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Prevalence and Mechanisms of Discrimination: Evidence from the Ride-Hail and Taxi Industries

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Abstract

Ride-hail services, including Uber and Lyft, have upended the taxi industry, but it remains unclear whether ride-hailing, like taxis, discriminates against riders based on race. To understand whether and when discrimination manifests in for-hire vehicle services, I conducted an audit of Uber, Lyft, and taxis in Los Angeles. Discrimination against black taxi riders resulted in far higher rates of trip cancellation and longer wait times compared with white riders. By contrast, ride-hailing dramatically reduced differences between riders. Findings suggest that discrimination occurs when people learn of rider characteristics and yield implications for how planners can use technology to deter discrimination.

Keywords

equity, taxi, transportation network company, ride-hail

Introduction

For decades, at least in the United States, car ownership has been imperative to accessing opportunities outside of the oldest and largest city centers (Gurley and Bruce 2005). One of the primary ways that travelers could access a car if they did not own one was to hail a taxi. Despite taxis' critical role in urban mobility, journalists have repeatedly found that taxis discriminate against black riders (Belcher and Brown 2015; Wrigley 2013). In 2012, ride-hailing services such as Uber and Lyft upended the taxi business model by connecting drivers and passengers through smartphone applications. Ride-hailing may represent a new chapter in car access, but it could also represent a new chapter of discrimination in for-hire vehicle services. No research has yet contrasted discrimination in phone-dispatched taxis versus ride-hail services. Findings from this paper, while specific to Los Angeles, yield profound implications for equitable access to opportunities and may dictate policy imperatives. In addition, different ride-hail and taxi hailing methods offer insights into the moment in which people discriminate.

This research examines the prevalence and mechanisms of ride-hail and taxi discrimination and equity in Los Angeles, the second largest American city and one of the earliest ride-hail markets. Specifically, I ask and answer two related questions: first, is there evidence of service discrimination—manifested in longer wait times and higher rates of canceled ride requests—by rider race, ethnicity, or gender on ride-hail and taxi services? And second, can different hailing platforms yield insights into when discrimination occurs? I answer these questions using an audit study of ride-hail and taxi services in Los Angeles. Findings yield implications for how planners and policymakers can use new technologies to deter discrimination and achieve equitable service for all travelers.

Literature Review

Access without Ownership

Car ownership in the United States is a dominant factor in personal mobility and has been causally linked with positive economic outcomes such as finding work (Sandoval, Cervero, and Landis 2011), being employed (Gurley and Bruce 2005), and earning higher wages (Raphael and Rice 2002). The need for at least occasional car access among carless Americans is evident in the bimodal income distribution of taxi users. As of 2009, households earning under $25,000 per year, who are disproportionately carless, made 17 percent of all trips, but 41 percent of all taxi trips (Schaller 2015). Although taxis have provided lifeline car access for decades, they are frequently unreliable (San Francisco Municipal Transportation Agency 2013) and have a documented history

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of discriminating against black riders (Belcher and Brown 2015; Wrigley 2013).

While taxis dominated the for-hire vehicle industry for decades, ride-hail companies—also known as transportation network companies (TNCs) or ridesourcing—upended the taxi business model in 2012 by connecting drivers with riders through smartphone applications. The two largest companies, Uber and Lyft, provide more than seventy-six million rides per month in the United States (Hartmans 2016). Despite its meteoric growth, ride-hailing has unclear implications for equity. Previous studies of ride-hail users, for example, report varyingly that ride-hail users are disproportionately high-income (Conway, Salon, and King 2018), but also that users living in low-income neighborhoods take more trips per person than users living in middle-income and higher income neighborhoods even after controlling for built environment characteristics (Brown 2019). Studies examining the geographic equity of ride-hail services overall report positive gains in equitable access across space (Brown 2019; Hughes and MacKenzie 2016), but less attention to date has been paid to equitable access at the individual level. While individual-equity spans many dimensions, and people may be barred from ride-hail services for a variety of reasons ranging from technological limitations (Brown 2019) to ride-hailing not adequately serving travelers with disabilities (Crawford 2018), this research focuses specifically on driver to rider racial and gender discrimination. In this research, I seek to understand whether and how discrimination manifests in ride-hailing; how that compares with taxis, when discrimination occurs; and how policy- or service-level interventions can deter future discrimination.

Discrimination in For-Hire Vehicle Services

Despite legal prohibitions against discrimination, such as the Civil Rights Act of 1964, discrimination in the taxi industry is documented across the county. Taxis in Washington, D.C., are 25 percent less likely to pick up a black rider than a white rider (Wrigley 2013). In Chicago, about half (48%) of black residents report that a cab "would ignore them and continue driving by" compared with about one-quarter (23%) of white residents (Belcher and Brown 2015). Similarly, 60 percent of white riders in Seattle were picked up by the first empty taxi that approached, compared with just 20 percent of black riders (Ge et al. 2016), and one in five taxis at Los Angeles International Airport refused to transport two undercover black police officers (Nelson 2016).

Early studies suggest that discrimination may also exist in ride-hailing. A study of nearly one-thousand ride-hail trips in Boston found that Uber/Lyft users having "African American sounding" names were more than twice as likely to have a ride canceled (10%) compared with those with "white sounding" names (5%; Ge et al. 2016, 12). While researchers found no evidence of racially biased wait times in Boston, black riders in Seattle waited longer for a ride-hail trip request to be accepted compared with white riders (Ge et al. 2016). In addition to racial bias, gender bias may also influence ride-hail trip cancellations; researchers in Seattle found that men traveling in low-density areas were more likely than women to have trips canceled (Ge et al. 2016). Higher cancellations for male riders, particularly by women drivers, may be due to perceived or actual risks of assault.

While early studies of ride-hail discrimination are suggestive, research on this subject remains limited. No studies have yet compared the relative levels of bias between phone-dispatched taxis and ride-hailing, nor have studies to date considered racial/ethnic bias beyond a black/white dichotomy.

Types and Timing of Discrimination

In addition to quantifying the effects of discrimination, understanding why or when people discriminate may guide policies or practices to deter discrimination. What motivates people to discriminate? First, people may *directly discriminate*. In direct discrimination (also referred to as taste-based discrimination), personal characteristics (such as race) motivate a negative outcome (Murphy 2002). For example, if a realtor refuses to sell to black home-seekers because they are black, this is a form of direct discrimination. Second, people may *proxy* or *statistically discriminate*. Statistical discrimination occurs when one uses observable individual characteristics as proxies for unobserved measures that vary across racial, ethnic, gender, or other groups (Alexander 1992; Murphy 2002). For example, a higher share of young households may default on mortgages compared with older households. If a banker refused to lend to a young household because she used age (observable) as a proxy for the likelihood of default (unobservable), she is committing statistical or proxy discrimination. Statistical discrimination may occur consciously or unconsciously, and people may act on unconscious biases even when they "consciously and sincerely support egalitarian principles and believe themselves to be non-prejudiced" (Dovidio, Kawakami, and Gaertner 2000, 138).

Research from other fields suggests that discrimination may occur in both split-second and prolonged decisions, particularly against people of different races and black relative to white individuals (Payne 2006). Discriminatory actions based on split-second judgments are particularly pertinent to for-hire vehicles, where drivers may make quick decisions based on the names and/or pictures of riders. Because taxi and ride-hail services offer different hailing methods, they present an opportunity to uncover the moment of discrimination and motivate policies or practices to counter discriminatory actions.

Data and Method

To assess the prevalence and timing of discrimination, I conducted an audit study of Lyft, Uber, and taxis; in sum, 1,704 ride-hail and taxi trips were completed as part of this

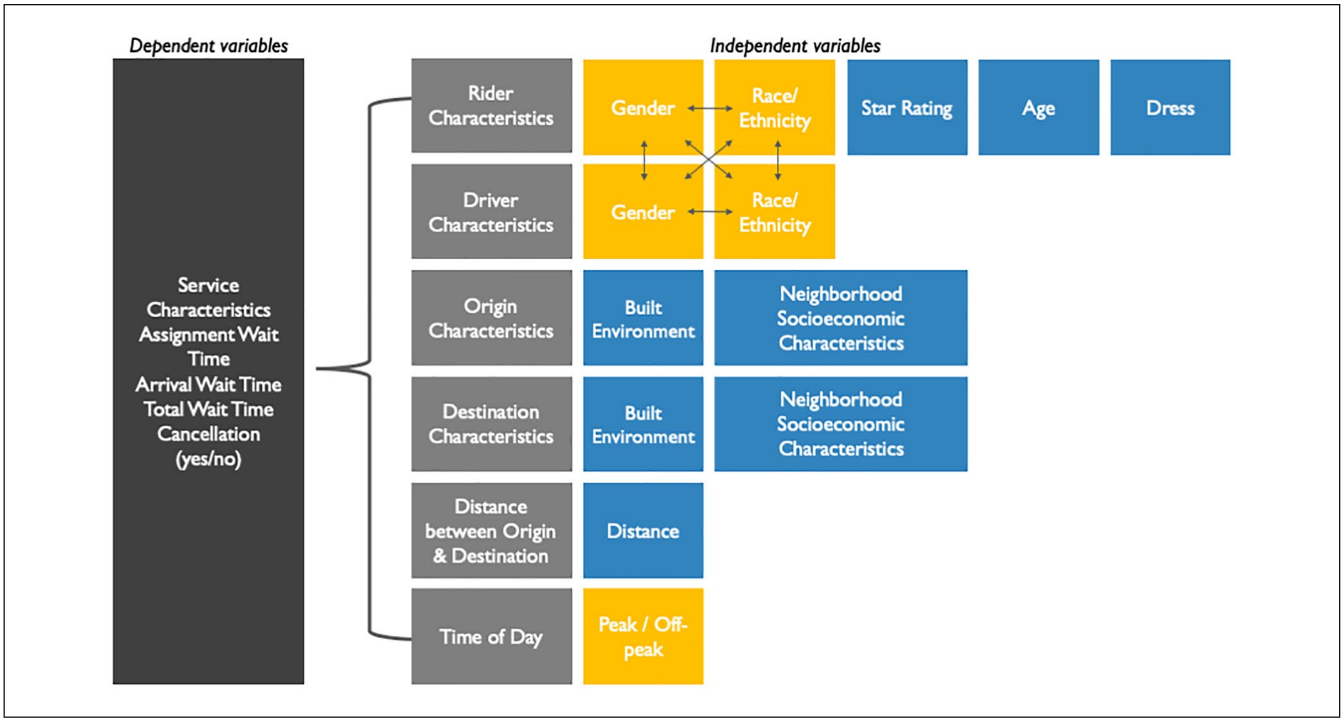

Figure 1. Conceptual model: Factors influencing ride-hail and taxi service.
Note: Arrows indicate interactions. Blue boxes indicate variables that are controlled for through study design. Gold boxes indicate variables of interest and variables controlled for statistically.

audit study. Audit studies are designed specifically to identify discrimination; in audits, people ("auditors") are sent into actual economic or social settings to measure how otherwise identical people are treated based on their gender, race, or ethnicity. Audits are the most prevalent field method for detecting discrimination and, outside of laboratories, offer the clearest evidence for how treatment varies by race (Bertrand and Mullainathan 2004; Yinger 2008). Audits are superior to surveys, which are prone to dishonest or inaccurate responses (Riach and Rich 2002), and are well established in economics (see Bertrand and Mullainathan 2004) and housing (see Edelman et al. 2017). Taxis, too, have been audited for decades (see, for example, Castillo et al. 2013; Ridley et al. 1989).

Discrimination may occur during three moments of interaction between the driver and passenger: (1) a rider hails a trip, (2) a driver accepts a trip, and (3) a driver approaches a rider. During each step, a driver either has or gains some knowledge about a rider's characteristics, which may affect driver actions and result in discriminatory service. The point at which a driver receives information about a rider—creating a new potential for discrimination—varies between Lyft, Uber, and taxis, which provides insight into the timing of discrimination. For example, at the time of a trip request, a Lyft driver sees a rider's name, pickup address, photo, star rating, and how many minutes they are from the driver. An Uber driver, by contrast, sees only a rider's star rating and the distance and time to reach the rider. Both Uber and Lyft drivers may choose to reject or accept a trip request, although both companies incentivize drivers to accept trips (Lyft 2017).

Conceptual Model

Driver actions toward a rider—specifically, the decisions to pass, cancel, or pick up a rider—are informed by driver perceptions of that rider's gender, age, dress, race/ethnicity, and (for Uber and Lyft) star ratings. Driver actions may be informed by the rider's location, destination, or time of day. The conceptual model depicted in Figure 1 shows how location, temporal, and rider characteristics combine to influence wait times and ride request cancellations. To isolate the variables of interest in this study—rider gender and race/ethnicity—I control for the other factors either statistically (in gold) or through study design (in blue). For example, I control statistically for peak period hails because rush hour congestion may slow driver arrival times.

Audit Locations

I limited audit locations to two Los Angeles neighborhoods to control for spatial variation in service quality observed in other studies (Ge et al. 2016; Hughes and MacKenzie 2016). Limiting observation geography effectively controls for proxy discrimination, in which people use observable neighborhood characteristics (such as its racial/ethnic makeup) as a proxy for unobservable characteristics (such as crime). In other words, if drivers discriminate against riders based on location, such discrimination should occur uniformly across riders hailing from the same locations and result in similar wait times and cancellation rates across riders.

The two audit sites each met three selection criteria: (1) proximity to the UCLA campus (accessible to student workers within about one hour on transit); (2) distance between sites (to minimize trip distance and therefore price); and (3) neighborhood built environment and socioeconomic characteristics. The first audit site is located in downtown Culver City, an independent city surrounded by the City of Los Angeles. The second site is located at the intersection of two Los Angeles neighborhoods, Baldwin Hills/Crenshaw and West Adams. Although only two miles apart, the two sites are remarkably—and intentionally—different. Site 1 has more than double the median household income of Site 2 ($111,000 vs. $53,000) and a majority of its residents are white, while Site 2 lies between neighborhoods that are majority black (Baldwin Hills/Crenshaw) and Hispanic (West Adams).

Although I do not test explicitly for service variation across space (i.e., do neighborhood characteristics predict wait times or cancellation rates), neighborhoods may themselves, or in conjunction with individual characteristics, affect service quality. Sites with divergent characteristics thus provide a test for how service might vary across space, which may inform future research.

Ride-Hail Companies

Lyft and Uber, the largest ride-hail companies in Los Angeles, each offer a variety of services including black car, shared, and extra-large vehicle services. This audit includes only trips made on UberX and Lyft, the unshared and most popular ride-hail option offered by the companies (Brown 2019). Unshared ride-hail services are also most parallel to dispatched taxis.

Taxi Services

Street-hails for taxi services are not permitted at either Site 1 or 2; therefore, I evaluate only phone-dispatched taxi services, which are more similar to Uber and Lyft compared with street-hail taxis.

Nine taxi franchises currently hold licenses to operate 2,361 taxis in the City of Los Angeles. The Los Angeles Department of Transportation (LADOT 2017, 7) assigns each company to primary service areas, where companies must maintain “acceptable service” to receive franchise extensions. Different taxi companies are permitted to pick up riders at Site 1 (City of Culver City) and Site 2 (City of Los Angeles). I audited the two largest taxi companies serving each location: Independent Cab Company and United Independent at Site 1 and LA Yellow Cab and United Independent at Site 2 (Culver City Finance Department 2017).[1] I analyzed taxis as a single service regardless of the company for three reasons. First, the dispatch process is identical across companies.[2] Second, because multiple taxi companies serve the same location, taxi service in an area is a sum of all service providers. And third, auditors reported that when a hailed taxi company had no available taxis, dispatchers referred them to a different company, creating relatively permeable service boundaries between taxi companies.

Riders

The auditors were eighteen riders recruited from the UCLA graduate and undergraduate student body. As discussed in the conceptual model, I expect discrimination to occur across five individual characteristics: star ratings, and driver perceptions of rider gender, age, race/ethnicity, and dress. To produce an unbiased estimate of discrimination across race/ethnicity and gender, I matched auditors across characteristics not tested in this research (age, star ratings, and dress; Murphy 2002). I recruited riders between twenty and thirty years old with ride-hail star ratings of 4.5 stars or higher.[3] To control for dress, riders were instructed to wear plain, nonflashy clothes, such as jeans and a plain t-shirt.

I recruited male and female riders across four racial/ethnic categories: Asian, black, Hispanic, and white. I analyze Asian and Hispanic riders within a single category as (1) people are poor judges of race or ethnicity, particularly if a person is of a different race or ethnicity (Gross 2009) and (2) no significant differences in wait times or cancellation rates existed between Asian and Hispanic riders. People primarily use facial features to identify others’ races and ethnicities (Zebrowitz, Montepare, and Lee 1993), but names may also provide signals and influence the treatment or service that people receive (Bertrand and Mullainathan 2004; Ge et al. 2016). In this study, riders were not recruited for names that signaled race or ethnicity, nor were they assigned aliases because both Uber’s and Lyft’s Terms and Conditions prohibit impersonation. Instead, mirroring reality, some riders had names often associated with a particular race/ethnicity, while others did not. For consistency, all riders uploaded new photos to Lyft depicting the rider’s face against a white backdrop (Uber does not share rider photos with drivers). Table 1 shows that, together, riders hailed 1,704 trips during nine weeks between October and December 2017.

Data Collection and Measurement

Riders collected data every day between 9:00 a.m. and 9:00 p.m. for nine weeks between October and December 2017. Riders did not collect data in the early mornings or late evenings due to budget constraints and concern for rider safety. In addition, no data were collected on Thanksgiving Day or the holiday weekend (November 23–26, 2017) as holidays may affect service levels and response times. Riders hailed

Table 1. Total Number of Trips by Rider Characteristics.

Rider	Lyft trips	Uber trips	Taxi trips	Total
Black	165	172	99	*436*
Female	70	72	39	*181*
Male	95	100	60	*255*
Asian/Hispanic	215	211	154	*580*
Female	107	100	81	*288*
Male	108	111	73	*292*
White	266	241	181	*688*
Female	83	81	56	*220*
Male	183	160	125	*468*
Total	646	624	434	1,704

rides to and from Sites 1 and 2, rotating between Lyft, Uber, and taxis. During each trip, riders recorded driver characteristics, wait times, whether a trip was canceled, and the reason for the cancellation.

Driver characteristics. Once in the car, riders observed driver characteristics. Auditors were trained to identify driver age, race, and ethnicity. Age was recorded as a decade measure (20–29, 30–39, etc.) as previous research finds that people typically judge age within six to seven years of actual age (Voelkle et al. 2012). Riders recorded race within four broad racial/ethnic categories: Asian, black, Hispanic, and white.

Wait times. Riders recorded three wait time variables: assignment, arrival, and total wait time. On Uber and Lyft, assignment wait time was the time that elapsed between pressing "Request" to hail a ride and when a driver was assigned to the trip. On taxis, riders recorded assignment wait time as the duration of the dispatcher phone call. On both ride-hail and taxis, riders recorded arrival wait time as the time passed between being assigned a driver and the moment when a driver pulled up to the rider. Total wait time is the sum of assignment plus arrival wait times, in other words the total time that elapsed between when a rider hailed a ride and the car arrived.

Reported taxi wait times should be interpreted as low estimates. Unlike Uber and Lyft, which had few repeat drivers across the entire study period, relatively few taxi drivers served each site, resulting in some drivers transporting multiple auditors between the same origins and destinations over the course of the study. Repeat taxi drivers expressed puzzlement over the repeated pick-ups and drop-offs or mentioned that they "just dropped someone off" at the same location. Although taxis did not know *why* repeated hails were made at the two locations—riders were explicitly trained not to tell drivers they were doing research—many taxi drivers came to anticipate the destination before a rider provided it to them. For example, one rider noted that the driver said he was going to "park . . . to wait for us since he has done a lot of this trip recently." With taxis anticipating business around the audit locations, wait times are likely artificially low.

Cancellations. Cancellations affect wait times and may signal discrimination. Riders experienced distinct types of cancellations, which I describe in turn. Uber and Lyft riders experienced two types of cancellations, both of which have been observed in previous research. Following Ge et al. (2016), riders recorded trips as *de facto* cancellations if, after twenty minutes, a driver made no attempt to contact them, no effort to pick them up, or drove in the opposite direction. Second, cancellations occurred when a driver "drops" or "cancels" on a rider, which places the rider back into the pool of unmatched riders from which they are assigned a new driver.

Taxi cancellations occurred in four ways: first, dispatchers refused to answer a call, which LADOT refers to as "Company Service Refusal"; second, dispatchers informed or later called a rider to say that no cabs were available; third, no taxi arrived within sixty minutes of assignment (no shows); or fourth, taxi drivers refused service to a passenger. Discrimination may occur in any of these cancellation scenarios at either the driver or the dispatcher level. In some cases, such as a taxi driver refusing to serve a passenger, the moment of discrimination is clear. In others, such as a "no show" taxi, the moment of discrimination could lie with either the dispatcher—by, for example, failing to relay a request to an available driver—or driver. Additional research is needed to determine the exact moment of discrimination in these more ambiguous circumstances.

Like wait times, reported taxi cancellations should be interpreted as low estimates. Learned behaviors appear to have reduced taxi no-show cancellation rates over the course of the study; no-show cancellations—when a taxi failed to arrive within sixty minutes of a hail—fell from 15 percent of taxi hails in October to about 6 percent in December (a significant difference, $p < .01$). Despite falling over time, Figure 2 shows that no-show cancellations remained the dominant cancellation type, comprising 59.5 percent of cancellations in the study period, and the plurality or majority of cancellation types each week.

Because drivers receive information about riders at different times, I am able to observe exactly when discrimination occurs. I hypothesize that the moment of discrimination occurs when a driver first learns rider information and sees or infers personal characteristics such as race, ethnicity, or gender. On taxis and Uber, discrimination would manifest as higher rates of cancellation for some rider groups; on Lyft, discrimination would yield longer assignment wait times for rider groups.

Methods

To estimate the association between rider characteristics and service outcomes (wait times and trip cancellations), I

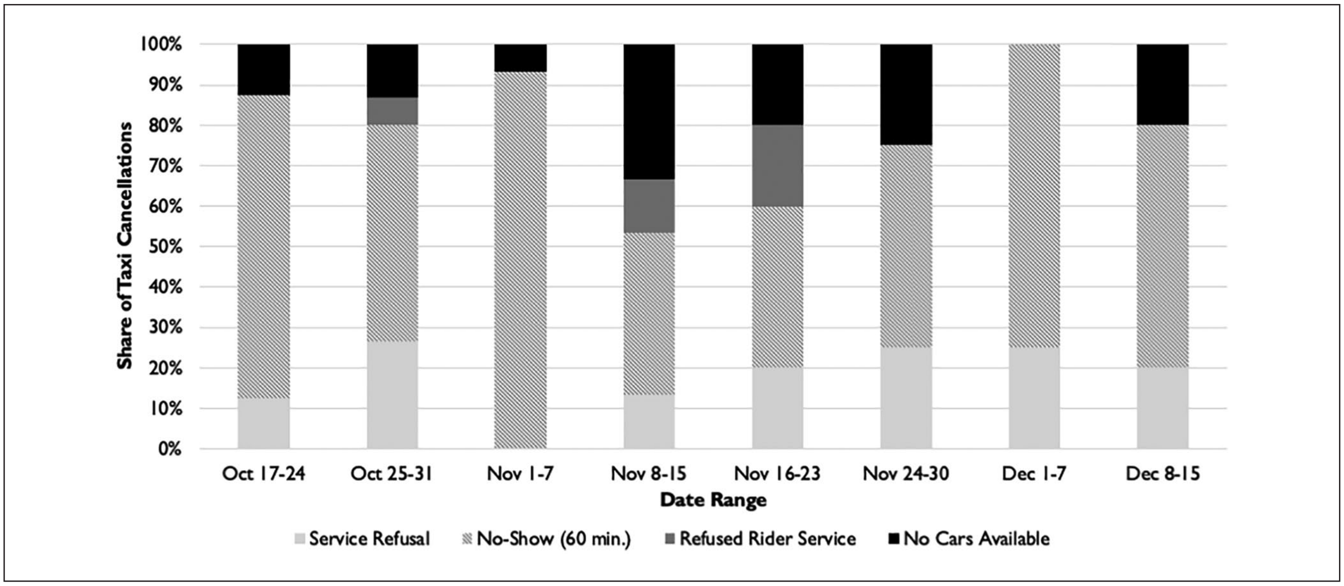

Figure 2. Share of taxi cancellations by type.

estimated three logistic regression models and nine linear regression models. For each dependent variable—trip cancellation, assignment time, arrival time, and total wait time—I specified three models, one for each Lyft, Uber, and taxis, to capture discrimination at different points in the trip hail process. Full model results are presented in Table 2; to more intuitively discuss the model results, I break results into focused discussions of the marginal effects that rider characteristics play in wait times and cancellation rates, holding other factors such as peak hour constant. I used the Stata *margins* command to estimate the predicted wait times and cancellation rates, including associated margins of error.

Previous research suggests that discrimination may occur at the intersection of gender and race (Assari and Caldwell 2017). However, in the final models presented here, I exclude the four-way interaction between driver and rider race, ethnicity, and gender presented in the conceptual model because the interaction was not statistically significant. In other words, interaction between driver and rider characteristics did not influence outcomes across riders; this conforms to previous research findings (Haider et al. 2011; Yinger 1986). The models presented here therefore include only interactions between rider gender and race/ethnicity.

While previous research observed spatial elements to service (Ge et al. 2016; Hughes and MacKenzie 2016), I find no differences in wait times or cancellations between ride-hail trips hailed at Sites 1 and 2. For taxis, however, wait times were significantly longer at Site 1 (Culver City) compared with Site 2 (Expo/La Brea) due to significantly ($p < .01$) longer average wait times on Independent Cab Company compared with the other evaluated taxi companies (thirty-two vs. twenty-one minutes). Due to these differences across taxi companies, I control for taxi company in all models.

Findings

Cancellations and wait times on ride-hail and taxi services reveal stark evidence for discrimination against black riders on taxis. Findings suggest that while ride-hailing does not eliminate discrimination against black riders, it dramatically narrows the gap between riders. Discrimination across services likewise reveals that drivers discriminate at the moment at which they learn of or infer rider characteristics.

Cancellations

Cancellations were far higher on taxis than on ride-hailing. Nearly 20 percent of taxi trips were canceled, most (11%) because a taxi did not arrive within one hour, but also because the dispatcher did not pick up the phone (3%), dispatchers reported that no cars were available (3%), the driver refused to transport the rider (1%), or other reasons (0.8%). By contrast, fewer than 4 percent of ride-hail trips were canceled. Cancellations yield different mobility outcomes across services. For Lyft and Uber, cancellations are associated with longer wait times; however, in 99.7 percent of "canceled" Uber and Lyft trips, riders still reached their destination. Cancelled taxi trips, however, resulted in riders never being picked up.

In addition to varying across services, rates of canceled trips varied by rider characteristics. Figure 3 shows the predicted probability that a trip is canceled based on a rider's race, ethnicity, or gender, controlling for peak-hour travel and taxi company; full model results are shown in Table 2. The starkest contrast in cancellations is between black and white taxi riders: black riders are 73 percent (or eleven percentage points) more likely to have a taxi driver cancel on

Table 2. Wait Times and Cancellation Model Results across Services and Rider Characteristics.

	Assignment wait times[a]			Arrival wait times[a]			Total wait times[a]			Trip canceled (Yes)[b]		
	Lyft	Uber	Taxi	Lyft	Uber	Taxi	Lyft	Uber	Taxi	Lyft	Uber	Taxi
Rider race (Baseline: White)												
Black	0.10*** (0.03)	0.14*** (0.05)	0.38* (0.22)	0.29 (0.36)	0.44 (0.43)	3.91* (2.25)	0.36 (0.38)	0.83* (0.44)	7.46*** (2.84)	0.38 (0.58)	1.55* (0.83)	0.59 (0.40)
Asian/Hispanic	−0.01 (0.03)	0.02 (0.05)	1.05*** (0.21)	0.27 (0.34)	−0.42 (0.41)	1.38 (2.05)	0.08 (0.36)	−0.32 (0.42)	1.93 (2.70)	−0.08 (0.64)	0.70 (1.00)	0.27 (0.40)
Rider women (Yes)	−0.01 (0.03)	−0.03 (0.05)	0.41* (0.22)	−0.00 (0.36)	0.37 (0.44)	−0.54 (2.12)	−0.11 (0.39)	0.41 (0.46)	−2.43 (2.86)	−1.18 (1.08)	0.69 (1.01)	−0.61 (0.54)
Black female	−0.07 (0.05)	−0.05 (0.08)	−0.60* (0.35)	1.37** (0.58)	0.16 (0.68)	7.17** (3.56)	1.35** (0.62)	−0.18 (0.70)	7.65* (4.59)	1.52 (1.26)	−0.70 (1.21)	0.50 (0.74)
Asian/Hispanic female	−0.08 (0.05)	0.00 (0.08)	−1.03*** (0.32)	0.23 (0.52)	0.51 (0.63)	1.72 (3.13)	0.31 (0.56)	0.43 (0.65)	3.85 (4.14)	1.78 (1.26)	−0.24 (1.28)	0.34 (0.70)
Taxi company (Baseline: United)												
LA Yellow Cab	—	—	−0.31* (0.16)	—	—	1.34 (1.60)	—	—	0.90 (2.12)	—	—	0.03 (0.34)
Independent	—	—	0.54*** (0.16)	—	—	9.67*** (1.65)	—	—	11.81*** (2.10)	—	—	0.45 (0.31)
Peak-hour trip (Yes)	0.01 (0.03)	0.10 (0.05)	−0.13 (0.20)	1.67*** (0.31)	1.31*** (0.37)	6.16*** (2.10)	1.77*** (0.33)	1.27*** (0.38)	9.07*** (2.59)	0.68 (0.44)	0.48 (0.54)	1.15*** (0.31)
Constant	0.48*** (0.02)	0.65*** (0.03)	1.21*** (0.16)	4.19*** (0.21)	4.93*** (0.26)	12.01*** (1.53)	4.90*** (0.23)	5.59*** (0.27)	16.37*** (2.04)	−3.33*** (0.40)	−4.44*** (0.72)	−1.98*** (0.33)

Note: $n = 646$ Lyft trips, 624 Uber trips, and 434 taxi trips. Peak-hour trips are those for which a rider is picked up on a weekday between 4:00 p.m. and 6:59 p.m. Robust standard errors are shown in parentheses.
[a]Linear regression.
[b]Logistic regression.
$^{*}p < .1$. $^{**}p < .05$. $^{***}p < .01$.

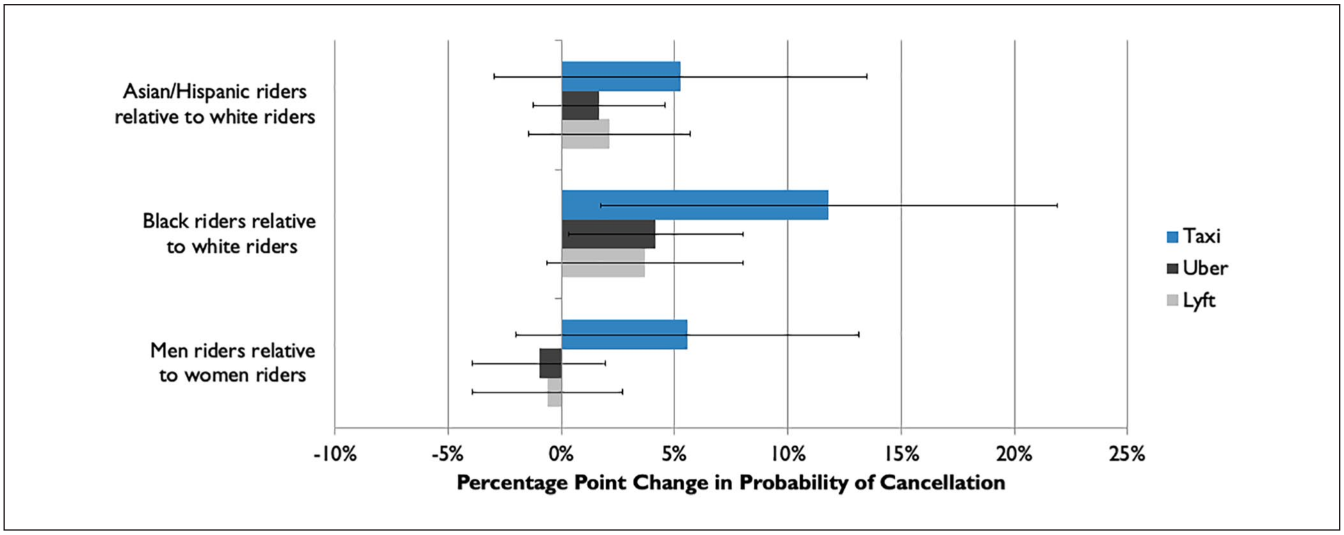

Figure 3. Percentage point change in probability of cancellation by rider characteristics.
Note: Error bars indicate 95% confidence intervals.

them compared with white riders; model predications reveal that more than one-quarter (26%) of black taxi hails are canceled compared with about 15 percent of trips hailed by white riders. Results suggest that discrimination against black riders has not lessened as early audit studies documented taxi discrimination in Washington, D.C., three decades ago (Ridley, Bayton, and Outtz 1989). On both Uber and Lyft, the difference in probability of a trip being canceled is just four percentage points higher for black compared with white riders, although the differences are not statistically significant on Lyft.

Only black riders experience significantly higher cancellation rates after controlling for time of day and taxi company; no meaningful differences exist between Asian, Hispanic, and white riders or between men and women on any service. Together, higher cancellation rates on Uber and taxis—on which a driver learns a rider's name only after being assigned to them—conform to expectations and suggest that the moment of discrimination occurs when a driver first learns of or infers rider characteristics.

Wait Time

Lyft and Uber provided consistently lower wait times compared with taxis. On average, Lyft and Uber riders waited 5.5 (95% confidence interval = [5.2, 5.6]) and 6.1 (95% confidence interval = [5.8, 6.3]) minutes, respectively, between ride request and driver arrival. Below, I discuss model results of the association between rider characteristics and three measures of wait time, controlling for time of day and taxi company. Table 2 presents full model results.

Assignment wait time. Figure 4 shows predicted assignment wait times by rider characteristics, controlling for peak periods and taxi company. Overall, differences in assignment wait times lend only moderate support to the hypothesis that discrimination occurs at the moment drivers learn of or infer rider characteristics. As hypothesized, black riders wait a longer time ($p < .01$) than white riders to be assigned to a Lyft driver, who view a rider's name and photo before accepting a trip request. Unexpectedly, however, black riders also wait longer to be assigned to an Uber driver ($p < .01$), and Asian and Hispanic riders wait longer for taxi dispatchers to confirm their hail requests ($p < .01$). How differences in Uber and taxi assignment times occur when all other factors are equal and drivers do not learn rider characteristics prior to trip acceptance is uncertain and requires additional investigation. No differences in assignment wait time exist between women and men on Uber or taxis, with men waiting just two seconds longer than women on Lyft, the differences are effectively zero. Assignment times contribute to total wait times, which are arguably the most important service quality to riders.

Arrival wait time. Controlling for rider characteristics, time of day, and taxi company, differences in arrival wait times are most strongly associated with time of day; drivers take between forty seconds and three minutes forty-one seconds longer to arrive during rush hour, all else equal, as drivers navigate through congested streets. Riders also waited longer for Independent Cab Company taxis to arrive, possibly because Independent Cab Company's smaller fleet—relative to United or LA Yellow Cab—means that fewer cars are available for dispatch or are farther away when called.

Waiting for a vehicle to arrive constitutes the bulk (86%) of total wait time; as a result, arrival time is closely correlated (0.99, $p < .01$) with total wait time. Associations

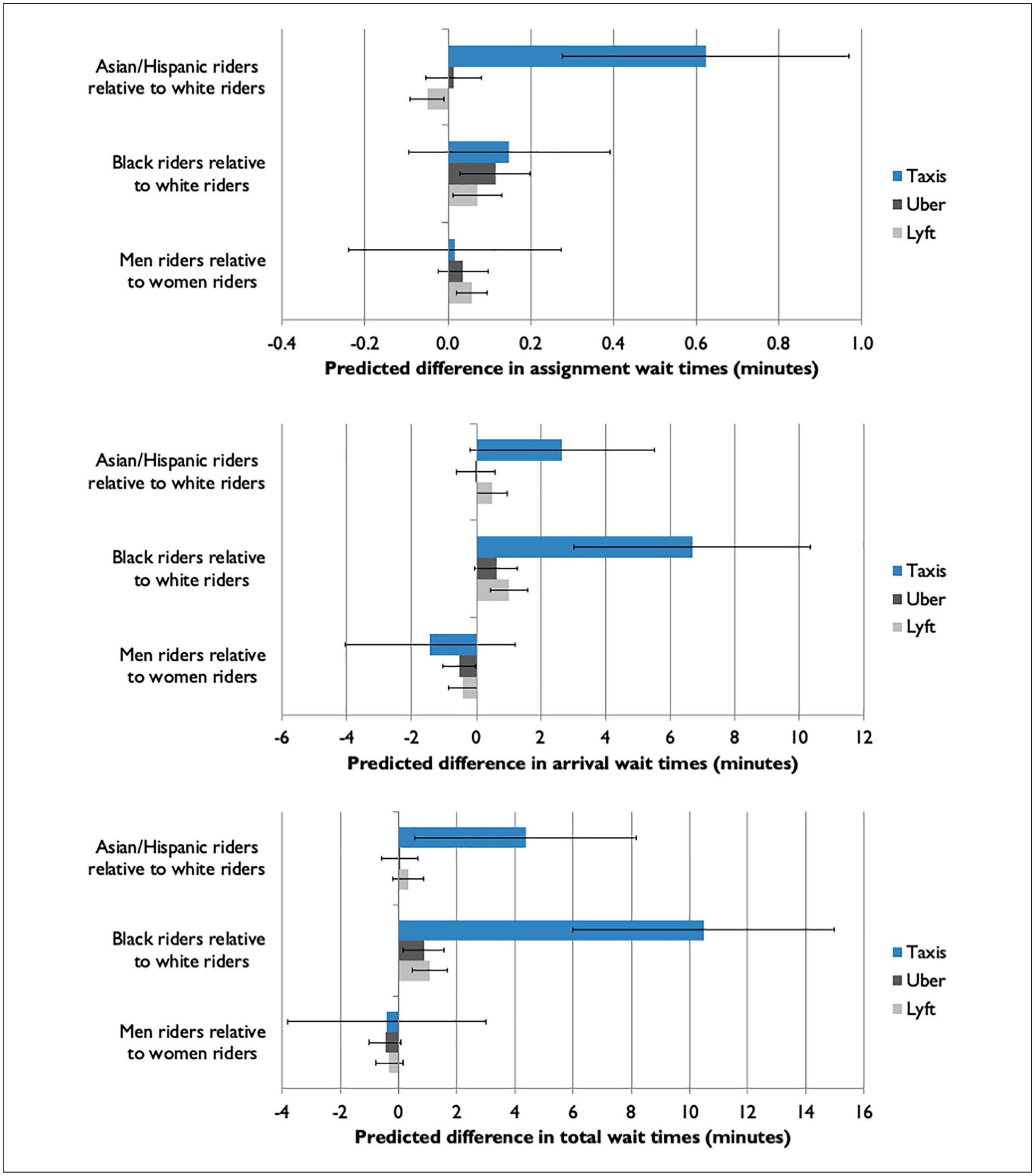

Figure 4. Predicted difference in wait times across services and rider race/ethnicities.
Note: Error bars indicate 95% confidence intervals based on robust standard errors.

between rider characteristics and arrival wait time are likewise reflected in the total wait time mode. The remainder of the discussion therefore focuses on total wait time.

Total wait time. Total wait time is the sum of assignment and arrival wait time, plus any additional wait time incurred by a cancellation. Figure 4 shows predicted wait times by rider characteristics and controlling for peak-hour travel and taxi company. Overall, driver bias results in black (but not Asian or Hispanic) riders waiting longer than white riders on Lyft, Uber, and taxis. Predicted differences in total wait times between black and white riders are statistically significant on all three services. While black riders wait fifty-four seconds longer than white riders on average for Uber and Lyft, the starkest differences by rider race occur on taxis. Black taxi riders waited 10.5 minutes longer on average than white riders, controlling for other factors.

Discussion

Results demonstrate that while ride-hailing has not eliminated driver biases, it has dramatically reduced the racial service gap still evident in taxis. Differences in hail methods across services suggest that discrimination occurs when drivers learn about or infer rider characteristics. Three ride-hail innovations may help to explain why unlawful discrimination manifests less in the ride-hail industry: (1) cashless payment, (2) driver and passenger ratings, and (3) instant reporting that increases driver accountability. These innovations hold lessons for future technology-enabled mobility services and beyond. In this discussion, I consider platform-specific and public sector interventions that may help to close the racial service gaps entirely.

From Taxis to Ride-Hail: Innovations that Deter Discrimination

Discrimination may manifest less on ride-hailing, first, because it is entirely cashless. Cash payments make drivers vulnerable to both robbery and fare evasion; taxi drivers in this study specifically voiced fears of fare evasion, but *only* to black male riders. In two instances, black auditors stated that the driver "demands cash instead [of a credit card] in fear that I wont [*sic*] pay upon completion of route" and claimed that "other passengers had scammed him at that same stop and he wanted to charge me upfront i[n] cash." Demanding cash may be discriminatory, or it may be tied to economic concerns, such as a driver worrying he will not be able to pay medallion rent at the end of an unproductive shift. Regardless, demanding cash and refusing to accept a credit card violate taxi users' rights in Los Angeles, where riders are entitled to pay with credit cards (City of Los Angeles 2018). By contrast, ride-hailing eliminates the risk of fare evasion because it automatically charges one's credit or debit card after a trip is completed.

Second, rider ratings may reduce proxy discrimination by drivers, who can use star ratings in lieu of observable traits to infer, for example, how safe or considerate a rider may be. Picking up strangers in one's car involves inherent risk, and taxi drivers face elevated rates of personal injury, robbery, and death (Menéndez, Socias-Morales, and Daus 2017). Unlike on taxis, ride-hail drivers have some prior knowledge of rider behavior through the rating system, which could reduce statistical discrimination as argued by Cui et al. (2016) about Airbnb. In addition to reducing statistical discrimination, ride-hail drivers can also rate and issue complaints about riders, which provides some recourse to poor rider behavior.

Finally, greater (perceived or actual) driver accountability on ride-hailing compared with taxis may deter discrimination; ride-hail users can quickly rate drivers and file service complaints, including complaints of discrimination. By contrast, auditors reported feeling that taxi drivers were not accountable for their actions. The one auditor who attempted—unsuccessfully—to file a complaint with a taxi company stated, "There's no accountability, I felt, with the taxis, 'cause you don't rate them. I tried calling them [the taxi company] and they didn't care." This rider is unlikely alone in encountering difficulties reporting complaints to taxi operators. In 2015, out of millions of taxi trips, just 223 riders logged complaints with LADOT (2017). Given rider experiences in this study, and reported dissatisfaction with taxis in other cities (San Francisco Municipal Transportation Agency 2013), limited formal complaints likely reflect underreporting rather than high satisfaction with taxi service.

Closing the Gap on Ride-Hailing

While technology has helped ride-hailing shrink the service gap across rider demographics, interventions on both the supplier and public sector side can help close the gaps entirely. The first intervention is supply side: driver retraining. While some may argue that widespread retraining is unnecessary because discrimination results from a few "bad apples," the "bad apples" thesis has been widely debunked by scholars who argue it a defensive mechanism used to deflect blame from institutions to individuals without acknowledging the underlying structures that allow discrimination to persist (Berard 2012). Active retraining sessions targeting specific stereotypes can reduce people's reflexive categorization of others based on stereotypes, such as canceling on a rider based on a split-second discriminatory action (Dovidio, Kawakami, and Gaertner 2000; Kawakami et al. 2000). Second, because much—albeit certainly not all—of racism today is fueled by unconscious stereotyping and prejudice (Burgess et al. 2007; Dovidio, Kawakami, and Gaertner 2000), techniques that raise people's awareness of the inconsistencies between their values and behaviors can motivate behavioral change (Dovidio, Kawakami, and Gaertner 2000). Cities may require driving training as part of their operation agreements with ride-hail companies.

Retraining is unlikely to eradicate either conscious or unconscious bias entirely. Therefore, ride-hail companies may institute four changes to deter drivers from acting on their biases: they may track discriminatory behavior, change *what* drivers see about riders, *when* drivers see rider information, or they may alter incentives for accepting and canceling rides.

The most direct way to curb discrimination is to identify discriminatory behavior—such as tracking driver cancellations to determine if driver actions are biased against certain rider groups—and hold drivers accountable for their actions. Companies could report biases to drivers, which may spur behavioral changes (Dovidio, Kawakami, and Gaertner 2000). Drivers who failed to alter their behaviors could be removed from the platform; companies must however exercise caution in their algorithmic auditing to ensure that false positives do not flag drivers whose cancellation patterns are due to chance rather than intent. Tracking driver discrimination over time could also be used to test the efficacy of other enacted antidiscrimination policies.

Ride-hail companies may also proactively deter discrimination by changing what information drivers see about riders or when they see it. Audit findings revealed moderate support for discrimination occurring when drivers learn about or infer rider characteristics. Studies in economics find that making online transactions entirely anonymous erases discrimination (Doleac and Stein 2013). Ride-hail companies, however, argue that photos and names create "digital trust profiles" to make riders and drivers feel secure (Dickey 2016). In addition, research on Airbnb finds that user ratings eliminate racial differences even when names and profile pictures are included (Cui, Li, and Zhang 2016), suggesting that removing rider photos may not be necessary so long as user ratings are preserved. This research shows, however, that while ratings may greatly reduce, they do not eliminate discrimination and additional measures are needed. An alternative to removing rider information, therefore, is to delay rider information until later in the trip, say, as a driver came within 100 ft. of a rider. While star ratings could still be shown at the trip outset, companies could potentially deter cancellations by delaying rider information until both riders and drivers have invested time into the trip; as with the other proposed policy solutions, companies would need to test this intervention to determine its effectiveness.

Finally, ride-hail companies could further incentivize high acceptance rates. For example, companies could provide financial bonuses—such as drivers recouping a higher share of fare revenues—if drivers accept 100 percent of trip requests. Companies could also further deter cancellations by requiring drivers to provide an explanation for why they canceled a trip, tracking drivers who cancel frequently, allowing fewer cancellations before a driver receives a "time out," or financially discouraging drivers from canceling in ways inverse to the incentives discussed above.

The public sector, too, has a role to play in deterring discrimination. To ensure companies do not violate antidiscrimination laws, they may conduct periodic industry audits, as was done for this study. Alternatively, they should consider using abundant ride-hail data, or requiring companies to collect and report data as a condition of operation, to monitor and deter discrimination. Planners will need to set tangible performance metrics—such as share of ride requests canceled or wait time variations controlling for location—to measure and enforce equitable service outcomes.

Conclusion

I find that taxi drivers' discrimination against black riders is as present today as it was in audit studies conducted three decades ago (Ridley, Bayton, and Outtz 1989); while taxi service overall was unreliable at best—nearly 20 percent of trips were canceled and riders waited twenty-four minutes on average to be picked up—it was worst for black riders. I observed no meaningful differences between white, Asian, and Hispanic riders, suggesting that discrimination is particularly acute and common for black residents, as other research documents (McLaughlin, Hatzenbuehler, and Keyes 2010). Taxis failed to pick up black riders for more than one-quarter of their trip hails (26.3%), compared with about one-fifth of trips hailed by Asian and Hispanic rider (19.9%) and one-seventh (14.4%) of trips hailed by white riders. By contrast, ride-hail services dramatically reduced the differences across rider characteristics. On taxis, black riders waited 10.5 minutes (52%) longer than white riders; by comparison, black riders waited less than a minute (fifty-four seconds, 15%) longer for ride-hail services than white riders. Findings suggest that discrimination occurs when people learn of or infer rider characteristics and yield implications for how policymakers can use new technologies to deter discrimination and achieve equitable service for all travelers.

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Notes

1. Jarvis Murray (Taxicab and Franchise Administrator, Los Angeles Department of Transportation), in conversation with the author, 2017.

2. Jarvis Murray (Taxicab and Franchise Administrator, Los Angeles Department of Transportation), in conversation with the author, 2017.
3. Average Uber/Lyft star ratings by rider race/ethnicity were as follows: Asian (4.93), black (4.83), Hispanic (4.81), and white (4.90).

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