Discrimination, Regulation, and Design in Ridehailing

by
Scott Middleton

B.A. in Urban Studies and History
Brown University 2010

Submitted to the Department of Urban Studies and Planning
in partial fulfillment of the requirements for the degrees of

Master in City Planning
and
Master of Science in Transportation
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2018

Author____
Department of Urban Studies and Planning
Department of Civil and Environmental Engineering
May 18, 2018

Certified by____
Jinhua Zhao
Associate Professor of Urban Studies and Planning
Thesis Supervisor

Accepted by____
Professor of the Practice Ceasar McDowell
Chair, MCP Committee
Department of Urban Studies and Planning

Accepted by____
Professor Jesse Kroll
Professor of Civil and Environmental Engineering
Chair, Graduate Program Committee

.

Discrimination, Regulation, and Design in Ridehailing

By

Scott Middleton

Submitted to the Department of Urban Studies and Planning
on May 24, 2018 in partial fulfillment of the
requirements for the degrees of Master in City Planning
and Master of Science in Transportation

Abstract:

In the past decade transportation network companies (TNCs) like Uber and Lyft have replaced, supplemented, and disrupted traditional modes of transportation. The rapid growth of these companies makes equitable access to their platforms an issue that is simply too big to ignore. Indeed, these ridehailing services have the potential extend an ugly legacy of discrimination in transportation services, or to deliver a more equitable mobility system for future generations.

In this vein, prior studies have provided evidence of discrimination between drivers and passengers in the context of ridehailing. This thesis extends research in three important ways. First, this thesis investigates rider-to-rider discriminatory attitudes in the context of dynamic ridesharing. To that end, this thesis uses data from a survey of 1,110 TNC users to argue that discriminatory attitudes toward fellow passengers of differing class and race are positively correlated with demographic and environmental characteristics, as well as one's generic social dominance orientation. Second, this thesis uses a second national survey of TNC users (n=1,113) to argue that the advent of autonomous ridesharing will exacerbate discriminatory attitudes toward fellow passengers in shared rides. What's more, this effect will be particularly acute with regard autonomous ridesharing with passengers of a different gender. Finally, this thesis proposes fourteen regulations and platform design interventions to prevent and mitigate possible discrimination in ridehailing and ridesharing. These interventions are vetted through a survey of national experts in ridehailing policy and design. Of these interventions, this thesis calls for additional data reporting requirements and a series of changes to TNC star rating systems.

Thesis Supervisor: Jinhua Zhao
Title: Edward H. and Joyce Linde Associate Professor of Transportation and City Planning

Acknowledgments

This thesis is dedicated to the memory of Professor Joseph Sussman, who passed away on March 20, 2018. I owe my time at MIT entirely to Joe, who saw potential in me and admitted me as an M.S. in Transportation student with a rather unconventional background. It is my pleasure to join the community of hundreds of students who worked with Joe during his 50 years at MIT. His memory is with me as I finish this work.

Many other hands have also contributed to this thesis: mentors who defied tedium to carefully read and guide my writing, friends who lifted my spirits, and generous experts who offered me crucial insight in interviews. I am indebted to you all. Specifically, I thank my thesis adviser, Professor Jinhua Zhao, my thesis reader Professor Jason Jackson, fellow members of the Urban Mobility Lab, the students of 1.011, my mother Peggy, and my frequent collaborators Annie Hudson, Ben Gillies, Yonah Freemark, and Joanna Moody. Additional thanks go to the Dwight David Eisenhower Transportation Fellowship Program for their intellectual and financial support of this research. A final word of thanks goes to Leonard Cohen, whose sage words inspired me to push through the doldrums and produce a final draft:

A fresh spider-web billowing like a spinnaker across the open window, and here he is the little master, sailing by on a thread of milk. Wish me luck admiral I haven't finished anything in a long time.

Contents

List of Figures

List of Tables

1 Introduction

Physical, digital, and financial access to shared transport services are valuable public goods and need thoughtful design to ensure use is possible and affordable by all ages, genders, incomes, and abilities.

Shared Mobility Principals for Livable Cities[1]

In the 2010s emerging transportation network companies (TNCs) like Uber and Lyft have replaced, supplemented, and disrupted traditional modes of transportation. They have transitioned from upstarts to important and potentially permanent players in the transportation industry. Furthermore, cost-reducing dynamic ridesharing and venture capital-backed rider subsidies have made TNCs more price competitive with public transit, suggesting a potentially enormous role for TNCs in the urban transportation of the future. Such scale makes equitable access to this platform an issue that is simply too big to ignore.

These ridehailing/ridesourcing services have the potential to exacerbate and extend our worst discriminatory tendencies as a society. From segregated buses to transit deserts to cab drivers refusing rides, the field of transportation has a long and disgraceful history of discrimination in the United States. Depending on their design, TNCs may either extend this ugly legacy or deliver a more equitable mobility system for future generations. As a society, we currently face a generational opportunity to harness the innovations of the sharing economy to support an equitable future. To do so, we must ensure that TNCs do not perpetuate age-old forms of discrimination in transportation,

[1]Taken from the Shared Mobility Principles for Livable Cities collaborative initiated by Robin Chase

but rather foster a more inclusive transportation culture.

1.1 Discrimination in Ridehailing and Ridesharing

Since 2009, TNCs have been providing smartphone users with an easy way to request point-to-point rides on-demand. While there are many TNCs in operation,[2] this thesis is primarily interested in the two leading TNCs in U.S.: Uber and Lyft. Together these two companies control 97.8 percent of the U.S. ridehailing market as of August 2017.[87] Unlike traditional taxi dispatch systems, TNC platforms link riders to one of many drivers currently connected to the company's application. As such, Lyft and Uber claim to be technology companies rather than transportation companies, and consider their drivers to be independent contractors rather than employees. While drivers have disputed this claim in courts, drivers remain classified as independent contractors in most political jurisdictions.

Recent studies have highlighted examples of discrimination enabled by these new forms of mobility. Most notably, Ge et al. (2016) argued that the pick-up decisions of individual Uber and Lyft drivers led to discriminatory outcomes for riders. Through two field experiments in Seattle and Boston, the researchers observed a significant difference in wait times and cancellations for otherwise identical riders with African American-sounding and white-sounding names, irrespective of the characteristics of the driver. The study also demonstrated that Uber and Lyft drivers take female riders for longer and more expensive rides than male riders.[44]

The 2016 study generated significant media attention, as well as a formal admonishment from Senator Al Franken to the CEOs of Lyft and Uber.[42] As ranking member of the Senate's Judiciary Subcommittee on Privacy, Technology, and the Law, Senator Franken urged application-based services not to accommodate bias and asked the companies to explain how they intend to prevent racial and gender discrimination on their platforms.

Uber's response to Senator Franken's letter revealed both the strengths and weaknesses of TNCs with regard to discrimination. Unsurprisingly, the response focused on the company's strengths. For example, Uber argued that TNCs have increased the availability of for-hire rides and improved transportation equity by reducing user costs and improving accountability for drivers. In a study funded by Uber, Smart et al. (2015) found that taxis dispatched by phone to low-income Los Angeles neighborhood took 2-3 times longer to arrive than UberX rides and cost roughly twice as much.[114] In an independent study Hughes and MacKenzie (2016) found that waiting times for UberX shared rides were actually lower in low-income and minority neighborhoods in Seattle than in higher-income, majority white neighborhoods after controlling for density, suggesting that adequate access to ridehailing is not necessarily restricted to wealthier or whiter areas.[58] Despite these potential advantages of TNCs, Uber's promises for mitigating the type of discrimination

[2]TNCs operating in the United States include Via, Wingz, Fasten, Fare, Get Me, Tride, and Liberty Mobility

observed by Ge et al. were vague and non-committal (e.g., reviewing policies and meeting with the researchers). The company could certainly do much more.

Whatever the merits of Uber's arguments about discrimination, the debate between Senator Franken and Uber focused solely on discrimination from drivers to riders. Both parties ignored the very real possibility that ridehailing platforms also provide riders with the ability to discriminate against drivers through their tips and service ratings. These two features of TNC platforms that have very real impacts on drivers' well-being; tips impact driver incomes while star ratings impact drivers' ability to find riders and even to participate in the market.

Increasingly, many TNC rides involve not just one driver and one rider, but also a second or third rider sharing the same ride through *ridesharing* products (e.g., uberPOOL and Lyft Line) a special category of *ridehailing* or *ridesourcing* services (e.g., UberBLACK).[3] In addition to driver-rider and rider-driver discrimination, it is conceivable that rider-rider discrimination will emerge as a critical issue in the future, particularly as autonomous ridesharing platforms become more ubiquitous.[4] Recent research at MIT has provided evidence that ridesharing users harbor feelings of prejudice towards passengers of different social class and race, and that these riders prefer to have early information about potential co-passengers (Sarriera et al. 2016). In the future, ridesharing and ridehailing companies might somehow allow passengers to avoid riders they don't like. Alternatively, TNCs may mitigate discrimination and even encourage positive social interactions between riders. However, it seems that they may need some help in achieving that goal.

1.2 Organization of this Thesis

Against this backdrop, the research questions of this thesis are: To what extent to which discrimination is demonstrably occurring through ridehailing and ridesharing platforms? Beyond driver-rider interactions, how might discrimination influence the interaction between fellow passengers in a shared ride? Given these possibilities, what are the most suitable regulatory and platform design tools for cities, TNCs, and other actors to prevent and mitigate discrimination and maximize the potential social good of shared mobility platforms?

This thesis will answer this question over the course of five chapters. Chapter 2, Discrimination and Prejudice in the Shared Mobility Context, presents discrimination as a potential disadvantage of ridehailing and a likely consequence of platform design. This introductory chapter asks to what extent discrimination is present in ridehailing and ridesharing; considers parallels in other industries and other platforms; and analyzes antecedents from the traditional taxicab industry. This

[3] While these terms are often used interchangeably, this thesis holds that the terms "ridesharing" and "ridehailing" have distinct meanings and uses them accordingly.

[4] While the arrival of fully autonomous ridesharing services is uncertain, there is great interest on the part of TNCs in this possibility. Uber has been piloting self-driving fleets in Pittsburgh and other cities since 2016. Lyft has announced its intention to offer the majority of its rides in self-driving cars by 2021.[55]

input is then formulated into a definition of discrimination in the context of shared mobility.

Chapter 3, Discriminatory Attitudes Between Ridesharing Passengers, expands upon existing studies of discrimination by hypothesizing about potential forms of discrimination that have not yet been studied in depth, particularly the unexplored realm of rider-rider discrimination. An analysis of existing survey data provides an empirical foundation for understanding discriminatory attitudes among various social groups. Chapter 4, Discriminatory Attitudes in Driverless Rides, expands on the analysis of Chapter 3 using new survey data to consider how the advent of autonomous vehicles may affect rider-rider discrimination.

Given the types of discrimination discussed in earlier chapters, Chapter 5, Regulatory and Design Interventions, considers strategies for mitigating and preventing discriminatory behavior through regulation and platform design. This chapter draws on existing TNC regulations from around the United States to propose a list of interventions for review. Although this chapter places a strong emphasis on regulation, it also acknowledges the important role of TNCs in reducing discrimination and considers what platform design interventions that these companies can apply to prevent discrimination. This chapter vets the various regulation and platform design interventions through semi-structured interviews with experts in public policy and shared mobility to evaluate the proposals according to their effectiveness, fairness, and implementability

The thesis closes with a discussion of next steps that researchers, government officials, and TNC executives can pursue given the findings of the thesis. Government regulators and TNC leaders will be empowered by the findings of this thesis to take action to address discrimination.

Ridehailing/ridesharing services have the potential to either exacerbate or discourage discrimination in transportation. Fortunately, conscious and informed decisions on the part of policymakers and TNCs can create a more equitable mobility system. The goal of this thesis is to provide theoretical and empirical evidence of the need for substantive interventions to support justice in shared mobility. By surveying TNC users, policymakers, advocates, and providers, this thesis will point to effective, fair, and implementable solutions that can help maximize the potential social good of the sharing economy.

2 Discrimination and Prejudice in the Shared Mobility Context

Whether you're a rider trying to get from A to B - or a partner wanting to earn money as a driver - your behavior matters.

Uber Community Guidelines

This chapter seeks to understand discrimination in the context of ridehailing and ridesharing. As the theoretical foundation of the thesis, this chapter begins with a description of the various methods available for measuring discrimination empirically. In the next section, this chapter considers parallels in other industries and other platforms, including antecedents from the traditional taxicab industry, that shed light on new forms of discrimination in the shared mobility sector. The chapter then summarizes the existing evidence of discrimination in shared mobility. Specifically, the chapter considers to what extent discrimination is present in ridehailing and ridesharing through a literature review drawing upon law, sociology, technology, and other fields. This evidence is categorized according to the methodologies used for measuring discrimination. Finally, this chapter offers a definition of discrimination in shared mobility that informs the analysis and interventions discussed in subsequent chapters.

2.1 Methodologies for Measuring Discrimination

In order to make sense of the various evidence of discrimination in TNCs, it is important to understand the broad methods for demonstrating discrimination in general. Several methods exist for measuring discrimination. Five general categories of measurement strategies include:

- Perceptions of discrimination;
- Reports by discriminators;
- Statistical analyses;
- Experimental approaches; and
- Studies of law/legal reports.

Examples of each strategy abound.[18] [99] Each measurement strategy also entails inherent challenges. Surveys of perceived discrimination, for example, are applicable to many industries and contexts, but may over- or underestimate discrimination according to respondents' respective sensitivity to or ignorance of discrimination. An example of this strategy is the Perceived Customer Discrimination scale put forward by Klinner to understand categorize customers' perception of discrimination during service interactions.[78] Reports from discriminators are also powerful, but likely to underrepresent discrimination due to issues of social desirability bias. Statistical analysis is a useful tool for measuring inequalities in outcomes (e.g., a residual race gap), but depends on available data and fails to control for all possible variables, leading to issues of exogeneity and endogeneity. Experimental approaches, by contrast, are highly controlled, but expensive to run and likely to produce very narrow findings. Finally, studies of legal reports offer useful summaries of instances of discrimination, but ignore acts that are not reported or litigated. Generally, these fail to correlate the number of legal complaints with the number of actual incidents of discrimination, or acknowledge the fact that allegations in a lawsuit are not proof that discrimination has occurred.[52] Vague definitions of discrimination exacerbate this problem. In order to overcome the respective shortcoming of each strategy, this thesis applies and considers studies that together apply all five methods of measuring discrimination in the context of ridesharing.

2.2 Parallels in Other Industries and Platforms

There are numerous examples of studies that apply the types of measures presented in the previous section to the question of discrimination in industries and platforms related to ridehailing. The following section presents evidence of discrimination in taxicabs, traditional/online consumer marketplaces, and shared economy platforms.

2.2.1 Antecedents in the Taxicab Industry

Discrimination in the taxicab industry from driver to rider and vice versa is an especially relevant case for this research. In a survey of cab drivers' receipts in New Haven, Ayres (2005) provided evidence that black cab drivers receive tips of approximately 1/3 less than white drivers.[12] In a famous 1989 study, Ridley et al. demonstrated experimentally that black people seeking to hail a taxi from the street were seven times more likely to be passed than white people in Washington, D.C. a finding that has been replicated and verified in many other studies.[103][113][10] These claims are in keeping with the popular perception of discriminatory cab drivers (i.e., "perception of discrimination"). A 2000 poll, for example, found that 43 percent of African Americans surveyed believe taxi drivers avoid picking up black passengers and 18 percent report that they themselves have been refused a ride.[1] Consensus on this particular form of discrimination is broad enough that in the 1990s the Giuliani administration instituted New York City's "Operation Refusal," in which law enforcement officers posed as riders and ticketed cab drivers for refusing rides. Notably, courts have held cab companies liable for the discriminatory actions of their drivers, offering a potential parallel for platforms like Uber and Lyft (see Floy-Mayers v. American Cab Co., Rhone v. Try Me Cab Co., Bolden v. J & R Inc., Greene v. Amritsar, or Mitchell v. DCX).

Arguably TNCs offer a solution to such discrimination. Ridehailing can, in theory, avoid the problem that people of color often face in hailing cabs by adding anonymity to the hailing process, presenting drivers with rider ratings, and using credit cards to ensure payment. Uber in particular has claimed that it reduces discrimination relative to taxicabs, arguing that 50 percent of Uber trips in Chicago begin or end in underserved neighborhoods (measured as median neighborhood income).[72] The company also boasts that it offers considerably more service to New York City's outer boroughs than traditional taxis.[84] Nonetheless, evidence strongly suggests a long history of discrimination in the industry that TNCs are currently disrupting. This evidence justifies careful consideration of discrimination in TNCs in order to avoid perpetuating this legacy of discriminatory behavior in transportation providers.

2.2.2 Discrimination in Traditional and Online Marketplaces

Discrimination, particularly racial discrimination, in public facilities is nothing new. Long after the Civil War, many businesses in the United States refused to serve or offered inferior services to non-white customers. Such exclusion limited economic opportunities for non-white people. However, certain forms of discrimination have technically been illegal in the United States since the Civil Rights Act of 1866, which prohibited race-based discrimination in the judicial system. As both enforcement and legislative civil rights protections have grown, so too has research into the presence of discrimination. Researchers have studied discrimination in the markets for labor, goods, and services for decades using the methods described above. Additionally, federal and state agencies have conducted regular audits for racial discrimination since the 1950s, offering abundant examples of discrimination in practice.

Nonetheless, discrimination persists in traditional (i.e., offline) marketplaces in ways that can inform the research of this thesis. Discrimination against homebuyers is a well-documented phenomenon. Scholars have also studied the discriminatory behavior of homebuyers themselves, offering a noteworthy parallel for rider-driver discrimination in a TNC context.[39] In the restaurant industry, customer exit surveys have shown evidence that diners tip black servers less than white coworkers regardless of service quality.[20] Researchers have also used questionnaires to show that diners rate the performance of same-race servers more favorably than different-race servers, offering a parallel to discrimination in TNC's version of customer appraisals: tips and star ratings.[20] Countless other studies have highlighted persistent discrimination in various other marketplaces, including employment, credit, and consumer markets (see Harris et al. 2005, Pager 2008, Massey 2005).

Whatever the status of discrimination in taxicabs and other offline markets, the arrival of online marketplaces has created new settings for discrimination. Since the early days of the Internet, there has been a persistent optimism that the anonymity of Internet users would render the web a race-blind, discrimination-free marketplace.[1] Indeed many marketplaces that match buyers and sellers, such as Expedia or Cars.com, offer little opportunity for discrimination by requiring sellers to commit to buyers on price alone. Morton et al. (2003), for example, used automobile transaction data to demonstrate that although black and Hispanic buyers pay roughly 2 percent more in face-to-face auto sales, this mark-up all but disappears when buyers use an autonomous online price quote service to find auto dealers.[91]

However, there is significant evidence that discrimination persists in online markets when fully anonymity is not present. In a study of baseball card auctions on eBay, for example, Ayres et al. (2011) found that photographs of cards held by African-American hands sold for roughly 20 percent less than cards held by Caucasian hands.[12] Similarly, Doleac and Stein (2013) found experimentally that prospective buyers were less likely to respond to otherwise identical Craigslist advertisements for iPod Nanos that included photographs of dark-skinned rather than light-skinned hands.[33, p. 490] In the context of online lending, Pope and Sydnor (2011) observed that credit applications with photographs of black borrowers were less likely to receive loans than similar listings with pictures of white borrowers on the peer-to-peer lending website Prosper.com.[100] What's clear from these examples is that online platform design, particularly the availability of photographs, can influence the likelihood of discriminatory outcomes.

Beyond photographs, a number of other authors have used racially distinctive names in experiments that have demonstrated the impact of race in online markets for apartment rentals, labor, and consumer auctions. An experimental study by Nunley et al. (2014) followed a well-known methodology by Bertrand and Mullainathan (2004) to demonstrate differential response rates to online job

[1]See, among others: "In the Great Web Bazaar"; Hall, Digital Dealing. See also Peter Steiner's famous 1993 New Yorker cartoon "On the internet, nobody knows you're a dog."

postings in which the job applicant's race is signaled with a white- or black-sounding name.[17, p. 2][95] A study from Carpusor and Loges (2006) used a similar methodology to demonstrate the effect of name-based ethnic stereotypes against Arabs in rental housing discrimination in Los Angeles County.[23] Hanson and Hawley (2016) extended this methodology to real estate and demonstrated experimentally that mortgage loan originators respond more frequently and with greater detail to email correspondence from loan seekers with white-sounding names.[49]

The arrival of big data analytics in the transportation sector hardly alleviates these concerns. In a study of data mining methods, Barocas and Selbst (2016) found that online databases often capture and perpetuate existing patterns of discrimination against historically disadvantaged groups. This can occur in a number of ways. Algorithms may solve problems in ways that affect protected classes differently, fail to address statistical biases, and otherwise reproduce past prejudice.[14, p. 672] In 2014 the Executive Office of the President produced the so-called "Podesta Report," which found that the use of personal information and big data analytics in markets such as housing, credit, and labor big data analytics threatened to undermine longstanding civil rights protections.[96, p. 1]

2.2.3 Discrimination in the Sharing Economy

Just as the arrival of online marketplaces in the 1990s extended traditional forms of discrimination onto the Internet, the advent of the sharing economy has created new platforms for discrimination. Over the past decade the sharing economy (also known as the peer-to-peer, on-demand, or platform economy) has been connecting providers and users with increasing intensity in sectors from retail to lodging to transportation.

The sharing economy offers many benefits: efficiency, flexibility, competition, and access to new resources. However, research has shown that the design of platforms can exacerbate social bias through the design of pricing mechanisms and ratings systems.[2] It follows, then, that sharing economy platforms have the power to channel the same explicit or implicit bias that pervades traditional and online marketplaces, as discussed in the preceding sections.

Given the growing importance of the sharing economy, researchers have begun applying experimental studies of discrimination to online freelancing marketplaces, including the short-term housing rental service AirBnB. Edelman & Luca (2016) demonstrated that requests from AirBnB guests with distinctively African-American names are less likely to be accepted than identical guests with distinctively white names, closely paralleling the phenomenon of Uber driver cancellations identified by Ge et al.[37] Similarly, Hannak et al. (2017) conducted a review of worker profiles in the freelance labor platforms TaskRabbit and Fiverr that identified correlations between gender/race

[2]See research on eBay platform design from Einav et al., "Sales Mechanisms in Online Markets"; Bolton, Greiner, and Ockenfels, "Engineering Trust". See also research extending these findings to AirBnB: Fradkin et al., "Bias and Reciprocity in Online Reviews."

and worker ratings, position in searches, and customer reviews.[48] This finding closely parallels concerns about discrimination in Uber star ratings. Finally, Thebault (2015) conducted a survey of TaskRabbit workers in the Chicago metropolitan area and found that workers were less likely to accept requests from customers in the city's socioeconomically disadvantaged South Side.[121, p. 272] This finding closely parallels the concern that Uber drivers may avoid neighborhoods with undesirable demographics. Together these studies point to discrimination as one important element of the larger transition from traditional modes of production to the sharing economy.

2.3 Evidence of Discrimination in Ridehailing and Ridesharing

Any argument for the existence of discrimination in ridehailing and ridesharing may be met with claims that these services actually improve equity in transportation. For example, it is likely the case that Uber and Lyft offer better service to customers in lower-income and minority neighborhoods than taxis ever have. Uber has used a simple regression model to argue that the probability of an Uber ride request going unfulfilled increases by 0.3 percentage points with every $1,000 increase in median income.[84] A 2016 survey by the Pew Research Center revealed that a majority of ridehailing users believe that ridehailing companies serve neighborhoods that taxis do not.[115, p. 30] Furthermore, it could be argued that a rising tide lifts all boats; Rayle and Cervero (2014) offered evidence that riders in San Francisco experience significantly shorter wait times for shared rides than taxi services, regardless of their personal characteristics.[102]

On a similar note, Li and Zhao used a series of interviews with stakeholders in the taxicab industry to suggest that taxi-hailing (e-hail) apps have the potential to improve rider-driver relationships by enhancing accountability and safety [82]. This paper also argued that these apps humanize these relationships by directly connecting passengers and drivers one pair at a time, thereby emphasizing the fact that there is a person at the other end of the app (relative to traditional means of taxi dispatch). The availability of names, ratings, and photos further humanizes this experience. While this paper focused on e-hailing apps rather than TNCs, many of these humanizing features also characterize ridehailing and ridesharing services.

Despite these probable improvements over the conventional taxi industry, it is certainly possible that the forms of discrimination prevalent in the traditional economy also affect the shared mobility economy. TNC riders, for example, are vulnerable to discrimination because drivers can reject or avoid them without offering any explanation.[124] However, demonstrating such discrimination is difficult. Uber may rightly claim, for example, that drivers cannot access riders' photographs or full names until they accept a ride, and thus cannot truly discriminate (although Uber drivers do see this information after accepting a ride, and Lyft drivers have access to this information before accepting, as of October 2017). Testing such theories through statistical analysis is difficult because user data are not typically available for research. What's more, relatively little case law has examined the problem of discrimination or civil rights violations in the platform economy to date.

However, scholars are beginning to investigate discrimination in ridehailing and ridesharing. Thebault-Spieker et al. (2015), for example, argued that TNC drivers may avoid low-income areas through a type of ridesharing "redlining" that leads to less service and higher prices in these neighborhoods.[121] More recently, Hughes and MacKenzie provided initial evidence that this is not the case. While the authors found that wait times in Seattle were shorter in denser parts of the city, they found that wait times were similar or even slightly lower in low-income and minority neighborhoods.[58]

At a higher level, TNCs have also faced criticism that their official coverage areas are discriminatory. In 2014 Uber faced criticism that its coverage area in the Dallas-Forth Worth metro area included wealthy areas of North Dallas, but excluded poorer neighborhoods in the south side of the city.[86] More recently, the *Washington Post* revealed that the ridesharing service Via was violating the District of Columbia's nondiscrimination laws by excluding predominantly black neighborhoods from its coverage area.[118] Nonetheless, the scale of most coverage areas has increased dramatically enough to nullify such arguments. In August 2017, Lyft, for example, expanded its coverage to the entire area of 40 U.S. states and 94 percent of the U.S. population.[60] Uber's coverage is smaller, but still substantial. Only the most rural areas are officially excluded from most ridehailing services.

Although geographic discrimination may be minimal, seminal research by Ge et al. (2016) discussed in the introduction to this thesis provided experimental evidence that the design of Uber and Lyft's platforms allows for discrimination on an individualized basis from drivers to riders. This study represents the most significant evidence of discrimination in TNCs to date and points to further research into cancellation and wait times across rider groups as well as the areas where drivers choose to serve and how this affects the rider experience.[44, p. 20]

Though they lack the experimental approach of Ge et al., other recent studies have highlighted the theoretical case for discrimination in TNCs. Calo and Rosenblat (2016), for example, argued the massive asymmetries of information between TNCs and their users (both riders and drivers) allow TNCs to anonymously channel the behavior of participants in potentially concerning ways. Uber, for example, has been known to manipulate consumer perceptions by exaggerating the number of cars available through the application before a rider makes a request, after which the so-called "phantom cars" disappear and a consumer faces a longer wait time than expected.[22, p. 6] Any company with such power to mislead and disadvantage participants, Calo and Rosenblat argue, deserves close attention from scholars especially with regard to potentially discriminatory practices.

Furthermore, Rosenblat et al. (2017) used a review of consumer behavior in online marketplaces and performance evaluations in managerial settings to argue that racial and gender bias is likely to influence TNC driver evaluations. Admittedly, without access to data on ratings or driver characteristics, such a determination is purely speculative. Anecdotally, however, online driver forums do suggest a belief that passengers' ratings of Uber drivers are likely to be biased in the aggregate. What's more, bias in ratings may lead to discriminatory termination practices by Uber. This is because the company's "star rating" system determines whether a driver can maintain access to the platform; Uber terminates drivers whose overall star rating scores fall below a certain cutoff for their market (roughly 4.6).[3] In fact, one Uber driver has already filed a U.S. Equal Employment Opportunity Council complaint on the grounds that discriminatory reviews cost him access to Uber's platform.[8]

Recent research has also explored how driver earnings vary according to driver characteristics. In particular, a 2018 paper published in conjunction with Uber analyzed earnings data for more than one million Uber drivers to find a 7% gender earnings gap among drivers. Cook et al. (2018) argued that this gap resulted from three factors that differ between men and women: experience on the platform (i.e., men have longer tenures), preferences over where/when to work (i.e., men have more flexibility), and preferences for driving speed (i.e., men drive faster). Notably, the authors argued that this pay gap exists "in the absence of discrimination" in a gig environment described as "gender-blind, transactional, [and] flexible."

Finally, discrimination against riders with disabilities is one form of discrimination in TNCs for which court cases and legal reports are available for review. TNCs have also been accused of discrimination in violation of the Americans with Disabilities Act, whose requirements apply specifically to taxi services. In several court cases, Uber passengers have alleged that the company discriminates against the blind and wheelchair users by refusing to accommodate their needs.[4] In response to these claims, Uber's attorneys have argued that as a technology company it does not fall under the jurisdiction of the ADA and that it is unable to control the actions of drivers, as they are independent contractors.[119] While Uber may deny its legal responsibility in this area, the company has launched products like UberWAV and UberASSIST to provide accessible fleets. However, the company has not attempted to accommodate riders with disabilities in its main fleet, opening the company to possible charges of segregation. Lyft, on the other hand, explicitly requires its riders to transport service animals in all situations.[62] When it comes to wheelchair accessibility, the company encourages drivers to make reasonable accommodations and promises to investigate any refusals of wheelchair users.[63]

Together, these studies and legal cases provide evidence of and the possibility for a wide range of discriminatory practices in the context of ridehailing. However, existing research has largely focused on the effect of discrimination from drivers to riders, in part due to the long history of such discrimination in transportation and other sectors. Additionally, much research on the sharing

[3]According to Uber's Community Guidelines: "There is a minimum average rating in each city. This is because there are cultural differences in the way people in different cities rate each other. We will alert you over time if your rating is approaching this limit, and you'll also get information about quality improvement courses that may help you improve. However, if your average rating still falls below the minimum after multiple notifications, you will lose access to your account. We may allow you to regain access to your account if you can provide proof that you completed one of these quality improvement courses." However, Uber does allow deactivated drivers the opportunity to begin driving again if they can provide proof that they've successfully taken a quality improvement course offered by third party experts. Furthermore, as of April 2018, Uber's Community Guidelines indicated that the company is "exploring ways to create an appeals process for the most contentious cases."

[4]See: Blind of California et al v. Uber Technologies, Inc. et al, U.S. District Court, Northern District of California, No. 14-04086; Heiwa Salovitz v. Uber Technologies, Inc. United States District Court, W.D. Texas, Austin Division

economy concentrates primarily on racial discrimination from whites to blacks. While these forms of discrimination certainly warrant scholarly attention, it is important to consider the many other forms of discrimination that may exist in ridehailing and ridesharing. To that end, this thesis seeks to fill existing research gaps through a more inclusive approach to understanding discrimination that includes multiple possible targets (i.e., race, gender, ethnicity, ability, etc.) and directions of discrimination (i.e., driver-rider, rider-driver, and rider-rider), as defined in the following section.

2.4 Defining Discrimination in the Shared Mobility Context

Drawing upon the evidence and theory presented in the preceding sections, the following section offers a broad definition of discrimination to guide the remainder of this thesis. In any context, discrimination is the unequal treatment, exclusion, or disadvantage of people on the basis of their membership in a particular group. This definition incorporates both "disparate impacts" (i.e., practices that are applied equally but nonetheless result in different treatment of protected groups) and "disparate treatment" (i.e., explicitly discriminatory practices). That is, discrimination includes decisions that are not explicitly based on group-level traits, but nonetheless produce outcomes favorable to in-groups and unfavorable to out-groups. [78]

In this thesis, discrimination is held distinct from prejudice (which refers to attitudes and expectations), stereotypes (which refers to beliefs and identify), and specific ideologies such as racism, sexism, ageism, and so on.[99] However, discrimination may be motivated by these phenomena. Understanding prejudice, in particular, is important for predicting, measuring, and understanding discrimination due to the common phenomenon of implicit bias - attitudes that unconsciously affect an individual's behavior. Implicit bias is notably difficult to counteract because it can involve people who genuinely do not intend to discriminate. As such, prejudice and implicit bias are studied in greater detail in Chapter 3 of this thesis.

In the context of shared mobility, this thesis puts forward a definition of discrimination that includes the following elements:

- Targets;
- Directionality;
- Mechanisms;
- Settings; and
- Outcomes.

Targets of discrimination in this context include the following protected classes: race, color, religion, sex, national origin, and disability. The first five characteristics on this list of protected classes is taken from Titles II and VII of the Civil Rights Act of 1964, which prohibits discrimination based on these characteristics in public accommodations and in employment respectively. Title III of the Americans with Disabilities Act of 1990 expanded similar civil rights protections to people with disabilities in public accommodations, including transportation.

The direction of discrimination is three-fold: driver-rider, rider-driver, and rider-rider. Each direction entails a variety of different mechanisms, as documented in the preceding section. Driver-rider discrimination, for example, is made possible through drivers' ability to cancel or refuse rides in response to a rider's photograph, name, or location. Rider-driver discrimination, on the other hand, is made possible through tipping and rating functions. Arguably, the former direction of discrimination is easier for TNCs to address due to their control over drivers and the information available to them.

Rider-rider discrimination, finally, is an emerging area of interest considering the future of autonomous ridesharing (see Chapters 3 and 4 for a more detailed discussion of this topic). The setting of discrimination may be physical (i.e., single-passenger trips, pooled trips) or virtual (i.e., action/inaction through the application).

In general, the outcomes of discrimination include avoidance, rejection, verbal harassment, physical attacks, and the overt or subtle denial of goods or services.[52] In this thesis, the outcome of greatest interest is subtle denial of services. For ridehailing/ridesharing users, this outcome can include longer wait times, more frequent cancellations, longer rides, lower ratings, or poor service, leading to inconvenience, inaccessibility, and lower quality of life. For drivers, the outcomes of discrimination include lower ratings, lower tips, and higher cancellations, all of which reduce drivers' ability to earn a living. See Table 1 for a summary of the directions, mechanisms, settings, and outcomes.

Direction	**Mechanism**	**Outcome**
Driver-Rider	Ignore ride requests	Longer wait time
Driver-Rider	Cancel ride requests	Longer wait time
Driver-Rider	Refuse entrance into vehicle	Longer wait time; frustration and helplessness
Driver-Rider	Poor service	Longer ride; higher cost
Rider-Driver	Low/no tip	Reduced income
Rider-Driver	Poor rating	Jeopardize income
Rider-Rider	Use of pooled ride	Frustration and helplessness

Table 1: *Forms of discrimination in shared mobility. Targets could include race, color, religion, sex, national origin, and disability.*

Such outcomes can lead to more abstract and meaningful consequences, such as negative and unpleasant emotions like frustration and helplessness.[78, p. 652-653] What's more, discriminatory outcomes limit connectedness by discouraging or preventing interactions between strangers. Greater connectedness offers many benefits to society; positive social interactions between riders, exposure to diverse socio-spatial environments, and arguably happier, healthier people. It has been demonstrated, for example, that brief interactions with strangers may expand capacity to engage with different cultures and develop new social sensibilities.[21, p. 5] Transportation systems that emphasize connectedness can help support equality of opportunity, increase social capital, and even decrease the cost of dependency and institutional care.[101, p. 27]

One final issue related to discrimination and TNCs is the idea of responsibility. Arguably, a discriminatory action by a driver, for example, occurs at the individual level. After all, a TNC cannot control the treatment of customers over such a vast number of direct interactions. On the other hand, courts have held taxicab companies responsible for the discriminatory actions of their drivers, complicating the notion that Uber and Lyft are neutral platforms with no control over discriminatory outcomes. Additionally, if courts define TNCs as employers rather than simple platforms that connect drivers and riders, then Title VII of the Civil Rights Act will apply.[5] In that case, these firms may be held responsible for discrimination against drivers, even if that discrimination is a product of customer preference. Regardless of the classification of TNC drivers, this thesis holds TNCs responsible for protecting riders and drivers from discrimination and governments responsible for enforcing anti-discriminatory standards. In this light, Chapter 5 investigates ways that TNCs and governments can fulfill these responsibilities respectively.

[5]Whether Uber meets the legal definition of "employer" is being fought out in courts and administrative agencies across the country. A 2015 decision of the California Labor Commission confirmed an individual plaintiff's claim that she was an employee of Uber. In the 2018 ruling Dynamex Operations West, Inc. v. Superior Court, the Supreme Court of California established a test of employment in which a worker is considered an employee if she performs a job as part of the usual course of a company's business. The implications of this decision may take many years to manifest themselves, but could eventually force TNCs to adhere to laws related to minimum wage, overtime, workers' compensation, payroll taxes, and the like.[109]

3 Discriminatory Attitudes Between Ridesharing Passengers

Through daily mobility, we socialize or seek solitude, negotiate our identify and perform a range of social roles; through mobility we may contest power relationships and claim our right to participate in society or we may be excluded and ignored.

Marco Brömmelstroet [21, p. 5]

3.1 Introduction

As noted in Chapter 2, numerous studies have provided evidence for driver-to-passenger discrimination in the context of ridehailing. Seminal research by Ge et al. (2016), for example, provided experimental evidence that the design of Uber and Lyft's platforms allows for discrimination from individual drivers to riders. Though lacking the experimental approach of Ge et al., other recent studies have highlighted the theoretical case for rider-to-driver discrimination in TNCs. Rosenblat et al. (2017) used a review of consumer behavior in online marketplaces and performance evaluations in managerial settings to argue that racial and gender bias is likely to influence TNC driver evaluations. Additionally, one recent legal paper even proposed a rule that would obligate large companies in the sharing economy to reduce or eliminate harm arising from customer bias against their employees, as an extension of these companies' legal obligation not to discriminate themselves [15]. Together, these studies and legal cases highlight the possibility of discrimination between drivers and riders in the context of ridehailing.

Rider-rider discrimination is also plausible, but no studies to date have provided evidence of discriminatory attitudes in the context of dynamic ridesharing. Additionally, no studies have yet considered the variation of discriminatory attitudes in accordance with ridesharing user characteristics. To address these gaps in the literature, this chapter provides an empirical assessment of the discriminatory attitudes among various social groups in cities with access to dynamic ridesharing.

This chapter examines class- and race-related variations in discriminatory attitudes between fellow passengers and tests the impact of one's generic social dominance orientation on discriminatory attitudes in the ridesharing context. To do so, this chapter uses data from a survey of 1,110 TNC users to create two structural equation models. These models address the following research topics: 1) correlation between discriminatory attitudes toward fellow passengers of differing class and race in the shared ride and respondent characteristics such as gender, age, race, and income 2) variation in these attitudes according to targets of discrimination (i.e., race and class) in ridesharing 3) the influence of respondent's generic social dominance orientation in discriminatory preferences in the ridesharing context. The results of these inquiries will inform decisions by TNCs and policymakers as they seek to foster positive social interactions between riders and limit the ability of passengers to avoid or discriminate against one another on the basis of race and class.

Section 3.2 of this chapter provides relevant background on the rise of dynamic ridesharing. Then Section 3.3 explains the data collected and presents two structural equation models created to analyze discriminatory attitudes in ridesharing. The chapter then presents seven key findings from these models and summarizes the behavior and policy implications of these findings in Section 3.4.

3.2 Emergence of Dynamic Ridesharing

Before exploring the possibility of discrimination in dynamic ridesharing, the following section provides a brief introduction to rise of dynamic ridesharing since 2014. Ridesharing, in the form of carpooling or vanpooling, has existed for decades. Informal forms of ridesharing, such as Morocco's *grands taxis* and other forms of shared rides, have long been common across the world. Although it has always promised door-to-door service, lower per-passenger travel costs, and congestion reduction, traditional carpooling has been at best marginally successful in the United States. Nonetheless many studies have analyzed traditional carpool programs in order to inform policies that might increase carpooling. A seminal 1977 study of employers carpooling programs argued that the most important barriers to ridesharing were 1) the habit of private driving and 2) the resistance to initiating contact and starting a carpool [34, p. 688].

The arrival of the dynamic ridesharing products uberPOOL and Lyft Line in 2014 challenged these two primary barriers to carpooling: reluctance to give up individual driving and resistance to initiating contact with strangers. Regarding the former, the critical importance of individual car use seems to be eroding in light of TNCs, car-sharing services, and broader cultural shifts. Studies such as Klein and Scott, for example, have presented evidence that Americans (particularly "Millenials," born in the 1980s and 1990s) are less likely to own cars than previous generations [77]. While many studies have argued that this trend may reverse as Millenials age, the fact remains that travel behavior has changed [94, 31]. Regarding the second barrier to carpooling, new rider-rider matching algorithms have made it easier for riders to initiate contact with one another through efficient and convenient platforms. While conventional carpooling matching programs focused largely on the daily commute, ridesharing algorithms now offer appealing on-the-fly and round-the-clock connections. What's more, dynamic ridesharing technology also offers greater accountability, convenience, and social connections, adding to its general appeal.[1]

As a result of these evolutions, TNC rides often involve not just one driver and one rider, but also additional riders sharing the same ride. Services like uberPOOL and Lyft Line operate much like these companies' more traditional ridehailing products, such as uberX. Riders input their locations and destinations and their app then displays the price for a solo ride, as well as a discounted price for a pooled ride (often less than 75 percent of the traditional rate). In the case of Uber and Lyft apps, the uberPOOL and Lyft Line options are the default choice for users as of this writing. Pooling is available to both single riders and pairs of riders, with a small surcharge charged for the second rider. Riders choosing the pool option may ultimately be the only rider to use the service, or they may encounter second or third pick-ups, although they pay the same price regardless of whether the ride is shared. The exact match rate is not known, but Uber has claimed that it is as high as 90 percent in high-traffic areas during commuting hours [66].[2] Once a shared ride is underway, the driver may receive a notification that there is another passenger nearby with a geographically similar location. While drivers can decline this pickup, doing so can lower their ratings, and so each request is likely to be accepted.

Of course, additional passengers increase the overall trip time for riders, creating the potential for frustration on the part of riders. Due to the potential of delaying other riders, Uber and Lyft both ask that their riders be considerate toward one another. Uber's website asks POOL users to be ready to go before their driver arrives [67]. Lyft's website goes one step further, encouraging Line users to be considerate with their baggage and to be mindful of language and conduct [Inc.]. However, as of this writing, neither Lyft nor Uber offer the option for riders to rate the conduct of other riders.

In light of this major evolution in ridesharing, recent research at MIT investigated ridesharing users' perceptions, positive and negative, of sharing time and space with strangers in the backseat of a car [107]. The paper *To Share or Not to Share: Investigating the Social Aspects of Dynamic Rideshar-*

[1]While the popularity of Lyft Line or uberPOOL relative to these company's other products is not known, Lyft claims, for example, that Line rides account for 40 percent of total rides in cities where it is available.

[2]Rates of sharing outside of high-traffic areas are likely considerably lower. 2018 analysis from the Rocky Mountain Institute, for instance, showed that Lyft Line requests in Chicago, San Francisco, and New York City accounted for about one-third of total Lyft rides (regardless of whether Line passengers are matched with additional rideres).[29]

ing used a survey of 1,110 TNC users across the United States to explore how people experience the social aspects of ridesharing. This survey data provides the foundation of this chapter.

Among other important findings, research by Sarriera et al indicated that many riders harbor discriminatory attitudes towards passengers of different social class and race. What's more, these passengers seem to prefer additional early information about these future passengers, thus supporting earlier research arguing that a lack of information about potential passengers was a barrier to acceptance of ridesharing [75]. Given the findings of this paper, it is conceivable that rider-rider discrimination is already a critical issue in shared rides. While drivers currently serve as a third party moderator of rider-rider relationships, these interactions may become more prominent as driverless, autonomous ridesharing platforms become more ubiquitous (See Chapter 4 for more discussion of this possibility). While TNCs may mitigate discrimination and encourage positive social interactions between riders, efforts to build passenger-to-passenger rapport and ensure accountability, trust, and positive connections are still a new domain for research. By evaluating discriminatory attitudes in the shared ride, this chapter represents a first step in this effort.

Additionally, several studies have investigated attitudes such as drivers' willingness to interact with strangers and their desire for autonomy and convenience, but few have considered the potentially discriminatory aspects of carpooling and dynamic ridesharing. Chaube et al., for example, determined that lack of trust deters riders from offering or accepting shared rides [24]. Deloach and Tiemann investigated the effect of personality type (i.e., introvert, extrovert), marital status, and other factors on willingness to carpool and found that the desire for socialization can affect ridesharing. This paper also found a significant relationship between personal characteristics like gender and the perceived need for autonomy and flexibility in ridesharing [32, p. 533-535]. By extension, additional research could determine whether there is a relationship between personal characteristics and discriminatory attitudes in the ridesharing context. The current chapter intends to fill that research gap.

3.3 Modeling Discriminatory Attitudes in Ridesharing

In light of the discussion above, the following section reviews and analyzes the results of Sarriera et al.'s national survey of Uber and Lyft users in order to model users' attitudes toward potential fellow passengers and discuss their discriminatory attitudes in the context of ridesharing.

3.3.1 Data

Sarriera et al. conducted the survey in June and July 2016 through Amazon Mechanical Turk, a crowdsourcing service that allows researchers to compensate human workers to answer questions or perform other tasks. The researchers built the survey through the online survey development service Qualtrics and used Mechanical Turk to recruit a broad sample of survey takers. One limitation of the use of Mechanical Turk for this task was the possibility that the survey takers may be incentivized to complete surveys quickly and without thought. As such, the researchers screened such behavior through two basic attention check questions (e.g., "Please select 'Agree' for this question"). For this research, we also applied five further tests of attention and logical consistency to the completed responses. Responses that failed two or more of the five tests were omitted responses, as were any respondents that reported zero Uber or Lyft trips in the past month. Of 1,222 respondents who completed the survey and passed the basic attention checks, 112 failed the attention tests. The final sample size of the analysis was 1,110 respondents, 850 of whom had previously used dynamic ridesharing.

As shown in Table 2, the survey respondents were relatively young, male, white, and educated in comparison to the American population. These characteristics largely coincide with the characteristics of Mechanical Turk users more broadly [70]. Compared to the population of TNC users, the respondents were fairly representative with regard to gender, age, education, and race. Geographically, the most respondents were in the metropolitan areas of Los Angeles, New York City, Chicago, San Francisco, Boston, Philadelphia, Washington, D.C., Atlanta, and Miami, which accurately represents the markets in which dynamic ridesharing technology first arrived and still sees heavy use.

3.3.2 Descriptive Statistics

In addition to basic demographics, the survey posed questions in the following categories: general travel behavior; opinion on and experience with uberPOOL and Lyft Line; generic attitude toward social dominance (referenced in Section 3.3.3); and specific preferences with respect to being paired with people of different backgrounds in shared rides. The six attitudinal questions within this last category are of special interest to this chapter because they assess the existence of and potential for discrimination in ridesharing services through stated preferences. These six questions are:

Class

- i1: I would prefer to avoid being paired with a passenger of a lower social class in shared rides
- i2: Pairing passengers from all social classes in shared rides is a good idea (a "reverse" preference, i.e., more agreement indicates a less discriminatory attitude)

Race[3]

- i3: Sharing a ride with a passenger of a different ethnicity could make me uncomfortable
- i4: Everyone should welcome passengers of all ethnicities in shared rides (reverse)
- i5: Grouping passengers of different races in shared rides is a recipe for trouble
- i6: It would be great to be paired in shared rides with passengers of all different races (reverse)

The survey asked respondents to indicate their agreement to these and other preferences according to a seven-step Likert scale (i.e., opinion statements from "strongly disagree" to "strongly agree"). In most cases, the demographic questions were structured as multiple choice questions. Table 2 presents an overview of respondent demographics while Table 3 provides an overview of responses to discriminatory preference questions. Table 3 reveals that, in general, a small but significant minority explicitly expressed discriminatory attitudes (i.e., 6.0 to 12.6 percent, depending on the attitude and the characteristics of the respondents). These stated preferences offer powerful insight, but are likely to under represent the prevalence of discriminatory attitudes due to social desirability bias [99]. However, despite the limitations of measuring discriminatory attitudes through such stated preference surveys, these descriptive statistics suggest that such attitudes do indeed exist within the population of ridehailing users.

[3]While each of these four questions focuses either on race or ethnicity, in practice it is difficult to differentiate the two phenomenon in measurement and modeling, so they are combined for the purposes of this chapter and referred to as racial or race preferences.

Table 2: *Demographics of respondents. n=1,110*

Characteristic	Count	Characteristic	Count
Males	58.6%	Black	9.1%
Parents	25.8%	Asian	10.1%
Single	40.5%	Hispanic	7.6%
Women w/ Children	13.3%	White	69.3%
Single Women	13.8%	Uses Sharing	76.5%
Unemployed	6.6%	Primarily Drives	53.2%
Students	13.6%	Primarily Uses Transit	20.4%
HS Education	6.8%	Primarily Uses TNC	10.5%
Some College	28.7%	Owns Car	68.6%
College Degree	47.8%	–	–
Graduate Degree	16.5%	–	–

Table 3: *Preferences of respondents, from "Strongly Disagree" (1) to "Strongly Agree" (7). n=1,110*

	1	2	3	4	5	6	7
i1: I would prefer to avoid being paired with a pass. of a lower social class in shared rides	29.8%	23.7%	10.5%	24.4%	5.7%	3.8%	1.8%
i2: Pairing passengers from all social classes in shared rides is a good idea	2.4%	3.9%	6.3%	29.0%	19.5%	24.2%	14.3%
i3: Sharing a ride with a pass. of a different ethnicity could make me uncomfortable	37.8%	28.0%	9.4%	15.3%	5.7%	1.9%	1.6%
i4: Everyone should welcome passengers of all ethnicities in shared rides	1.2%	1.2%	3.6%	16.3%	14.0%	27.0%	36.5%
i5: Grouping passengers of different races in shared rides is a recipe for trouble	31.7%	26.5%	12.2%	17.8%	5.8%	3.2%	2.0%
i6: It would be great to be paired in shared rides with passengers of all different races	1.7%	4.1%	4.1%	31.4%	17.1%	27.7%	13.5%

Table 4, meanwhile, presents a series of bivariate cross-tabulations between demographics (particularly race and gender) and the six survey questions related to discrimination and ridesharing. This table suggests several simple correlations. Notably, a greater share of white or Asian respondents agree with discriminatory statements such as "Sharing a ride with a passenger of a different ethnicity could make me unconformable," relative to black or Hispanic respondents. Conversely, a greater share of black respondents agree with anti-discriminatory statements such as "Everybody should welcome passengers of all ethnicities in shared rides." The relative responses of men and women suggest that men agree more with the discriminatory statements.

Furthermore, a Mann-Whitney-Wilcoxon test revealed that several of these questions have significantly different answers for different groups of riders. In particular men and women are nonidentical populations (at the .01 significance level) for all preferences. White and nonwhite respondents are nonidentical populations for preferences i3 and i4. Black and non-black respondents are nonidentical populations for four out of six preferences: i2, i3, i4, and i6. Given these findings, the structural equation models presented in the following section examine the variations of discriminatory attitudes and the relationship between such attitudes and a generic social dominance orientation.

Table 4: *Cross-tabulations: Discriminatory preferences by selected rider characteristics*

i1: I would prefer to avoid being paired w/ a pass. of a lower social class									
Race	Weak	Med.	Strong	n	Gender	Weak	Med.	Strong	n
White	5.8%	3.6%	2.1%	770	Male	6.3%	4.1%	1.8%	651
Black	5.0%	5.9%	1.0%	101	Female	4.6%	3.3%	1.8%	454
Hispanic	4.8%	1.2%	1.2%	84	-	-	-	-	-
Asian	7.1%	6.3%	1.8%	112	-	-	-	-	-
i2: Pairing passengers from all social classes in shared rides is a good idea									
Race	Weak	Med.	Strong	n	Gender	Weak	Med.	Strong	n
White	6.8%	4.4%	2.7%	770	Male	7.4%	4.6%	2.3%	651
Black	5.0%	1.0%	3.0%	101	Female	4.8%	2.9%	2.9%	454
Hispanic	6.0%	2.4%	2.4%	84	-	-	-	-	-
Asian	6.3%	4.5%	1.8%	112	-	-	-	-	-
i3: Sharing a ride with a passenger of a diff. ethnicity could make me uncomfortable									
Race	Weak	Med.	Strong	n	Gender	Weak	Med.	Strong	n
White	6.5%	1.7%	2.2%	770	Male	6.5%	2.0%	2.0%	651
Black	2.0%	2.0%	0.0%	101	Female	4.6%	1.8%	1.3%	454
Hispanic	4.8%	2.4%	0.0%	84	–	–	–	–	–
Asian	5.4%	3.6%	1.8%	112	–	–	–	–	–

Legend: n: Number of Respondents;

Weak: Somewhat (dis)agree; Medium: (Dis)agree; Strong: Strongly (dis)agree

i4: Everyone should welcome passengers of all ethnicities in shared rides									
Race	Weak	Med.	Strong	n	Gender	Weak	Med.	Strong	n
White	3.9%	0.6%	1.4%	770	Male	4.8%	1.7%	1.8%	651
Black	1.0%	2.0%	2.0%	101	Female	2.0%	0.4%	0.4%	454
Hispanic	6.0%	3.6%	0.0%	84	-	-	-	-	-
Asian	3.6%	2.7%	0.9%	112	-	-	-	-	-
i5: Grouping passengers of different races in shared rides is a recipe for trouble									
Race	Weak	Med.	Strong	n	Gender	Weak	Med.	Strong	n
White	5.8%	3.2%	2.5%	770	Male	6.3%	2.6%	2.3%	651
Black	5.9%	4.0%	1.0%	101	Female	5.1%	4.0%	1.5%	454
Hispanic	4.9%	0.0%	1.2%	84	-	-	-	-	-
Asian	7.1%	4.5%	0.9%	112	-	-	-	-	-
i6: It would be great to be paired in shared rides with pass. of all different races									
Race	Weak	Med.	Strong	n	Gender	Weak	Med.	Strong	n
White	4.0%	4.5%	1.6%	770	Male	4.8%	4.8%	2.2%	651
Black	3.0%	2.0%	1.0%	101	Female	3.3%	3.3%	1.1%	454
Hispanic	10.7%	2.4%	3.6%	84	-	-	-	-	-
Asian	1.8%	6.3%	2.7%	112	-	-	-	-	-

Legend: n: Number of Respondents;

Weak: Somewhat (dis)agree; Medium: (Dis)agree; Strong: Strongly (dis)agree

3.3.3 Factor-Based Structural Equation Models

The following section uses the data described above to create conceptual models of self-reported discriminatory attitudes among various social groups. These models use factor-based structural equation models to assess the probability of a choice (i.e., the Likert-scale preferences described above) against explanatory variables (i.e., sociodemographic characteristics like age, gender, and income).[4] These models also include as explanatory variables additional information about respon-

[4]Explanation of coefficient names: isMale = whether the respondent is male; hasChildren = whether the respondent has 1 or more children; womenChildreni = interaction term indicating whether a respondent is a women living with a child;

dents' home counties: percentage of the population that is white and 2016 election results.[5]

This section presents two structural equation models (SEMs) that estimate latent factors that combine observable covariate Likert-scale responses, and analyze the relationships *between* the latent variables by combining measurement models and structural models. In particular, these two models group indicators of discrimination into three factors which we regress against the sociodemographic variables considered above. The three factors are:

- **Race and Ethnicity Factor (F_Race):** A simultaneous linear regression of the four race preferences described above (i.e., i3, i4, i5, and i6), which have a Cronbach's alpha of 0.842.[6]
- **Class Factor (F_Class):** A simultaneous linear regression of the two class preferences described above (i.e., i1 and i2), which have a Cronbach's alpha of 0.682.
- **Social Dominance Orientation Factor (F_SDO):** A simultaneous linear regression eight additional Likert-scale questions measuring respondents' attitudes towards the relative status of different social groups in general, which have a Cronbach's alpha of 0.899. These statements are:
  - S1: Some groups of people must be kept in their place
  - S2: Groups at the bottom are just as deserving as groups at the top ("reverse" preference)
  - S3: It's probably a good thing that certain groups are at the top and other groups are at the bottom
  - S4: An ideal society requires some groups to be on top and others to be on the bottom
  - S5: Groups at the bottom should not have to stay in their place (reverse)
  - S6: Some groups of people are simply inferior to other groups
  - S7: No one group should dominate in society (reverse)

EduLow = whether a respondent indicates their highest level of education as "High School / GED" or "Some College" ("College Degree" is the reference case); EduHigh = whether a respondent indicates their highest level of education as "Graduate Degree or Higher"; isBlack/Asian/Hispanic = whether the respondent is black/Asian/hispanic; primarilyDrive/Transit = the respondent's primary model of travel; ownsCar = whether the respondent owns a car; Income = respondent's reported income; percentWhite = percentage white population in respondent's county; percentGOP = percent vote for GOP candidate in 2016 presidential election in respondent's county

[5] Demographic information at the county level was collected from the U.S. Census Bureau's 2015 American Community Survey 5-year estimates, aggregated to the county level and paired with respondents based on their reported ZIP codes. County-level 2016 election results were collected from Townhall.com's collated county-by-county election results, as scraped and formatted by data scientist Tony McGovern. Full results are available here: https://townhall.com/election/2016/president/

[6] Cronbach's alpha provides a coefficient of reliability from 0 to 1. A score closer to 0 indicates that items are more independent of one another (i.e., not correlated or no covariance). The coefficient approaches 1 as the number of items with high covariances are included.

– S8: Group dominance is a poor principle (reverse)

Accounting for reverse-worded preferences and the number of items included in each factor, each of these three factors has a reasonably strong Cronbach's alpha measure. Additionally, the correlations presented in Table 5 demonstrate consistent correlation among all Likert-scale preferences, justifying various factor formulations. In keeping with the logical similarity of the questions being grouped, it is reasonable to expect that these factors reveal underlying latent variables manifested by a set of observed indicators. This finding justifies the application of SEM and the creation of the continuous factor variables listed above.

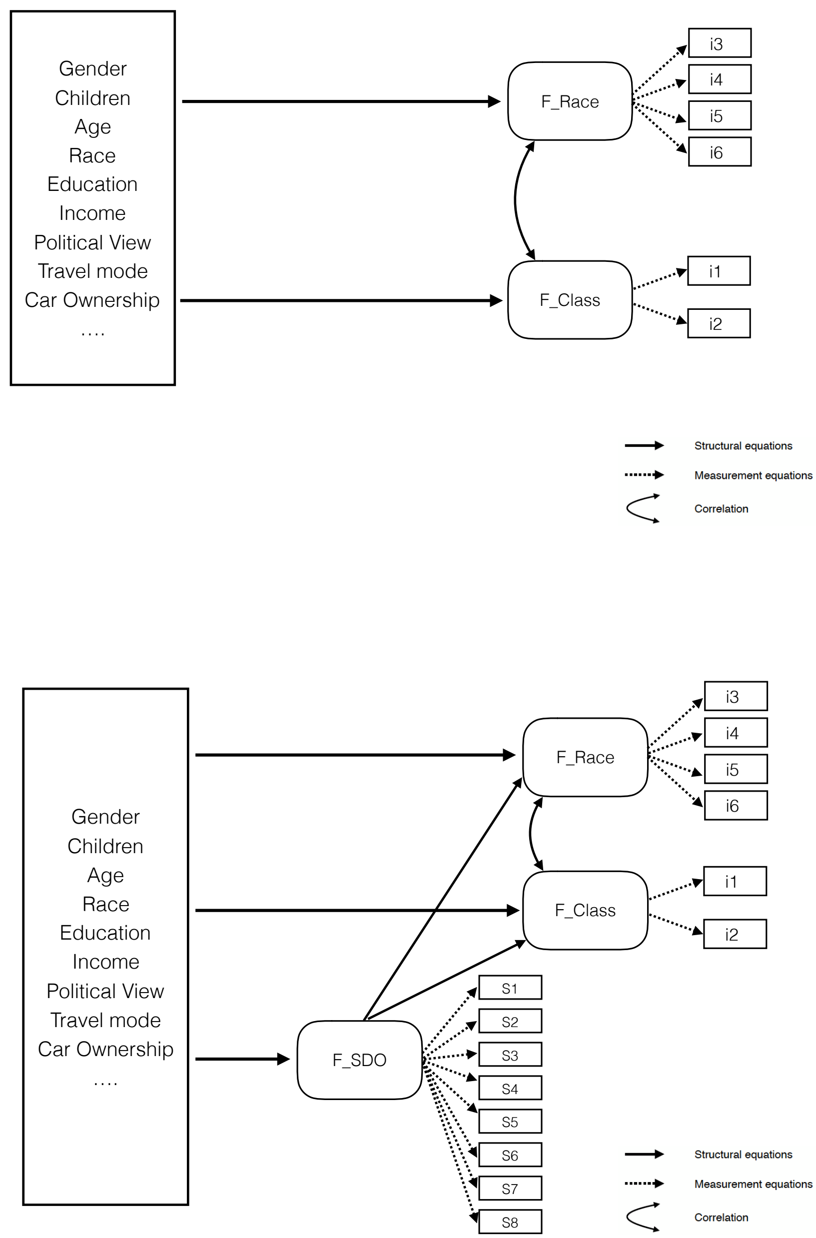
Table 5: *Correlation table for SEM analysis. Preferences are corrected for positive or negative directionality. p<0.05 for all pairs*

	i1	i2	i3	i4	i5	i6	F_SDO
i1	1	–	–	–	–	–	–
i2	0.519	1	–	–	–	–	–
i3	0.583	0.464	1	–	–	–	–
i4	0.523	0.571	0.684	1	–	–	–
i5	0.573	0.472	0.634	0.564	1	–	–
i6	0.426	0.642	0.496	0.567	0.496	1	–
F_SDO	0.513	0.434	0.573	0.590	0.492	0.469	1

Figure 1 illustrates two structural equation models constructed in the software MPlus Version 8. These models group observable discriminatory indicators (i.e., ridesharing preference and social dominance orientation questions) into multiple latent factors (i.e., F_Race, F_Class, and F_SDO). These factors are then regressed against sociodemographic information about respondents. Rounded rectangles represent latent variables and square rectangles represent measurement variables.

SEM Model 1 hypothesizes that sociodemographics can partly explain stated discriminatory preferences (as a stand-in for actual discriminatory behavior in ridesharing). SEM Model 2 adds the social dominance orientation factor and asks how attitudes toward social dominance in general influence attitudes in shared rides. The hypothesis behind SEM Model 2 is that generic social dominance preferences influence discriminatory preferences in the setting of a shared ride and that sociodemographics correlate to both social dominance attitudes and ridesharing-specific attitudes.

Figure 1: *Hypothesized Structural Equation Models 1 (top) and 2 (bottom)*



Both hypothesized models have mixed indices of fit, as indicated in Table 7. Comparative fit indices (CFIs) of 0.97 and 0.963 respectively indicate that the models fit the data better than more restricted baseline models. The models also both have high Tucker-Lewis indices (TLIs) of 0.953. However, the 90 percent confidence interval of the root mean square error of approximation (RMSEA) is 0.059-0.072 for SEM Model 1 and 0.065-0.072 for SEM Model 2. These confidence intervals indicate that there is very low probability that the RMSEA is less than 0.05. Using the RMSEA levels presented by MacCallum, Browne and Sugawara, the models achieve mediocre fit [83]. Nonetheless, the CFI and TLI measures of fit are strong enough to obviate the need for post-hoc model modifications. As such, the hypothesized models appear to fit the data well enough to support the hypothesized structure.

Table 7 also summarizes the standardized coefficients (and significance levels) for the explanatory variables included in the structural equations that support the two models. These variables include sociodemographic characteristics, information about the respondents' environment, and respondent travel behavior. The variables percentGOP, SDO, Age, and Income are continuous. All other variables are binary. Each coefficient represents the respective variable's effect on the respective factor score. In SEM 1, for example, the coefficient of isMale on F_Class is 0.341, indicating that the model predicts a male respondent's F_Class factor score to be 0.341 standard deviations higher than a female respondent's. The coefficient of percentGOP on F_Race is 0.623. Because percentGOP is presented as a decimal between 0 and 1, this means that an increase of 30 percentage points in percentGOP would increase a respondent's predicted factor score by 0.19 standard deviations. Table 6 presents the estimates of the measurement equations in SEM 1 and 2. Each of these coefficients has a p-value of less than 0.01.

Table 6: *Standardized measurement coefficients for SEM 1 and 2 (All are significant at the 0.99 confidence level)*

	SEM 1		*SEM 2*			
	F_Class	F_Race	F_Class	F_Race	F_SDO	
i1	.76	–	.78	–	$S1$	.89
i2	.78	–	.76	–	$S2$	.73
i3	–	.85	–	.86	$S3$	.92
i4	–	.85	–	.85	$S4$	.82
i5	–	.80	–	.79	$S5$	.70
i6	–	.77	–	.75	$S6$	.87
–	–	–	–	–	$S7$	.89
–	–	–	–	–	$S8$	.79

Table 7: *Structural Equations Models 1 and 2: Standardized coefficients for explanatory variables, including sociodemographics, environment, and travel behavior*

		SEM 1			*SEM 2*
	F_CLASS	F_RACE	F_CLASS	F_RACE	F_SDO
Demographics					
isMale	0.341***	0.423***	0.056	0.121*	0.416***
hasChildren	-0.18	-0.145	-0.152	-0.114	-0.042
womenChildreni	0.455***	0.398***	0.241	0.166	0.319**
Age	0.004	0.005	0.003	0.004	0.001
Socioeconomics					
EduLow	0.012	0.018	-0.066	-0.062	-0.111
EduHigh	-0.047	-0.117	-0.023	-0.089	-0.039
Income	0.022***	0.01	0.017***	0.004	0.0007
Race					
isBlack	-0.103	-0.115	0.019	0.008	-0.17
isAsian	0.189	0.168	-0.038	-0.078	0.338***
isHispanic	-0.019	-0.015	0.003	0.006	-0.029
Environment					
WhiteMaj	0.124	0.262**	0.063	0.198**	0.088
percentGOP	0.345	0.623**	-0.084	0.172	0.624***
Travel Behavior					
primarilyDrive	0.003	-0.162*	0.085	-0.073	-0.123
primarilyTransit	-0.17	-0.111	-0.018	0.049	-0.222**
ownsCar	0.055	0.133	-0.036	0.036	0.133
SDO	-	-	0.694***	0.726***	-
RMSEA Estimate:	0.065 (0.059-0.072)		0.068 (0.065-0.072)		
CFI/TLI	0.97	0.953	0.963	0.953	

*p<0.1; **p<0.05; ***p<0.01

Table 8: *SEM 2: Standardized direct, indirect, and total effects of selected variables*

isMale to F_CLASS	Estimate	isMale to F_RACE	Estimate
Total	0.34***	Total	0.42***
Indirect (via F_SDO)	0.29***	Indirect (via F_SDO)	0.30***
Direct	0.06	Direct	0.12*
womenChildreni to F_CLASS		womenChildreni to F_RACE	
Total	0.46***	Total	0.40***
Indirect (via F_SDO)	0.22**	Indirect (via F_SDO)	0.23**
Direct	0.24	Direct	0.17

*p<0.1; **p<0.05; ***p<0.01

The results presented in Figure 1 and Tables 7 and 8 confirm the hypotheses explained above. In particular, the results of SEM Models 1 and 2 reveal significant direct and indirect effects among the sociodemographic indicators and latent variables under consideration. According to Table 7, several characteristics have significant variables across multiple models, as noted in the findings below. In general, the sign of these coefficients does not vary between SEM 1 and 2, regardless of significance. Direct effects apparent in the models represent the effect of an independent variable (e.g., gender) directly on the dependent variable (e.g., discriminatory attitudes in the ridesharing context). Indirect effects represent the effect of independent variables on dependent variables through a mediating variable (e.g., social dominance orientation factor). The total effect represents a combination of direct and indirect effects [111]. Findings supported by these models include the following:

Effect of Personal Characteristics on Attitude

Finding 1: Male respondents and women with children have significantly more discriminatory responses to both race and class preferences. Income has a significant direct effect on class preferences, but no significant correlation with race preferences. Age and education have no significant effect on class or race preferences.

Finding 2: For respondents that live in counties in which a larger share of the electorate voted for the Republican candidate in the 2016 presidential election, there is an effect on race preferences but no effect on class preferences.

Finding 3: A respondent's race per se does not have a significant effect on discriminatory attitudes, but the combination of race and environment does. Specifically, white respondents that live in majority white counties are more likely to hold discriminatory attitudes with regard to race (no effect is observed regarding class preferences). Taking the share of a population that is white as a suitable proxy for the overall diversity of an area in the United States, this finding indicates that white riders living in less diverse communities may be more likely to harbor discriminatory attitudes. However, the measure of an area's whiteness (percent white population in a county) alone is not significant when included in the models (not shown in the tables above).

Finding 4: Whether a respondent primarily uses transit as a travel mode has a significant negative effect on a respondent's social dominance orientation. However, no travel behavior variables have a significant direct effect on discriminatory attitudes when included in the model, suggesting that discrimination is specific more to the individual than to the mode of choice.

Effect of Social Dominance Orientation on Attitude

Finding 5: Table 7 shows that F_SDO has the strongest effect on discriminatory attitudes in ridesharing. This suggests that individuals who agree with social dominance orientation questions are also more likely to hold discriminatory preferences in the context of shared rides. Table 8 shows how F_SDO works as an intermediary between sociodemographics and discriminatory attitudes in the shared ride, and reports the direct, indirect and total effects of the selected variables. For example, isMale has a total effect of 0.42 on F_Race, including the indirect effect of 0.30 via F_SDO and the direct effect of 0.12. In contrast, the effect of isMale on F_Class is dominated by the indirect effect via F_SDO.

Finding 6: The factors F_Race and F_Class are highly correlated with one another in both SEM 1 and SEM 2. The impact of F_SDO on F_Race and F_Class respectively is also similar (0.73 and 0.69 respectively). However, there are still important distinctions between the variables influencing F_Race and those influencing F_Class. In particular, WhiteMaj and percentGOP have significant total effects on F_Race, but not F_Class. The opposite is true of income, which has a significant direct effect on F_Class, but not on F_Race.

Finding 7: isAsian has a significant effect on F_SDO but no direct effect on F_Race or F_Class. This finding suggests that this sociodemographic indicator may influence social dominance attitudes in general, but does not explain discrimination in the shared ride context.

3.4 Discussion

This chapter explored the phenomenon of discriminatory attitudes in the shared ride and demonstrated substantial variation across user characteristics using hypothetical Likert-scale questions. Our first major behavioral finding is that discriminatory attitudes toward passengers of differing class and race in the shared ride are positively correlated with respondents that are male or are women with children. Respondents' race alone has no significant impact on discriminatory attitudes, but white respondents in majority white counties are more likely to hold such attitudes. The second major finding is that one's generic social dominance orientation strongly influences his/her discriminatory attitudes in ridesharing, supporting the claim that behavior in shared mobility platforms can reflect long-standing social dominance attitudes.

This chapter measured respondents' stated attitude about discrimination in the context of a shared ride. Further research could confirm our findings and also model the connection between these discriminatory attitudes and actual discriminatory behavior. In particular, this chapter suggests four avenues for further research.

First, an implicit association test (IAT) could confirm that passengers hold the discriminatory attitudes discussed in the analysis above. As noted earlier, stated preferences are likely to under represent discriminatory attitudes due to social desirability bias. IAT is a tool from social psychology research that offers a potential solution to this problem. In particular, IAT associates words and photographs to specific response keys on a keyboard and then measures differential response times to determine the strength of respondents' automatic preferences [46]. IAT has been applied in other transportation behavior research (such as predicting users' primary commute mode choice) and could be applied to testing automatic preferences for fellow passengers in a shared ride [88].

Second, experimental methods could consider causality in ridesharing and discrimination. That is, does the ridesharing context cause a change (i.e., exacerbation or mitigation) in the discriminatory attitudes of passengers? Third, additional surveys could ask respondents about how their attitudes affect other behaviors in the TNC context, such as tipping and rating. These questions could be posed either implicitly or explicitly. Even a blunt question such as "When deciding whether to tip, do you consider the driver's race?" would reveal a lower bound of discrimination, despite the social desirability bias. Finally, repeating the same survey after a major policy or platform change could provide a comparison that reveals how discriminatory attitudes change in response to an intervention or other shift. The 2016 presidential election (which occurred four months after the survey was complete) could provide an interesting natural experiment, given the observed impact of respondents' counties' electoral history on discriminatory responses.

Exactly how these discriminatory attitudes could manifest themselves in a shared ride is also a topic for further research and discussion. Currently ridesharing matching algorithms are efficiency-oriented and ignore passengers' socioeconomic characteristics. However, given the attitudinal findings of this chapter, it is worth considering how a shared ride user could use the sharing platform to discriminate against another rider. For one, any TNC rider who is inclined to discriminate against fellow passengers might avoid shared services altogether, thereby altering the demographics of the pool of shared ride users. Second, ridesharing services already provide riders with certain actionable information about their fellow passengers. For example, Lyft Line users who are paired with an additional passenger can view the name of their fellow passengers when they are matched with a ride already in progress. Because the app provides this information well before the ride arrives, the passenger is theoretically able to cancel the ride if he deems the other passenger unsuitable. Relatedly, Zhang and Zhao are developing preference-based matching methods that go beyond efficiency criteria to incorporate various types of passenger preferences, but point out that not all individual preferences are socially respectable and caution against the potential misuse of such preference-based matching algorithms [126].

Likewise, the results of this chapter suggest that if TNCs were to allow passengers to express preferences about one another, some number of users may discriminate against riders based on race and class. While this feature is only a counterfactual today, it is conceivable that Uber or Lyft might one day implement features that incorporate preference matching or provide riders with information about one another, given enough popular user support. Indeed in our survey, many respondents indicated a preference for seeing another passenger's profile photo (26.6 percent) or name, gender, and age (33.4 percent) *before* entering the ride. Furthermore, it is reasonable to think that some riders would also take advantage of a feature that allowed them to indicate preferences for characteristics of fellow passengers, such as race or class.

While this chapter does not call for specific changes in TNC operations or regulations, it does point out the need for TNCs and regulators to draw what Zhang and Zhao call a "boundary between acceptable and unacceptable articulations of preferences." That is, the ridesharing industry and society at large should think seriously about which expressions of preferences are legitimate/illegitimate and then avoid preference-based matching methods that could facilitate discrimination based race or class. As such, this chapter calls on TNCs and policymakers to limit the ability of passengers to avoid or discriminate against one another on the basis of race or class.

While this chapter has expanded upon existing studies of discrimination by hypothesizing about potential rider-rider discrimination, Chapter 4 expands on the analysis further by considering how the advent of autonomous vehicles may affect rider-rider discrimination.

4 Discriminatory Attitudes in Driverless Rides

I think autonomous driving's just going to become normal. Like an elevator. They used to have elevator operators, and then we developed some simple circuitry to have elevators just come to the floor that you're at, you just press the button.

Elon Musk [57]

4.1 Introduction

While an exact prognostication is impossible, it is safe to say that autonomous vehicles (AVs) will become increasingly common in the coming years. What's more, ridesharing fleets will be among the first applications of self-driving vehicles for one important reason: taxis get used more and result in lower per-mile vehicle costs. Indeed, Waymo launched autonomous taxi service in the suburbs of Phoenix in 2018 and General Motors has announced plans to launch an autonomous ridesharing service in multiple cities in 2019.[7] Uber has been piloting self-driving fleets in Pittsburgh since 2016 and Lyft has announced its intention to offer the majority of its rides in self-driving cars by 2021.[55] In the words of Elon Musk, self-driving cars are "just going to become normal." If this is the case, it is also critical that we, as a society, determine what interpersonal relations in autonomous shared rides are "just going to become normal" as well.

Chapter 3 considered rider-rider discriminatory attitudes in the context of dynamic ridesharing (e.g., uberPOOL and Lyft Line) and provided an empirical assessment of the discriminatory attitudes among various social groups. Chapter 4 expands this research to the topic of rider-rider discriminatory attitudes in driverless rides, a new domain for research. This chapter is motivated by the concern that rider-rider discrimination will emerge as a critical issue in the future as autonomous ridesharing platforms become more ubiquitous. While drivers, as a third party, may currently moderate the rider-rider relationship, these interactions will become more fraught as AVs and driverless ridesharing platforms become ubiquitous. Without a driver, rider-rider relations will become considerably more intimate, leading to possible safety concerns and exacerbating discomfort with difference. Riders may fear the absence of a driver to enforce of social norms, witness possible misconduct, and moderate interactions. As a result, passengers may have a harder time establishing trust and accountability among one another, necessitating interventions to facilitate positive rider-rider interactions.

In light of this concern, the following chapter uses data from a second national survey of TNC users (n=1,113) to address the following research topics: 1) The impact of the driverless context[1] on discriminatory attitudes between fellow passengers in an autonomous rideshare; 2.) Variation in this impact according to the target of discrimination, particularly race, class, and gender;[2] 3.) Variation in this impact according to sociodemographic and environmental characteristics such as gender, race, age, income, and political environment. By expanding the research of Chapter 3 to the AV context, the answers to these questions will further inform long-range decisionmaking regarding autonomous ridesharing policy and service provision.

Section 4.2 of this chapter explains the data collected for this research and presents descriptive statistics. Section 4.3 then compares stated discriminatory preferences in the current ridesharing context and the future autonomous ridesharing context. The paper then presents key findings from this analysis and summarizes the behavior and policy implications of these findings in Section 4.3.3.

4.2 Data and Descriptive Statistics

In light of the discussion above, the following section introduces a 2018 survey of Uber and Lyft users completed to model users' attitudes toward potential fellow passengers in the driverless context. The survey is similar to the Sarriera et al. (2016) survey presented Chapter 3. As with the 2016 survey, the updated survey was built through the online survey development service Qualtrics and

[1]This chapter uses the terms "driverless context," "autonomous context," and "AV context" interchangeably. The status quo of ridesharing with human drivers is referred to as the "traditional ridesharing context" or simply ridesharing/RS.

[2]In this chapter, race- and class-based discriminatory attitudes are referred to as such. Gender-based preferences are not referred to as "discrimination," which connotes an undesirable attitude. Rather, gender preferences may reflect very legitimate safety concerns on the part of females regarding ridesharing with male strangers in a confined, private space. Indeed, allowing women to avoid shared rides with men may be a responsible, even desirable feature.

administered through Amazon Mechanical Turk, a crowdsourcing service that allows researchers to compensate human workers to answer questions or perform other tasks. As before, the use of Mechanical Turk for this task risked the possibility that the survey takers might complete the survey quickly and without thought. As such, the 2018 data screened such behavior through two basic attention check questions (e.g., "Please select Agree for this question"). Of the 2,126 raw responses received, 1,446 passed these two attention checks and were eligible for analysis. Eligibility is defined as indication that 1) UberPOOL/Lyft Line is available in a respondent's city and 2) they had used Lyft or Uber in the past 30 days. For this research, we also applied five further tests of attention and logical consistency to the completed responses. Responses that failed two or more of the five tests were omitted. Of 1,442 respondents who past the first filter, a further 329 failed the attention tests. The final sample size of the analysis was 1,113 respondents, 833 of whom had previously used dynamic ridesharing.

4.2.1 Descriptive Statistics

As shown in Table 9, the survey respondents were relatively young, male, white, and educated in comparison to the American population. As with the 2016 data presented in Chapter 3, these characteristics largely coincide with the characteristics of Mechanical Turk users more broadly [70]. In comparison to the 2016 data, the 2018 data included more responses from women, parents, Asian respondents, and students, and fewer responses from white or Hispanic participants. Compared to the population of TNC users, the respondents were fairly representative with regard to gender, age, education, and race. The 2018 survey also asked respondents for their party affiliation and choice of presidential candidate in the 2016 election. With just 16.2 percent of responses coming from registered Republicans and 21.2 percent from individuals who voted for Donald Trump in the 2016 election, the data is far from representative of the national population.[3] Nonetheless, any lack of representativeness is accounted for in the modeling approach presented in Section 4.3.

[3]Naturally the political views of TNC users as a group are not known. However, TNC users are younger and more urban than the general population, so it is reasonable to surmise that they are a more heavily Democratic group.

Table 9: *Demographics of respondents. n=1,113*

Characteristic	Count	Characteristic	Count
Males	54.4%	Black	10.0%
Parents	31.6%	Asian	12.8%
Single	36.7%	Hispanic	6.5%
Women w/ Children	17.3%	White	64.2%
Single Women	14.1%	Uses Sharing	74.8%
Unemployed	6.8%	Registered Republican	16.2%
Students	4.7%	Voted GOP	21.2%
HS Education	6.7%	Uber User (only)	33.2%
Some College	25.8%	Lyft User (only)	5.6%
College Degree	48.9%	–	–
Graduate Degree	18.5%	–	–

In addition to basic demographics, the survey posed questions in the following categories: level of satisfaction with uberPOOL and Lyft Line; generic attitude toward social dominance (see the Social Dominance Orientation questions presented in Chapter 3); personal characteristics such as introversion and friendliness; opinion on possible interventions to prevent discrimination in ride-hailing;[4] and specific preferences with respect to being paired with people of different backgrounds in shared rides and driverless shared rides. The ten attitudinal questions within this last category are of special interest to this paper because they allow for the comparison of discriminatory attitudes in the current ridesharing context and a future autonomous ridesharing context. To clarify this distinction, the survey presented users with the following text in between the two sets of questions related to discriminatory attitudes:

> *The next question will ask you to explain your opinion about shared rides in a future with self-driving Lyft and Uber vehicles (also known as driverless or autonomous vehicles, or AVs). These companies are already experimenting with driverless ride service, and are likely to expand. In the following questions, consider how you would feel in a shared ride with no driver in the car.*

The survey asked respondents to indicate their agreement to twenty discriminatory attitude questions according to a seven-step Likert scale (i.e., opinion statements from "strongly disagree" to

[4]The results of these questions are presented in Chapter 5

"strongly agree"). Table 10 provides an overview of responses to these questions, according to pairs of corresponding questions in traditional and autonomous ridesharing respectively. Table 10 reveals that, in general, a small but significant minority explicitly expressed discriminatory attitudes (i.e., 6.0 to 15.9 percent, depending on the question) in the current ridesharing context. However, Table 10 also reveals that a greater share of respondents agreed with discriminatory attitudes in the driverless context (i.e., 11.0 to 33.6 percent). For each question pair, a greater number of respondents agreed with discriminatory attitudes in the driverless context. This difference ranges from 3.5 percentage points for RS/AV3 (discriminatory class preference) to 18.2 percentage points for RS/AV8 (gender preference).

Despite these findings, there are several important limitations to the comparison. As noted in Chapter 3, stated preferences such as these are likely to under represent the prevalence of discriminatory attitudes due to social desirability bias.[99] In the case of the 2018 data, another limitation is the directness with which the survey asked respondents to consider the driverless context. By emphasizing the absence of drivers in the preparatory text, for example, the survey may prompt respondents to feel less comfortable with driverless ridesharing. The exact phrasing of the questions themselves may also have a large impact on respondents' reactions. Terms like "autonomous," "self-driving," and "driverless" refer to the same phenomenon, for example, but are likely to prompt very different associations for respondents. However, despite these limitations, the obvious shift in attitude with and without drivers suggests that the arrival of autonomous ridesharing will indeed influence discriminatory attitudes among ridesharing users. Section 4.3 explores this shift in greater detail.

Table 10: *Preferences of respondents (with and without drivers present), from "Strongly Disagree" (1) to "Strongly Agree" (7). n=1,113*

	1	2	3	4	5	6	7
RS1: Grouping passengers of different races in shared rides is a recipe for trouble	29.4%	30.1%	12.0%	15.2%	7.4%	3.6%	2.3%
AV1: Without a driver present, grouping passengers of different races in shared rides is a recipe for trouble	23.9%	21.7%	13.3%	19.6%	10.5%	6.1%	4.9%
RS2: It would be great to be paired in shared rides with passengers of all different races	1.7%	3.7%	4.0%	28.3%	17.4%	27.0%	17.8%
AV2: It would be great to be paired in driverless shared rides with passengers of all different races	8.8%	7.7%	7.1%	26.0%	16.3%	20.5%	13.7%
RS3: I would prefer to avoid being paired with a passenger of a lower social class in shared rides	30.8%	26.8%	9.6%	16.9%	8.1%	4.5%	3.3%
AV3: I would prefer to avoid being paired with a passenger of a lower social class in shared rides when there is no driver present	27.3%	21.7%	13.6%	18.0%	8.0%	6.6%	4.9%
RS4: Pairing passengers from all social classes in shared rides is a good idea	2.8%	4.2%	6.6%	28.0%	17.3%	22.5%	18.7%
AV4: Pairing passengers from all social classes in driverless shared rides is a good idea	6.8%	6.6%	9.4%	30.4%	17.4%	16.4%	12.8%
RS5: Sharing a ride with a passenger of a different ethnicity could make me uncomfortable	41.5%	26.5%	10.9%	10.6%	6.9%	2.1%	1.5%
AV5: Sharing a ride with a passenger of a different ethnicity could make me uncomfortable when there is no driver present	32.1%	22.0%	11.6%	14.9%	10.0%	4.6%	4.9%

	1	2	3	4	5	6	7
RS6: Everyone should welcome passengers of all ethnicities in shared rides	1.4%	1.4%	3.1%	10.7%	13.8%	31.7%	37.7%
AV6: Everyone should welcome passengers of all ethnicities in driverless shared rides	3.7%	3.4%	3.9%	19.6%	16.1%	26.3%	27.0%
RS7: Sharing a ride with a passenger of a different gender could make me uncomfortable	36.9%	26.1%	10.7%	11.1%	10.2%	3.8%	1.2%
AV7: Sharing a ride with a passenger of a different gender could make me uncomfortable when there is no driver present	22.9%	19.5%	11.1%	12.9%	15.3%	10.8%	7.5%
RS8: Pairing men and women together in shared rides is a good idea.	2.7%	3.5%	7.0%	35.1%	16.4%	20.4%	14.8%
AV8: Pairing men and women together in driverless shared rides is a good idea.	8.4%	10.3%	12.8%	31.5%	14.1%	13.0%	9.9%
RS9: I prefer not to be paired with passengers who are different from me	32.7%	25.5%	14.0%	14.4%	7.6%	3.6%	2.2%
AV9: I prefer not to be paired with passengers who are different from me when there is no driver present	23.5%	19.6%	12.8%	20.4%	12.3%	6.4%	4.9%
RS10: Sharing a ride with a stranger is a good opportunity for me to meet someone with a different background	2.8%	3.6%	5.6%	19.6%	27.6%	21.9%	19.0%
AV10: Sharing a ride with a stranger is a good opportunity for me to meet someone with a different background, even when there is no driver present	6.2%	6.0%	6.8%	25.1%	22.4%	17.8%	15.7%

4.3 Modeling and Analysis

The following section uses the data described above to address the three research topics presented in Section 4.1: 1) The impact of the driverless context on discriminatory attitudes between fellow passengers in a ridesharing; 2.) Variation in this impact according to the target of discrimination;

3.) Variation in this impact according to sociodemographic and environmental characteristics such as gender, race, age, income, and political environment. Section 4.3.1 uses a comparison of means and distributions to address the first two topics. Section 4.3.2 presents a series of linear regression models addresses the third topic.

4.3.1 Comparison of Means and Distributions

A simple paired t-test allows researchers to compare two population means where an observation in one sample (i.e., discriminatory attitudes in ridesharing) can be easily paired with observations in another sample that varies in one important way (i.e., these same attitudes in a driverless context or some other "treatment"). Given the close connections between the pairs of Likert-scale questions presented in Table 10, the paired t-test is an appropriate method for considering the impact of the driverless context on discriminatory attitudes between fellow passengers in an autonomous rideshare. In this light, Table 11 presents the results of four simple comparisons. The column "Overall" compares the average of the ten questions on discriminatory attitudes in ridesharing to the average of the ten corresponding questions in the driverless context. The other three columns offer more specific comparisons between the averages of the race-, class-, and gender-based discriminatory attitude questions. "Gender," for example, refers to the average of the preferences RS7/AV7 and RS8/AV8.

Table 11: *Paired t-test results*

	Overall	Race	Class	Gender
Difference of Means	0.55^{***}	0.53^{***}	0.37^{***}	0.81^{***}
95% Confidence Interval	(0.50,0.60)	(0.47,0.59)	(0.31,0.44)	(0.73,0.89)

*p<0.1; **p<0.05; ***p<0.01

Table 11 shows that the difference in means between the overall discriminatory attitudes in the current context and in the driverless context is 0.55, with a 95 percent confidence interval of 0.50 to 0.60. This difference indicates that, on average, respondents considering the driverless context indicate discriminatory attitudes roughly a half-point higher on a seven-point Likert-scale. Considering more specific targets of discrimination, Table 11 indicates that a greater difference is observed for gender-based preferences (0.81) and a lesser difference is observed for class-based discrimination (0.37).

Figure 2 offers another representation of this phenomenon. In the scatter plot comparison of overall attitudes, the points above and to the left of the black 45 degree line represent respondents who indicated an increase in discriminatory attitudes when there is no driver present. Such an increase is observed for most of the responses. Darker dots represent a greater number of responses at that particular combination of attitudes with and without a driver. The darkest dots are clustered on and slightly above the 45 degree line, as the shift in attitudes is, on average, only 0.55 points. Not surprisingly, the largest increases in discriminatory attitude are observed from the respondents with the least discriminatory initial responses; any respondent who indicated strong agreement with a discriminatory attitude, for example, cannot increase his agreement further in the autonomous context. The three other subfigures present a similar trend; discriminatory attitudes increase the most for respondents who start at the lowest level of agreement. Neutral responses indicate the least amount of change in the driverless context.[5]

Figure 2: *Comparison of Discriminatory Attitudes in Autonomous and Traditional Ridesharing Context, by Target of Discrimination*

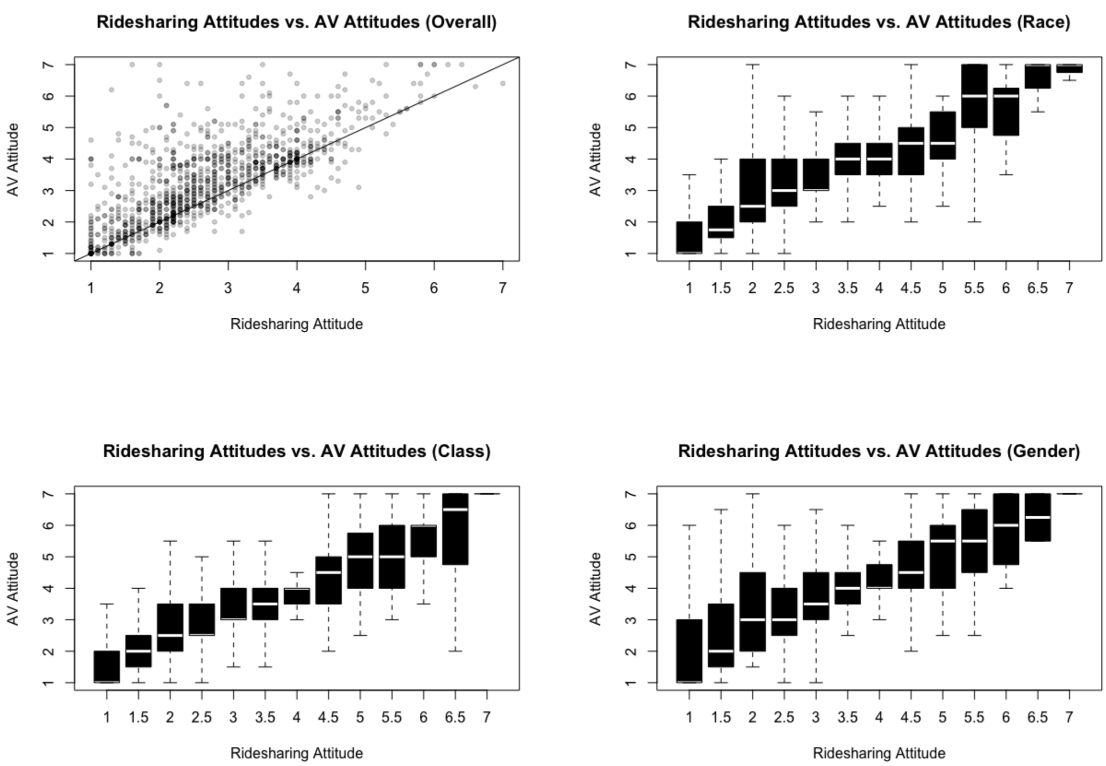
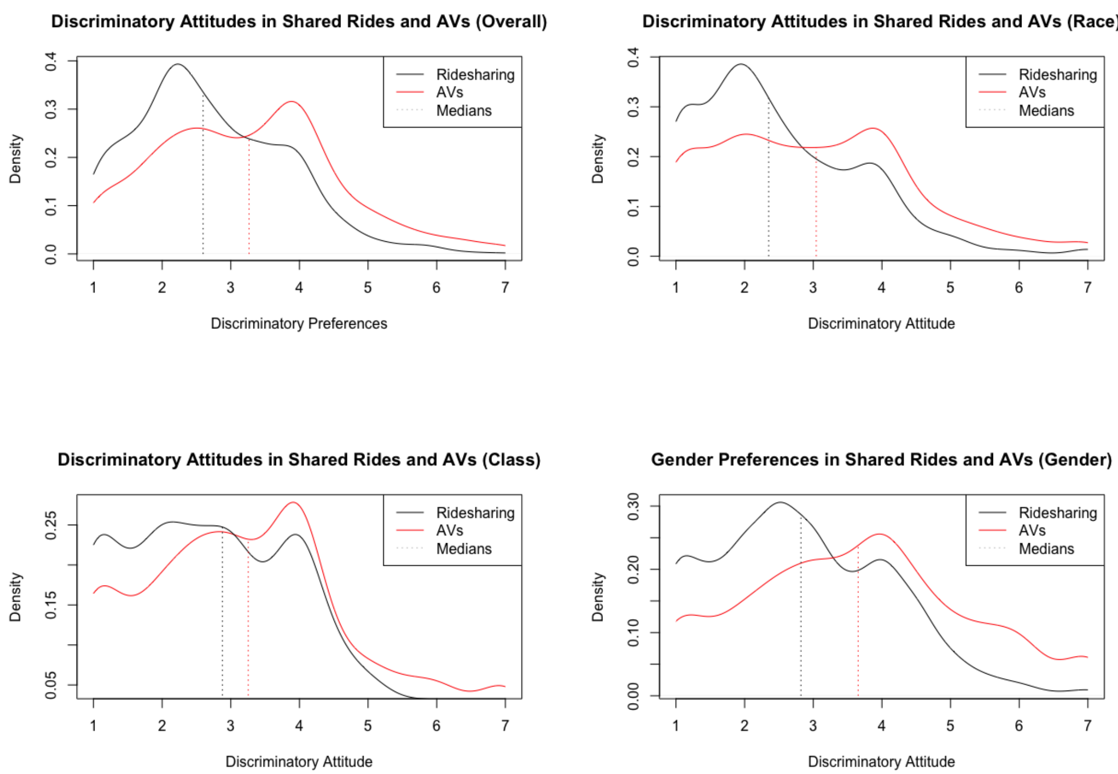


Figure 3 compares not the means, but the distributions of discriminatory attitudes in the two contexts under consideration. In particular, Figure 3 presents four probability density functions of

[5]These three subfigures are presented as box plots rather than scatter plots for legibility reasons: the averages for gender preferences and for race- and class-based discriminatory attitudes comprise fewer indicators than the overall attitudes, and thus a smaller, discrete number of possible values.

discriminatory attitudes according to the target of discrimination: race, class, and gender, as well as an overall average of discriminatory attitudes. Each probability density function presents the relative likelihood that a discriminatory attitude will take a particular value in each of the two contexts. Accordingly, the subfigures indicate a greater density of discriminatory responses (i.e., responses greater than 4) in the driverless context, regardless of target. The shift in median, however, is greatest for gender preferences and the least for class-based attitudes (in keeping with the means of differences presented in Table 11). The modes (represented by the peak of the distribution) in each pair of distributions also increases considerably between the ridesharing context and the autonomous context (e.g., from 2.2 to 4.0 for the overall discriminatory attitudes).

Figure 3: *Comparison of Distributions by Target of Discrimination: Discriminatory Attitudes in Autonomous and Traditional Ridesharing Context*



4.3.2 Variations in Effect

Section 4.3.1 presented evidence that the driverless context will exacerbate discriminatory attitudes between fellow passengers in the ridesharing context. The following section explores variation in this effect according to passengers' sociodemographic and environmental characteristics.

Tables 12 through 14 present the results of several linear regression models that explore how discriminatory attitudes in both traditional and autonomous ridesharing vary according to personal characteristics. These models assess the correlation between a choice (i.e., Likert-scale preferences) and various explanatory variables related to the respondent sociodemographics.[6] These models also include as explanatory variables additional information about respondents' home counties: percentage of the population that is white and 2016 election results.[7]

The models presented in Table 12 differ in their dependent variables. "Overall" refers to the average of ten discriminatory indicators in the ridesharing context, while "Race," "Class," and "Gender" refer to the averages of their respective indicators only. There is a pair of models for each dependent variable: one that controls for respondents' social dominance orientation and one that does not. Tables 13 and 14 following a similar structure, but with different dependent variables. Table 13 presents the averages of AV attitudes while Table 14 presents the difference between respondents' attitudes in the ridesharing and AV context.

Table 12 presents several findings. As expected, there is a significant positive correlation between social dominance orientation and discriminatory attitudes of all types. Next, while there is a significant negative correlation between female respondents and discriminatory attitudes with regard to race and class, there is a positive correlation with regard to gender preferences. Black and Asian respondents have significantly more discriminatory attitudes for class and class/race respectively, but only when social dominance orientation is not included in the model. Hispanic respondents have significantly less discriminatory responses across the board, but only when the model controls for social dominance orientation. Respondents who voted for Donald Trump have more discriminatory class- and gender-based attitudes only when not controlling for social dominance orientation (likely due to the correlation between this factor and support for Donald Trump). Respondents who have used sharing have less discriminatory responses across the board, when controlling for social dominance orientation, suggesting that either 1) the experience of sharing discourages discriminatory attitudes or 2) those with less discriminatory attitudes are more likely to use sharing. Finally, respondents who use only Uber have more discriminatory attitudes toward passengers of differing class and race, but only when social dominance orientation is not included in the model.

[6]Many of these variables are identical to those presented in Chapter 3 and those presented in Table 9. Explanation of additional coefficient names: Female = whether the respondent is female; WomenChildren = interaction term indicating whether a respondent is a woman living with a child; SingleWomen = interaction term indicating whether a respondent is a single woman; Age = respondent's reported age (reported in ranges and assigned midpoint of range); percentWhite = percent of a county's population that is white; Income = respondent's reported income (reported in ranges and assigned midpoint of range); IncomeAboveAverage = interaction term indicating whether a respondent's income exceeds the AHI for their respective county, UberOnly = a respondent indicated that Uber is the only ridehailing app on his/her phone, SDAvg = an average of eight indicator questions related to one's generic social dominance orientation (see Chapter 3 for more detail.

[7]This information was collected from the U.S. Census Bureau's 2015 American Community Survey 5-year estimates, aggregated to the county level and paired with respondents based on their reported ZIP codes.

Table 13 confirms many of the phenomena presented in Table 12, with a few noteworthy differences in the AV context. First, age, which previously had no significant relationship, is now correlated with more discriminatory attitudes for race and class, but not gender. Similarly, above average incomes are correlated with discriminatory class- and race-based attitudes in the AV context only. percentGOP is negatively correlated with gender preferences, while the effect previously observed for respondents who use Uber exclusively disappears in the AV context. All of these findings suggest that discriminatory attitudes will differ in the driverless ridesharing context, particularly for older riders and women. Similarly, Table 14 shows significant increases in discriminatory attitudes between the two contexts for women (race and gender preferences only), age (race and class preferences only), and women with children (race only). Notably, a respondent's social dominance orientation has no significant relationship with the difference in attitudes.

The most important of these findings is that the attitudes of women appear to be most influenced by the driverless context of autonomous ridesharing, likely due to safety concerns in the privacy and seclusion of a driverless ride. Given such concerns, it is difficult to determine whether unwillingness for a female rider to share a ride with a male driver should be considered discrimination (i.e., and unacceptable and illegitimate articulation of preference), or a prudent act of self-protection.[8]

[8]The debate surrounding the Boston start-up Safr offers a relevant parallel. The company's platform is available only to female riders and drivers. While the motivations of these restrictions are pure, the company and others like it have also faced criticism related to discrimination in pubic accommodation, as well as gender-based hiring that may violate Title VII of the Civil Rights Act. Similar concerns have been raised regarding male membership in all-female gyms and other places of public accommodation.

Table 12: *Linear Regression Models 1-8: Ridesharing Attitudes*

	Dependent variable:							
	Overall		Race		Class		Gender	
	With SD	Without SD	With SD	Without SD	With SD	Without SD	With SD	Without SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Demographics								
Female	−0.031	−0.111	−0.133	-0.222^{*}	-0.338^{***}	-0.436^{***}	0.431^{***}	0.385^{***}
Children	−0.062	−0.032	−0.022	0.011	−0.168	−0.132	0.083	0.100
Single	−0.114	−0.023	−0.044	0.057	-0.197^{*}	−0.088	−0.188	−0.136
WomenChildren	0.072	0.088	0.048	0.065	0.287^{*}	0.306	−0.142	−0.133
SingleWomen	0.060	−0.072	−0.021	−0.169	0.158	−0.002	0.168	0.092
Age	0.002	−0.004	0.004	−0.003	0.002	−0.006	−0.002	−0.005
Black	−0.030	0.180	0.004	0.237	0.045	0.299^{*}	−0.019	0.101
Asian	−0.019	0.264^{**}	0.017	0.332^{**}	−0.090	0.252	−0.047	0.115
Hispanic	-0.329^{**}	−0.071	-0.303^{**}	−0.017	−0.250	0.062	-0.411^{**}	−0.264
Socioeconomics								
Unemployed	−0.095	−0.073	−0.137	−0.112	0.013	0.040	−0.095	−0.082
Student	−0.113	−0.049	−0.186	−0.115	−0.036	0.041	−0.028	0.008
Income	0.0002	−0.001	−0.0003	−0.002	0.002	0.0002	−0.0004	−0.001
IncomeAboveAverage	0.005	0.123	−0.001	0.130	−0.077	0.066	0.059	0.127
Voting								
Republican	0.036	0.184	0.031	0.195	0.097	0.276^{*}	0.017	0.101
Trump	0.171^{*}	0.626^{***}	0.242^{**}	0.748^{***}	0.169	0.719^{***}	0.105	0.365^{***}
percentGOP	−0.311	−0.346	−0.124	−0.163	−0.208	−0.250	−0.574	−0.594
Environment								
WhiteMaj	−0.095	0.036	−0.032	0.114	−0.164	−0.005	−0.115	−0.040
percentWhite	0.003	0.004	0.00001	0.001	0.003	0.004	0.006	0.007
Travel Behavior								
UseShare	-0.120^{*}	−0.021	-0.132^{*}	−0.022	-0.147^{*}	−0.028	-0.196^{**}	−0.140
UberOnly	0.079	0.146^{**}	0.087	0.161^{**}	0.096	0.176^{*}	0.011	0.049
SDAvg	0.489^{***}	–	0.544^{***}	–	0.592^{***}	–	0.280^{***}	–
Constant	1.405^{***}	2.510^{***}	1.156^{***}	2.385^{***}	1.419^{***}	2.756^{***}	2.026^{***}	2.658^{***}
R^2	0.373	0.098	0.407	0.124	0.338	0.099	0.114	0.049
Adjusted R^2	0.360	0.080	0.394	0.106	0.325	0.081	0.095	0.030

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: *Linear Regression Models 9-16: AV Attitudes*

	Dependent variable:							
	Overall		Race		Class		Gender	
	With SD	Without SD	With SD	Without SD	With SD	Without SD	With SD	Without SD
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Demographics								
Female	0.212*	0.129	0.020	−0.074	−0.028	−0.125	0.808***	0.761***
Children	−0.100	−0.069	−0.139	−0.104	−0.156	−0.120	0.189	0.207
Single	−0.094	−0.0004	−0.050	0.055	−0.142	−0.033	−0.051	0.002
WomenChildren	0.312*	0.328*	0.419**	0.437**	0.353*	0.371*	−0.093	−0.084
SingleWomen	0.121	−0.016	0.019	−0.136	0.067	−0.092	0.304	0.226
Age	0.011***	0.004	0.016***	0.009*	0.010**	0.002	−0.001	−0.004
Black	−0.001	0.216	0.101	0.345*	−0.014	0.237	0.038	0.162
Asian	0.039	0.331**	0.129	0.459***	0.107	0.446**	−0.115	0.052
Hispanic	−0.237	0.030	−0.229	0.071	−0.253	0.056	−0.318	−0.166
Socioeconomics								
Unemployed	−0.192	−0.168	−0.267*	−0.240	−0.189	−0.162	0.014	0.027
Student	0.011	0.077	0.002	0.076	−0.003	0.073	0.089	0.127
Income	−0.001	−0.002*	−0.002	−0.003**	0.0001	−0.001	−0.002	−0.003
IncomeAboveAverage	0.150	0.272**	0.134	0.271**	0.057	0.199	0.242*	0.311**
Voting								
Republican	−0.008	0.144	−0.010	0.162	−0.048	0.129	0.031	0.118
Trump	0.200*	0.670***	0.242*	0.771***	0.258*	0.803***	0.127	0.395***
percentGOP	−0.493	−0.528	−0.010	−0.050	−0.186	−0.227	−1.219***	−1.239***
Environment								
WhiteMaj	−0.102	0.034	−0.043	0.109	−0.169	−0.012	−0.068	0.009
percentWhite	0.002	0.002	−0.001	−0.0002	−0.002	−0.001	0.007	0.007
Travel Behavior								
UseShare	−0.161*	−0.059	−0.059	0.056	−0.131	−0.013	−0.347***	−0.289**
UberOnly	0.050	0.119	0.078	0.156*	0.072	0.152	−0.005	0.034
SDAvg	0.506***	–	0.570***	–	0.586***	–	0.288***	–
Constant	1.714***	2.856***	1.130***	2.416***	1.762***	3.086***	2.776***	3.427***
R^2	0.279	0.080	0.300	0.092	0.273	0.076	0.134	0.091
Adjusted R^2	0.264	0.061	0.286	0.075	0.258	0.058	0.116	0.073

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: *Linear Regression Models 17-24: Difference Between AV and Ridesharing Attitudes*

	Dependent variable:							
	Overall		Race		Class		Gender	
	With SD	Without SD	With SD	Without SD	With SD	Without SD	With SD	Without SD
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Demographics								
Female	0.243^{***}	0.240^{***}	0.153	0.149	0.310^{***}	0.311^{***}	0.377^{***}	0.376^{***}
Children	−0.038	−0.037	−0.116	−0.115	0.012	0.012	0.107	0.107
Single	0.020	0.023	−0.006	−0.002	0.056	0.055	0.137	0.139
WomenChildren	0.240^{*}	0.240^{*}	0.371^{**}	0.372^{**}	0.066	0.066	0.049	0.050
SingleWomen	0.060	0.056	0.040	0.033	−0.092	−0.090	0.136	0.134
Age	0.008^{***}	0.008^{***}	0.012^{***}	0.012^{***}	0.008^{*}	0.008^{*}	0.001	0.001
Black	0.029	0.036	0.097	0.108	−0.059	−0.062	0.058	0.061
Asian	0.057	0.067	0.112	0.127	0.197	0.194	−0.068	−0.063
Hispanic	0.092	0.101	0.075	0.088	−0.003	−0.006	0.094	0.098
Socioeconomics								
Unemployed	−0.096	−0.095	−0.129	−0.128	−0.203	−0.203	0.109	0.109
Student	0.124	0.126	0.187	0.191	0.033	0.032	0.118	0.119
Income	-0.001^{*}	-0.002^{*}	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
IncomeAboveAverage	0.144^{*}	0.149^{*}	0.135	0.141	0.134	0.133	0.183	0.185
Voting								
Republican	−0.044	−0.039	−0.041	−0.033	−0.145	−0.147	0.014	0.017
Trump	0.029	0.045	−0.001	0.023	0.090	0.084	0.022	0.030
percentGOP	−0.182	−0.183	0.114	0.113	0.022	0.023	−0.644	−0.645
Environment								
WhiteMaj	−0.007	−0.002	−0.011	−0.005	−0.005	−0.006	0.047	0.049
percentWhite	−0.002	−0.001	−0.001	−0.001	−0.005	−0.005	0.0002	0.0002
Travel Behavior								
UseShare	−0.041	−0.038	0.073	0.079	0.016	0.015	−0.151	−0.149
UberOnly	−0.029	−0.027	−0.008	−0.005	−0.024	−0.025	−0.016	−0.015
SDAvg	0.017	–	0.025	–	−0.006	–	0.008	–
Constant	0.309	0.347^{*}	−0.027	0.031	0.344	0.331	0.750^{**}	0.769^{**}
R^2	0.062	0.061	0.048	0.047	0.033	0.033	0.039	0.039
Adjusted R^2	0.043	0.043	0.028	0.028	0.013	0.014	0.019	0.020

Note: *p<0.1; **p<0.05; ***p<0.01

4.3.3 Discussion

In expanding on the results of Chapter 3, this chapter sought to address the following research topics: 1) The impact of the driverless context on discriminatory attitudes between fellow passengers in an autonomous rideshare; 2.) Variation in this impact according to the target of discrimination; and 3.) Variation in this impact according to sociodemographic and environmental characteristics such as gender, race, age, income, and political environment. In summarizing and modeling the survey results, the analysis of this chapter supports the following claims: 1) The driverless context will exacerbate discriminatory attitudes between fellow passengers; 2) Gender preferences will see the greatest increase upon the arrival of autonomous ridesharing, likely due to legitimate safety concerns rather than discriminatory attitudes; 3) The size of the impact of autonomous rides is positively correlated with riders who are female, older, and have above average incomes.

The results of this chapter call for further confirmatory research into the effect of the driverless context on discriminatory attitudes in the driverless shared ride. In particular, the research presented in this chapter could be replicated with photographs of traditional and driverless shared rides, to ensure that respondents understand how the ridesharing context will change with the arrival of autonomous vehicles. If the results of this chapter are indeed correct, further research should consider how autonomous ridesharing policy and service provision may counteract the increase in discriminatory attitudes. Autonomous ridesharing vehicles could, for example, provide a physical barrier between passengers to alleviate possible safety concerns. Video surveillance in vehicles could further encourage trust in ridesharing services and promote openness to share rides with strangers. Rules about the size of parties and possible combinations of groups may also improve safety. In addition to bolstering safety, autonomous ridesharing services could also take efforts to improve comfort with difference by establishing new norms of social conduct suited to this new space.

Although AVs offer a technological solution to many of society's problems, the introduction of AVs and driverless ridesharing will also present new challenges to inclusion and social cohesion. The absence of the driver as an enforcer of social norms, witness to possible misconduct, and moderator of passenger-to-passenger interactions will revolutionize the experience of sharing a ride. Much as the arrival of the automobile revolutionized society, the arrival of AVs promises to bring many unforeseen social consequences, including new forms of discrimination. Thoughtful consideration of the social impacts of AVs can help society anticipate the positive impacts of driverless ridesharing while also forestalling the potential downsides, including exclusion, discrimination, and insufficient sharing.

5 Regulatory and Design Interventions

> *All people, regardless of age, race, color, gender, sexual orientation and gender identity, national origin, religion, or any other protected category, should benefit from Emerging Mobility Services and Technologies, and groups who have historically lacked access to mobility benefits must be prioritized and should benefit most.*
>
> SFCTA Guiding Principles for Emerging Mobility Services and Technologies

5.1 Introduction

The following chapter presents proposed methods of counteracting discrimination in ridehailing and ridesharing through regulatory and platform design interventions. The chapter begins with a brief history and overview of existing TNC regulations in the United States in order to provide context on the TNC regulatory landscape. This chapter then reviews a list of seven regulatory options, both currently in place and hypothetical, that could influence the discriminatory outcomes identified elsewhere in the literature and in this thesis. This chapter also acknowledges the important role of transportation network companies (TNCs) in reducing discrimination and explores seven platform design interventions for mitigating discrimination. The various regulation and platform design options (collectively referred to as "interventions") are vetted through semi-structured interviews with experts in public policy and shared mobility. These experts were asked to evaluate each intervention according to three dimensions: fairness, effectiveness, and implementability. Finally, the popular support of each intervention is tested through a survey of 1,113 ridehailing users across the United States. Additional questions raised in this chapter include: What are cities, states, and TNCs already doing to prevent or mitigate discrimination? How would stakeholders react to these interventions? What regulations from other industries or platforms offer useful examples? Should TNCs be told how to eliminate discrimination, or allowed to develop their own methods? What legal foundations support the proposed strategies? At what point would regulations to address inequality pose an undue burden on operators?

5.2 Background: TNC Regulations

As with other players in the sharing economy, the large TNCs have experienced rapid growth accompanied by intense debates over regulation, resulting in a wide range of new regulations and policy measures across jurisdictions. This regulation occurs primarily at two scales: state and city. At the state level, these policies have emphasized issues such as passenger safety, insurance liability, data reporting, trade dress, and fares. At the local level, dozens of cities have enacted regulations related to TNC operations, licensing, and fees within their boundaries. To date, there has been very little regulatory action focused on protecting consumers and employees from discrimination through ridehailing platforms.

5.2.1 History of TNC Regulations

The State of California was the first to regulate TNC operations at the state level. In 2010, the San Francisco Municipal Transportation Agency (SFMTA) demanded that Uber cease operations in the city on the grounds that it was operating an unlicensed taxi service.[125] A year later, the California Public Utilities Commission (CPUC) issued a cease-and-desist letter to the three largest TNCs in the state (Uber, Lyft, and SideCar) on similar grounds. Although these actions were later reversed, in 2013 the CPUC voted to classify TNCs as a new category of service within the commission's regulatory purview. In 2014, California enacted Assembly Bill 2293 (also known as the Passenger Charter-party Carriers' Act), which set liability insurance coverage requirements for TNCs and their drivers and officially authorized the CPUC as the agency with regulatory responsibility for TNCs.[3]

Executive action at the CPUC prefaced legislative efforts in other states. In 2014 Colorado's Senate Bill 125 became the first TNC regulation in the United States created through legislative action.[35] Also known as the Transportation Network Company Act, the legislation authorized the use of mobile ridehailing apps and established insurance requirements, but exempted TNC drivers from fingerprinting and criminal background checks.[1] Over the next two years, many states followed suit. In August 2016, for example, the Massachusetts General Court passed a law that formally legalized

[1]Instead, the Colorado law called for TNC self-regulation of background checks, a trend that continued in other states.

TNCs and gave the Massachusetts Department of Public Utilities (DPU) regulatory authority over the industry.

As of 2018, Oregon and Vermont are the only two states that have no state TNC regulation (notably, Vermont has no large cities and Oregon's largest city has extensive municipal control of TNCs).[89] Five additional states have TNC legislation that addresses insurance liability requirements only: Washington, Alabama, Minnesota, Louisiana, and Hawaii. In the remaining 43 states, regulations vary widely, but most include provisions for permits and fees, background checks, regulatory authority, driver eligibility requirements, and liability insurance. However, the level of enforcement of such rules is often minimal. In most states TNCs are effectively self-regulated with the threat of audit, although there is often no publicly available data on whether TNCs comply with state requirements. For the most part, drivers rarely interact directly with state regulators.

In addition to executive and legislative action, legal action against TNCs over the past decade has also defined rules for the TNC industry, albeit only by applying existing regulations and decisions to the new industry. Several lawsuits have alleged violations of prevailing worker protections (often related to rights claims and the classification of drivers as employees), consumer protections (typically related to safety, accessibility, or fares), and fair competition laws (usually from taxi competitor plaintiffs).[26, p. 32] O'Connor v. Uber Technologies, Inc. is a particularly noteworthy example of a wage protection and worker classification lawsuit in the industry. Filed in 2013, by a Boston-based attorney, this case became the first to see a large class of Uber drivers certified by a court and sought legal determination of drivers as employees for wage purposes. After three years of litigation the plaintiffs sought to settle the case, but this settlement was rejected by the courts and the case remains unresolved.

In other cases, legal action has prompted the adoption of new formal rules for the industry. In 2012, for example, the Chicago taxicab industry sued Uber for violation of city and state laws designed to protect public safety, consumer protection, and fair competition practices, an issue later resolved by the adoption of formal regulations in 2014.[104] In other cases, state agencies (e.g., utilities commissions, departments of motor vehicles, and private for-hire vehicle regulators) issued cease-and-desist notifications to TNCs in response to a variety of violations. Often these notifications led to formal regulations governing TNCs, as with the Virginia Department of Motor Vehicles' 2014 cease-and-desist letter, which preceded the 2015 legalization of TNCs in Virginia.[41] In some cases, social media campaigns by Uber drivers (as in Washington, DC in 2012) or donations from TNCs to political group seeking to protect TNC operations (as in Seattle in 2014) helped pave the way for the legalization of TNCs.[25][117]

As of 2017, 42 states required name-based, commercial background checks. Massachusetts requires more robust background checks (i.e., government-administered Criminal Offender Record Information background checks), but no states require fingerprint-based background checks. At the local level, some cities, including New York City, do require fingerprint-based background checks.

5.2.2 Structure of TNC Regulatory Landscape

Unlike the regulation of motor vehicles (which occurs exclusively at the state level) or the conventional taxicab industry (which occurs primarily at the local level), the authority responsible for regulating TNCs in the United States is much more complex. While most states have established TNC regulatory frameworks, the scope of these regulations and the responsibility for their enforcement varies widely.

Naturally, TNCs thrive in cities, where density and scale provide the critical mass of providers and consumers that allow these platforms to succeed. Nonetheless, only a handful of cities have retained their authority to regulate TNCs. In some cases, states with major cities allow those jurisdictions to establish more specific regulations, in part due to the legacy of taxi regulation in those cities. The Pennsylvania Public Utilities Commission, for example, regulates all for-hire companies in the state, but has carved out an exception for the City of Philadelphia. In New York City and Chicago the respective state agencies have set a minimum for regulation, but then allowed these cities to enact additional regulation on top of established minimum standards. Very large cities like New York have been able to exert considerable leverage in debates over regulation as largest livery markets with established histories of city regulation. In the absence of formal state regulations, cities like Portland are typically not restricted in the TNC regulations that they can pass. As a result, they have also retained a greater degree of regulatory authority and enforcement power relative to many other cities.

Despite these examples, state preemption of local action is more common. In the United States, local governments exist at the pleasure of the states. State legislatures define and limit the jurisdiction and legal capacity of municipalities.[43] This is increasingly the case in the context of ridehailing, in part due to lobbying pressure from large TNCs, who prefer to deal with a smaller number of regulatory schema.[2] As of 2018, 41 states have passed laws that completely or partially prevent municipalities from setting rules for TNCs.[19] North Carolina's Senate Bill 541, for example, established statewide regulation of TNCs and also forbade county and municipal governments from enacting additional regulations, fees, and license requirements.[112] Perhaps the most famous example of state preemption comes from Austin, Texas, where an ordinance requiring TNC drivers to submit to fingerprint-based background checks inspired Uber and Lyft to withdraw from the market in protest in 2016. However, in May 2017, the Texas legislature passed House Bill 100, which defined the regulation of TNCs as exclusive power and function of the state.[89] As a consequence,

[2]There is considerable debate on the goals of the industry's legislative interventions. Companies like Lyft and Uber characterize state legislation as preferable to a confusing "patchwork" of local laws that stymie innovation and inhibit expansion. Critics of the industry argue that there is no evidence that local regulations have impaired the growth of TNCs. Not surprisingly, state regulations are usually less onerous than local rules. Critics claim that TNCs support state preemption because state lawmakers have the ability to protect TNCs' classification of drivers as independent contractors, thereby exempting drivers from employment protections such as state minimum wage, collective bargaining rights, unemployment insurance, workers' compensation, anti-discrimination protection, fair chance hiring and paid sick leave.[19]

existing regulations in Austin and 19 other Texas cities were nullified and municipalities across the state lost the ability to impose further taxes, licenses, or other requirements on TNCs. Preemption has also granted enforcement authority to the state police or other state regulators, which has presented a challenge to the enforcement of TNC regulations.

In general, courts have enforced state preemption, thereby allowing TNCs to take legal action against cities with regulations that might contradict state laws.[11] Nonetheless, some cities have sued to contest state preemption of their regulatory authority. In 2017, California Senate Bill 182 (also known as the Passenger Charter-party Carriers' Act) prohibited local jurisdictions from requiring that drivers residing outside their jurisdiction obtain a business license to operate as a driver for a TNC.[3] The San Francisco City Attorney's Office, in cooperation with the San Francisco Municipal Transportation Agency, sued the state in February 2018 on the grounds that SB 182 constitutes an illegal preemption of authority.[4] City Attorney Dennis Herrera attested, "Uber and Lyft need to play by the same rules as every other business in San Francisco."[98] While the San Francisco City Attorney may be taking an unusually aggressive role in championing local regulation of TNCs, a positive outcome in this case may also inspire other cities to argue for protection of local authority in this arena. However, if preemption remains the standard regulatory paradigm for states and cities, then new TNC regulations will need to gain approval through state governments, which are arguably more sensitive to corporate lobbying than to the concerns of urban policymakers.[19]

Given the limitations of city-level regulation of TNCs, it is important to understand the powers that have been reserved by the states. The California Public Utilities Commission is a useful starting point for understanding state regulation of TNCs because it served as a model for many other states. In general, the CPUC has very broad powers; it can enact any rules not explicitly prohibited by the state constitution. In fact, in 2013 the CPUC essentially granted itself the authority to regulate TNCs as an extension of its authority over the limousine industry (see Docket R.12-12-011). While this power came from the discretion of the commissioners, the state legislature later implicitly supported and clarified the CPUC's authority. Since 2013, the CPUC has continued its open rulemaking proceedings for TNCs, resulting in a quasi-legislative process involving many participants. Commissioner Liane Randolph has the authority to propose changes and create a ruling indicating that the CPUC will open a new phase of deliberation, at which point the CPUC solicits comments from TNCs, the taxicab industry, consumer groups, and others. After reviewing and filing comments, the commissioner and a judge review and draft proposed decisions and mail them to affected parties before holding a majority-rules vote among the five commissioners.

To date, the regulation of the TNCs has remained a primarily state and local affair, with the federal government remaining uninvolved. However, Title VI of Civil Rights Act applies to any public

[3]Prior to Senate Bill 182, the California Public Utilities Commission had permitted local business registration requirements and airport permit requirements in San Francisco and other cities.

[4]The San Francisco Municipal Transportation Agency also routinely submits comments to the on-going CPUC rulemaking proceedings (https://www.sfmta.com/reports/tnc-rulemaking-proceedings-sfmta-comments)

agency receiving federal funding to provide transportation services, and may provide an avenue for enforcing nondiscrimination policies in TNCs. In recent years, several transit agencies that receive federal funding[5] have partnered with ridehailing companies as a low-cost way of providing transit or paratransit services. These agencies have an obligation to comply with Title VI rules and regulations (much as public contractors must conduct their services in a nondiscriminatory way). That is, programs that receive federal funds cannot distinguish among individuals on the basis of race, color or national origin regarding the program services or benefits that they provide. Partnerships between TNCs and transit agencies are a relatively new domain, but it is possible that one day these agencies will face federal requirements for providing nondiscriminatory services.

5.3 Interview Methodology

Against the regulatory backdrop described in the previous section,the remainder of this chapter will review a list of regulatory and platform design interventions that could prevent and mitigation possible discrimination in ridehailing. In order to evaluate the interventions presented in the following sections, knowledgeable stakeholders in the industry were identified to represent the perspective of regulators, policymakers, TNCs, academics, and driver advocates (the viewpoint of passengers is discussed in Section 5.6). The representatives identified and interviewed during this process are listed in Table 15. Each interviewee was invited by email to a 60 minute telephone conversation and sent an interview guide similar to the one presented in Appendix A.

[5]Including through the Federal Transit Administration's Mobility on Demand (MOD) Sandbox program, which provides federal funding explicitly to support such partnerships and other MOD initiatives.

Table 15: *Organizations represented in interview process*

Organization	Representative
Government	
New York Taxi & Limousine Commission	Rodney Stiles
Office of Anonymous New York City Councilmember	#1
Anonymous Portland Private For-Hire Transportation Program Representative	#2
Anonymous California Public Utilities Commission Representative	#3
San Francisco Municipal Transportation Agency	Kate Toran
San Francisco County Transportation Authority	Warren Logan
San Francisco Transportation Authority Commission Chair	Aaron Peskin
Anonymous U.S. DOT Office of Civil Rights Representative	#4
Indiana State Representative	Matt Lehman
Anonymous City Attorney's Office Representative	#5
Industry	
Fasten, Inc.	Vlad Christoff
Anonymous TNC Policy Staff	#6
Anonymous TNC Policy Staff	#7
Anonymous TNC Policy Staff	#8
Academia	
Wesleyan Science and Society Program	H.C. Robinson
Northeastern Cybersecurity and Privacy Institute	Christo Wilson
Shared Use Mobility Center	Cassie Halls
Transit Center	Zak Accuardi
Driver Advocates/Other	
National Employment Law Project	Rebecca Smith
Open Society Leadership in Government Fellow	Jenny Yang
The Rideshare Guy Blog and Podcast	Harry Campbell
Anonymous Attorney and Driver Advocate	#9
Anonymous Journalist Covering TNCs	#10

During the telephone interviews, interviewees were asked to comment on a list of regulatory and platform interventions. Interviewees were asked to comment on each intervention according to three dimensions: effectiveness, fairness, and implementability. Each dimension is discussed below.

1. **Effectiveness** An effective intervention is one that offers a clear connection to the policy objective it seeks to address. Moreover, an effective intervention is also likely to achieve its stated objective. While the inherent benefit of effective interventions is clear, effectiveness is also desirable because stakeholders are more likely to view a change favorably when it is clear how it relates to a worthy objective.

2. **Fairness** While regulations aim, broadly, to reduce harm, satisfying this goal far from straightforward. Fair regulations convey benefits that exceed their costs, but also address possible inequities in the distribution of costs and benefits, often between firms and consumers. Fair regulations are also able to reconcile conflicting policy objectives where a tool employed to address one issue may have adverse effects on another. Reducing passenger wait times, for example, may improve service for passengers, but might also increase the number of the vehicles on the road, exacerbating congestion, air pollution, etc. Where such a conflict exists, the benefits of a fair policy justify its costs and externalities. A fair intervention can withstand criticism related to trade-offs and costs. Furthermore, regulations must treat equals as equals; regulations should address an entire industry (i.e., TNCs) and not individual firms (i.e., Lyft). Fair regulations should also avoid advantaging or disadvantaging incumbents firms.

3. **Implementability** An implementable intervention is simply one that is both realistic and feasible. An implementable regulation is one that is relatively easy to enforce given the regulator's available resources. Alternatively, the most implementable regulation may be that which is most difficult to evade. Either way, if a regulation is implementable, then compliance will be high and obstruction will be low. With regard to ridehailing specifically, the most implementable regulations are often those that face the least resistance from industry, such as commercial background checks.

5.4 Proposed Regulatory Interventions

This section proposes several new regulations for TNCs. Each subsection begins with sample regulatory text for a generic jurisdiction and agency. This text is typically adapted from existing regulations. The sample text is for illustrative purposes only, and should not be interpreted as a recommendation per se.

Beyond the regulation text, each subsection also describes the intent of the regulation, presents precedents for the policy, and summarizes expert reactions to the effectiveness, fairness, and implementability of the proposal. Precedents for each proposal are a particularly important part of the discussion, as public agencies generally find it easier to adopt a new policy if another jurisdiction has succeeded with a similar effort. Finally, each subsection seeks to place the proposed intervention in the context of the contested political process surrounding ridehailing regulation.

These regulations can be divided along several dimensions. Regulations can be direct (i.e., the regulator defines in concrete detail what actions are permissible), discretionary (i.e., the regulator provides certain standards to be met and allows firms to choose the best means of compliance), or incentive-based (i.e., the regulator delegates decision-making to the firm, who may enjoy rewards when they meet certain targets).[51] Regulations may also be categorized as "informing" or "enforcing."[106] An informing regulation, for example, would require TNCs to share a rate schedule with customers, but would not mandate any specific rate per-mile or per-minute. An enforcing regulation, on the other hand, might set a specific rate.[106] Finally, regulations may either target dedicated policies at TNCs as a new entity or apply existing policies to TNCs. Many of the regulatory proposals in this section fall into the latter category. They are inspired by existing taxicab regulations on the logic that if they can be applied to taxis they can be applied to TNCs. Furthermore, taxis are a suitable model for this research because equitable access is the goal of many taxi regulations.

As noted in Chapter 2, this thesis seeks to address two forms of discrimination: disparate impacts (i.e., systemic or passive discrimination) and disparate treatment (i.e., explicit and intentional discriminatory practices). The formulation of a policy depends on the form of discrimination under consideration. Requiring minimum levels of service, for example, addresses disparate impacts (implicit discrimination), while audits and training seek to address disparate treatment (explicit discrimination).

In discussing each proposal, the following section attempts to predict the reaction of regulators and TNCs. With regard to regulators, anti-discrimination may compete with other policy goals, such as congestion relief. Nonetheless, it may be possible for regulations to forestall possible discrimination while also addressing other concerns, such as fair pay for drivers. As for the TNCs, this section considers a documented history of antagonism to regulation as a precedent for future responses. Examples of adversarial reactions from TNCs abound. In 2016, when the Chicago City Council sought to extend taxicab industry rules (i.e., background checks, fingerprinting, and vehicle inspections) to TNCs, Uber launched a blog post titled "A Chicago Without UberX" that threatened to leave the city.[85] A more famous example is Uber's efforts to defeat a New York City Council bill to cap the number of vehicles the company could operate in New York City. In this case, Uber used advanced methods to promote its anti-regulatory agenda, particularly an in-app feature known as "de Blasio View" that projected long wait times if the cap were finalized.[40] Given the TNCs' access to customer contact information and their popularity with consumers, they are well positioned to turn customers into grassroots lobbyists that can help legitimize the companies' lobbying campaigns.

Despite such antagonism, it is also the case that thoughtful, clear, and consistent regulation can actually offer a benefit to TNCs by adding certainty to their future business environment. Furthermore, it is difficult to argue that new regulations have done much to stem the growth of the TNC businesses; New York City, for example, has implemented a series of rules for TNCs during a period of explosive growth in ridehailing trips in the city. Finally, it is also possible that TNCs may benefit from regulations that compel their drivers to behave in a certain way without jeopardizing the companies' classification of drivers as independent contractors. For these reasons, it is not necessarily the case that TNCs will resist efforts at regulation.

5.4.1 Require TNCs to report information that may provide evidence of discrimination

> *Unless otherwise specified or approved, TNCs operating in [Jurisdiction] will provide the following information to the [Agency] electronically and in an approved format and timeframe for all trips: pick up location and destination; date and time of trip start/finish; length of time elapsing between the passenger's service request and start of the trip; the fare(s) paid for the trip; the driver name and public driver identification number; and all information provided by the TNC to passengers and to drivers*
>
> *TNCs shall also provide the following information in relation to trips requested and not provided due to the cancellation or rejection of the request: pick-up location and destination if applicable; date and time the trip was requested; stated cause of the cancellation or rejection; and all information provided by the TNC to passengers and to drivers.*

A common theme that emerged during the expert interviews is that no government agency should propose a new regulation without an informed understanding of the problem that the regulation seeks to address. Furthermore, in a data-rich industry like ridehailing, companies collect huge amounts of information on their services. While this information could provide evidence of discrimination, the public sector often has limited access to such information. Without data, agencies can only postulate and conjecture. As such, data sharing requirements are an obvious starting point for any effort to limit discrimination in TNCs.

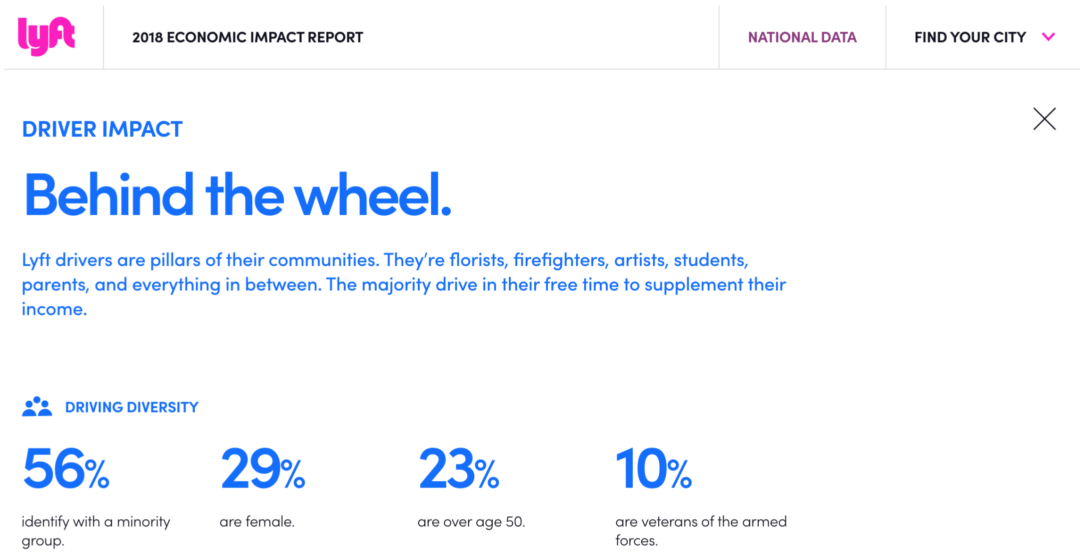
As Ge et al. (2016) noted, TNCs have access to data such as cancellations and wait times that could be analyzed across geography and driver/rider characteristics for evidence of discrimination.[44, p. 20] Other data that could be useful in measuring discrimination include individual-level tip, rating, and earnings data. Furthermore, while such data could help reveal some discriminatory trends, rider and driver demographics would also be necessary to test hypotheses related to discrimination. TNCs may claim, rightly, that they do not regularly collect information on driver or rider demographics, and that the rider information they do have is not necessarily correct or accurate. Additionally, TNCs may argue that they don't track users' race or gender because they do not want to intrude on riders' privacy.[50] Nonetheless, these companies could easily and legally ask users to optionally self-report this information during on-boarding (for drivers) or sign-up (for riders). In fact, Lyft already analyzes driver demographics through a sampling method as part of its national economic impact reports, thereby demonstrating willingness and ability to collect this information (see Figure 4). Similarly, in 2015 Uber published a consultant's survey of drivers that reported on drivers' gender, age, race, ethnicity, and other characteristics.[65] What's more, Lyft's privacy policy indicates that for any users who sign up using a Facebook account, the company receives basic information from Facebook profiles, including gender.[62] Finally, Lyft's privacy policy also indicates that the company may receive additional demographic information about users through their third party partners.

Although examples are limited, there is precedent for cities and states to establish data sharing requirements. As of 2017, 34 states require TNCs to retain data on driver and trip records. Of these, just six states require actual data sharing.[89, p. 13] The California Public Utilities Commission collects ride fulfillment data, but does not collect data on wait times, although it is within the CPUC's authority to require such data. The Colorado Public Utilities Commission requires that TNCs report data on driver refusals to transport a passenger after being matched, including the identity of each involved driver, the pickup address, the intended destination, and the reason the driver refused the ride.[27] In addition to these state-level examples, the cities of Chicago, Houston, New Orleans, New York City, Portland, San Antonio, and Seattle have all imposed data reporting requirements on TNCs. The City of Portland, for example, collects information on cancellations and wait times by geography, although no information is provided on the identify of the driver. New York City's Taxi & Limousine Commission (TLC) is one of the few city agencies in the United States that requires TNCs to provide granular data on a trip-by-trip basis.[11] Furthermore, the TLC and other public sector entities, such as Seattle's King County Records and Licensing Services, collect demographic information as part of the licensing of TNC, taxi, and for-hire drivers. In New York, the TLC also collects self-reported demographic information and has nearly complete demographic data on the more than 100,000 licensed drivers in the city. In Canada, Toronto's Municipal Code Sub-section 546-116 (which served as an inspiration for the sample regulation at the top of this Section) requires that TNCs report records of pick-up and drop-off locations, the time elapsing between service request and start of the trip, and average wait times for accessible vehicles.[97]

Nonetheless, current data sharing practices are inadequate in several regards. In some situations, TNCs have not complied with these regulations; the New York Taxi & Limousine Commission forced Uber to curtail its operations in 2015 after declining to provide required trip data.[123] In some cases, agencies are not able to share the information that they do collect from TNCs. The CPUC, for example, has decided not to share TNC data with other agencies and jurisdictions in the state.[6]

[6]Data sharing in California has been a particularly thorny issue. In 2017, the San Francisco City Attorney Office subpoenaed data from Lyft and Uber, including the data that the companies were already reporting to the CPUC. The City Attorney is interested is using this data to investigate issues related to discrimination, congestion, fair pair for drivers, driver drowsiness, and more. While Lyft readily admitted the city's legal right to such information, exactly

Figure 4: Lyft's 2018 Economic Impact Report measured and presented driver demographics nationwide and city-by-city



TNCs often withhold information and carefully curate what data they do release. Often, TNCs share analysis rather than raw data.[7] Furthermore, many data-sharing partnerships established between TNCs and cities have failed to satisfy expectations. A pioneering voluntary partnership between Uber and the City of Boston has offered limited insight for city planners, with a former Uber employee commenting, "I'm not actually sure that the data we provided to Boston will be particularly helpful from a planning perspective."[122]. Additionally, Uber's "Movement" initiative has published only highly aggregated data, limited in geographic scope. In the absence of actionable data, public agencies have attempted to collect or scrape this information themselves. In 2017, Boston's Metropolitan Area Planning Council surveyed 1,000 ridehailing passengers to collect information about their demographics, their travel patterns, and their choice of ridehailing over other modes of transportation. [45]

The TNCs themselves have often opposed additional data sharing on the grounds that they are protecting valuable trade secrets and the privacy of their users. However, many in the public sector believe that trade secrets and competition are an insufficient argument for refusing public access to

who should have access to the data has been a further point of contention, with Lyft requesting that the city attorney office sign a protective order limiting data sharing to city attorney's and certain subject matter experts from other city agencies. Uber, meanwhile, has agreed to share only of some of the information requested by San Francisco, as of May 2018.

[7]Examples of this trend abound. Lyft's annual Economic Impact Report is essentially a list of descriptive statistics. The reports from Uber's public policy team (called "Uber Under the Hood") are frequent, but quite selective with the analysis they present.

travel data. Furthermore, the data privacy argument fails in light of the fact that public agencies are often tasked with safeguarding personally identifiable information.

While improved access to data is essential for many of the following proposals, better information could also support many policy efforts unrelated to discrimination. In particular, data disclosure is essential to enforcing just about any ridehailing regulations and standards (e.g., effective occupancy rates and average mile/gallon standards, both of which have important implications for sustainability goals). Furthermore, this call for additional data sharing is consistent with much of the discourse around progressive urban policymaking. NACTO's 2017 City Data Sharing Principles, for example, call for TNCs to collect and share information that provides important insights to urban planners, including trip routing information, travel time, pick-up and drop-off locations, vehicle occupancy, non-revenue vehicle miles traveled (i.e., "deadheading" miles), vehicle dwell times, the availability/demand of wheelchair accessible vehicles, and denied/declined/canceled rides.[93] Such information could help cities manage streets, curb space, and vehicles, and much of it could also support efforts to better understand discrimination in ridehailing. In short, data-sharing agreements can clearly help inform effective transportation decision making. If data requests are specific and accurate and if privacy protections are provided, then additional data requirements should be considered fair and implementable.

5.4.2 Require wait times to be similar in areas with similar demand

> *The [Agency], to ensure that citizens have similar access to transportation, requires that all TNCs operating in [Jurisdiction] shall report the length of time elapsing between the moment a passenger places a service request and the start of the trip. For TNCs, wait times shall be averaged across n analysis zones of identical area, and the average wait time for each zone shall be normalized according to the zone's population density. These normalized wait times shall then be ranked, and the wait time ratio in the lowest-performing zone for that TNC shall not be greater than α percent below the normalized wait time in the zone where wait times are shortest.*

One form of potential discrimination in ridehailing that has attracted the considerable media attention is geographic discrimination from drivers to riders. There is a consistent concern that TNC drivers avoid neighborhoods that are lower-income or predominantly minority, likely due to the legacy of such discrimination in taxicabs, transit routes, and other transportation services. While geographic discrimination is certainly not the only feasible form of discrimination through TNC platforms, it is a potential problem that suggests an obvious, if difficult to implement, regulatory solution. In particular, a minimum level of service provision could ensure that quality-of-service metrics such as pick-up wait times and acceptance rate (i.e., acceptances over requests) are similar across a city. Such a provision would ensure that level of service is not affected by the personal characteristics of riders or the neighborhoods where rides originate.

However, it is unrealistic to expect an equivalent level of service in dense and sprawling areas of a city. A requirement that all wait times in a coverage zone fall within a certain threshold, for example, would likely be unworkable for TNCs.[8]. This is because a density of ride requests is essential to attracting drivers to an area; drawing drivers to dispersed areas is a much greater challenge. TNCs might reasonably oppose minimum level of service provisions on the grounds that is impossible to guarantee a specific level of service as long as their drivers retain the individual discretion to accept or refuse rides. That is, TNCs cannot direct drivers toward a neighborhood that is not producing a great number of ride requests. However, TNCs currently offer a suite of incentives to influence driver locations (most notably Uber's "Surge Pricing" and Lyft's "Prime Time"). TNCs could use similar incentives to direct drivers toward underserved areas.[9][10] Furthermore, the transition to autonomous vehicle fleets will heighten the importance of geographic fairness while also removing human discretion from the equation.

Nonetheless, a flat minimum level of service requirement across a city might present an unfair or unrealistic burden for TNCs. That is, although this change would seem fair to riders, it may be unimplementable, as any constraint on who can be matched with whom makes it harder for ridehailing platforms to function. One possible solution to this problem would be the following four step process:

1. Divide a city into n zones
2. Measure average wait time for all trips originating in each zone for each TNC
3. Normalize wait times according to each zone's population density
4. Require a similar ratio across all zones

A city could, for example, require that the lowest-performing zone must be more than α percent below the zone with the fastest response times. Accordingly, a city would need to normalize wait times according to some function, as stylized in Equation 5.1. Then, a city would ensure that individual TNCs satisfy the requirement presented in Equation 5.2). Such a rule would draw upon local governments' taxi regulatory authority and require additional data collection provisions (see the information sharing proposal in Section 5.4.1), but would allow TNCs to determine how best to structure their services to satisfy this requirement for equitable service.

[8]Some cities do require maximum wait times, but these are typically quite high, and not usually a burden for TNCs to satisfy. The City of Portland, for example, stipulates a maximum 30 minute wait time (including for accessible vehicles) Nearly all rides in the city satisfy this requirement. See City Code and Charter 16.40.240: TNC Company Operating Responsibilities and Prohibitions.

[9]A wheelchair-accessible vehicle incentive program in San Francisco provides a relevant precedent. This program allows drivers to bypass the first-in, first-out queue for pick-ups at SFO airport in exchange for picking up wheelchair-accessible rides in lower-density outlying neighborhoods of San Francisco.

[10]Chicago offers another relevant precedent. In 2016 rule change to TNC fees, the Chicago City Council authorized the city to assess a $0.40 trip fee, but allowed TNCs to claim a 50 percent reimbursement for trips that include a pick-up or drop-off in an area designated as an underserved area.[11]

$$NWT = f(WaitTime, Density) \tag{5.1}$$

$$\frac{NWTworst - NWTbest}{NWTbest} \leq \alpha \tag{5.2}$$

Determining an appropriate value for α and an appropriate function for normalizing wait times across different zones in a city would be a matter of considerable further research. Indeed, determining the relationship between density and effort to maintain a certain level of service is a nuanced question requiring thoughtful analysis. Nonetheless, these two equations summarize the proposal at a policy level.

Most of the experts spoken to agreed that requirements for providing service in general is a good idea. However, many experts considered a specific minimum level-of-service too costly to implement. As a result, this intervention could easily present a barrier to entry for new entrants to a city's ridehailing market. It may protect incumbents rather than citizens. However, small, upstart TNCs could be exempted from this requirement in order to avoid an unfair burden on companies with very small fleets. In one relevant precedent, the Seattle Department of Transportation requires that all carsharing services offer service across all the city's neighborhoods after an allowable gradce period of two years. While the rule exists to ensure service to low-income communities, the caveat exists to avoid unfairly favoring incumbents in the carsharing space.[11]

Naturally, a city should only enact this regulation where there is an observed problem that such a requirement would help solve. Unfortunately many jurisdictions currently lack the data necessary to demonstrate differential wait times in different zones or neighborhoods. In California however, the CPUC does collect confidential TNC wait time and acceptance rate data aggregated to the ZIP code level. Through their analysis they have found a close match in acceptance rate across ZIP codes (see Figure 5), indicating that perhaps such an intervention is not needed in their jurisdiction. Just the same, the CPUC and other agencies could use the information they collect to conduct a much broader analysis to determine whether such a regulation is necessary. If a city finds no geographic imbalance in level of service, then this policy is not needed.

[11]SDOT Director's Rule 01-2016, changes to Seattle Municipal Code (SMC) Chapter 11.23.160

Figure 5: *CPUC analysis demonstrating similar acceptance rates in one higher-income ZIP code (94080) and one lower-income ZIP code (94124) in 2014*

requests originating from 94124 (San Francisco - Bayview)

	1 am	2	3	4	5	6	7	8	9	10	11	12 pm	13	14	15	16	17	18	19	20	21	22	23	12 am	Avg.
Sunday	71%	73%	69%	82%	83%	94%	95%	88%	92%	93%	89%	91%	91%	95%	92%	86%	80%	90%	90%	90%	91%	89%	88%	82%	87%
Monday	79%	85%	88%	86%	95%	94%	91%	95%	95%	94%	93%	94%	94%	93%	89%	95%	94%	91%	94%	92%	94%	90%	90%	88%	93%
Tuesday	65%	73%	74%	87%	89%	97%	94%	91%	95%	96%	97%	93%	96%	95%	95%	95%	91%	94%	96%	91%	70%	90%	92%	79%	91%
Wednesday	80%	69%	91%	77%	94%	100%	93%	92%	94%	97%	95%	94%	90%	95%	93%	98%	97%	93%	95%	95%	91%	94%	88%	82%	93%
Thursday	71%	85%	87%	70%	90%	92%	94%	94%	95%	94%	95%	94%	96%	97%	91%	97%	96%	91%	94%	95%	90%	89%	72%	96%	92%
Friday	71%	66%	88%	92%	86%	94%	97%	93%	90%	96%	94%	96%	93%	95%	92%	94%	92%	92%	94%	94%	93%	87%	89%	68%	91%
Saturday	77%	71%	77%	91%	89%	91%	95%	92%	93%	89%	93%	90%	88%	91%	94%	89%	91%	91%	92%	93%	92%	86%	80%	84%	89%
Average	74%	73%	78%	83%	89%	94%	94%	92%	93%	94%	94%	93%	92%	94%	92%	93%	91%	92%	93%	93%	88%	88%	84%	80%	91%

requests originating from 94080 (South San Francisco)

	1 am	2	3	4	5	6	7	8	9	10	11	12 pm	13	14	15	16	17	18	19	20	21	22	23	12 am	Avg.
Sunday	83%	79%	79%	92%	87%	94%	98%	100%	93%	94%	94%	85%	95%	94%	90%	88%	86%	97%	90%	85%	93%	91%	84%	79%	90%
Monday	94%	93%	89%	91%	100%	96%	96%	92%	93%	96%	95%	96%	96%	97%	96%	95%	91%	97%	95%	92%	94%	93%	90%	85%	94%
Tuesday	78%	75%	67%	95%	100%	96%	97%	95%	96%	96%	98%	96%	93%	96%	99%	97%	95%	96%	92%	96%	95%	88%	91%	91%	95%
Wednesday	67%	68%	82%	88%	84%	94%	96%	94%	98%	96%	96%	98%	93%	97%	96%	96%	96%	96%	93%	96%	91%	86%	86%	85%	94%
Thursday	78%	70%	93%	96%	86%	97%	95%	95%	96%	98%	96%	95%	96%	97%	97%	92%	95%	96%	96%	96%	94%	91%	98%	88%	95%
Friday	79%	91%	87%	95%	97%	93%	94%	95%	91%	97%	98%	96%	96%	96%	93%	95%	97%	93%	92%	94%	98%	91%	86%	83%	94%
Saturday	89%	81%	84%	95%	95%	95%	83%	93%	94%	95%	96%	88%	90%	90%	91%	92%	94%	92%	95%	95%	91%	89%	85%	81%	91%
Average	83%	80%	82%	93%	92%	95%	94%	95%	94%	96%	96%	94%	95%	96%	95%	94%	94%	95%	93%	94%	94%	90%	88%	83%	94%

lowest highest

*Based on 2014 submissions; analysis of 2015 submissions is ongoing

36

5.4.3 Require mandatory driver training to include diversity and sensitivity

> *Licensed TNCs must ensure that all TNC Drivers successfully complete approved trainings within 30 days of TNC Driver certification by the [Agency] in each of the following subject areas: 1. State and federal civil rights protections, including but not limited to the Title II of the Civil Rights Act of 1964 and the Americans with Disabilities Act. 2. Relevant penalties for discriminatory behavior under state and federal law. 3. Appropriate service for passengers with disabilities, including the obligation to accommodate service animals. 4. Discrimination in passenger ratings according to a passenger's race, color, religion, sex, national origin, or ability.* 5. Sensitivity to cultural, ethnic, and linguistic differences in a service industry.

Another possible regulatory solution to mitigate discrimination would be to require TNCs to train their drivers on diversity, sensitivity, and anti-discrimination policies. There is considerable precedent for mandatory driver training. Three state jurisdictions (California, Nebraska, and the District of Columbia) require TNCs to establish some form of driver training. However, these states neither provide training nor audit the training provided by TNCs.[89, p. 45] The CPUC *recommends*, but does not require specific content such as safety and insurance requirements. Agencies such as the CPUC also require reporting on the number of drivers completing training courses. Cities with regulatory authority require more specific training regimen. To be granted a TLC drivers license in New York City, for example, drivers must complete 24 hours of training, including a wheelchair-accessible vehicle (WAV) course. The New York TLC is also working with the New York Human Rights Commission on expanding training on accessibility issues. The City of Portland, meanwhile, requires that TNCs ensure that drivers complete approved online trainings on topics such as city code provisions, traffic safety principles, and customer service.[12] Some cities are also considering implementing a test for TNC drivers or more intensive continuing education programs to ensure that drivers review content at regular intervals. Theoretically there is no restriction on the type or extent of training that cities such as Portland could require of TNC drivers, although the TNCs themselves may oppose any additional burden placed on their drivers.

While driver diversity training appears implementable, there is little evidence that it would be effective in mitigating discrimination. Indeed research focused on diversity training for employees is inconclusive. Some researchers argue for its benefits to both employees (i.e., reduction in workplace discrimination) and employers (i.e., increase in productivity and hiring gains).[28] Other researchers view training as ineffective or even harmful, on the grounds that training is usually too brief to be significant and that it can leave minority groups feeling even more "vulnerable and victimized."[56] But while scholars have questioned the effectiveness of diversity training, it is nonetheless a common practice for large employers[13] that could also help reduce incidents of discrimination in ridehailing and ridesharing. Offering diversity, sensitivity, and anti-discrimination training to drivers as part of their on-boarding process may very well prevent discriminatory outcomes for passengers by communicating the importance of avoiding discrimination, introducing drivers to state and federal civil rights protections, and highlighting penalties for discriminatory behavior. Such training would, at a minimum, encourage drivers to recognize that they may be acting on their biases, even if they are not aware of it. Arguably, such training could also be used to improve the rider experience more broadly. On those grounds, diversity training may be in the interests of riders, drivers, and the TNCs themselves.

While diversity training is not common in the ridehailing industry, such a training concept is not totally foreign, particularly with regard to accessibility for passengers with disabilities. The Chicago Municipal Code requires TNCs to train their drivers "not to discriminate against people with disabilities in their passenger ratings. It shall be a violation of this chapter for a driver to rate a passenger based upon a disability."[14] TNCs also voluntarily provide training on this issue. Uber provides optional online training modules to drivers who would like to participate in the uberASSIST program, in which drivers offer extra assistance to passengers with disabilities.[69] Lyft also offers a brief driver training video on the company's wheelchair and accessibility policy.[61] Be-

[12] See Portland City Code and Charter 16.40.270 TNC Driver Certification Requirements, from which the sample regulatory text at the beginning of this section is adapted.

[13] There is evidence that the majority of large American employers undertake diversity training; a 1995 survey of the 50 largest American industrial firms found that 70 percent offered formal diversity management and training.[16]

[14] Municipal Code of Chicago Chapter 9-115-140(b). Jurisdictions such as Chicago might also consider taking this regulation one step further by establishing a private right of action in response to violations of this provision.[4]

yond accessibility issues, Uber also provides training to its white collar employees on topics such as "why diversity and inclusion matter" and "building inclusive teams," alongside many other diversity efforts instituted in response to a 2017 investigation and report led by former U.S. Attorney General Eric Holder.[68] While these precedents may be fragmentary, it is reasonable to think that these companies might adopt additional training for drivers, whether they are mandated to or not.

However, one major difference between TNC driver training and front line diversity training at a company like General Electric or IBM is the employment status of those being trained. Whether or not TNCs are motivated to reduce discrimination from drivers to riders, they are unlikely to adopt any policy that threatens the contractor status of their drivers. Given this obstacle, regulation may be the key to implementing diversity training. While a voluntary company-wide driver training program may be efficient, consistent, and implementable, required training on a city-by-city or state-by-state basis may be more a more realistic outcome.

One shortcoming of driver training programs is fairness. The problem is that training would address only discrimination that originates from the drivers themselves. However, drivers are already incentivized through the rating system to provide respectful, high-quality service to riders. Riders, on the other hand, face no financial incentive to avoid discrimination against drivers (although their own star ratings may discourage active discrimination). Riders, however, are difficult to train in a systematic way because they do not require any specific authorization or license to use ridesharing apps. Conceivably, however, these apps could require brief "training" for riders on topics such as tipping, rating, and respectful conduct (see Section 5.5.3).

5.4.4 Strengthen service-all provisions and prohibit TNC drivers from refusing rides based on destination and rider characteristics

> *Licensed TNCs shall establish a policy of zero tolerance for discrimination or discriminatory conduct on the basis of a protected characteristic under [Local Statute] while a driver is logged into a TNC's digital dispatch. Discriminatory conduct may include: refusal of service on the basis of a protected characteristic (including refusal of service to an individual with a service animal), or refusal of service based on the pickup or drop-off location of the passenger.*
>
> *Furthermore, licensed drivers shall not ask the destination of a passenger until the passenger has entered the private for-hire vehicle. Additionally, a TNC's digital dispatch may not require passengers to input destination information until the passenger enter the private for-hire vehicle. If a passenger voluntarily inputs such information, a TNC's digital dispatch may not convey passenger destination information to licensed drivers until the passenger has entered the vehicle*

In large American cities, the taxicab industry has long been subject to service-all rules that require drivers to provide transportation to passengers regardless of their destination or personal characteristics. Such rules often discourage destination-based discrimination by prohibiting taxi drivers from asking a passenger's destination until the customer has entered the vehicle. Rules in cities like New York and Washington, D.C. also prohibit dispatchers from conveying a passenger's destination to the driver before pick-up.[53] In some jurisdictions, like San Francisco, taxi passengers with disabilities are not obligated to communicate their disability to dispatchers. However, the taxicab industry has a long history of flouting these types of requirements and the penalty for asking about a customer's destination is typically a minor fine.[76]

Many cities and states have extended similar rules to TNCs. In the District of Columbia, the Vehicle-for-Hire Innovation Amendment Act of 2014 (from which the regulatory text at the beginning of this section is adapted) requires that any TNC using digital dispatch must provide service in the entire District, and that drivers may not refuse rides based on destination.[5] Similarly, the Seattle City TNC Ordinance forbids drivers from refusing to transport any person, except in certain extreme situations.[11, p. 20] Likewise, in the City of Portland "No TNC driver shall... refuse to transport to a requested destination within the City of Portland any passenger of proper demeanor whose request for service has been accepted on the TNC app."[15] In Colorado, TNCs must provide services to the public in a nondiscriminatory manner, regardless of "geographic location of the departure point or destination" or the "race; ethnicity; gender; sexual orientation; gender identity; or disability" of the passenger, once the driver and rider have matched.[16] In California, both taxis and for-hire vehicles must take passengers anywhere they want to go within a very high distance threshold. Chicago's TNC City Ordinance indicates that TNCs have an affirmative duty to respond to requests in underserved areas.[17] To promote equitable access, Chicago also requires that TNCs allow passengers opt not to share their ratings with drivers (Uber responded by removing passenger ratings altogether). In the District of Columbia, rider ratings are permitted only if riders may view their own ratings and only if TNCs obscure rider ratings from drivers until after the driver accepts a ride request from that customer.[18] Despite these precedents, service-all rules are not universal in ridehailing; the New York TLC does not require TNC drivers to accept all rides. Many other cities and states have not clarified whether TNC drivers can refuse rides or whether the TNCs themselves must monitor driver behavior.

Although service-all rules exist in many places, destination-based discrimination is arguably less likely through TNCs than traditional taxicabs because drivers may feel reassured by 1) the ability to rate riders and 2) the guarantee of secure payment through the mobile app. Furthermore, TNC drivers are not typically aware of a rider's destination before pick-up and riders are not required to provide such information.[64] As a result, a quasi-contract between driver and rider is already established before the rider enters the car. Refusing a ride at that point would leave a very traceable

[15] City of Portland 16.40.280 TNC Driver Conduct Requirements and Prohibitions

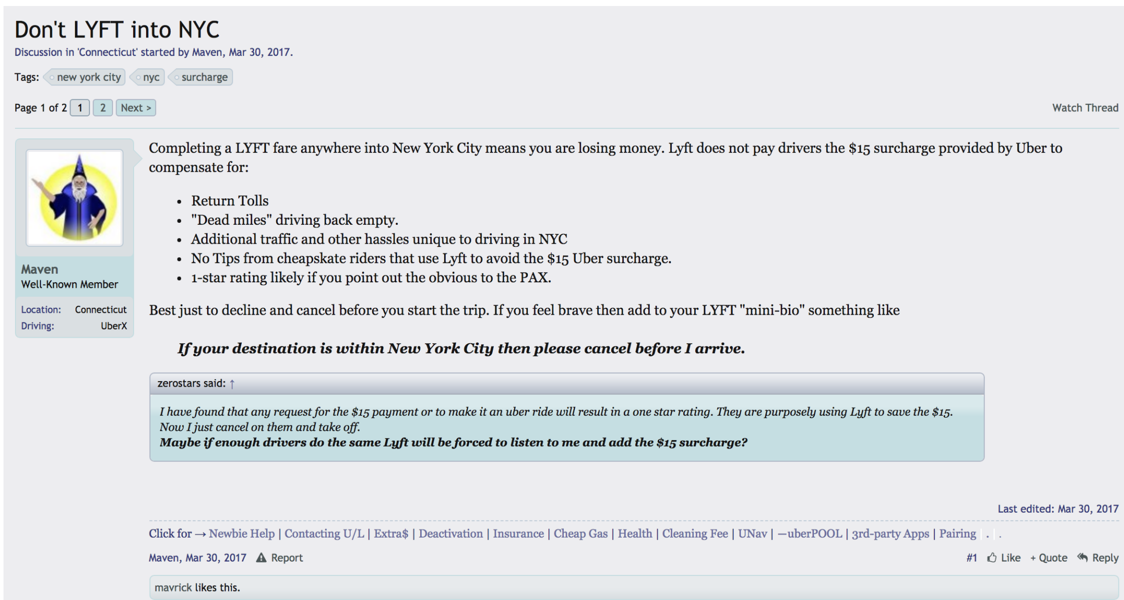
[16] Although this statute requires TNC drivers to transport passenger with disabilities (or refer them to another driver with an accessible vehicle), TNC drivers are not liable for discrimination unless the TNC has received a complaint in writing and "failed to reasonably address the alleged violation." Colorado Revised Statutes Title 40 Utilities §40-101-605 6(a)

[17] Chapter 9-115-180 of the Municipal Code of Chicago[4]

[18] D.C. Code Chapter 50-331(b)(8)

record. Nonetheless, and drivers may be tempted to avoid shorter rides or a ride to areas where they feel they will not be able to find another fare. One common example of this problem is that TNC drivers in New Jersey can make drop-offs in New York City, but are not permitted to accept trips that start and end in New York. As a result, drivers anecdotally refuse such rides, seemingly with impunity (see Figure 6).

Figure 6: *Lyft Driver Forum*



Don't LYFT into NYC

Discussion in 'Connecticut' started by Maven, Mar 30, 2017.

Tags: new york city nyc surcharge

Page 1 of 2 1 2 Next >

Watch Thread

Maven
Well-Known Member
Location: Connecticut
Driving: UberX

Completing a LYFT fare anywhere into New York City means you are losing money. Lyft does not pay drivers the $15 surcharge provided by Uber to compensate for:

- Return Tolls
- "Dead miles" driving back empty.
- Additional traffic and other hassles unique to driving in NYC
- No Tips from cheapskate riders that use Lyft to avoid the $15 Uber surcharge.
- 1-star rating likely if you point out the obvious to the PAX.

Best just to decline and cancel before you start the trip. If you feel brave then add to your LYFT "mini-bio" something like

If your destination is within New York City then please cancel before I arrive.

zerostars said: ↑

I have found that any request for the $15 payment or to make it an uber ride will result in a one star rating. They are purposely using Lyft to save the $15. Now I just cancel on them and take off.
Maybe if enough drivers do the same Lyft will be forced to listen to me and add the $15 surcharge?

Last edited: Mar 30, 2017

Click for → Newbie Help | Contacting U/L | Extra$ | Deactivation | Insurance | Cheap Gas | Health | Cleaning Fee | UNav | —uberPOOL | 3rd-party Apps | Pairing

Maven, Mar 30, 2017 Report #1 Like + Quote Reply

mavrick likes this.

Recent lawsuits have considered the extent of TNC's service-all obligations under the Americans with Disabilities Act (ADA).[19] Lyft and Uber have responded by confirming their policy of reprimanding or deactivating drivers who discriminate based on ability or location,[20] but have also denied any legal duty to do so under the ADA or other statute.[74, p. 171] Although the exact penalty for ride cancellations is vague and variable, drivers with above average cancellations often receive warning messages from Uber, which drivers informally refer to as "nastygrams." Uber's policies also suggest that avoiding passengers so can eventually result in driver deactivation.

While TNCs may discourage such behavior, the public sector could still play an important role. However, current public enforcement of service-all rules, where they exist, is nil. One possible solution would be for regulators to clarify the consequences of violations and then commit a enforcement squad to either auditing drivers (see Section 5.4.7) or responding to user complaints. In

[19]See McPhail v. Lyft, Inc.,; Salovitz v. Uber Technologies., Inc.; Complaint, National Federation of the Blind, California v. Uber Technologies., Inc.

[20]Uber's driver deactivation policy states "it is not acceptable to discriminate on the basis of a rider's destination." Presumably Uber can only hand down such a punishment in response to rider complaints.

jurisdictions where there are no service-all provisions for for-hire vehicles, instituting such a rule would be a necessary first step.[21]

Despite its potential advantages, this type of regulation faces two main criticisms. First, TNC drivers already face financial pressure to accept as many rides as possible and any regulation that increases this burden may be unfair to drivers. Arguably, drivers need to retain the right to refuse certain rides in the case of emergency or extreme circumstances, such as a ride over a tremendous distance. What's more, drivers may need to refuse some rides in order to be compensated fairly, particularly when jurisdictional issues could result in possible deadhead rides. Second, cities should demonstrate that passengers are being refused service based on their destinations or demographics before seeking to solve the problem. Most cities would be unable to do so, and even those cities with adequate data access many not observe a problem, calling into question the effectiveness of this intervention.

5.4.5 Service compris/mandated tipping provisions

> *Licensed TNCs shall charge all passengers a fee equivalent to α% of the per-mile and per-minute fare. Payment of this fee must be in the same payment medium as the fare payment itself, and the fee must be conveyed directly to the licensed TNC driver at the same time and in the same manner as fare payment, without any reduction or commission charged on the α% fee.*
>
> *According to specifications from the [Agency Director,] licensed TNC drivers shall post visible and prominent decals in their for-hire vehicles indicating that service gratuities are included in the fare charged through the in-app payment system.*

While there is limited information available on discriminatory tipping practices in ridehailing, evidence from other industries suggests that it could be a problem. In fact, before introducing in-app tipping in June 2017, Uber itself argued that tipping was inherently unfair because of customers' racial biases.[9] Uber's claim drew upon research from the traditional service industry. In a survey of taxicab receipts, Ayres (2005) provided evidence that black cab drivers receive tips of approximately 1/3 less than white drivers.[13] This finding led Ayres to call for "service compris" regulations that mandate tipping, on the theory that any move to limit customer discretion would reduce the opportunity for customers to discriminate. Specifically, Ayres proposed that taxicab regulators increase metered prices by 15% and also require vehicles to display "Tip Included" decals. In addition to directly stopping passengers from discriminating against minority drivers, Ayres postulated that this change might also reduce driver discrimination against minority passengers that drivers may perceive as inferior tippers.

While no cities have implemented Ayres' proposal, service compris provisions might eliminate the

[21] As of 2017, 36 states and the District of Columbia require TNCs to have nondiscrimination policies.[90] Of these, the majority forbid discrimination based on destination or rider characteristics.

possibility of discriminatory tipping. Because tips drivers retain 100% of their tips by law, requiring tipping in TNCs (and in taxicabs) would also have the benefit of increasing driver earnings at no direct cost to platforms like Lyft and Uber. According to estimates from New York's Independent Drivers Guild, in-app tipping has the potential to increase the earnings of full-time TNC drivers by more than $8,000 per year.[73] Furthermore, cities have implemented already TNC tipping rules, so there is some precedent for public involvement in TNC tips. In 2017, the New York City TLC passed a rule requiring that all for-hire vehicle passengers must be provided a way to pay tips through the same method of payment used for the trip itself, shortly after Uber introduced in-app tipping in anticipation of the rule.[38] In that light, perhaps mandatory tipping *options* are a more reasonable intervention than mandatory tipping *amounts*.

While mandatory tipping is legally feasible, it also drew stronger resistance from experts than any other intervention proposed in this effort. First, there is a powerful cultural notion that tipping should be discretionary and should not be mandated. Second, regulators have shown little interest in regulating the pricing of TNCs in any way. In general, these agencies do not want to interfere with pricing in a competitive market. Additionally, if any city were to institute an additional mandatory fee, it is likely that politicians would prefer to earmark the fund for a public service of some kind, such as driver education, accessible service, or community benefit, rather than allowing it to accumulate directly to drivers. Third, it would be difficult to determine systematically whether tip amounts are based on race or any other individual characteristic, calling in to question the effectiveness of this intervention. Finally, advocates for fair pay argue that drivers should be paid a base minimum wage and that that cost should be transferred to the cost of the ride, rather than through a tipping mechanism. In March 2018, for example, New York's Independent Drivers Guild submitted a petition to the TLC calling for higher, regulated per mile and per minute rates.[47]

Given the shortcomings of the tipping proposal, an alternative solution might involve the use of defaults. Ridehailing apps could ask passengers to select a standard tip to pay all drivers unless the rider specifically changes the default.[22] Social science points to the power of defaults in influencing behavior, and the default tip could prevent casual discrimination without eliminating passenger discretion entirely.

5.4.6 Charge fixed fares between destinations

> *Licensed TNCs are required to file specific fare amounts between each pair of origin and destination zones within [Jurisdiction] identified by [Agency Director]. TNC drivers must charge all passengers traveling between specific zones the published fare. Fares can be modified only upon approval of the [Agency].*

[22] Currently the default tip action for the Lyft and Uber apps is no tip at all. While the Lyft app requires riders to acknowledge the possibility of tipping before completing a ride, Uber's app minimizes acknowledgement of the tipping feature. Smaller TNCs may have different defaults. The ridehailing app Fasten, which operated in the United States from 2015 to 2018, formerly set a default tip of $1, which riders could then alter if they chose to

Research from Ge et al. suggested that some TNC drivers take female riders for longer, more circuitous, and more expensive rides than male riders.[44, p. 18] One obvious solution to this problem would be for regulators to establish or approve fixed fares between destinations and thereby eliminate financial incentives to lengthen rides.

Aligning driver incentives and rider goals such that both parties desire the direct route is certainly sensible design. However, while 41 states require TNCs to disclose their fares, no jurisdiction currently sets distance-based fares for TNCs.[89, p. 20] While intuitive, this proposal, like mandatory tipping, met with considerable resistance from experts in the field who argued that mandating fares is nearly impossible and likely unnecessary.

One major argument against fixed fares is that upfront pricing in TNCs is rendering this issue obsolete. Introduced in 2016 and now available in most markets, Lyft and Uber's upfront pricing features eliminate the possibility of overcharging by allowing riders to agree to a fixed rate before accepting a ride.[23] Even without upfront pricing, circuitous routes are less of a problem with TNCs than with taxicabs because passengers can see the suggested route on smart phones (theirs or the driver's). Passengers are more likely to know when they are taken for a longer ride. Finally, setting specific fares would involve an intense political challenge to ensure that the changes in cost are equitable for driver and for riders. These considerations call into question both the effectiveness and the fairness of the proposed intervention.

Another argument against fixed fares is that regulators have moved away from rate-setting in for-hire transportation in general, even where cities have the authority to set rates for TNCs. Cities have long exerted control over fares in the conventional taxicab industry, but have not typically sought to influence rates paid by TNC customers.[108] Some agencies, such as the California Public Utilities Commission and the New York Taxi & Limousine Commission, do require TNCs to report rate schedules but do not require specific per-mile or per-minute rates. Theoretically these agencies do require transportation providers to charge fares within their established rate schedule, but such rules are difficult to enforce. As such, there is little appetite for additional rate-setting on the part of many regulators, making the implementation of this intervention a major challenge.

5.4.7 Conduct public sector audits of driver behavior

> *Licensed TNC drivers shall make their vehicles available to compliance audits and enforcement actions upon request by authorized city personnel or law enforcement officers.*

The Ge et al. paper also suggested that one way of restricting discrimination would be performing periodic audits of driver behavior that appears to be discriminatory in nature.[44, p. 20] While it would be impossible for an auditing effort to reach all TNC drivers (in New York City, for example,

[23] Of course it is possible that TNCs may quote different fares for an identical ride, according to a customer's characteristics. However, such price discrimination is unrelated to the decisions of individual drivers and thus outside the scope of this thesis.

there are over 100,000 licensed for-hire vehicle drivers), audits could be used to verify suspicions of discriminatory behavior emerging from complaints or data analysis.[54] Audits could be conducted by the platforms themselves or by public sector enforcement squads.

There are many precedents for auditing discriminatory behavior in other industries. Public officers have conducted audits for offline markets since the Civil Rights Era; the Civil Rights Division of the Department of Justice, for example, has officers pose as tenants to audit landlords. There is also some precedent for public sector audits of TNC drivers. The Colorado Public Utilities Commission, for example, randomly audits drivers for compliance with requirements related to licensing, registration, insurance, vehicle inspection, and other issues. The New York TLC has a workforce of roughly 100 patrol officers that enforce city laws and TLC administrative rules against illegal street hails and other violations. They also arrange for WAV rides to test the availability of accessible rides. The Portland For-Hire Vehicle Program has a team of 9 officers that conduct daily ride audits. Some audits involve curbside inspections at pickup. In some audits, drivers pose as riders and observe driver conduct, before conducting the audit at the destination (drivers are paid for their time in both types of audits). Officers also hail rides in neighborhoods across the city to look for evidence of geographic discrimination. Common violations include driving without a license, lack of insurance, and picking up street hails. Portland conducts more than 3000 street audits per year, while most cities conduct fewer than 150.

Audits may also focus on investigating complaints of discrimination filed by private individuals. While many regulators already respond to complaints from riders, the creation of a specific TNC civil rights office could improve upon ad hoc complaints processes by centralizing complaints, collecting data, investigating individual TNC drivers, and establishing clear procedures for warnings or fines. Similar procedures exist in the taxicab industry. The New York TLC, for example, has a consumer complaints unit that investigates 311 complaints, often in response to taxi drivers that refuse to pick up passengers. Similarly, the District of Columbia Taxicab Commission (DCTC) hears complaints of taxicab discrimination from private individuals and has the authority to hold adversarial hearings to investigate claims[24] Furthermore, the District of Columbia Office of Human Rights also has the power to investigate complaints of unlawful discrimination in all places of public accommodation.

In addition to auditing drivers and investigating complaints, public agencies may build awareness of these efforts by publishing advertisements and posting signs at locations where people tend to hail rides, such as airport TNC zones, hotels, and nightclubs. Advertisements could state that TNC drivers are prohibited from discriminating on the basis of race, color, religion, sex, national origin, disability, or place of residence or business. The City of Chicago has experimented with this idea; a 2016 ordinance requires all TNC to display a sign informing passengers they can call 311 to report complaints.[81]

As with many regulatory proposals, there is also a parallel process that TNCs can and do adopt

[24]Chapter 7 of Title 31 of the D.C. Municipal Regulations.[120]

themselves. With regard to complaints, TNCs certainly already hear and process complaints from drivers and riders. At Lyft, riders and drivers can submit complaints by hotline or by email, and each complaint prompts a response from the Critical Response Team or the Trust and Safety Team. Despite the existence of such complaint procedures, there are also arguments in favor of the public sector investigating complaints of discrimination. First, a public office may be more impartial. In general, TNCs often lend more credibility to riders than drivers in responding to complaints, particularly with regard to accusations of unsafe driver behavior.[25] Second, TNCs often respond to individual incidents with a relatively minor response: promising that an offending driver will never again match with the rider who submitted the complaint. Agencies such as New York's Taxi & Limousine Commission may be able to provide more appropriate accountability for drivers, particularly given their authority to revoke a TNC licenses.

Despite the advantages of public-sector audits, this idea also invites many criticisms. For one, it would present a major administrative burden to investigate drivers and issue decisions in a timely manner, thereby limiting the implementability of the idea. Acquiring adequate evidence to issue an actual citation would also present a major challenge to implementation. Second, TNCs themselves may resist or evade additional efforts to audit their drivers as evidenced by Greyball, an Uber initiative that sought to mislead regulators and interfere with enforcement.[26] Finally, audits may not be effective or necessary, as many jurisdictions already receive complaints about TNCs.[27] These complaints do not often highlight issues of discrimination (pricing and perceived overcharging is a much more common matter of complaint). Finally, another argument against the creation of a TNC investigation unit is that it would be unfair to create an office that targets the TNC industry exclusively. That is, a better solution may be a more centralized place to investigate transportation discrimination more broadly, such as an office of human rights or a city attorney's office.

5.5 Platform Design Interventions

While Section 5.4 proposed and analyzed several new regulations for TNCs, the following section presents a series of platform and service design interventions aimed at limiting discrimination in ridesharing apps. These are changes that TNCs can voluntarily make to their apps or their services without regulatory intervention. Each subsection will describe the intent of the intervention, present precedents for the intervention, and describe expert reactions to the proposal along the three dimensions of effectiveness, fairness, and implementability.

[25] However, when investigating complaints against drivers, TNCs do often refer to a driver's background (i.e., rating and ride history) to inform the company's response to complaints about drivers.

[26] Uber developed the tool Greyball in 2014. The tool used data collected from the company's platform to identify officials who might seek to restrict or audit ridehailing drivers.[71]

[27] The consumer affairs branch of the California Public Utilities Commission, for example, receives and logs complaints. The CPUC encourages constituents to contact the industry with their complaint first, but also investigates possible infractions, such as double charging or wrongful termination of a ride. New York's TLC received 343 passenger complaints of refused pickups in 2017, an increase from 220 in 2016 and 60 in 2015.[54]

Relative to regulatory changes, this type of intervention offers the advantage of greater flexibility in implementation. TNCs can easily implement pilot new features, test the results, and scale the intervention to more cities and more rides. What's more, TNCs, as market designers, set the rules for their platforms, including rating mechanisms and the information that is available and actionable to users. Each of the following interventions assumes that TNCs should take responsibility for the treatment of both riders and drivers through their platforms. By characterizing and addressing problematic behavior, TNCs can draw a line between acceptable and unacceptable conduct and promote a service free from discrimination.

However, the obvious disadvantage of these TNC-driven interventions is that the TNCs may not be motivated to make anti-discrimination changes unless public action compels them to do so. There are countless incidents that could limit public trust in TNCs to change course without outside pressure from regulators.[28] Furthermore, the large TNCs often minimize the extent to which their platforms influence driver behavior in order to protect their ability to classify drivers as independent contractors rather than employees. That is, TNCs may seek to protect their business model by avoiding even minor interventions like requiring drivers to post anti-discrimination policies in their vehicles.

Nonetheless, there are two key arguments in favor of the TNCs themselves taking a leading role in anti-discriminatory interventions. First, each of these proposals is likely to benefit TNCs by improving satisfaction with their service, for both riders and drivers. Furthermore, TNCs arguably have the responsibility to make an active effort to limit possible discrimination, whether or not government actors compel them to. There is certainly no doubt that Lyft and Uber have adequate technological and creative capabilities, as well as robust data on drivers and riders.

In comparison to the previous section, many of the interventions in this section deal with discrimination from riders to drivers. This is due to the conundrum of discrimination by customers identified in Bartlett and Gulati (2016). First, public agencies are limited in their ability to regulate discrimination by customers and generally find it easier to regulate firms instead. Second, large firms collect enormous amounts of information about their customers' preferences and habits that they can use to restrict discriminatory preferences by structuring customers' choices, influencing their habits, and distributing the costs of discrimination that cannot be eliminated.[15] Finally, because TNCs have an obvious legal obligation not to discriminate under employment and public accommodations laws, they are arguably obligated to limit similar types of discrimination by their customers. Thus, TNCs should design their services and their platforms to reduce the possibility of customer discrimination even if the role of the state in this effort is limited. TNCs need not necessarily institute identical interventions, but where customer bias affects the opportunities of its employees, they should take steps to reduce or eliminate that harm.

Further, many of the interventions in this section deal with the qualitative and numeric reputation

[28]Examples include Uber's reluctance to introduce in-app tipping, delays in disclosure of data breaches, and the notorious case of Greyball, mentioned in the previous section

systems featured in ridehailing apps (see Sections 5.5.3, 5.5.6, and 5.5.7). Few regulations have addressed these reputation (or star rating) systems or how this information is used.[74] Regulators have not taken an active role in monitoring reputation systems and TNCs have an incentive to keep these systems proprietary and private. However, these scores can effectively exclude drivers and raters from TNC services and thus may raise worker and consumer protection issues. As such, this section considers options for TNC platforms to prevent discrimination through the design of their reputation systems. Similarly this section presents steps that TNCs can take to prevent discriminatory behavior through the design of in-app information sharing (see Section 5.5.1).

5.5.1 Further anonymize riders and drivers

While information sharing between drivers and riders is an essential component of TNCs' value proposition, responsible decisionmakers must subject this information sharing to scrutiny and examination. In the digital economy, platforms such as Lyft and Uber choose which information is available to parties during a transaction. Ridehailing platforms currently provide information to riders and drivers that could facilitate discriminatory behavior: names, photographs, ratings, and vehicle information. Uber riders, for example, can cancel a ride within two minutes of a match, which offers plenty of time for them to consider a driver's name, photograph, or even vehicle type and then cancel the ride with impunity (a cancellation within this time frame has no impact on their ability to find a new ride). While drivers face higher consequences for cancellations (see Section 5.4.4), Ge et al. provide evidence that some drivers may cancel rides based on rider information.

As the stewards of identifying information, TNCs also have the power to prevent the sharing of information that may facilitate discrimination. Where this information is also irrelevant or unnecessary, TNCs should do so. The challenge in platform design, then, is determining which information is necessary for ridehailing to work when and when this information is needed. Table 16 provides an overview of what information is available to Lyft and Uber users at each steps of the ride matching process.[29] Table 16 also presents a subjective "Ideal" information sharing design, based on what information could conceivably facilitate discrimination and what information is necessary to share with riders and drivers to make a successful match.

To their credit, TNCs obscure some of the information in Table 16 at critical moments in the ride matching process. Both Lyft and Uber, for example, obscure passenger destination from drivers until well after they have accepted the ride. Last names are never shared at all, as they are irrelevant to the matching process. However, TNCs may be able to further restrict discrimination by providing riders and drivers with additional anonymity. Many of these bits of information could be eliminated, delayed, or replaced with unique passcodes in order to prevent the opportunity for discrimination, particularly ride cancellation. Photographs, for example, are arguably unnecessary and could be done away with entirely. First names are more important for confirming matches, but

[29]Notably, there is no verification that passenger names or photographs are connected in any way to riders' actual identities, but other information can be assumed to be accurate.

could easily be replaced with passcodes to verify identify. Alternatively, first names could remain hidden until a driver arrives for pick-up. Currently, Uber displays this information after making a match and Lyft before, as shown in see Figures 7 and 8.[80, 79] Adding additional anonymity to the overall matching process summarized in Table 16 could offer an effective, low-cost strategy for preventing possible discrimination.

Table 16: *Information availability through Lyft and Uber platforms*

Information	Uber	Lyft	Ideal
To Drivers			
Passenger Rating	Before accepting match	Before accepting match	No change
Passenger Photograph	Never	Before accepting match	Never
–		During passenger rating	Never
Pick-Up Location	Before accepting match	Before accepting match	No change
Est. drive time to pickup	Before accepting match	Before accepting match	No change
Class of Request	Before accepting match	Before accepting match	No change
Passenger First Name	After accepting match	Before accepting match	After arriving for pickup
–	During passenger rating	During passenger rating	No change
Passenger Last Name	Never	Never	No change
Passenger Destination	After commencing ride	After arriving for pickup	After commencing ride
Long Ride Notifications	Before accepting ride	Before accepting ride	No change
Passenger Contact Information	Never	Never	Never
To Riders			
Driver Rating	After driver accepts match	After driver accepts match	Never
Driver Photograph	After driver accepts	After driver accepts match	After arriving for pickup
	During driver rating	During driver rating	Never
Driver First Name	After driver accepts match	After driver accepts match	After arriving for pickup
–	During driver rating	During driver rating	No change
Driver Last Name	Never	Never	No change
Vehicle (photo and license plate)	After driver accepts match	After driver accepts match	No change
Driver Contact Information	Never	Never	No change

From the perspective of TNCs, the primary arguments against additional anonymity are 1) the need to verify correct matches and 2) the desire to create a friendly and personalized atmosphere inside a ride. The first need is clearly resolvable through other means, including passcodes and devices such as Lyft's Amp feature, a colorful dashboard light that changes color to match riders' Lyft app.[30]

[30] One limitation of this new color coding system is that not all Lyft drivers have access to the Amp hardware. Lyft chooses to offer only to certain qualified drivers because the technology is expensive at scale and driver turnover is high.

The second need is more difficult to resolve. If TNCs want drivers to greet riders by name, then first names must be provided. However, one solution would be to allow riders to select a personalized nouns or emoji for themselves (e.g., cactus, robot), thereby retaining some level of personalization but also ensuring greater anonymity. Furthermore, changing the timing of information availability, at least, is unlikely to impact the atmosphere of a ride. Delaying driver/rider information until a driver indicates that she has arrived for pick-up would also offer a benefit: at this point in the process both rider and driver have invested time into initiating a ride and will be less likely to cancel. In light of these practical workarounds, further anonymizing riders and drivers should be seen as an implementable solution to preventing possible discrimination.

Figure 7: *Uber driver app, before (left) and after (right) accepting a ride*

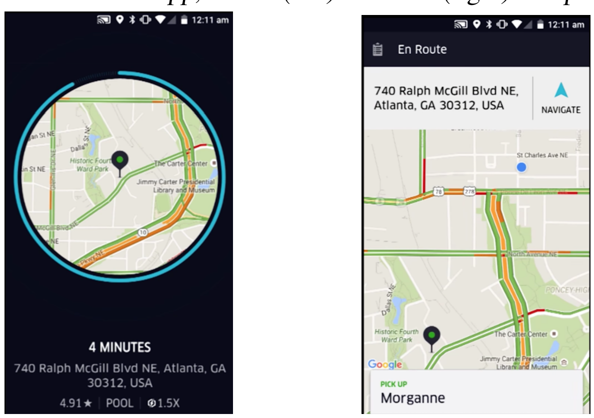
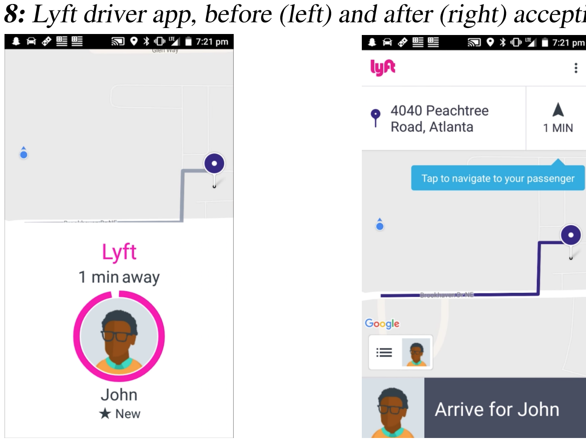


Figure 8: *Lyft driver app, before (left) and after (right) accepting a ride*



5.5.2 Make names and photos smaller in the app

Short of removing information like names and photographs from their apps, TNCs could also consider reducing the salience of identifying information. While the impact of salience on behavior is difficult to measure, there is precedent for such an intervention in the sharing economy. In 2016, Airbnb announced that it would experiment with "reducing the prominence of guest photos in the booking process" in order to reduce possible discrimination from Airbnb hosts to African-American guests.[92] Similarly, TNCs could experiment by making names and photographs smaller, black-and-white, or otherwise harder to read. This change could be made to information that is available before a match is made, after a made is made, or during the rating process (see Table 16). This approach would preserve the benefit of sharing this information (i.e., confirming matches, building relationships), while possibly reducing the negative consequences in a fair and costless way. However, the effectiveness of such an intervention is unproven.

Nonetheless, this proposal has many disadvantages. First and foremost, removing information from platforms is a simpler and more direct way to prevent discrimination than reducing their salience.[36] Second, drivers often respond to requests when driving, which involves reading small dialog boxes (particularly for uberPOOL and Lyft Line "Next Trip Requests") on the fly. If drivers make pick-up decisions based on passenger names, making names harder to read could lead to unsafe behavior. This criticism does not extend to reducing the salience of driver names/photographs during the driver rating process for passengers, who are presumably not driving. Nonetheless, the issue of driver safety poses a major challenge to the implementation of this intervention. Despite these limitations, TNC user experience research groups could experiment with information salience to determine whether such an intervention might change driver behavior without jeopardizing safety.

5.5.3 Increase burden for riders to negatively rate drivers

Studies have argued that the use of rider ratings to assess TNC drivers exposes these workers to the biases of riders, whether overt or implicit. As noted in Chapter 2, a low average star rating leads to Uber and Lyft "deactivating" drivers. Consequently, a seemingly neutral ratings system may facilitate discrimination. Indeed, in the anonymous and private act of rating a driver, riders have the power to pass along false information influenced by prejudice and bias. However, revising TNCs' reputation systems offers the potential to eliminate or reduce such acts of discrimination. There are many options for doing so, all of which would essentially make it more difficult for riders to negatively rate drivers without good cause.

The process for rating drivers through an app like Lyft or Uber is extremely straightforward. Typically, riders simply tap a number of stars, from 1 to 5, then the app presents an optional comment box and the rider taps "Select." As such, it is easy for riders to give careless or arbitrary negative ratings.[31] What's more, it is difficult to correct a rating given in error. Furthermore, the apps provide no indication of what criteria riders should use for rating and no information on how rating data are used (including possible deactivation of drivers).[32]

Section 5.4.3 discussed the possible value of driver training in reducing discrimination. One shortcoming of this approach was that it focused on educating the driver and ignored the role of the rider. Of course, educating riders of customer presents two main challenges: riders are far more numerous than drivers and the requirements to become a rider are far less involved. Nonetheless, changes to the rider app could easily educate riders about how to rate their drivers, either through an explicit click-through training or by increasing the burden to provide a low rating (with or without good cause). Many ridehailing apps currently use adjectives such as "Excellent" or statements like "Tell Us What You Loved" to guide riders, and additional rider education could expand on such features.

Beyond educating riders, TNCs could also require that riders explain negative reviews (through the comment box) in order for the reviews to be counted in a driver's average rating. One drawback of this approach is that such a requirement would discourage riders from giving low ratings, and would thus suppress rating frequency. As a consequence, driver ratings would rise and the variation among ratings would decrease, thereby eroding the utility of the ratings system.

Another option for discouraging discriminatory or arbitrary negative ratings would be to offer a series of checkboxes during the rating process. Alternatively, TNC platforms may ask riders to judge drivers along a set of criteria (i.e., cleanliness, politeness) as opposed to a catch-all five-star scale. Checkboxes or criteria-specific ratings could more specifically address possible reasons for a negative review, such as unsafe driving, dirty vehicles, or rude drivers. Of course, bias could still influence rider ratings (i.e., a rider may rate a driver as "rude" due to the driver's ethnicity or some other factor outside her control), but checkboxes would at least require the rider to put some reflection into the rating process. TNCs could also choose to ignore negative ratings when riders do not follow-up with an explanation of the rating.[33] A similar system existed in the ridehailing app Fasten. Nonetheless, the company found that 98% of rides received positive ratings, and that very few riders left negative ratings unexplained.

Alternatively, TNCs may be able to use rating data to address this issue without needing to influence rider behavior. First, TNCs could using algorithmic filtering to detect unfair or biased reviewers. Ebay, for example, has developed algorithms that identify high levels of negative feedback toward members of a particular race or gender, who can then be given an advantage in ratings.[50] Second,

[31]For Lyft and Uber, a negative rating is considered any rating less than five stars.

[32]There is one minor exception to this statement. The Lyft app indicates that riders will not be paired again with a driver they rate at three or fewer stars. However, this does not educate the rider about the ratings threshold for driver access to the app.

[33]Currently riders are not required to complete reviews, and qualitative feedback is completely voluntary. Drivers, on the other hand, are required to rate passengers. On the Lyft app, drivers are given a set period of time to rate riders, after which riders receive a default five stars.

TNCs could normalize ratings from individual drivers by controlling for the variation in rater behavior. For example, a three-star rating from a rider who routinely gives drivers low ratings could affect a driver's average rating less severely than the same rating from a rider who gives out mostly five stars. Finally, TNCs may also control ratings for factors outside a driver's control, such as weather, surge pricing, or time-of-day.[34] Such a system may offer an alternative to standardizing ratings through rider education or platform changes.

One final intervention related to driver ratings would be creating a mechanism for drivers to challenge their ratings. Currently, TNCs offer complaint hotlines for minor grievances, but do not usually provide a forum for drivers to challenge false or unfair reviews.[35] What's more, most TNCs report drivers ratings and reviews anonymously. While this anonymous approach protects rider privacy, it also makes it difficult for drivers to contest negative reviews or to understand what incidents contribute to low reviews. Anecdotes from online driver forums highlight driver frustration with the lack of information to prove claims of inappropriate ratings.[6] By deanonymizing ratings, TNCs could give drivers the ability to dispute ratings and provide ride-specific evidence. Such a mechanism already exists in New York due to the efforts of the Independent Drivers Guild, an organization of New York ridehailing drivers affiliated with the Machinists Union. Following a 2016 agreement between IDG and Uber, New York drivers can appeal deactivations resulting from low ratings to the Uber Deactivation Appeals Panel. The IDG may also represent drivers in their appeals.[110]

Each variation of this intervention would seek to add fairness to the driver rating process. Whether any of these actions would be effective in routing out unfair or discriminatory ratings is a matter of experimentation, but the logic of these interventions is sound. As for the implementability of increasing the burden for riders to rate drivers negatively, these interventions should be both technologically feasible and politically palatable for TNCs. Indeed, TNCs rely on credible reputation systems to improve the quality of their platforms and encourage users to trust the service.

5.5.4 Increase burden for drivers to negatively rate riders

Arguably, fairness in driver ratings is more important than fairness in passenger ratings. This is because drivers lose access to their source of income completely upon deactivation due to low ratings. Riders, on the other hand, are likely to find rides even after receiving negative reviews. Plus their income is not at stake, just their ability to hail rides. Nonetheless, there are also interventions that TNCs could make to ensure greater fairness in driver ratings of passengers. Indeed all of the suggestions from Section 5.5.3 could apply to rider ratings: educating drivers about ratings, requiring drivers to explain negative reviews, adding additional rating criteria, normalizing ratings,

[34]There is some precedence for this manipulation of ratings. Uber, for example, doesn't penalize drivers for negative ratings related to traffic.

[35]In hearing a deactivated Uber driver's wrongful termination claim, the 2013 court case Alatraqchi v. Uber Technologies, Inc. established that TNCs are not required to offer drivers the opportunity to challenge their reviews.[2]

ignoring discriminatory ratings, and allowing passengers to contest negative ratings. On a related note, Uber currently provides riders the ability to view their own star ratings through the app, but Lyft does not. Neither app allows riders to view ride-specific ratings. Arguably, this design choice prevents riders from understanding and addressing inappropriate ratings.[36]

5.5.5 Track driver ratings and look for discriminatory patterns

Given the many challenges that may prevent the public sector from collecting ratings or demographic data from TNCs, a more implementable solution to possible discrimination in driver ratings would be for the companies to track this information themselves and then investigate or act on possible discriminatory patterns. By measuring ratings according to characteristics such as race and gender, TNCs could easily determine whether discriminatory ratings from riders are a statistical problem in the aggregate (naturally, no driver is deactivated due to an isolated bad rating). Such data tracking efforts would need to be voluntary; while there are existing EEOC requirements for large employers to track data on workforce demographics, that requirement does not extend to contractor workforces.

TNCs could also take action to temper ratings that appear to be discriminatory in nature (See Section 5.5.3 for discussion of possible interventions). TNCs could, for example, use driver rating data to normalize ratings according to membership in protected classes shown to have lower ratings overall.

Although this idea is implementable from a practical and technological perspective, TNCs may object to this idea on several grounds. First, TNCs may claim that they have no way of tracking driver demographics. However, as discussed in Section 5.4.1, collecting such information is feasible and driver demographics are already available to some degree. Second, TNCs may claim that tracking such information would expose the companies to litigation. However, TNCs could track driver demographics under privilege of an attorney, which would prevent the data from being discoverable in court. Overall, there are many arguments in favor of tracking information that may provide evidence of discrimination: it would help ensure fairness in ratings, it would effectively inform the debate over discrimination, it is a low-cost intervention, and it may even help TNCs counter claims of discrimination.

5.5.6 Decouple ratings from access to the app

As noted elsewhere in this thesis, drivers lose access to ridehailing apps when their ratings fall below a city-specific threshold chosen by a city's general manager. This criterion lends considerable

[36] In rare cases, regulators have required that TNCs disclose this information. The D.C. Vehicle for Hire Innovation Amendment Act (D.C. CODE Chapter 50-331(b)(8) requires that TNC users be allowed to access to their own reputation score.

weight to driver ratings and may lead to a case of discrimination when these ratings are themselves discriminatory in nature. One extreme solution to this problem would be for TNCs to stop using driver rating data as the means of deactivating drivers altogether. That is, TNCs could decouple drivers' ratings from their access to the app.

This intervention would acknowledge that setting a sharp cutoff for access to their driver apps is unfair to drivers. Whether or not driver ratings are potentially discriminatory, relaxing the emphasis on rider ratings would certainly improve working conditions for drivers. Rating cut-offs (roughly 4.6 stars) are often not far below average ratings (roughly 4.8 stars), which often leads to considerable anxiety over ratings. What's more, a city's specific cut-off level is not necessarily obvious to drivers. In an ethnographic survey of TNC drivers in Boston, Robinson (2017) observed that the Uber Services Agreement did not explain this cut-off and that most drivers were not familiar with the terms of this document in any case.[105, p. 54] Indeed, drivers receive no training on how to improve their ratings and can only guess at which rides have produced low ratings, further exacerbating ratings anxiety for precarious drivers.

While this intervention would relieve driver anxiety, it suffers from a crucial shortcoming that negatively affects its effectiveness, fairness, and implementability. The primary problem with this intervention is that decoupling ratings from driver status removes TNCs' primary mechanism for removing drivers that are truly bad, from a safety or customer experience perspective. Furthermore, the use of ratings to ensure desirable behavior is another core value proposition of ridehailing. As such, this intervention is not considered feasible or advisable in any way.

However, it is possible to implement a more nuanced intervention that somehow reduces the primacy of driver ratings. Specifically, TNCs could either develop a method of filtering driver ratings (see Section 5.5.3) or adopt additional methods of evaluating a driver's performance, such as in-person evaluations, undercover audits (see Section 5.4.7, or other data on driver behavior (see Section 5.5.7). Indeed there are few examples of another service industry that relies on user feedback so exclusively to make employment decisions.[37] Employers such as retailers, airlines, or universities do collect feedback from shoppers, passengers, and students respectively, but they also use other performance indicators to evaluate workers.

5.5.7 Validate driver ratings with other data

As noted in Section 5.5.6, moving beyond driver ratings altogether is an overly extreme reaction to possible discrimination. As an alternative, TNCs could adopt additional methods of evaluating a driver's performance, including the use of data to evaluate driver behavior and validate negative reviews. Such a move would widen the basis on which drivers are evaluated and offer an effective solution to the threat of discriminatory or thoughtless driver ratings. While it may be difficult

[37]Given the status of TNC drivers as independent contractors, a TNC would not consider a driver deactivation as an "employment decisions," but this term is used here for the sake of comparison to other industries.

to know exactly what happens during a ride, validating driver ratings with ground truth data is technologically possible (i.e., implementable). It is also more objective (i.e., fair) than the current rating scheme.

In particular, vehicle telematics data (of the type collected by companies like True Motion and Nexar) could be helpful in validating ratings and complaints from riders. Smart phone-based sensors are already using video analysis, machine learning, and computer vision to monitor road conditions, record events, and improve safety on the road. This same information (i.e., speed, rapid acceleration, hard breaking, dangerous cornering, congestion) offers an immediate method for identifying high-risk drivers without any need for potentially discriminatory input from riders. Beyond telematics, TNCs could also use communications between drivers and riders to verify complaints from riders.[38]

It is difficult to know with certainty what data TNCs are collecting, but Lyft's Privacy Policy indicates that the company collects "mobile sensor data from drivers' devices (such as speed, direction, height, acceleration or deceleration) to improve location accuracy and analyze usage patterns."[62] Furthermore, Uber has been known to record information on hard breaking and speed through the accelerometer in drivers' phones. While the company may not collect this information for the explicit purpose of evaluating drivers,[39] Uber has been using accelerometer data to track behavior since 2017. The company has not yet used this data for any ratings- or earnings-related initiatives.

Naturally, drivers may perceive additional data collection or analysis as an invasion of privacy. Nonetheless such data collection may protect drivers from unwarranted low ratings. Indeed some drivers already use video/audio footage for self-protection.[40] However, drivers must pay for these cameras themselves. Furthermore, such data could also support positive incentives for drivers, such as an insurance savings tie-in for safe driving behavior. Beyond discrimination, this kind of information would promote safe driving and Vision Zero efforts, which are in place in many cities where TNCs operate.

5.5.8 Post anti-discrimination policy in all vehicles

As of 2018, 37 states require TNCs to adopt a nondiscrimination policy of some kind.[89, p. 20] Such requirements typically aim to ensure equal access for passengers with disabilities (i.e., accepting service animals, equal fares for passengers with disabilities). The Municipal Code of Chicago, for example, requires that TNCs train their drivers not to discriminate against people with disabili-

[38] According to Lyft's Privacy Policy, the company's third party phone and text facilitator provides Lyft with the date and time of phone calls and SMS messages, the content of SMS messages, and recordings of phone calls made on the Lyft platform.[62]

[39] It has been argued that Uber collects this data to support the development of autonomous vehicles, which require detailed high-precision 3D base-maps to function

[40] Typically regulators allow drivers to use cameras as long as they post warnings in the vehicle that the ride will be recorded.

ties in their passenger ratings.[41] In keeping with these laws, Lyft and Uber both currently maintain anti-discrimination/nondiscrimination policies in the "Terms and Conditions" that all drivers and riders must agree to before using the apps (see Figures 9 and 10). Appendix B offers greater detail on TNC company policies that relate to discrimination.

Figure 9: *Lyft Anti-Discrimination Policies*

Anti-Discrimination Policies

Discrimination against passengers or drivers on the basis of race, national origin, religion, gender, gender identity, physical or mental disability, medical condition, marital status, age, or sexual orientation is not allowed, and can result in deactivation from the platform.

Lyft is committed to maintaining an inclusive and welcoming community, and our mission is ensuring people who need rides most are able to get them. Refusing passengers with service animals is a violation of our terms of service. Discrimination of any kind may result in the offender's immediate deactivation.

Figure 10: *Uber Nondiscrimination Policy*

Legal

Uber Non-Discrimination Policy

Uber seeks to ensure that safe, reliable, and high-quality transportation options are available to everyone. Uber and its affiliates therefore prohibit discrimination against riders or drivers based on race, religion, national origin, disability, sexual orientation, sex, marital status, gender identity, age or any other characteristic protected under applicable federal or state law. Such discrimination includes, but is not limited to, refusing to provide or accept services based on any of these characteristics. Any rider or driver found to have violated this prohibition will lose access to the Uber platform.

However, these policies are not presented in an obvious way to users during sign-up or during the use of Lyft or Uber services. Although state and local regulations often require nondiscrimination policies for TNCs, these regulations do not typically involve specific requirements for the content,

[41] Municipal Code of Chicago Chapter 9-115-140.

dissemination, or enforcement of these policies. One low-cost strategy for raising awareness of discrimination in these platforms would be for TNCs to require drivers to post their anti-discrimination policies in their vehicles.

There is certainty precedent for such a move. TNC drivers are often required to display the "trade dress" of their respective companies on their vehicles. Transit agencies around the United States often post Title VI notifications and contact information for civil rights complaints regarding their service. In the case of TNCs, posting these policies would likely educate customers and alert them to the issue.

From the perspective of TNCs, the main objection to implementing this idea relates to the question of driver classification. In particular, TNCs may object to such a requirement on the grounds that drivers are 1099 contractors, not employees. TNCs often emphasize the fact that driver vehicles are the personal property of their drivers, and not part of a company-owned fleet. However, examples of TNC requirements for driver vehicles abound (e.g., trade dress, vehicle year requirements) and TNCs could likely require drivers to post policies in their vehicles at little risk to driver classification. Naturally, cities could compel TNCs to establish this driver requirement through regulation as well.

Another concern with this intervention is that effectiveness of posting anti-discrimination policies is unproven and arguably unlikely to influence behavior. Airbnb illustrates this point. In response to evidence of discrimination occurring on its platform, Airbnb updated its nondiscrimination and made it more salient in 2016.[42] Online market scholar Benjamin Edelman responded to the change with skepticism that a restated policy and a compulsory checkbox would actually discourage hosts from discriminating through the Airbnb platform.[36] However, overall posting anti-discrimination policies is likely to be a benign, if not transformative intervention.

5.6 Survey of Popular Support

As part of the research presented in Chapter 4, a survey of Uber and Lyft users was conducted between March 23 and April 3, 2018 using Amazon Mechanical Turk. The final sample size of the analysis, after screening for attention and eligibility, was 1,113 respondents. Chapter 4 provides additional information on the methods behind this survey and the demographics of this sample.

In addition to questions about the users' discriminatory preferences in the context of shared rides, the 2018 survey asked respondents to indicate their level of support for the public and private interventions to prevent possible discrimination. The survey presented respondents with a very

[42] Since November 2016, Airbnb has required its users to accept the following nondiscrimination policy: "By joining this community, you commit to treat all fellow members of this community, regardless of race, religion, national origin, disability, sex, gender identity, sexual orientation or age, with respect, and without judgment or bias."

brief summary of possible discrimination in ridehailing[43] and then asked about their generic level of support for public and private interventions to discourage possible discrimination. Table 17 summarizes the results of these questions.

Table 17: *Survey Responses: Support for Interventions*

	"Definitely Yes"	"Probably Yes"	"Not Sure"	"Definitely Not"
Do you think that it would be appropriate for your city to do something about possible discrimination in platforms like Lyft and Uber?	37.2%	32.2%	22.9%	7.1%
Do you think that it would be appropriate for Lyft and Uber to do something about possible discrimination on their platforms?	47.9%	34.4%	13.3%	4.4%

Despite the limitations of such a blunt question, these two survey questions indicate that there is general support for anti-discrimination interventions among ridehailing users. In particular, there is even greater support for private-sector interventions than for public policy or regulations aimed at reducing discrimination in the industry.

In addition to a general level of support for interventions, the survey asked respondents to react to the interventions presented in this chapter according to a seven-step Likert scale ranging from "Strongly Oppose" to "Strongly Support." Figures 11 and 12 present reactions to the specific interventions discussed in this chapter. Broadly speaking, most interventions enjoyed support of riders. In particular, all of the platform interventions except for "Make Information Smaller" enjoyed more than 50% support. Of the regulatory interventions, four interventions received more than 50% support: "Data Reporting," "Similar Wait Times," "Driver Training," and "Audits." Not surprisingly, the interventions that related to the cost of rides (i.e., "Mandatory Tipping" and "Fixed Fares") received less support. Regarding the platform design interventions, all interventions other than "make information smaller" enjoyed over 60% support. "Make information smaller," while seemingly the least popular idea, also received the greatest number of responses of "Neither Support nor Oppose," suggesting either ambivalence or confusion about the nature of the intervention.

[43]The survey prompt read: According to the 2016 paper Racial and Gender Discrimination in Transportation Network Companies, the results of field experiments suggested that Uber drivers are prone to discriminate against African American riders, resulting in longer wait times and more cancellations for riders with African American-sounding names. The researchers also found that drivers take female passengers on longer rides. At the same time, at least one ridesharing driver has filed a complaint with the Equal Employment Opportunity Commission (EEOC) arguing that he was deactivated based on low passenger ratings that were racially motivated.

Figure 11: *Popular Support for Proposed Policies*

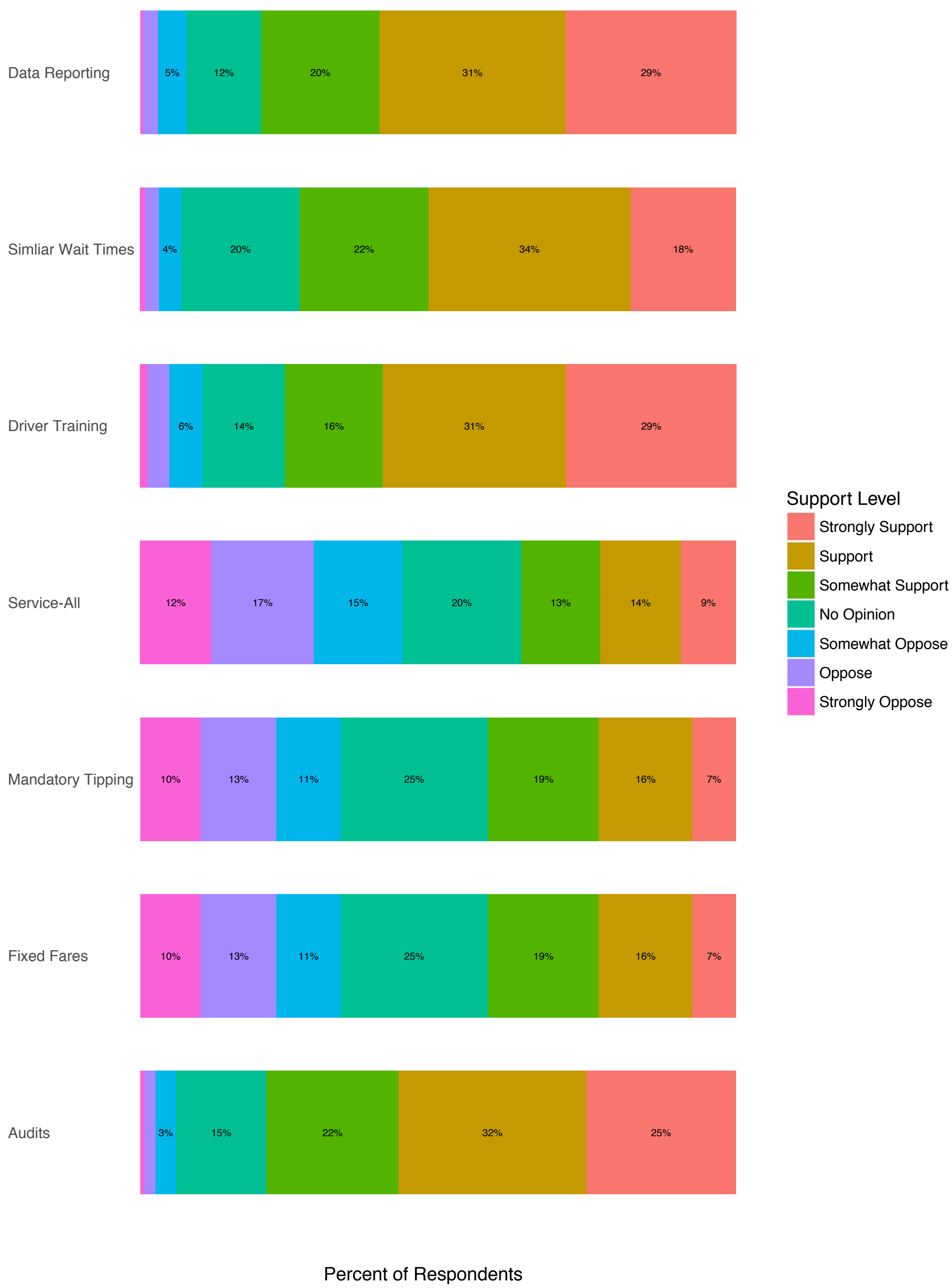
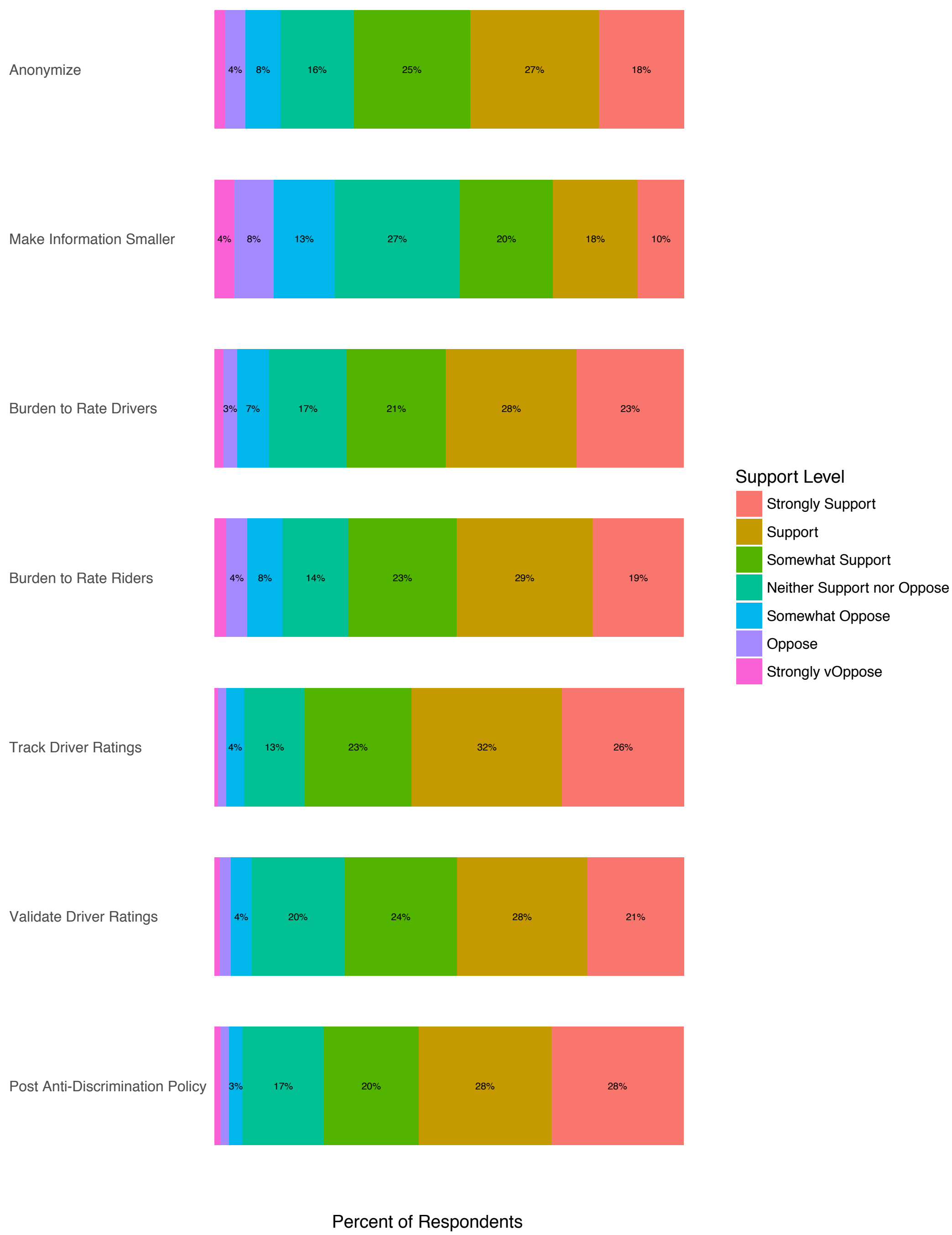


Figure 12: *Popular Support for Proposed Platform Interventions*



Despite the results of this survey, the popularity of these interventions should not be overstated. The respondents presented respondents with very brief descriptions of each intervention and the risk of misinterpretation is high. Furthermore, the survey did not explain the costs of any interventions to the respondents, so it is no surprise that nearly all interventions received considerable support.

Nonetheless, the survey results demonstrate in a preliminary way that the strategies discussed in this chapter could be politically feasible and popular with TNC users. Given that the best strategies fail if imposed on a resistant culture, popular support can facilitate the implementation of these interventions. As such this survey of popular support may prove critical to public decisionmakers who seek to understand popular sentiment toward ridehailing services. As noted in Dawes and Zhao (2017), government actors to date have a limited understanding of public opinion on ridehailing.[30] Given that user attitudes can predict policy preferences, a strong understanding of constituent perspectives can thus help governments make popular, and therefore implementable, interventions to the ridehailing industry.

5.7 Discussion

This chapter provided a review of regulatory and design options available to prevent and mitigate discrimination. These options were drawn from existing regulations as well as interviews with experts in the ridesharing industry. These experts represented a diversity of perspectives on the appropriate role of TNCs and their regulators. Interviewees commented on the implementability, effectiveness, and fairness of each possible solution. Interventions that satisfy all three dimensions are recommended for further study and implementation. Such interventions include data reporting requirements, increasing the burden for negatively rating drivers and riders, tracking driver ratings, and validating ratings through additional data. Scholars and policymakers may consider other interventions, but man yf these interventions suffer from questionable effectiveness, unfair costs and trade-offs, or significant obstacles to implementation. Tables 18 and 19 summarize the discussion of each intervention.

Although some of the above interventions may be advisable, the proposed interventions share common weaknesses. In particular, they all rely on assumptions about the nature of discrimination and would therefore benefit from additional data collection and analysis. Although intended to be exhaustive, it is also possible that other reasonable interventions are omitted from this thesis.

Table 18: *Summary of Regulatory Interventions; "+/-" indicates that an intervention does/does not satisfy a given dimension of evaluation. "?" indicates that there is insufficient evidence whether an intervention will satisfy a given dimension.*

	Effective	Fair	Implementable
Data Reporting	+	+	+
Similar Wait Times	+	+	-
Driver Training	?	-	+
Service-All	-	-	+
Mandated Tipping	?	-	+
Fixed Fares	-	-	-
Audits	-	-	-

Table 19: *Summary of Platform Design Interventions; "+/-" indicates that an intervention does/does not satisfy a given dimension of evaluation. "?" indicates that there is insufficient evidence whether an intervention will satisfy a given dimension.*

	Effective	Fair	Implementable
Anonymize	+	+	-
Make Information Smaller	?	+	-
Burden for Rating Drivers	+	+	+
Burden for Rating Riders	+	+	+
Track Driver Ratings	+	+	+
Validate Driver Ratings	+	+	+
Post Anti-Discrimination Policy	?	+	+

Many of the ideas raised in this chapter point to larger shifts in the industry that could alleviate potential discrimination along with other ills. The classification of drivers as employees, in particular, is one way to discourage discrimination by providing drivers with employment protections (in particular, Title VII of the Civil Rights Act of 1964), in addition to offering greater income security and other basic labor rights that such a move would extend to drivers. Rather than making elaborate changes to ensure that drivers have fair access to ridehailing platforms, federal or state policy could, for example, provide for direct, automatic coverage of on-demand workers under core labor laws. State laws sometimes follow a similar approach by characterizing certain workers as statutory employees for specified purposes, regardless of how businesses might otherwise characterize the relationship.[116, 6] There is local precedent as well. As of this writing, the New York City Council is currently considering a bill to extend the existing City Human Rights Law - one of the most expansive *local* anti-discrimination laws in United States - to freelancers and independent contractors. Similar, Washington State's freedom from discrimination statute protects contractors, as well as an employees, from employment discrimination.[6]

One other major change in the ridehailing industry warrants special attention. During the interviews with industry experts, one persistent theme was the hope that the arrival of autonomous vehicles and autonomous ridehailing fleets will solve any discrimination concerns by eliminating the human element from the equation. There are two reasons to be cautious about such a claim. First, Chapter 3 offers evidence that discrimination between riders is a potential problem separate and apart from the interaction between drivers and riders. Chapter 4, meanwhile, argues that the replacement of drivers with AVs may even exacerbate such rider-rider discrimination. Second, even without drivers, rider access to ridehailing services may still vary in problematic ways, particularly origin/destination, physical ability, and ability to pay. While this thesis has focused primarily on potentially discriminatory actions by riders and drivers, fairness in access and algorithms supersedes the individual decisions of users. The human element will persist. Without thoughtful design in the industry, discrimination will persist as well.

6 Conclusion

New and emerging technologies have the potential to break down barriers, but we must work to ensure that these advances expand the horizons of all Americans.

U.S. Senate Subcommittee on Privacy, Technology, and the Law [42]

Transportation network companies like Uber and Lyft are replacing, supplementing, and disrupting traditional modes of transportation at a rapid pace. The benefits of ridehailing and ridesharing are numerous: improved accessibility for riders with disabilities, improved service in historically underserved neighborhoods, convenient pick-ups, alternatives to intoxicated driving, flexible work hours, and opportunities to bridge social divides. At the same time, these services present many costs and uncertainties: congestion impacts, disruption of traditional industries, unfair labor practices, and possibly erosive effects on transit ridership. Through that lens, this new form of travel offers the potential to either exacerbate or forestall discrimination in transportation. Given the complex outcomes of the ridehailing revolution, equitable access to TNC platforms for drivers and riders is the critical issue that motivated this thesis. In that light, this thesis sought to consider how ridehailing services might better deliver the equitable mobility system of the future.

6.1 Key Findings

Against this backdrop, this thesis extended existing research on discrimination and ridehailing in three important ways. First, Chapter 3 investigated rider-to-rider discriminatory attitudes in the context of dynamic ridesharing. In doing so, this thesis found that discriminatory attitudes toward passengers of differing class and race in the shared ride are positively correlated with respondents that are male or are women with children. Respondents' race alone has no significant impact on discriminatory attitudes, but white respondents in majority white counties are more likely to hold such attitudes. The second major finding of Chapter 3 is that one's generic social dominance orientation strongly influences his/her discriminatory attitudes in ridesharing, supporting the claim that behavior in shared mobility platforms can reflect long-standing social dominance attitudes.

Second, Chapter 4 provided evidence that the advent of autonomous ridesharing will exacerbate discriminatory attitudes toward fellow passengers in shared rides. What's more, this effect will be particularly acute with regard autonomous ridesharing with passengers of a different gender. The size of the impact of autonomous rides was found to be positively correlated with riders who are female, older, and have above average incomes.

Finally, this thesis proposed fourteen regulations and platform design interventions to prevent and mitigate possible discrimination in ridehailing and ridesharing. These interventions were vetted through a survey of national experts in ridehailing policy and ridehailing design, then analyzed for their effectiveness, fairness, and implementability, as well as their popular support among ridehailing passengers. According to these criteria, Chapter 5 called for additional data reporting requirements and a series of changes to the TNCs' star rating systems as two important and advisable interventions to limit discrimination.

6.2 Further Research

This thesis suggests several critical directions for future research.

The findings of Chapter 3, in particular, call for four topics of future research to confirm and expand upon findings. First, an implicit association test (IAT) could confirm that passengers hold the discriminatory attitudes discussed in the analysis above. Second, additional research could model the connection between discriminatory attitudes and actual discriminatory behavior. Specifically, experimental methods could consider causality in ridesharing and discrimination (i.e., does the ridesharing context cause a change in discriminatory attitudes of passengers?). Third, additional surveys could ask respondents about how their attitudes affect other behaviors in the TNC context, such as tipping and rating. Fourth, given that we repeated the similar surveys in 2016 and 2018, further research could use these data to measure whether the 2016 presidential election or other intervening event may have affected discriminatory attitudes over time.

The findings of Chapter 4, meanwhile, call for further confirmatory research into the effect of the driverless context on discriminatory attitudes in autonomous rideshares. In particular, Chapter 4 provides an analytical foundation upon which researchers can replicate this study with photographs of traditional and driverless shared rides rather than simple text questions. Doing so would ensure that respondents visualize how the ridesharing context might change with the arrival of AVs. Such research could also inform the interior design of autonomous ridesharing vehicles with regard to equity, safety, and socialization. If the results of this chapter are indeed correct, further research could also consider how autonomous ridesharing policy and service provision may counteract the increase in discriminatory attitudes (e.g., physical barriers, grouping strategies, video surveillance, etc.)

Broadly speaking, Chapter 5 calls for improved data collection that could also unlock many areas of future research, such as measuring disparate discriminatory impacts in the geographic provision of service, driver star ratings, tips, and other metrics of interest. The lack of data to prove or disprove such phenomena is the key limitation in understanding, and therefore eliminating, discrimination in the ridehailing industry. Apart from data analysis, each of the interventions discussed in Chapter 5 would require further research before being implemented. Requiring wait times to be similar in similar areas of demand, for example, would first require robust research on how much variation between zones should be allowed in level of service and what the costs of providing such service would be.

6.3 Reflection

In response to the rapid growth of ridehailing services, policymakers and leaders in the industry have acted quickly to establish new paradigms of service and regulation. New standards for the industry continue to emerge and evolve, pointing to the need for thoughtful dialogue and continued reflection. Fortunately, conscious and informed decisions on the part of regulators and TNCs can emphasize the benefits of ridehailing and limit its societal costs. As a researcher, I am fortunate to have engaged directly with a set of national experts who were open to discussing discrimination in this dynamic industry.

Often in my conversations with leaders from academia, industry, and policy, I heard that discrimination, while undesirable, is not seen as a critical issue for TNCs. Some experts pointed out that TNCs certainly offer a broader and more accessible service than taxicabs, or that there is no evidence of systemic discrimination in TNC service. Others pointed out that driver incentives are correctly aligned to provide accessible service to riders. In the other direction, many people argued that riders have no real reason to discriminate against drivers at all. Finally, some experts argued that the advent of autonomous ridesharing will eliminate the problem of possible discrimination by removing human judgment from process of matching rides.

There is certainly merit to some of these arguments: Uber drivers go places that taxis have historically ignored and autonomous rideshare vehicles will behave as they are programmed to. Nonetheless, these arguments understate 1.) the need for definitive and data-driven research on discrimination in TNCs and 2.) the remarkable persistence of discriminatory attitudes across time and technological progress. My view is that all possible vectors of discrimination in ridehailing warrant scrutiny and must remain a part of the ridehailing debate until researchers prove that they do not exist.

In this light, it is my hope that this thesis provides theoretical and empirical evidence of the need for interventions to support justice in shared mobility. In particular, I believe that this thesis demonstrates the existence of concerning discriminatory attitudes between fellow passengers in the shared ride. By surveying and interviewing TNC users, policymakers, advocates, and providers, this thesis also identifies anti-discriminatory interventions that are effective, fair, and feasible. By summarizing constituent perspectives on these proposals, this research can help cities, TNCs, and other actors act confidently as they seek to mitigate discrimination in the sharing economy.

Naturally, any new policy change also presents possible costs: more expensive service, efficiency losses, and political resistance. Private companies easily reach firm decisions on trade-offs between benefits and costs, or between conflicting goals like revenue and driver retention. Setting public policy, however, is more difficult. Policymakers often lay out conflicts and debates, and then consider the issues *ad infinitum*. Furthermore, the most difficult policies to enact are those that offer a dispersed benefit to certain actors (e.g., drivers or riders) at a concentrated cost to somebody else (e.g., TNCs). Such is the nature of making policy amid ridehailing's challenging political questions. Should cities, for example, demand additional data from the ridehailing industry? Should cities enforce rules at any cost? This thesis considers such costs and trade-offs in both regulatory interventions and platform design changes. An exact determination of how to balance benefits and costs, however, requires political judgment that is beyond the scope of this thesis. Nonetheless, I hope that this work will open such conversations.

In closing, I reiterate the importance of several next steps that government officials and industry decisionmakers can pursue to address discrimination in ridehailing. These include stronger data reporting requirements, reformed reputation systems for drivers and riders, greater attention to driver ratings, and validation of ratings through data. The role of research in the implementation of these and other ideas is clear. Fortunately, TNCs sit atop massive accumulations of data and promote a culture of rapid experimentation. Many questions lie open for further research by TNCs and their partners in academia. How do discriminatory attitudes relate to actual discriminatory behavior? How can the design of vehicles affect attitudes in driverless ridesharing? How are attitudes evolving in response to technology and politics?

If we can decide, as a society, the answer to these questions, then we can prevent new forms of discrimination from emerging. As a result, ridehailing services can become platforms of serendipity, unity, and cohesion. With this goal in mind, leaders in transportation can and should support a society in which we all ride, together.

Appendices

A

A Sample Interview Guide

Background: My masters thesis at MIT deals with the idea of discrimination in ridesharing/ridehailing. This work is partly inspired by the 2016 paper Racial and Gender Discrimination in Transportation Network Companies. The first draft chapter (complete) used a survey of UberPOOL/Lyft Line users to ask whether users hold discriminatory attitudes about their co-passengers in shared rides, and found that people who hold such views in general are likely to apply those views in the shared ride as well.

For my next chapters, I would like to propose a few platform design changes (i.e., information availability) and regulatory solutions and then test these with riders, drivers, and people in the industry for their effectiveness, fairness, and implementability. I am in the early stage of this work, but I greatly appreciate any input you can offer to my work!

Regulatory/Policy Options: What is your reaction to each of the following interventions in terms of how effective, fair, and implementable it is?

1. Require TNCs to report information that may provide evidence of discrimination
2. Require wait times to be similar in areas with similar demand
3. Require mandatory driver training to include diversity and sensitivity
4. Strengthen service-all provisions (i.e., prohibit TNC drivers from refusing rides based on destination and rider characteristics)

5. Service compris provisions (i.e., mandated tipping to remove customer discretion)
6. Charge fixed fares between destinations
7. Conduct public sector audits of driver behavior

Platform/TNC Options: What is your reaction to each of the following interventions in terms of how effective, fair, and implementable it is?

1. Further anonymize passengers and drivers
2. Make names and photos smaller
3. Perform in-person audits of driver behavior
4. Increase burden for riders to negatively rate drivers
5. Track driver ratings and look for discriminatory patterns
6. Decouple ratings from access to the app
7. Validate driver ratings with other data
8. Post anti-discrimination policy in all vehicles

General Questions:

- How would stakeholders (especially drivers, but also riders, regulators, platforms) react to these interventions?
- Who else should I speak with?
- What other solutions may exist to mitigating discrimination, to the extent that it exists?
- Should TNCs be told how to eliminate discrimination, or allowed to develop their own methods?
- What opportunities exist for TNCs to promote serendipitous interaction that break down stereotypes?
- What obligation do TNCs have to address discrimination on their platforms?
- What would you change about this interview process?

B

B Lyft and Uber Non-Discrimination Policies

In addition to the policies summarized in Figures 9 and 10, Uber's Community Guidelines and Lyft's Terms of Service elaborate on the companies' policies toward discrimination. Lyft's list of restricted activities, for example, includes the following: "With respect to your use of the Lyft Platform and your participation in the Services, you agree that you will not: ...discriminate against or harass anyone on the basis of race, national origin, religion, gender, gender identity, physical or mental disability, medical condition, marital status, age or sexual orientation." Uber's Community Guidelines go into greater detail on discriminatory activities that are forbidden through its services. Table 20 summarizes Uber Community Guidelines related to discrimination.

Table 20: *Uber Community Guidelines relevant to discrimination*

Respect each other	Remember that when you use Uber you will meet people who may look different or think differently from you. Please respect those differences. We want everyone to feel welcome when they use Uber.
Why riders can lose access to Uber: Ensuring a respectful, safe environment for all drivers and riders	Here are some reasons why you could lose access to Uber as a rider: ... Use of inappropriate and abusive language or gestures. For example, asking overly personal questions, using verbal threats, and making comments or gestures that are aggressive, sexual, discriminatory, or disrespectful.
Why riders can lose access to Uber: Discrimination	Uber has a zero tolerance policy towards discrimination of any kind. This means you will lose access to your account if you are found to have discriminated against drivers or other riders based on their race, color, religion, national origin, disability, sexual orientation, sex, marital status, gender identity, age or any other characteristic protected under applicable law.
Why drivers can lose access to Uber: Safety	Actions that threaten the safety of drivers and riders will be investigated and, if confirmed, lead to permanent deactivation of your account. For example: ... Use of inappropriate and abusive language or gestures. For example, asking overly personal questions, using verbal threats, and making comments or gestures that are aggressive, sexual, discriminatory, or disrespectful.
Why drivers can lose access to Uber: Fraud	Fraudulent activity undermines the trust on which Uber is built. That's why we are constantly on the lookout for fraud by riders and drivers who are gaming our systems. What leads to you losing access to your account? We will deactivate any account or accounts associated with fraudulent activity, which may include: deliberately increasing the time or distance of a trip; accepting trips without the intention to complete, including provoking riders to cancel; creating dummy rider or driver accounts for fraudulent purposes; claiming fraudulent fees or charges, like false cleaning fees; and intentionally accepting or completing fraudulent or falsified trips.

Heading	Policy
Why drivers can lose access to Uber: Discrimination	We have a zero tolerance policy towards discrimination of any kind at Uber. It is unacceptable to refuse to provide services based on characteristics like a person's race, color, religion, national origin, disability, sexual orientation, sex, marital status, gender identity, age or any other characteristic protected under relevant federal, state, or local law. Actions like these may result in permanent deactivation of your account. In addition, it is not acceptable to discriminate on the basis of a rider's destination... It is not a violation of these guidelines to pass on a trip because the trip does not work for you - for example, it would interfere with a personal commitment or prior obligation, such as a job, a doctor's appointment, a school pick-up, or a family event. But canceling trips or using features in the Uber app to avoid receiving trip requests solely for the purpose of avoiding a particular neighborhood due to the characteristics of the people or businesses that are located there violates these guidelines and may cause you to lose access to your account. We also want to help increase the transportation options for riders with disabilities. That's why we have information available for drivers on this topic... We expect drivers using the Uber app to comply with all relevant state, federal and local laws governing the transportation of riders with disabilities, including transporting service animals.

C

C MIT Committee on the Use of Humans as Experimental Subjects (COUHES) Approval

MIT Committee On the Use of Humans as Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
Building E 25-143B
(617) 253-6787

To:	Scott Middleton
From:	Leigh Firn, Chair COUHES
Date:	02/28/2018
Committee Action:	**Exemption Granted**
Committee Action Date:	02/28/2018
COUHES Protocol #:	1802251873
Study Title:	Discrimination and Regulation in Ridehailing and Ridesharing (2nd Application)

The above-referenced protocol is considered exempt after review by the Committee on the Use of Humans as Experimental Subjects pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

If the research involves collaboration with another institution, then the research cannot commence until COUHES receives written notification of approval from the collaborating institution's IRB.

Unless informed consent is waived by the IRB, use only the most recent, IRB approved and stamped copies of the consent form(s).

Adverse Events: Any serious or unexpected adverse event must be reported to COUHES within 48 hours. All other adverse events should be reported in writing within 10 working days.

Amendments: Any changes to the protocol, including changes in experimental design, equipment, personnel or funding, must be approved by COUHES before they can be initiated, except when necessary to eliminate apparent immediate hazards to the subject.

Human subjects training is required for all study personnel and must be updated every 3 years.

You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with COUHES, original signed consent forms, and study data.

D

D Full Mechanical Turk Questionnaire (2018)

Perceptions of Dynamic Ridesharing

Start of Block: Default Question Block

Q1 Thank you for your interest in participating in the “Perceptions of Dynamic Ridesharing” survey. Please note that you must have used services from Lyft or Uber in the past to participate in this survey. You must also live in a city in the United States that offers Lyft Line or UberPOOL services. The survey is being conducted by graduate researchers at MIT, and the information you provide will only be used for academic purposes. Participation in this survey is voluntary, and it should take about 15 minutes of your time. You may decline further participation in the survey at any time without adverse consequences. If you choose to participate in the survey you understand that your responses to the survey questions will be stored and accessed by the researcher. However, any responses you give will remain anonymous and confidential, and all data will only be reported in an aggregate format (by reporting only combined results and never reporting original ones). All questionnaires will be concealed, and no one other than then primary investigator and assistant researchers will have access to them. The data collected will be stored in the HIPPA-compliant, Qualtrics--secure database until it has been deleted by the primary investigator. Any questions can be directed to mitdynamicridesharingsurvey@gmail.com.

Q2 I have read and understood the above consent form and desire of my own free will to participate in this study.

- ○ Yes (1)
- ○ No (2)

Skip To: End of Survey If I have read and understood the above consent form and desire of my own free will to participate i... = No

End of Block: Default Question Block

Start of Block: Block 1

Q3 Have you ever used Uber or Lyft?

◯ Yes (1)

◯ No (2)

Skip To: End of Survey If Have you ever used Uber or Lyft? = No

End of Block: Block 1

Start of Block: Block 2

Q53 Companies such as Uber or Lyft have recently introduced carpool versions of their regular ride-hailing services in a number of cities in the United States. These services (known as "Uber Pool" and "Lyft Line") match riders heading in the same direction, so that they can share a ride at a lower price than traditional Lyft and Uber services. This survey will ask for your perception about these services, in particular, UberPool and Lyft Line.

Q4 In what ZIP code do you live? UberPool or Lyft Line must be available in this ZIP code to continue.

____

Q5 Is UberPool or Lyft Line (the carpool versions of Uber or Lyft) available in your city?

◯ Yes (1)

◯ No (2)

◯ I am not familiar with UberPool or Lyft Line (3)

Skip To: End of Survey If Is UberPool or Lyft Line (the carpool versions of Uber or Lyft) available in your city? != Yes

End of Block: Block 2

Start of Block: Block 3

Q6 Have you ever used UberPool or Lyft Line?

- ◯ Yes (1)
- ◯ No (2)

---

*

Q7 Please state the approximate number of trips you took using Uber or Lyft (including UberPool/Lyft Line, if any) in the last 30 days:

____

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

*

Q8 Please state the approximate number of trips you took using UberPool or Lyft Line in the last 30 days (must be less than or equal to the number entered above):

____

Page Break

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q9 Overall, what do you estimate as the percentage of your total Uber or Lyft trips taken with UberPool or Lyft Line (must be between 0 and 100)?

____

Display This Question:

If Have you ever used UberPool or Lyft Line? = No

Q10 Would you ever consider using UberPool or Lyft Line in the future?

- Yes (1)
- No (2)
- Not sure (3)

End of Block: Block 3

Start of Block: Block 7

Q28 Have you ever served as a driver for Uber or Lyft?

- Yes (1)
- No (2)

End of Block: Block 7

Start of Block: Block 8

Q31 Which of the following apps do you have on your smartphone?

- ◯ Uber (1)
- ◯ Lyft (2)
- ◯ Both Uber and Lyft (3)
- ◯ I do not have these apps on my phone (4)

Display This Question:

If Which of the following apps do you have on your smartphone? = Both Uber and Lyft

Q32 In the last 30 days, which ridesharing app have you used more frequently?

- ◯ Uber (1)
- ◯ Lyft (2)
- ◯ I use each app about 50% of the time (3)
- ◯ Not sure (4)

Page Break

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q13 Please state your opinion about the following statement:

	Agreement						
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Overall, I prefer UberPool or Lyft Line to UberX or Lyft (where I am the only passenger in the ride). (1)	○	○	○	○	○	○	○

Display This Question:

If Please state your opinion about the following statement: : Agreement = Strongly disagree

Or Please state your opinion about the following statement: : Agreement = Disagree

Or Please state your opinion about the following statement: : Agreement = Somewhat disagree

Q56 Why do you prefer Uber X or Lyft (where you are the only passenger in the ride) to UberPool or Lyft Line?

- ☐ I don't want to deviate from the most direct route (1)
- ☐ I want to reach my destination quickly (2)
- ☐ I do not want to share space with a stranger (3)
- ☐ I don't want to wait for another passenger (4)
- ☐ I am worried the other passenger won't show up (6)
- ☐ Other (5)

End of Block: Block 8

Start of Block: Block 10

Q14 Please state your opinion about the following statement:

	Satisfaction									
	Very unsatisfied 1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	8 (8)	9 (9)	Very satisfied 10 (10)
Thinking about the service you use most frequently (i.e., Lyft or Uber), how satisfied are you with their overall service? (1)	○	○	○	○	○	○	○	○	○	○

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q15 Please state your opinion about the following statement:

	Satisfaction									
	Very unsatisfied 1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	8 (8)	9 (9)	Very satisfied 10 (10)
Thinking about the service you use most frequently (i.e., Lyft or Uber), how satisfied are you with UberPool or Lyft Line specifically? (1)	○	○	○	○	○	○	○	○	○	○

End of Block: Block 10

Start of Block: Block 4

Q11 Regarding shared rides in UberPool or Lyft Line, please state your opinion about the following statements:

	Agreement						
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)

It would be great to be paired in shared rides with passengers of all different races. (1)	○	○	○	○	○	○	○
Grouping passengers of different races in shared rides is a recipe for trouble. (2)	○	○	○	○	○	○	○
I would prefer to avoid being paired with a passenger of a lower social class in shared rides. (3)	○	○	○	○	○	○	○
Pairing passengers from all social classes in shared rides is a good idea. (4)	○	○	○	○	○	○	○
Sharing a ride with a passenger of a different ethnicity could make me uncomfortable. (5)	○	○	○	○	○	○	○
Everyone should welcome passengers of all ethnicities in shared rides. (6)	○	○	○	○	○	○	○
Sharing a ride with a	○	○	○	○	○	○	○

passenger of a different gender could make me uncomfortable. (7)							
Pairing men and women together in shared rides is a good idea. (8)	○	○	○	○	○	○	○
I prefer not to be paired with passengers who are different from me. (9)	○	○	○	○	○	○	○
Sharing a ride with a stranger is a good opportunity for me to meet someone with a different background. (10)	○	○	○	○	○	○	○

Page Break

Q51 The next question will ask you to explain your opinion about shared rides in a future with self-driving Lyft and Uber vehicles (also known as driverless or autonomous vehicles, or AVs). These companies are already experimenting with driverless ride service, and are likely to expand. In the following question, consider how you would feel in a shared ride with no driver in the car.

Page Break

Q49 Regarding shared rides in UberPool or Lyft Line **when there is no driver present**, please state your opinion about the following statements:

	Agreement						
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)

It would be great to be paired in driverless shared rides with passengers of all different races. (1)							
Without a driver present, grouping passengers of different races in shared rides is a recipe for trouble. (2)							
I would prefer to avoid being paired with a passenger of a lower social class in shared rides when there is no driver present. (3)							
Pairing passengers from all social classes in driverless shared rides is a good idea. (4)							
Sharing a ride with a passenger of a different ethnicity could make me uncomfortable when there is no driver present. (5)							

Everyone should welcome passengers of all ethnicities in driverless shared rides. (6)	○	○	○	○	○	○	○
Sharing a ride with a passenger of a different gender could make me uncomfortable when there is no driver present. (7)	○	○	○	○	○	○	○
Pairing men and women together in driverless shared rides is a good idea. (8)	○	○	○	○	○	○	○
I would prefer not to be paired with passengers who are different from me when there is no driver present. (9)	○	○	○	○	○	○	○
Sharing a ride with a stranger is a good opportunity for me to meet someone with a different background, even when there is no driver	○	○	○	○	○	○	○

present. (10)

Page Break

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q40 Regarding your personal experience in UberPool or Lyft Line, please answer the following questions:

	Frequency					
	Never (1)	Once in a while (2)	About half of the time (3)	Most of the time (4)	Every UberPool or Lyft Line ride I take (5)	Not sure (6)
How often are you paired with another passenger? (3)	o	o	o	o	o	o
How often are you paired with a passenger of the opposite gender? (4)	o	o	o	o	o	o
How often are you paired with a passenger of a different race or ethnicity? (1)	o	o	o	o	o	o
How often are you paired with a passenger of a different social class? (2)	o	o	o	o	o	o

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q44 Regarding your personal experience in UberPool or Lyft Line, please state your opinion about these characteristics of your fellow passengers:

	Expectations						
	Fell far below expecations (1)	Fell below expectations (2)	Slightly fell below expectations (3)	Met expectations or I didn't notice (4)	Slightly exceeded expectations (5)	Exceeded expectations (6)	G ex exp

Interesting (i.e., exceeding expectations means they were more interesting than I expected) (1)	○	○	○	○	○	○
Clean (i.e., exceeding expecations means they were more clean than I expected) (2)	○	○	○	○	○	○
Friendly (i.e., exceeding expectations means they were more friendly than I expected) (3)	○	○	○	○	○	○
Respectful (i.e., exceeding expectations means they were more respectful than I expected) (4)	○	○	○	○	○	○

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q46 Regarding your personal experience in UberPool or Lyft Line, please state your opinion about these characteristics of your fellow passengers:

	Expectations

	Fell far below expecations (1)	Fell below expectations (2)	Slightly fell below expectations (3)	Met expectations or I didn't notice (4)	Slightly exceeded expectations (5)	Exceeded Expectations (6)	(ex exp
Boring (i.e., exceeding expectations means they were more boring than I expected) (1)	◯	◯	◯	◯	◯	◯	
Dirty (i.e., exceeding expectations means they were more dirty than I expected) (2)	◯	◯	◯	◯	◯	◯	
Rude (i.e., exceeding expectations means they were more rude than I expected) (3)	◯	◯	◯	◯	◯	◯	
Annoying (i.e., exceeding expectations means they were more annoying than I expected) (4)	◯	◯	◯	◯	◯	◯	

Page Break

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q45 Regarding your personal experience in UberPool or Lyft Line, please state your opinion about the following statements:

	Agreement						
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Based on my experience with fellow passengers, I am less likely to use UberPool or Lyft Line again. (1)	○	○	○	○	○	○	○
I look forward to meeting passengers in shared rides, even if they are different from me. (2)	○	○	○	○	○	○	○

Display This Question:

If Have you ever used UberPool or Lyft Line? = Yes

Q17 In general, would you prefer to be paired in an UberPool or Lyft Line ride with someone ...?

○ Similar to you (1)

○ Different from you (2)

○ I am indifferent (3)

End of Block: Block 4

Start of Block: Block 6

Q16 Please state your opinion regarding the following statements: "I consider myself..."

	Agreement						
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Extroverted (1)	○	○	○	○	○	○	○
Anxious (2)	○	○	○	○	○	○	○
Open to new experiences (3)	○	○	○	○	○	○	○
Please select "agree" for this line (4)	○	○	○	○	○	○	○
Reserved or quiet (5)	○	○	○	○	○	○	○
Sympathetic or warm (6)	○	○	○	○	○	○	○
Cautious (7)	○	○	○	○	○	○	○

Skip To: End of Survey If Please state your opinion regarding the following statements: "I consider myself..." != Sympathetic or warm

Q27 Please state your opinion regarding the following statements:

	Agreement						
	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor	Somewhat agree (5)	Agree (6)	Strongly agree (7)

disagree
(4)

Some groups of people must be kept in their place. (1)	○	○	○	○	○	○	○
Groups at the bottom are just as deserving as groups at the top. (2)	○	○	○	○	○	○	○
It's probably a good thing that certain groups are at the top and other groups are at the bottom. (3)	○	○	○	○	○	○	○
An ideal society requires some groups to be on top and others to be on the bottom. (4)	○	○	○	○	○	○	○
Groups at the bottom should not have to stay in their place. (5)	○	○	○	○	○	○	○
Some groups of people are simply inferior to	○	○	○	○	○	○	○

other groups. (6)							
No one group should dominate in society. (7)	○	○	○	○	○	○	○
Group dominance is a poor principle. (8)	○	○	○	○	○	○	○

Page Break

Q18 What is your age?

____

Q19 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Other (3)

Q20 What is the highest level of education you have completed?

- ○ Less than high school (1)
- ○ High school/GED (2)
- ○ Some college (3)
- ○ College degree (4)
- ○ Graduate degree or higher (5)

Q21 What is your combined annual household income?

- ◯ Less than $30,000 (1)
- ◯ $30,000-$49,000 (2)
- ◯ $50,000-$74,999 (3)
- ◯ $75,000-$99,999 (4)
- ◯ $100,00-$149,000 (5)
- ◯ $150,00-$199,999 (6)
- ◯ $200,000 or more (7)

Q22 What is your occupation status?

- ◯ Employed (1)
- ◯ Student (2)
- ◯ Not employed (3)

Q42 What is your party affiliation?

- ◯ Registred Democrat (1)
- ◯ Registered Republican (2)
- ◯ Registered Independent (3)
- ◯ Not registered/other (4)

Q41 How did you vote in the 2016 presidential election

- Voted for Donald Trump (1)
- Voted for Hillary Clinton (2)
- Voted for another candidate (3)
- Did not/could not vote (4)

Q23 What race or ethnicity do you identify as?

- White or Caucasian (1)
- Black or African American (2)
- Hispanic or Latino (3)
- Asian (4)
- Native American (5)
- Pacific Islander (6)
- Middle Eastern (7)
- Other (8)
- Prefer not to answer (9)

Q24 What is your relationship status?

- ○ Single (1)
- ○ In a relationship (2)
- ○ Married or in a domestic partnership (3)
- ○ Other (4)

Q25 Do you have children living with you?

- ○ Yes (1)
- ○ No (2)

Page Break

End of Block: Block 6

Start of Block: Block 9

Q33 According to the 2016 paper Racial and Gender Discrimination in Transportation Network Companies, the results of field experiments suggested that Uber drivers are prone to discriminate against African American riders, resulting in longer wait times and more cancellations for riders with African American-sounding names. The researchers also found that drivers take female passengers on longer rides. At the same time, at least one ridesharing driver has filed a complaint with the Equal Employment Opportunity Commission (EEOC) arguing that he was deactivated based on low passenger ratings that were racially motivated.

Q34 Do you think that it would be appropriate for your city to do something about possible discrimination in platforms like Lyft and Uber?

○ Definitely yes (1)

○ Probably yes (2)

○ Not sure (3)

○ Definitely not (5)

Display This Question:

If Do you think that it would be appropriate for your city to do something about possible discrimina... != Definitely not

Q39 How supportive would you be of the following changes in your city?

	Support						
	Strongly oppose (1)	Oppose (2)	Somewhat oppose (3)	Neither support nor oppose (4)	Somewhat support (5)	Support (6)	Strongly support (7)

Require wait times to be similar in areas with similar demand. (1)	○	○	○	○	○	○	○
Require Uber and Lyft to report information on that may provide evidence of discrimination, such as cancellations and wait times. (2)	○	○	○	○	○	○	○
Require driver training on diversity and sensitivity. (3)	○	○	○	○	○	○	○
Prohibit Uber and Lyft drivers from knowing a rider's destination before he/she enters the vehicle. (4)	○	○	○	○	○	○	○
Require uniform tipping, like "gratuities" for large restaurant parties. (5)	○	○	○	○	○	○	○
Charge fixed fares between destinations to prevent females from being charged higher fares. (6)	○	○	○	○	○	○	○

Conduct public sector audits of driver behavior. (7)	○	○	○	○	○	○	○

Q37 Do you think that it would be appropriate for Lyft and Uber to do something about possible discrimination on their platforms?

○ Definitely yes (1)

○ Probably yes (2)

○ Not sure (3)

○ Definitely not (5)

Display This Question:

If Do you think that it would be appropriate for Lyft and Uber to do something about possible discri... != Definitely not

Q35 How supportive would you be of the following changes?

	Support						
	Strongly oppose (1)	Oppose (2)	Somewhat oppose (3)	Neither support nor oppose (4)	Somewhat support (5)	Support (6)	Strongly support (7)

Anonymize passengers and drivers (i.e., provide a unique passcodes rather than names) to prevent name-based discrimination (1)	○	○	○	○	○	○	○
Make names and photos smaller to prevent name- and photo-based discrimination. (2)	○	○	○	○	○	○	○
Perform periodic in-person audits of driver behavior (3)	○	○	○	○	○	○	○
Require drivers to explain low ratings for riders (4)	○	○	○	○	○	○	○
Please select "somewhat oppose" for this line (5)	○	○	○	○	○	○	○
Require riders to explain low ratings for drivers (6)	○	○	○	○	○	○	○
Track driver ratings and look for discriminatory patterns (7)	○	○	○	○	○	○	○
Validate driver ratings with other data,	○	○	○	○	○	○	○

like speed and acceleration (8)							
Post anti-discrimination policy in all vehicles (9)	○	○	○	○	○	○	○

End of Block: Block 9

Bibliography

[1] (2000). Press Release, ABC News: Perception vs. Experience in Racial Discrimination.

[2] (2013). Alatraqchi v. Uber Technologies, Inc.

[3] (2014a). California AB-2293: Transportation network companies: insurance coverage.

[4] (2014b). Municipal Code of Chicago: Chapter 9-115 Transportation Network Providers.

[5] (2014c). Vehicle-for-Hire Innovation Amendment Act of 2014.

[6] (2017). The On-Demand Economy and Anti-Discrimination Protections: Policymakers and Agencies Can Better Protect On-Demand Workers From Discrimination. Technical report, National Employment Law Project.

[7] (2018). Self-driving cars offer huge benefitsâĂŤbut have a dark side. *The Economist*.

[8] Adams, D. (2016a). Boston-based attorney argues Uber star ratings are racially biased. *Boston Globe*.

[9] Adams, D. (2016b). Uber resists adding tipping to its app. *Boston Globe*.

[10] Ambinder, L. P. (1995). Dispelling the Myth of Rationality: Racial Discrimination in Taxicab Service and the Efficacy of Litigation Under 42 USC 1981. *Geo. Wash. L. Rev.*, 64:342.

[11] Authority, S. F. C. T. (2017). TNC Regulatory Landscape: An Overview of Current TNC Regulation in California and Across the Country. Technical report, SFCTA.

[12] Ayres, I., Banaji, M. R., and Jolls, C. (2011). Race effects on eBay. *Rand Journal of Economics*, 46(4).

[13] Ayres, I., Vars, F. E., and Zakariya, N. (2004). To insure prejudice: Racial disparities in taxicab tipping. *Yale LJ*, 114:1613.

[14] Barocas, S. and Selbst, A. D. (2016). Big data's disparate impact. *California Law Review*, 104(671).

[15] Bartlett, K. T. and Gulati, G. M. (2016). Discrimination by Customers. *Duke Law School Public Law & Legal Theory Series*, No. 2015-4.

[16] Bendick, M., Egan, M., and Lofhjelm, S. (2001). Workforce diversity training: From anti-discrimination compliance to organizational development. *Human Resource Planning*, 24(2):10–25.

[17] Bertrand, M. and Mullainathan, S. (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review*, 94(4):991–1013.

[18] Blank, R., Marilyn Dabady, and Constance F. Citro, editors (2004). *Measuring Racial Discrimination*. National Academies Press, Washington, D.C.

[19] Borkholder, J., Montgomery, M., Chen, M. S., and Smith, R. (2018). How Transportation Network Companies Buy, Bully, and Bamboozle Their Way To Deregulation. Technical report, National Employment Law Project.

[20] Brewster, Z. W. and Lynn, M. (2014). Black White Earnings Gap among Restaurant Servers: A Replication, Extension, and Exploration of Consumer Racial Discrimination in Tipping. *Sociological Inquiry*, 84(4):545–569.

[21] Brommelstroet, M., Nikolaeva, A., Glaser, M., Nicolaisen, M. S., and Chan, C. (2017). Travelling together alone and alone together: mobility and potential exposure to diversity. *Applied Mobilities*, 2(1):1–15.

[22] Calo, R. and Rosenblat, A. (2017). The Taking Economy: Uber, Information, and Power.

[23] Carpusor, A. G. and Loges, W. E. (2006). Rental Discrimination and Ethnicity in Names. *Journal of Applied Social Psychology*, 36(4):934–952.

[24] Chaube, V., Kavanaugh, A. L., and Perez-Quinones, M. A. (2010). Leveraging Social Networks to Embed Trust in Rideshare Programs. In *2010 43rd Hawaii International Conference on System Sciences*, pages 1–8.

[25] Chen, B. X. (2012). Uber, Maker of Summon-a-Car App, Wins in Washington. *New York Times*.

[26] Collier, R. B., Dubal, V., and Carter, C. (2017). The Regulation of Labor Platforms: The Politics of the Uber Economy. *University of California, Berkeley*, page 42.

[27] Colorado Department of Regulatory Agencies, P. U. C. (2016). Code of Colorado Regulations (CCR) 723-6: Rules Regulating Transportation by Motor Vehicle.

[28] Cox, T. H. (1994). *Cultural Diversity in Organizations: Theory, Research & Practice*. Berrett-Koehler Publishers, San Francisco.

[29] Crow, A. and Klock-McCook, E. J. (2018). Does Lyft Alleviate City Traffic? Looking at the VMT Efficiency Metric.

[30] Dawes, M. and Zhao, J. (2016). User Identification of and Attitude Toward Dynamic Ridesourcing Services. *Transportation Research Board 2017*.

[31] Delbosc, A. (2017). Delay or forgo? A closer look at youth driver licensing trends in the United States and Australia. *Transportation*, 44(5):919–926.

[32] DeLoach, S. B. and Tiemann, T. K. (2012). Not driving alone? American commuting in the twenty-first century. *Transportation*, 39(3):521–537.

[33] Doleac, J. L. and Stein, L. C. (2013). The Visible Hand: Race and Online Market Outcomes. *The Economic Journal*, 123(572):F469–F492.

[34] Dueker, K., Bair, B., and Levin, I. (1977). Ride sharing: psychological factors. *Transp. Eng. J.; (United States)*, page 685.

[35] Dupuy, D. (2017). *The Regulation of Transportation Network Companies*. PhD thesis, University of Michigan.

[36] Edelman, B. (2016). Response to Airbnb's Report on Discrimination.

[37] Edelman, B. G. and Luca, M. (2016). Digital Discrimination: The Case of Airbnb.com. SSRN Scholarly Paper ID 2377353, Social Science Research Network, Rochester, NY.

[38] Etherington, D. (2017). NYC passes tipping option rule that applies to ride-hailing apps. *TechCrunch*.

[39] Fennell, L. A. (2017). Searching for Fair Housing. *Boston University Law Review*, 97:349–424.

[40] Flegenheimer, M. (2015). De Blasio Administration Dropping Plan for Uber Cap, for Now. *The New York Times*.

[41] Forster, D. (2014). Virginia DMV orders Lyft, Uber to stop operating. *Virginian-Pilot*.

[42] Franken, A. (2016). Letter to Travis Kalanick and Logan Green.

[43] Frug, G. and Barron, D. (2008). *City Bound: How States Stifle Urban Innovation*. Cornell University Press.

[44] Ge, Y., Knittel, C. R., MacKenzie, D., and Zoepf, S. (2016). Racial and Gender Discrimination in Transportation Network Companies. Working Paper 22776, National Bureau of Economic Research.

[45] Gehrke, S. R., Felix, A., and Reardon, T. (2018). Fare Choices: A Survey of Ride-Hailing Passengers in Metro Boston Report #1. Technical report, Metropolitan Area Planning Council.

[46] Greenwald, A. G., Nosek, B. A., and Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology*, 85(2):197–216.

[47] Guild, I. D. (2018). Press Release: Uber and Lyft Drivers Petition NYC for a Ride-Hail Minimum Wage. Technical report, IDG.

[48] Hannak, A., Wagner, C., Garcia, D., Mislove, A., Strohmaier, M., and Wilson, C. (2017). Bias in Online Freelance Marketplaces: Evidence from TaskRabbit and Fiverr. pages 1914–1933. ACM Press.

[49] Hanson, A., Hawley, Z., Martin, H., and Liu, B. (2016). Discrimination in mortgage lending: Evidence from a correspondence experiment. *Journal of Urban Economics*, 92(Supplement C):48–65.

[50] Harman, G. (2014). The sharing economy is not as open as you might think. *The Guardian*.

[51] Harrington, W. (2008). The Design of Effective Regulations of Transport. *OECD/ITF Joint Transport Research Centre Discussion Paper*, (2).

[52] Harris, A.-M., Henderson, G., and Williams, J. D. (2005). Courting customers: assessing consumer racial profiling and other marketplace discrimination. *Journal of Public Policy & Marketing*, 24 (Spring):163–71.

[53] Harris, L. A. (2002). Taxicab Economics: The Freedom to Contract for a Ride. *Georgetown Journal of Law & Public Policy*, 1:195–222.

[54] Harshbarger, R. (2018). Email correspondence with the author.

[55] Hawkins, A. J. (2016). Lyft's president says majority of rides will be in self-driving cars by 2021. *The Verge*.

[56] Hemphill, H. and Haines, R. (1997). *Discrimination, Harassment, and the Failure of Diversity Training: What to Do Now*. Greenwood Publishing Group.

[57] Hollister, S. (2015). Elon Musk Describes the Future of Self-Driving Cars.

[58] Hughes, R. and MacKenzie, D. (2016). Transportation network company wait times in Greater Seattle, and relationship to socioeconomic indicators. *Journal of Transport Geography*, 56:36–44.

[Inc.] Inc., L. About Lyft Line ridesharing.

[60] Inc., L. (2017a). Lyft Is Now Live Across 40 States.

[61] Inc., L. (2018a). Anti-Discrimination Policies.

[62] Inc., L. (2018b). Service animal policy.

[63] Inc., L. (2018c). Wheelchair Policy.

[64] Inc., U. T. (2014). With Uber, Everyone Rides.

[65] Inc., U. T. (2015). New Survey: Drivers Choose Uber for its Flexibility and Convenience.

[66] Inc., U. T. (2017b). It's a Beautiful (Pool) Day in the Neighborhood | Uber Blog.

[67] Inc., U. T. (2017c). What Is uberPOOL?

[68] Inc., U. T. (2018d). Diversity At Uber: Building A Great Place To Work.

[69] Inc., U. T. (2018e). uberASSIST Education Guide | Uber.

[70] Ipeirotis, P. G. (2010). Demographics of Mechanical Turk. SSRN Scholarly Paper ID 1585030, Social Science Research Network, Rochester, NY.

[71] Isaac, M. (2017). How Uber Deceives the Authorities Worldwide. *New York Times*.

[72] Kalanick, T. (2016). Uber Response to Senator Franken.

[73] Katz, M. (2017). How Drivers Are Finally Outfoxing Uber. *Wired*.

[74] Katz, V. (2015). Regulating the sharing economy. *Berkeley Tech. LJ*, 30:1067.

[75] Kearney, A. and De Young, R. (1995). A Knowledge-Based Intervention for Promoting Carpooling. *Environment and Behavior*, 27.

[76] Kitch, E. W., Isaacson, M., and Kasper, D. (1971). The Regulation of Taxicabs in Chicago. *The Journal of Law and Economics*, 14(2):285–350.

[77] Klein, N. J. and Smart, M. J. (2017). Millennials and car ownership: Less money, fewer cars. *Transport Policy*, 53(Supplement C):20–29.

[78] Klinner, N. S. and Walsh, G. (2013). Customer perceptions of discrimination in service deliveries: Construction and validation of a measurement instrument. *Journal of Business Research*, 66(5):651–658.

[79] Knope, J. (2016a). How To Use The Lyft App. *The Rideshare Guy Blog and Podcast*.

[80] Knope, J. (2016b). How To Use The Uber Driver App. *Maximum Ridesharing Profits*.

[81] Lentino, C. (2016). Uber, food trucks and Airbnb: ChicagoâĂŹs 3 biggest over-regulation stories from 2016.

[82] Li, C. and Zhao, J. (2015). Humanizing travel: how e-hail apps transform stakeholder relationships in the US taxi industry. In *Transportation Research Board 94th Annual Meeting*.

[83] MacCallum, R. C., Browne, M., and Sugawara, H. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1(2):130–149.

[84] MacDonald, A. (2014). Uber economic study: Uber serves underserved neighborhoods in Chicago as well as the Loop. Does taxi?

[85] Maidenberg, M. (2016). Surprise: Uber, Lyft hate proposed ride-hailing regulations. *Crain's Chicago Business*.

[86] Martyn, A. (2014). Uber and Lyft Are Being Accused of Redlining Again, But Is That Actually Happening?

[87] Molla, R. (2017). Uber's market share has taken a big hit. *Recode*.

[88] Moody, J. and Zhao, J. (2018). Using the Implicit Association Test to Understand Travel Behavior: A Case Study on Social Status Bias in Car vs. Bus Mode Choice, Working Paper.

[89] Moran, M., Ettelman, B., Stoeltje, G., Hansen, T., and Pant, A. (2017). Policy Implications of Transportation Network Companies. Technical report, Texas A&M Transportation Institute PRC 17-70 F.

[90] Moran, M. E. and Board, M. (2017). *Ride-Hailing and the Public Good: An Analysis of the Privatization of Public Transit via Uber and Lyft in American Cities*. PhD thesis, University of Chicago.

[91] Morton, F. S., Zettelmeyer, F., and Silva-Risso, J. (2003). Consumer information and discrimination: Does the internet affect the pricing of new cars to women and minorities? *Quantitative marketing and Economics*, 1(1):65–92.

[92] Murphy, L. W. (2016). Airbnb's Work to Fight Discrimination and Build Inclusion: A Report Submitted to Airbnb. Technical report, Airbnb.

[93] NACTO (2017). National Association of City Transportation Officials City Data Sharing Principles. Technical report.

[94] Newbold, K. B. and Scott, D. M. (2017). Driving over the life course: The automobility of Canada's Millennial, Generation X, Baby Boomer and Greatest Generations. *Travel Behaviour and Society*, 6(Supplement C):57–63.

[95] Nunley, J. M., Pugh, A., Romero, N., and Seals, R. A. (2014). An Examination of Racial Discrimination in the Labor Market for Recent College Graduates: Estimates from the Field. *Auburn University Department of Economics Working Paper Series*, pages 2014–06.

[96] of the White House, E. O. (2014). Big Data: Seizing Opportunities, Preserving Values.

[97] of Toronto, C. (2016). Toronto Municipal Code Chapter 546, Licensing of Vehicles-for-Hire.

[98] Office, S. F. C. A. P. (2018). Herrera asks court to invalidate state law that gives preferential treatment to Uber and Lyft.

[99] Pager, Devah, H. S. (2008). The Sociology of Discrimination: Racial Discrimination in Employment, Housing, Credit, and Consumer Markets. *Annu Rev Sociol.*, 34:181–209.

[100] Pope, D. G. and Sydnor, J. R. (2011). What's in a Picture? Evidence of Discrimination from Prosper.com. *Journal of Human Resources*, 46(1):53–92.

[101] Quigley, R. and Thornley, L. (2011). Literature Review on Community Cohesion and Community Severance: Definitions and Indicators for Transport Planning and Monitoring. *Report to New Zealand Transport Agency*.

[102] Rayle, L., Shaheen, S., Chan, N., Dai, D., and Cervero, R. (2014). App-based, on-demand ride services: Comparing taxi and ridesourcing trips and user characteristics in san francisco university of california transportation center (uctc). Technical report, UCTC-FR-2014-08.

[103] Ridley, S., Bayton, J. A., and Outtz, J. H. (1989). Taxi Service in the District of Columbia: Is it Influenced by Patron's Race and Destination? *Washington, DC Lawyer's Committee for Civil Rights Under the Law*.

[104] Roberts, J. (2012). Chicago cab companies sue hip car service Uber for pocketing 50% of driver tips.

[105] Robinson, H. (2017). *Making a Digital Working Class: Uber Drivers in Boston, 2016-2017*. PhD thesis, MIT, Cambridge, Massachusetts.

[106] Sappington, D. E. M. D. (1994). Principles of regulatory policy design. Technical Report WPS1239, The World Bank.

[107] Sarriera, J. M., German Escovar Alvarez, Andrew Alesbury, Timothy Scully, Jinhua Zhao (Corresponding author), and Blynn, K. (2016). To Share or Not to Share: Investigating the Social Aspects of Dynamic Ridesharing. *Transportation Research Board 2017*.

[108] Schaller, B. (2007). Entry controls in taxi regulation: Implications of US and Canadian experience for taxi regulation and deregulation. *Transport Policy*, 14(6):490–506.

[109] Scheiber, N. (2018). Gig Economy Business Model Dealt a Blow in California Ruling. *The New York Times*.

[110] Scheiber, N. and Isaac, M. (2016). Uber Recognizes New York DriversâĂŹ Group, Short of a Union. *The New York Times*.

[111] Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., and King, J. (2006). Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review. *Journal of Educational Research*, 99(6):323–337.

[112] Senate, N. C. (2015). An Act to Regulate Transportation Network Companies.

[113] Siegelman, P. (1998). Racial discrimination in everyday commercial transactions: What do we know, what do we need to know, and how can we find out. *A national report card on discrimination in America: The role of testing*.

[114] Smart, R., Rowe, B., Hawken, A., Kleiman, M., Mladenovic, N., Gehred, P., and Manning, C. (2015). Faster and cheaper: how ride-sourcing fills a gap in low-income Los Angeles neighborhoods. *BOTEC Analysis Corporation (July 2015)*.

[115] Smith, A. (2016). Shared, Collaborative and On Demand: The New Digital Economy. Technical report, Pew Research Center.

[116] Smith, R. and Leberstein, S. (2015). Rights on Demand: Ensuring Workplace Standards and Worker Security In the On-Demand Economy. Technical report, National Employment Law Project.

[117] Soper, T. (2014). Seattle ride-sharing regulations suspended; Mayor wants to negotiate with stakeholders. *GeekWire*.

[118] Stern, M. J. (2018). A D.C. Ride-Sharing Service Illegally Discriminated Against Minority Communities for Nearly Two Years. *Slate Magazine*.

[119] Strochlic, N. (2015). Uber: Disability Laws Don't Apply to Us. *Daily Beast*.

[120] The Equal Rights Center (2003). Service Denied: Responding to Taxicab Discrimination in the District of Columbia. Technical report, ERC.

[121] Thebault-Spieker, J., Terveen, L. G., and Hecht, B. (2015). Avoiding the South Side and the Suburbs: The Geography of Mobile Crowdsourcing Markets. pages 265–275. ACM Press.

[122] Vaccaro, A. (2016). Highly touted Boston-Uber partnership has not lived up to hype so far. *boston.com*.

[123] Wallsten, S. (2015). The Competitive Effects of the Sharing Economy: How is Uber Changing Taxis? Technical report, Technology Policy Institute.

[124] Wortham, J. (2014). Ubering While Black.

[125] Yvkoff, L. (2010). Uber lives on despite SFMTA cease-and-desist.

[126] Zhang, H. and Zhao, J. (2017). Mobility Sharing as a Preference Matching Problem. *Working Paper*.