6,988	2,443	21,031
	Asian, Native Hawaiian, or Other Pacific Islander	3,224	718	3,110	1,056	8,108
	American Indian or Alaska Native	0	0	0	0	0
	Non-White	13,592	2,436	10,408	3,779	30,215
	Total Unique Hosts	174,577	46,197	174,897	105,665	501,336
Female	Black	238	53	183	113	587
	White	54,497	17,318	64,140	40,081	176,036
	Hispanic	4,551	692	3,006	1,051	9,300
	Asian, Native Hawaiian, or Other Pacific Islander	1,360	191	1,288	451	3,290
	American Indian or Alaska Native	0	0	0	0	0
	Non-White	6,051	928	4,466	1,615	13,060
	Female (All Races)	79,499	21,361	82,967	49,657	233,484
Male	Black	311	24	208	180	723
	White	52,755	16,451	56,376	37,437	163,019
	Hispanic	5,389	968	3,982	1,392	11,731
	Asian, Native Hawaiian, or Other Pacific Islander	1,765	526	1,683	591	4,565
	American Indian or Alaska Native	0	0	0	0	0
	Non-White	7,442	1,507	5,83	2,150	11,099
	Male (All Races)	73,782	20,492	72,477	45,382	212,133

Table 2: Descriptive Statistics by Race and Sex Subgroup

Group	Variable	Observations	Mean	Median	Std. Dev.	Max
All	Nightly Price (dollars)	587,548	162.41	112.00	231.77	10,000
	Percent of Month Booked	321,828	70.95	87.10	33.32	100
	Number of Listings	587,548	7.91	2	47.16	1,717
	Number of Bedrooms	587,548	1.49	1	1.08	21
	Review Score	587,548	95.24	97	6.76	100
	Superhost	587,548	0.45	-	0.50	1
Black	Nightly Price (dollars)	2,025	150.58	100.00	227.99	3,000
	Percent of Month Booked	1,054	69.07	83.33	33.18	100
	Number of Listings	2,025	2.55	2	2.55	19
	Number of Bedrooms	2,025	1.45	1	0.95	5
	Review Score	2,025	94.83	97	6.53	100
	Superhost	2,025	0.40	-	0.49	1
Non-white	Nightly Price (dollars)	49,372	138.63	98.00	202.63	9,999
	Percent of Month Booked	22,031	71.22	86.67	32.81	100
	Number of Listings	49,372	4.54	2	8.60	302
	Number of Bedrooms	49,372	1.38	1	0.99	13
	Review Score	49,372	94.28	96	7.29	100
	Superhost	49,372	0.37	-	0.48	1
White	Nightly Price (dollars)	538,176	164.59	115.00	234.14	10,000
	Percent of Month Booked	299,797	70.93	87.10	33.36	100
	Number of Listings	538,176	8.22	2	49.20	1,717
	Number of Bedrooms	538,176	1.50	1	1.09	21
	Review Score	538,176	95.33	97	6.71	100
	Superhost	538,176	0.46	-	0.50	1
Black Females	Nightly Price (dollars)	821	150.99	100.00	315.31	3,000
	Percent of Month Booked	398	67.71	83.60	34.75	100
	Number of Listings	821	2.02	1	1.60	10
	Number of Bedrooms	821	1.46	1	0.94	5
	Review Score	821	94.98	97	5.86	100
	Superhost	821	0.47	-	0.50	1
Black Males	Nightly Price (dollars)	1,204	150.30	100.00	140.31	1,500
	Percent of Month Booked	656	69.89	83.33	32.19	100
	Number of Listings	1,204	2.91	2	2.98	19
	Number of Bedrooms	1,204	1.45	1	0.96	5
	Review Score	1,204	94.73	97	6.96	100
	Superhost	1,204	0.35	-	0.48	1

the price distribution has a long right-tail, the mean price for all demographic subgroups is much larger than the median nightly price. This skewness varies for the three racial groups in Table 2, with the maximum price charged by a Black host ($3,000) being only the 93rd percentile of all prices charged. A similar pattern exists for the distribution of the number of listings owned by each unique host, where the maximum number of listings owned by a Black host (19) is only the 91st percentile of the overall distribution of number of listings for hosts of all races and ethnic groups.

The number of observations on the percent of month booked variable is smaller than the number of observations for each of the other variables, as it is constructed from the calendar data, which does not include all active listings in the two largest cities in the sample (New York and Los Angeles). However, there is no reason to believe that the sample of listings included in the calendar dataset is systematically different from the population of listings, so this should not bias the results.

I include the *Superhost* variable, as it likely strongly predicts a renter's perception of a host's ability and competence. It is a designation awarded by Airbnb to differentiate between high and low quality hosts, serving as a comprehensive quality metric that reflects the host's interactions and the quality of each of their properties. It mainly reflects the host's quality of service, requiring that a host has at least 10 stays in a year, has a 90% or higher response rate, has at least 80% 5-star reviews, and rarely cancels confirmed reservations. As reflected in Table 2, 46% of white hosts are Superhosts, while only 40% of Black hosts and 37% of hosts of colour hold the designation. Further broken down by gender, 47% of Black female hosts and only 35% of Black male hosts are Superhosts. The difference in the percentages between Black and white, people of colour and white, and Black males and Black females are all significant at the 1% level (see Figure 1).

Also reflecting how potential customers might view a host's ability is the review score, which ranges from 20-100 and reflects the accuracy of the host's description of the unit, the unit's cleanliness, the ease of check in, the host's communication, the location of the unit, and the perceived value. When comparing White to Black hosts and White to hosts of colour, the means of this score are statistically different, ranging from 95.33 for white hosts to 94.28 for non-white hosts. While this may not seem like a large difference, given that the 75th percentile is a score of 100, and the 25th percentile is a score of 94, small variations in the score indicate large changes in the unit's place in the distribution of review scores.

Figure 1: Difference in Means Tests by Race and Gender Subgroup

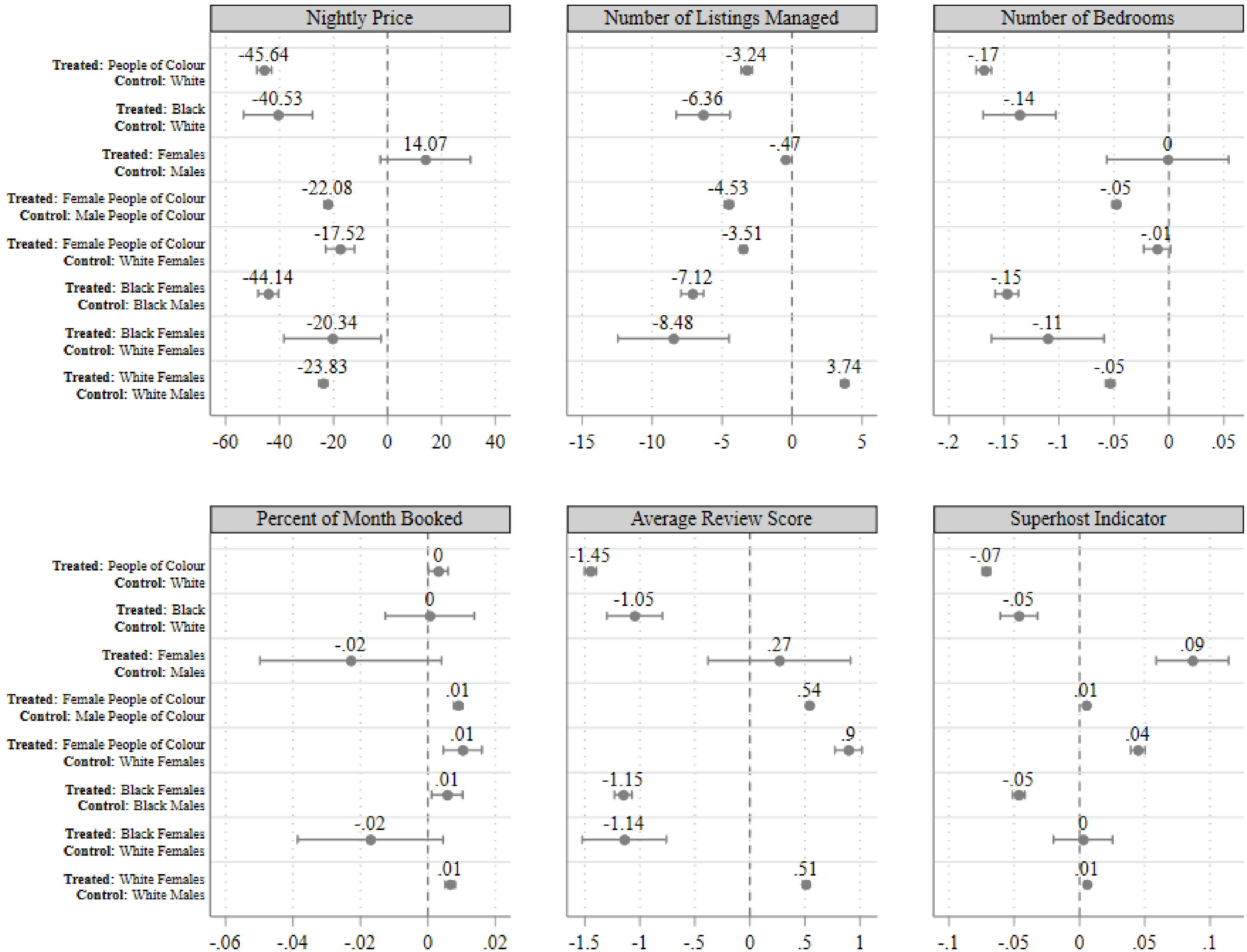


Figure 1 indicates whether the means of six variables of interest are statistically different between the race and gender subgroups. Note that the first group in the reported differences is denoted the treated group, and the second group is the control group. The differences are the mean value for the control group subtracted from the mean value for the treatment group, so negative values indicate that the mean for the treatment group is lower than for the control group. This is consistent with the methodology in my matching model, described in more detail below, providing a comparison to motivate this approach.

The first and second rows compare white hosts with Black hosts and people of colour. Note that both sets of differences have the same sign. On average, white hosts charge more per night, manage more listings, have larger units as measured by the number of bedrooms, have higher reviews, and are more likely to be superhosts than Black hosts and people of colour. They also book a smaller proportion of each month than people of colour on average.

The sixth and seventh rows compare Black female hosts to Black male and white female hosts. The price and booking ratio differences are only statistically different from zero at the 10% level; however, these differences indicate that Black men charge a lower price, have a higher booking ratio, manage more listings, and are less likely to be superhosts than Black women. Additionally, Black women charge a lower price, own fewer listings, have smaller units, and have lower review scores than white women on average.

Given these differences in variables of interest, most notably nightly price, it is likely that race is related to the amount charged per night, and that discrimination against hosts of colour may be occurring. However, given that the mean unit size is also larger for white hosts, the price difference may simply reflect a difference in the type of unit owned by hosts in each racial and ethnic group. Additionally, if hosts from a particular racial group are disproportionately located in less desirable locations, we would observe this racial price differential. Finally, hosts of colour may be more likely to undervalue the service they provide, and thus choose a price below that which the market would bear. Thus, analysis beyond simply observing the difference in means is necessary.

4 Empirical Methodology

I begin by examining the relationship between an Airbnb host's race and their success in the Airbnb market as measured by nightly price charged and percentage of the month booked. I first use an Ordinary Least Squares approach as represented by Equation 1:

$$Y_{it} = \alpha + \sum_{k \in \{R\}} \gamma_k R_{ik} + X_{it}\Omega + \tau_t + \phi_i + u_{it} \tag{1}$$

Where Y_{it} is the outcome variable (log nightly price and percentage of nights booked per month) for unit i in month t. R_{ik} is the percentage of all mortgage applicants with the same first name as the host of unit i who are members of the ethnic or racial group k, where k is: Black; Hispanic; Asian, Native Hawaiian, or other Pacific Islander; American Indian or Alaska Native; and more than one race. The reference group is white hosts. As an example, R_{iB} is the percentage of mortgage applicants with the same first name as the host of unit i who are Black or African American (hereafter called the probability conditional on their first name that host i is Black, or simply the conditional probability of being Black). These are continuous variables ranging from 0 to 1. τ_t are month fixed effects, incorporated to capture time-varying impacts that affect all Airbnb hosts equally. X_{it} is the vector of individual unit and host attributes as well as city time trends[8]. ϕ_i is the combination of location fixed effects, which takes two forms. First:

$$\phi_i = NBH_i * Zip_i$$

This is the interaction between neighbourhood (Nbh) and zip code (Zip). Because neighbourhoods do not fit perfectly within zip codes or vice versa as neighbourhoods are an unofficial geographic boundary defined by the unit's host and zip code regions are an official geographic boundary defined by the United States Postal Service, I also include a separate specification using

[8]Host response rate and average response time, number of listings the host manages, if the host is a "superhost", the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property and room types, the security deposit and cleaning fee amounts, the number of guests included, the minimum and maximum stay lengths, the number of reviews, the overall review rating, and interaction between city and month.

additive fixed effects:

$$\phi_i = NBH_i + Zip_i$$

Where Nbh_i is a dummy variable equal to one if unit i is located in a particular neighbourhood and Zip_i is a dummy variable equal to one if unit i has a particular zip code. This formulation is used when there are individual characteristics that are correlated within multiple different geographic measures – in this case neighbourhoods and zip code boundaries. Because neighbourhoods are an unofficial location definition determined by the individual host, they may more accurately reflect the political or ethical views that are correlated within a community, as hosts may identify themselves or their unit with a similar ideological and geographic group. This means that "soft" unobservables such as attitude, ideology, and political views may be more highly correlated at the neighbourhood level. Additionally, within these neighbourhoods, zip codes may more accurately predict the regional correlation of income, public services, or other "hard" metrics, and these unobserved covariates that are correlated at the zip code level may also affect the outcome variables. Thus, in this case, including additive fixed effects may more accurately capture the location-correlated unobservables. My preferred specification includes these additive location fixed effects.

Following the literature indicating the importance of intersectionality in evaluating discrimination (Harnois, 2014), I examine whether racial and gender-based discrimination occur in the market for short-term rental accommodations; I begin with a simple Ordinary Least Squares approach through which I evaluate the relationship between a host's race and gender, and their nightly price and the number of nights booked in a month.

$$Y_{it} = \alpha + \sum_{k \in \{R\},\ j \in \{S\}} [\gamma_{jk} R_{ik} G_{ij}] + \gamma_{fw} W_i F_i + X_{it} \Omega + \tau_t + \phi_i + u_{it} \tag{2}$$

Y_{it}, R_{ik}, X_{it}, τ_t, and ϕ_i are defined as above. R is the set of racial and ethnic group categories excluding white. S is the set of genders in my sample (male and female). G_{ij} is the probability conditional on their first name that host i has gender j. W_i is the conditional probability that host i is white, and F_i is the conditional probability that host i is a woman. Thus, this specification includes interaction terms for each race and gender group except white men, which is the omitted category. These interaction terms represent the conditional probability ranging from 0 to 1 that host i is in each combination of racial or ethnic group and gender category, excluding the interaction between the probability of being white and the probability of being male. The sum of all the possible interactions (including white and male) is equal to 1, so the coefficients on each of the interaction terms in the regression represent the change in the dependent variable in comparison with the mean value for white males. For example, γ_{fw} represents the change in the dependent variable associated with being a white female host in comparison with an otherwise observably identical white male host.

I additionally incorporate a propensity score matching approach, as it allows me to more intuitively estimate a causal relationship, comparing multiple treatment and control groups. Because I have no reason to believe that there is a linear relationship between each of the observed covariates and my outcome variable of interest, and because there is no way to estimate the form of the relationship for each covariate, a semi-parametric matching specification allows me to assess the impact of race and gender on price and quantity without specifying the form of the relationships in advance. There are three major assumptions required to use a propensity score matching approach and to interpret the estimates as causal. First, I must assume that the selection on observables assumption holds; this indicates that all of the relevant differences between my treatment and control groups are captured by my regressors. Additionally, the common support assumption must hold, which indicates that there is a non-treated observation with the same characteristics as each treated observation for matching. I check this assumption by observing the densities of the estimated propensity scores for my treatment and control groups and trimming observations that fall outside the region of common support, which is the portion of the distributions of propensity scores for the treatment and control groups that overlap.[9] Finally, the unconfoundedness (or ignorability)

[9] These densities can be found in Appendix B

assumption must hold. This indicates that treatment can be viewed as random for individuals with the same background variables.

I match on propensity score estimated using a logit regression of my treatment variable (dummy indicating whether the host is in each of my race and gender subgroups) on the unit and host attributes discussed above in addition to location fixed effects[10]. In propensity score matching, the standard rule in variable selection is to include variables that are related to the outcome (in this case nightly price) but not the treatment (in this case, being a member of a minority group as defined by race and sex). This reduces bias of the estimated treatment effects because in a typical application of propensity score matching, a variable related to the outcome may also affect the treatment, and thus if not included in the propensity score estimation, it may cause omitted variable bias (Brookhart et al., 2006).

In my matching specification I use a balance of probabilities approach wherein the "treatment" variable is a dummy variable indicating if, given the conditional probability of belonging to each racial and ethnic group, it is more likely than not that the host belongs to the race or sex group of interest[11]. Thus, for the first specification, the treatment dummy is equal to one if the conditional probability of being in any of the non-white racial or ethnic groups is greater than the conditional probability of being white. While this is not a perfect measure of an individual host's race, given the relatively small percentage of people of colour who apply for mortgages (the sample from which the conditional probabilities are generated), and given the fact that an individual's race is self-reported, the balance of probabilities approach may be reasonable. I conduct this method for each of the following combinations of treatment and control groups.

Specification 1 uses hosts of colour as the treatment group and matches them with white hosts; specification 2 uses Black hosts as the treatment group and matches them with similar white hosts; specification 3 compares female and male hosts; specification 4 matches women of colour with

[10]Host response rate and average response time, number of listings the host manages, if the host is a "superhost", the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property and room types, the security deposit and cleaning fee amounts, the number of guests included, the minimum and maximum stay lengths, the number of reviews, the overall review rating, the observation month, and the neighbourhood, zip code, and city.

[11]The formal mathematical definition for this condition is presented in Section 3.

men of colour; specification 5 matches women of colour and white women; specification 6 matches Black women and Black men; specification 7 matches Black women and white women; and specification 8 matches white women with white men. These specifications allow me to observe the differences between the race and gender groups as a whole as well as observing the effect of race and sex individually on discrimination towards hosts with intersectional identities.

After generating the propensity score, I conduct one-to-one nearest neighbour matching through which each host in the treatment group is matched with at least one host in the control group based on similarity of the propensity score. Once matched, I estimate the treatment effect of being in the treatment group on the nightly price charged, which, given that the outcome variable is continuous, is simply the difference in mean outcomes between the treated group and the matched control.

Additionally, pairs within the matched sample are arguably not independent observations (Imbens, 2004; Austin, 2011), as observations within the matched pairs have similar propensity scores and thus have baseline covariates coming from the same multivariate distribution. This means that matched subjects are more likely to have similar outcomes than two randomly selected observations. Thus, I must separately estimate the variance of the estimated treatment effect and evaluate its statistical significance. I use a paired t test, as suggested by Austin (2011) to calculate the standard errors from the regressions.

5 Results

5.1 Ordinary Least Squares Model

5.1.1 The Relationship between Race and Price/Quantity

The coefficient estimates presented in Table 3 indicate that there is a relationship between a host's race and the nightly price that they can charge for their Airbnb listings as well as the percentage of the month that their unit is booked. The conditional probabilities of being in each of the six race or ethnic group categories sum to one, and the omitted race category is white hosts. The coefficient estimates from Panel A represent the percent change in average price associated with being in each of the five racialized categories in comparison with being white.

Specification (1) includes no controls or fixed effects; specification (2) includes unit attribute controls including the size and occupancy of the unit as well as the property and room types, which include private apartments, private rooms in a shared apartment, and shared rooms; specification (3) includes unit and host attribute controls; specification (4) adds listing attributes; specification (5) adds neighbourhood, zip code, and city fixed effects; and specification (6) adds month fixed effects and a city linear time trend. The coefficient estimates indicate the effect of a one-unit increase in the conditional probability of being in each of the race and ethnic group categories, which is equivalent to a 100% increase in the probability of being in each of the racial groups, as the conditional probabilities range from 0 to 1[12].

In terms of price, after including all relevant controls and fixed effects, the coefficient estimates indicate that there is a negative effect on price associated with being a Hispanic host or an Asian host in comparison with an otherwise equivalent listing managed by a white host. This effect ranges from -4.3% for Hispanic hosts to -3.4% for Asian hosts, and is consistently negative across all specifications.

[12]For example, the regression output indicates that a 100% increase in the conditional probability of being Black is associated with an $e^{\hat{\beta}} - 1$ percent change in price and a $\hat{\beta}$ percentage point change in the percent of a month that the unit is booked.

Table 3: Regression Output from Equation 1 – Price and Percent of Month Booked

PANEL A: Logarithm of Price						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Conditional Probability of Being:						
Black	-0.406***	-0.132***	-0.0878***	-0.0936***	0.0426***	0.0406***
	(0.0118)	(0.00840)	(0.00887)	(0.00873)	(0.00807)	(0.00808)
Hispanic	-0.325***	-0.0995***	-0.0510***	-0.0503***	-0.0344***	-0.0347***
	(0.00404)	(0.00281)	(0.00303)	(0.00311)	(0.00287)	(0.00287)
Asian, Native Hawaiian,	-0.345***	-0.142***	-0.106***	-0.0822***	-0.0437***	-0.0441***
or Other Pacific Islander	(0.00534)	(0.00381)	(0.00398)	(0.00400)	(0.00388)	(0.00389)
American Indian or Alaska Native	-1.070***	0.574***	0.880***	0.179	0.229	0.251
	(0.232)	(0.170)	(0.176)	(0.178)	(0.160)	(0.160)
More than one race or ethnic group	-0.409	-0.328*	0.566***	-0.153	0.214	0.205
	(0.264)	(0.184)	(0.194)	(0.188)	(0.182)	(0.182)
Constant	4.880***	4.818***	5.240***	4.362***	4.190***	4.189***
	(0.00109)	(0.0305)	(0.0348)	(0.0288)	(0.0247)	(0.0249)
Observations	1,222,811	1,221,453	853,693	693,356	587,479	584,715
R-squared	0.008	0.498	0.572	0.616	0.731	0.731
PANEL B: Percent of Month Booked						
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Conditional Probability of Being:						
Black	-0.0928***	-0.111***	-0.0894***	-0.0812***	-0.0482***	-0.0449***
	(0.00686)	(0.00671)	(0.00843)	(0.00910)	(0.0101)	(0.00960)
Hispanic	-0.00512**	-0.0315***	-0.0195***	-0.0148***	-0.0319***	-0.0312***
	(0.00243)	(0.00239)	(0.00309)	(0.00332)	(0.00374)	(0.00352)
Asian, Native Hawaiian,	0.00309	-0.0122***	0.00276	0.00961**	0.00602	-0.00106
or Other Pacific Islander	(0.00303)	(0.00296)	(0.00386)	(0.00413)	(0.00470)	(0.00444)
American Indian or Alaska Native	-0.154	-0.272**	-0.289*	-0.322*	-0.170	-0.207
	(0.122)	(0.120)	(0.158)	(0.170)	(0.187)	(0.175)
More than one race or ethnic group	0.902***	0.505***	0.254	0.625***	0.339	0.259
	(0.140)	(0.137)	(0.182)	(0.195)	(0.219)	(0.205)
Constant	0.796***	0.736***	0.644***	0.345***	0.381***	0.406***
	(0.000544)	(0.0218)	(0.0289)	(0.0368)	(0.0407)	(0.0372)
Observations	716,930	716,429	487,800	422,553	321,722	320,638
R-squared	0.000	0.045	0.038	0.045	0.105	0.227
Unit Attribute Controls		X	X	X	X	X
Host Attribute Controls			X	X	X	X
Listing Attribute Controls				X	X	X
Additive Location Fixed Effects					X	X
Month Fixed Effects and City Time Trend						X

Notes: Robust standard errors in parentheses. Unit attribute controls include: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, and the room type. Host attribute controls include: host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, and the interaction between the name order and the number of hosts attached to the listing. Listing attribute controls include: the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, and average review rating. Additive location fixed effects include neighbourhood, zip code, and city effects. Time fixed effects include month and a city by month time trend.

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

Surprisingly, the final specification indicates a positive effect on price associated with being Black, corresponding to a 4.1% increase in nightly price over an equivalent property managed by a white host. However, without location and time fixed effects, the estimated relationship between nightly price and being Black is negative, indicating that unit location is the major driver of observed price differences between units managed by Black hosts and those managed by white hosts. This is not surprising given the history of racial segregation and redlining in the United States that has significantly impacted economic prosperity and the geographic distribution of Black homeowners in America (Ananat, 2011). While the final specification indicates that all else equal, Black hosts charge a higher nightly price than white hosts, the impact of geographic location on price as evidenced by the change in the sign of the coefficient observed after including location fixed effects is likely indicative of institutional discrimination against Black people. This result points to the role of discriminatory institutions potentially including redlining, explicit segregation, and other historic discriminatory policies in determining the economic outcomes of Black people. Thus, it is important to note that the effect of geography on price associated with being Black is itself a form of institutional discrimination that has resulted in Black property owners disproportionately being located in low-price locations.

After including all relevant controls and fixed effects, the effect of being American Indian or Alaska Native or multiracial is not statistically different from zero. These effects disappear after the inclusion of listing attribute controls, indicating that these are the drivers of price differences between listings managed by white hosts and those managed by Native American or multiracial hosts. Importantly, while the final specification indicates that the effect of being a member of these two racialized groups is not statistically different from zero, this likely occurs not because there is no discrimination, but because the variation in the conditional probabilities is so low that no effect can be estimated.

In terms of quantity, there is a negative effect associated with being Black of approximately 4.5 percentage points. In a typical 30-day month, this corresponds to a decrease of approximately 1.35 nights, which at the mean price of $158.77 for Black hosts corresponds to a revenue decrease of \$214.34 per month on average. The result is similar for Hispanic hosts, where the estimated effect is a 3.1 percentage point decrease in the proportion of the month that is booked, which corresponds to a 0.93-night decrease, and at the mean price for Hispanic hosts of \$156.85, an approximate revenue decrease of \$145.87 per month or \$1,750.44 per year.[13]

It is important to assess the price and quantity effects in conjunction. After including location fixed effects, there is a negative quantity effect and a positive price effect associated with being Black. This may be explained either by Black hosts having increased their prices to compensate for low quantity demanded or receiving a lower quantity of bookings because they set their prices above those for identical units managed by white hosts.

Because the proportion of mortgage applicants who identify as American Indian or Alaska Native or as belonging to more than one race or ethnic group are extremely small (see Appendix A Table 2), there is very little variation in the conditional probabilities of a host falling in either of those categories. Thus, the standard errors are large and there is not a detectable statistically significant effect on price or quantity. It is important to note that this result does not indicate that there is no discrimination against hosts who identify as American Indian or Alaska Native or as multi-racial, but simply that there is insufficient data to address this question.

5.1.2 The Relationship between Race, Gender, and Price/Quantity

I next estimate Equation 2, which includes interactions between the conditional probabilities of being in each of the five racialized categories and the conditional probability of being female as well as interactions between the conditional probabilities of being in each of the five racialized categories and the conditional probability of being male. It finally includes the interaction between the conditional probability of being white and being female, so the omitted category is white male hosts.

The coefficient estimates indicate that both race and gender play a role in determining the price that an Airbnb host can charge as well as the proportion of each month that their unit is booked.

[13] Note that these coefficient estimates are expressed as a percentage point change rather than a percent change as with the regressions on price.

Table 4a: Regression Output from Equation 2 – Price

PANEL A: Logarithm of Price VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Conditional Probability of Being:						
Male and Black	-0.390***	-0.0712***	-0.0576***	-0.0469***	0.0815***	0.0798***
	(0.0181)	(0.0128)	(0.0133)	(0.0132)	(0.0116)	(0.0116)
Male and Hispanic	-0.352***	-0.0977***	-0.0473***	-0.0558***	-0.0285***	-0.0289***
	(0.00529)	(0.00362)	(0.00387)	(0.00398)	(0.00360)	(0.00361)
Male and Asian, Native Hawaiian,	-0.319***	-0.137***	-0.106***	-0.0765***	-0.0373***	-0.0382***
or Other Pacific Islander	(0.00827)	(0.00591)	(0.00617)	(0.00624)	(0.00615)	(0.00617)
Male and American Indian	-1.855***	0.786***	0.650**	-0.253	0.169	0.172
or Alaska Native	(0.391)	(0.281)	(0.281)	(0.282)	(0.260)	(0.260)
Male and more than one race	3.568***	0.964***	2.250***	0.0933	0.290	0.260
or ethnic group	(0.474)	(0.329)	(0.339)	(0.337)	(0.309)	(0.310)
Female and White	-0.0603***	-0.0190***	-0.0124***	-0.0302***	-0.0127***	-0.0131***
	(0.00229)	(0.00165)	(0.00172)	(0.00170)	(0.00162)	(0.00162)
Female and Black	-0.408***	-0.171***	-0.106***	-0.129***	0.0114	0.00890
	(0.0159)	(0.0113)	(0.0122)	(0.0118)	(0.0112)	(0.0112)
Female and Hispanic	-0.348***	-0.124***	-0.0712***	-0.0777***	-0.0590***	-0.0596***
	(0.00629)	(0.00451)	(0.00491)	(0.00504)	(0.00460)	(0.00460)
Female and Asian, Native Hawaiian,	-0.462***	-0.186***	-0.127***	-0.123***	-0.0674***	-0.0677***
or Other Pacific Islander	(0.00890)	(0.00624)	(0.00661)	(0.00670)	(0.00619)	(0.00619)
Female and American Indian	-0.607**	0.458**	1.158***	0.471*	0.496**	0.538**
or Alaska Native	(0.302)	(0.231)	(0.245)	(0.253)	(0.222)	(0.222)
Female and more than one race	-2.115***	-0.671***	-0.146	0.103	0.392*	0.394*
or ethnic group	(0.327)	(0.229)	(0.244)	(0.237)	(0.237)	(0.237)
Constant	4.908***	4.829***	5.258***	4.378***	4.214***	4.213***
	(0.00164)	(0.0306)	(0.0350)	(0.0292)	(0.0248)	(0.0250)
Observations	1,221,471	1,220,115	852,869	692,744	586,936	584,180
R-squared	0.010	0.498	0.572	0.616	0.731	0.731
Unit Attribute Controls		X	X	X	X	X
Host Attribute Controls			X	X	X	X
Listing Attribute Controls				X	X	X
Additive Location Fixed Effects					X	X
Month Fixed Effects and City Time Trend						X

Notes: Robust standard errors in parentheses. Unit attribute controls include: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, and the room type. Host attribute controls include: host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, and the interaction between the name order and the number of hosts attached to the listing. Listing attribute controls include: the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, and average review rating. Additive location fixed effects include neighbourhood, zip code, and city effects. Time fixed effects include month and a city by month time trend.

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

Table 4b: Regression Output from Equation 2 – Percent of Month Booked

PANEL B: Percent of Month Booked						
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Conditional Probability of Being:						
Male and Black	-0.0607***	-0.0693***	-0.0605***	-0.0559***	-0.0410***	-0.0419***
	(0.0101)	(0.00986)	(0.0124)	(0.0136)	(0.0148)	(0.0141)
Male and Hispanic	-0.00456	-0.0298***	-0.0192***	-0.0122***	-0.0300***	-0.0276***
	(0.00312)	(0.00307)	(0.00398)	(0.00428)	(0.00484)	(0.00455)
Male and Asian, Native Hawaiian, or Other Pacific Islander	-0.00658	-0.0209***	-0.00760	-0.00602	-0.0126*	-0.0190***
	(0.00449)	(0.00437)	(0.00576)	(0.00622)	(0.00698)	(0.00656)
Male and American Indian or Alaska Native	0.165	0.279	0.144	0.292	0.326	-0.0761
	(0.194)	(0.192)	(0.245)	(0.263)	(0.292)	(0.276)
Male and more than one race or ethnic group	1.053***	0.894***	0.514*	0.975***	1.054***	1.029***
	(0.225)	(0.220)	(0.301)	(0.326)	(0.354)	(0.332)
Female and White	0.0103***	0.00847***	0.00417***	0.00458***	0.00408**	0.00452***
	(0.00114)	(0.00112)	(0.00146)	(0.00157)	(0.00180)	(0.00168)
Female and Black	-0.119***	-0.142***	-0.111***	-0.0981***	-0.0501***	-0.0443***
	(0.00967)	(0.00945)	(0.0119)	(0.0126)	(0.0142)	(0.0134)
Female and Hispanic	0.00612	-0.0241***	-0.0153***	-0.0132**	-0.0295***	-0.0312***
	(0.00391)	(0.00383)	(0.00494)	(0.00528)	(0.00577)	(0.00547)
Female and Asian, Native Hawaiian, or Other Pacific Islander	0.0283***	0.00744	0.0221***	0.0292***	0.0287***	0.0228***
	(0.00538)	(0.00523)	(0.00681)	(0.00720)	(0.00826)	(0.00797)
Female and American Indian or Alaska Native	-0.380**	-0.668***	-0.722***	-0.896***	-0.656**	-0.397
	(0.171)	(0.169)	(0.225)	(0.242)	(0.265)	(0.247)
Female and more than one race or ethnic group	0.778***	0.285	0.167	0.535**	-0.0298	-0.186
	(0.188)	(0.184)	(0.240)	(0.255)	(0.295)	(0.276)
Constant	0.790***	0.731***	0.641***	0.336***	0.375***	0.399***
	(0.000792)	(0.0217)	(0.0291)	(0.0370)	(0.0410)	(0.0375)
Observations	716,355	715,854	487,430	422,288	321,521	320,436
R-squared	0.001	0.045	0.038	0.045	0.106	0.227
Unit Attribute Controls		X	X	X	X	X
Host Attribute Controls			X	X	X	X
Listing Attribute Controls				X	X	X
Additive Location Fixed Effects					X	X
Month Fixed Effects and City Time Trend						X

Notes: Robust standard errors in parentheses. Unit attribute controls include: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, and the room type. Host attribute controls include: host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, and the interaction between the name order and the number of hosts attached to the listing. Listing attribute controls include: the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, and average review rating. Additive location fixed effects include neighbourhood, zip code, and city effects. Time fixed effects include month and a city by month time trend.

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

The omitted category from the regression is hosts who are expected to be white males, and so the coefficients on each of the conditional probabilities represent the difference in price charged and booking ratio associated with being a member of each of the gender and race/ethnic group categories over being a white male. For example, a one-unit (or 100%) increase in the probability of being Black and male is associated with an $e^{\hat{\beta}} - 1$ average percent change in the nightly price over an otherwise equivalent white male host. Note that this 100% change in the probability of being a member of each of the sex and race subcategories is the same as switching a binary variable from zero to one; hence, from here forward I interpret the coefficients from Tables 4a and 4b as being the effect associated with being a member of each of the categories in comparison with the omitted category (white males).

In terms of price, Table 4a indicates that in the preferred specification, being a Black man is associated with an 8.3% increase in price over an otherwise equivalent white man. The sign on this coefficient changes from negative to positive after including location fixed effects, which has similar implications to those discussed previously. There is a similar result for Black women wherein the coefficient changes from a -12.1% change to not statistically different from zero with the addition of location fixed effects. Thus, both male and female Black hosts are disproportionately located in low-price neighbourhoods, which affects the prices they can charge. While this result does not provide conclusive evidence for anti-Black discrimination in the market for short-term rentals, it does indicate that Black Airbnb hosts are disproportionately disadvantaged due to the location of their properties.

Consistent with the previous result, Table 4a indicates that both Hispanic men and women charge a lower nightly price than equivalent white male hosts. For women, this effect is a 5.8% decrease in nightly price, and for men, this effect is a slightly smaller 2.8% decrease over equivalent white male hosts. Similarly, being Asian and female is associated with a 9.3% decrease in nightly price, and being Asian and male is associated with a 3.7% decrease in nightly price. These results are consistent with the intersectional theory of discrimination (Crenshaw, 1989), which indicates that discrimination is not additive. If an individual is both a member of a marginalized racial group and a member of a marginalized gender group, the level of discrimination they face is not simply the sum of the two levels of discrimination that they would face if they were a member of each of the two groups alone. This definition is a simplification of the theory, which allows for significantly more than two dimensions of discrimination. For example, under an additive model, the effect on price of being a Hispanic woman would simply be the sum of the levels of discrimination faced by Hispanic people and women, which would result in an estimate of a 4.1% decrease in nightly price associated with being a Hispanic female. This is significantly lower than the reported estimate of -5.8%, indicating that there is an intersectional discrimination "premium" associated with being a member of more than one marginalized group.

While the above discussion and back-of-the-envelope calculation are a simplification of feminist intersectional theory, the conclusion is the same as if the theory were implemented in whole; hosts with intersectional identities face a greater degree of discrimination than the sum of the parts.

In terms of the percent of each month that a host's property is booked, Table 4b indicates that being Black and male is associated with a 4.2 percentage point decrease in the average percent of the month that a unit is booked. For simplicity, I call this the booking ratio. The sign of this coefficient does not change with the addition of controls, and its magnitude changes minimally, indicating that none of the added controls is a major driver of the relationship between being a Black male and the booking ratio. Similarly, being male and Hispanic is associated with a 2.8 percentage point decrease in the booking ratio and being male and Asian is associated with a 1.9 percentage point decrease in the final specification.

Being white and female is associated with a 0.45 percentage point decrease in the booking ratio, and while this is statistically different from zero, it is not practically significant. In a 30-day month, this translates to a reduction in bookings of 0.135 nights. In contrast, being Black and female is associated with a 4.4 percentage point decrease over an equivalent white male host and being female and Hispanic is associated with a 3.1 percentage point decrease.

Table 5a: Regression Output from Equation 2 by Region – Price

PANEL A: Logarithm of Price	**NORTHEAST**		**MIDWEST**		**WEST**		**SOUTH**	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conditional Probability of Being:								
Black (and Male)	-0.0517**	0.104***	-0.528***	-0.0861	0.0265	0.1809***	-0.107***	0.0539***
	(0.0203)	(0.0181)	(0.0702)	(0.0710)	(0.0237)	(0.0215)	(0.0234)	(0.0208)
Hispanic (and Male)	-0.0713***	-0.0267***	-0.193***	-0.0819***	-0.0769***	-0.0273***	-0.0598***	-0.0422***
	(0.00656)	(0.00562)	(0.0159)	(0.0150)	(0.00594)	(0.0056)	(0.00949)	(0.00959)
Asian, Native Hawaiian, or	-0.0796***	-0.0367***	0.00180	0.00105	-0.136***	-0.0749***	-0.0179	-0.000494
Other Pacific Islander (and Male)	(0.0106)	(0.00967)	(0.0281)	(0.0305)	(0.00870)	(0.0088)	(0.0148)	(0.0144)
American Indian or	-3.440***	-3.557***	1.907*	-1.726*	1.038**	1.5874***	1.010*	2.255***
Alaska Native (and Male)	(0.502)	(0.455)	(1.001)	(1.000)	(0.467)	(0.446)	(0.536)	(0.497)
More than one race or	5.058***	4.077***	6.465***	13.92***	-2.448***	-3.2123***	-3.363***	-4.024***
ethnic group (and Male)	(0.596)	(0.485)	(1.578)	(1.620)	(0.551)	(0.565)	(0.597)	(0.567)
Female (and White)	-0.0269***	-0.00627**	-0.103***	-0.0856***	-0.0206***	-0.0102***	-0.0262***	-0.00637**
	(0.00327)	(0.00281)	(0.00746)	(0.00739)	(0.00259)	(0.0026)	(0.00310)	(0.00313)
Female and Black	-0.308***	-0.0838***	0.452***	0.703***	-0.0887***	-0.0303	-0.217***	-0.0709***
	(0.0192)	(0.0159)	(0.0565)	(0.0648)	(0.0189)	(0.0186)	(0.0225)	(0.0227)
Female and Hispanic	-0.126***	-0.0406***	-0.214***	-0.0145	-0.0385***	-0.0665***	-0.135***	-0.122***
	(0.00781)	(0.00641)	(0.0251)	(0.0251)	(0.00738)	(0.0068)	(0.0119)	(0.0126)
Female and Asian, Native Hawaiian,	-0.0174	-0.0349***	-0.171***	-0.208***	-0.208***	-0.0691***	-0.204***	-0.0570***
or Other Pacific Islander	(0.0110)	(0.0100)	(0.0260)	(0.0284)	(0.00940)	(0.0085)	(0.0194)	(0.0182)
Female and American Indian	-1.991***	-0.0474	-4.371***	-5.602***	0.157	0.8063**	4.663***	2.340***
or Alaska Native	(0.380)	(0.316)	(1.681)	(1.650)	(0.372)	(0.350)	(0.487)	(0.440)
Female and more than one race	0.0902	1.224***	16.89***	15.59***	-0.265	0.0537	-4.132***	-3.605***
or ethnic group	(0.380)	(0.338)	(1.916)	(2.002)	(0.286)	(0.301)	(0.548)	(0.529)
Constant	4.388***	4.300***	4.604***	4.398***	4.202***	4.090***	4.483***	4.426***
	(0.0908)	(0.0558)	(0.127)	(0.108)	(0.0335)	(0.0330)	(0.0662)	(0.0591)
Observations	168,894	165,817	62,138	54,346	270,494	211,882	191,218	153,213
R-squared	0.623	0.747	0.550	0.660	0.672	0.782	0.619	0.682
Additive Location Fixed Effects		X		X		X		X
Month Fixed Effects and City Time Trend		X		X		X		X

Notes: Robust standard errors in parentheses. All specifications include unit, host, and listing attributes. Unit attribute controls include: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, and the room type. Host attribute controls include: host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, and the interaction between the name order and the number of hosts attached to the listing. Listing attribute controls include: the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, and average review rating. Additive location fixed effects include neighbourhood, zip code, and city effects. Time fixed effects include month and a city by month time trend.

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

Table 5b: Regression Output from Equation 2 by Region – Percent of Month Booked

PANEL B: Percent of Month Booked	**NORTHEAST**		**MIDWEST**		**WEST**		**SOUTH**	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conditional Probability of Being:								
Black (and Male)	-0.0475	-0.0703**	-0.0741	-0.0374	-0.0502	0.0227	-0.0408**	-0.0336*
	(0.0292)	(0.0281)	(0.0532)	(0.0557)	(0.0352)	(0.0495)	(0.0179)	(0.0180)
Hispanic (and Male)	-0.0615***	-0.0376***	0.00267	-0.00810	0.00409	-0.00541	-0.0163**	-0.0356***
	(0.00734)	(0.00704)	(0.0120)	(0.0123)	(0.00955)	(0.0137)	(0.00751)	(0.00773)
Asian, Native Hawaiian, or	0.00620	0.0136	0.0758***	0.0733***	-0.0490***	-0.0255	-0.0349***	-0.0900***
Other Pacific Islander (and Male)	(0.0123)	(0.0119)	(0.0153)	(0.0153)	(0.0119)	(0.0163)	(0.0110)	(0.0110)
American Indian or	-0.333	-0.741	0.751	-0.818	0.407	-0.568	0.414	0.431
Alaska Native (and Male)	(0.539)	(0.559)	(0.672)	(0.689)	(0.648)	(0.965)	(0.391)	(0.385)
More than one race or	-1.461**	-1.001	4.452***	3.428***	-0.342	0.474	1.379***	1.334***
ethnic group (and Male)	(0.701)	(0.678)	(1.079)	(1.049)	(0.704)	(0.928)	(0.472)	(0.456)
Female (and White)	-0.00860**	-0.00329	0.0358***	0.0234***	0.000957	-0.00501	0.00414*	0.00499**
	(0.00360)	(0.00347)	(0.00446)	(0.00454)	(0.00319)	(0.00443)	(0.00238)	(0.00245)
Female and Black	-0.0911***	-0.0448*	-0.0899***	0.00730	-0.0497*	0.0600*	-0.119***	-0.0791***
	(0.0245)	(0.0243)	(0.0336)	(0.0337)	(0.0281)	(0.0364)	(0.0200)	(0.0208)
Female and Hispanic	-0.0392***	-0.0414***	-0.0555***	-0.0719***	-0.0798***	-0.0546***	0.0280***	0.00723
	(0.00884)	(0.00839)	(0.0146)	(0.0149)	(0.0126)	(0.0174)	(0.00876)	(0.00895)
Female and Asian, Native Hawaiian,	0.000801	0.00902	-0.0486**	-0.0152	0.00813	0.0444**	0.0699***	0.0289**
or Other Pacific Islander	(0.0123)	(0.0119)	(0.0217)	(0.0244)	(0.0139)	(0.0203)	(0.0131)	(0.0139)
Female and American Indian	-0.225	-0.463	-3.780***	-2.811***	-1.145**	-0.545	-0.354	-0.0219
or Alaska Native	(0.553)	(0.519)	(0.875)	(0.858)	(0.503)	(0.570)	(0.341)	(0.349)
Female and more than one race	1.120**	0.471	-1.912**	-2.980***	0.469	0.377	0.315	-0.349
or ethnic group	(0.468)	(0.475)	(0.869)	(0.906)	(0.463)	(0.640)	(0.439)	(0.428)
Constant	0.700***	0.730***	0.683***	0.636***	0.271***	0.542***	0.419***	0.422***
	(0.0403)	(0.0442)	(0.140)	(0.0964)	(0.0765)	(0.108)	(0.0503)	(0.0517)
Observations	67,179	66,116	60,329	52,905	108,207	51,896	186,573	149,518
R-squared	0.064	0.221	0.051	0.213	0.030	0.223	0.057	0.230 height
Additive Location Fixed Effects		X		X		X		X
Month Fixed Effects and City Time Trend		X		X		X		X

Notes: Robust standard errors in parentheses. All specifications include unit, host, and listing attributes. Unit attribute controls include: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, and the room type. Host attribute controls include: host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, and the interaction between the name order and the number of hosts attached to the listing. Listing attribute controls include: the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, and average review rating. Additive location fixed effects include neighbourhood, zip code, and city effects. Time fixed effects include month and a city by month time trend.

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

5.1.3 Relationships between Race, Gender, and Price/Quantity by Region

Because the history of racial discrimination in the United States highlights the vast regional differences in attitudes and behaviour toward people of colour, I separately estimate equation 2 for each of the four major regions in the United States. The cities included in each of these regions in my dataset can be found in Table A.1 in Appendix A.

The coefficient estimates reported in Table 5a indicate that the relationships between being in each of the race and gender subcategories and nightly price differ substantially between the four regions. Being a Black man is associated with a percent change in nightly price ranging from an increase of 5.5% in the South to an increase of 19.7% in the West in comparison with otherwise equivalent white male hosts. Being male and Hispanic is associated with a reduction in nightly price ranging from -2.6% in the Northeast to -7.9% in the Midwest, and similarly being Asian, Native Hawaiian, or Pacific Islander and male is associated with a -3.6% effect in the Northeast and a -7.4% decrease in the West. The results are not surprising given the figures presented in Table 4a.

In the Northeast and South, being a Black woman is associated with a decrease in nightly price ranging from -8.0% to -6.8%, while in the Midwest, being a Black woman is associated with a 101.9% increase in nightly price charged over an equivalent white male host. Note that these figures must be considered in the context of the distribution of the conditional probabilities of being a Black female. The average probability of being a Black female in the Midwest is 1.9%, so doubling the probability that the average host in the Midwest is a Black female (or increasing the conditional probability of being a Black female by 1.9%) translates to a 1.94% increase in nightly price.

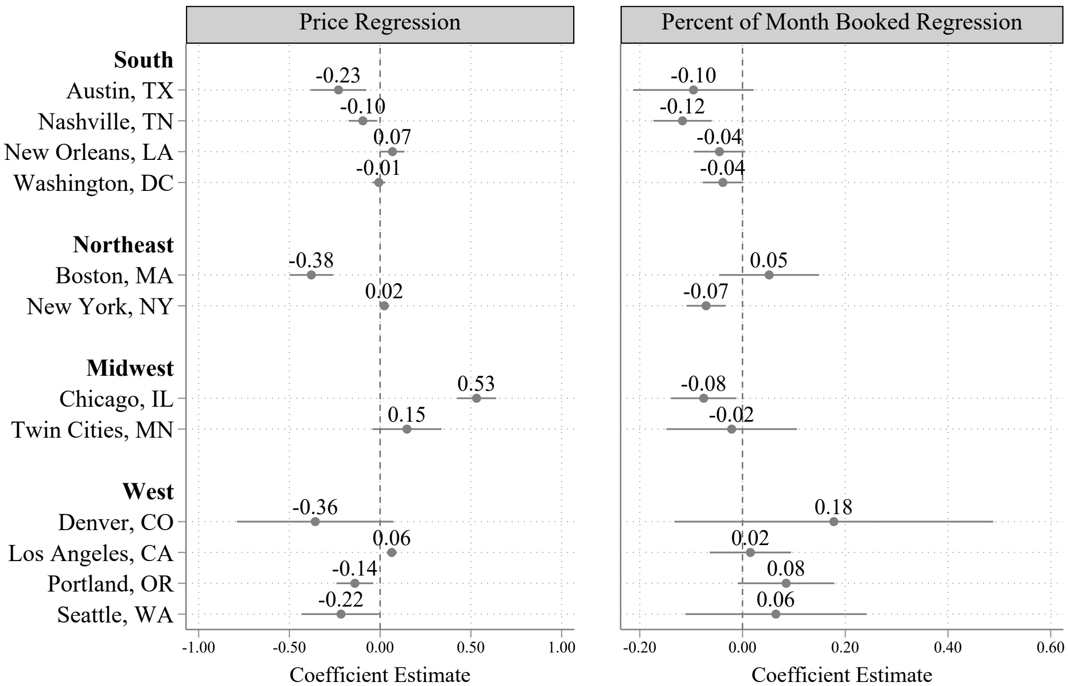
In the Northeast, being male and Native American is associated with an average decrease in nightly price of -97.15%, while in the West, being male and Native American is associated with a 386% increase, and in the South, it is associated with an 853% increase on average. Similarly to my discussion of interpreting the coefficients on being multiracial, these must be examined in the context of the distributions of the conditional probabilities of being Native American. In all three regions of interest, the mean conditional probability of being Native American and male is 0.16%, which indicates that in the Northeast, doubling the average male host's probability of being Native American is associated with a 0.155% decrease in nightly price. Similarly, in the West, doubling the probability that the average host is Native American results in a 0.62% increase in nightly price, and in the South, it results in a 1.36% increase in comparison with a white male host.

Additionally, in the Midwest, being female and Native American is associated with a 99.6% decrease in nightly price, while in the South, being female and Native American is associated with a 938% increase in nightly price. As above, I re-evaluate these coefficients in the context of the distribution of the conditional probabilities. The mean conditional probability of being Native American and female in the South is 0.16% and in the Midwest is 0.15%. Doubling the probability that the average host in each region is Native American translates to a 1.5% increase in price in the South and a -0.15% decrease in price in the Midwest.

Finally, I estimate Equations 1 and 2 by city to evaluate the heterogeneous effects observed by region. Full regression output is contained in Appendix A, and coefficient estimates and 95% confidence intervals are presented in figures 2 - 5. The coefficient estimates are grouped by region.

Figure 2 plots the coefficient estimates of estimating equation 1 individually by city where the omitted category is white hosts. The cities in the figure are sorted by region from top to bottom: South, Northeast, Midwest, and West, so the figure is easily comparable to the previous results presented by region. This again includes the controls for individual unit, host, and listing attributes as well as the fixed effects from my preferred specification. The left panel of Figure 2 indicates the coefficient estimates on the conditional probability of being Black from the regression on price. The coefficient on the probability of being Black varies widely between cities, ranging from a 31.6% reduction in price in Boston to a 69.9% increase in price in Chicago. The only cities for which the coefficient estimate is not significant at the 10% level are the Twin Cities and Washington DC. While Denver has one of the largest estimated price discrepancies between Black and white Airbnb hosts (a 30.23% price reduction), the sample size is relatively small, and there is little variation in the conditional probability of being Black, so the confidence interval is wide, and the coefficient estimate is extremely imprecise.

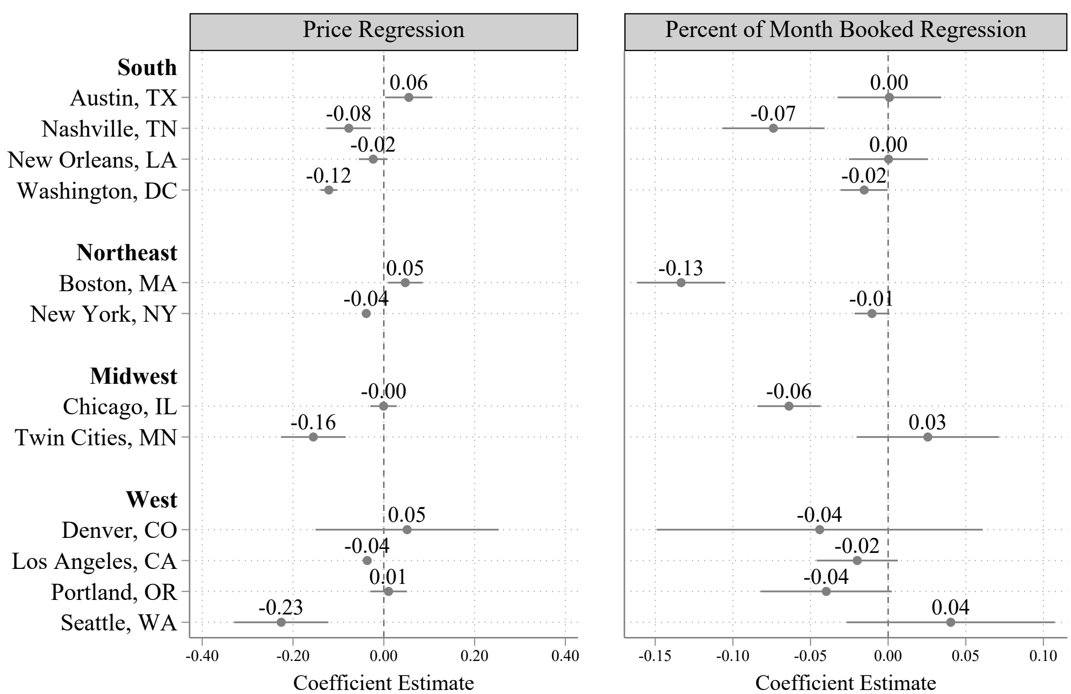
Figure 2: Coefficient Estimates on the Conditional Probability of Being Black



The right panel of Figure 2 plots the coefficient estimates from estimating equation 1 where the dependent variable is the booking ratio. The point estimates are consistently negative in the South and Midwest, and consistently positive in the West. However, in the West, none of the coefficient estimates are statistically different from zero, and in the South, only Nashville, TN has a statistically significant negative coefficient of -11.3 percentage points. Both Chicago and New York have negative and statistically significant estimated relationships between being Black and the booking ratio, with effects of -7.7 and -6.8 percentage points respectively.

For almost all cities in the West, Midwest, and Northeast, the coefficients on the conditional probability of being Black have opposite signs from the price and quantity regressions. In these cases, the result is consistent with a movement along the demand curve, which may be cause by Black hosts choosing higher prices and thus receiving fewer booked nights, or Black hosts increasing their prices to try to compensate for a low quantity demanded. In contrast, coefficients from the price and quantity regressions with the same sign may indicate that there are separate aggregate demand curves for identical properties managed by a Black host and properties managed by a white host. For all cities in the South except Nashville, the coefficients on the conditional probability that a host is Black from the price and quantity regressions are negative. This likely indicates that demand for a property managed by a Black host is below demand for an identical property managed by a white host.

Figure 3: Coefficient Estimates on the Conditional Probability of Being Hispanic



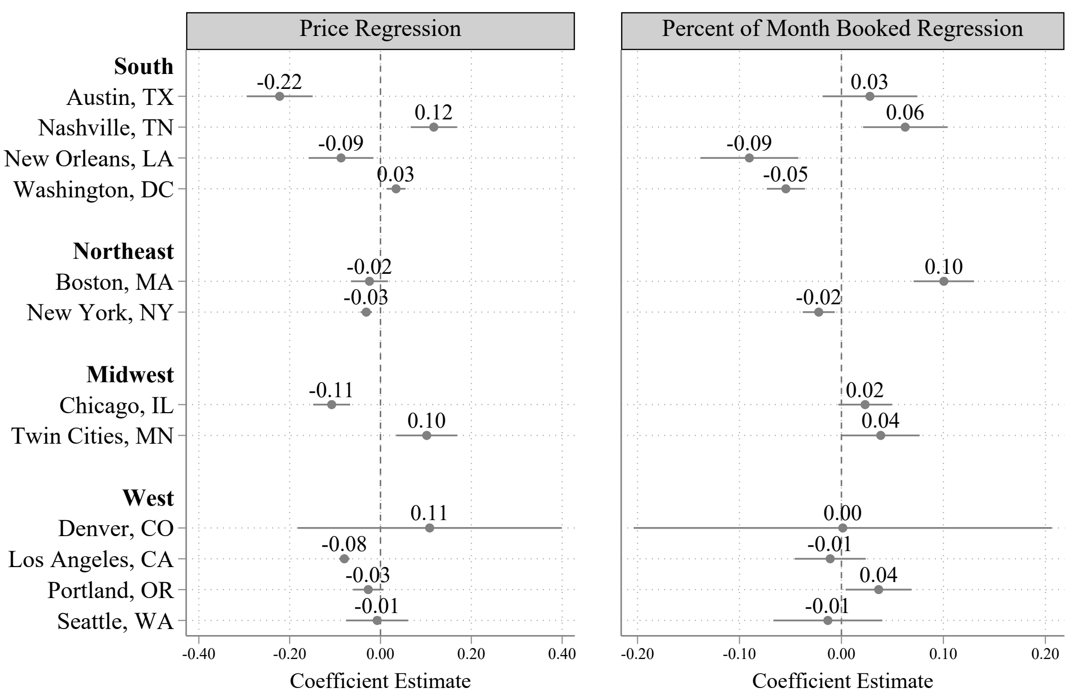
There is a large range of estimates for the coefficient on the probability of being Hispanic from the regression on log nightly price. The estimates range from a 20.55% reduction in price in Seattle, which is significant at the 1% level, to a 6.18% increase in nightly price in Austin, which is significant at the 5% level. The only cities for which the coefficient on the conditional probability of being Hispanic is not significant at the 5% level are Chicago, Denver, Portland, and New Orleans, meaning that the only cities with a statistically significant increase in price associated with an increase in the probability that a host is Hispanic are Austin and Boston, with increases of

6.18% and 4.08% respectively.

The right panel of Figure 3 plots the coefficient estimates on the conditional probability of being Hispanic from the regression of the booking ratio. These estimates are statistically different from zero only for Nashville (-7 percentage points), Washington DC (-2 percentage points), Boston (-13 percentage points), and Chicago (-6 percentage points).

It is again important to assess the coefficients from the price and quantity regressions in conjunction. Both estimated relationships are negative and statistically different from zero in Nashville and Washington DC, indicating that there is likely a separate (lower) demand curve for properties managed by Hispanic hosts in comparison with identical properties managed by white hosts. In contrast, in Boston, the coefficient estimate from the regression of price is positive, while the coefficient estimate from the regression of the booking ratio is negative, which may be indicative of a movement along the demand curve.

Figure 4: Coefficient Estimates on the Conditional Probability of Being Asian, Native Hawaiian, or Other Pacific Islander

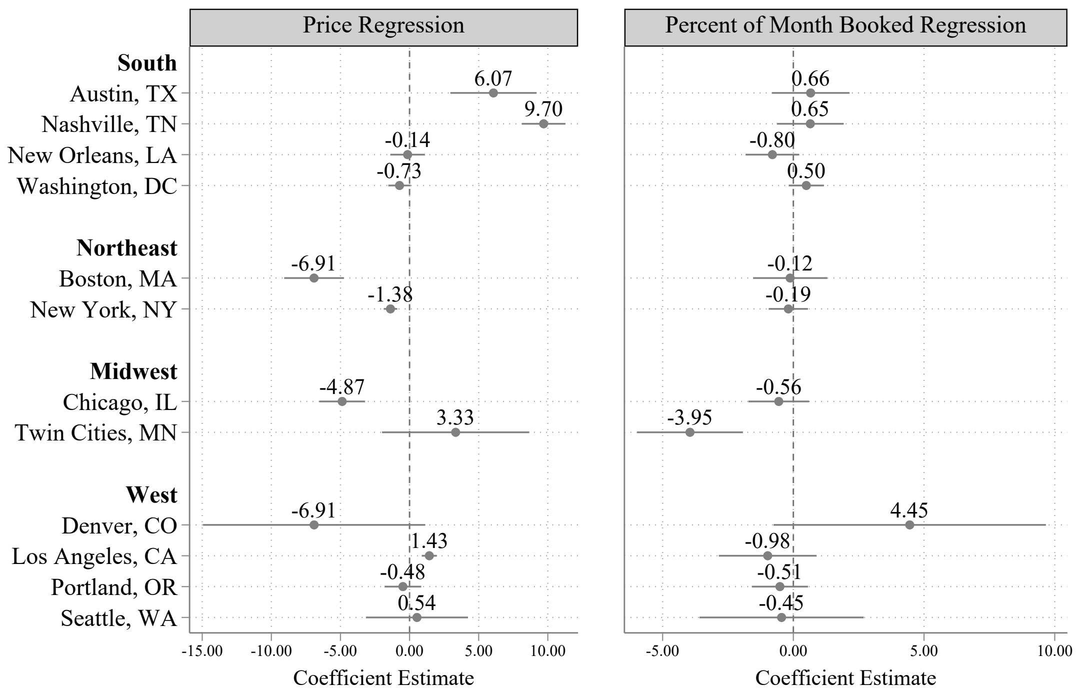


For the coefficient estimates from the regression of price on the conditional probability of being Asian, Native Hawaiian, or other Pacific Islander, there are not clear regional trends. In the South, Austin and New Orleans have negative coefficient estimates (-19.75% and -8.61% respectively), while Nashville and Washington DC have positive coefficient estimates (12.75% and 3.05% respectively). The Midwest is similarly divided, with a positive coefficient estimate of 10.5% in the Twin Cities and a negative coefficient estimate of -10.42% in Chicago. There are also negative estimated relationships in New York (where being Asian, Native Hawaiian, or other Pacific Islander is associated with a -2.95% change in nightly price) and Los Angeles, where the estimated effect is -7.69%.

The relationships between being Asian, Native Hawaiian, or other Pacific Islander and the booking ratio are similarly not correlated within regions. For the South, the effect is positive in Nashville (6 percentage points), and negative in New Orleans and Washington DC (-9 percentage points and -5 percentage points respectively). Similarly, in the Northeast the estimated effect is positive in Boston (10 percentage points) and negative in New York (2 percentage points).

In assessing the coefficient estimates from the regressions of price and quantity together, the effects are both positive in Nashville, which may indicate that there is a separate (higher) demand curve for properties owned by hosts who are Asian, Native Hawaiian, or other Pacific Islander in comparison with identical properties owned by white hosts. In contrast, the effects are both negative in New Orleans and New York, indicating that there may be a lower demand for properties managed by Asian, Native Hawaiian, or other Pacific Islander hosts in comparison with white hosts in those cities.

Figure 5: Coefficient Estimates on the Conditional Probability of Being American Indian or Alaska Native



For the coefficient estimates from the regression of price on the conditional probability of being Native American or Alaska Native, the Twin Cities, Portland, Seattle, and New Orleans all have coefficient estimates that are not significant at the 10% level. As previously, because the conditional probability of being Native American or Alaska Native is so small (the largest city average being 0.16 percent in Boston) we must discuss the interpretation of these coefficients in the context of the average conditional probability in each city. The coefficient estimate for Boston is -701%, and the average conditional probability of being Native American or Alaska Native is 0.16%, so doubling the probability that the average host in Boston is Native American is associated with a 1.12% decrease in price charged.

I additionally estimate equation 2 by city. Estimation results can be found in Appendix A.

When estimating equation 2 by city, the probability of being Black and male has the largest negative effect in Boston with a point estimate of -42% and the probability of being Black and female has the largest negative effect in Seattle, with a point estimate of -36%. These estimates are both statistically significant at the 1% level.

The effect of being Hispanic and male varies much less by city than the previously examined coefficients. For most cities, the average estimated effect is between zero and ten percent, with only Seattle having a large negative effect of 31%. Similarly for the effect on being Hispanic and female, the largest estimated effects are in Nashville, Washington DC, and the Twin Cities each with an effect close to -22%.

5.2 Matching Model

In addition to Ordinary Least Squares, I conduct a similar analysis using a Propensity Score Matching approach. I begin by estimating a propensity score for multiple treatment categories: female hosts, hosts of colour, Black hosts, female hosts of colour, Black female hosts, and white female hosts. These indicators are created from the conditional probabilities using the inclusion criteria defined in section 3. I then create eight categories of matched pairs: hosts of colour with white hosts; Black hosts with white hosts; female hosts with male hosts; female hosts of colour with male hosts of colour; female hosts of colour with white female hosts, Black female hosts with Black male hosts; Black female hosts with white female hosts; and white female hosts with white male hosts. These pairings allow me to estimate the average treatment effect on the treated of being in each of the treatment groups in comparison with each of the control groups.

In order to satisfy the common support assumption, I only include observations that form part of the common support region. As suggested by Austin (2011), I drop observations with propensity scores outside of the common support region. These values are reflected in the Min P-score and Max P-score columns of Table 6. See Appendix B for kernel densities of the propensity scores for each treatment and control pair to highlight the common support region.

For the price model presented in Panel A, all of the statistically significant estimated treatment effects are negative, indicating that each of the treatment groups has a lower mean price than each of their matched control groups. There is not a statistically significant estimated difference between the price charged by Black hosts and white hosts, but given the result of my OLS analysis above, it

Table 6: Estimated Average Treatment Effects from Matching Model

PANEL A: Logarithm of Price

Treatment Group	Control Group	ATET	Standard Error	Obs.	Min P-Score	Max P-Score
People of Colour	White	-0.0517***	0.0034	584,149	-	0.22
Black	White	-0.0187	0.0158	536,150	-	0.2
Women	Men	-0.0213***	0.0018	711,955	0.2	0.8
Women of Colour	Men of Colour	-0.0124*	0.0067	48,718	-	0.15
Women of Colour	White women	-0.0467***	0.0052	290,772	-	0.15
Black Women	Black Men	0.0064	0.0308	1,981	-	0.012
Black Women	White Women	-0.0563***	0.0219	262,941	-	0.012
White Women	White Men	-0.0329***	0.0022	537,439	0.2	0.8

PANEL B: Percent of Month Booked

Treatment Group	Control Group	ATET	Standard Error	Obs.	Min P-Score	Max P-Score
People of Colour	White	0.00297	0.92	320,669	-	0.22
Black	White	-0.0358*	-2.39	299,179	-	0.2
Women	Men	0.00606***	4.48	385,764	0.2	0.8
Women of Colour	Men of Colour	0.0126*	2.08	21,830	-	0.15
Women of Colour	White Women	0.0125*	2.46	158,266	-	0.15
Black Women	Black Men	-0.141***	-5.02	1,053	-	0.012
Black Women	White Women	-0.0955***	-3.94	145,890	-	0.012
White Women	White Men	0.00400*	2.55	299,547	0.2	0.8

is likely that this null result masks opposing effects for Black male and Black female hosts. People of colour charge on average 5.17% less than their white matched counterparts. Women charge on average 2.13% less than matched men. Women of colour charge 1.24% less than otherwise equivalent men of colour. Women of colour charge 4.67% less than equivalent white women. Black women charge 5.63% less than white women; and white women charge 3.29% less than white men.

These results indicate that not only are there differential outcomes for women and people of colour in comparison with men and white hosts, but this discrepancy is greater for individuals with intersectional identities.

For the quantity model presented in Panel B, the relationships are less clear-cut. Properties managed by Black hosts have on average 3.58 percentage points fewer booked nights in a month than otherwise equivalent properties managed by white hosts. Properties managed by Black women have 14.1 percentage points fewer nights booked than those managed by Black men, and they have 9.55 percentage points fewer booked nights than those managed by white women. When assessing the average treatment effects on price and quantity together for Black women, there are negative estimated treatment effects for both, indicating that the demand curve for properties managed by Black women is lower than that for identical properties managed by white women.

I additionally estimate the first matching specification (hosts of colour compared with white hosts) and the third matching specification (female hosts compared with male hosts) by city to observe the geographic distribution of the level of racial and sex-based discrimination. I would have liked to include replications of each of the matching specifications outlined above, but there is insufficient data within each city for the remaining specifications.

See Figure 6 and Figure 7 for visual depictions of the estimated average treatment effects on the treated from my matching model. They indicate that there are large differences in the nightly prices and number of booked nights faced by women and people of colour in the market for short term rentals. Washington DC is the only included city for which the estimated treatment effect on nightly price of being a person of colour is positive and statistically significant. For the remaining

Figure 6: Estimated ATET on Hosts of Colour vs. White Hosts by City

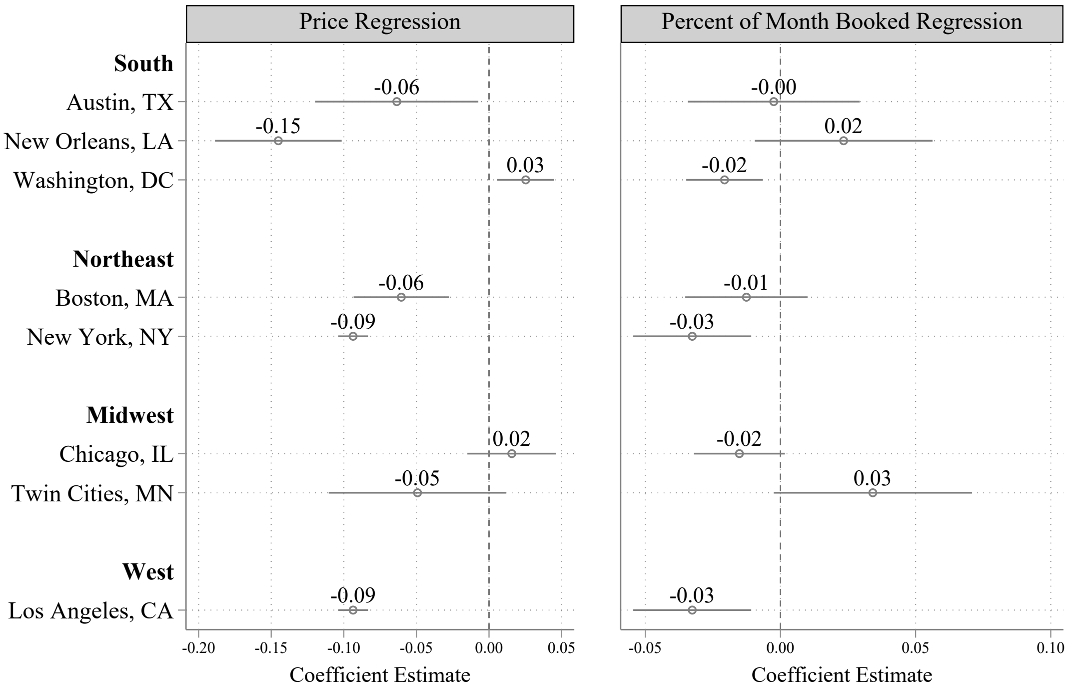
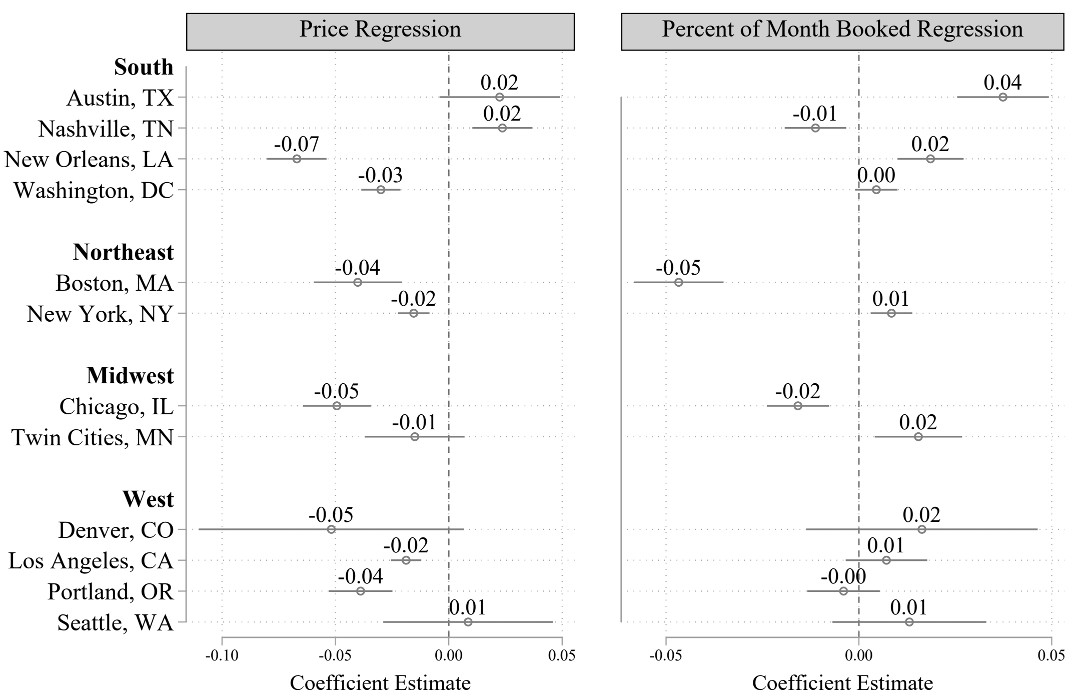


Figure 7: Estimated ATET on Women vs. Men by City



cities, the average treatment effects on the treated that are statistically different from zero are negative, indicating that all else equal, hosts of colour charge between 5% and 15% less than equivalent white hosts.

For the booking ratio model, there are no cities with positive average treatment effects of being a person of colour in comparison with being white. The estimated effects are negative and approximately equal to 3 percentage points in Washington DC, New York, and Los Angeles.

Similarly, Nashville is the only city for which the effect of being female on price is positive and statistically significant. For the remaining cities, women charge up to 7% less than equivalent male hosts. In contrast, the average treatment effects vary much more widely for the quantity model, ranging from an estimated effect of 4 percentage points in Austin to an estimated effects of -5 percentage points in Boston. The estimated treatment effect on price has an opposite sign to that on quantity for all cities except Boston and Chicago, where both estimates are negative, indicating that women face a lower demand curves than men for identical properties.

6 Robustness Tests

In order to test the conditional independence assumption, most studies evaluate the pre-treatment trends in the control and treatment groups to observe whether they followed parallel paths prior to the intervention. Because the “treatment” that I consider is race or gender, which is “assigned” at birth, this approach is impossible. Thus, in order to test the sensitivity of my results to bias introduced by unobserved factors, I follow the approach suggested by Oster (2017), which allows me to test how important the unobservable covariates would need to be relative to the observables to negate the estimated effect. Oster’s method builds on the approach suggested by Altonji et al. (2005). She connects the bias with coefficient stability to allow the test to be used not only under the null hypothesis of zero treatment effect, which is one of the major limitations of Altonji, Elder and Taber’s method. Using her method, I find a range of absolute values of delta[14] from 0.016 to 0.901. A delta value of 0.016 indicates that the effect of unobservables on the dependent variable would have to be 62.5 times[15] as large as the effect of observables to negate the estimated effect. A delta value of 0.901 indicates that the effect of unobservables would have to be 1.1 times as large as that of observables. Oster’s rule of thumb is a delta value less than or equal to one, so my results are robust to the selection on observables test. See Table 7 for the precise delta estimates.

Because Airbnb listings have multiple fields that allow the host to describe their property in words, and because there may be a relationship between the host’s race, gender, or ethnic group and certain characteristics of their writing style that affect the demand for their property (Colley and Todd, 2002), I additionally incorporate text-analysis controls as a robustness check. Racial differences in writing style may be due to differences in access to education (Berlak, 2005), literacy skills (De Anda and Hernandez, 2007), or simply differences in culture-specific vernacular (Pullum, 1999), and gender differences may additionally be due to . Using a machine learning algorithm developed for Python called TextBlob (Loria, 2018), I assess the “polarity” and “subjec-

[14]Delta is a test statistic that indicates the relative importance of unobservables to observables that would be required to eliminate the estimates effect

[15]This is calculated as $1/\delta$

Table 7: Estimates of Selection on Observables

	MODEL			
INDEPENDENT VARIABLE:	**Equation 1**		**Equation 2**	
Conditional Probability of Being:	Quantity	Price	Quantity	Price
Black (and male)	0.504	-0.348	0.188	-0.638
Hispanic (and male)	-0.338	0.403	-0.901	0.384
Asian, Native Hawaiian, or other Pacific Islander (and male)	-0.016	0.403	-0.734	0.417
American Indian or Alaska Native (and male)	-0.739	-0.186	0.024	0.478
More than one race (and male)	0.150	-0.226	-0.224	0.074
White and female	-	-	0.078	0.816
Black and female	-	-	-0.873	-0.044
Hispanic and female	-	-	-0.162	0.624
Asian, Native Hawaiian, or other Pacific Islander and female	-	-	0.161	0.379
American Indian or Alaska Native and female	-	-	-0.181	-0.191
More than one race and female	-	-	-0.031	-0.113

tivity" of each of the five host-written fields. The subjectivity measure ranges from 0 to 1, where 0 indicates the language is very objective, and 1 indicates the language is very subjective. This captures the extent to which the host uses language such as "I think" or "I believe" rather than concrete language. The polarity measure also ranges from 0 to 1, and it captures how positive or negative the sentiment of the writing is. For example, the phrase "the neighbourhood is amazing" would receive a higher polarity score than the phrase "the neighbourhood is good". I also add controls for the number of misspelled words in each text field, which I calculate using the Quantitative Discourse Analysis Package in R (Rinker, 2020).

Columns (2) and (5) of Table 8 report the estimated coefficients from my preferred specification of Equation 2 with added controls for the subjectivity, polarity, and number of misspelled words in each of the five paragraph fields. Columns (1) and (4) report the coefficient estimates from my preferred specification without the text controls for comparison. Adding the text controls does not significantly change any of the coefficient estimates; however, the magnitude does increase for Black men, indicating that on average their writing style may lead consumers not to book their properties, which in turn may force Black men to charge lower prices.

In order to assess the relationship between my OLS and matching models, I additionally re-estimate equation 1, but I replace the continuous conditional probability variables with the group indicator variables used in my matching specification. For example, in the first row of Table 8, the coefficient estimate in column (1) indicates the effect of increasing the conditional probability of being Black and male by one unit (or 100%), while the coefficient estimate in column (3) indicates the effect of being classified as Black and male (i.e. having a higher conditional probability of being Black than the conditional probabilities for the other five race or ethnic groups and having a greater than 50% conditional probability of being male). There are no reported estimates for being American Indian or Alaska Native or more than one race, as there are no hosts for whom the conditional probability of being in either of those groups is greater than the probabilities of being in any of the other four groups.

I also assess the robustness of my propensity score matching results by adjusting my specification. First, I redefine my group indicator variables to be equal to one if the conditional probabilities are greater than 75% (rather than simply if the probability is greater than each of the other group probabilities). This definition minimally effects my results, except for the comparing the prices charged by Black and white hosts where the original classification resulted in an affect that was not statistically different from zero, but under the 75% classification, provides an estimated effect of -3.9% associated with being Black. Additionally, under the new classification, the effect on quantity of being a person of colour is approximately 3.6% and significant at the 1% level. The quantity effect is smaller for the specification comparing Black women with Black men (going from -14% to not practically different from zero) and for the specification comparing Black women to white women (going from -9.5% to -1.4%).

In the last column of Table 9, I restrict the sample to each of my treatment and control groups (using the original balance of probabilities classifications), and estimate an OLS equation with a treatment dummy and all of the controls from my preferred OLS specification. The estimates are not substantially different from the matching results for the price model, but because the sample is much smaller than my full OLS sample, the estimates from the quantity model are much less precise.

Table 8: Regression Output from OLS Model with Text-Analysis Controls and Group Indicators

	PANEL A: Log of Price			PANEL B: Percent of Month Booked		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Male and Black	0.0798***	0.0860***	0.0232**	-0.0419***	-0.0422***	-0.0136
	(0.0116)	(0.0116)	(0.00941)	(0.0141)	(0.0141)	(0.0124)
Male and Hispanic	-0.0289***	-0.0280***	-0.0135***	-0.0276***	-0.0270***	-0.0222***
	(0.00361)	(0.00360)	(0.00275)	(0.00455)	(0.00455)	(0.00352)
Male and Asian, Native Hawaiian, or Other Pacific Islander	-0.0382***	-0.0411***	-0.0369***	-0.0190***	-0.0193***	-0.00675
	(0.00617)	(0.00618)	(0.00462)	(0.00656)	(0.00657)	(0.00480)
Male and American Indian or Alaska Native	0.172	0.195	-	-0.0761	-0.0808	-
	(0.260)	(0.261)		(0.276)	(0.276)	
Male and more than one race or ethnic group	0.260	0.254	-	1.029***	1.016***	-
	(0.310)	(0.310)		(0.332)	(0.331)	
Female and White	-0.0131***	-0.0139***	-0.0142***	0.00452***	0.00447***	0.000917
	(0.00162)	(0.00162)	(0.00108)	(0.00168)	(0.00168)	(0.00113)
Female and Black	0.00890	0.0100	-0.00873	-0.0443***	-0.0434***	-0.00724
	(0.0112)	(0.0112)	(0.0125)	(0.0134)	(0.0134)	(0.0163)
Female and Hispanic	-0.0596***	-0.0592***	-0.0446***	-0.0312***	-0.0321***	-0.00744*
	(0.00460)	(0.00460)	(0.00337)	(0.00547)	(0.00547)	(0.00380)
Female and Asian, Native Hawaiian, or Other Pacific Islander	-0.0677***	-0.0659***	-0.0453***	0.0228***	0.0227***	0.0198***
	(0.00619)	(0.00619)	(0.00473)	(0.00797)	(0.00798)	(0.00629)
Female and American Indian or Alaska Native	0.538**	0.524**	-	-0.397	-0.394	-
	(0.222)	(0.222)		(0.247)	(0.247)	
Female and more than one race or ethnic group	0.394*	0.478**	-	-0.186	-0.196	-
	(0.237)	(0.236)		(0.276)	(0.276)	
Constant	4.213***	4.217***	4.213***	0.399***	0.386***	0.395***
	(0.0250)	(0.0251)	(0.0251)	(0.0375)	(0.0375)	(0.0375)
Observations	584,180	584,180	584,180	320,436	320,436	320,436
R-squared	0.731	0.731	0.731	0.227	0.227	0.227

Notes: Columns (1) and (4) are the original OLS specification (Equation 4). Columns (2) and (5) are the original specification with text-analysis controls including the subjectivity, polarity, and number of spelling errors in each written field. Columns (3) and (6) are the original specification with the conditional probabilities replaced with the group indicator variables. Robust standard errors in parentheses. Unit attribute controls include: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, and the room type. Host attribute controls include: host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, and the interaction between the name order and the number of hosts attached to the listing. Listing attribute controls include: the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, and average review rating. Additive location fixed effects include neighbourhood, zip code, and city effects. Time fixed effects include month and a city by month time trend.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Regression Output from Matching Model with Redefined Race Indicators and Using OLS

PANEL A: Logarithm of Price				
Treatment Group	**Control Group**	**ATET**	**ATET using Redefined Race Indicators**	**OLS Estimate**
People of Colour	White	-0.0517***	-0.0478***	-0.0224***
Black	White	-0.0187	-0.0394***	0.0156**
Female	Male	-0.0213***	-0.0213***	-0.0113***
Female People of Colour	Male People of Colour	-0.0124*	0.00136	-0.00912**
Female People of Colour	White Females	-0.0467***	-0.0243***	-0.0301***
Black Females	Black Males	0.0064	0.00622	0.00587
Black Females	White Females	-0.0563***	-0.0149***	0.00192
White Females	White Males	-0.0329***	-0.0225***	-0.0148***
PANEL B: Percent of Month Booked				
Treatment Group	**Control Group**	**ATET**	**ATET using Redefined Race Indicators**	**OLS Estimate**
People of Colour	White	0.00297	-0.0361***	-0.0103***
Black	White	-0.0358*	-0.0309***	-0.0108
Female	Male	0.006***	0.006***	0.00230**
Female People of Colour	Male People of Colour	0.0126*	0.00790*	0.0112**
Female People of Colour	White Females	0.0125*	-0.0113***	-0.00247
Black Females	Black Males	-0.141***	0.00747*	0.0444
Black Females	White Females	-0.0955***	-0.0146***	-0.00248
White Females	White Males	0.00400*	0.00863***	0.000877

Notes: Column 3 is the original matching specification for comparison. Column 4 uses redefined group classifiers where the indicator variables are turned on only if the conditional probability is greater than 75%. Column 5 presents results from an OLS model where the dependent variable is regressed on a treatment indicator (using the original balance of probabilities classification) and the following controls: the number of guests the unit accommodates, the number of bedrooms and bathrooms, the property type, the room type, host response rate and time, number of listings managed by the host, whether the host is a superhost, whether they have a profile picture, the order in which the host's name appears on the listing, the interaction between the name order and the number of hosts attached to the listing, the security deposit, cleaning fee, number of guests included with the nightly price, minimum stay length, maximum stay length, number of reviews, average review rating, additive location fixed effects, month fixed effects, and a linear city time trend. Robust standard errors in parentheses.

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

7 Conclusion

People of colour who own and manage Airbnb listings charge generally lower nightly prices and receive fewer booked nights than their white peers. Hosts who are Hispanic, Asian, Native Hawaiian, or other Pacific Islander charge approximately 4% less than white hosts with equivalent units, listings, host profiles, and property locations. They also receive approximately 3 percentage points (or around one night) fewer booked days per month. The results including both race and sex controls show a similar story. Hosts who are male and Hispanic, Asian, Native Hawaiian, or other Pacific Islander charge approximately 3% less per night than their white male counterparts, and female hosts in the same racial or ethnic group categories charge approximately 6% less per night than white male hosts with similar properties. Additionally, Hispanic men, Hispanic women, and Asian men have approximately 2 percentage points (or 0.6 nights) fewer bookings per month, and Asian women have approximately 0.7 more booked nights per month than white males.

The differences for Black hosts are more complicated to interpret. After including location controls, Black hosts charge 4.1% more per night than equivalent white hosts; however, without controlling for location, Black hosts charge 8.9% less than white hosts with similar units, host profiles, and listings. This indicates that in a given location, Black hosts charge more per night than white hosts; however, on average, Black hosts disproportionately own properties in low-price neighbourhoods. The effect of being Black on the percent of a month that the property is booked is unambiguously negative and approximately equal to 1.3 fewer nights per month.

When examining the effects by race and sex and including controls for location, Black male hosts charge 8.3% more than white males and the estimated effect on price of being a Black female is not statistically different from zero; however, as above, without location effects, Black men charge 4.6% less and Black women charge 12.1% less per night. This again indicates that in a given neighbourhood, Black hosts charge more per night (or the same nightly price in the case of Black women), but that Black hosts disproportionately own properties in low-price areas. It is important to note that this result does not indicate that racism does not affect Black Airbnb hosts.

In fact, my results suggest that the legacy of segregation continues to negatively affect even those among the most economically successful Black Americans.

In order to assess these results in the context of discrimination, I first discuss Lawrence and Keleher's (2004) definitions of the four forms of discrimination. Individual racism is the most straightforward form and is often what people think of when they think of racism. It involves a person treating a person differently because of their race. This can be broken down into two categories: interpersonal racism, where one person discriminates against another; and internalized racism, where someone treats themself differently because of their race. There is a large body of literature in psychology indicating that internalized racism causes people of colour to disproportionately undervalue themselves, and that this can result in lower socio-economic status (David et al., 2019; Pyke, 2010; D. R. Williams, 1999).

Additionally, systemic racism describes when societal structures and institutions result in differential outcomes or treatment of people of different races. This also takes two forms. First, institutionalized racism occurs when laws, rules, or customs of an institution are designed to result in differential outcomes by race. Typical examples of this are redlining, Jim Crow, and police racial profiling laws. Second, structural racism refers to institutions (and the interactions between them), causing differential outcomes by race without explicit intent. A salient example of this is the racial differences in COVID-19 mortality. Numerous studies have found that people of colour are disproportionately dying of COVID-19 and that this disparity is a direct result of structural racism (Egede and Walker, 2020; Garcia et al., 2021; Khazanchi et al., 2020). For example, because of segregation and historic oppression, low-income Black Americans tend to live in poor urban centres where homes are very close together and illnesses spread quickly (Yang et al., 2021). In contrast, low-income white Americans tend to live in rural areas where there is less opportunity for virus transmission (Price-Haywood et al., 2020).

My results raise the question: to what degree are these disparities explained by consumer behaviour, and what portion can be attributable to imperfect information and hosts not fully accounting for demand? For Asian and Hispanic Airbnb hosts (who see both a negative price and quantity effect), the answer is relatively clear. While the market for Airbnb rentals is clearly not perfectly competitive, I assume that hosts select initial prices based on the prices of similar properties and adjust their prices over time in response to demand. Thus, the observed price and quantity for a given property should take into account the demand for properties with the same attributes. If hosts continually update prices until they reach equilibrium, and if at equilibrium, properties owned by people of colour have a lower price and quantity than equivalent properties owned by white people, then consumers' demand for properties managed by people of colour is necessarily lower than demand for identical properties managed by white hosts.

If hosts of colour were more likely to undervalue their property and choose a price below the equilibrium (a hypothesis consistent with internalized racism), then assuming demand is equal for identical properties owned by white and by Hispanic or Asian hosts, the quantity effect would be positive for hosts of colour. Because we see both negative price and quantity effects, this indicates that demand for units owned by Hispanic and Asian hosts is below demand for otherwise identical properties managed by white hosts. This implies that interpersonal racism is occurring.

In contrast, if hosts select a price which they never update in response to demand, and people of colour choose higher prices than those that white hosts charge for an identical unit, then a simple supply and demand framework implies that the quantity demanded for a unit owned by a person of colour will be lower than the quantity demanded for a unit owned by a white host. Thus, for Black hosts, for whom the price effect is positive and the quantity effect is negative, we cannot infer whether or not they face the same demand curve as white hosts for identical properties.

However, Black hosts charging more per night and having fewer booked nights may be consistent with separate supply schedules among Black and white hosts. Assuming they face the same demand curve, supply of properties owned by Black hosts must be lower than supply of otherwise identical properties owned by white hosts. This result cannot address whether Black Airbnb hosts face interpersonal discrimination, and separate supply schedules are not necessarily indicative of systemic racism. On the other hand, the negative coefficients from the price regression without location fixed effects may be indicative of structural racism. Black hosts disproportionately being located in low-price (and thus less desirable) neighbourhoods and zip codes is likely to be a result of historic segregation, which continues to oppress even the most economically successful Black Americans.

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Appendix A

Table A1: List of Included Cities by Region

Region 1: Northeast	**Region 2: Midwest**	**Region 3: West**	**Region 4: South**
Boston, MA	Chicago, IL	Denver, CO	Asheville, NC
New York City, NY	Columbus, OH	Los Angeles, CA	Austin, TX
	Twin Cities, MN	Portland, OR	Nashville, TN
		Seattle, WA	New Orleans, LA
			Washington, DC

Table A2: Racial Composition by City

	Mean	Std. Dev.	Max
AUSTIN, TX			
Black	0.033	0.049	0.914
Hispanic	0.063	0.147	0.960
White	0.852	0.192	1
Native American	0.002	0.003	0.094
Asian	0.048	0.109	1
More than one race	0.001	0.002	0.059
BOSTON, MA			
Black	0.033	0.048	0.879
Hispanic	0.082	0.176	0.969
White	0.808	0.238	1
Native American	0.002	0.003	0.065
Asian	0.074	0.165	1
More than one race	0.001	0.003	0.030
CHICAGO, IL			
Black	0.036	0.056	0.914
Hispanic	0.086	0.177	0.948
White	0.812	0.224	1
Native American	0.002	0.003	0.042
Asian	0.063	0.133	1
More than one race	0.002	0.003	0.042
DENVER, CO			
Black	0.030	0.041	0.890
Hispanic	0.054	0.130	0.972
White	0.873	0.161	1
Native American	0.001	0.002	0.057
Asian	0.040	0.072	1
More than one race	0.001	0.002	0.045
LOS ANGELES, CA			
Black	0.040	0.061	0.914
Hispanic	0.090	0.183	1
White	0.797	0.238	1
Native American	0.002	0.003	0.094
Asian	0.070	0.152	1
More than one race	0.002	0.003	0.059
NASHVILLE, TN			
Black	0.034	0.059	0.914
Hispanic	0.043	0.098	0.945
White	0.881	0.148	1
Native American	0.002	0.003	0.094
Asian	0.039	0.081	1
More than one race	0.002	0.002	0.033

	Mean	Std. Dev.	Max
NEW YORK, NY			
Black	0.041	0.065	1
Hispanic	0.103	0.198	0.987
White	0.788	0.243	1
Native American	0.002	0.003	0.094
Asian	0.065	0.139	1
More than one race	0.002	0.003	0.091
NEW ORLEANS, LA			
Black	0.046	0.066	0.890
Hispanic	0.055	0.126	0.942
White	0.856	0.169	1
Native American	0.002	0.003	0.057
Asian	0.040	0.076	0.989
More than one race	0.002	0.002	0.045
PORTLAND, OR			
Black	0.031	0.044	0.621
Hispanic	0.046	0.105	0.934
White	0.871	0.161	1
Native American	0.001	0.003	0.094
Asian	0.048	0.106	1
More than one race	0.002	0.002	0.032
SEATTLE, WA			
Black	0.033	0.048	0.759
Hispanic	0.063	0.138	0.945
White	0.834	0.214	1
Native American	0.002	0.003	0.094
Asian	0.068	0.161	1
More than one race	0.002	0.003	0.059
TWIN CITIES, MN			
Black	0.031	0.047	0.914
Hispanic	0.043	0.100	0.969
White	0.876	0.158	1
Native American	0.002	0.002	0.060
Asian	0.047	0.107	1
More than one race	0.002	0.002	0.032
WASHINGTON, DC			
Black	0.039	0.065	1
Hispanic	0.070	0.156	0.974
White	0.831	0.207	1
Native American	0.002	0.003	0.060
Asian	0.057	0.121	1
More than one race	0.002	0.003	0.045

Table A3: Output from Regression of Price by City - Northeast and Midwest

	NORTHEAST				MIDWEST			
VARIABLES	BOSTON, MA		NEW YORK, NY		CHICAGO, IL		TWIN CITIES, MN	
Black (and Male)	-0.379***	-0.547***	0.0232*	0.134***	0.531***	-0.0859	0.148	0.00571
	(0.0613)	(0.119)	(0.0124)	(0.0182)	(0.0552)	(0.0800)	(0.0972)	(0.153)
Hispanic (and Male)	0.0473**	0.00776	-0.0386***	-0.0327***	-0.000462	-0.0968***	-0.155***	-0.0754*
	(0.0195)	(0.0247)	(0.00436)	(0.00562)	(0.0149)	(0.0157)	(0.0364)	(0.0451)
Asian, Native Hawaiian, or	-0.0243	-0.0504*	-0.0313***	-0.0343***	-0.107***	-0.147***	0.102***	0.258***
Other Pacific Islander (and Male)	(0.0208)	(0.0304)	(0.00650)	(0.0102)	(0.0208)	(0.0328)	(0.0342)	(0.0682)
American Indian or	-6.910***	-12.75***	-1.380***	-2.042***	-4.873***	-3.384***	3.335	2.167
Alaska Native (and Male)	(1.102)	(1.282)	(0.249)	(0.450)	(0.844)	(1.122)	(2.717)	(2.677)
More than one race or	3.545***	6.434***	2.205***	4.083***	19.28***	17.01***	1.055	3.697
ethnic group (and Male)	(1.231)	(1.703)	(0.280)	(0.505)	(1.517)	(1.738)	(1.946)	(3.665)
Female (and White)		-0.0525***		0.000182		-0.128***		0.000337
		(0.00978)		(0.00294)		(0.00839)		(0.0154)
Female and Black		-0.281***		-0.0704***		0.762***		0.298**
		(0.0741)		(0.0163)		(0.0736)		(0.131)
Female and Hispanic		0.0539**		-0.0461***		0.00641		-0.287***
		(0.0272)		(0.00659)		(0.0272)		(0.0614)
Female and Asian, Native Hawaiian,		-0.0778**		-0.0280***		-0.239***		-0.159**
or Other Pacific Islander		(0.0348)		(0.0105)		(0.0291)		(0.0729)
Female and American Indian		-4.952**		0.0824		-7.920***		3.949
or Alaska Native		(1.981)		(0.317)		(1.279)		(4.832)
Female and more than one race		1.450		1.316***		20.95***		2.463
or ethnic group		(1.928)		(0.347)		(2.498)		(2.546)
Constant	4.079***	4.137***	4.266***	4.302***	4.247***	4.270***	3.912***	3.898***
	(0.0714)	(0.0723)	(0.0570)	(0.0571)	(0.135)	(0.134)	(0.274)	(0.276)
Observations	18,965	18,954	147,040	146,863	36,220	36,213	18,134	18,133
R-squared	0.715	0.716	0.752	0.752	0.656	0.659	0.680	0.680

Table A4: Output from Regression of Price by City - West

	WEST							
VARIABLES	**DENVER, CO**		**LOS ANGELES, CA**		**PORTLAND, OR**		**SEATTLE, WA**	
Black (and Male)	-0.357	-0.333	0.0641***	0.231***	-0.139***	-0.492***	-0.215*	0.0863
	(0.220)	(0.355)	(0.0147)	(0.0225)	(0.0517)	(0.0905)	(0.111)	(0.166)
Hispanic (and Male)	0.0514	0.0618	-0.0366***	-0.0219***	0.0105	0.000147	-0.226***	-0.371***
	(0.103)	(0.128)	(0.00449)	(0.00580)	(0.0207)	(0.0318)	(0.0530)	(0.0740)
Asian, Native Hawaiian, or	0.108	0.340	-0.0796***	-0.0792***	-0.0270	-0.0930***	-0.00740	0.116**
Other Pacific Islander (and Male)	(0.148)	(0.281)	(0.00591)	(0.00946)	(0.0169)	(0.0246)	(0.0350)	(0.0571)
American Indian or	-6.905*	-12.77*	1.430***	2.806***	-0.484	-6.221***	0.536	-5.646*
Alaska Native (and Male)	(4.101)	(7.526)	(0.279)	(0.475)	(0.676)	(1.461)	(1.884)	(3.164)
More than one race or	-4.930	-17.60***	-1.585***	-4.434***	4.280***	8.620***	-1.192	-8.304**
ethnic group (and Male)	(3.524)	(5.736)	(0.276)	(0.621)	(0.932)	(1.626)	(1.649)	(4.096)
Female (and White)		-0.0335		0.000276		-0.0628***		-0.0458**
		(0.0312)		(0.00290)		(0.00640)		(0.0184)
Female and Black		-0.361		-0.0475**		0.0712		-0.456***
		(0.312)		(0.0197)		(0.0619)		(0.144)
Female and Hispanic		-0.0336		-0.0669***		-0.0456*		-0.0752
		(0.216)		(0.00697)		(0.0274)		(0.0730)
Female and Asian, Native Hawaiian,		-0.214		-0.0666***		-0.0401		-0.196***
or Other Pacific Islander		(0.145)		(0.00907)		(0.0273)		(0.0551)
Female and American Indian		-1.874		0.599		1.276**		7.282**
or Alaska Native		(4.461)		(0.410)		(0.651)		(3.166)
Female and more than one race		1.089		-0.159		0.402		1.510
or ethnic group		(3.825)		(0.316)		(1.182)		(1.836)
Constant	3.497***	3.570***	4.109***	4.116***	3.857***	3.918***	3.422***	3.510***
	(0.293)	(0.289)	(0.0345)	(0.0343)	(0.0878)	(0.0909)	(0.181)	(0.180)
Observations	2,553	2,553	180,258	179,996	24,434	24,427	3,817	3,813
R-squared	0.610	0.611	0.794	0.794	0.656	0.658	0.712	0.715

Table A5: Output from Regression of Price by City - South

	SOUTH							
VARIABLES	AUSTIN, TX		NASHVILLE, TN		NEW ORLEANS, LA		WASHINGTON, DC	
Black (and Male)	-0.229***	-0.106	-0.0951**	-0.222***	0.0680**	0.210***	-0.00717	0.0407*
	(0.0783)	(0.172)	(0.0402)	(0.0456)	(0.0336)	(0.0597)	(0.0182)	(0.0229)
Hispanic (and Male)	0.0551**	0.0369	-0.0772***	0.00358	-0.0234	-0.0850***	-0.121***	-0.0631***
	(0.0265)	(0.0401)	(0.0249)	(0.0335)	(0.0161)	(0.0205)	(0.00939)	(0.0110)
Asian, Native Hawaiian, or	-0.222***	-0.241***	0.117***	0.166***	-0.0869**	-0.0454	0.0342***	0.0274**
Other Pacific Islander (and Male)	(0.0370)	(0.0626)	(0.0259)	(0.0430)	(0.0364)	(0.0866)	(0.0107)	(0.0136)
American Indian or	6.070***	0.145	9.700***	3.508***	-0.140	2.031	-0.728*	0.808
Alaska Native (and Male)	(1.591)	(2.775)	(0.803)	(1.165)	(0.640)	(1.760)	(0.414)	(0.556)
More than one race or	5.322***	11.50***	-7.340***	-11.22***	-1.024	-3.390	-3.880***	-2.493***
ethnic group (and Male)	(1.573)	(2.428)	(0.916)	(1.727)	(1.081)	(2.170)	(0.452)	(0.568)
Female (and White)		-0.00497		0.00520		-0.0549***		0.00464
		(0.0123)		(0.00702)		(0.00742)		(0.00412)
Female and Black		-0.274***		0.00539		-0.0939**		-0.0781**
		(0.0862)		(0.0698)		(0.0366)		(0.0310)
Female and Hispanic		0.0713**		-0.211***		0.0118		-0.196***
		(0.0355)		(0.0363)		(0.0287)		(0.0160)
Female and Asian, Native Hawaiian,		-0.214***		0.116***		-0.209***		0.0251
or Other Pacific Islander		(0.0630)		(0.0396)		(0.0418)		(0.0240)
Female and American Indian		8.533***		14.96***		-0.0691		-2.005***
or Alaska Native		(2.290)		(1.294)		(0.722)		(0.680)
Female and more than one race		0.903		-5.597***		1.778		-4.314***
or ethnic group		(2.197)		(1.125)		(1.243)		(0.673)
Constant	3.554***	3.551***	3.925***	3.982***	4.232***	4.217***	4.885***	4.896***
	(0.400)	(0.399)	(0.147)	(0.150)	(0.111)	(0.110)	(0.0500)	(0.0498)
Observations	15,026	15,018	34,402	34,396	37,761	37,761	66,090	66,038
R-squared	0.731	0.731	0.654	0.655	0.661	0.663	0.710	0.710

Table A6: Output from Regression of Percent of Month Booked by City - Northeast and Midwest

	NORTHEAST				MIDWEST			
VARIABLES	BOSTON, MA		NEW YORK, NY		CHICAGO, IL		TWIN CITIES, MN	
Black (and Male)	0.0518	0.0280	-0.0709***	-0.0605**	-0.0755**	-0.0526	-0.0212	-0.0105
	(0.0496)	(0.0785)	(0.0194)	(0.0300)	(0.0324)	(0.0638)	(0.0648)	(0.109)
Hispanic (and Male)	-0.133***	-0.135***	-0.0104*	-0.00533	-0.0638***	-0.0234*	0.0255	0.0625**
	(0.0145)	(0.0176)	(0.00570)	(0.00740)	(0.0104)	(0.0137)	(0.0234)	(0.0268)
Asian, Native Hawaiian, or	0.100***	0.0728***	-0.0223***	-0.0297**	0.0232*	0.0510***	0.0385**	0.0824***
Other Pacific Islander (and Male)	(0.0151)	(0.0234)	(0.00800)	(0.0132)	(0.0134)	(0.0182)	(0.0195)	(0.0300)
American Indian or	-0.122	-0.202	-0.191	-0.818	-0.558	0.378	-3.953***	-7.101***
Alaska Native (and Male)	(0.723)	(1.009)	(0.383)	(0.666)	(0.591)	(0.761)	(1.033)	(1.650)
More than one race or	-0.718	0.690	0.0774	-1.148	-0.928	2.471**	1.582	6.274**
ethnic group (and Male)	(1.139)	(1.403)	(0.391)	(0.757)	(0.785)	(1.171)	(1.220)	(2.611)
Female (and White)		-0.0297***		0.00948**		0.0259***		0.0149*
		(0.00807)		(0.00376)		(0.00556)		(0.00825)
Female and Black		0.130**		-0.0795***		-0.00920		-0.0234
		(0.0647)		(0.0263)		(0.0373)		(0.0848)
Female and Hispanic		-0.174***		-0.00680		-0.0870***		-0.0204
		(0.0250)		(0.00860)		(0.0158)		(0.0438)
Female and Asian, Native Hawaiian,		0.0903***		-0.0144		-0.0418		-0.0101
or Other Pacific Islander		(0.0270)		(0.0128)		(0.0287)		(0.0469)
Female and American Indian		-2.521*		0.104		-2.926***		-1.551
or Alaska Native		(1.465)		(0.538)		(1.036)		(1.496)
Female and more than one race		-1.497		0.710		-4.349***		-0.0176
or ethnic group		(1.904)		(0.473)		(1.098)		(1.606)
Constant	0.367***	0.386***	0.771***	0.755***	0.531***	0.522***	0.801***	0.795***
	(0.0818)	(0.0807)	(0.0460)	(0.0466)	(0.106)	(0.106)	(0.0942)	(0.0949)
Observations	18,488	18,478	47,713	47,638	35,149	35,142	17,764	17,763
R-squared	0.222	0.224	0.213	0.214	0.184	0.186	0.298	0.298

Table A7: Output from Regression of Percent of Month Booked by City - West

	WEST							
VARIABLES	**DENVER, CO**		**LOS ANGELES, CA**		**PORTLAND, OR**		**SEATTLE, WA**	
Black (and Male)	0.178	0.150	0.0154	0.0176	0.0849*	0.0328	0.0649	-0.0874
	(0.158)	(0.243)	(0.0404)	(0.0631)	(0.0478)	(0.101)	(0.0899)	(0.154)
Hispanic (and Male)	-0.0441	-0.0381	-0.0199	-0.00848	-0.0399*	-0.0415	0.0403	0.123***
	(0.0535)	(0.0665)	(0.0134)	(0.0168)	(0.0215)	(0.0306)	(0.0342)	(0.0401)
Asian, Native Hawaiian, or	0.00133	0.144	-0.0110	-0.0440	0.0365**	-0.00361	-0.0133	-0.0163
Other Pacific Islander (and Male)	(0.104)	(0.161)	(0.0178)	(0.0272)	(0.0165)	(0.0236)	(0.0272)	(0.0342)
American Indian or	4.452*	8.219	-0.980	-2.570	-0.513	0.233	-0.450	1.468
Alaska Native (and Male)	(2.657)	(5.513)	(0.954)	(1.675)	(0.549)	(1.375)	(1.602)	(2.062)
More than one race or	3.019	-5.724	1.867**	1.160	-1.171	1.120	-0.610	-3.482
ethnic group (and Male)	(2.772)	(6.019)	(0.750)	(1.536)	(0.745)	(1.285)	(1.725)	(3.158)
Female (and White)		-0.00856		-0.00689		-0.000666		-0.0115
		(0.0215)		(0.00768)		(0.00621)		(0.0141)
Female and Black		0.195		-0.000716		0.117**		0.200*
		(0.236)		(0.0539)		(0.0550)		(0.118)
Female and Hispanic		-0.0712		-0.0514**		-0.0427		-0.0949*
		(0.0938)		(0.0224)		(0.0315)		(0.0570)
Female and Asian, Native Hawaiian,		-0.139		0.0216		0.0948***		-0.0243
or Other Pacific Islander		(0.158)		(0.0298)		(0.0315)		(0.0515)
Female and American Indian		3.933		0.337		-0.836		-3.193
or Alaska Native		(3.573)		(1.329)		(0.616)		(2.548)
Female and more than one race		7.182**		2.331***		-2.791***		0.550
or ethnic group		(2.840)		(0.886)		(1.017)		(2.182)
Constant	0.447*	0.491*	0.690***	0.685***	0.427***	0.425***	0.769***	0.740***
	(0.244)	(0.255)	(0.112)	(0.112)	(0.123)	(0.123)	(0.156)	(0.153)
Observations	2,524	2,524	21,806	21,768	23,832	23,825	3,783	3,779
R-squared	0.122	0.124	0.195	0.196	0.247	0.248	0.108	0.112

Table A8: Output from Regression of Percent of Month Booked by City - South

	SOUTH							
VARIABLES	AUSTIN, TX		NASHVILLE, TN		NEW ORLEANS, LA		WASHINGTON, DC	
Black (and Male)	-0.0954	-0.157	-0.117***	-0.155***	-0.0449*	0.000568	-0.0382*	-0.00625
	(0.0598)	(0.114)	(0.0289)	(0.0405)	(0.0256)	(0.0389)	(0.0200)	(0.0246)
Hispanic (and Male)	0.000800	0.0121	-0.0739***	0.0358	0.000258	-0.0180	-0.0154**	-0.0495***
	(0.0170)	(0.0239)	(0.0168)	(0.0226)	(0.0130)	(0.0161)	(0.00770)	(0.0102)
Asian, Native Hawaiian, or	0.0279	-0.0187	0.0625***	-0.0365	-0.0903***	0.00349	-0.0545***	-0.112***
Other Pacific Islander (and Male)	(0.0237)	(0.0387)	(0.0211)	(0.0298)	(0.0245)	(0.0389)	(0.00953)	(0.0131)
American Indian or	0.663	-4.059**	0.649	1.996*	-0.800	1.208	0.497	-0.00173
Alaska Native (and Male)	(0.759)	(1.801)	(0.653)	(1.033)	(0.524)	(1.167)	(0.344)	(0.444)
More than one race or	1.161	1.242	-5.959***	-1.939	0.156	-4.489***	1.778***	3.629***
ethnic group (and Male)	(1.061)	(1.827)	(0.728)	(1.240)	(0.820)	(1.370)	(0.375)	(0.528)
Female (and White)		0.0178**		0.00928*		0.0122**		0.000216
		(0.00787)		(0.00526)		(0.00555)		(0.00364)
Female and Black		-0.115		-0.0404		-0.0933***		-0.0930***
		(0.0711)		(0.0422)		(0.0352)		(0.0360)
Female and Hispanic		-0.000467		-0.225***		0.0457*		0.0338***
		(0.0252)		(0.0255)		(0.0235)		(0.0114)
Female and Asian, Native Hawaiian,		0.121***		0.194***		-0.135***		0.0301*
or Other Pacific Islander		(0.0353)		(0.0372)		(0.0369)		(0.0173)
Female and American Indian		2.828***		-0.144		-1.117*		0.953*
or Alaska Native		(0.739)		(0.866)		(0.602)		(0.563)
Female and more than one race		1.059		-8.803***		2.748**		0.252
or ethnic group		(1.416)		(0.905)		(1.101)		(0.552)
Constant	0.613***	0.591***	0.290***	0.313***	0.399***	0.392***	0.458***	0.465***
	(0.168)	(0.167)	(0.100)	(0.101)	(0.0842)	(0.0839)	(0.103)	(0.103)
Observations	14,642	14,636	33,429	33,425	36,963	36,963	64,544	64,494
R-squared	0.208	0.211	0.265	0.266	0.230	0.231	0.193	0.194

Appendix B

Figure 8: Densities of Propensity Scores – Black vs. White

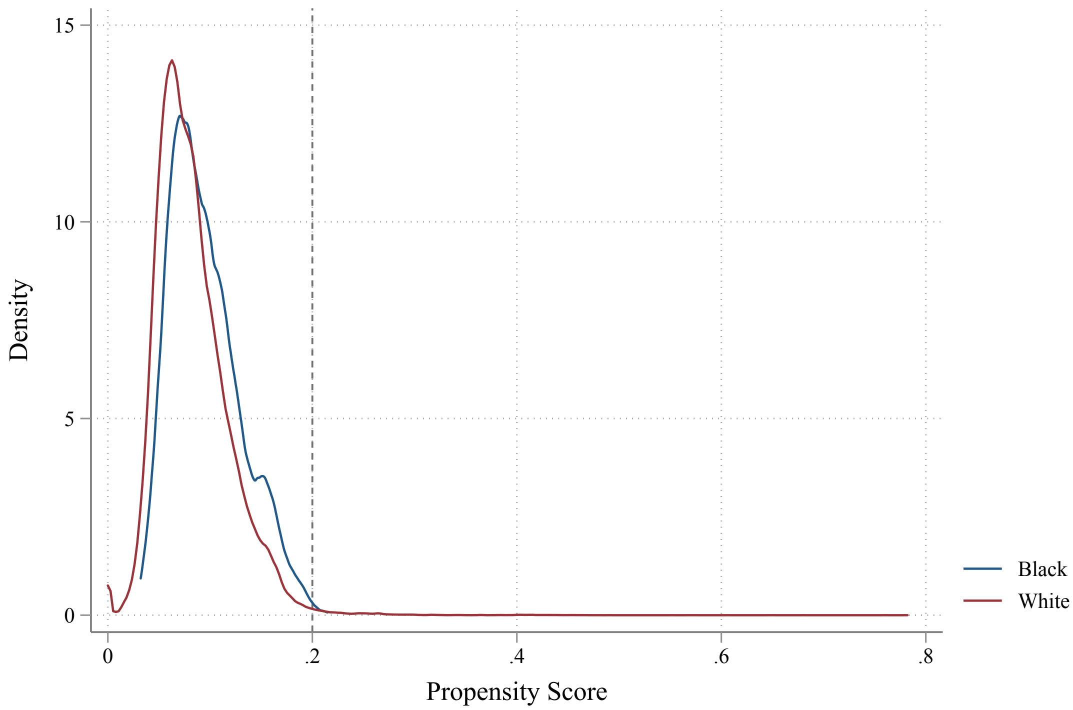

Figure 9: Densities of Propensity Scores – People of Colour vs. White

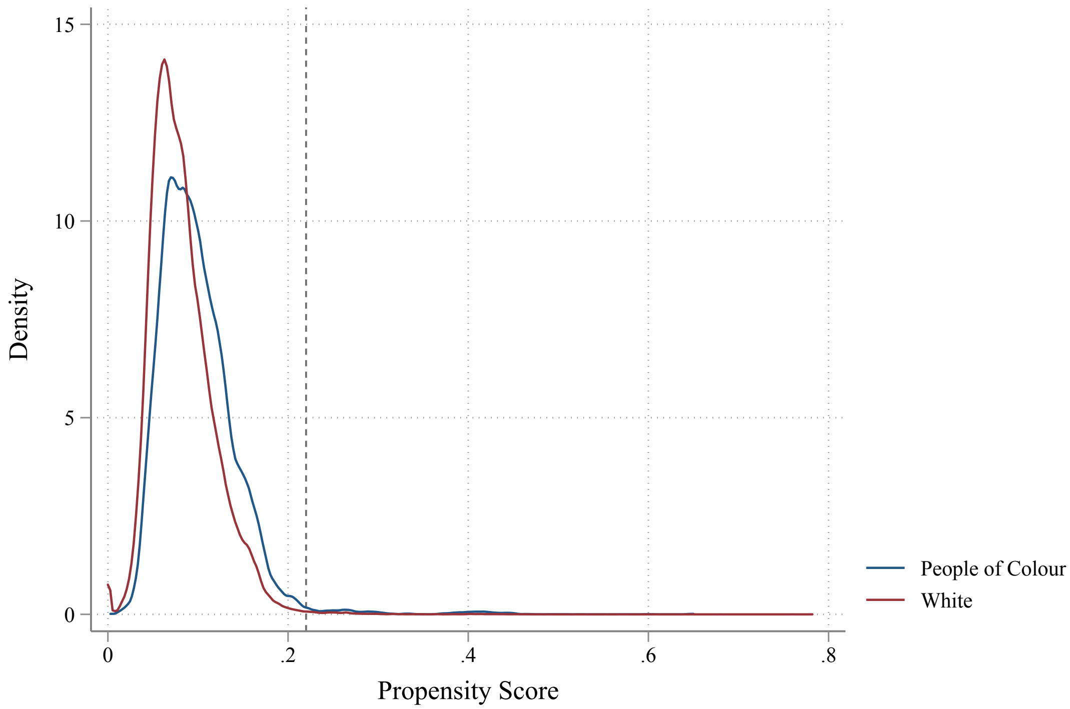

Figure 10: Densities of Propensity Scores – Women vs. Men

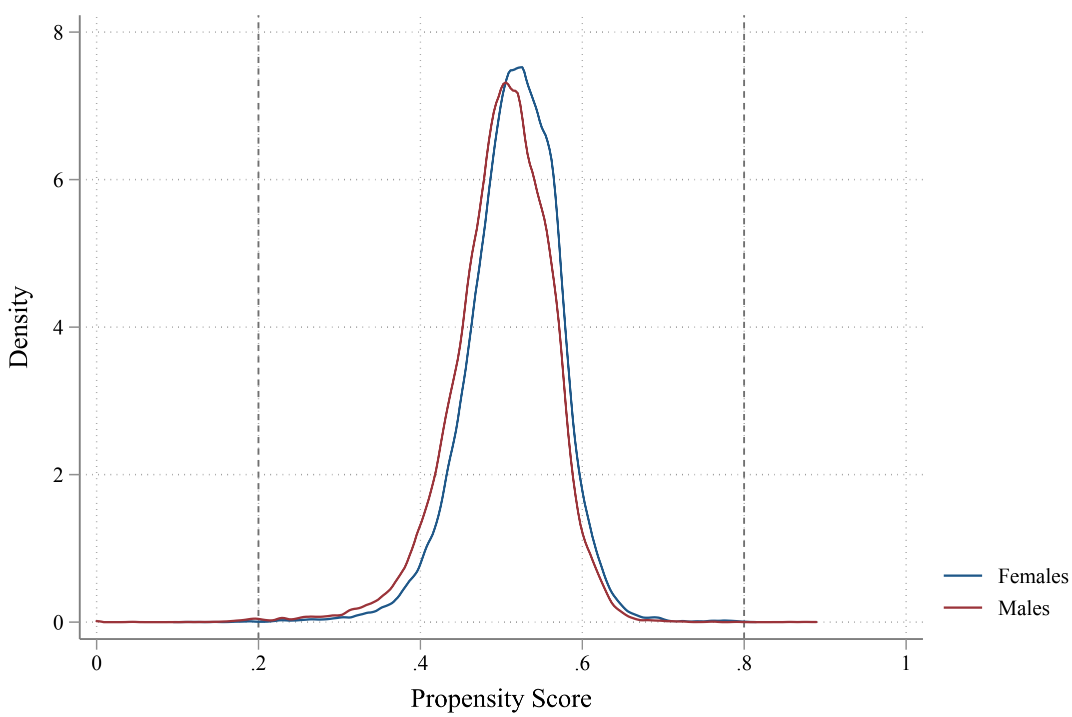

Figure 11: Densities of Propensity Scores – Women of Colour vs. Men of Colour and White Women

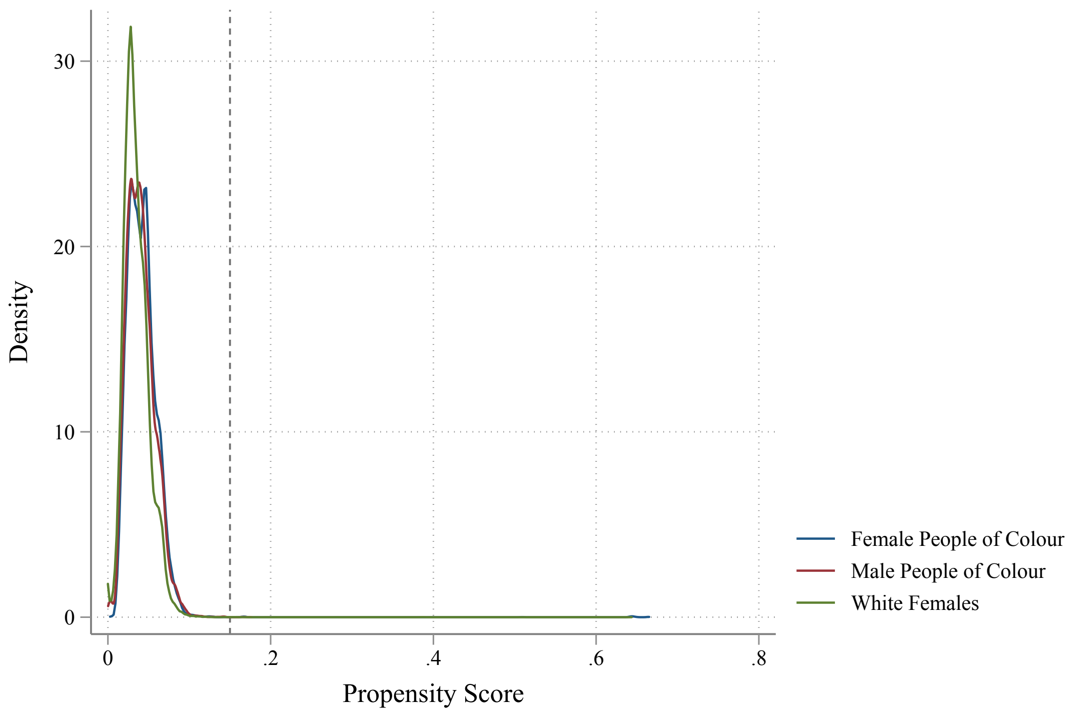

Figure 12: Densities of Propensity Scores – Black Women vs. Black Men and White Women

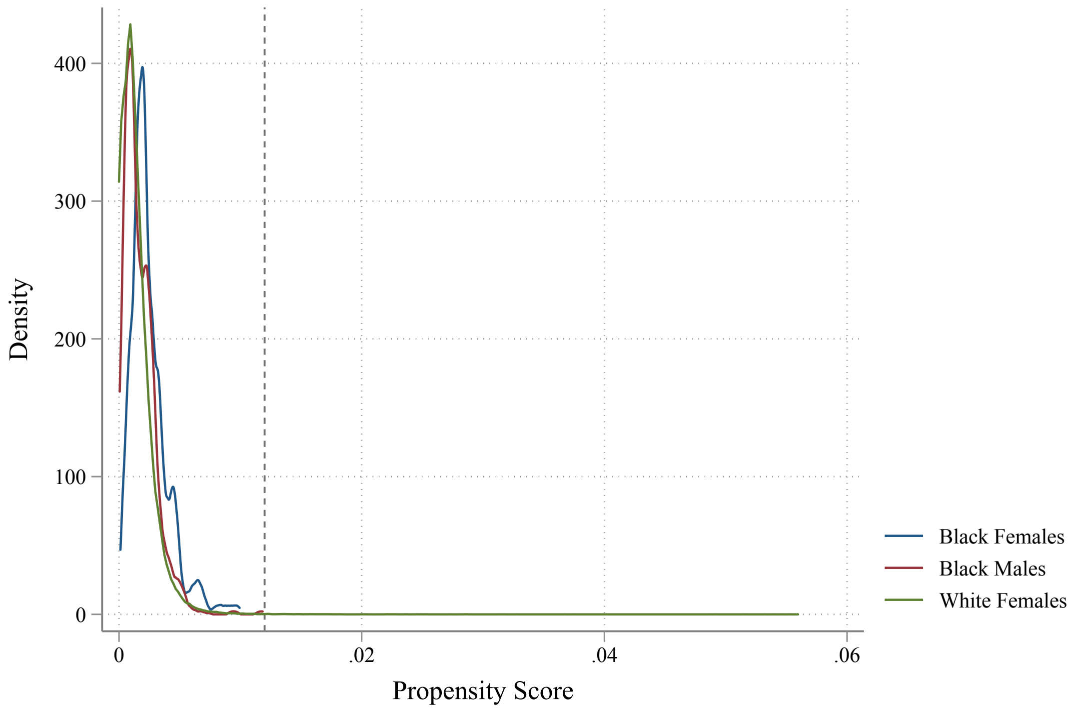

Figure 13: Densities of Propensity Scores – White Women vs. White Men