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Ridehail Revolution:

Ridehail Travel and Equity in Los Angeles

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Urban Planning

by

Anne Elizabeth Brown

2018

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ABSTRACT OF THE DISSERTATION

Ridehail Revolution:

Ridehail Travel and Equity in Los Angeles

by

Anne Elizabeth Brown

Doctor of Philosophy in Urban Planning

University of California, Los Angeles, 2018

Professor Brian D. Taylor, Chair

A stark mobility divide separates American households with and without cars. While households with cars move easily across space, households without cars face limited access to opportunities. But no longer. Ridehail companies such as Uber and Lyft divorce car access from ownership, revolutionizing auto-mobility as we know it. Despite its high-tech luster, we do not yet know how ridehailing serves different neighborhoods and travelers, and who, if anyone, is left behind. The closest historical analog to new ridehail services is the taxi industry, which has a history of discrimination, particularly against black riders and neighborhoods. Ridehail services may discriminate less than taxis and extend reliable car access to neighborhoods underserved by taxis. Or they may not.

In this study, I pose and answer three questions about ridehail access and equity in Los Angeles. First, what explains the geographical distribution of ridehail trips across neighborhoods? Second, what explains ridehail use by individuals? Finally, is there evidence of racial or gender discrimination on ridehail and taxi services? To answer these questions, I relied on two novel data sets. First, I used trip-level data to evaluate ridehail travel in neighborhoods and by individuals. Second, I conducted an audit study of ridehail and taxi services to evaluate if and how wait times and ride request cancellation rates vary by rider race, ethnicity, or gender.

I find that ridehailing extends reliable car access to travelers and neighborhoods previously marginalized by the taxi industry. Ridehailing served neighborhoods home to 99.8 percent of the Los Angeles County population. Strong associations between ridehail use and neighborhood household vehicle ownership suggests that ridehailing provides auto-mobility in neighborhoods where many lack reliable access to cars. For most users, ridehailing filled an occasional rather than regular travel need, and a small share of avid users made the majority of ridehail trips. While hailing shared rides was common in low-income neighborhoods, I also find that people shared less if they lived in racial or ethnically diverse neighborhoods. Finally, audit data reveal high levels of discrimination against black riders by taxi drivers. Black riders were 73 percent more likely than white riders to have a taxi trip cancelled and waited between six and 15 minutes longer than white riders, all else equal. By contrast, ridehail services nearly eliminate the racial-ethnic differences in service quality. Policy and platform-level strategies can erase the remaining mobility gap and ensure equitable access to ridehailing and future technology-enabled mobility services.

The dissertation of Anne Elizabeth Brown is approved.

Evelyn A. Blumenberg

Michael K. Manville

Martin Wachs

Daniel Sperling

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2018

DEDICATION

To my parents, my sisters, and Luke.

For everything.

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ACKNOWLEDGEMENTS

I owe thanks to a great many people for their help in this research. I am first and foremost indebted to my advisors and committee members, Evelyn Blumenberg, Martin Wachs, and Michael Manville, Daniel Sperling, and especially Brian Taylor, for their invaluable feedback from the beginning to end of this project. None of this would have been possible without your unflagging support.

UCLA Institute of Transportation Studies staff, particularly Juan Matute, Whitney Willis, and Madeline Brozen provided the moral, bureaucratic, and advisory support to get me through all the red tape. Eighteen UCLA students spent nearly 1,800 hours in the field collecting data for this project; this research is in part a product of their devoted and careful work. Whitney LaValle provided data collection assistance and proved herself to have an unparalleled eye for detail. Brad Rowe at BOTEC generously shared lessons learned from their own audit study. Jarvis Murray at the Los Angeles Department of Transportation provided taxi data and valuable insight into taxi data collection more broadly. A special thanks to Peter Day and Peter Gigante of Lyft for the many hours we spent discussing and negotiating the data that made this research possible. It was a pleasure to work with you both. Finally, thanks to my peers at UCLA; learning from them has made the road I traveled infinitely smoother.

This research was funded by the UCLA Institute of Transportation Studies and the UCLA Graduate Division.

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CHAPTER 1. INTRODUCTION

In 2011 and 2012, ridehail companies including Uber and Lyft launched a transportation revolution by connecting drivers to riders through smartphone applications. Less than six years later, those same companies provide over 12 million trips per day around the world (Carson 2018). The meteoric rise of these new modes has captivated investors, riders, planners, and policymakers alike. Despite intense interest, policymakers have been largely unsuccessful in obtaining data from ridehail companies. As a result, we do not yet understand how these modes serve different neighborhoods and travelers, and who, if anyone, is being left behind.

Ridehailing presents an opportunity to redefine car access, which, until recently, has been nearly synonymous with car ownership. For decades, at least in the United States, car ownership has been imperative to accessing opportunities outside of the oldest and largest city centers (Kawabata and Shen 2007, Gurley and Bruce 2005). As a result, a stark mobility divide has grown and persisted between households with cars, who easily move across space, and households without cars, who have disproportionately low-income, are non-white, and face limited access to opportunities (NHTS 2017). For example, carless young adults (ages 16-36) make only two trips and travel just two miles per day compared to young adult drivers, who make four trips and travel 24 miles per day on average (Ralph 2017). With cars providing critical mobility and access, car ownership has been causally linked with positive economic outcomes such as finding work (Sandoval, Cervero, and Landis 2011), being employed (Gurley and Bruce 2005, Ong 2002), earning higher wages (Raphael and Rice 2002), and gaining better access to supermarkets and healthy foods (Walker, Keane, and Burke 2010).

Even when they do not own one, zero-car households gain access to cars by carpooling, borrowing a car, carsharing, taxis, or informal services such as gypsy cabs (NHTS 2017, Kim 2015, Schaller 2015). The need for at least occasional car access among carless Americans is evident in the bimodal income distribution of taxi users. As of 2009, households earning less than $25,000 per year, who are disproportionately carless, made 17 percent of all trips, but 41 percent of all taxi trips (Schaller 2015, NHTS 2017).

Taxis, however, are frequently unreliable (San Francisco Municipal Transportation Agency 2013, Smart et al. 2015), suffer from a chronic supply shortage (Schaller 2007), and provide poor service in many low-income neighborhoods (Austin and Zegras 2012). Even more troubling, unlawful discrimination against riders, particularly black riders, may undermine access or exclude people entirely. For example, taxi drivers often avoid communities of color (LaMendola 1991) and are less likely to pick up a black rider than they are a white rider (Wrigley 2013, Belcher and Brown 2015).

Ridehailing offers an opportunity to provide cheaper, faster, and more reliable car access compared to taxis, but the potential equity implications of ridehail services remain unclear. Journalists and researchers find conflictingly that ridehailing provides robust and poor service in low-income neighborhoods and communities of color (Stark and Diakopoulos 2016, Motavalli 2015, Smart et al. 2015, Hughes and MacKenzie 2016). Ridehail drivers, like taxis, may also discriminate against individual riders, resulting in longer wait times and higher trip cancellation rates for black and male riders in some cities (Ge et al. 2016). In addition, we do not yet understand the associations between the built environment, resident characteristics, and ridehail use, or their implications for equity.

This research examines ridehail equity and access in Los Angeles, the second largest American city and one of the earliest ridehail markets. Specifically, I ask and answer three questions: First, what explains the geographical distribution of Lyft trips across neighborhoods? Second, what explains the frequency of Lyft use by individuals? And finally, is there evidence of service discrimination—manifested in longer wait times and higher rates of cancelled ride requests—by rider race, ethnicity, or gender on ridehail and taxi services? In answering these questions, I aim to address broader issues of how ridehailing may affect the current divide in car access. In other words, does this ridehail revolution perpetuate current mobility inequities, or can it help to bridge the existing mobility gap?

I answer questions of neighborhood service and individual use in Part I using trip-level Lyft data for Los Angeles County. In Part II, I present results of a ridehail industry audit in which I evaluate if wait time and ride request cancellation rates vary by rider race, ethnicity, or gender. Finally, in Part III, I discuss implications of these findings for ridehail policy.

In a Nutshell: Narrowing—but Not Erasing—the Mobility Gap

Part I

In Part I, I examine the built environment, socioeconomic, and amenity factors associated with 1) neighborhood Lyft service (the number of trips beginning and ending in a neighborhood) and 2) individual Lyft use (the number and types of trips an individual makes). I find no evidence that neighborhoods are systematically excluded from Lyft service based on the characteristics of their residents as they have been by the taxi industry (LaMendola 1991, Austin and Zegras 2012, Spiegelman 2016); instead, Lyft service is remarkably ubiquitous throughout Los Angeles County. Between September and November 2016, Lyft served neighborhoods home to 99.8 percent of the county's population. Widespread Lyft use suggests that planning for ridehail services is not just limited to neighborhoods located in the urban core, but across a wide array of built environments.

For most users, ridehailing fills an occasional rather than regular travel need, and a small share of users make the majority of trips. While 40 percent of users made less than one trip per month, another 10 percent of users completed more than half of all Lyft trips to, from, or within Los Angeles County.

Although Lyft users live disproportionately in high-income neighborhoods relative to the Los Angeles population, users living in low-income neighborhoods took Lyft more frequently. Neighborhood income and car ownership data suggest that Lyft use is inversely associated to auto resources in a neighborhood rather than a simple function of income, and that Lyft may provide auto-mobility in neighborhoods without reliable access to cars. Shared Lyft Line trips comprised about one-quarter of all Lyft trips in Los Angeles County; while people shared more in low-income neighborhoods, people shared less if they live in racial or ethnically diverse neighborhoods, which is consistent with the carpooling literature (Charles and Kline 2006). Lower Lyft use in majority-Asian and Hispanic neighborhoods, even after controlling for local factors, suggests either that car access without ownership is already being met in these neighborhoods through carpooling or informal services, or that barriers to ridehailing—such as lower smartphone, data plan, or banking access—inhibit access.

Part II

While data from Lyft in Los Angeles suggest that people are not denied ridehail access based on where they live, driver discrimination, documented for decades in the taxi industry (Ridley, Bayton, and Outtz 1989), may create profound inequities in service access based on rider race, ethnicity, or gender.

The audit study reveals that little has changed in the taxi industry since audits three decades ago (Ridley, Bayton, and Outtz 1989). While taxi service overall was remarkably poor—10 percent of taxis did not arrive within one hour—it was worst for black riders. Black riders were 73 percent (or 11 percentage points) more likely to have a driver cancel on them compared to white riders. On both Uber and Lyft, the difference in probability of a trip being cancelled was four percentage points higher for black compared to white riders. Notably, however, cancellations on taxis meant that one-quarter of black taxi riders never reached their destination. On Uber and Lyft, 99.7 percent of riders reached their destination even if one driver cancelled a trip; in other words, while unlawful discrimination precludes many black riders from taxi service, driver biases on Uber and Lyft result in delayed, but not denied, mobility.

Differences by rider race persisted even when riders were picked up. On taxis, black riders waited 52 percent longer (between about 6 and 15 minutes) than white riders; by comparison, black riders waited between 11 seconds and 1 minute 43 seconds longer for ridehail services than white riders. In other words, while ridehailing does not appear to erase the gap between black and white riders, it comes close.

With no meaningful differences observed either among Asian, Hispanic, or white riders or between men and women, the results of this audit study are consistent with research finding that discrimination is most acute and common for black residents (Avery, McKay, and Wilson 2008, McLaughlin, Hatzenbuehler, and Keyes 2010, LaVeist, Rolley, and Diala 2003). Differences in hail methods across services suggest that discrimination occurs when drivers learn about or infer rider characteristics, yielding implications for when policymakers or ridehail companies could act to close the service gap entirely.

Part III

In Part III, I synthesize results and offer implications for ridehail policy. Specifically, I first consider how ridehail innovations help combat the spatial inequities of taxi services. Such innovations provide lessons for both taxi services and future innovative mobility services. Second, based on findings of Lyft use in Los Angeles, I discuss policies to overcome barriers to ridehail access by seniors and travelers without smartphones or bank accounts. Third, I review three explanations for why rates of discrimination are lower on ridehail services compared to taxis and how both platform-specific and public sector interventions can help to close the remaining service gap entirely. Fourth, I recommend that cities avoid blanket requests for big data, and instead request targeted ridehail data connected to actionable performance metrics. I conclude with directions for future research to answer outstanding questions and promote equitable mobility in this ridehail revolution.

CHAPTER 2. LITERATURE REVIEW

Car ownership in the United States is nearly universal. Ninety-two percent of American households own at least one vehicle (U.S. Census Bureau 2015a), and with good reason: in the U.S., car ownership confers positive economic outcomes such as finding work (Sandoval, Cervero, and Landis 2011), being employed (Gurley and Bruce 2005, Ong 2002), working more hours (Gurley and Bruce 2005), higher wages (Raphael and Rice 2002), better access to supermarkets and healthy foods (Walker, Keane, and Burke 2010), and accessing and staying in low-poverty neighborhoods (Dawkins, Jeon, and Pendall 2015). However, while car ownership yields many benefits, the costs of owning and maintaining a car can financially burden households or preclude them from auto ownership entirely (Waller 2005). As of 2015, 10.6 million American households did not own a car (U.S. Census Bureau 2015a). Some of these carless households may of course *choose* not to own a car, but 80 percent of households cite constraint over choice as the reason for not owning a car (Brown 2017). In other words, for most Americans, not owning a car represents a mobility barrier rather than a chosen freedom. In addition to carless households, car-deficit households—those with more drivers than cars—also face mobility constraints as they coordinate potentially conflicting demands on the household vehicle. While car access may be gained without ownership, ridehail's predecessors—such as taxis, carpooling, and car sharing—each face challenges and limitations that make them far from ideal substitutes to ownership.

The Automobility Divide

Car ownership is affected by personal characteristics, the built environment, household income, and the presence and quality of driving alternatives (Polzin et al. 2013). Since the 1960s, household car ownership has increased, both in terms of the share of households that own at least one car, and in the number of cars per household (Polzin et al. 2013). Despite rising car ownership, over 10 million American households today do not own a car, and another 15 percent of households have fewer cars than drivers (U.S. Census 2015, NHTS 2009). Meaningful differences in car ownership and access exist across space and households. In metropolitan areas over three million people, about 13 percent of households do not own a car compared to six percent of households living outside of metro areas. Differences in car ownership likewise persist across race and ethnicity. Although the share of black and Hispanic households without a car has nearly halved since the 1970s and 1980s, rates of carlessness among these two groups remain far above that of white households. As of 2016, 23 percent of black households and 11 percent of Hispanic households did not own a car compared to just six percent of white households (NHTS 2017).

Carless households also have disproportionately low-incomes. Nationally, 20 percent of low-income households (under $30,000) do not own a car compared to just four percent of higher-income households (over $110,000) (NHTS 2017). Households earning under $35,000 are also 1.5 times more likely to have a car deficit (fewer cars than people) compared to households earning higher incomes (NHTS 2009). Cars are expensive to purchase, insure, and maintain (Blumenberg 2004, Ong and Stoll 2007, Garasky, Fletcher, and Jensen 2006), and households spend about $8,500 on average each year to own and operate a car (AAA 2017, Bureau of Labor Statistics 2016a).[1] Of course, owning a car does not guarantee that it works. Cars in low-income households (<$30,000) are two years (21%) older than the average car (NHTS 2017), which influences their reliability; only 62 percent of low-income households report having access to a reliable car versus 86 percent of higher-income households (Garasky, Fletcher, and Jensen 2006).

Despite their high costs, cars remain the dominant mode of travel for even the poorest households, who still make about three-quarters of all trips by car (Pucher and Renne 2003). Cars enable trip chaining, flexible travel (Hensher and Reyes 2000), and point-to-point mobility that affords greater access to opportunities and jobs compared to public transit (Kawabata and Shen 2007, Hess 2005, Grengs 2010, Shen 1998). Households with cars also travel more than those without cars, enabling access to more and/or farther flung activities and destinations. For example, in

[1] Household vehicle expenses vary greatly by income. For example, households earning under $30,000 per year spend, on average, about $4,000 per year to own and operate a car (Bureau of Labor Statistics 2016a).

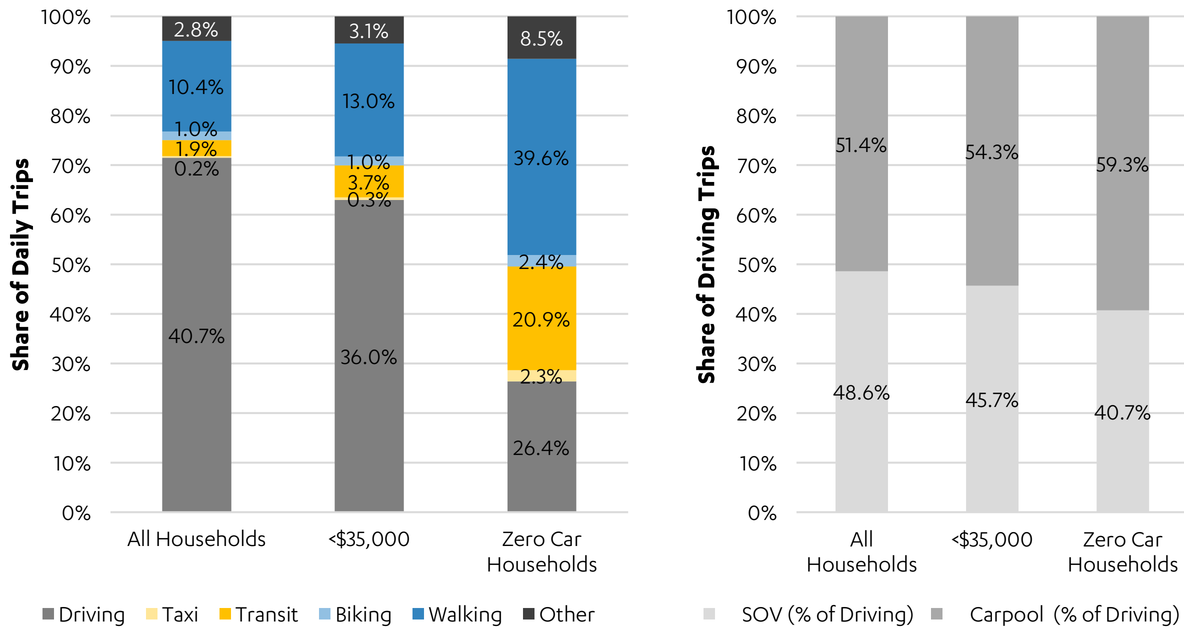
California in 2012, people in households with cars traveled on average 28 miles per day, compared to just 12 miles traveled by people in carless households. People in auto-deficit households fell in the middle, traveling fewer miles and making fewer trips compared to households with at least one car per driver, but traveling further and making more trips compared to carless households (California Department of Transportation 2012).

Access Without Ownership

With cars expensive to own and operate, many households, particularly poor households, either do not own a car, or frequently cycle in and out of car ownership (Klein and Smart 2015). So how do the poorest travelers still make three-quarters of trips by car despite owning fewer or no cars (Pucher and Renne 2003)?

Prior to ridehailing, carless households could gain automobility—access to a car—through five primary alternatives: carpooling, borrowing a car, car sharing, informal services (such as jitneys), or taxicabs. Figure 1 shows how both income and especially car ownership influence mode split and how many low-income households rely disproportionately on shared modes compared to higher-income households (see also Pucher and Renne (2003), Blumenberg (2013)). However, while auto access without ownership may relieve financial burdens, each of these ownership alternatives yields challenges.

Figure 1. Mode Split Across All, Low-income, and Zero-car Households



Source: National Household Travel Survey (2009).

Carpooling and Borrowing

Distinct from carsharing—in which multiple people alternate use of a single car—carpooling occurs when multiple people ride in one car simultaneously. Most carpools form between household members; in Los Angeles, just 15 percent of carpools are external carpools formed by people from different households and with different trip origins and/or destinations (California Department of Transportation 2012).

Carpooling is popular among the carless, who carpool for about 60 percent of driving trips (NHTS 2009). Research finds that rates of carpooling fall as household income rises and that demographic and trip characteristics play larger roles in decisions to carpooling than built environment factors (Ferguson 1997, 1995). Carpooling increases among immigrant households and households with fewer cars than workers (Teal 1987, Blumenberg 2013). Households carpool more on longer trips, and on shopping, social, and school trips than they do on work trips (Pucher and Renne 2003, Teal 1987).

However, rates of carpooling have decreased over time. Between 1970 and 2015, carpool commuting fell from about 20 percent to just nine percent (Polzin 2016, Parkany 1999). One potential explanation for carpooling's decline is that both carpooling and borrowing a car often prove logistically complicated, lack flexibility, and require additional time to pick up and drop off carpool members (Hunt and McMillan 1997, Chaube, Kavanaugh, and Perez-Quinones 2010). Travelers report "not having to prearrange a carpool" as a "very important" factor in choosing ridehailing (Miller et al. 2016).

Car Sharing

Car sharing services—such as Zipcar or Car2go—provide short-term car rentals that charge customer by the time used or distance traveled. Research finds that car sharing provides a lower-cost alternative to car access compared to ownership (Duncan 2011). To increase affordability, some cities waive car share membership fees for low-income households (Shaheen, Cohen, and Chung 2009) and some car share programs partner with low-income housing developments to increase car share access (Daley 2014). Despite these efforts, car share members continue to be more highly educated and earn middle to high incomes compared to non-members (Millard-Ball et al. 2005). For example, in California, less than one percent of households earning under $35,000 hold a car share membership compared to 2.4 percent of households earning over $100,000 (California Department of Transportation 2012). One potential explanation for uneven car share membership across income is geographical inequities rather than disinterest among low-income populations. Begin (2011) found that car share networks are more limited in low-income compared to higher-income neighborhoods. Even where car share vehicles are physically available, barriers such as a lack of credit card, lower computer or internet access, or language barriers may inhibit low-income carless residents from participating in car sharing (Daley 2014).

Taxis

Finally, in addition to informal cabs, licensed taxis have long-provided a way to purchase car access one ride at a time. Taxi users have—perhaps counterintuitively—a bimodal income distribution, with use concentrated among very-high and very-low-income travelers. As of 2009 in the U.S., households earning less than $25,000 per year—who make up about one-quarter of American households—made 17 percent of all trips, but 41 percent of all taxi trips (Schaller 2015, NHTS 2009). Taxis fill a similar automobility gap for carless households; while carless households made only four percent of all trips in 2009, they took over half (53%) of all taxi trips (Schaller 2015).

Although taxis provide a mobility safety net for carless travelers, they are rife with geographic and group inequities. Taxi supply often falls short of demand (Schaller 2007), resulting in poor coverage that creates service gaps in low-income neighborhoods (Austin and Zegras 2012). “People on the South Side have fallen out of the business of calling taxis because they can’t get one” says Chicago Taxidrivers Community Council secretary Peter Ali Enger, highlighting that uneven supply means that taxis are not a viable option everywhere (Cohen 2015).

One primary reason for taxi service gaps is the strict limits most American cities place on taxi supply. Taxi limits date to the 1930s when the “oversupply of vehicles, reckless driving in competition for passengers and wildly fluctuating fares” motivated cities to limit and price taxi entry into the market. Cities typically regulate the number of taxis through a medallion system or quantity cap (Badger 2014). Today, taxis continue to be heavily regulated by cities and local jurisdictions, which impose rules such as permissible pickup locations, vehicle standards, and fare rates (King and Saldarriaga 2018). In dispatch-dominated markets such as Los Angeles, such regulations create barriers to entry that result in supply shortages everywhere (Schaller 2007).

Service gaps also exist due to imperfect information (Schaller 2007), meaning that drivers do not know where other drivers or potential riders are. With riders spread unevenly across space, taxi drivers often play the numbers game and cluster where they anticipate riders will materialize, regardless of how many drivers already serve these areas. Interrelated supply and demand creates a positive feedback loop (Yang, Wong, and Wong 2002) and further concentrates the limited taxi supply into dense areas, often with more business and high-income travelers such as downtown hotels and airports. Riders outside of taxi hot spots may, therefore, face longer wait times or have no street hail opportunities. For example, about one-quarter of taxi riders in San Francisco report poor availability and 10 percent specifically cite service issues with long wait times outside of downtown (San Francisco Municipal Transportation Agency 2013). Taxi companies are attempting to fill information gaps by launching smartphone applications (apps). Some newly-minted apps mimic ridehailing and connect riders to the nearest cab regardless of company (see for example Curb (2017)). Other taxis apps, however, offer more antiquated user interfaces that mirror online booking.

Imperfect information is just one explanation for spatially uneven taxi service. Varied service across neighborhoods may be due to nefarious reasons—such as discrimination and redlining[2] of certain neighborhoods—but they could also be explained by economic pragmatism. For example, taxis may shun New York's low-income outer boroughs to avoid dead-heading.[3] Without a passenger, the taxi must return empty to a high-demand area, resulting in a fare-less return trip, foregone revenue, and wasted fuel (King and Saldarriaga 2018). Cab drivers in Chicago attribute neglect of low-income communities of color primarily to economic concerns such as dead-heading, but acknowledge that racism and fear also come into play (Cohen 2015). For example, drivers may avoid neighborhoods that they perceive as dangerous (LaMendola 1991)[4] or refuse to serve predominantly black neighborhoods (Ridley, Bayton, and Outtz 1989). I discuss issues of historical and unlawful discrimination by taxi drivers in greater detail later in this chapter.

In addition to being spatially uneven, taxi service is notoriously unreliable. In San Francisco, 15 percent of weekday and 28 percent of weekend taxis took more than 30 minutes to arrive or did not

[2] Redlining is the practice of denying services to residents living in certain areas either by raising prices or by locating services outside of neighborhoods, effectively barring access.

[3] Dead-heading occurs when a driver carries a fare-paying rider one way, but makes the return trip without a passenger.

[4] Taxi drivers are justified in their concern for personal safety; in 2007, homicide rates for taxi drivers were 20 to 30 times higher than for all workers on average (Chen 2014).

show up at all (San Francisco Municipal Transportation Agency 2013). In a field experiment in low-income Los Angeles neighborhoods, riders waited between four and 57 minutes for a dispatched taxi to arrive (Smart et al. 2015).

Informal Transportation

Unpermitted or unlicensed for-hire vehicles—known varyingly as gypsy cabs, jitneys, and hacks among other names—provided informal point-to-point travel in cities long before Uber and Lyft joined their ranks.[5] Although jitneys are perhaps the most visible informal for-hire vehicles (see Cervero (1998), Valenzuela et al. (2005), King and Goldwyn (2014)), informal gypsy cabs and hacks are more akin to ridehailing as they operate point-to-point rather than along scheduled routes. In other words, jitneys act more like informal transit, while gypsy cabs operate like informal taxis.[6] Scholars typically view informal for-hire services three ways: 1) as a market response to unmet demand, 2) as a threat to transit and poor protection for the informal for-hire workers, and/or 3) as low-cost opportunities that improve transit services (King and Goldwyn 2014). Informal services provide mobility safety nets and "flourish in areas or amongst groups that are excluded by transit agencies and private operators" (King and Goldwyn 2014, 187). One prominent example of informal taxi service are Baltimore "hacks," which are unlicensed for-hire vehicles that respond to the "unavailability or ineffectiveness of formal transit services" (Johnson 2013). Hacks are cheaper than legal taxis and have an unwritten, but established pricing structure based on time, convenience, and distance (Johnson 2013). By serving areas that taxis avoid out of safety concerns (Hernandez 1992, LaMendola 1991), profitability concerns, or racial discrimination (Spiegelman 2016), informal services provide vital point-to-point car services where alternatives either do not exist or are too expensive. Despite their

[5] Uber and Lyft now legally operate in many cities. However, many cities barred early operations of these companies, viewed as unlicensed and unregulated taxi services. In 2013, the California Public Utilities Commission passed regulations legalizing TNCs, setting an example for other states, and paving the way for their rapid, legal expansion (Rayle and Flores 2016).

[6] Considerable diversity likewise exists among jitney services. For example, many *camionetas*—jitneys run by immigrants for immigrants—offer point-to-point services (Valenzuela, Schweitzer, and Robles 2005).

benefits, however, informal services may be plagued by safety issues, with both passengers and drivers victimized in robberies and assaults (Hernandez 1992, Vozzella 2009).

Cities respond differently to informal cab services. In some cases, they turn a blind eye towards informal operations. In other cases, motivated by safety concerns, fears that informal services poach transit riders, and lobbying from the taxi industry, cities slap hack and jitney drivers with heavy fines and misdemeanor charges (Vozzella 2009, Blasi and Leavitt 2006). Less frequently, cities attempt to license informal services. Attempts to formalize such services have largely met with failure; researchers attribute these failures to a variety of reasons ranging from poor branding to program-mandated service gaps that jitney operators could not overcome without subsidies (King and Goldwyn 2014).

The Rise of Ridehailing

In 2012, ridehail companies—also known as transportation network companies (TNCs) and ridesourcing—upended the taxi business model by connecting drivers with riders through smartphone applications. This new, direct connection between riders and drivers eliminates the previously-discussed information gap that has long plagued the taxi industry. Ridehailing eliminates the need for drivers to guess where riders will be and connects drivers with riders in real time. What is not yet known is if and how these new services affect car access across space and individuals, and if unlawful discrimination has persisted despite the technological shift.

Currently, Uber and Lyft dominate the ridehail market; the SharesPost (2018) consumer survey estimate that as of 2017, the two companies controlled 82 percent of the ridehail market.[7,8]

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[7] Uber serves the lion's share of the ridehail market, although its market share is falling over time. Between 2016 and 2017, Uber's market share fell from 76 to 65 percent while Lyft's correspondingly rose from 10 to 18 percent (SharesPost 2018).

[8] Although the reigning industry titans, Uber and Lyft are not the sole ridehail services. Other companies crop up at rapid rates, seeking to serve or carve out their own market share or cater to specific groups. For example, Moovn aims to serve domestic and international cities under-served or not yet served by Uber or Lyft, and allows riders to schedule rides up to one month in advance (Finley 2016). See Jane Go, an Orange County-based company, launched in 2016 and caters to women drivers and riders who are "thinking twice about using traditional apps out of fear for their safety"

Launched in 2011 and 2012, Uber and Lyft provide more than 76 million rides per month in the United States (Hartmans 2016) and nine out of ten American adults in major metropolitan areas have heard of the ridehail apps (Clewlow and Mishra 2017). While most Americans know about ridehailing, studies report varying levels of ridehail adoption (ridehail adopters are people who have and use ridehail apps) in the U.S. In a 2016 nationally representative survey of American adults, Clewlow and Mishra (2017) find that 30 percent of American adults have used ridehailing at least once. Smartphone-use surveys, too, hint at the rising popularity of ridehailing. While only 0.4 percent of travelers took a taxi trip on a given survey day in 2009 (NHTS 2009), 11 percent of all smartphone users—and 17 percent of American smartphone users aged 18-29—reported using their smartphone to reserve a taxi or ridehail vehicle in 2015 (Smith, McGeeney, Maeve, et al. 2015).

Ridehailing alters how people pay for car access. In 2016, the average American household spent about $8,500 to finance, maintain, fuel, and finance a car (AAA 2017). Drivers previously bore the full cost of ownership. Under ridehailing, however, costs are instead shared across many passengers who contribute through small per-mile payments. Ridehailing also shifts car travel costs from lump-sum payments into small per-trip payments. Similar to pay-as-you-drive insurance, which trades per-month insurance premiums for a per-mile insurance rate, paying per-trip may benefit low-income travelers, who typically drive fewer miles per day and thus pay more per-mile to own and insure a car compared to high-income households (California Department of Transportation 2012, Bordoff and Noel 2008).

Despite its meteoric growth, ridehailing is still something of an enigma to policymakers and researchers. While planners and policy makers are eager to understand how, where, and when people use ridehailing in order to plan for and integrate it with other transportation modes, ridehail companies have thus far proven reticent to share their data with either cities or researchers, citing commercial confidentiality and customer privacy as primary objections. The current state of ridehail

(Cavanaugh 2016). Also in 2016, RideApp launched as "a black-community focused app" that allows riders to book ahead or pay with cash (Washington 2016).

knowledge stems from rare data sharing exceptions (Bialik et al. 2015, Schaller 2017, Feignon and Murphy 2018), use of ridehail application programming interfaces (APIs)[9] (Hughes and MacKenzie 2016, San Francisco County Transportation Authority 2017), and local and national surveys of ridehail users (Rayle et al. 2016, Clewlow and Mishra 2017, Henao 2017, Gehrke, Felix, and Reardon 2018).

In the next two sections, I first review the state of the research and our emerging understanding of who uses ridehailing and where it operates. Following this, I discuss the decades-long history of unlawful discrimination in the taxi industry and how preliminary research suggests that discrimination also occurs in ridehailing despite its radical differences from traditional taxi models.

Where and When are Ridehail Trips Made?

A growing number of studies provide insight into the demographics, trip purposes, and motivations of ridehail users (Henao 2017, Rayle et al. 2016, Smith, McGeeney, Maeve, et al. 2015, Clewlow and Mishra 2017, Gehrke, Felix, and Reardon 2018, Circella 2018), including some studies that have used Uber and/or Lyft data to report temporal and geographic patterns of ridehailing at city-wide scale (Schaller 2017, Feignon and Murphy 2018). Using ridehail trip origin, destination, distance, and duration data provided in a For Hire Vehicle Study in New York City, Schaller (2017) found that ridehail use has grown most in the early mornings (4-8am), in the late afternoon when changing taxi shifts result in cab shortages (4-6pm), and in the late evenings (9pm-12am). Feignon and Murphy (2018), too, found heavy ridehail use during evening hours, as well as on weekends. Feignon and Murphy (2018) used remarkably widespread data spanning five regions (Chicago, Los Angeles, Nashville, Seattle, and Washington, D.C.); however, one unidentified ridehail company only provided the researchers with aggregate trip count data at the zip code level. Because zip codes are large—the average zip code in Los Angeles County is 13 square miles and contains eight census tracts—each is home to a wide diversity of residents and built environments, precluding a more fine-grained

[9] Application program interfaces (APIs) are sets of protocols and tools for developers to build software applications. In this case, it allowed researchers to query Uber wait times from specific places and at specific times.

geographical analysis. Therefore, while both Schaller (2017) and Feignon and Murphy's (2018) findings are illuminating, additional research is needed to better understand patterns of ridehail access across more fine-scaled geographies and outside of New York's unique context.[10]

Unlike traditional taxi service, ridehailing directly connects drivers to riders, which could help distribute ridehail vehicles evenly across space. Unlike taxis—which gather where street hails or dispatches are common—ridehail apps connect drivers to the rider closest to them. Thus rather than driving to areas with *expected* demand—as taxis do because they do not know the location of other drivers or potential riders—ridehail drivers can respond to *actual* demand in real time.

With thousands of drivers, ridehail and taxi services may suffer from a collective action problem, in which drivers acting independently may collectively depress service in some neighborhoods. For example, individual drivers avoiding an area that each perceives as dangerous (LaMendola 1991) may together effectively eliminate service in that neighborhood (Cohen 2015). While ridehail companies acknowledge driver autonomy, including drivers' right to accept or decline requests (Lyft 2017a), they incentivize drivers to serve areas with unmet demand and to accept all trips. For example, in areas with more riders than drivers, companies "surge" (raise) trip prices to attract more drivers to the area. Second, companies encourage drivers to accept trip requests by placing drivers in "time out"[11] for cancelling multiple trips in a row (The Rideshare Guy 2016) or by providing financial bonuses for maintaining high acceptance rates (Lyft 2017a).

Reports of geographic service equity are mixed. Media outlets report lower service levels and longer wait times in low-income and communities of color (Stark and Diakopoulos 2016, Motavalli 2015). In contrast, researchers find that ridehail operators serve neighborhoods across income

[10] New York City's robust taxi and transit network make the region an outlier among North American cities. The New York City Taxi and Limousine Commission licenses and regulates about 100,000 drivers and over 50,000 vehicles (NYC Taxi & Limousine Commission 2017); the City of Los Angeles, by contrast, operates just 2,361 vehicles, despite being the second largest city in the country (Los Angeles Department of Transportation 2017b). New York City is similarly unique with transit. In 2016, over one-third (36%) of unlinked passenger trips were made on transit agencies based in New York City (Federal Transit Administration 2016).

[11] "Time outs" last between two and 30 minutes, during which a driver cannot accept any new trip requests (The Rideshare Guy 2016).

groups (Feignon and Murphy 2018) and extend car access to areas neglected by taxis (Schaller 2017, Gehrke, Felix, and Reardon 2018). In addition, Hughes and MacKenzie (2016) found virtually no difference in expected wait times between trips beginning in low- versus high-income neighborhoods.

Comparing ridehailing to taxis provides an instructive baseline against which to consider both trip geography and the balance between driver supply and rider demand. In New York, taxi service is spatially uneven (Qian and Ukkusuri 2015) and research finds that ridehailing serves the city's outer boroughs better than taxis (Bialik et al. 2015). Ridehailing is also growing faster where taxi service falls short; between June 2013 and 2016, Manhattan added 670,000 additional ridehail trips, while over two million trips were added to the inner and outer boroughs[12] where yellow cab service is scarcer and density is lower (Schaller 2017). These findings suggest that ridehailing offers access to car services beyond neighborhoods previously well-served by taxis. With the exception of New York, however, no research has yet investigated the spatial distribution of ridehail service across a region and at a fine-grained scale; the absence of research is primarily due to a lack of data, which the largest ridehail companies—Uber and Lyft—rarely share with researchers.[13]

Who Uses Ridehailing?

Relatively little is yet known about ridehail users. Early studies include a San Francisco intercept survey (Rayle et al. 2016), onboard interviews of Uber and Lyft passengers (Henao 2017, Gehrke, Felix, and Reardon 2018), surveys in select U.S. metropolitan areas (Feignon and Murphy 2018, Clewlow and Mishra 2017),[14] and a national panel survey of American adults (Smith 2016). These studies offer first

[12] Schaller (2017) defined "inner" boroughs as northern Manhattan, western Queens, and Brooklyn. The remainder of Queens, Brooklyn, the Bronx, and Staten Island are the "outer" boroughs.

[13] Data from New York include Uber origin locations published as part of a Freedom of Information Act request in 2014 (Bialik et al. 2015), and 2014-2015 ridehail trip origin, destination, distance, and duration data provided for a For Hire Vehicle Study (Schaller 2017).

[14] The seven metropolitan areas include: Boston, Chicago, Los Angeles, New York, San Francisco, Seattle, and Washington, D.C.

insights into who uses ridehailing, how people use these services, and how ridehailing compares to taxis.

Nearly one-quarter (21%) of American adults living in major metropolitan areas have personally hailed a ridehail vehicle, with an additional nine percent riding with friends but not hailing rides themselves (Clewlow and Mishra 2017). Research suggests, however, that ridehail adoption is higher in Los Angeles than nationally; Circella (2018) found that in Los Angeles, 44 percent of urban residents, 30 percent of suburban, and 15 percent of rural residents have adopted ridehailing.

Of metro area riders, the plurality (41%) use ridehail services one to three times per month, and about one-quarter (24%) use ridehailing on either a weekly or daily basis (Clewlow and Mishra 2017). Ridehail frequency, however, varies greatly by geography: just three percent of rural and suburban users use ridehailing at least once per week compared to nearly one-quarter (23%) of urban adults (Circella 2018).[15]

In addition to being more urban, ridehail users are disproportionately young. Nationally, about one-third of adults under 30 have used ridehailing, compared to just four percent of people 65 and older (Smith 2016, Clewlow and Mishra 2017). In San Francisco, nearly three-quarters (73%) of intercepted ridehail users in San Francisco were under 34, although this is likely a high estimate (Rayle et al. 2016).[16] Unlike the general population, about three-quarters of surveyed seniors had never heard of ridehail services, and older adults rely least on ridehailing to meet their mobility needs (Vivoda et al. 2018). Younger seniors (ages 65 to 69) are four times more likely to own smartphones and a higher share uses ridehailing compared to older seniors, suggesting that low ridehail adoption by seniors may be a cohort rather than age effect (Anderson and Perrin 2017, Clewlow and Mishra 2017). If so, we would expect higher ridehail use among seniors in the future as Baby Boomers age.

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[15] Sample is representative based on spatial distribution of California population (Circella 2018). Geographical differences are not due to service gaps in rural areas. Uber serves the entire state of California, including remote rural areas. However, high costs and wait times may preclude use in some rural areas. Lyft is not available in some small cities or rural areas.

[16] Rayle et al. (2016) oversampled Friday and Saturday evenings in "locations expected to have a high concentration" of ridehail users (p. 170).

Ridehailing may help maintain seniors' mobility after they can no longer drive, and seniors who know about ridehailing report higher satisfaction with their mobility options compared to seniors who do not know about ridehailing (Vivoda et al. 2018). While most seniors reported no interest in ridehailing, those who were interested reported barriers to access such as anxiety about paying for services in advance or online (Shirgaokar 2018).

Ridehail use also divides along household resource lines. Nationally, a larger share of higher-income and college-educated households have used ridehail services compared to lower-income and less-educated households (Smith 2016); Clewlow and Mishra (2017) found that affluent college-educated adults have ridehail adoption rates double that of lower-income, less-educated adults.

Ridehail adopters are disproportionately carless compared to the general population (Gehrke, Felix, and Reardon 2018, Clewlow and Mishra 2017); for example, 35 percent of ridehail users in San Francisco do not own a car compared to 19 percent of the city population (Rayle et al. 2016), although differences likely vary greatly across metropolitan areas. At the same time, a higher share of ridehail users own a car compared to people who *only* ride transit (Clewlow and Mishra 2017); this is perhaps unsurprising given that, on average, transit riders have very low incomes (see for example Giuliano (2005)) and may be priced out of both car ownership and ridehailing.

While the media hypes ridehailing as transport for the wealthy, citing users' above-average household incomes and less use by low-income households (Rodionova 2016, Davies 2016), academic research is mixed on the relationship between ridehailing and income. Some research reports increasing ridehail adoption with income (Clewlow and Mishra 2017), while others report that ridehail users have disproportionately low- to middle-incomes (Gehrke, Felix, and Reardon 2018). Using intercept surveys, Rayle et al. (2016) found that nearly one-third of ridehail users in San Francisco earned *under* the city median income and that users drive less but made eight percent more trips than they did before ridehailing began (Rayle et al. 2014). Such findings suggests that ridehailing may be increasing users' overall mobility, albeit slightly.

When and For What Purposes Do People Use Ridehailing?

Surveys consistently report social and leisure trips as the most common reasons for ridehailing, although the exact share of trips varies by survey. In a representative sample of residents in seven large metropolitan areas, Clewlow and Mishra (2017) find that, nationally, 38 percent of ridehail users report regularly hailing ridehail services for going to bars and parties, followed by restaurants and cafes (24%), family and community events (13%), and shops and services (11%). Rayle et al. (2016) report even higher rates of ridehail use for social or leisure trips (66%), although the authors acknowledge that their sampling frame—three downtown locations during Wednesday, Friday, and Saturday evenings—captures "primarily evening trips to dining and entertainment venues" and that other trip purposes are underrepresented (p. 171). Travelers also use ridehail for work; Rayle et al. (2016) found that 16 percent of intercepted ridehail users were traveling for work, and Henao (2017) found that work was an origin or destination for 30 percent of surveyed trips. Work travel also appears to be more common over time; in 2017, 18 percent of surveyed consumers reported work as the most common ridehail destination compared to about 12 percent in 2016 (SharesPost 2018).[17]

Across regions, average recorded ridehail trip are quite short, between two and four miles; in Los Angeles, Feignon and Murphy (2018) estimated that the average trip length is about three miles.[18] By comparison, the average trip (all modes) in Los Angeles is 6.8 miles and the average car trip is 8.5 miles (California Department of Transportation 2012). In New York, ridehail trips are longer compared to taxis on average (5.4 vs. 3.0 miles, respectively), likely reflecting greater ridehail service in New York's outer boroughs compared to taxis (Schaller 2017).

Ridehail users travel differently compared to the general public, differences that are likely at least in part due to users' more urban locations. Frequent ridehail users also walk, take transit, bikeshare, and car share more than less frequent users or nonusers (Smith 2016). Reports on how

[17] Ridehail trip purposes from city and national-based surveys are consistent with internal Lyft surveys. Among Lyft users in Los Angeles, the most common purpose is to go to restaurants and entertainment (73%) followed by traveling to the airport (56%), leisure trips (48%), work travel (35%), visiting friends and family (33%), completing errands (27%), and grocery shopping (15%) (Lyft 2018a).
[18] Feignon and Murphy (2018) calculated trip distance as the straight-line distance between the geographic center of the trip origin zip code and the trip destination zip code.

often users substitute other modes with ridehailing are quite mixed and substitution likely varies by location, alternative transportation options, and survey methodology. The plurality (22 to 41%) of users report that they took ridehailing in lieu of either transit (Rayle et al. 2016, Henao 2017, Gehrke, Felix, and Reardon 2018) or a car (18 to 46%)(Clewlow and Mishra 2017, Rayle et al. 2016, Henao 2017). An additional 10 to 12 percent of users report ridehailing instead of walking or biking (Rayle et al. 2016, Henao 2017). Relatively few users (5 to 12%) reported that they would not have made the trip at all without ridehailing (Rayle et al. 2016, Henao 2017, Clewlow and Mishra 2017, Gehrke, Felix, and Reardon 2018).

The relationship between transit and ridehailing remains murky. Preliminary studies suggest that ridehailing serves three roles: 1) connecting people to transit (first/last mile), 2) substituting transit, or 3) providing mobility when transit is not available. Likely, ridehailing fulfills each of these functions to varying extents in different locations and at different times. While only six to 13 percent of ridehail trips connect to transit, closer to one-quarter (21 to 23%) of ridehail users report having used ridehailing to connect to transit at least once (Feignon and Murphy 2018, Henao 2017, Lyft 2018a).

While the plurality of transit riders have never used ridehail services, five to 39 percent of transit riders report substituting transit on their most recent ridehail trip (Feignon and Murphy 2018). Modal substitution appears primarily related to speed, reliability, and cost tradeoffs. Nationally, Clewlow et al. (2017) found that American adults who substitute ridehailing for transit cite slow transit speeds as a primary motivator; speed and reliability considerations also help to explain modal shifts reported in cities[19] and ridehailing's popularity relative to taxis.[20]

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[19] A majority of ridehail users in Boston report "quicker than transit" as the main reason for choosing ridehailing (Gehrke, Felix, and Reardon 2018). Rayle et al. (2016) found that 30 percent of ridehail users report short wait times and short trip durations as motivations for ridehail use. Similarly, over one-quarter of Lyft users in Los Angeles report using Lyft when transit does not operate (Lyft 2018a).

[20] Field observations in New York and Los Angeles suggest that shorter, more reliable wait times and lower prices may partially explain ridehail's popularity over traditional taxis (Smart et al. 2015, BOTEC 2015). Ridehailing typically provides shorter wait times and lower-price trips compared to taxis. While over 92 percent of ridehail riders waited fewer than 10 minutes for a ride to arrive, only 35 and 39 percent of riders seeking dispatched and hailed taxis, respectively, waited fewer than 10 minutes

Finally, in addition to substitution effects, ridehailing can also complement transit by expanding car access across space and time. Feignon and Murphy (2018) found that between 13 and 32 percent of nationally-surveyed ridehail users report ridehailing when transit was not available.

Technology as a Barrier to Ridehail Access

While ridehail use has exploded in recent years, low-income adults still face considerable barriers to access. Two primary barriers to access—also prevalent in the car share and bikeshare literature (Ogilvie and Goodman 2012, Clark and Curl 2016)—are access to a smartphone or bank account, both of which are necessary to summon a ridehail vehicle.[21,22] In 2015, about 9 percent of Los Angeles metropolitan area residents were entirely unbanked, and an additional 20 percent were underbanked, meaning that they may have a bank account, but rely heavily on cash or checks rather than bank services such as loans or credit cards (FDIC 2016). While the share of households that are unbanked and underbanked is falling over time, banking status continues to vary greatly along racial, ethnic, income, and age lines. Overall, unbanked and underbanked status is higher among younger, less educated, low-income, and non-white populations (see Table 1).

(Rayle et al. 2016). Also attractive to riders, ridehail trips were less than half the price of identical trips by taxi in Los Angeles (Smart et al. 2015), and 10 percent of surveyed ridehail users report that ridehailing was the cheapest travel option available during their previous trip (Rayle et al. 2016).

[21] Both Uber and Lyft allow hailing from a computer; however, to confirm a ride, riders must enter a cellphone number to receive texted ride details. So while a smartphone is not *technically* required, a cellphone is. In addition, not having a cellphone with a data plan dramatically reduces the number of places from which potential users can hail a ride.

[22] Beginning in 2016, Uber experimented with allowing cash in select international locations, such as Singapore and Sri Lanka; however, cash options remain unavailable in the U.S. (Uber 2016b, a). In addition to major credit and debit cards, Lyft accepts PayPal and Apple Pay (both of which require, at minimum, a bank account), as well as prepaid cards (Lyft 2018b).

Table 1. Banking Status and Smartphone Access in the United States

	Unbanked (%)	Underbanked (%)	Smartphone Access (%)
All	7.0	19.9	67.1
Banked			71.1
Underbanked			75.5
Unbanked			42.9
Income			
<$15,000	25.6	24.3	43.9
$15,000 - $30,000	11.8	23.6	50.6
$30,000 - $50,000	5.0	23.7	64.6
$50,000 - $75,000	1.6	20.2	73.9
$75,000+	0.5	13.4	84.1
Education			
Less than High School	23.2	25.9	41.4
High School	9.7	22.2	57.6
College degree	1.1	14.5	79.7
Age			
15 to 24	13.1	29.4	82.5
25 to 34	10.6	24.5	84.0
35 to 44	8.9	22.7	80.9
45 to 54	6.7	21.1	75.4
55 to 64	5.8	18.5	63.2
65+	3.1	13.0	38.2
Race/Ethnicity			
Asian	4.0	21.0	75.4
Black	18.2	31.1	63.5
Hispanic	16.2	29.3	66.3
Other	11.1	27.5	69.3
White	3.1	15.6	67.3

Source: FDIC (2016).

The share of unbanked households rises sharply in immigrant and undocumented populations. Immigrant banking status is strongly correlated with country of origin and positively associated with years of education and years in the United States (New York City Department of Consumer Affairs 2013). In addition, a documented immigrant is half-again as likely (71%) to be banked compared to an undocumented resident (48%) (FDIC 2016). With about 815,000 undocumented residents in Los Angeles as of 2013 (Hill and Hayes 2015), the FDIC reports an "unknown" banking status for 10 percent of Los Angeles households, which is double the national rate (5%) (FDIC 2016). As a result, a greater share of Los Angeles residents may face barriers to ridehail access compared to cities with lower shares of foreign-born residents.

In part due to banking limitations, cash continues to be an important fare medium in transportation. In 2015, the share of New York taxi trips paid using a credit card increased with the fare price; only about half of taxi trips less than $10 were paid by credit card (Schneider 2015).[23] King and Saldarriaga found that immigrant and unbanked status are strong predictors for cash taxi fares, which produces "clear spatial dimensions of the propensity of riders to pay cash" (King and Saldarriaga 2017b, 1). These findings suggest that travelers who can *only* use cash to pay for travel may be excluded from ridehailing. Indeed, 12 percent of non-ridehail users reported not being able to pay in cash as the largest reason for not using ridehail apps (SharesPost 2018).

In addition to banking access, survey respondents report not owning a smartphone as a "somewhat" to "very" important reason for not using ridehailing (Miller et al. 2016). As of January 2018, more than three-quarters of all Americans owned a smartphone (Pew Research Center 2018), but Table 1 shows that smartphone access varies across households. Smartphone access is strongly related to economic factors and increases with educational attainment and income. Higher shares of under- and fully-banked households own a smartphone (73%) compared to unbanked households (43%) (FDIC 2016). Smartphone use remains low among poorer households; only 41 percent of LA Metro riders (median household income $15,918) owned a smartphone, which is consistent with the national average shown in Table 1 (Los Angeles County Metropolitan Transportation Authority 2015). Young adults (25 to 34 years old) have the highest rate of smartphone access (84%) and access decreases with age regardless of income, which likely reflects a cohort rather than aging effect. Geography also affects smartphone ownership, with higher access in versus outside of metropolitan areas (70% vs. 57%) (FDIC 2016). Unlike banking status, however, smartphone access appears less tied to immigrant status; nationally, nearly the same share of foreign-born non-citizen households own a smartphone (66.5%) compared to U.S. born households (67.2%) (FDIC 2016).

[23] It is possible that more people pay in cash than *must* pay in cash due to pressures placed on them by taxi drivers to pay in cash. Taxi drivers often prefer cash fares both because credit cards deduct a 5 percent fee from fares, and also because credit cards may take a few days to remit payments back to drivers (Cab 2014).

Finally, even among households that own smartphones, data plan limitations may constrain use; nine percent of non-ridehail users in 2017 reported that "Ridesharing apps take up my phone data plan" was their largest reason for abstaining from ridehail use (SharesPost 2018).

Unlawful Discrimination in the Transportation Service Industry

Discrimination in transportation, as in other sectors, is not necessarily illegal. For example, companies may refuse to serve people based on ability to pay and apps may only service smartphone owners. General tenets of unlawful discrimination are enshrined in federal law[24] and include denying service to, excluding, or in other ways discriminating against individuals based on their race, color, national origin, sex, religion, or familial status.

Table 2 shows that unlawful discrimination may manifest in either higher prices or reduced or denied service. Of primary interest to this research is unlawful discrimination, particularly in the taxi industry, that takes the form of denied or degraded service.

Table 2. Forms of Unlawful Discrimination

	Examples
Discrimination Takes the Form of Higher Prices	--New Car Sales (Ayres and Siegelman 1995, Ayres 1991) --Other types of sales or repair services
Discrimination Takes the Form of Denial or Degradation of Service or Opportunity	--Housing (Yinger 1997) --Employment (Bendick, Jackson, and Reinoso 1994) (Bertrand and Mullainathan 2004) --Restaurants (Siegelman 1998, Riesch and Kleiner 2005) --Car Rentals (Siegelman 1998) --Shopping (Siegelman 1998) --Taxis (Ridley, Bayton, and Outtz 1989, Belcher and Brown 2015, Wrigley 2013)

Adapted from Siegelman (1998).

What motivates people to discriminate? First, people may *directly discriminate*. In direct discrimination, personal characteristics (such as race) are the direct reason for a negative outcome (Murphy 2002). For example, if a realtor does not sell to black home-seekers because they are black, this is a form of direct discrimination. Second, people may *proxy* or *statistically discriminate*.

[24] Such as the Civil Rights Act of 1964, the Fair Housing Act, and Title IX of the Education Amendments of 1972, among others.

Statistical discrimination occurs when one uses observable individual characteristics as proxies for unobserved measures that vary across racial, ethnic, gender, or other groups (Murphy 2002, Alexander 1992). For example, a higher share of young households may default on mortgages compared to older households. If a banker refused to lend to a young household because she used age (observable) as a proxy for the likelihood of default (unobservable), she is committing statistical or proxy discrimination. People may act on unconscious biases even when they "consciously and sincerely support egalitarian principles and believe themselves to be non-prejudiced" (Dovidio, Kawakami, and Gaertner 2000, 138). Alexander (1992) argues unconscious biases are "relatively shallow psychologically, because they rest on biases that are rejected at the conscious level. Once made aware of their unconscious biases, the discriminators are quite likely to abandon the tainted preferences" (p. 181).

Other scholars use the taxi industry's long-standing reputation of rampant discrimination as a barometer for discrimination in America: contextualizing racial bias in the National Basketball Association, Justin Wolfers, Professor of Economics and Public Policy and the University of Michigan once said: "There's bias on the basketball court…but less than when you're trying to hail a cab at midnight" (Schwarz 2007). Wolfers' assertion reflects evidence of taxi discrimination across the U.S.: in Washington, D.C., taxis are 25 percent less likely to pick up a black rider than a white rider (Wrigley 2013); in Chicago, nearly half (48%) of black residents report that a cab "would ignore them and continue driving by" compared to 23 percent of white residents (Belcher and Brown 2015); in Seattle, 60 percent of white riders were picked up by the first empty taxi that approached, compared to only 20 percent of black riders (Ge et al. 2016); and at Los Angeles International Airport, taxis refused one-in-five ride requests by two undercover black police officers (Nelson 2016). Potential reasons for such race-based discrimination are discussed in the conceptual framework in Chapter 6.

Race-based discrimination evidenced in the taxi industry is illegal; Section 601 of Title VI of the Civil Rights Act of 1964 states:

"No person in the United States shall, on the ground of race, color, or national origin, be excluded from participation in, be denied the benefits of, or be subjected to discrimination under any program or activity receiving Federal financial assistance."

Taxis are typically subject to Title VI regulations in two ways. First, taxis often receive federal dollars, either directly from the Federal Transit Administration, or from cities and transit agencies, which contract taxis to provide jobs access reverse commuting services, voucher programs, or rides for seniors (Federal Transit Administration 2018a, c). Second, taxi licenses are typically granted by cities and airports, which are themselves beholden to Title VI, and which explicitly forbid taxi discrimination. The Los Angeles Taxicab Rules and Regulations of the Board of Taxicab Commissioners, for example, forbids "any action, behavior, practice or prejudicial treatment based on race, creed, color, ancestry, national origin, ethnicity, religion, age, sex, gender identity, sexual preference, marital status, medical condition or disability" and states that "[d]iscriminatory based trip refusals shall result in permit revocation" (Los Angeles Department of Transportation 2016, 6, 38).[25] Taxi discrimination at airports is barred at the federal level by the Federal Aviation Administration:

"The airport sponsor and any of his lessees, concessionaires, or contractors must offer to all members of the public the same degree and type of service without regard to race, color, or national origin. This rule applies to fixed base operators, restaurants, snack bars, gift shops, ticket counters, baggage handlers, car rental agencies, limousines and taxis franchised by the airport sponsor, insurance underwriters, and other businesses catering to the public at the airport" (Federal Aviation Administration 2016, 3).

Despite prohibition at multiple levels of government, discrimination remains rampant in the taxi industry. It remains to be seen, however, whether unlawful discrimination exists in ridehailing, in addition to taxis, as suggested by a few early studies. A study of nearly one-thousand ridehail trips in Boston found that Uber/Lyft users having "African American sounding" names were more than twice as likely to have a ride cancelled (10%) compared those with "white sounding" names (5%) (Ge et al. 2016, 12). While researchers found no evidence of racial bias in Boston, black riders in Seattle waited significantly longer for a ridehail trip to be accepted compared to white riders (Ge et al. 2016).[26] Ge et

[25] "Discriminatory based discourtesies" and "Discriminatory based dismissals or discharges" are likewise cause for revoking taxi permits (Los Angeles Department of Transportation 2016, 36, 38).

al. (2016) provide first insight into possible discrimination in ridehailing; however, like previous studies of taxi discrimination (Nelson 2016, Belcher and Brown 2015, Wrigley 2013), findings are limited to differences between black and white riders and do not examine potential biases against other races or ethnicities.

In addition to racial bias, gender bias may also influence ridehail trip cancellations; men traveling in low-density areas were more likely than women to have trips cancelled (Ge et al. 2016). Higher cancellations for male riders, particularly by women drivers, may be due to perceived—and actual—risk of assault by female drivers, who face assaults ranging from verbal threats to homicides at rates 60 times higher than the national average (Mayhew 2000).

While taxi driver, and perhaps to a lesser extent, ridehail driver behaviors are suggestive of racial and gender discrimination, research on this subject remains limited. No studies have yet compared the relative levels of bias between taxis and ridehailing, nor have studies to date considered racial/ethnic bias beyond a black/white dichotomy.

An Uncertain Future

Ridehailing offers an opportunity to provide cheaper, faster, and more reliable car access compared to taxis, but the potential equity implications of ridehail services remain unclear. Research to date suggests that ridehailing may provide superior access in low-income neighborhoods compared to taxis (Smart et al. 2015, Hughes and MacKenzie 2016), but also that driver discrimination still results in longer wait times and higher cancellation rates for black riders (Ge et al. 2016). In addition, most research on Uber, Lyft, and/or taxi service does not explicitly consider equity implications (Schaller 2017, Feignon and Murphy 2018, Clewlow and Mishra 2017, Rayle et al. 2016), and we do not yet

[26] Although the studies both tested for racial bias, the methodology was slightly different between the Boston and Seattle field studies. In Seattle, white and black students were sent into the field; while they had different racial identities, they did not assign particular names to any of the riders. In Boston, Ge et al. (2016) assigned the same passenger to two accounts. One account was given an "African American sounding" name, while the other account was assigned a "white sounding" name. Racial biases were observed based on the assigned race of the name rather than the racial identity of the individual, who could "plausibly travel as a passenger of either race" (Ge et al., 2016, 12).

understand the association between the built environment, resident characteristics, and ridehail use. To address these gaps in knowledge, I address outstanding questions about the spatial distribution of ridehail trips and users by using a new and rich origin-destination dataset of Lyft trips in Los Angeles County, and by conducting a ridehail audit to determine whether and how ridehail service quality varies by rider race/ethnicity and gender.

PART I: WHAT EXPLAINS RIDEHAIL GEOGRAPHY AND USE?

CHAPTER 3. LYFT IN LOS ANGELES: HYPOTHESES, DATA, AND METHODS

Chapters 3 to 5 answer two distinct research questions about ridehail travel in Los Angeles: first, what factors are associated with the spatial distribution of ridehail (Lyft) service? And second, what factors are associated with individual ridehail (Lyft) trip-making? In each, I consider how new technologies may upend the mechanisms through which discrimination in the taxi industry manifested. I hypothesize that, after controlling for neighborhood income and built environment factors, *no relationship exists between Lyft travel and neighborhood racial/ethnic composition.* Two potential explanations motivate this hypothesis. First, ridehail companies bridge the information gap that has long plagued the taxi industry; because ridehail companies know where riders and drivers are, they can raise prices to attract drivers to underserved areas. Second, drivers do not know a rider's destination prior to pick up; fearing poor ratings from riders, drivers may be unwilling to refuse to drive a passenger to a particular neighborhood as happens with taxis. Once a trip is completed, drivers are matched to a new riders based on proximity.

The following sections detail the trip-level data obtained directly from Lyft and the additional data and methods used to assess ridehail trips and individual use in Los Angeles. An improved understanding of patterns of both ridehail trips and users will inform policymakers and analysts who currently seek to integrate ridehailing into travel demand models and understand how people use this still-new mode. Results will likewise answer accusations by critics that ridehail drivers avoid particular neighborhoods (see for example Motavalli (2015) and Kohler (2015)) and guide emerging regulations to ensure equitable access to ridehail services.

Obtaining Ridehail Data

To understand factors associated with neighborhood Lyft service and individual Lyft use, I obtained trip-level records for every Lyft trip originating and/or ending in Los Angeles County in September, October, and November 2016. Physically larger than Delaware and Rhode Island combined, Los Angeles County is home to more than 10 million people (U.S. Census 2016b) and includes 158 cities and unincorporated places (Los Angeles Times 2017). Its neighborhoods range from dense urban communities, to sprawling suburbia, to remote mountain towns. In addition, Southern California's year-round temperate climate minimizes the need to analyze seasonal travel effects, making three months of data generalizable to annual ridehail use in the county.

Lyft Trip Sample

For each trip taken to, from, or within Los Angeles County between September and November 2016, Lyft provided the information listed in Table 3.

Table 3. Lyft Trip Data

Variable	Description
Traveler identification number	Unique to each user
User billing zip code	Most recent zip code on file[2]
Census tract of trip origin	
Census tract of trip destination	
Time of day	Four-hour time of day intervals (1:00am - 3:59am, 4:00am - 6:59am, etc.)
Weekday	Yes/no
Trip price[1]	$2.50 categories ($0-$2.50, $2.51-$5.00, etc.)
Trip distance	Five-mile categories (0-5 miles, 5-10 miles, etc.)
Shared ride service	Lyft Line, yes/no

[1]Price is the amount of money the passenger paid for the ride, excluding tips. Due to coupons or promotions, the amount a passenger paid for a ride could be as low as zero. [2]Users may update payment options over time. Lyft provided the billing zip code for the most recent payment form.

Lyft collects billing zip codes, but not users' home addresses. I use billing zip codes to identify users' home census tracts using methods described in the following section. To protect traveler privacy, Lyft provided trip origin and destination census tract identifiers rather than exact addresses or geographical coordinates. While census tracts make it impossible to identify exact trip origin and destinations, they pair easily with external data sources and therefore enable analysis of the associations between socioeconomic and built environment factors and Lyft travel. Again to protect user identity, Lyft provided trip distance, price, time of day, and day of week as categorical variables. Using both day of week and time of day variables, I identified trips taken during the morning peak (weekdays, 7:00am - 8:59am) and evening peak periods (weekdays, 4:00pm - 6:59pm). Finally, Lyft provided a Lyft Line dummy variable (yes/no). Lyft Line is Lyft's rideshare service launched in August

2014. It groups riders traveling the same direction into shared ride carpools and discounts rides up to 60 percent (Lyft 2017b), making Lyft Line an attractive cost-competitive option for price-sensitive travelers.

In total, 828,616 users took over 6.3 million trips between September and November 2016 to, from, or within Los Angeles County. To explore the associations between Lyft service and local built environment and socioeconomic factors (Research Question 1), I first connected all Lyft trips to external census tract data. To explore factors associated with Lyft use by individuals (Research Question 2), I then identified where users live. I describe the socioeconomic and built environment data and methods to identify users' home neighborhoods in the following sections. I present descriptive statistics of Lyft trips in Chapter 4 and Lyft users in Chapter 5.

Data Limitations

While these Lyft data are unmatched by any previously available to researchers and present a complete picture of Lyft travel over a three-month period, they face two primarily limitations. First, these data suffer from external population validity, in that—while they represent the entire population of Lyft trips during the time—findings may not be generalizable to ridehailing as a mode because rider and trip populations on Lyft may or may not be comparable to other ridehail services. Second, the Lyft data used in this research are not associated with rider demographic or economic data, such as people's race, ethnicity, or income. To obtain such data, researchers have administered surveys (Gehrke, Felix, and Reardon 2018, Rayle et al. 2016, Henao 2017). Compared to survey samples, these data are more robust as they provide a population of trips. Thus, despite these limitations, findings provide both a foundation for future research and a critical resource for policy makers to better understand how and where Lyft travel fits into urban transportation.

Connecting Lyft Trips to Neighborhood Data

Neighborhood Data

To understand what neighborhood elements are associated with Lyft service and use, I include independent socioeconomic, built environment, and amenities data listed in Table 4 and further described below. I collected all data at the census tract level and refer to "census tract" interchangeably as "neighborhood."

Table 4. Neighborhood Data, Variables, and Sources

Socioeconomic		**Built Environment**		**Amenities**	
Variable	*Source*	*Variable*	*Source*	*Variable*	*Source*
Median household income	ACS [DP03]	Population density (people/sq. acre)	EPA (2014) [d1b]	Number of jobs in Arts, Food, and Recreation[1]	LEHD (2015b) [cns17, cns18]
% Zero vehicle households	ACS [DP04]	Employment Density (jobs/sq. acre)	EPA (2014) [d1c]		
% Ages 15-34	ACS [DP05]	Road Network density	EPA (2014) [d3a]		
% Hispanic	ACS [DP05]	Number of transit stops per square mile	Bureau of Transportation Statistics (2017)		
% NH Asian/Black/ Other/White	ACS [DP05]	Number of on- and off-street parking spaces per square mile	Chester et al. (2015)		

Variables or tables of original data indicated in brackets. ACS refers to the 2011-2015 five-year American Community Survey. NH indicates not Hispanic or Latino. EPA refers to the 2014 Smart Location Database produced by the Environmental Protection Agency. LEHD refers to the Longitudinal Employer-Household Dynamics program. [1]I include all jobs from two NAICS categories in this variable: NAICS 71 (Arts, Entertainment, and Recreation) an NAICS 72 (Accommodation and Food Services). These categories include a diversity of opportunities that may serve as trip generators and attractors such as bars, restaurants, museums, performing arts centers, and sports facilities.

Socioeconomic Data

Socioeconomic data from the 2011-2015 American Community Survey (ACS) reflect auto access and household resources (percent zero-vehicle households, median household income), which are strong predictors of mode choice and travel behavior (Van Acker and Witlox 2010, Blumenberg and Pierce 2012). Neighborhood income may also be a basis for service exclusion or redlining, in which low-income neighborhoods receive less or more expensive service compared to higher-income neighborhoods (Ong and Stoll 2007). To present a clearer picture of a neighborhood's economic standing relative to other neighborhoods in Los Angeles County, I classified neighborhoods as low, middle, or high-income based on their median household income. Low-income neighborhoods are those in the lowest-income quartile (≤$38,319 median household income), middle-income are census tracts with median household incomes in the middle 50 percent ($38,320 to $76,364), and high-income are neighborhoods with median household incomes in the highest-income quartile (≥$76,365). Table 5 shows the share of Los Angeles County census tracts and population across the three income groups.

Table 5. Income Group Categories

	Share of Census Tracts[1]	**Share of Los Angeles population[2]**
Low (≤$38,319)	24.5%	23.2%
Middle ($38,320-$76,364)	49.1%	51.6%
High (≥$76,365)	26.4%	25.2%
Total	*100%*	*100%*

[1]Share of census tracts that fall within these income ranges. [2]Share of Los Angeles County population living in the census tracts within these income ranges. Source: U.S. Census (2015a).

In addition to resource variables, I included the proportion of a tract's population between the ages of 15 and 34, as multiple studies find that ridehail users are disproportionately young (Rayle et al. 2016, Clewlow and Mishra 2017, Gehrke, Felix, and Reardon 2018).

Finally, I included the racial and ethnic composition of a neighborhood, which—in addition to income—is a primary characteristic across which service exclusion or redlining occurs (Ong and Stoll 2007, Spiegelman 2016). Researchers find that people use the racial or ethnic makeup of a neighborhood as a proxy for perceived criminal threat and victimization. Indeed, Chiricos et al. (2001, 322) found that "crime threat may be 'ethnically coded' as well as 'race coded'" and that both racial/ethnic majorities and minorities perceive greater crime risk proximate to either Hispanic or black neighborhoods, despite the fact that many immigrant neighborhoods are actually safer (MacDonald, Hipp, and Gill 2013). In the taxi industry, researchers have attributed avoidance of these communities to racism, fear for personal safety, and perceptions that they are economically less rewarding (Cohen 2015, Ridley, Bayton, and Outtz 1989, LaMendola 1991, Vidich 1976).

Los Angeles remains relatively segregated by race and ethnicity; the Los Angeles-Long Beach-Glendale metropolitan area ranks 14th in black-white segregation, first in Hispanic-white segregation, and fourth in Asian-white segregation (Logan and Stults 2011).[27] The high degree of segregation means that perceptions of dominant racial or ethnic groups in an area may affect Lyft drivers' decisions to serve them. To capture this, I used ACS racial/ethnic data to classify neighborhoods into racial and ethnic majority categories.[28] I defined a racial/ethnic majority as a race or ethnicity that comprises more than 50 percent of neighborhood residents. I classified neighborhoods without a clear racial or ethnic majority as "No majority." Table 6 shows that most (78%) Los Angeles County residents live in a neighborhood with a clear racial or ethnic majority, while Figure 2 shows the average racial and ethnic composition within each of these categories. Together, Table 6 and Figure 2 demonstrate the remarkable level of racial/ethnic segregation that persists in Los Angeles County.

Table 6. Neighborhood Racial/Ethnic Majority Categories

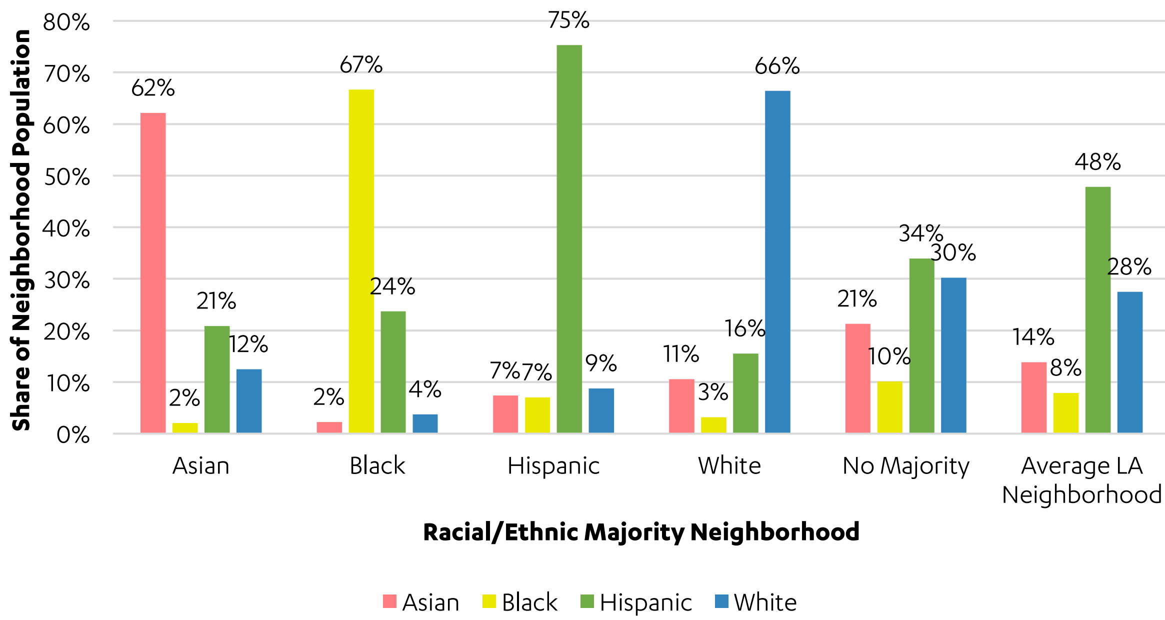
Racial/Ethnic Majority	**Share of Census Tracts**	**Share of Los Angeles Population**
Asian	6.1%	5.2%
Black	2.4%	2.4%
Hispanic	46.1%	47.6%
White	24.1%	23.2%
No majority	21.4%	21.7%
Total	*100%*	*100%*

Source: U.S. Census (2015a).

[27] Logan and Stults (2011) compute dissimilarity indices across U.S. metropolitan regions using 2010 U.S. Census data. The dissimilarity index reflects how evenly two groups are spread among census tracts within a given metropolitan region. The authors rank metropolitan areas with the largest Asian, black, and Hispanic populations based on their dissimilarity indices from most to least segregated. The authors rank 50 metropolitan regions for black-white and Hispanic-white segregation and 40 metropolitan regions for Asian-white segregation.

[28] All races include individuals who identify as "Non-Hispanic", such as "Non-Hispanic Asian." In other words, "Hispanic" is a discrete category without overlap with the other groups. In Los Angeles, most Hispanic individuals would fall under the racial category "white" (55%), while the plurality of others (40%) identify as "some other race alone" (U.S. Census Bureau 2015a).

Figure 2. Composition of Racial/Ethnic Majority Neighborhoods



Source: U.S. Census (2015a).

Built Environment Characteristics

Built environment characteristics describe the physical environment of a neighborhood rather than the people who live there. Understanding how the built environment affects travel behavior is a subject of continual fascination and debate for both researchers and policymakers. However, while researchers understand associations between the built environment and other modes—for example, that density supports higher transit use, fewer vehicle miles traveled (Ewing and Cervero 2010), and higher car share level of service (Celsor and Millard-Ball 2007)—we do not yet understand the relationship between the built environment and ridehail use. Given that the built environment is a primary mechanism through which planners alter cities and possibly travel behavior, understanding its relationship with ridehail use is paramount.

Researchers measure the built environment in many ways. While many researchers rely only on various measures of density (such as population, employment, and activity densities), others assert that the built environment affects travel through the five D's: density, design, diversity, distance to transit, and destination accessibility (Ewing and Cervero 2010). Given the interplay between the five D's, some researchers use composite variables to incorporate multiple elements of the built environment within a single continuous or categorical measure (see for example Hamidi et al. (2015)) and Voulgaris et al. (2017)).

Given the range of ways to quantify the built environment, I tested three combinations of density and composite built environment variables. Each model includes a measure of on-street and off-street parking given the large role parking plays in driving behavior (Shoup 2011, Weinberger, Seaman, and Johnson 2009, Weinberger 2012). I present the full model results in Appendix A. I selected final best-fit model specifications based on the Akaike and Bayesian information criteria (AIC/BIC).[29] The final models include the six density metrics listed in previously in Table 4. Appendix B shows the spatial distribution of each of these density measures across Los Angeles County.

I derived transit stop density (stops/square mile) from the Bureau of Transportation Statistics' (2017) National Transit Map database, which provides the latitude and longitude of fixed route transit stops. To calculate stop density, I summed all transit stops within a tract and divided by the tract land area; while the presence of transit stops does not reflect service frequency, this variable nonetheless provides a snapshot of where residents can access transit and the relative density of that access. Transit stop density is positively correlated with both employment and residential density, which research associates with travel mode choice (Ewing and Cervero 2010).

Neighborhood Amenities

The types of destinations in a neighborhood affect trip generation and attraction rates (Ortúzar and Willumsen 2011). Therefore, including specific neighborhood attractions and amenities—such as shops, restaurants, entertainment venues, etc.—helps to distinguish between areas that have similar activity densities, but that generate or attract travelers differently. For example, one might expect a commercial neighborhood that includes a mix bars and restaurants to attract more people than

[29] The AIC and BIC each provide a measure of model fit. Each is designed to avoid over-fitting a model to the data by balancing goodness of fit with model simplicity.

would a cluster of industrial jobs. While workers would travel to and from the latter, bars and restaurants may attract both workers as well as customers from across the city.

Surveys reveal that socializing, leisure, and entertainment are the most common reasons that people ridehail (Clewlow and Mishra 2017, Rayle et al. 2016, Lyft 2018a). Nationally, 62 percent of ridehail users report that they most commonly use ridehail to travel to/from bars, parties, and restaurants (Clewlow and Mishra 2017). Based on these previous results, I expect high levels of Lyft service in areas with more social and recreational amenities. To measure neighborhood amenities, I use the number of jobs per square mile in the "Arts, Entertainment, and Recreation" and "Accommodation and Food Services" sectors obtained from the Longitudinal Employer-Housing Dynamics (LEHD) program (U.S. Census Bureau 2015b). These categories include a variety of opportunities and represent locations that generate and attract diverse trips as described in the footnote of Table 4.

Identifying Where Lyft Users Live

To examine how Lyft use varies across individuals, I first identified the types of neighborhoods in which users live. However, I cannot assume that individual residents have the same characteristics as the neighborhood in which they live; to do so would be an ecological fallacy, which occurs when one ascribes group-level data to an individual member of that group. For example, a person living in a low-income neighborhood does not necessarily have a low-income. However, I may still use neighborhood characteristics to explain personal Lyft use without ascribing group-level attributes to an individual. Rather than discussing Lyft use by low-income travelers, for example, I describe Lyft use by people who live in low-income neighborhoods.

Lyft only collects users' billing zip codes, not home addresses. I devised a four-step method to narrow the home geography from zip code to census tract to allow for more nuanced observations across users. First, I assumed that the billing zip code is the home zip code, as people typically pay bills (including credit card bills) from home.[30] Second, I identified all users who had home zip codes in Los Angeles County.

Table 7 shows where users lived and the share of trips made by each resident group. Together, Los Angeles County residents comprised over two-third (69%) of users and made 89 percent of all trips. I excluded users with billing zip codes outside of Los Angeles from the Lyft user analysis because I was unable to connect them to a home census tract. Appendix C further discusses where non-resident Lyft users are from and how their Lyft trips compare to those of Los Angeles residents.

Table 7. Users by Residential Location

User by Residential Location	**Number (Share) of Users**	**Number (Share) of Trips**
Domestic Users	820,941 (99%)	6,292,733 (99%)
California	695,630 (84%)	5,644,072 (89%)
Los Angeles	571,115 (69%)	5,146,684 (81%)
International Users	7,675 (1%)	47,535 (1%)
Total	*828,616 (100%)*	*6,340,268 (100%)*

Sample: All users and trips.

To identify home census tracts for Los Angeles residents, I next identified the census tract that the user most commonly traveled to or from within his/her home zip code.[31] I coded this census tract as a user's home tract. This step assumed that home is the most common trip origin or destination for ridehail, like all, modes. For example, Henao (2017) found that 70 percent of ridehail trips began or ended at home,[32] which is on par with the share of all trips that are home-based (70-75%) (National

[30] Some Lyft accounts may be business accounts; however, Lyft itself does not differentiate between personal and business zip codes. Therefore, some users may be assigned a home address at their work location. This would result in an inflated number of Lyft users living in employment centers. The number of misidentified home addresses, however, is likely limited for two reasons. First, Lyft Business Profiles were introduced at the end of April 2016 (Lyft 2016), less than four months before data were assembled for this study. And second, people riding Lyft for work trips may also use personal rather than business cards for trips and seek reimbursement (if provided) from their employer.

[31] Los Angles Lyft users made, on average, nine trips. Of Lyft users who live in Los Angeles, 25 percent took one trip, 32 percent took two to four trips, 19 percent took five to nine trips, and 24 percent took more than 10 trips. Not all Lyft users took a trip within their home zip code.

[32] Contrastingly, Rayle et al. (2016) found that only 40 percent of surveyed San Francisco ridehail users began at home. These estimates may be low, however, and "mostly due to the location of the intercept surveys" (p.29), which oversampled evening trips in specific neighborhoods (Henao 2017).

Household Travel Survey 2009). Using this method, I identified 72 percent of Los Angeles residents' home census tracts.

The remaining users made no trips to or from tracts within their home zip code (for example, someone who only used Lyft to travel between work and the airport), or made an equal number of trips to/from multiple tracts within the home zip code. For these users, I used ArcGIS to assign the home census tract as the geographical center of the home zip code.[33] I discuss the geographic distribution of Lyft users in Chapter 5.

Lyft Service and Individual Use

Ridehail access is about both the neighborhoods it serves and the people who ride it. I refer to the number of Lyft trips that begin or end in a neighborhood as "Lyft service," and to Lyft travel by an individual rider as "Lyft use." The unit of analysis in the "service" analysis is a neighborhood (census tract) and the unit of analysis in the "use" analysis is an individual rider. I elaborate further on both the neighborhood and user analyses and their associated methods below.

Lyft Service

Measurement

Two dependent variables quantity neighborhood Lyft service: 1) the total number of Lyft trips, and 2) the number of Lyft trips per capita (jobs + residents). Each Lyft trip serves two neighborhoods: the neighborhood in which a trip begins and the neighborhood in which it ends. Therefore, to best reflect the level of Lyft service in a neighborhood, I counted every trip that either originated or ended in a neighborhood.

Methods

I first describe Lyft service in Los Angeles County, including average prices, distances, and temporal patterns. Second, I present spatial distributions of trips as they relate to both the built environment

[33] On average, zip codes within Los Angeles County contain eight census tracts.

and socioeconomic characteristics. Third, I estimated two linear regression models (see Figure 3) to determine which socioeconomic, built environment, and amenity factors are associated with neighborhood Lyft service in Los Angeles. The two models include all trips taken in Los Angeles County between September and November 2016. Although independent neighborhood variables correlate with one another, postestimation tests reveal that multicollinearity does not bias model results. I present findings in Chapter 4.

Figure 3. Neighborhood Analysis Schema

Research Question	Unit of Analysis	Model Type	Model Dependent Variables	Model Independent Variables (census tract variables)
What factors are associated with the spatial distribution of Lyft service?	Neighborhood (census tract)	Linear Regression	Total Trips (ln)	**Built Environment** Population density (ln) Employment density (ln) Road network density Transit stop density (ln) On-street parking density (ln) Off-street parking density (ln) **Socioeconomic Characteristics** Neighborhood income category Neighborhood racial/ethnic majority category % Zero vehicle households % ages 15-34 **Neighborhood Amenities** # of Arts, Food, & Rec. workers (ln)
		Linear Regression	Trips per capita (resident + job) (ln)	

(ln) indicates that the natural log of a variable was used; highly-skewed variables were log-transformed to better meet model requirements.

Lyft Use

The neighborhood service analysis investigates factors that are associated with the number of trips to and from a neighborhood, but does not consider *who* makes those trips. For example, many trips may begin or end in a low-income neighborhood with plentiful nightlife destinations. Lyft may pickup and drop-off many passengers in the neighborhood, but these passengers may be exclusively nightlife patrons rather than residents. Distinguishing between neighborhood service and users is important for understanding who benefits from Lyft service and not just where the trips are made. The user analysis, presented in Chapter 5 therefore examines factors that are associated with individual Lyft use; where the unit of analysis in the Lyft service analysis is the neighborhood, the Lyft user analysis focuses on the individual.

Measurement

In this research, I define Lyft users as people who hailed one or more Lyft between September and November 2016. The number of users is likely an underestimate of Lyft riders as it excludes people who have Lyft accounts but did not take a trip during this time period, as well as people who ride Lyft with friends or family but do not hail Lyft themselves. To avoid an ecological fallacy, I describe users based on the neighborhoods in which they live; for example, I describe Lyft users as "living in a low-income neighborhood" rather than having a low-income. I measure individual Lyft use across a number of travel metrics including: total number of trips, share of trips made on Lyft Line, average price, and average trip distance.

Methods

In addition to descriptive statistics, I sought to understand the association between home neighborhood characteristics and individual Lyft use. I therefore estimated a series of regression models described in Figure 4. I specified a negative binomial model for total trips, which are over-dispersed count data, and logistic regression models for percentage dependent variables (share of trips on Lyft Line). As with Lyft service models, postestimation tests reveal no issues of multicollinearity. The user analysis includes only Lyft users in the sample who are residents of Los Angeles County (n=571,115, 69% of total sample). I present descriptive statistics and model results in Chapter 5.

Figure 4. User Analysis Schema

Research Question	Unit of Analysis	Model Type	Model Dependent Variables	Model Independent Variables (census tract variables)
What factors are associated with individual Lyft use?	User	Negative binomial	1. Total Trips	**Built Environment** Population density (ln) Employment density (ln) Road network density Transit stop density (ln) On-street parking density (ln) Off-street parking density (ln) **Socioeconomic Characteristics** Neighborhood income category Neighborhood racial/ethnic majority category % Zero vehicle households % ages 15-34 **Neighborhood Amenities** # of Arts, Food, & Rec. workers (ln)
		Logit	1. Share of trips on Lyft Line	
		Multiple linear	1. Average trip cost 2. Average trip distance	

(ln) indicates that the natural log of a variable was used; highly-skewed variables were log-transformed to better meet model requirements.

CHAPTER 4. WHAT EXPLAINS THE SPATIAL DISTRIBUTION OF LYFT SERVICE?

In this chapter, I examine the distribution of Lyft service (the number of trips beginning and ending) across Los Angeles neighborhoods. I first describe Lyft trips in Los Angeles County, which provides the most comprehensive and fine-grained analysis of ridehail travel to date. Second, I discuss model results that reveal the relative strength of associations between Lyft travel and local built environment, socioeconomic, and amenity factors.

Lyft Trips in Los Angeles

Between September and November 2016, riders made over 6.34 million Lyft trips to, from, and within Los Angeles County. Of these trips, 83 percent (5.29 million) started and/or ended in the City of Los Angeles. While estimates from other regions suggest that Lyft provides only about one-quarter of all ridehail trips (Schaller 2017), Lyft alone completed five times as many trips per month compared to taxis in the City of Los Angeles (1.76 million vs. 405,000 per month) (Los Angeles Department of Transportation 2017a). The staggering comparison between taxis and Lyft—the *smaller* of the two primary ridehail companies serving Los Angeles (Uber is the larger)—demonstrates the scale that ridehail services have achieved relative to taxis in just a few short years of operation.

Of the 6.34 million Los Angeles County Lyft trips, the vast majority originated (99.99%) or ended (98.70%) in the county.[34] Table 8 shows that nearly one-quarter (22.6%) of Lyft trips were taken during peak hours (weekdays, 6:00 – 8:59am, 4:00 – 6:59pm), over one-quarter (29.2%) were taken on Lyft Line, and six percent of trips were made to or from one of Los Angeles County's three commercial airports.[35] Trips cost $9.66 on average, although this average is skewed by a small number

[34] While most Lyft users headed to destinations within Los Angeles County, a small minority traveled to adjacent counties such as Orange (0.89%), Riverside (0.03%), San Bernardino (0.22%), and Ventura (0.15%). A full list of origin and destination counties can be seen in Appendix C.

[35] Most Lyft airport trips were to/from Los Angeles International Airport (LAX) (5.5%), followed by Burbank (0.5%), and Long Beach (0.2%). On average, airport trips are longer and more expensive than non-airport trips, although including or excluding airport trips from analysis does not alter overall results (airport trips are included in all presented results). Appendix D discusses differences between airport and non-airport Lyft trips, including trip characteristics, geographical distributions, and prevalence by neighborhood types.

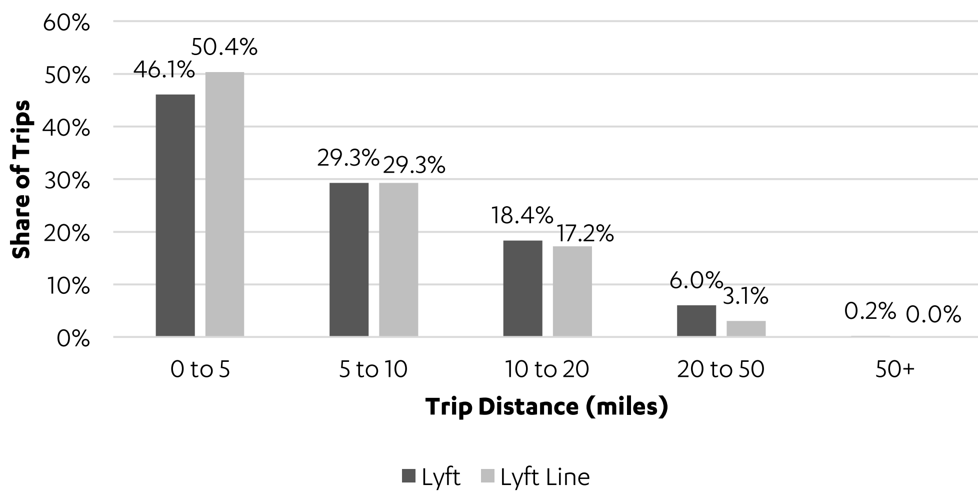
of high-priced long-distance trips. Median trip prices—including for peak hour and Lyft Line trips—were $6.25, which is about 3.5 times the price of a single transit trip ($1.75) on Los Angeles' largest transit agency, LA Metro.

Table 8. Lyft Trip Descriptive Statistics

	Number	**Share Peak-Hour**	**Share Airport Trips**	**Mean (Median) Price**	**Mean (Median) Distance**
All Trips	*6,340,268 (100%)*	22.6%	6.2%	$9.66 ($6.25)	7.4 (7.5)
Lyft	*4,487,924 (70.8%)*	21.6%	8.1%	$10.23 ($6.25)	7.7 (7.5)
Lyft Line	*1,852,344 (29.2%)*	25.0%	1.7%	$8.30 ($6.25)	6.7 (2.5)

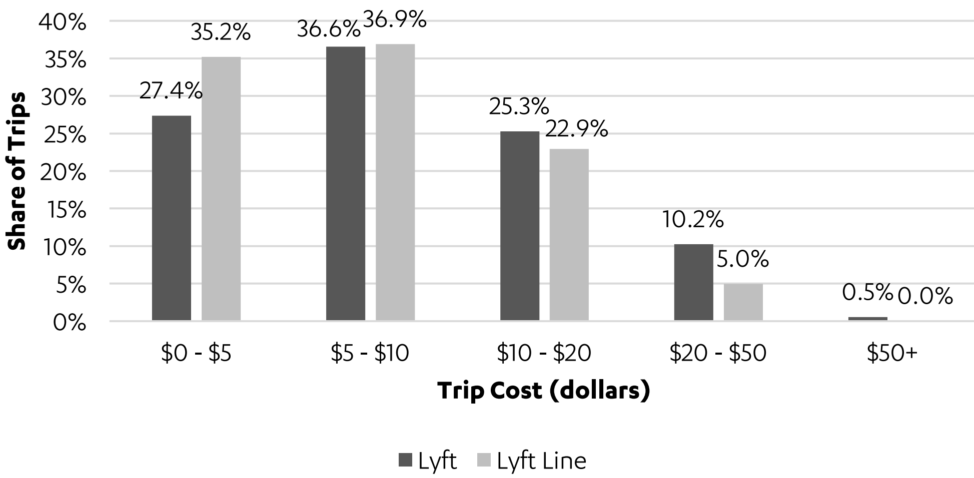
The majority of Lyft and Lyft Line trips were relatively short and low priced. Figure 5 shows that nearly half of Lyft trips (46%) were shorter than 5 miles, and about three-quarters were less than 10 miles.

Figure 5. Lyft and Lyft Line Distance Distribution



Two-thirds of Lyft trips cost under $10. As advertised, shared Lyft Line trips were lower-priced on average compared to regular Lyft trips. Figure 6 shows that over one-third of Lyft Line trips cost less than $5 compared to just over one-quarter of regular Lyft trips.

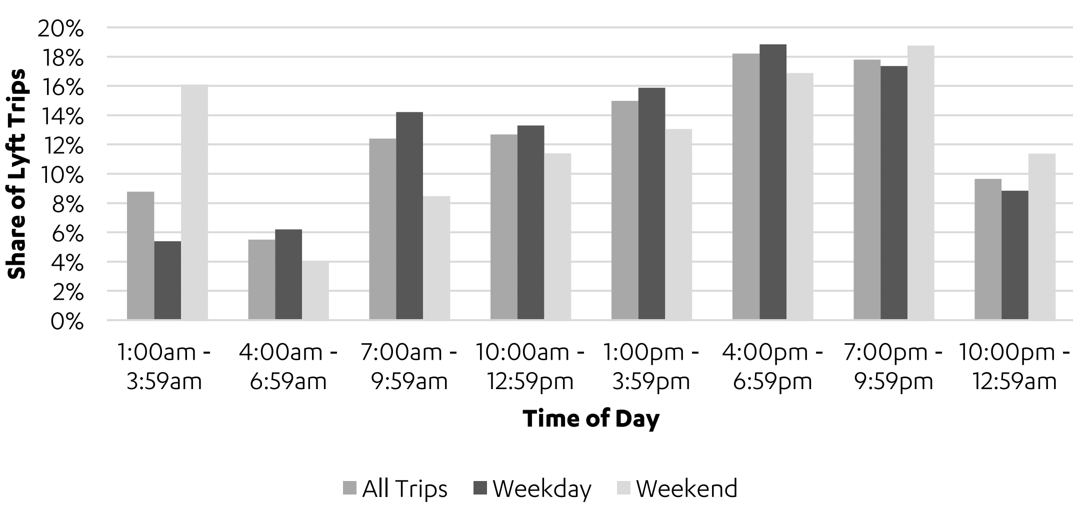
Figure 6. Lyft and Lyft Line Price Distribution



Temporal Distribution of Lyft Trips

Figure 7 shows the temporal distribution of Lyft trips on weekends compared to weekdays. About one-third (32%) of trips were taken on the weekend, slightly higher than the share of all trips taken on weekends (28%) (California Department of Transportation 2012). In general, the number of Lyft trips increased throughout the day between 4:00am and 9:59pm. A large spike in trips occurred on the weekend between 1:00am-3:59am, likely reflecting nightlife activity and/or a lack of other transportation options. Commute-hour peaking also occurred, particularly during the evening rush hour, as people travel to and from work and school.

Figure 7. Temporal Distributions of Lyft Trips



Traffic congestion occurs at all times of the day, but is particularly concentrated during peak periods (rush hour), when many people are trying to travel at the same times. With two-thirds of peak travel congested (Federal Highway Administration 2005), peak-hour travel vexes planners and policy makers who worry about lost time, wasted fuel, and emissions. Los Angles is notorious for its traffic congestion and a 2017 study reported Los Angeles as the "world's most traffic-clogged city" (Associated Press 2017). Texas Transportation Institute (2016) data show that in 2014, congestion cost each car commuter in Los Angeles an additional 25 gallons of gas, 80 hours, and $1,700 per year. Cities are now thinking of ways that ridehailing either contributes to or may ameliorate peak-hour congestion.

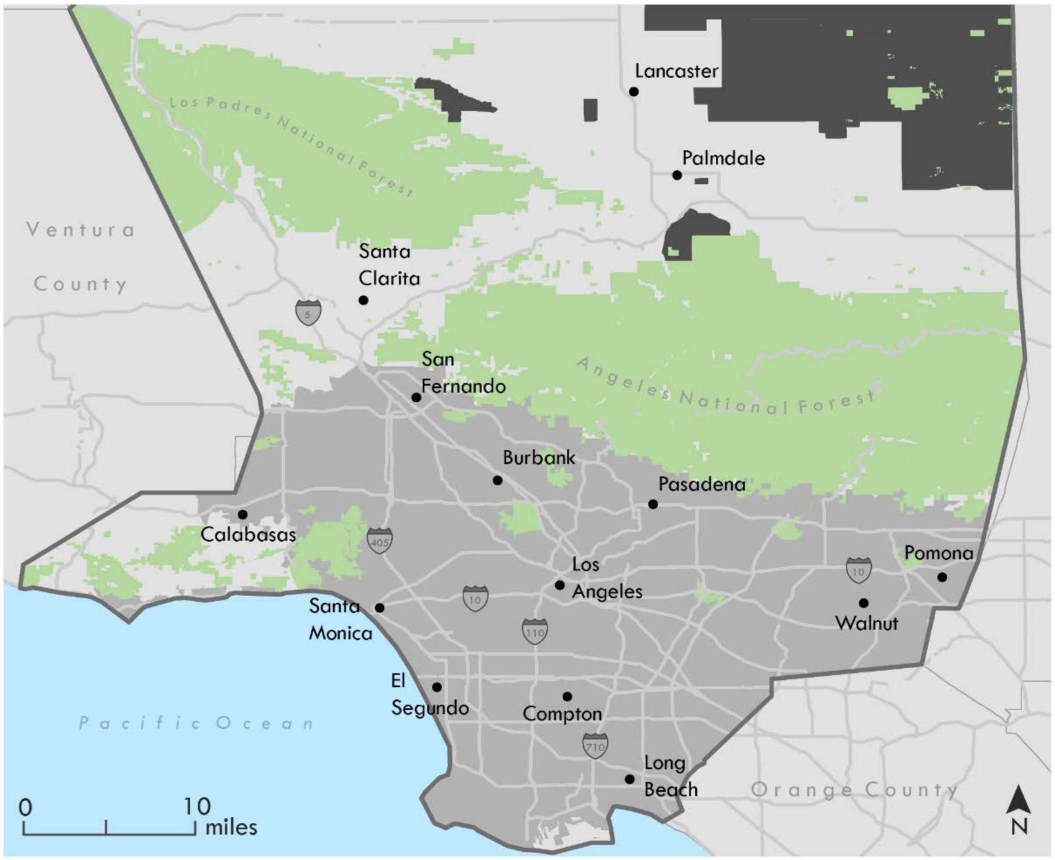
Overall, Lyft travel during peak hours is broadly consistent with all car travel during peak hours. Riders took nearly one-quarter (23%) of Lyft trips during peak hours, with 10 percent of trips taken on weekdays between 6:00am and 8:59am (morning peak) and 13 percent taken on weekdays between 4:00pm and 6:59pm (evening peak). These findings are consistent with Feignon and Murphy (2018) and with the share of all car trips taken during peak hours in Los Angeles County (California Department of Transportation 2012).

Peak-hour Lyft trips were seven miles long on average, the same average distance as all car trips taken during peak periods in Los Angeles (7.1 miles) (California Department of Transportation 2012). While Lyft does not collect occupancy data, 32 percent of peak-hour Lyft trips were on shared Lyft Line compared to just 12 percent of peak-hour drivers who carpooled with non-household members (California Department of Transportation 2012). Higher Lyft Line use during peak hours relative to regular driving suggests that Lyft may foster inter-household carpooling during rush hour and transport more people compared to an equivalent number of personal vehicles.

The Geographical Distribution of Lyft Trips

Between September and November of 2016, Lyft served nearly every census tract in Los Angeles County, home to 99.8 percent of the county's population (U.S. Census Bureau 2016). Figure 8 shows the few places where people made zero Lyft trips to or from. These areas are clustered in the far northeastern sections of the county, much of which is sparsely populated. Saddleback Butte State Park, Phacelia Wildlife Sanctuary, and agricultural land dominate much of these areas.

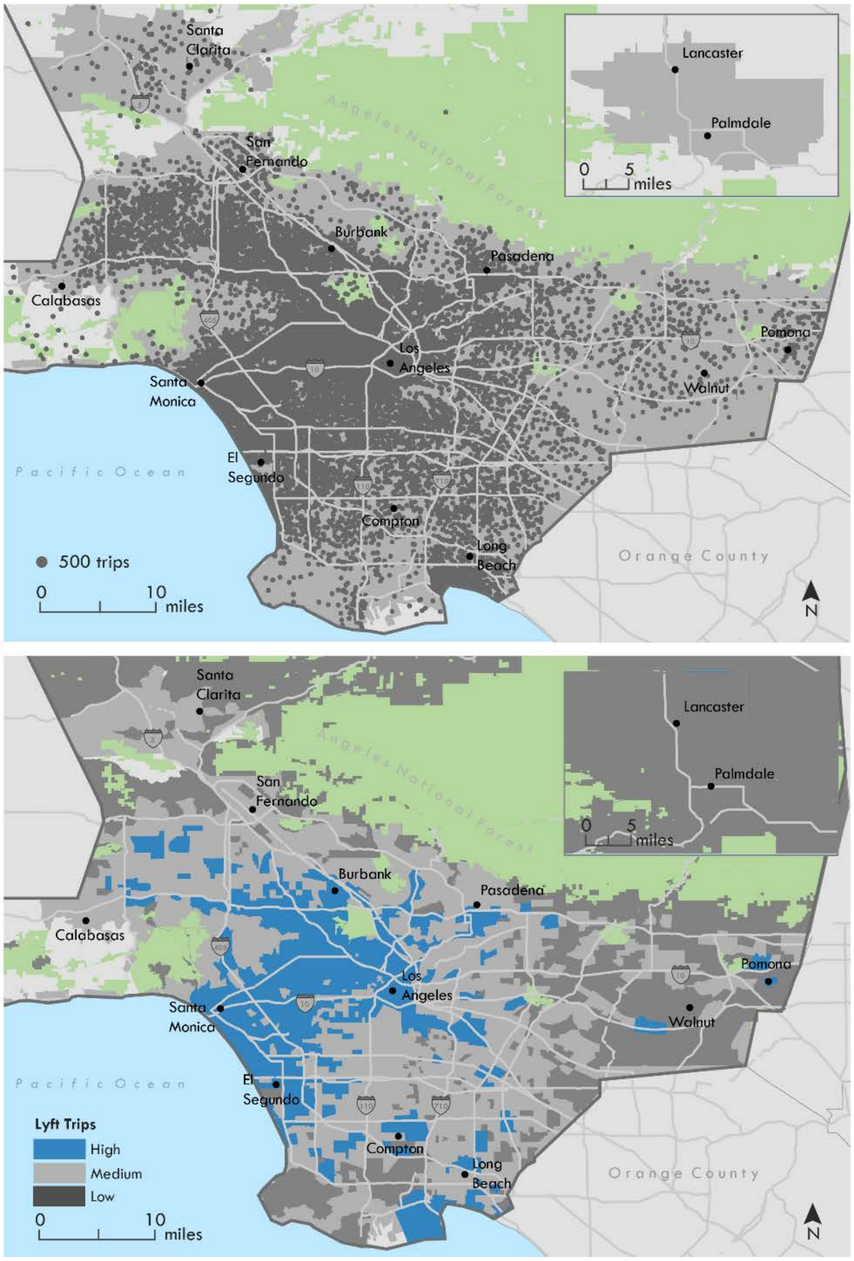
Figure 8. Census Tracts with No Trips



Not pictured: Catalina Island, which also had zero Lyft trips. Catalina Island, however, does not allow cars of any; on Catalina, the golf cart is king.

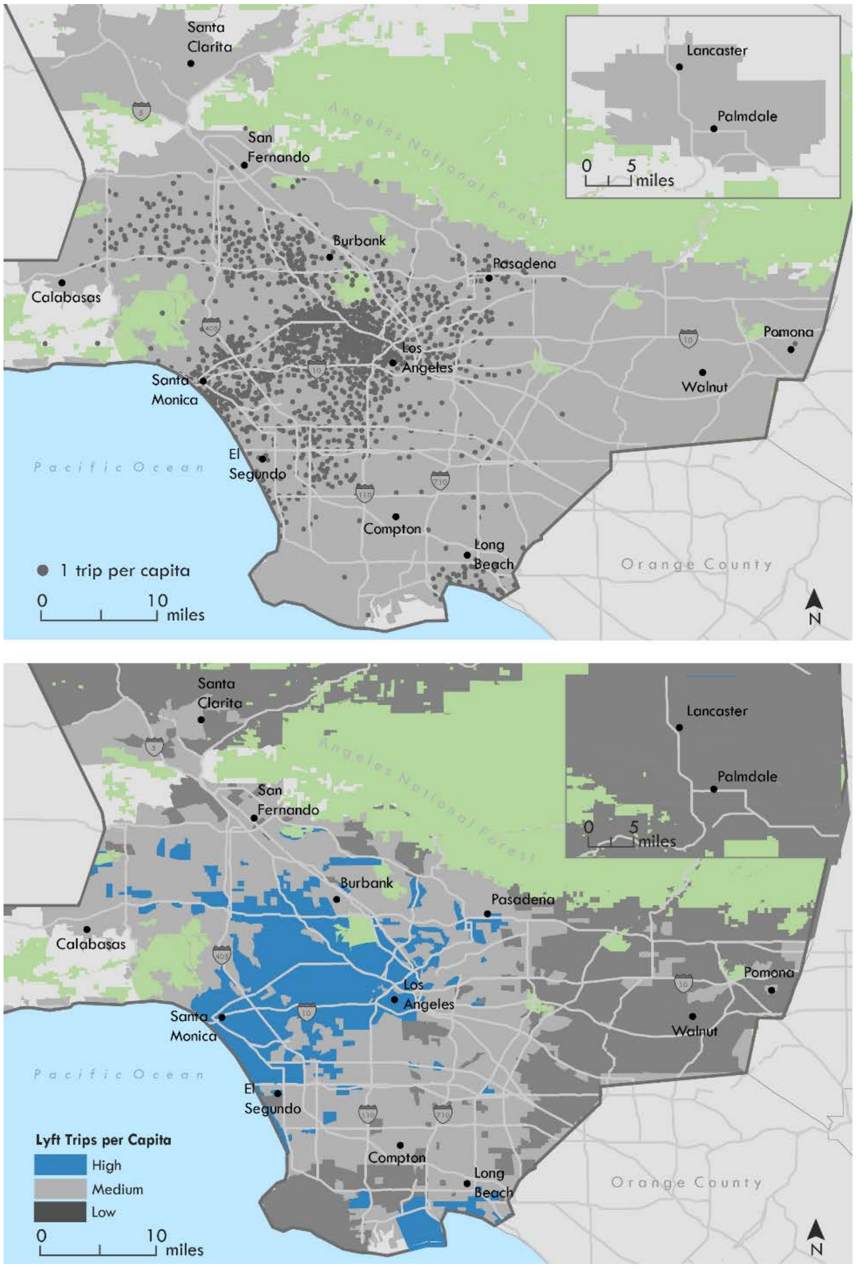
Figure 9 shows the spatial distribution of Lyft trips, and Figure 10 shows the per-capita (workers plus residents) trip distribution to account for the spread of jobs and residents across the county. Despite their different units of analysis (total trips versus trips per capita), the figures are broadly similar. High concentrations of Lyft trips span major activity corridors and centers. Lyft trips per capita (Figure 10) falls with distance from the urban core and in neighborhoods south of downtown, many of which have lower-incomes and higher shares of non-white and zero-car households. I discuss the associations between Lyft service and neighborhood built environment and resident socioeconomic characteristics later in this chapter.

Figure 9. Distribution of Lyft Trips



Note: Areas with high Lyft trips are the top 25 percent of neighborhoods (5,478 to 354,643 trips), areas with medium Lyft trips are in the middle 50 percent of neighborhoods (1,171 to 5,427 trips), and areas with low Lyft trips are in the lowest 25 percent of neighborhoods (1 to 1,170 trips).

Figure 10. Distribution of Lyft Trips Per Capita (Residents + Jobs)



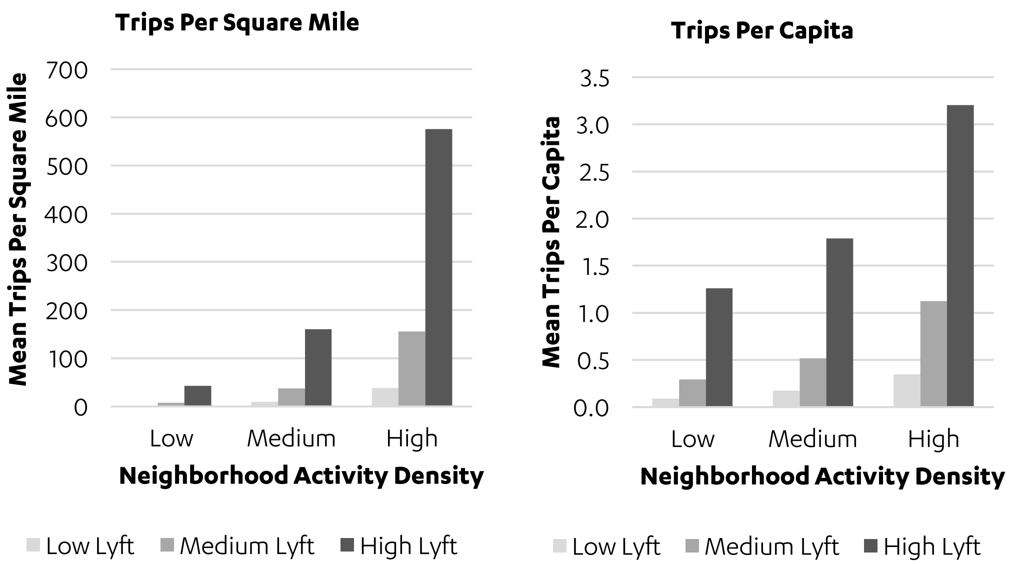
Note: Areas with high Lyft trips per capita are the top 25 percent of neighborhoods (0.96 to 11 trips), areas with medium Lyft trips per capita are in the middle 50 percent of neighborhoods (0.23 to 0.95 trips), and areas with low Lyft trips per capita are in the lowest 25 percent of neighborhoods (0 to 0.22 trips).

Having shown where Lyft trips are (almost everywhere) and are not (almost nowhere), I take a deeper look into the spatial patterns of Lyft trips across three dimensions: the built environment, neighborhood socioeconomic characteristics, and neighborhood amenities.

Lyft Trips and Density

Figure 11 shows Lyft across high, medium, and low-activity-density neighborhoods.[36] As expected, high-density neighborhoods had more Lyft trips per square mile and per capita compared to medium or low-density neighborhoods. High-density neighborhoods with high Lyft use had an additional one to one-and-a-half trips per capita compared to medium- and low-density neighborhoods, respectively.

Figure 11. Lyft Trips Across Low-, Medium-, and High-Density Neighborhoods



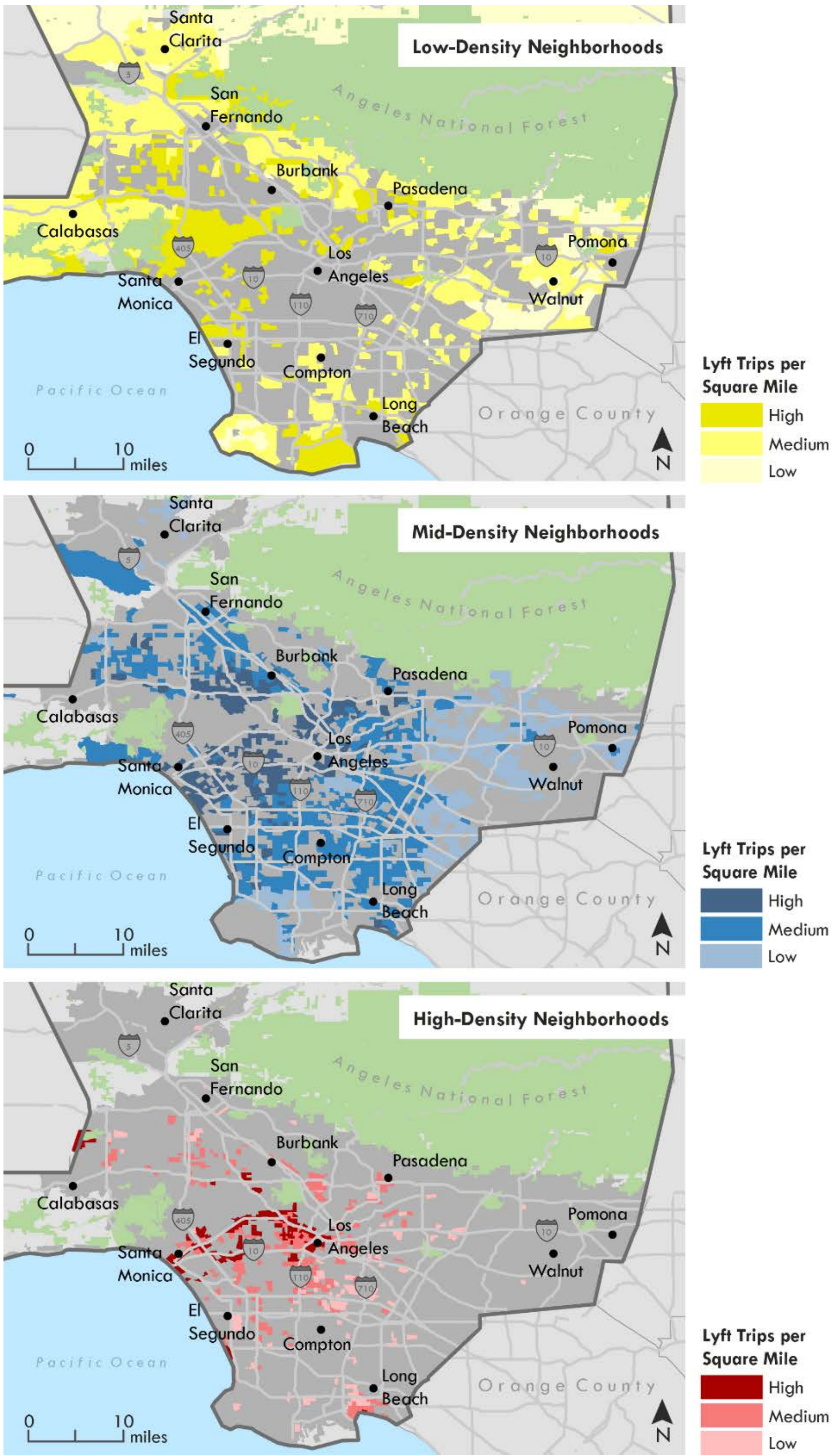
Activity density is the number of residents plus workers per acre. On average, there are 8, 22, and 61 workers plus residents per acre in low-, medium-, and high-activity-density neighborhoods, respectively. Source: Environmental Protection Agency (2014).

Figure 12 shows neighborhood densities and Lyft use across space. Neighborhood density is highest in and around the Los Angeles downtown core and along the Wilshire corridor stretching between downtown Los Angeles and Santa Monica. Medium density neighborhoods are distributed throughout the county and low-density neighborhoods generally lie in more peripheral areas. Within each of these three neighborhood density groups, high-Lyft use is typically found in tracts closest to

[36] Neighborhood activity density (residents + workers) and Lyft use both reflect quartile distributions. For both activity density and Lyft use, "low" indicates the bottom quartile, "medium" indicates the middle 25 to 75 percent, and "high" indicates the top quartile.

the downtown core. Notably, nearly 10 percent of all Lyft trips in Los Angeles County started or ended in downtown Los Angeles alone.

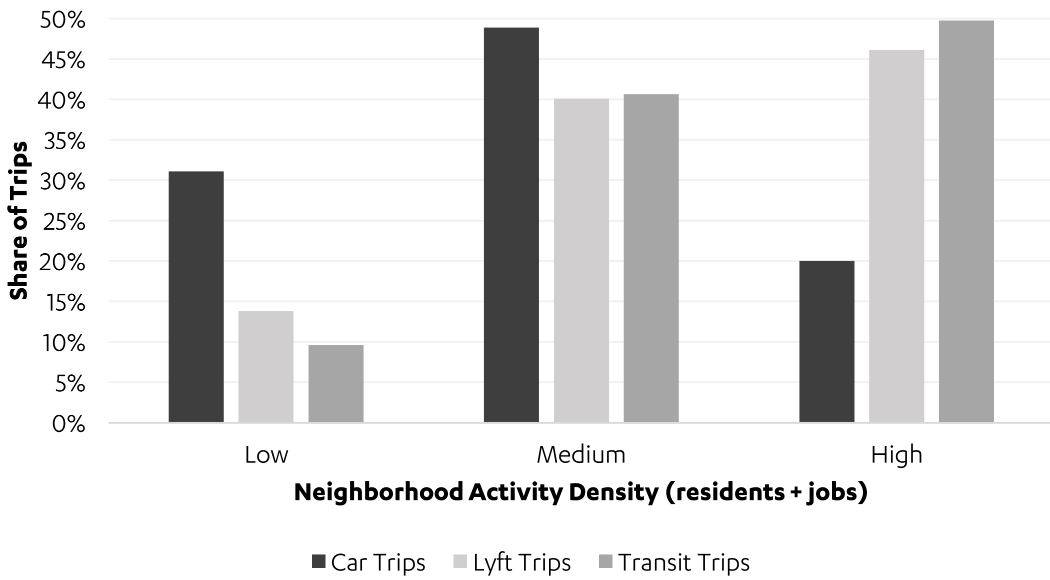
Figure 12. Activity Density vs. Lyft Trips per Square Mile



Density and Lyft use are both defined by quartiles. “High” is the top quartile; “low” is the bottom quartile, and “middle” is the middle 50 percent of tracts.

Figure 13 shows the share of Lyft trips, car trips, and transit trips in low-, medium-, and high-density neighborhoods. Despite being a form of car travel, the distribution of Lyft trips resembles transit more closely than it does car trips. Forty-six percent of Lyft trips were made in high-density neighborhoods, more than two times the share of car trips (20%), and just slightly under the share of transit trips made in these same neighborhoods (50%)(California Department of Transportation 2012).

Figure 13. Share of Car, Transit, and Lyft in Low, Medium, and High-Density Neighborhoods



Source: California Department of Transportation (2012).

Table 9 quantifies Lyft characteristics across the three density levels. The number of Lyft trips per capita in high-density areas was nearly double that in middle-density areas. More Lyft trips in dense urban areas could reflect shorter matching times between riders and drivers due to greater concentrations of both. More trips in dense areas may also reflect the availability and price of parking, which tends to be scarcer and pricier in dense downtown centers. Ridehail users consistently cite difficult-to-find or expensive parking as a top reason to ride Uber and Lyft (Clewlow and Mishra 2017, Henao 2017, Gehrke, Felix, and Reardon 2018), suggesting that parking push factors may motivate increased ridehail use.

Lyft trips in dense areas were also shorter and lower cost compared to trips in low- and middle-density neighborhoods. Trip distances conform to expectations that travel distances are shorter in dense areas because destinations are closer together (Karathodorou, Graham, and Noland 2010, van de Coevering and Schwanen 2006). Shared ridehail use also varied across neighborhood densities. One-third of trips were shared on Lyft Line in high-density neighborhoods compared to 21 and 27 percent of trips in low- and middle-density neighborhoods, respectively. I explore shared Lyft Line travel further in Chapter 5.

Table 9. Lyft Trip Characteristics Across Low, Medium, and High-Density Neighborhoods

Descriptive Statistics	**Mean Trips per capita**	**Mean Trip Distance (miles)**	**Mean Trip Price**	**% Line**	**% Peak**
Low-Density	0.49	14.97	$17.80	20.9%	21.8%
Medium-Density	0.75	8.22	$10.57	27.1%	22.3%
High-Density	1.46	6.90	$9.02	32.9%	22.3%

In summary, Lyft is nearly ubiquitous and serves a wide range of built environments in Los Angeles County. Like trip-making more generally, Lyft trips concentrated and were shorter in denser neighborhoods. Compared to other car trips, however, Lyft trips were disproportionately urban. The distribution of Lyft across low-, middle-, and high-density neighborhoods is far closer to transit than to other car trips.

The Socioeconomic Characteristics of Neighborhoods Served by Lyft

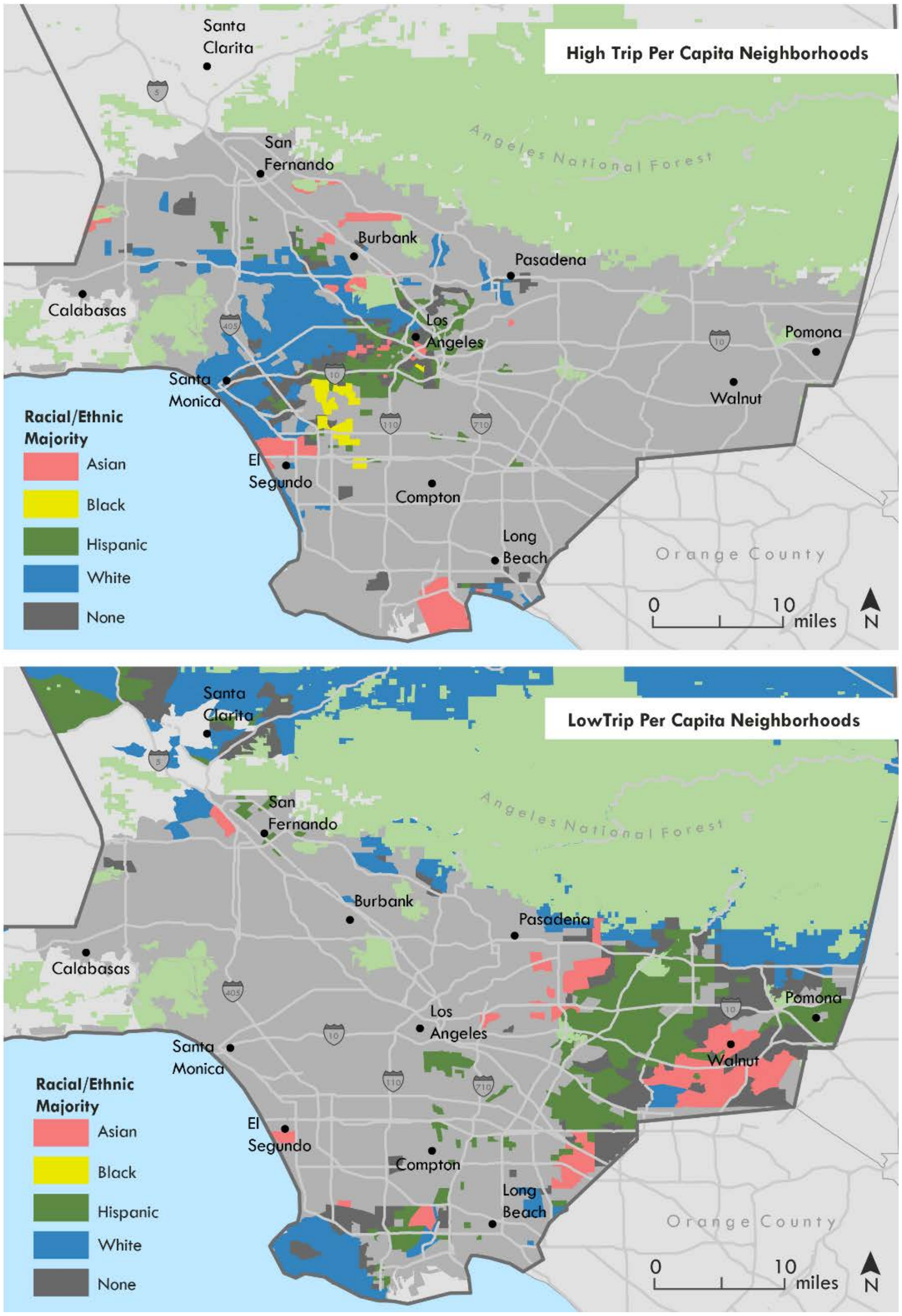
Understanding the spatial distribution of Lyft trips across neighborhood socioeconomic characteristics helps to answer questions both of ridehail travel behavior and whether drivers avoid neighborhoods based on residents' characteristics. In this section, I examine how Lyft service varies across the two neighborhood socioeconomic factors most commonly raised in the taxi and discrimination literatures: race/ethnicity and income.

Race and Ethnicity

Figure 14 shows the racial/ethnic majority in tracts with the most and fewest Lyft trips per capita.

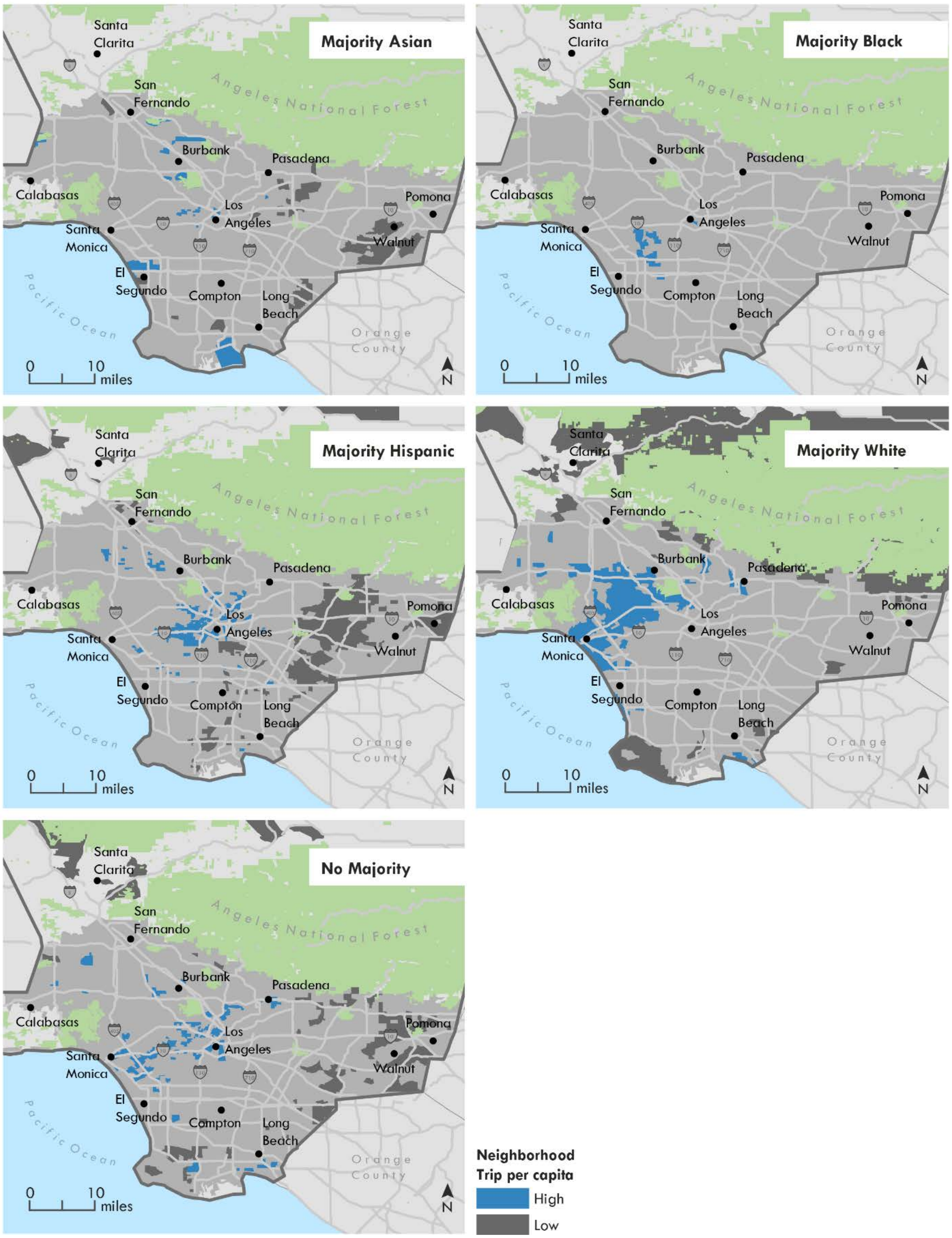
Figure 15 shows the inverse: high and low trips per-capita across racial/ethnic majority neighborhoods. The figures highlight that a neighborhood's location within the county, rather than its racial/ethnic composition, appears to be a primary driver of Lyft trips per capita. High-trip per capita areas cluster in central Los Angeles, while most low-trip per capita tracts situate in more outlying, suburban areas. Majority-Asian, Hispanic, and white neighborhoods fall into both high- and low-trip per capita categories. By contrast, no majority-black neighborhoods fall into the low-trip per capita category.

Figure 14. Racial/Ethnic Majorities in Low- and High-Lyft Trip Per Capita Neighborhoods



High and low trip per capita areas are defined as the top and bottom quartile, respectively.

Figure 15. Lyft Trip Per Capita Across Racial/Ethnic Majority Neighborhoods



High and low trip per capita areas are defined as the top and bottom quartile, respectively.

Figure 16 shows that nearly half (48%) the Los Angeles population lives in a majority-Hispanic neighborhood; however, just over one-quarter (28%) of Lyft trips began and/or ended in these neighborhoods. In addition, Lyft trips disproportionately began and/or ended in majority-black, majority-white, and no-majority neighborhoods, relative to the proportion of the population living in these neighborhoods.

Figure 16. Share of Lyft Origins and Destinations Across Racial/Ethnic Majority Neighborhoods

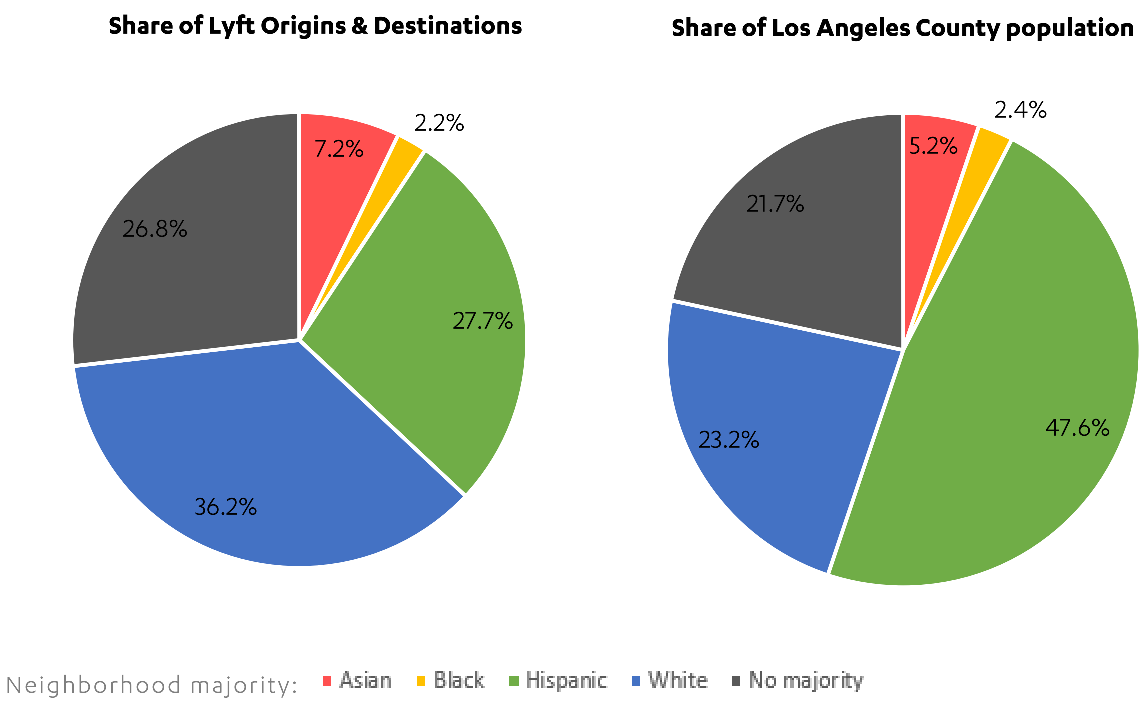


Table 10 quantifies Lyft trip characteristics across racial/ethnic majority neighborhoods. I explore the relative strengths of associations between race/ethnicity, median-household income, and built environment factors later in this chapter; presently, I focus only on how Lyft service varies across different racial/ethnic majority neighborhoods. On average, majority white neighborhoods had more Lyft trips per capita compared to any other neighborhood group. Majority-white neighborhoods are starkly different from other neighborhood groups in their average socioeconomic characteristics; however, apart from per capita Lyft trips, Lyft travel in majority-white neighborhoods was similar to Lyft travel in other neighborhoods.

Table 10. Lyft Trip Characteristics by Neighborhood Racial/Ethnic Majority

Neighborhood racial/ethnic majority	**# Trips per capita**[1]	**Mean Trip Distance (miles)**	**Mean Trip Price**	**Mean % Line**	**Mean % Peak**	**Tract Median Income**	**% of HHs, Zero Cars**	**Cars per capita**	**Mean Activity Density**[1]
White	1.27	10.04	$12.41	24.51%	21.78%	$92,641	5.7%	0.56	22.6
Black	1.00	7.47	$9.59	38.61%	23.21%	$48,375	14.9%	0.47	26.7
No Majority	0.96	10.98	$13.60	23.09%	22.74%	$63,357	8.6%	0.48	28.8
Asian	0.82	8.95	$11.56	24.51%	23.89%	$64,498	8.4%	0.49	25.8
Hispanic	0.60	8.81	$11.08	29.93%	21.80%	$44,170	12.9%	0.38	32.4
Average	*0.86*	*9.55*	*$11.96*	*27.04%*	*22.16%*	*$61,239*	*10.0%*	*0.45*	*28.8*

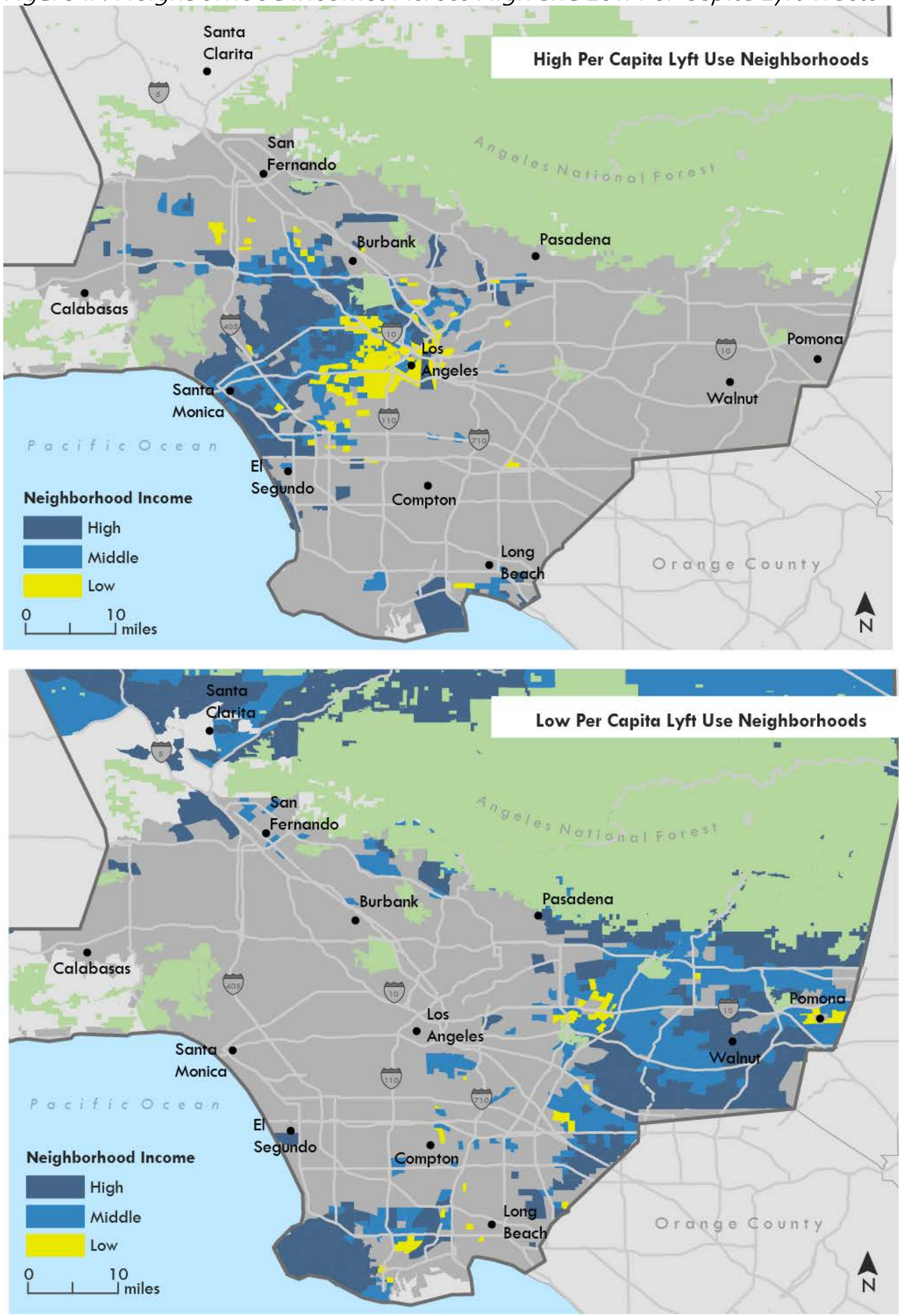
[1]Total residents plus jobs. Source: Environmental Protection Agency (2014), U.S. Census (2015a).

Majority-black neighborhoods depart most from other neighborhoods in terms of average Lyft travel. Second only to majority-white neighborhoods in per capita Lyft service, majority-black neighborhoods had shorter (7.5 miles), cheaper ($9.59), and more shared (Lyft Line) trips (39%) compared to the average neighborhood. Majority-black neighborhoods are similar to majority-Hispanic neighborhoods in terms of median household income and share of households without a car. However, Lyft travel per capita was 67 percent higher in majority-black neighborhoods than in majority-Hispanic neighborhoods, where average Lyft service was just 0.6 trips per capita. With median household incomes of only $4,000 less than majority black neighborhoods, the remarkably low number of trips per capita in majority Hispanic neighborhoods is unlikely explained by income alone. Other possibilities include differences in smartphone and banking access, residential location differences, or higher rates of carpooling in majority-Hispanic communities. I discuss these possible explanations further in Chapter 5.

Neighborhood Median Household Income

A clear geographical pattern in per-capita Lyft use emerges again across low, middle, and high-income neighborhoods. Figure 17 shows the income distribution across areas with high- and low-per capita Lyft use. All three income groups are present in high and low Lyft use areas, but a notable cluster of high-use areas exist in centrally-located neighborhoods, many of which have low-income. By comparison, many of the outlying low-use areas have high-incomes.

Figure 17. Neighborhood Incomes Across High and Low Per Capita Lyft Tracts



High and low per capita tracts are those in the top and bottom quartile of Lyft use per capita, respectively. High income (≥$76,365), Middle income ($38,320-$76,364), Low-income (≤$38,319).

Table 11 quantifies the service differences across low, middle, and high-income neighborhoods. With the exception of peak hour trips, trip characteristics present a gradient across incomes, with low-income neighborhoods at one end, high-income at the other, and middle-income in between. On average, trips were shortest, most shared, and cheapest in low-income neighborhoods, and longest, least shared, and most expensive in high-income neighborhoods. Low-income neighborhoods also had the *most* trips per capita, on average, about 25 percent more than middle and high-income neighborhoods. A disproportionate share of Lyft trips were made in both low-income and high-income neighborhoods relative to their share of Los Angeles County population and jobs; this bimodal distribution mirrors the distribution of taxi trips observed nationally (Schaller 2015).

Table 11. Lyft Trip Characteristics by Neighborhood Income

Neighborhood Income	**# Trips per capita[1]**	**Mean Trip Distance (miles)**	**Mean Trip Price**	**Mean % Line**	**Mean % Peak**	**Share of Trips**	**Share of Los Angeles County Population + Jobs**
Low (≤$38,319)	1.01	8.6	$10.73	34.4%	22.0%	25.3%	22.1%
Middle ($38,320-$76,364)	0.81	9.6	$12.01	26.2%	22.0%	46.4%	50.6%
High (≥$76,365)	0.83	10.4	$13.00	21.8%	22.6%	28.4%	27.3%
Average/Total	*0.86*	*9.6*	*$11.96*	*27.0%*	*22.2%*	*100%*	*100%*

[1]Total residents plus jobs. Source: Environmental Protection Agency (2014).

Together, spatial patterns of Lyft service in Los Angeles do not suggest that certain areas are excluded based on the race, ethnicity, or income of their residents alone. However, the data do not speak to whether or how service qualities such as wait times and cancellation rates may vary across neighborhoods. While estimated wait times are shorter in low-income areas (Hughes and MacKenzie 2016), no research yet evaluates how actual wait times or cancellations vary across neighborhoods. This remains an area for future research.

Amenities in Neighborhoods Served by Lyft

The number of neighborhood amenities per square mile increases with activity density. Table 12 shows that high-amenity areas had more trips per capita, shorter and cheaper trips, and were disproportionately shared (on Lyft Line) compared to trips made to and from tracts with fewer amenities. Regression models presented later in this chapter explore whether density alone predicts trip frequency, or if social and recreation amenities are specifically associated with ridehail service as suggested by previous research (Henao 2017, Clewlow and Mishra 2017, Rayle et al. 2016).

Table 12. Lyft Trip Characteristics Across Neighborhood Amenities

Number of Amenities per square mile[1]	# Trips per capita[2]	Trip Distance	Trip Price	% Line	% Peak	Mean Activity Density[3]
Low	0.43	12.42	$14.99	25.9%	21.5%	20.4
Middle	0.73	9.24	$11.64	27.0%	22.2%	26.1
High	1.56	7.37	$9.62	28.4%	22.6%	42.4

[1]Low corresponds to the bottom quartile (≤0.19 jobs/sq. mile), Middle corresponds to the middle two quartiles (0.19 – 2.11 jobs/sq. mile), and High corresponds to the top quartile (≥2.12 jobs/sq. mile). See Chapter 3 for additional information on neighborhood amenities data. [2]Jobs plus residents. [3]Jobs plus residents per square mile. Source: Environmental Protection Agency (2014).

Factors Associated with Neighborhood Lyft Service

While descriptive statistics suggest associations between Lyft service and neighborhood characteristics, regression models identify the relative strength of these associations while holding other potential determinants constant. I present results of two models in Table 13; each model measures the association between Lyft service and neighborhood built environment, socioeconomic characteristics, and amenities. In the first model, I measure Lyft service (dependent variable) as the total number of neighborhood Lyft trips; in the second, I measure Lyft service as the number of Lyft trips per capita (jobs plus residents) to account for neighborhood density.[37]

The associations between neighborhood factors and the two measures of Lyft service are broadly similar, and I discuss model results in parallel in the following sections. Overall, the models reveal that Lyft service is associated with characteristics of the neighborhood's built environment, resident characteristics, and local amenities.

[37] For example, if each person in a neighborhood took one Lyft trip, a neighborhood with 100 residents would have ten times the number of Lyft trips compared to a neighborhood with ten residents. A per capita measure accounts for such differences.

Table 13. Factors Associated with Neighborhood Lyft Service

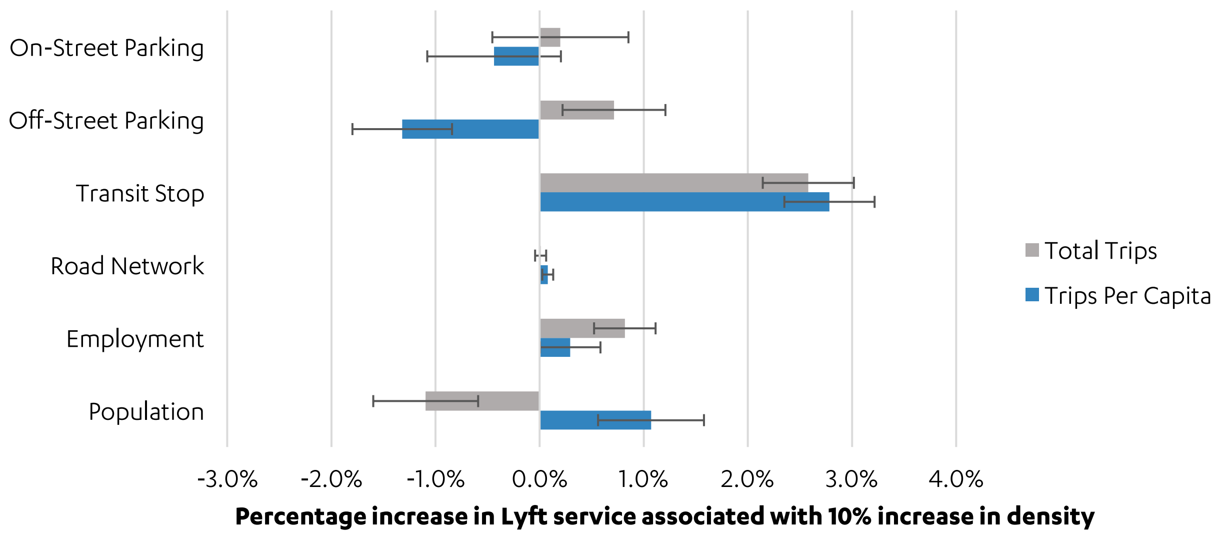
	Total Lyft Trips (ln)			**Lyft Trips Per Capita (ln)**[1]		
Built Environment	*Coef.*	*St. Error*	*Sig.*	*Coef.*	*St. Error*	*Sig.*
Population Density (people/acre) (ln)	-0.115	0.027	**	0.112	0.027	***
Employment Density (jobs/acre) (ln)	0.086	0.016	***	0.031	0.016	**
Road Network Density	0.001	0.003	NS	0.008	0.003	***
Transit Stop Density (stops/sq. mile) (ln)	0.267	0.023	***	0.288	0.023	***
On-street parking (spaces/sq. mile)	0.021	0.035	NS	-0.046	0.035	NS
Off-street parking (spaces/sq. mile)	0.075	0.026	***	-0.139	0.026	***
Tract Socioeconomic Characteristics						
Neighborhood Income Group *(Baseline: Middle)*						
Low-Income	-0.135	0.054	**	-0.071	0.053	NS
High-Income	0.067	0.052	NS	0.046	0.052	NS
Percent Zero Vehicle Households	2.005	0.254	***	2.185	0.251	***
Percent ages 15-34	2.561	0.231	***	2.328	0.228	***
Neighborhood Racial/Ethnic Majority *(Baseline: No Majority)*						
Asian	-0.396	0.079	***	-0.431	0.078	**
Black	0.376	0.111	***	0.410	0.109	***
Hispanic	-0.352	0.047	***	-0.438	0.046	***
White	0.491	0.052	***	0.516	0.052	***
Tract Amenities and Land Use						
Number of Workers in Arts, Service, per sq. mile (ln)	0.171	0.014	***	0.129	0.014	***
Constant	6.283	0.125	***	-2.109	0.124	***
Adjusted R^2	0.543			0.499		

Linear regression. [1]Jobs plus residents. NS not significant, * p<0.1, ** p<0.05, *** p<0.01.

Lyft and the Built Environment

Lyft service is overall positively associated with density. Figure 18 shows the percentage change in Lyft service (both total trips and trips per capita) is associated with a 10 percent increase in the five measured densities, controlling for other factors. Relative to socioeconomic factors, discussed next, built environment variables are weakly associated with Lyft service. Transit stop density has the strongest association with Lyft service; a 10 percent increase in the number of transit stops per square mile is associated with about a 2.5 percent increase in Lyft service. The associations between population and off-street parking density diverge between Lyft trips and trips per capita. A 10 percent increase in population density is associated with a one percent increase in Lyft trips per capita, but also a one percent decrease in total Lyft trips, controlling for other factors. Similarly, a 10 percent increase in off-street parking density is associated with about a 0.8 percent increase in total Lyft trips, but a 1.4 percent decrease in Lyft trips per capita.

Figure 18. Associations between Built Environment Variables and Lyft Service

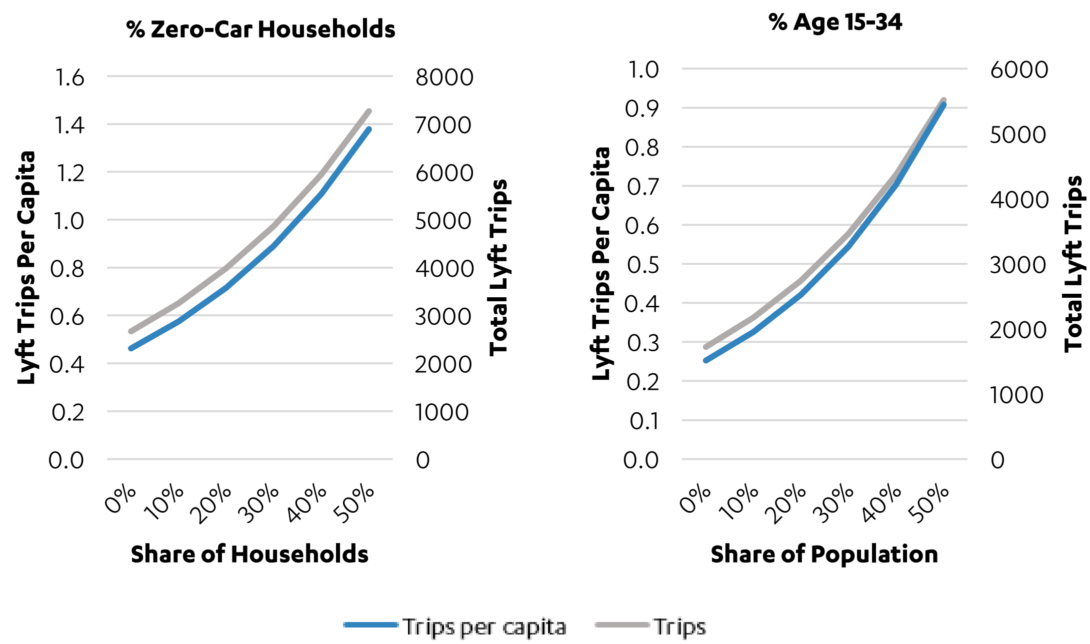


Error bars indicate 95% confidence intervals.

Lyft and Neighborhood Socioeconomic Characteristics

Like the built environment, neighborhood socioeconomic characteristics are associated with Lyft service. The strongest association between both total Lyft trips and Lyft trips per capita is with the share of the population between 15 and 34 years old and the share of households without a car. Figure 19 shows predicted Lyft trips and trips per capita when a neighborhood has between zero and 50 percent of households without a car and between zero and 50 percent of residents ages 15 to 34, holding other neighborhood characteristics constant. For every 10 percent increase in the share of households without a car, Lyft service is predicted to increase between 22 and 30 percent. For every 10 percent increase in the share of the population between age 15 and 34, Lyft service is predicted to rise about 25 percent. More Lyft trips in neighborhoods home to more young adults may reflect youths' increased ridehail adoption, as documented by previous researchers: nationally, Clewlow and Mishra (2017) find that over one-third (36%) of adults between age 18 and 29 have used ridehailing compared to just four percent of adults over 65 years old. Alternatively, the positive association between Lyft use and young adults could represent barriers that older adults face in accessing ridehail services.

Figure 19. Association between Lyft Service, Household Car Ownership, and Population Age

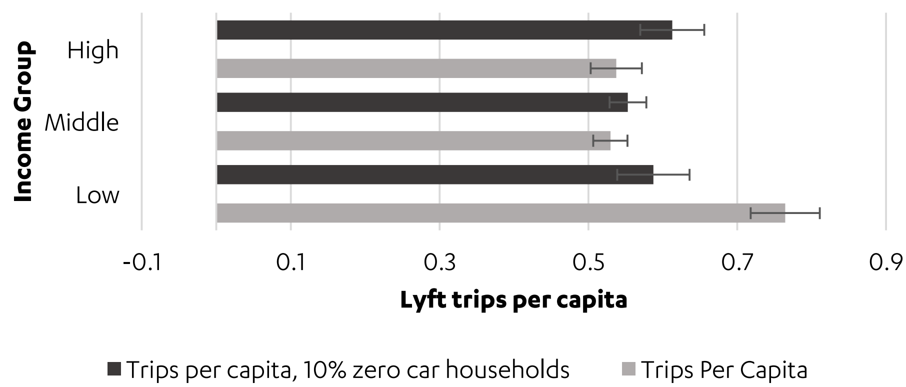


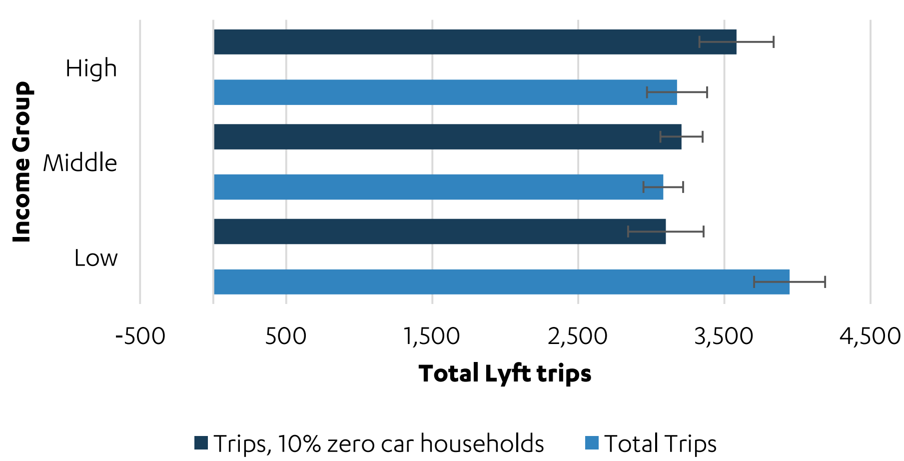
Neighborhood income group and share of zero-car households both reflect the financial resources in a neighborhood,[38] and yet they present, at first glance, conflicting results. While the share of zero-car households is the second strongest—and positive—predictor of Lyft service in both models, low-income neighborhoods are associated with less Lyft service. Why might this be? One explanation is that Lyft is a normal good; people with higher incomes use more of it, all else equal. However, in this case, the income groups are not equal in all respects. Specifically, access to personal vehicles, which may substitute for ridehailing, varies greatly across neighborhood income; on average, 21 percent of households in low-income neighborhoods do not own a car compared to less than four percent of households in high-income neighborhoods.

[38] Neighborhood median household income is negatively correlated (-0.58, $p<0.05$) with the share of households owning zero vehicles.

Figure 20 shows how car ownership affects predicted Lyft service. Predicting service using the mean characteristics of low-, middle-, and high-income neighborhoods, Lyft service is actually *higher* in low-income neighborhoods. Holding the share of households without a car constant at 10 percent, however, predicts more service in high-income neighborhoods. In other words, the high Lyft service in low-income neighborhoods is not related to income per se, but rather the access that income provides to ridehailing's close substitute, the household car. Predicted values also suggest that Lyft neighborhood service mirrors the bimodal distribution of taxi service, with more service in high- and low-income neighborhoods (Schaller 2015).

Figure 20. Lyft Service Across Income Groups

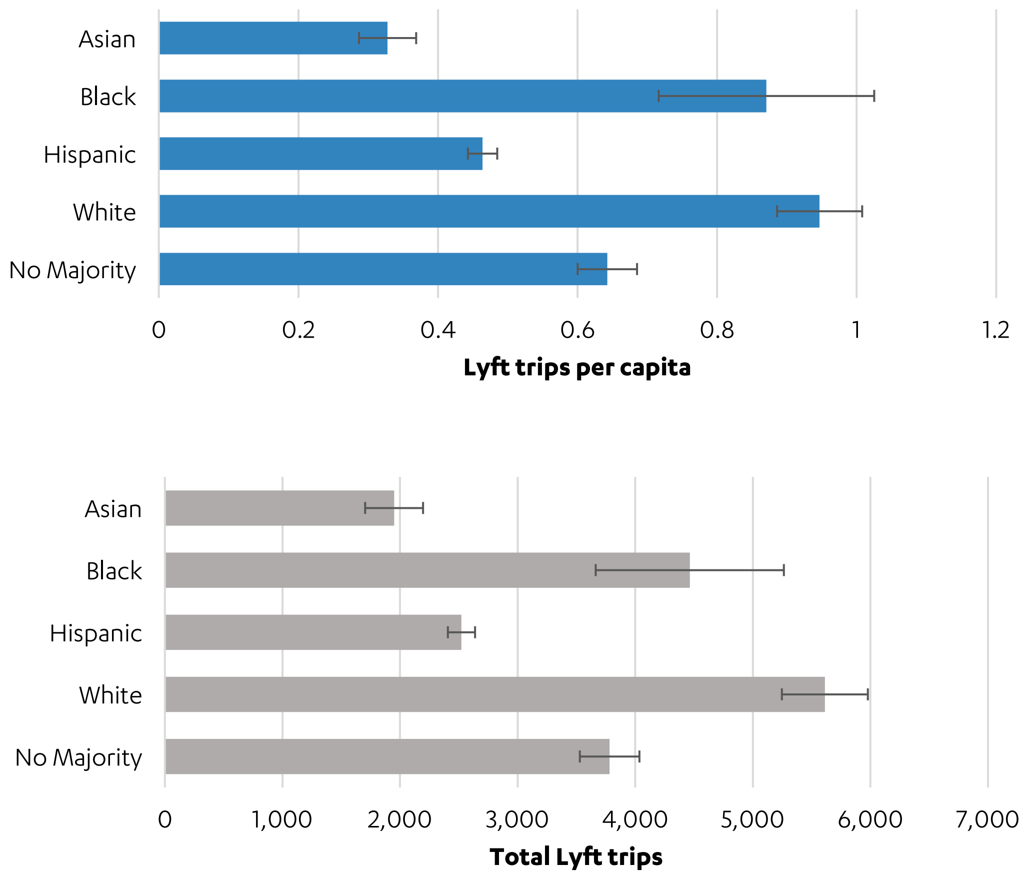




Error bars indicate 95% confidence intervals.

Compared to neighborhoods with no racial majority, majority-white and majority-black neighborhoods are associated with significantly more Lyft service, while majority-Asian and Hispanic neighborhoods are associated with significantly less service. Figure 21 shows predicted Lyft service across the five neighborhood groups. Unlike neighborhood income, differences remain even when setting household vehicle ownership or income equal. Fewer trips in majority Asian and Hispanic neighborhoods, even after controlling for built environment factors and income, may relate to how residents themselves use Lyft, which I explore in Chapter 5.

Figure 21. Lyft Service Across Racial/Ethnic Majority Neighborhoods

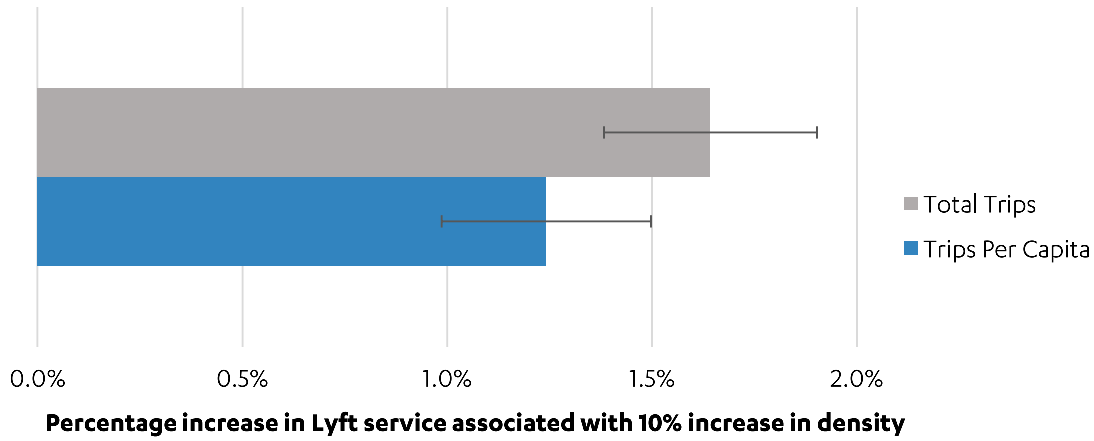


Error bars indicate 95% confidence intervals.

Lyft and Neighborhood Amenities

Surveyed ridehail users report that social and leisure activities (visiting friends, going to bars, etc.) are the most common ridehail trip purpose (Clewlow and Mishra 2017, Rayle et al. 2016, Henao 2017, Gehrke, Felix, and Reardon 2018, Feignon and Murphy 2018). Model results show that stated trip purposes translate into more service in areas where social and leisure activities concentrate. In both models, more workers per square mile in arts, food, and recreation is positively associated with Lyft service. Because both models already control for density, this finding suggests that not just the number of activities influence Lyft use, but also the types of activities in a neighborhood.

Figure 22. Association between Lyft Service and Neighborhood Amenities



Error bars indicate 95% confidence intervals.

CHAPTER 5. WHAT EXPLAINS INDIVIDUAL LYFT USE

Lyft pickups and drop-offs in a neighborhood does not necessarily mean that neighborhood residents are riding Lyft. For example, if 100 Lyft trips start or end in Los Angeles' Koreatown, are people visiting the neighborhood's abundant bar and restaurant scene making these trips or are residents? Distinct from Research Question 1—which focuses on *where* Lyft serves people—Research Question 2 investigates *who* Lyft serves and specifically, the factors associated with individual Lyft use.

This chapter focuses only on Lyft users who live in Los Angeles County. More than two-thirds (69%) of users who rode Lyft between September and November live in Los Angeles County; residents, however, travel differently than non-residents. Appendix C discusses where non-residents live and how their Lyft travel differs from residents. In a nutshell: compared to residents, non-residents make significantly longer and fewer trips, a higher share of which are to or from one of Los Angeles' three major airports.

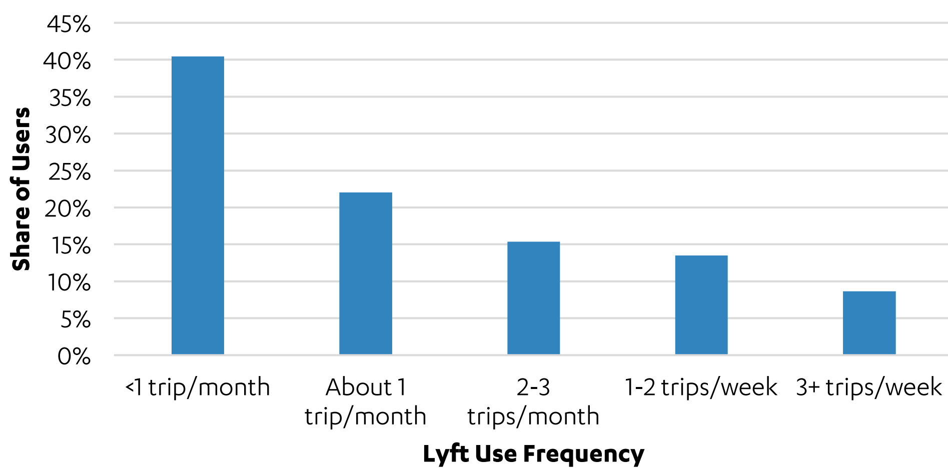
In total, 571,115 unique users living in Los Angeles County took at least one Lyft trip between September and November 2016. Together, these users comprise 6.5 percent of Los Angeles County residents age 15 and older (U.S. Census Bureau 2016). Users' share of the total population likely underestimates both the total number of Lyft users and the total number of Lyft riders; users who did not make a trip during this time period are excluded from this sample, as are Lyft riders who rode with friends or family but did not hail a trip themselves. This estimate also does not reflect full ridehail adoption among the Los Angeles population as it excludes those who rode other ridehail services; nationally, Clewlow and Mishra (2017) estimate that 21 percent of American adults have hailed a ridehail trip and an additional nine percent have ridden with others but not installed the app themselves.

I divide this chapter into five sections. I first discuss how frequently individuals ride Lyft. Second, I explore the spatial distribution of Los Angles Lyft users and the types of neighborhoods in which they live compared to the average Angeleno. Third, I discuss how Lyft use varies by residents living in low-, middle- and high-income neighborhoods. Fourth, I compare Lyft use by residents living in neighborhoods with different racial/ethnic majorities. Finally, I present results from negative binomial, logistic, and linear regression models that show the relative importance of built environment and socioeconomic factors associated with individual Lyft-use.

How Frequently Do People Ride Lyft?

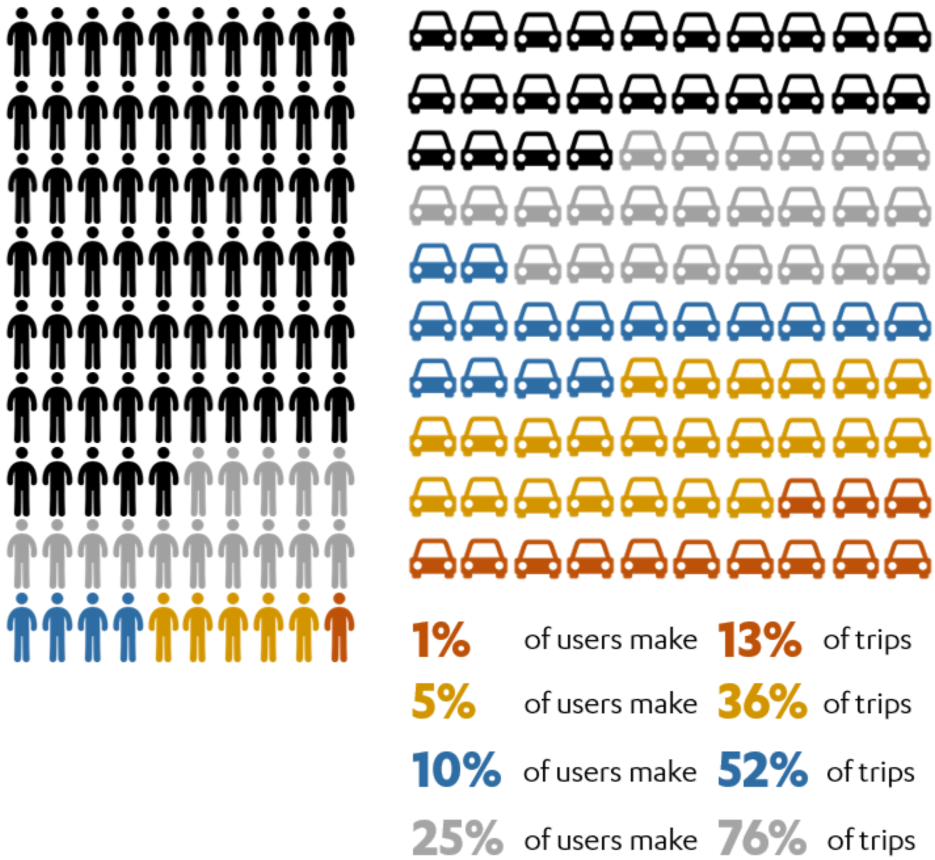
The majority of Lyft users ride Lyft only occasionally; Figure 23 shows that 40 percent of users took less than one trip per month, while just one-fifth (22%) of riders made one or more Lyft trip per week. These findings suggest that while Lyft has become a staple mode for some travelers, most travelers use Lyft sporadically to fill occasional modal gaps or trip-specific needs; these findings are consistent with both national and California data (Circella 2018, Clewlow and Mishra 2017).

Figure 23. Distribution of Lyft Use Frequency



Similar to transit, where a small fraction of riders make the majority of trips (Manville, Taylor, and Blumenberg 2018), Lyft use is highly asymmetrical. Figure 24 shows that 10 percent of Lyft users made over half (52%) of Lyft trips, the top five percent of riders made one-third (36%) of all trips.

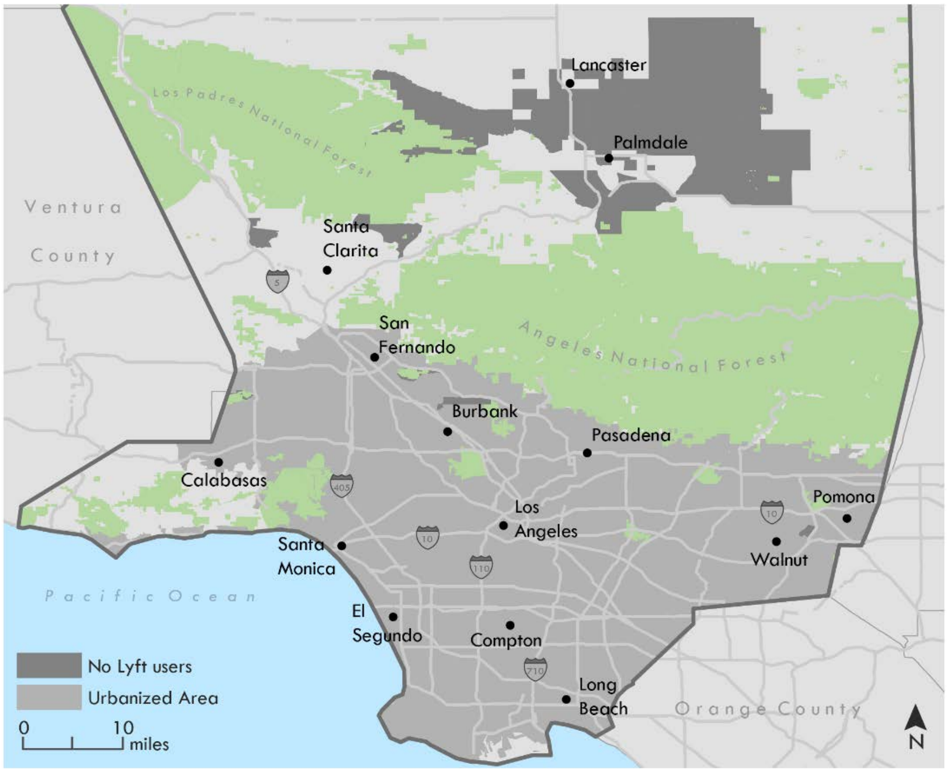
Figure 24. Lyft Users and Trips



Where do Lyft-Riding Angelenos Live?

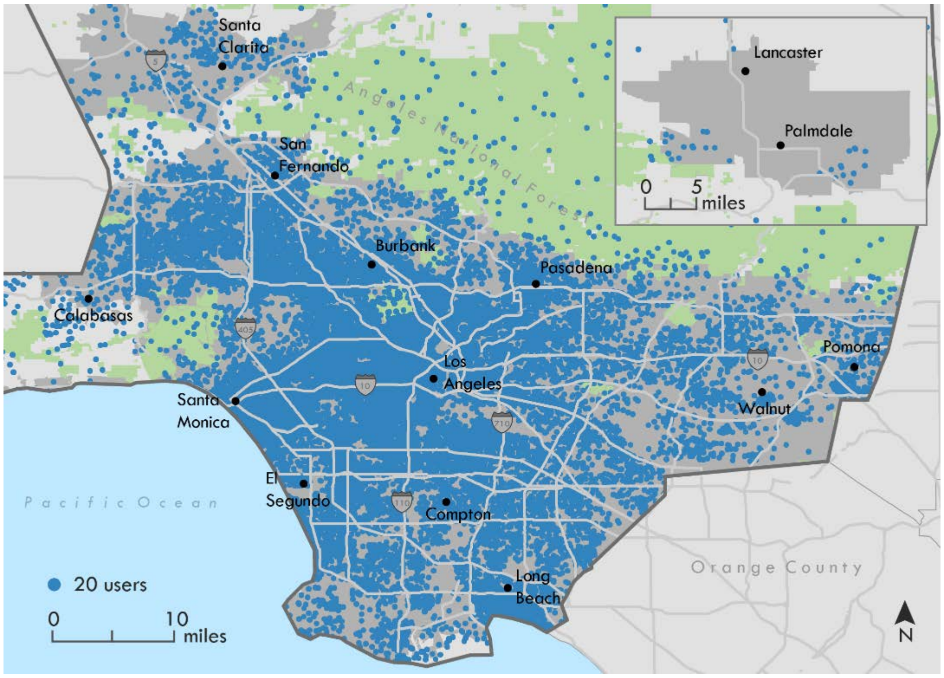
Lyft users live almost everywhere in Los Angeles; nearly every tract (98%, n=2,287) in Los Angeles County was home to a Lyft user who took at least one Lyft trip between September and November 2016. Figure 25 shows that tracts with no users are in the far northeastern sections of the county, surrounding Saddleback Butte State Park, Phacelia Wildlife Sanctuary, agricultural land, and the low-density, medium-sized cities of Palmdale and Lancaster.

Figure 25. Tracts with No Lyft Users



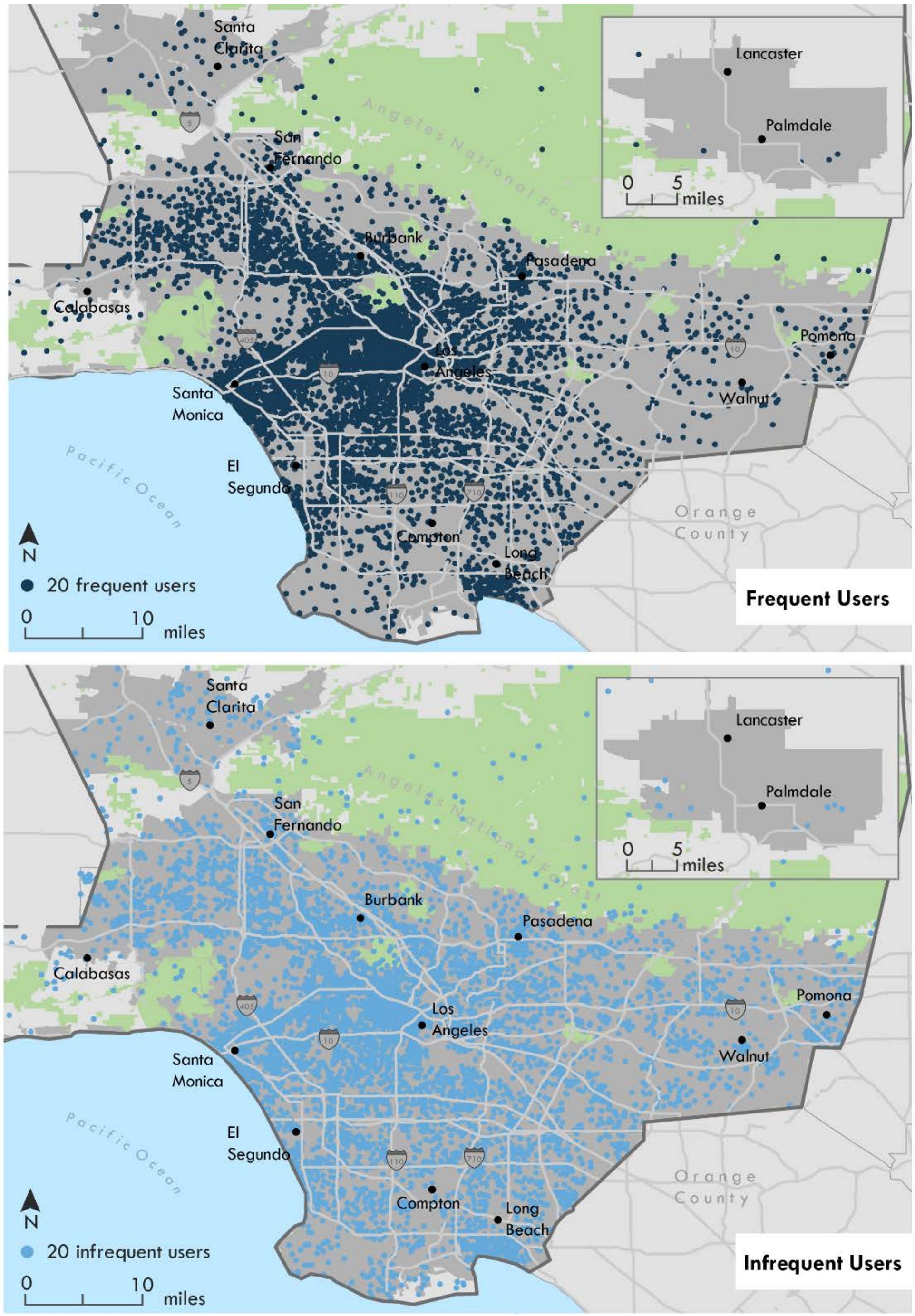
In contrast to Figure 25, which shows where Lyft users are not located (almost nowhere), Figure 26 shows where Lyft users are located (almost everywhere). Like trips, Lyft users are more concentrated in the densest centers of the county and less concentrated in more outlying, suburban areas.

Figure 26. Distribution of Lyft Users



While Lyft users live nearly everywhere, frequent and infrequent Lyft users have different spatial distributions. Figure 27 shows that both frequent and infrequent Lyft users live throughout the county, but frequent users are clustered more tightly around the urban core compared to infrequent users. Compared to infrequent users, frequent users live in neighborhoods that are denser, more transit-rich, and differ in their demographic and socioeconomic characteristics (see Table 14). Both infrequent and frequent users live in neighborhoods with more transit service and in neighborhoods that are disproportionately black and white compared to the county as a whole.

Figure 27 Distribution of Frequent vs. Infrequent Lyft Users



Frequency is determined by trip quartile. Frequent users are those that fall into the top quartile of trips made (9+ trips over 3 months), while infrequent users are in the bottom quartile (1 trip over 3 months).

Table 14. Home Tract Averages for Frequent vs. Infrequent Lyft Users

	Frequent Lyft User[1]	Infrequent Lyft User[1]	Sig.[2]	Los Angeles County
Built Environment				
Population Density	28.3	22.4	***	22.1
Employment Density	12.8	9.0	***	6.6
Transit Stop Density	42.5	31.7	***	26.3
Tract Socioeconomic Characteristics				
Household Income	$58,655	$64,867	***	$61,239
% Renter	65.8%	55.9%	***	53.0%
% Zero Vehicle HHs	12.9%	10.1%	***	10.0%
Commute Mode				
% SOV[3]	68.4%	71.7%	***	72.1%
% Carpool	8.4%	9.0%	***	10.1%
% Transit	9.6%	7.2%	***	7.4%
% Walk	4.4%	3.8%	***	3.0%
% Other	2.8%	2.4%	***	2.3%
Age				
% Ages 15-34	32.9%	30.8%	***	30.1%
% Ages 35-64	39.3%	39.7%	***	39.1%
% Ages 65+	11.8%	12.5%	***	12.1%
Race/Ethnicity				
% Hispanic	40.2%	40.8%	***	47.8%
% Asian	13.9%	14.8%	***	13.9%
% Black	8.4%	7.8%	***	3.3%
% Other	0.71%	0.74%	***	0.7%
% White	34.3%	33.5%	***	27.5%

[1]Frequent and infrequent users refer to the top (9+ trips over three months) and bottom (1 trip over three months) quartile of users in terms of total number of trips taken, respectively.
[2]Significance between frequent and infrequent users, NS Not Significant, * p<0.1, **p<0.05, ***p<0.01. Sources: U.S. Census (2015a), Environmental Protection Agency (2014). [3]SOV indicates Single Occupancy Vehicle.

Lyft Users in High- and Low-Income Neighborhoods

As discussed in Chapter 2, taxis users have historically had disproportionately very-high and very-low incomes; as of 2009, households earning less than $25,000 per year made 17 percent of all trips, but 41 percent of all taxi trips (Schaller 2015). With ridehailing offering on-demand car service similar to taxis, one might expect ridehail users to also have disproportionately high and low-income. Instead, Table 15 shows that users living in low-income neighborhoods made more Lyft trips per person on average compared to users living in either middle- or high-income neighborhoods. While previous research finds that ridehail adoption rises with income (Clewlow and Mishra 2017), no research has yet examined trip frequency across different income groups. These findings suggest that although a higher share of people living in higher-income neighborhoods have used ridehailing at least once (i.e., are infrequent users, see Table 14), ridehailing likely serves very different roles for different income groups. Many users living in high-income neighborhoods already have reliable car access and make three car trips per day on average;[39] for many of these users, Lyft may fill more niche trip purposes, such as going to the airport,[40] business trips, or going out at night. Users living in low-income neighborhoods, by contrast, may have low—or zero—personal car access and therefore use Lyft to provide rather than supplement auto-mobility.

Table 15. Average Trip Characteristics Across Neighborhood Income

	Mean Trips per User[1]	**Mean % Line Trips**	**Mean % Peak Trips**	**Mean Distance**	**Mean Price**	**Share of Users**	**Share of Los Angeles population**
Low (≤$38,319)	10.5	27.4%	21.3%	7.7	$9.98	23.9%	23.2%
Middle ($38,320-$76,364)	9.0	20.0%	20.5%	8.7	$11.13	49.3%	51.6%
High (≥$76,365)	7.7	15.8%	20.5%	9.6	$12.38	26.8%	25.2%
Average/Total	*9.0*	*20.6%*	*20.7%*	*8.7*	*$11.19*	*100%*	*100%*

[1]Number of trips over the three-month study period. Source: U.S. Census (2015a).

In addition to Lyft trip frequency, trip distance and price occur across an income gradient. Lower-price and shorter-distance trips in low-income neighborhoods may reflect the geography of lower-income neighborhoods (see Figure 28), which tend to be denser and thus destinations closer together compared to higher-income neighborhoods. Relatively short and cheap trips may also reflect the types of trips made by users in different neighborhoods.

[39] High-income households in Los Angeles make about one additional regular car trip per day compared to low-income households (3 vs. 2 trips); this is partly due to far higher-rates of carlessness among low-income compared to high-income households (18% vs. 2%). Even among households that own cars, high-income households have more cars per household on average than low-income households (2.3 vs. 1.5 cars) (California Department of Transportation 2012).

[40] Twenty-eight percent of users living in high-income neighborhoods made one or more trip to the airport over the three-month period compared to 14 percent of users living in low-income neighborhoods.

Before ridehailing, low-income households relied frequently on other shared car modes such as carpooling, borrowing cars, car sharing, informal services such as jitneys, and taxis (Pucher and Renne 2003, Blumenberg 2013). Reliance on shared car services extends to present Lyft use, and users living in low-income neighborhoods made over one-quarter (27%) of their Lyft trips using Lyft Line on average. By comparison, users living in middle- and high-income neighborhoods made 20 and 16 percent of their trips using Lyft Line, respectively. Varying rates of sharing across incomes may reflect spatial differences, or differing time-sensitivity and willingness to share a ride with other social classes (Sarriera et al. 2017).

Figure 28. Lyft Use Across Neighborhood Income

High income (≥$76,365), Middle income ($38,320-$76,364), Low-income (≤$38,319).

Lyft Users by Neighborhood Racial-Ethnic Makeup

The share of Lyft users living in the five racial/ethnic-majority neighborhoods relative to the share of the Los Angeles population in each speaks to relative Lyft adoption. Ridehail adopters are people who have and use ridehail apps. Table 16 shows that, relative to the share of the Los Angeles population, a disproportionately low share of users live in majority-Hispanic neighborhoods and a disproportionately high share of users live in majority-white neighborhoods.

The lower share of Lyft users in majority-Hispanic neighborhoods may reflect banking or technological barriers to Lyft access in these neighborhoods. Spanish-only speaking households have far lower rates of smartphone ownership (47%) compared to households where Spanish is not the only spoken language (68%) (FDIC 2016). In addition, smartphone access—or at least the data plans that smartphones require—may be ephemeral, particularly for groups who rely on them most. For example, Smith (2015) finds that 44 percent of smartphone users lost service at some point or another due to financial constraints. This was particularly common among groups who relied on smartphones to access to the internet: low-income, black, and Latino users are all twice as likely to have cancelled or lost service at some point compared to higher-income and white users (Smith, McGeeney, Duggan, et al. 2015). Without a smartphone or data plan, travelers cannot hail Lyft.

Table 16. Average Trip Characteristics for Users Across Majority Racial/Ethnic Neighborhoods[1]

	Mean Trips per User	Mean % Line Trips	Mean % Peak Trips	Mean Distance	Mean Price	Median Household Income	Share of Users	Share of LA Population
Asian	7.45	20.27%	21.43%	9.51	$12.21	$57,976	5.2%	5.2%
Black	10.23	25.85%	21.39%	8.45	$10.79	$51,494	2.4%	2.4%
Hispanic	9.08	23.62%	20.32%	8.28	$10.59	$42,333	36.4%	47.6%
White	9.03	17.40%	20.62%	9.04	$11.69	$87,557	33.6%	23.2%
No Majority	9.08	20.14%	21.00%	8.73	$11.23	$58,646	22.4%	21.7%
Average/Total	*9.0*	*20.6%*	*20.7%*	*8.7*	*$11.19*	*$62,233*	*100%*	*100%*

[1]Over three-months. Source: U.S. Census (2015a).

Adoption, however, belies striking differences in how Lyft use varies across residents living in different racial/ethnic-majority neighborhoods. Users living in majority-Asian neighborhoods made the fewest trips per person (7.45) on average, while residents in majority-black neighborhoods made the most trips per person (10.23) on average. The number of Lyft trips per person aligns closely with the share of zero car households. As discussed in Chapter 4, majority-black and majority-Hispanic neighborhoods have far higher shares of zero-car households (15 and 13 percent, respectively) compared to either majority-white or majority-Asian neighborhoods (nine and six percent, respectively). Together, adoption and frequency statistics suggest that while a higher-share of residents living in majority-white neighborhoods adopt Lyft, how often individuals use Lyft aligns more closely with the availability of other modes of car access, including personal vehicle ownership.

In addition to trip frequency and Lyft adoption, average trip price, distance, and sharing varies across racial/ethnic-majority neighborhoods. Figure 29 shows Lyft use frequency across the five racial/ethnic-majority neighborhoods; with different built environmental characteristics, it remains unclear if and how neighborhood racial/ethnic composition associates with Lyft use. I explore the relative strengths of the associations between neighborhood built environment and socioeconomic characteristics and individual Lyft use in the following sections. I present associations in five sections, one for each of four dependent variables: total trips, share of trips on Lyft Line, average distance, and average price.

Figure 29. Lyft User Trip Frequencies Across Racial/Ethnic Majority Neighborhoods

Factors Associated with Individual Lyft Use

Total Trips

Table 17 identifies the associations between neighborhood built environment, socioeconomic, and amenities factors and the number of Lyft trips that an individual made.

Table 17 . Neighborhood Characteristics Associated with Users' Lyft Trip Frequency

Built Environment	**Coef.**	**St. Error**	**Sig.**
Population Density (people/acre) (ln)	0.080	0.003	***
Employment Density (jobs/acre) (ln)	0.004	0.002	***
Road Network Density	-0.001	0.000	***
Transit Stop Density (stops/mile) (ln)	0.077	0.002	***
On-street parking (spaces/sq. mile) (ln)	-0.005	0.003	NS
Off-street parking (spaces/sq. mile) (ln)	-0.021	0.003	***
Tract Socioeconomic Characteristics			
Neighborhood Income Group *(Baseline: Middle)*			
Low-Income	0.018	0.006	***
High-Income	-0.026	0.005	***
Percent Zero Vehicle Households	0.644	0.026	***
Percent ages 15-34	0.223	0.022	***
Neighborhood Racial/Ethnic Majority *(Baseline: No Majority)*			
Asian	-0.146	0.009	***
Black	0.155	0.011	***
Hispanic	-0.037	0.005	***
White	0.105	0.005	***
Tract Amenities & Land Use			
Number of Workers in Arts, Service, per sq. mile (ln)	0.008	0.001	***
Constant	1.681	0.012	***

Negative binomial regression. NS not significant, * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

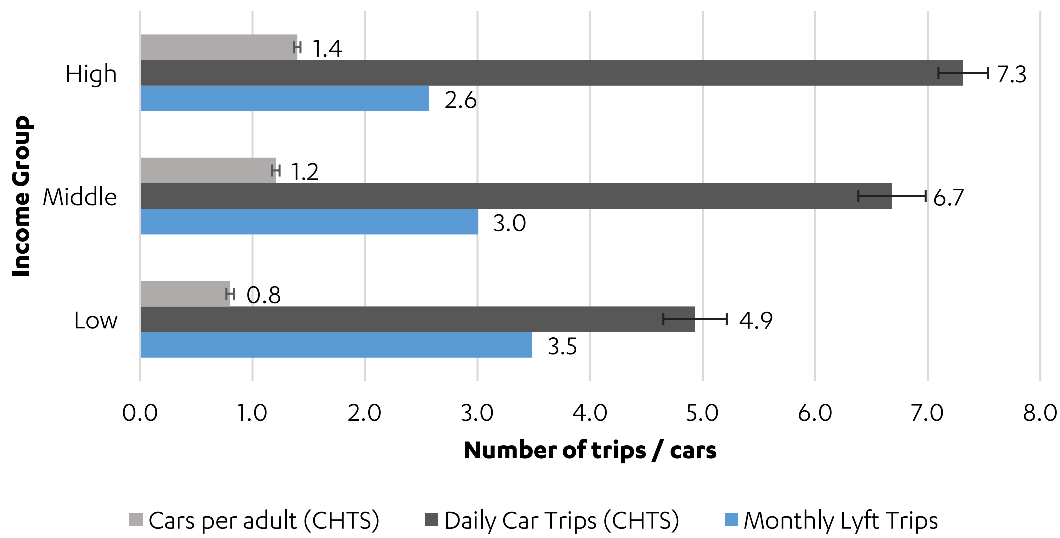
Holding other potential determinants constant, living in a denser neighborhood is positively associated with Lyft trip frequency. The exceptions are road network and off-street parking density, which are negatively associated with Lyft use, all else equal. In general, a 10 percent increase in any one of the density variables is associated with less than a 0.1 percent increase or decrease in the number of trips an individual makes, holding other factors constant. The association between density and Lyft use is weaker than that between Lyft use and neighborhood socioeconomic factors.

The strongest predictor of individual Lyft use is the share of households in a user's home neighborhood without a car. Every 10 percent increase in the share of households without a car is associated with a seven percent increase in the number of Lyft trips a user makes; this association is inverse to the one typically observed in travel survey data. In Los Angeles, zero-car households make just one car trip per day compared to car-owning households, who make seven daily car trips on average (California Department of Transportation 2012).

The association between zero-car households in a neighborhood and individual Lyft use holds across income groups, although the association between income and Lyft use is relatively weak when separated from car ownership. Moving from a middle- to high-income neighborhood is associated with a 1.8 percent decrease in trips, and moving from a middle- to a low-income neighborhood is associated with a 2.6 percent increase in trips.

Together, neighborhood income and car ownership data suggest that Lyft use is inversely associated to auto resources in a neighborhood rather than a simple function of income. Figure 30shows that low-income households make just two-thirds the number of car trips and own half the number of cars per adult compared to high-income households (California Department of Transportation 2012). While low-income households have less personal auto access, households living in low-income neighborhoods make 36 percent more Lyft trips per month compared to users living in high-income neighborhoods. In other words, Lyft use is highest where ready substitutes to car access—the household car—are scarcest.

Figure 30. Predicted Number of Lyft vs. Car Trips and Ownership Across Incomes



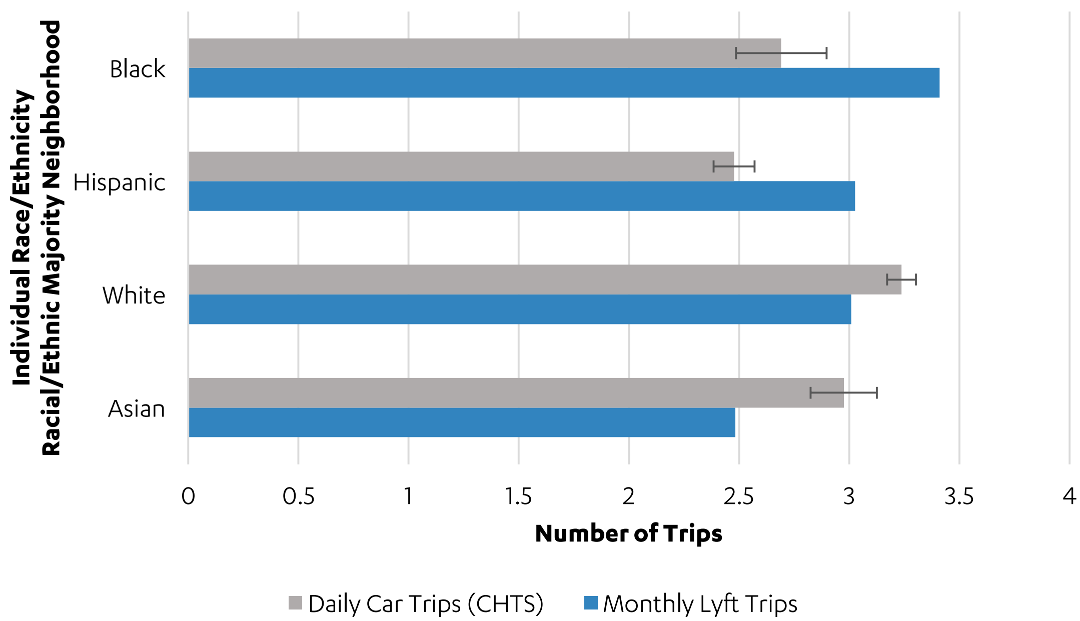
Source: California Household Travel Survey (2012). Adults are survey respondents age 20 or older. CHTS data are reported at the household level. Error bars indicate 95% confidence intervals.

Living in neighborhoods with higher percentages of young adults (ages 15 to 34) is the second largest and positive predictor of individual Lyft use; every 10 percent increase in the share of the population between ages 15 and 34 is associated with a two percent increase in the number of Lyft trips an individual makes. The association between neighborhood population age and Lyft use suggests that in addition to young adults adopting ridehailing at higher rates compared to older adults (Clewlow and Mishra 2017, Rayle et al. 2016, Henao 2017), people living in areas with many young adults take Lyft more frequently, all else equal. Frequent Lyft use by younger adults may reflect a greater awareness of ridehailing,[41] more active nightlives, and/or greater technology literacy and smartphone adoption (FDIC 2016). Or, rather than representing young adult attraction to ridehail services, the association could reflect barriers that older adults face to ridehail access, such as lack of a smartphone or discomfort paying for services over the internet (Shirgaokar 2018).

[41] Although Clewlow & Mishra (2017) find that only 10 percent of all adults in American cities have never heard of ridehailing.

Contrary to expectations, the racial/ethnic composition of a neighborhood is associated with the total number of Lyft trips an individual makes, even after controlling for the built environment and neighborhood income; the direction of this effect for different racial/ethnic groups is intriguing. Riders living in majority-Asian and majority-Hispanic neighborhoods take significantly fewer trips per person, on average, while riders living in majority-black and majority-white neighborhoods take significantly more trips than those living in more diverse neighborhoods, all else equal. There are a number of possible explanations for these patterns. First, it may again reflect relative levels of car ownership in these neighborhoods; similar to patterns observed with income, Figure 31 shows that daily car trips by race/ethnicity are nearly inverse to Lyft use. However, holding the share of households without a vehicle constant does not erase differences across racial/ethnic-majority neighborhoods.

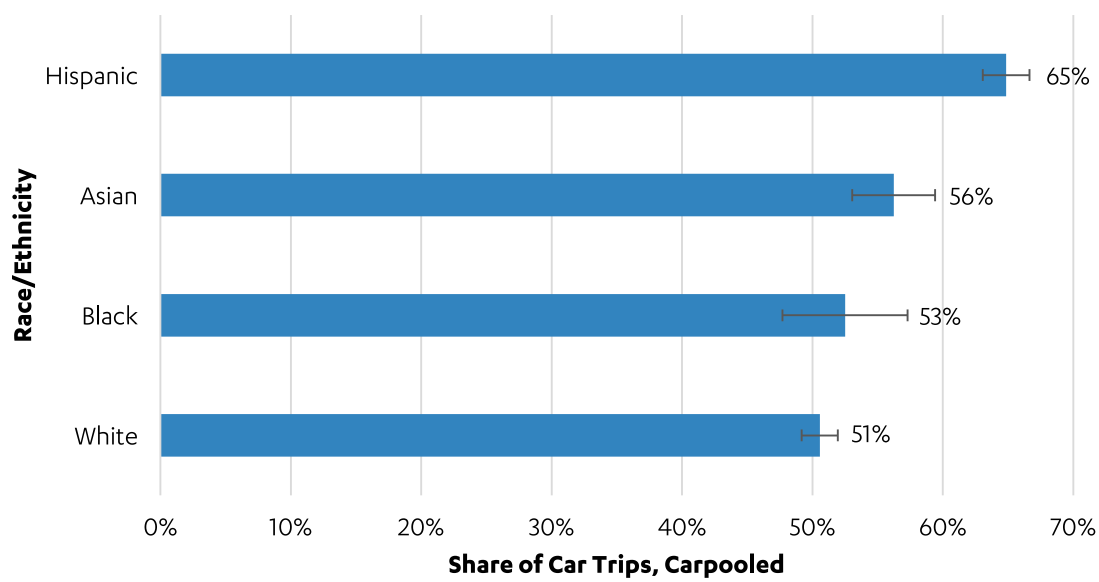
Figure 31. Lyft vs. Car Trips by Race/Ethnicity



Source: California Household Travel Survey (2012). Error bars indicate 95% confidence intervals.

A second explanation for these differences is that people use existing vehicle resources differently across neighborhoods. For example, immigrants living in immigrant-communities carpool at higher rates for all trip purposes than do native-born adults or immigrants living in non-immigrant neighborhoods (Blumenberg and Smart 2014). Indeed, Figure 32 shows that in Los Angeles, Asian and Hispanic drivers made a higher share of their trips in a carpool (with both family members and non-members) compared to either white or black travelers (California Department of Transportation 2012). Car access in majority-Asian and majority-Hispanic neighborhoods may therefore be met, to some extent, by pooling together limited auto resources. Additionally, auto resources in majority-Asian neighborhoods may be more plentiful than the share of zero car household would suggest. While about 8.5 percent of households in majority-Asian households do not own a car—on par with other neighborhoods—more than one-quarter of households living in majority-Asian neighborhoods have *more than three cars* compared to about 20 percent of households living in non-majority Asian neighborhoods. It is therefore possible that households living in majority-Asian neighborhoods perceive no need for ridehailing because their demand for car access if fully sated by the vehicles they own. Another possibility for car access, specifically in majority-Hispanic neighborhoods are *camionetas*, informal jitney services which are used primarily by Mexican immigrants to gain access to flexible transportation (Valenzuela, Schweitzer, and Robles 2005).

Figure 32. Carpooling Across Race/Ethnicity



Source: California Household Travel Survey (2012). Error bars indicate 95% confidence intervals.

Importantly in the context of taxi drivers' chronic and unlawful refusal to serve communities of color—particularly majority-black neighborhoods (LaMendola 1991)—spatial discrimination does not appear to affect overall Lyft trip-making. Spatial data, however, provide only one clue into potential discrimination in ridehailing. Discrimination may also manifest in longer wait times or higher cancellation rates; I examine these facets of discrimination in Part II.

Shared Trips

Table 18 shows the associations between a user's home neighborhood and the share of Lyft trips that they make on Lyft Line, Lyft's rideshare service. The strongest associations with shared use are with the share of households without a car and the share of the population between ages 15 and 34. All else equal, a 10 percent rise in the share of carless households and the share of the population between 15 and 34 years old is associated with a respective 2.5 and 2.3 percent increase in the share of trips a person makes on Lyft Line.

Living in a neighborhood with a racial/ethnic majority is associated with a user making a higher share of trips on Lyft Line. These findings suggest that people are more willing to hail a shared ride when the odds of sharing it with someone of the same race/ethnicity are higher; findings are consistent with previous research, which finds that people are more likely to carpool when surrounded by neighbors of the same race (Charles and Kline 2006). In addition, previous ridesharing research finds that between seven and 24 percent of any given racial/ethnic group report being neutral to uncomfortable with sharing a ride with a person of a different race or ethnicity (Sarriera et al. 2017).

Living in a low-income neighborhood is associated with taking a higher share of trips on Lyft Line compared to middle-income neighborhoods. Users living in low-income neighborhoods make 27 percent of trips on Lyft Line compared for 20 and 16 percent of users living in middle- and high-income neighborhoods, respectively. This suggests that users living in lower-income neighborhoods are either more price-sensitive and/or more willing to share rides; previous research finds evidence for both possibilities (Sarriera et al. 2017).

Finally, built environment associations suggest that, overall, living in denser neighborhoods with more people, jobs, and transit per square mile, is associated with making a higher share of Lyft trips on Lyft Line. As with Lyft use frequency, the built environment has a weaker association with ridesharing compared to neighborhood socioeconomic factors.

Table 18. Share of Trips on Lyft Line

Built Environment	**Coef.**	**St. Error**	**Sig.**
Population Density (people/acre) (ln)	0.082	0.005	***
Employment Density (jobs/acre) (ln)	0.002	0.003	NS
Road Network Density	-0.006	0.001	***
Transit Stop Density (stops/mile) (ln)	0.114	0.004	***
On-street parking (spaces/sq. mile) (ln)	0.013	0.006	**
Off-street parking (spaces/sq. mile) (ln)	-0.057	0.005	***
Tract Socioeconomic Characteristics			
Neighborhood Income Group *(Baseline: Middle)*			
Low-Income	0.145	0.010	***
High-Income	-0.008	0.010	NS
Percent Zero Vehicle Households	1.171	0.047	***
Percent ages 15-34	1.094	0.037	***
Neighborhood Racial/Ethnic Majority *(Baseline: No Majority)*			
Asian	0.040	0.016	**
Black	0.331	0.020	***
Hispanic	0.054	0.009	***
White	0.020	0.009	**
Tract Amenities & Land Use			
Number of Workers in Arts, Service, per sq. mile (ln)	-0.058	0.001	***
Constant	-1.637	0.024	***

Logistic regression. NS not significant, * p<0.1, ** p<0.05, *** p<0.01.

Trip Price and Distance

Table 19 shows that factors associated with users' average distance traveled are nearly identical to those associated with average price paid; this is logical as Lyft price is based partly on trip distance and the two variables are near-perfectly correlated (0.94, $p<0.05$). With the exception of off-street parking density, the density of a home user's neighborhood is negatively associated with average trip distance and price, likely reflecting shorter distances between destinations in dense areas. Living in a low-income neighborhood is associated with taking shorter and cheaper trips, all else equal, although the actual differences are quite small. Moving from a middle- to low-income neighborhood is associated with a 31-cent decrease in trip cost and a one-quarter mile shorter trip. The opposite holds for living in a high-income neighborhood, although the association is even weaker. As with other Lyft use variables, the share of young adults and zero-car households are strongly associated with trip distance and price. A 10 percent increase in the share of young adults and zero-car households in a neighborhood is associated with a respective one and two percent decrease in trip distance, all else equal.

Compared to neighborhoods with no racial/ethnic majority, living in a majority-black, Hispanic, or white neighborhood is associated with shorter and lower-price trips. Living in a majority-Asian neighborhood, by contrast, is associated with more expensive and longer trips, controlling for other factors. These patterns may reflect price-sensitivity, willingness to use Lyft, and/or a need for car access on short rather than medium or long-distance trips.[42]

[42] Unlike the other models presented in this research, the associations between neighborhood characteristics and trip price and distance change when airport trips are excluded (not shown). Excluding airport trips preserves the direction and relative magnitudes of all coefficients *except* neighborhood racial/ethnic categories. When airport trips are excluded, users living in majority-Asian, black, and Hispanic neighborhoods each take longer and more expensive trips compared to users living in neighborhoods with no racial/ethnic majority. Excluding airport trips, people living in majority-white neighborhoods make shorter and lower cost trips all else equal. This difference (compared to when all trips are included) reflects the distribution of airport trips across neighborhoods: users living in majority-white neighborhoods make about half of all airport trips and users living in no-majority neighborhoods make another quarter. Users living in majority-Asian, black, and Hispanic neighborhoods made only 23 percent of airport trips, despite taking 44 percent of non-airport Lyft trips. For more detail on Lyft airport trips, see Appendix D.

Table 19. Average Trip Price and Distance

Built Environment	**Distance** *Coef.*	*St. Error*	*Sig.*	**Price** *Coef.*	*St. Error*	*Sig.*
Population Density (people/acre) (ln)	-0.530	0.015	***	-0.481	0.015	***
Employment Density (jobs/acre) (ln)	-0.027	0.009	***	-0.602	0.018	***
Road Network Density	-0.016	0.001	***	-0.035	0.010	***
Transit Stop Density (stops/mile) (ln)	-0.373	0.013	***	-0.013	0.002	***
On-street parking (spaces/sq. mile) (ln)	-0.018	0.018	NS	-0.026	0.022	NS
Off-street parking (spaces/sq. mile) (ln)	0.276	0.014	***	0.323	0.017	***
Tract Socioeconomic Characteristics						
Neighborhood Income Group *(Baseline: Middle)*						
Low-Income	-0.264	0.031	***	-0.314	0.037	***
High-Income	0.076	0.028	***	0.152	0.034	***
Percent Zero Vehicle Households	-1.634	0.145	***	-1.910	0.175	***
Percent ages 15-34	-1.263	0.114	***	-1.414	0.138	***
Neighborhood Racial/Ethnic Majority *(Baseline: No Majority)*						
Asian	0.721	0.047	***	0.904	0.057	***
Black	-0.548	0.061	***	-0.667	0.073	***
Hispanic	-0.319	0.026	***	-0.419	0.032	***
White	-0.218	0.026	***	-0.159	0.032	***
Tract Amenities & Land Use						
Number of Workers in Arts, Service, per sq. mile (ln)	-0.138	0.008	***	-0.109	0.010	***
Constant	11.613	0.068	***	14.511	0.082	***

Linear regression. NS not significant, * p<0.1, ** p<0.05, *** p<0.01.

PART II: DISCRIMINATION IN THE RIDEHAIL INDUSTRY

CHAPTER 6. AUDIT DATA AND METHODS

Spatial patterns of Lyft service in Los Angeles discussed in Part I suggest that people are not denied service solely based on where they live. However, such data tell us little about individual experiences. Rider-level discrimination may result in varied wait times and cancellation rates across travelers even when overall trip-making in a given neighborhood is high.

In Part II, I investigate evidence of discrimination across rider race, ethnicity, and gender in the ridehail and taxi industries. To do this, I conducted an audit study of Lyft, Uber, and taxis. Audit studies are field experiments designed specifically to identify discrimination; in audits, people ("auditors") are sent into actual social or economic settings to measure how otherwise identical people are treated based on their race, ethnicity, or gender. Audits are the most common field method for detecting discrimination and, outside of laboratories, offer the cleanest evidence for how treatment varies by race (Bertrand and Mullainathan 2004, Yinger 2008). Audits are superior to surveys, which are prone to inaccurate or dishonest responses (Riach and Rich 2002), and are well-established in economics (for a highly-publicized example, see Bertrand and Mullainathan (2004)) and housing (for a recent example, see Edelman et al. (2016)). Taxis, too, have been the subject of audits for decades (see for example Ridley et al. (1989) and Castillo et al. (2013)).

More recently, researchers used the audit methodology to investigate discrimination in ridehailing. Smart et al. (2015) aimed to uncover wait time and price differences between UberX and taxis, but did not report if or how service varied across riders. Ge et al. (2016) conducted extensive analysis in both Seattle and Boston, which yielded different results. In Seattle, the researchers measured differences in wait times between black and white riders on three services (UberX, Lyft, and Flywheel)[43] and found evidence of discrimination of black riders on UberX as well as differences across gender. In Boston, researchers limited analysis to UberX and Lyft but found no differences between white and black riders. The contrasting findings between Seattle and Boston could stem

[43] Flywheel is a taxi-hailing app. As of 2018, Flywheel is available in San Francisco, Seattle, and Portland (Flywheel 2018).

from any number of factors, and one advantage of audits is that experiments may be replicated in other places. In Part II, I build on the foundation laid by Ge et al. (2016) and Smart et al. (2015) and evaluate discrimination present on Lyft, Uber, and taxis.

Field Locations

This study focuses on whether taxi and ridehail service qualities (wait times and cancellation rates) vary systematically by rider race, ethnicity, or gender. To control for other factors that might influence service quality, I limited the audit study to young adults (to control for age) and two Los Angeles neighborhoods (to control for spatial variation in service quality).

Service qualities (wait times and cancellation rates) may vary across neighborhoods. For example, Ge et al. (2016) found higher cancellation rates in less dense neighborhoods in Boston and Hughes and MacKenzie (2016) found shorter estimated wait times in low-income neighborhoods. However, assessing service variation across neighborhoods is not the goal of this research. Instead, I aim to assess variation across *individuals*, and therefore control for neighborhood characteristics by limiting the number of field sites; this approach differs from Ge et al. (2016) who measured wait times and cancellation rates across dozens of locations. While their approach has the advantage of evaluating service at multiple locations, reduced sample sizes at each location makes it more difficult to attribute observed differences to riders' characteristics rather than location.[44] By limiting field sites, I effectively control for proxy discrimination, in which people use observable neighborhood characteristics (such as racial/ethnic makeup) as a proxy for unobservable characteristics (such as crime). For example, if a driver refuses to serve a location because he fears crime, he should refuse all ride requests regardless of who makes them. In this case, service quality may vary between neighborhoods, but should not vary across riders hailing from the same location.

[44] For example, in Seattle, riders collected data at approximately 57 locations (Ge et al. 2016, 39); this means, for the 208 Uber trips collected, fewer than four observations would have been made at each location. With eight hired research assistants in the Seattle project, bias may have been introduced depending on the locations different riders traveled to. While Ge et al. (2016) control for pickup location characteristics using U.S. Census data, Census data may not capture all or latent characteristics of a site such as poor lighting or historical perceptions of crime.

I selected two field sites based on three criteria: 1) proximity to the UCLA campus (accessible to fieldworkers within about one hour on transit); 2) distance between sites (to minimize trip distance and therefore price); and 3) neighborhood built environment and socioeconomic characteristics. The first fieldwork site is located in downtown Culver City, an independent city surrounded by the City of Los Angeles. The second site is located where two Los Angeles neighborhoods, Baldwin Hills/Crenshaw and West Adams, abut. Figure 33 shows the two sites relative to one another and their location in Los Angeles County. Although only two miles apart, the two field sites are remarkably—and intentionally—different. Table 20 shows the socioeconomic and built environment characteristics of the two neighborhoods compared to the Los Angeles average. Site 1 has nearly double the median household income of Site 2 and a majority of its residents are white. In contrast, Site 2 lies between neighborhoods that are majority black (Baldwin Hills/Crenshaw) and majority Hispanic (West Adams). While both sites have relatively high residential densities (18 and 23 people per acre at Site 1 and Site 2, respectively), Site 1 has far lower shares of transit commuters and zero-vehicle households compared to Site 2.

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

Figure 33. Field Site Locations

Table 20. Field Site Characteristics

	Site 1	Site 2		
	Culver City	*Baldwin Hills/ Crenshaw*	*West Adams*	*Los Angeles County*
Median Household Income	$110,913	$52,864	$52,324	$56,196
Race/Ethnicity[1]				
% NH Asian	14.2%	5.1%	1.4%	14.1%
% NH Black	7.1%	60.3%	27.4%	8.0%
% NH White	51.4%	5.1%	4.6%	26.7%
% NH Other Race	1.0%	1.5%	0.5%	5.1%
% Hispanic	26.2%	28.1%	66.1%	48.3%
Population Density[2]	17.6	22.0	23.2	
Employment Density[3]	11.2	7.2	6.3	
% Zero-Vehicle Households	7.5%	20.9%	14.4%	9.7%
% Commute by Transit	3.4%	14.1%	11.4%	6.8%
% Young Adults (20-34)	24.3%	27.8%	32.3%	23.1%

[1]NH indicates not Hispanic or Latino. "% Hispanic" includes all races. [2]People per acre. [3]Jobs per acre.
Sources: U.S. Census Bureau (2015a, 2016), Environmental Protection Agency (2014).

In addition to quantifiable built environment and socioeconomic differences between the neighborhoods, the two sites—because they are in different cities, Culver City (Site 1) and Los

Angeles (Site 2)—are served by different taxi companies.[45] I discuss taxi service at each site further in the following sections.

Ridehail and Taxi Services

Unlike previous research, which tested differences between only two services at a time (Ge et al. 2016, Smart et al. 2015), this research tests for rider discrimination across the two dominant ridehail companies (Uber and Lyft) as well as taxis, which have a long history of discrimination against people of color (Wrigley 2013, Belcher and Brown 2015). Below, I describe what we know about each service in Los Angeles.

Uber and Lyft

Both Uber and Lyft began operating in Los Angeles in early 2013. By the fall of 2016, Lyft provided a startling 2.1 million trips per month (see Chapter 4). While the number of Uber trips serving Los Angeles is not publicly available, data from New York City (the only city with both Uber and Lyft trip count data) suggest that Lyft travel comprises a relatively small fraction of all ridehail use. In New York City, Lyft trips account for only 12 percent of the ridehail market (Schaller 2017).

Although Lyft and Uber each offer a variety of services—including shared, black car, and extra-large vehicle services[46]—this research focuses on only Lyft and UberX, the unshared and most popular ridehail option offered by Lyft and Uber, respectively.[47] While planners are particularly intrigued by ride*sharing*'s promises of reduced congestion, lower emissions, and more affordable services, shared rides introduce greater wait and travel time variability, depending on whether a driver is picking up another passenger on the same shared ride, or detouring to drop off some

[45] Recall from Chapter 2 that taxicabs in California, and indeed in much of the U.S. are regulated and licensed to pick up passengers by local jurisdictions.

[46] As of 2017, Lyft offered six services: Lyft (regular), Line (shared), Plus (6 seats), Premier (high-end), Lux (black car), and Lux SUV (6 seats, black car). Uber similarly offered six services: UberX (regular), POOL (shared), three "premium" services (Black, Select, Lux), and two extra-seats options (UberXL and SUV).

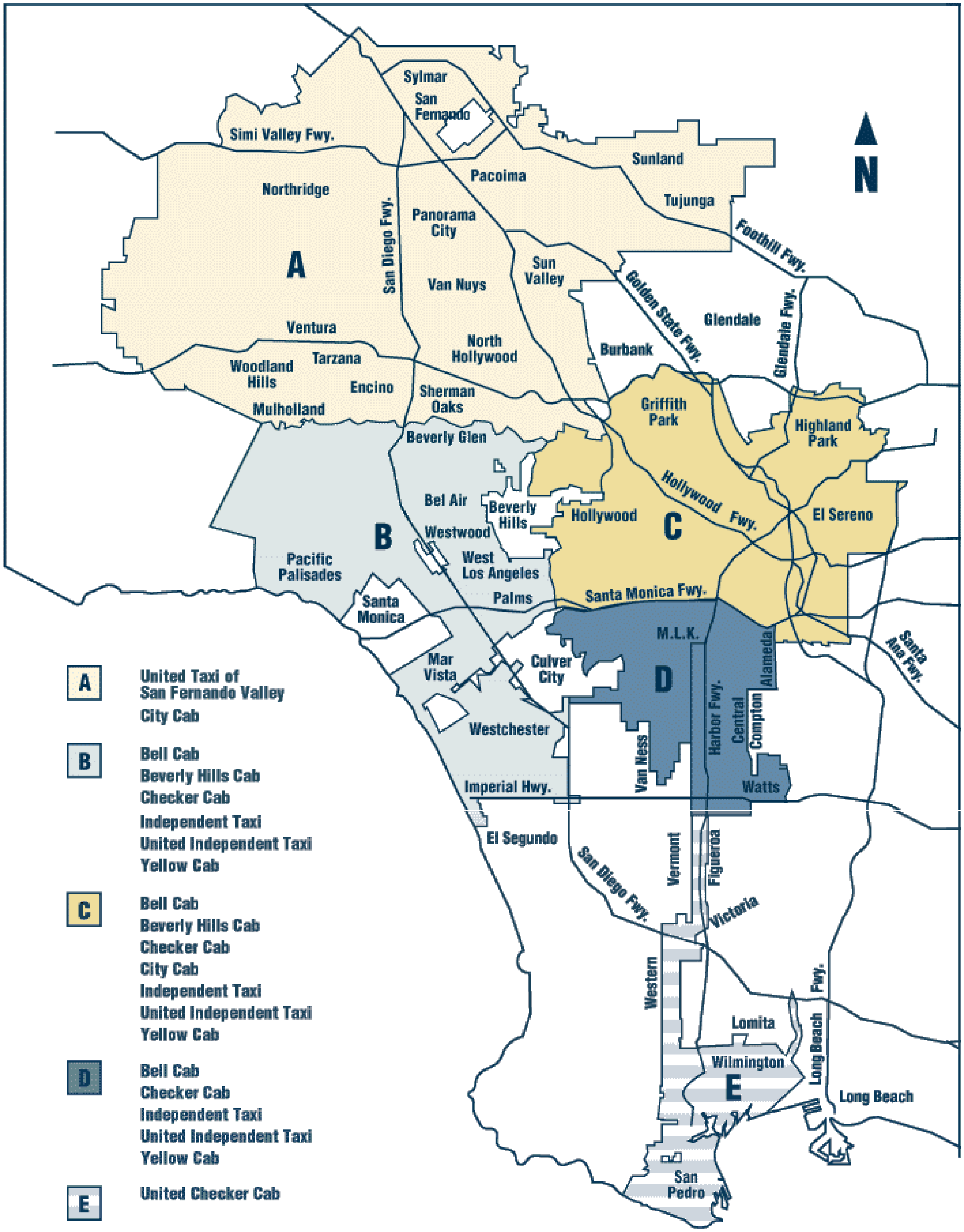
[47] Between September and November 2016, regular Lyft accounted for 71 percent of Lyft service in Los Angeles County; shared Lyft Line accounted for the remaining 29 percent (see Chapter 4).

passengers before others. Rideshare (uberPOOL and Lyft Line) services are also not as comparable to taxis, which do not offer shared services. Therefore, I assess wait times, cancellation rates, and discrimination across only the non-shared services, Lyft and UberX.

Taxis

As of July 2016, the City of Los Angeles licensed 2,361 taxis to operate, an increase of just 58 taxis since 2000, a time period over which the city added 281,000 residents (Los Angeles Department of Transportation 2017b, U.S. Census Bureau 2000, U.S. Census 2016a). Nine taxi franchises currently hold licenses to operate in the City of Los Angeles, and each is assigned to primary service areas (see the map in Figure 34). Taxis must maintain "acceptable service in their primary service area in order to maintain...[the] privilege" of operating at Los Angeles International Airport (LAX) and to receive franchise extensions (Los Angeles Department of Transportation 2017b, 7). The City penalizes taxi companies if more than 10 percent of callers wait between 30 and 60 minutes and/or if more than five percent of callers wait more than 60 minutes (Los Angeles Department of Transportation 2017b). In general, a higher share of pre-arranged taxi trips arrive on time (within 15 minutes) compared to requests for immediate pick up. However, more prompt pre-arranged services may be of little consolation to the majority of taxi riders: 85 percent of LA Yellow cabs hailed in Zone D (where Site 2 is located) in 2015 requested immediate pickup.

Figure 34. Taxi Service Zones in the City of Los Angeles



Source: City of Los Angeles Taxi Services (2017).

Site 1, located in Culver City, is not within one of the five Los Angeles Department of Transportation (LADOT) service areas shown in Figure 34. Site 2, located in south-central Los Angeles, is located in Service Zone D. In 2013, LADOT highlighted Zone D as an area with "service deficiencies" (Los Angeles Department of Transportation 2015, 48). As a result, the Board of Taxicab Commissioners raised the performance targets in this zone and offered monetary incentives to improve service (Los Angeles Department of Transportation 2015).[48] While service has improved moderately over time, the most recent LADOT taxi report shows that Zone D remains among the worst served areas in the city. Only one of the five companies operating in the zone achieves a "good" performance rating (United Independent), with the others receiving "satisfactory" (LA Checker Cab), "poor" (Independent Taxi Owners' Association), or "unsatisfactory" performance ratings (LA Yellow Cab, Bell Cab). Within Zone D, LADOT (2017b) reports 12 to 14-minute average wait times across companies.

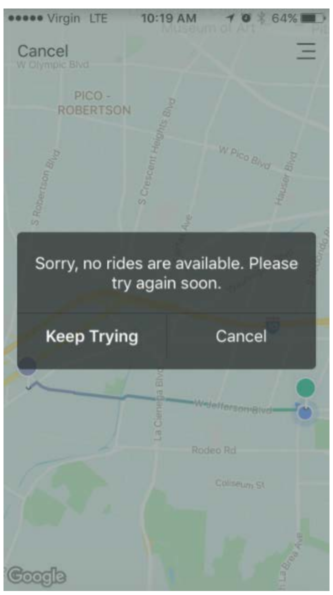
Taxis are not permitted to pick up street-hail rides in either of the two field locations;[49] therefore, I evaluate only dispatched taxi services, which have previously been evaluated in audit studies (Smart et al. 2015, Ge et al. 2016) and are more similar to Uber and Lyft compared to street-hail taxis. I analyze taxis as a single service regardless of the company involved for three reasons. First, the manner of hailing a taxi is identical across companies. Second, because multiple taxi companies serve the same location, taxi service in an area is a sum of all service providers. And third, auditors reported that when a hailed taxi company had no available taxis, dispatchers often referred them to a different company. In other words, the service divisions between taxi companies may be somewhat permeable.

[48] Drivers assigned to work in Zone D receive a $50 per week bonus. Dispatchers who improve response times (serve more callers within 15 minutes) within Zone D also receive a $25 per week bonus (Los Angeles Department of Transportation 2015).

[49] Street hailing is permitted only in downtown Los Angeles and Hollywood (Los Angeles Downtown News 2010). Los Angeles originally forbade taxis from standing or stopping on streets out of safety and traffic congestion concerns (Southern California Association of Governments 2009).

In an attempt to create a research design parallel to the Uber and Lyft analysis, I first designed taxi hails to use the Curb taxi app (previously "Taxi Magic"), which is advertised as the "#1 taxi app in the U.S. that connects you to fast, convenient and safe rides in 65 cities" (Curb 2017). The Curb app mirrors the interface of Uber or Lyft and partners with some of Los Angeles' largest taxi companies to provide an app (rather than phone-based) dispatch service. However, over the course of three days, five riders made 32 attempts to hail a taxi with Curb. Each time, riders were informed that no taxis were available (see Figure 35). I explored other taxi apps to replace Curb, but each fell far short of providing acceptable service.[50] In lieu of app-based dispatching, riders called taxi dispatchers to hail taxis. While not fully parallel to the way in which passengers request Uber and Lyft rides, it does reflect the hailing experience for the majority of taxi riders. As of April 2017, only about nine percent of taxis (7,400 of approximately 82,600 taxi trips) were hailed by app in the City of Los Angeles (Los Angeles Department of Transportation 2017a, d).

Figure 35. Curb App, No Taxis Available



[50] For example, I tested apps for the two largest taxi dispatchers in Los Angeles. LA Yellow Cab (the largest taxi dispatcher) both uses the Curb app *and* operates its own app, RideYellow. RideYellow was deemed unusable as trial rides 1) double-charged a rider, 2) continually crashed, and 3) directed a driver to an origin/drop-off about a half-mile from the rider's actual origin and destination (which were correctly entered into the app). United Independent Taxi (the second largest dispatcher in Los Angeles) operates its own app. This app provided a mobile version of website booking but was unusable as the app would never fully load to allow a rider to actually hail a taxi.

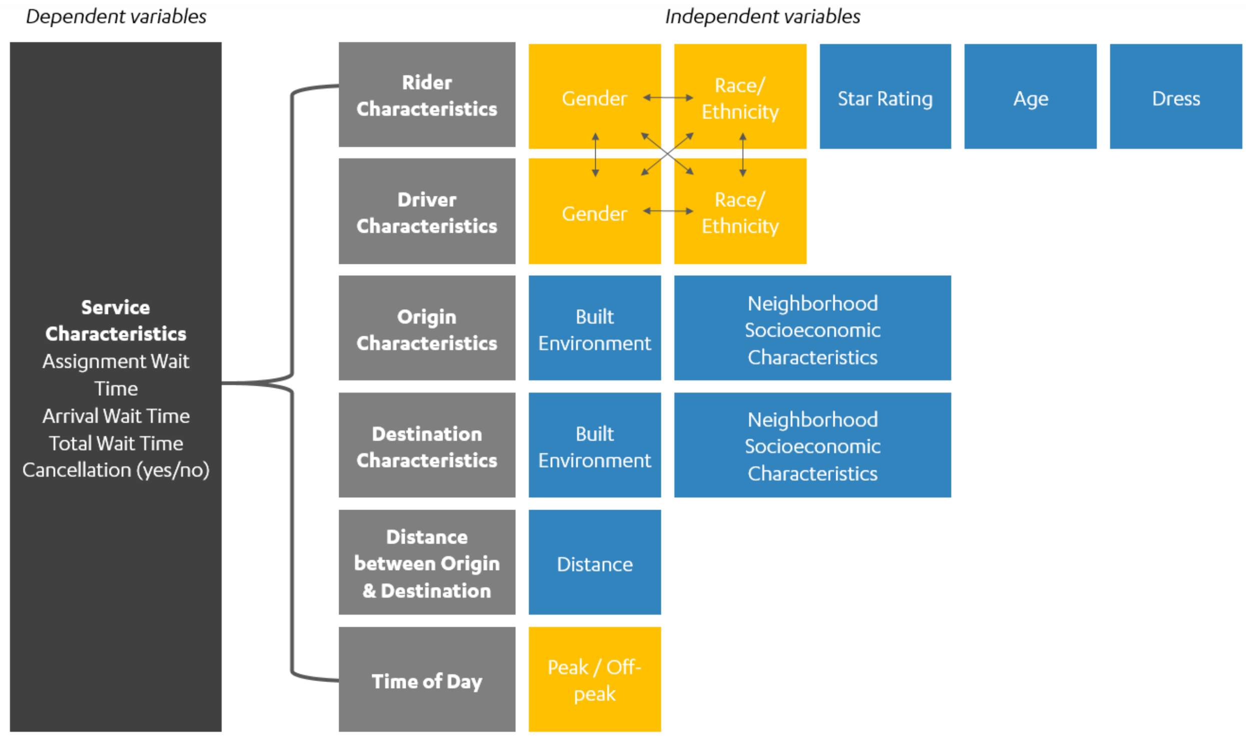
Different taxi companies are licensed to pick up in Culver City (Site 1) and in the City of Los Angeles Zone D (Site 2). For this study, I selected the two largest taxi companies that serve each site: United Independent and Independent Cab Company at Site 1, and LA Yellow Cab and United Independent at Site 2.[51]

Conceptual Model

Driver actions toward a rider—specifically, the decisions to pick up, pass, or cancel on a rider—are informed by driver perceptions of that rider's age, gender, race/ethnicity, dress, and (for Uber and Lyft) star ratings. The conceptual model depicted in Figure 36 shows that rider characteristics together with other trip factors are associated with wait times and ride request cancellations. To isolate the variables of interest in this study—rider gender and race/ethnicity—I control for the other factors either statistically (in yellow) or through study design (in blue), as discussed above. For example, I control statistically for peak period hails because rush hour congestion may slow driver arrival times.

[51] As of October 2017, LA Yellow Cab operated about 756 taxis and United Independent operated about 294 taxis (Los Angeles Department of Transportation 2017a). United Independent serves both Sites 1 and 2. The other taxi companies licensed to pick up in Culver City (Site 1) operate primarily out of other cities: Beverly Hills Cab Company and Metro Cab both operate primarily in the City of Santa Monica. The final taxi company licensed to pick up in Culver City is Culver City Yellow, which is a division of United Independent (Culver City Finance Department 2017).

Figure 36. Conceptual Model: Factors Influencing Ridehail and Taxi Service



Arrows indicate interactions. Blue boxes indicate variables that are controlled for through audit study design. Gold boxes indicate variables of interest and variables controlled for statistically.

Figure 37 shows the three interaction points between the driver and passenger during which unlawful discrimination may occur: rider hails trip, driver accepts trip, and driver approaches rider. During each step, a driver 1) has or gains some knowledge about a rider's characteristics, and 2) takes one of two actions based on this information. Driver actions may produce discriminatory service experiences at each step. The point at which a driver receives information about a rider—when a new opportunity for discrimination occurs—varies between Lyft, Uber, and taxis. For example, Figure 38 shows that, prior to accepting a ride, a Lyft driver sees a rider's name, address, star rating, photo, and how many minutes they are from the driver. An Uber driver, by contrast, sees only a rider's star rating and the distance and time to reach the rider. Both Uber and Lyft drivers may choose to accept or reject a trip request, although both services incentivize drivers to accept trips.[52] For all services, unlawful discrimination may also occur when a driver approaches a rider, sees a rider, and draws additional conclusions about race, gender, or other rider characteristics.

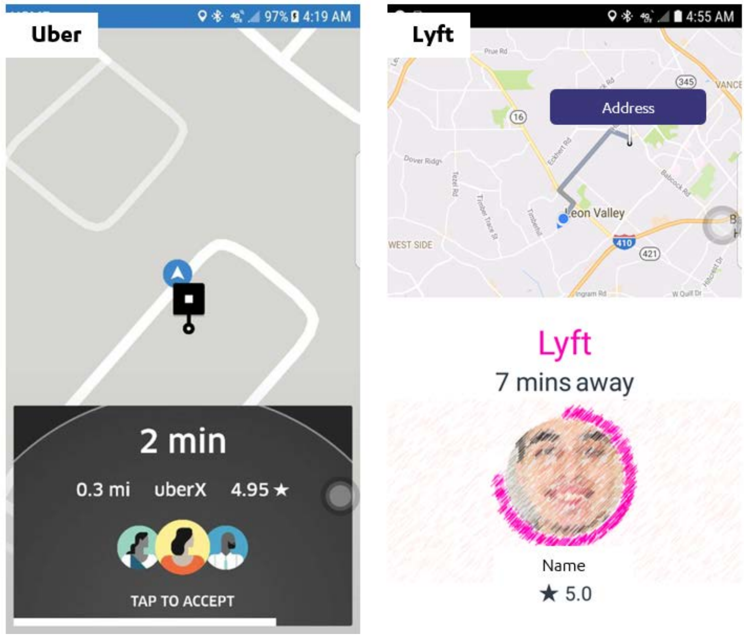
Because drivers receive information about riders at different times, I am able to compare different vectors of discrimination; in other words, I am able to observe exactly when discrimination occurs. I hypothesize about the moment of discrimination in the following section.

Figure 37. When Might Unlawful Discrimination Occur?

Driver Behavior	Taxi	Lyft	Uber
Step 1 Rider Hails Trip			
New Rider Info Known	Name, Location	Name, Location, Star Rating, Photo, Distance/Time to Rider	Location, Star Rating, Distance/Time to Rider
Action	Assign / not assign to taxi driver	Pass or accept ride request; must maintain certain acceptance rate	Pass or accept ride request; get a "time out" if ignore two in a row
Discrimination Manifest	Higher rate of rider informed no taxis available	Longer initial ("assignment") wait times	None expected
Step 2 Driver Accepts (Uber/Lyft) / Assigned (Taxi) Rider			
New Rider Info Known	Name, Location	No additional info	Name
Action	Taxi driver may choose not to show up	Cancel or pick up	Cancel or pick up
Discrimination Manifest	Higher cancellation rates (no shows)	None expected	Higher cancellation rates
Step 3 Driver Approaches Rider			
New Rider Info Known	Gender, race/ethnicity, age, physical appearance	Gender, race/ethnicity, age, physical appearance	Gender, race/ethnicity, age, physical appearance
Action	Cancel or pick up	Cancel or pick up	Cancel or pick up
Discrimination Manifest	Higher cancellation rates	Higher cancellation rates	Higher cancellation rates
Step 4 Ride Begins			

[52] Lyft requires drivers to maintain a certain acceptance rate. Uber imposes a "time out" if a driver ignores two ride requests in a row; during this time out period, a driver may not receive new ride requests.

Figure 38. What Drivers See on Uber vs. Lyft Prior to Accepting Ride Request



I have obscured the Lyft rider face, name, and address in these screenshots to protect privacy.

Hypotheses

Assuming that drivers discriminate as soon as they learn a rider's characteristics, I offer three hypotheses about the moments and types of discrimination that occur in ridehail and taxi services. First, I *hypothesize that on Lyft, non-white riders will wait longer between pressing "request" and being assigned to a driver* as drivers "pass" (i.e., not accept) non-white riders at higher rates than white riders. By contrast, I do not expect longer "assignment" wait times on Uber or taxis, because drivers have no information on riders prior to accepting a request and thus have no basis on which to discriminate.

Second, I *hypothesize higher cancellation rates for non-white riders and men hailing taxis and Uber compared to white riders.* Uber drivers learn a rider's name immediately following trip acceptance and may use the name to infer (correctly or incorrectly) rider gender or race/ethnicity. Based on this judgment, drivers then choose to pick up a rider or cancel the ride. On taxis, either the dispatcher or driver may discriminate. A taxi dispatcher may wrongly inform a rider that no taxis are available or might not pass the request on to drivers. Taxi drivers may then opt not to pick up a rider; while I cannot determine whether the dispatcher or driver discriminates, discrimination by either would result in higher rates of cancellations. I do not expect discriminatory cancellations on Lyft as drivers see rider names and pictures prior to accepting a trip; in other words, the moment of discrimination has already passed.

Finally, I hypothesize that driver characteristics are not associated with unlawful discrimination as previous research finds that discrimination occurs both between and within racial groups. For example Ayres and Siegelman (1995) found that black perspective car buyers were quoted higher prices compared to white buyers and that the price differences were not influenced by whether the seller or the dealership owner was black; these findings are consistent in housing industry audits (Yinger 1986) and studies of unconscious bias (Haider et al. 2011).

Riders

In this audit study, the "auditors" are 18 riders recruited from the UCLA graduate and undergraduate student body. As discussed in the conceptual model, I anticipate that discrimination may occur across five individual characteristics: star ratings, and driver perceptions of rider age, gender, race/ethnicity, and dress. In order to produce an unbiased estimate of discrimination across race/ethnicity and gender, I matched auditors across individual characteristics not being tested (specifically age, star ratings, and dress) (Murphy 2002). I recruited only riders between 20 and 30 years old with star ratings of 4.5 stars or higher. I controlled for dress by instructing riders to wear plain, non-flashy clothes, such as jeans and a plain t-shirt.[53]

I recruited male and female riders in three racial/ethnic categories: black, white, and what I term "other" (which included Asian and Hispanic riders). I grouped Asian and Hispanic riders into a single category as people are poor judges of race or ethnicity, particularly if a person is of a different race or ethnicity (see for example Gross (2009), Sporer (2001)).[54] People primarily use facial features

[53] While I did not check rider dress each day, I frequently saw riders as they began or ended a shift. The riders I observed were consistently dressed in plain and inconspicuous clothing as instructed.

[54] In addition, no statistically significant differences in wait times or cancellation rates were observed between Hispanic and Asian riders.

to identify others' races and ethnicities (Zebrowitz, Montepare, and Lee 1993), but names may also provide signals and thus influence the service or treatment that people receive (Ge et al. 2016, Bertrand and Mullainathan 2004). For example, Ge et al. (2016) found that Uber/Lyft users with "African American sounding" names were twice as likely to have a ride cancelled (10%) compared to those with "white sounding" names (5%). In this study, riders were neither recruited for names that signaled race or ethnicity, nor were riders assigned aliases because both Uber and Lyft's Terms and Conditions prohibit impersonation. Instead, mirroring reality, some riders had names commonly associated with a particular race/ethnicity, while others did not.[55] For consistency, all riders uploaded new profile photos to Lyft showing the rider's face against a white backdrop (Uber does not show rider photos to drivers).

Table 21 shows that, together, riders hailed 1,704 trips during nine weeks between October and December 2017.

Table 21. Total Number of Trips by Rider Characteristic

Rider	**Lyft Trips**	**Uber Trips**	**Taxi Trips**
Black	165	172	99
Female	70	72	39
Male	95	100	60
Asian/Hispanic	215	211	154
Female	107	100	81
Male	108	111	73
White	266	241	181
Female	83	81	56
Male	183	160	125
Total	*646*	*624*	*434*

Data Collection and Measurement

Riders collected data every day between 9:00am and 9:00pm, seven days per week for nine weeks between October and December 2017. Collection across days of the week accounts for potential

[55] However, no consistently significant differences emerged across different riders within the same gender and racial/ethnic category.

weekday service variations. Riders did not collect data in the late evenings or early mornings due to budget constraints and concern for rider safety in the field. In addition, no data were collected on Thanksgiving Day or the holiday weekend (November 23-26, 2017) because holidays may affect service levels and response times relative to other days.

Three data collection methods minimized the chances of "piggyback" rides (i.e., hailing the same driver for back to back trips), which could both artificially depress wait times and/or arouse suspicion among drivers. First, no more than three riders—each working independently—were in the field collecting data at any one time. Second, riders were instructed to wait five minutes between rides to allow drivers to clear the area. And third, riders were instructed to rotate through services (e.g. hail an Uber then Lyft then taxi) and also between taxi companies. Despite these precautions, a small number of piggyback rides did occur. On Uber and Lyft, just 14 out of 1,704 trips (<1%) were recorded as piggyback rides. Driver arrival and total wait times were significantly shorter for piggyback rides than for other trips; therefore, I exclude piggyback rides from all wait-time analyses.

Unlike Uber and Lyft, which had few repeat drivers across the entire study period—taxis proved more problematic due to the limited number of drivers serving each site. As a result, taxi drivers frequently expressed puzzlement over the repeat pick-up and drop-off locations or mentioned that they "just dropped someone off" at the same location. Although taxis did not know *why* repeated hails were made at the two locations—riders were explicitly trained not to tell drivers they were doing research—many taxi drivers came to anticipate the destination before a rider provided it to them. For example, one rider noted, "Had this driver before, and he already knew where I wanted to go." I discuss the implications of this later in the "Limitations" section of this chapter.

Table 22 lists data, collection methods, and measurements. The data for taxi and Uber/Lyft mirror one another despite different hailing techniques. Appendix E depicts the full data collection process in graphical form.

Table 22. Data Collection Methods and Definitions

Data	Collection Method	Measurement	
		Taxi	*Uber and Lyft*
Assignment Wait Time	Timer	Time elapsed between when called taxi dispatcher and when rider hung up with taxi dispatcher.[2]	Time elapsed between when hit "request" ride and when a driver was assigned and en route.
Arrival Wait Time	Timer	Time elapsed between when hung up with taxi dispatcher and when taxi arrived.	Time elapsed between when driver assigned and when vehicle arrived.
Distance	Receipt[1]	Distance in miles	Distance in miles
Price (no tip)	Receipt[1]	Price in dollars	Price in dollars
Cancellation	Varies	Yes/no; type	Yes/no; type
Driver Characteristics	In-person observation; app-screenshot	Driver age, race/ethnicity, and gender	Driver age, race/ethnicity, and gender

[1]Uber and Lyft email receipts to riders. Taxi companies are legally required to provide printed receipts to passengers (Los Angeles Department of Transportation 2017b). [2]A rider typically waited longer on the first hail compared to subsequent trips. Following the first trip, riders were typically routed through automated dispatch systems, which recognized the name, number, and previous destinations.

Wait Times

Uber and Lyft riders first entered their trip origin and destination. They then started their phone stopwatch; when the app assigned a driver, riders recorded the first time point (assignment wait time). Riders also took a screenshot of the app that showed a driver's photo. Screenshots were used in order to 1) cross-check the accuracy of recorded data, and 2) assess a driver's identity if they cancelled a ride request. For taxis, riders started the timer before calling the taxi dispatcher. Riders recorded assignment wait time as the dispatch call duration.

After a driver was assigned, the taxi, Uber, and Lyft methodology was identical. Riders recorded the second time point (arrival wait time) at the moment when a driver pulled up directly in front of the rider (as opposed to when, for example, the driver came into sight). Consistent timing minimized potential variation in data due to collection practices. Riders used phone stopwatches to record all wait times. Riders took one screenshot of each trip timer and uploaded screenshots to a central database. Wait times were later transcribed into a database. I calculated total wait time as the sum of assignment plus arrival wait times; in other words, the time elapsed between when a rider hailed a ride and the car arrived.

Driver Characteristics

Once in the car, riders observed driver age, gender, and race/ethnicity. Riders observed driver characteristics rather than interviewed drivers due to Institutional Review Board (IRB) requirements. Riders were permitted to talk with drivers as they would normally do; in some conversations, drivers volunteered information about themselves, such as if they worked full or part-time. In all instances, drivers offered information during casual conversation rather than in response to pointed or pre-determined interview questions.

I trained auditors to identify people consistently across the three driver characteristic variables. Riders recorded age as a decade measure (20 to 29, 30 to 39, etc.) because previous research finds that people typically estimate age within six to seven years of actual age (Voelkle et al. 2012). Riders recorded race within broad racial/ethnic categories: Asian, black, Hispanic, and white. Riders could also identify common ethnicities within each race,[56] write in another race/ethnicity, or provide additional notes on drivers that they perceived as multi-racial/ethnic.

Cancellations

In some cases, drivers cancelled on a rider after being assigned to the trip. Cancellations affect wait times and may signal discrimination. Riders experienced distinct types of cancellations, which I describe in turn below.

Uber and Lyft riders experienced two types of cancellations, both of which have been observed in previous research. First, following Ge et al. (2016), riders marked trips as *de facto* cancellations if, after 20 minutes, a driver made no attempt to contact them, no attempt to pick them up, or drove in the opposite direction.[57] Second, cancellations occur when a driver explicitly "drops"

[56] For example, riders were trained to distinguish between ethnically East Asian (Chinese, Korean, Thai etc.) and South Asian (Bangladeshi, Indian, etc.). Riders also distinguished Middle Eastern from white drivers.

[57] Why would drivers wait so long for a rider to cancel rather than canceling a trip themselves? Uber and Lyft both incentivize a high trip acceptance rate and penalize drivers for cancelling a ride. Uber does this by putting riders in "time out" if they cancel trips more than two or three times in a row. When this happens, a driver cannot receive new ride requests for a set period of time, ranging from two to 30 minutes (The Rideshare Guy 2016). Lyft takes a different approach, but to a similar end.

or “cancels” on a rider; when this happens, a rider reenters the pool of unmatched riders and is assigned a new driver. When this happened, riders recorded two additional time points: 1) when a driver dropped them, and 2) when they were assigned a new driver. Riders also took a screenshot of the newly-assigned driver. The data collection methodology then reverted to that of a typical trip.

Taxi riders experienced three types of cancellations. First, riders marked trips as cancelled if a dispatcher failed to answer a call; LADOT refers to this as “Company Service Refusal” (Los Angeles Department of Transportation 2017b). Second, riders record a cancelled trip if a dispatcher informed or later called a rider to say that no taxis were available.[58] And finally, riders recorded a trip cancellation if no taxi arrived within 60 minutes of assignment. For each type of cancellation, a rider recorded the elapsed time between hail and cancellation. Appendix E depicts the cancellation data collection process for both taxi and ridehail services in graphical form.

Methods

In addition to presenting descriptive statistics for wait times and cancellation rates across services and rider characteristics, I estimated three logistic regression models and nine linear regression models as illustrated in Figure 39 and Figure 40. I specified separate models for cancellation rate, assignment time, arrival time, and total wait time to capture discrimination at different points in the ride hail process.

Each model includes rider race/ethnicity interacted with rider gender as previous research suggests that discrimination may occur at the intersection of these characteristics (Assari and Caldwell 2017). However, in the final models presented here, I exclude the four-way interaction between driver and rider race, ethnicity, and gender presented in the conceptual model (Figure 36)

Driver incentives—such as Power Driver Bonuses and Average Hourly Guarantees—hinge on average acceptance rates, which are calculated as a ratio of rides completed to rides requested. If a driver cancels a trip, their acceptance rate falls; however, if a *rider* cancels a trip, the driver’s acceptance rate is unaffected (Lyft 2017a). In other words, a driver can capture more Lyft incentives if a rider cancels instead of the driver.

[58] Riders were often called 20 to 40 minutes later and informed that no taxi was available after originally being told that a taxi would arrive soon.

because the interaction was not statistically significant.[59] In other words, interaction between driver and rider characteristics did not influence outcomes across riders; this conforms to previous research findings (Ayres and Siegelman 1995, Yinger 1986, Haider et al. 2011). Because a four-way interaction model is unduly cumbersome to present and interpret and because it yielded no additional insight into the interactions among driver and rider characteristics, the models presented here include only interactions between rider gender and race/ethnicity.

Figure 39. Cancelled Trip Model Specifications

Research Question	Unit of Analysis	Model Type	Model Dependent Variables	Model Independent Variables
What factors are associated with a cancelled trip request?	1. Uber Trips 2. Lyft Trips 3. Taxi Trips	Logistic Regression	Cancellation (yes/no)	Rider race/ethnicity * Rider gender Peak Trip Taxi company (where applicable)

* indicates interaction

Figure 40. Wait Times Model Specifications

Research Question	Unit of Analysis	Model Type	Model Dependent Variables	Model Independent Variables
What factors are associated with the time elapsed between ride hail and when a driver is assigned?	1. Uber Trips 2. Lyft Trips 3. Taxi Trips	Linear Regression	Assignment time (minutes)	Rider race/ethnicity * Rider gender Peak Trip Taxi company (where applicable)
What factors are associated with the time elapsed between driver assignment and driver arrival?	4. Uber Trips 5. Lyft Trips 6. Taxi Trips		Arrival time (minutes)	
What factors are associated with total time elapsed between ride hail and driver arrival?	7. Uber Trips 8. Lyft Trips 9. Taxi Trips		Total wait time (minutes)	

* indicates interaction

[59] For example, following the Lyft model for assignment wait time, I ran the *contrast* command in Stata to conduct contrast and linear hypothesis tests after estimation. I found that with four degrees of freedom, the interaction term produced an F-statistic of 1.65, which is not statistically significant ($p>F=0.1614$). Non-significance may also be due to relatively small sample sizes given a four-way interaction model.

Limitations

Due to their limited number, taxi drivers often drove more than one rider over the course of the study. Repeat drivers occasionally remarked on the high volume of trips being hailed to and from Site 1 and Site 2, an observation that may have altered their behavior. Remarked one rider: the driver said he was going to "park…to wait for us since he has done a lot of this trip recently." These comments occurred despite precautions taken to discourage such behavior, including capping the number of riders in the field at a given time, rotating between services to minimize the likelihood of repeat or return trips, and ceasing to hail a taxi company for the remainder of the morning or afternoon following a driver's suspicious comment. Riders noted that taxis appeared to adjust behavior and wait nearby in anticipation of upcoming trips; this affected both taxi wait times and cancellation rates. While average wait times dipped only two minutes between October and December (not statistically significant), and remained higher on average compared to Uber and Lyft wait times throughout the course of the study, learned behavior by some drivers may have depressed individual wait times. Wait times should therefore be interpreted as low estimates of taxi wait times. Learned behavior also appears to have reduced taxi no-show cancellation rates over the course of the study; no-show cancellations—when a taxi failed to arrive within 60 minutes of a hail—fell from 15 percent of taxi hails in October to about 6 percent in December (a significant difference, $p<0.01$). This suggests that when taxi drivers anticipate business, they are more likely to show up.[60] Like wait times, cancellation rates reported in this study should be interpreted as low estimates.

Finally, to measure discrimination across rider gender, race, and ethnicity, I assume that drivers correctly perceive rider characteristics and vice versa; however, research finds that people are relatively poor judges of each, particularly for those who do not fall squarely into binary categories, such as multiracial individuals (Pauker and Ambady 2009). In general, people use facial features, skin

[60] This may be because taxi *passenger* no-shows are endemic to the taxi industry; Los Angeles city taxi companies reported about one-third of trips as "no-shows" on average in March 2017 (Los Angeles Department of Transportation 2017c). Of course, no-shows may result from either driver or passenger behavior; passengers may be at fault if they fail to show up at the pickup location, or taxis may be at fault if passengers abandon the pickup location after exceedingly long wait times.

tones, names, and hair cues to make judgments about people's race, ethnicity, and gender (Maddox 2004, Bertrand and Mullainathan 2004, Goshen-Gottstein and Ganel 2000). People's ability to recognize characteristics often hinges on their own identity, and people are typically better at recognizing others that share their racial, ethnic, gender, or age identity (Wright and Stroud 2002, Gross 2009, Wiese 2012). Therefore, it is possible that if a driver misidentified a rider's race, ethnicity, or gender, she/he behaved differently towards a rider than she/he otherwise would have. Riders, too, may have misidentified drivers, which would affect the interaction between rider and driver characteristics, which I found did not affect outcomes.

CHAPTER 7. AUDIT FINDINGS

In this chapter, I first present general findings about Uber, Lyft, and taxis. I then discuss the racial/ethnic and gender differences observed across riders and services.

Does Location Matter?

As I discussed in Chapter 6, Site 1 and Site 2 differed in racial/ethnic composition and income despite being only two miles apart. I therefore tested whether wait times (including assigned, pickup, and total wait times) and cancellation rates were significantly different for the two sites. Cancellation rates were not significantly different for any service. In addition, no measures of wait times varied by location for Uber or Lyft. For taxis, however, all wait times were significantly longer at Site 1 (Culver City) compared to Site 2 (Expo/La Brea). Longer wait times at Site 1 are explained by significantly ($p<0.01$) longer average wait times when using Independent Cab Company compared to the other two taxi companies evaluated in this study (32 vs. 21 minutes). Due to these differences across taxi companies, I control for the hailed taxi company in all models.

Who Drives the Car?

Consistent with previous research, I find that Uber and Lyft drivers in Los Angeles are more similar to the general population than they are to taxi drivers (Hall and Krueger 2015). Table 23 shows that while less than one percent of taxi drivers were female, about one in five Uber and Lyft drivers was a woman; overall, driver characteristics observed in this study are similar to data Lyft published about driver demographics in Los Angeles (Lyft 2018a). Lyft and Uber drivers are also younger than both taxi drivers and the county as a whole; over half (57%) of ridehail drivers in Los Angeles are under 40 years old compared to about one-third of taxi drivers.

Hispanic drivers comprise about one-third of ridehail drivers; while this falls below the share of Hispanic residents in Los Angeles, it is far above the share of Hispanic taxi drivers (4%). One-third of both ridehail and taxi drivers were identified as black compared to just eight percent of the county population. Finally, about one-quarter of ridehail drivers were identified as white, compared to nearly half of taxi drivers and over half of the county population. While I found no significant interaction between driver race/ethnicity and rider race/ethnicity (see Chapter 6), the differences between driver race and ethnicity between ridehail and taxis is instructive. Unlike taxi drivers, who are racial/ethnically distinct from the general population, ridehail drivers more closely mirror the demographic makeup of the general population. In addition, while taxi drivers typically work full-time, Lyft and Uber fill more ad-hoc employment roles, including supplementing other incomes or providing flexible work during transitions or gig-based work.[61] The transitory nature of employment in Uber and Lyft and their similar demographic makeup compared to the general population suggests that discrimination observed in ridehailing may be a microcosm of discrimination in the American workforce more broadly rather than confined to these services.

[61] Some drivers worked full-time for Lyft or Uber or part-time in addition to their primary day jobs, which ranged widely from artists to firefighters to actors. The prevalence of part-time driving conforms to previous research and with results from an internal Lyft survey, which finds that 93 percent of Lyft drivers report driving fewer than 20 hours per week (Lyft 2018a, Hall and Krueger 2015); this contrasts with taxi drivers, 81 percent of whom work at least 35 hours per week (Schaller 2016). In addition, ridehail driver tenure differs from taxi drivers; while two-third of Uber and Lyft drivers have driven less than six months (SherpaShare 2015), the median Los Angeles taxi driver has driven for 9.5 years (Blasi and Leavitt 2006).

Table 23. Lyft, Uber, and Taxi Driver Characteristics

	Lyft	Uber	Taxi	Taxi and Chauffer Drivers, U.S.	Los Angeles County Population
Sex/Gender[1]					
Female/Women	21%	19%	1%	3%	51%
Male/Men	79%	81%	99%	97%	49%
Total	100%	100%	100%	100%	100%
Age					
<20	1%	1%	0%	1%	8%
20 to 29	30%	25%	3%	14%	19%
30 to 39	29%	29%	10%	19%	18%
40 to 49	24%	23%	32%	21%	17%
50 to 59	13%	17%	39%	22%	16%
60+	3%	6%	17%	23%	21%
Total	*100%*	*100%*	*100%*	*100%*	*100%*
Race/Ethnicity[2]					
Asian	10%	14%	*20%*	3%	14%
East Asian	*6%*	*10%*	1%	-	-
South Asian	*4%*	*4%*	*19%*	-	-
Black	30%	24%	31%	6%	8%
Hispanic	35%	32%	4%	3%	48%
White	25%	29%	*45%*	89%	53%
Middle Eastern	*8%*	*11%*	*31%*	-	-
White	*18%*	*18%*	*15%*	-	-
Other/Unknown	0%	1%	0%	-	30%
Total	*100%*	*100%*	*100%*	*100%*	

[1]Gender observed for Lyft, Uber, and taxi drivers. Sex was recorded by the Bureau of Labor Statistics and Los Angeles County. [2]Racial and ethnicity categories vary by data source. The U.S. Census records Hispanic status regardless of race. A large overlap exists between residents who report being Hispanic (48%) and identify being an "Other" race (30%). Sources: Bureau of Labor Statistics (2016b), U.S. Census (2016).

Descriptive Service Characteristics

Wait Times

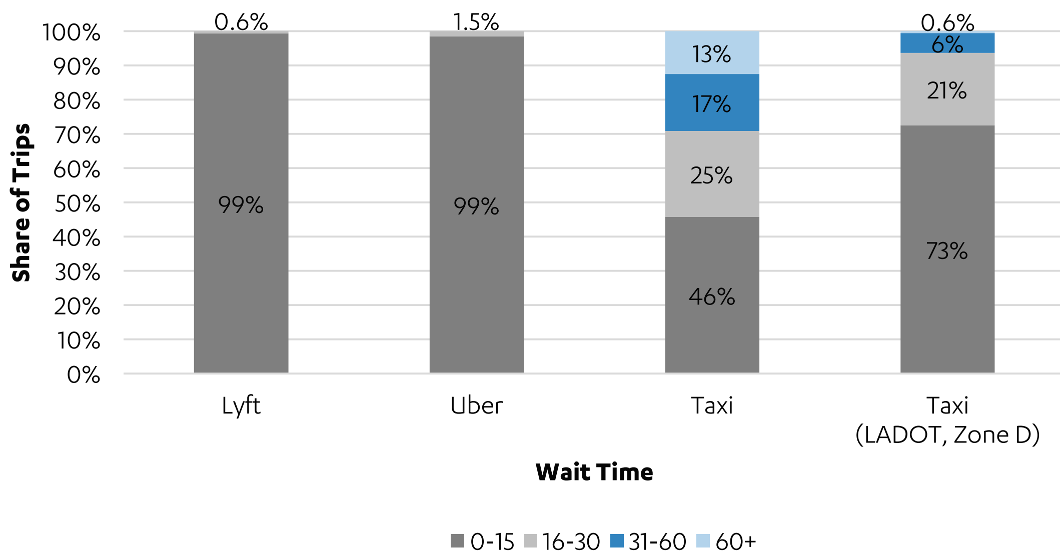
Lyft and Uber provided consistently lower wait times compared to taxis. On average, Lyft and Uber riders waited 5.5 [5.2 to 5.6, 95% CI][62] and 6.1 [5.8 to 6.3, 95% CI] minutes, respectively, between ride

[62] CI indicates confidence interval.

request and driver arrival. By contrast, riders waited four times longer (24.3 [22.5 to 26.2, 95% CI] minutes) for the average taxi trip and more than one in ten (11%, n=44) taxis failed to arrive within one hour.

As discussed in Chapter 6, taxi wait times observed in this study are likely low estimates; but even these low estimates are far worse than official reports. LADOT (2017b) reported 13 minute average wait times in 2015 and that just 0.6 percent of riders waited one hour or more. In fact, the entire distribution of wait times observed in this project diverged from those publicly reported. Figure 41 shows how the distribution of total taxi wait times contrasts to Uber, Lyft, and LADOT data. While 99 percent of Uber and Lyft trips arrived within 15 minutes, less than half (46%) of taxi trips did, far below the 73 percent reported by LADOT (2017b).

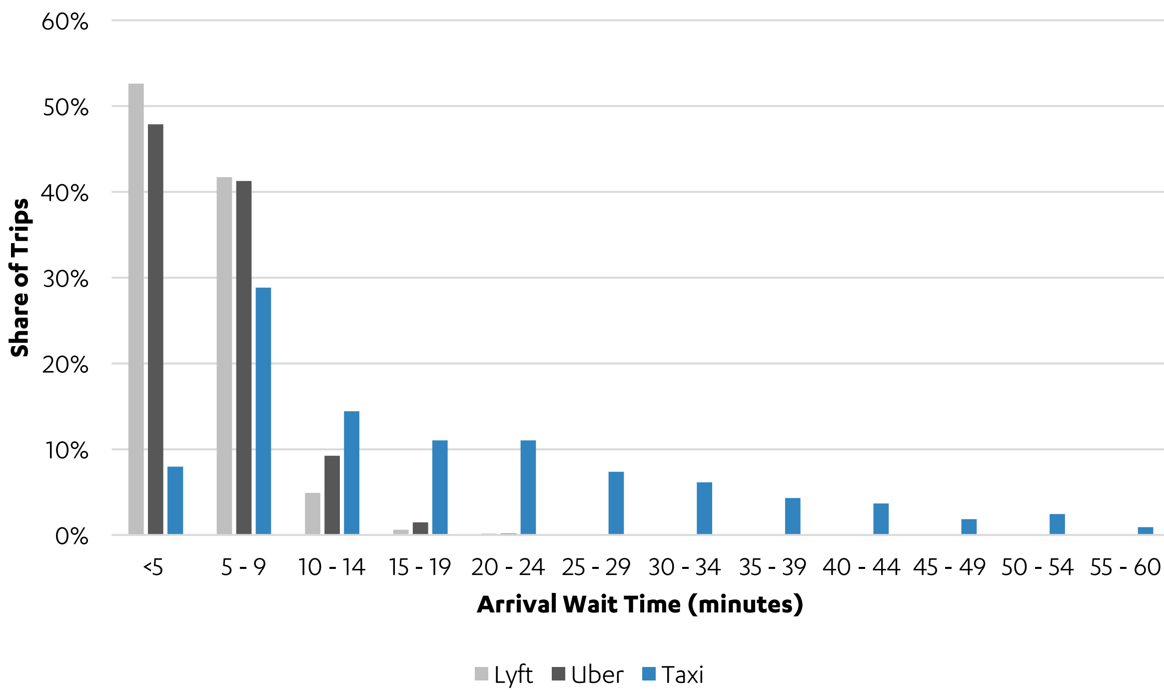
Figure 41. Distribution of Total Wait Times



The 60+ Taxi category includes taxis that did not show up within one hour and those that took longer than one hour to arrive including time required to hail a ride through taxi dispatcher. Source: LADOT (2017b) Table 4.G.5.

More varied wait times produce uncertainty and reduce reliability. For example, if a traveler needs to get to work by 9:00am and they can expect their ride to arrive anywhere from two to 62 minutes (if at all), how do they decide when to hail the vehicle? Figure 42 shows the distribution of arrival wait times (the time between when a rider hailed a ride and the vehicle arrived) across Lyft, Uber, and taxis. While Lyft and Uber wait times are highly clustered between about one and eight minutes, taxi wait times span the entire hour, undermining a rider's ability to predict when a vehicle will arrive or when they will reach their destination.

Figure 42. Arrival Time Reliability Across Services



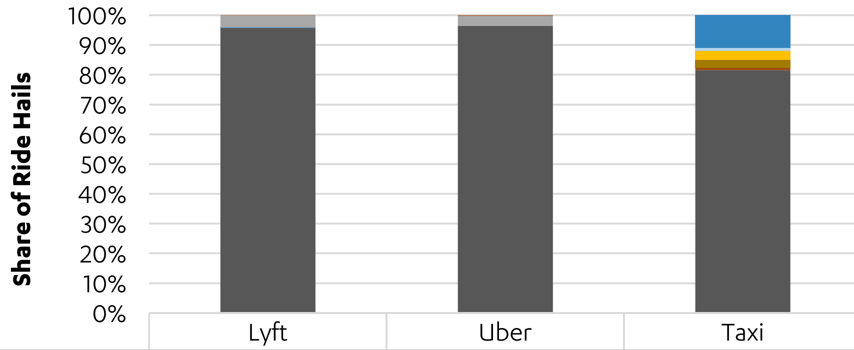
Trip Cancellations

Trips were cancelled for a variety of reasons; I outline cancellation types and frequencies in Figure 43. While the majority of trips occurred without incident, taxi trips were cancelled at far higher rates than ridehail trips. Nearly 20 percent of taxi riders did not receive a ride because the taxi dispatcher did not pick up the phone, no taxis were available, a taxi did not arrive within one hour, or a taxi refused to provide a ride upon arrival. By contrast, zero Uber trip requests and just four (0.6%) Lyft trip requests were not completed.[63] Even when Lyft or Uber riders experienced cancellations (i.e., a driver

[63] The no-show Lyft requests followed the methodology of Ge et al. (2016) and are considered "de-facto" cancellations, meaning that a driver made neither any attempt to pick the rider up nor any attempt to contact the rider for 20 minutes. For example, one rider explained: "Drove in the opposite direction of my pickup location and continued driving that way not making any attempt to turn around." In another case, the driver passed the rider and proceeded to drive onto the freeway in the opposite direction of the rider.

dropped them), they were assigned to a new driver 18 seconds later on average and picked up shortly after.

Figure 43. Cancellation Types Across Services



	Lyft	Uber	Taxi
No pick up (wait 60 min)			11.0%
Refused rider service			1.0%
No cars available			3.0%
Dispatch didn't pick up phone			2.8%
Other	0.2%	0.2%	0.8%
Driver cancelled	3.9%	3.4%	
No pick up (wait 20 min)	0.3%	0.0%	
Pickup without incident	95.7%	96.5%	81.5%

While the majority (95%) of taxis cancellations occurred because taxis never arrived (either because the dispatcher did not pick up the phone, no cars were available, or no taxis were available), in four cases, riders were refused service after a taxi arrived. Taxi drivers refused service in one of two ways. First, in two cases, the driver drove off before a rider could get in the car. One rider (Hispanic, female) stated that the "Driver passed by and did a U-turn but never returned just drove off." The other rider (black, male) stated that "Driver finally came and I was walking toward car, drove off!" Second, drivers refused service on payment grounds; drivers issued payment-based refusals issued twice, each time to a black male rider. On these two occasions, the riders stated that the driver "demands cash instead [of a credit card] in fear that I wont [sic] pay upon completion of route" and that the driver claimed that "other passengers had scammed him at that same stop and he wanted to charge me upfront i[n] cash." Demanding cash may be discriminatory or it may be tied to economic reasons, such as a driver fearing he will not be able to cover medallion rent at the end of an unproductive shift. Regardless, cash demands and refusal to accept a credit card violate taxi users' rights in Los Angeles, where taxi riders are entitled to pay for a trip using a credit card (City of Los Angeles 2018).

Distance and Price Variation

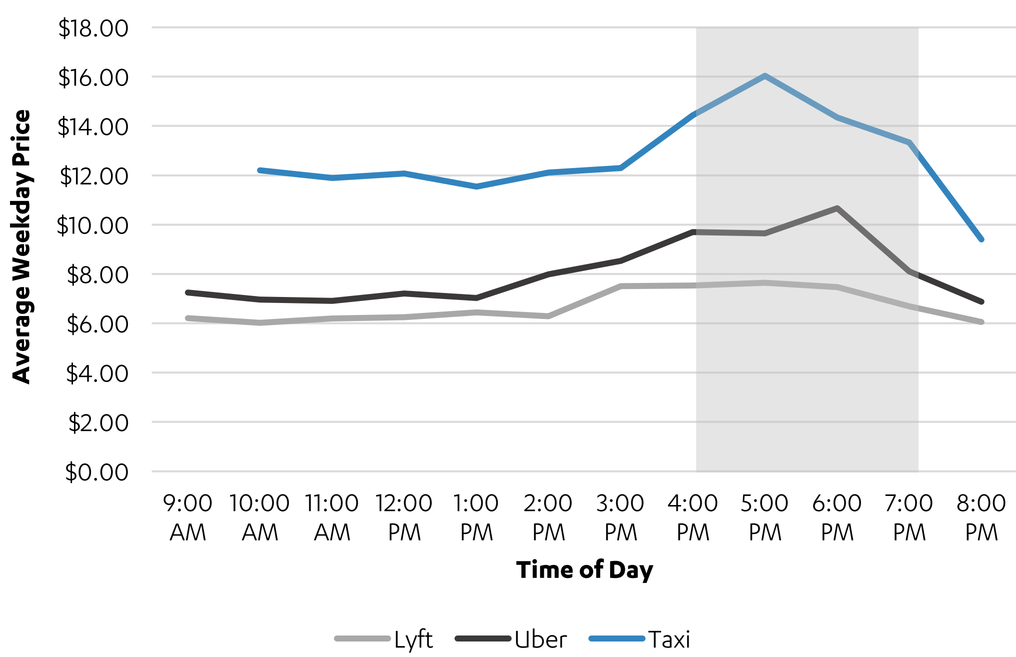
Uber and Lyft vary prices by trip distance, time traveled, and the number of drivers relative to the number of riders (i.e., how busy it is). As a result, substantial price variation existed across the same route; Table 24 shows that ridehail prices ranged from about $5 for both services up to about $15 and $21 for Lyft and Uber, respectively. About two-thirds (64%) of the most expensive trips (top 1% of trips) occurred during the evening peak period, and about one-third were during the Friday evening peak alone. Figure 44 shows the increase in average prices during weekday peak periods.

Table 24. Price Statistics: Uber, Lyft, Taxis

	Lyft	Uber	Taxi
Min	$5.60	$5.16	$8.25
Max	$15.09	$20.73	$22.45
Mean	$6.53	$7.78	$11.99
Standard Deviation	$1.18	$1.91	$2.87
Coefficient of Variation	0.181	0.246	0.239

Prices exclude tips.

Figure 44. Mean Weekday Trip Price



Shaded area indicates pickup during peak evening period (4:00 – 6:59 pm). Prices do not include tips.

Despite the price variation, Uber and Lyft remained significantly ($p<0.01$) cheaper than taxis at any point in the day, which holds with previous research (Smart et al. 2015). Particularly interesting is that taxi prices varied even *more* than Uber and Lyft. Taxis, too, charge based on miles driven and travel time; the peak-hour price bump likely reflects longer travel times on congested rush hour roads. Varied taxi prices, however, also stem from a range in trip distances. With numerous possible routes between Sites 1 and 2, the median trip distance across all services was 2.3 miles, and the minimum distance was 1.28 miles. Therefore, it is shocking that about 10 percent of taxi trips were more than four miles long, driving up both the total meter charge and associated tip. Taxi trips longer than four miles were $5 more expensive (excluding tip) on average than those shorter than four miles.[64] About 10 percent of taxi drivers made at least one long ride; in other words, long trips were not isolated to a single driver making repeated long trips, but instead occurred sporadically across all taxi drivers. Familiar with the route, riders noted the long taxi routes, commenting "Seemed like he went an unnecessarily long route" and "I had to give directions after an extremely circuitous route." Unlike Ge et al. (2016), who observed that drivers took female riders on longer routes, I observe no difference in trip length by rider gender.

Unlawful Discrimination in the Ridehail and Taxi Industries

In this section, I discuss how cancellation rates and wait times varied across rider race, ethnicity, and gender. For both cancellations and wait times, I present descriptive statistics followed by model results.

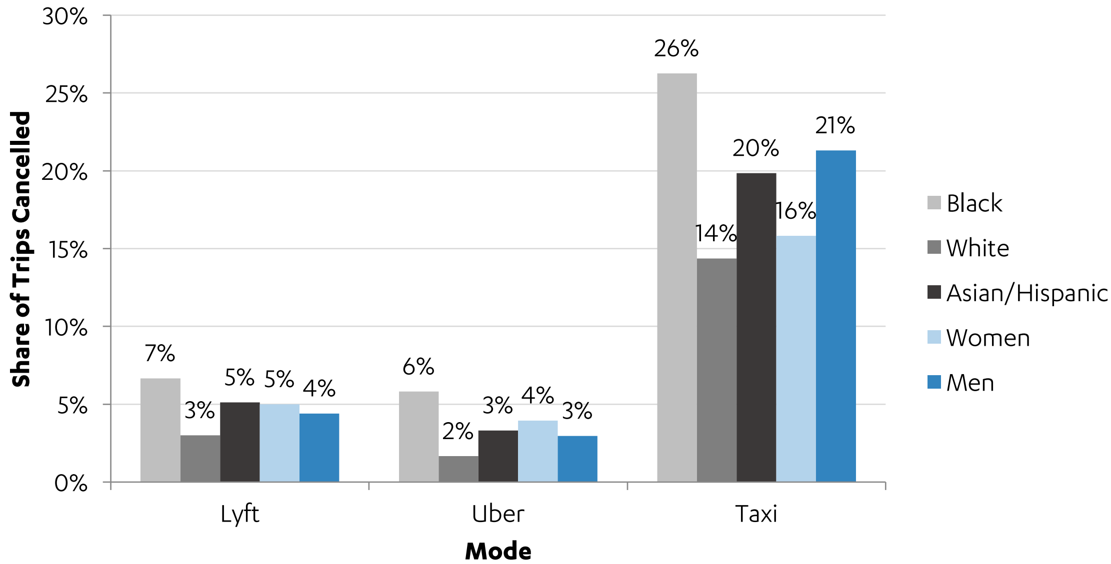
Cancellations

Figure 45 highlights that—in addition to stark variation across services—cancellation rates vary across rider race, ethnicity, and gender. Across all services, cancellation rates were lowest for white riders, moderate for Asian and Hispanic riders, and highest for black riders. Uber and Lyft drivers

[64] By comparison, less than one percent of Lyft and Uber trips were longer than four miles; these trips were only $1.50 more expensive than trips under four miles, likely because other factors such as "prime time" surcharges also affect price and thus distance plays a smaller role in pricing.

cancelled on men and women at nearly equal rates, but taxis cancelled on a higher share of men than women.

Figure 45. Share of Trips Cancelled by Service and Rider Characteristics

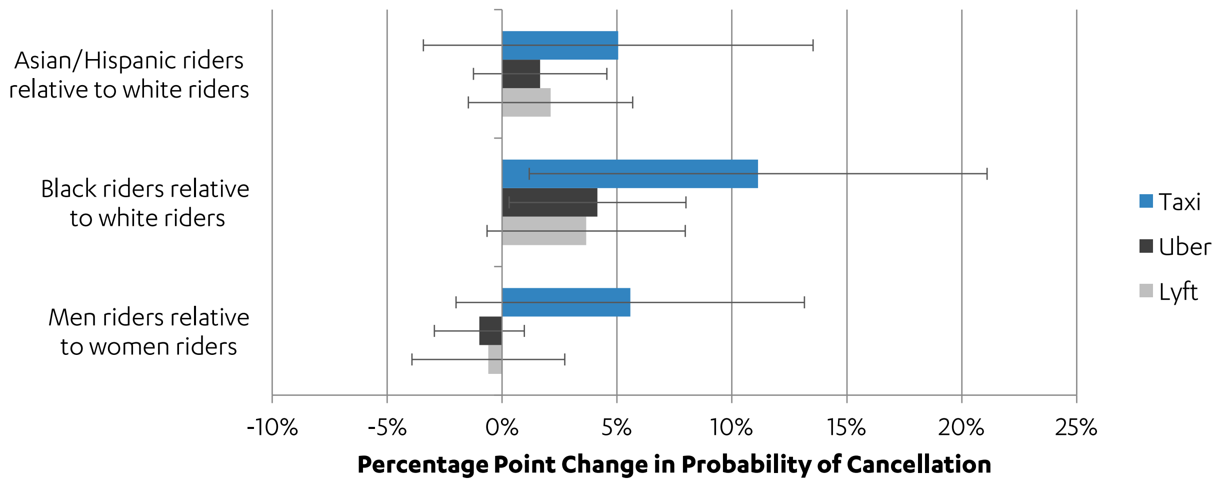


How important are rider characteristics in predicting trip cancellations? Figure 46 shows the predicted probability that a trip is cancelled, controlling for rider characteristics, peak hour travel, and taxi company. I present full model results in Table 31 in Appendix F. The starkest contrast is between black and white taxi riders: black taxi riders are 73 percent (or 11 percentage points) more likely to have a driver cancel on them compared to white riders; model predications show that more than one-quarter (26%) of black taxi hails are canceled compared to about 15 percent of trips hailed by white riders. These results suggest that discrimination against black riders has not waned since audit studies conducted three decades ago (Ridley, Bayton, and Outtz 1989). On both Uber and Lyft, the difference in probability of a trip being cancelled is only four percentage points higher for black compared to white riders, although I cannot rule out chance in the differences observed on Lyft.[65] Together, cancellation rates suggest that the moment of discrimination occurs when drivers first

[65] Predicted differences in the probability of having a trip cancelled between white and black riders is significant at the 95 percent confidence interval for Uber, but not significant at any confidence level for Lyft. In other words, although black riders have about a four percentage point increased probability of having a Lyft driver cancel on them compared to white riders, I cannot rule out chance in explaining these differences.

learn of or infer rider characteristics, although the effects are far greater on taxis than on Uber. Black riders are the only group with significantly higher cancellation rates after controlling for time of day and taxi company; no meaningful differences exist between either Asian/Hispanic and white riders or between men and women on any service.

Figure 46. Percentage Point Change in Probability of Cancellation by Rider Characteristics



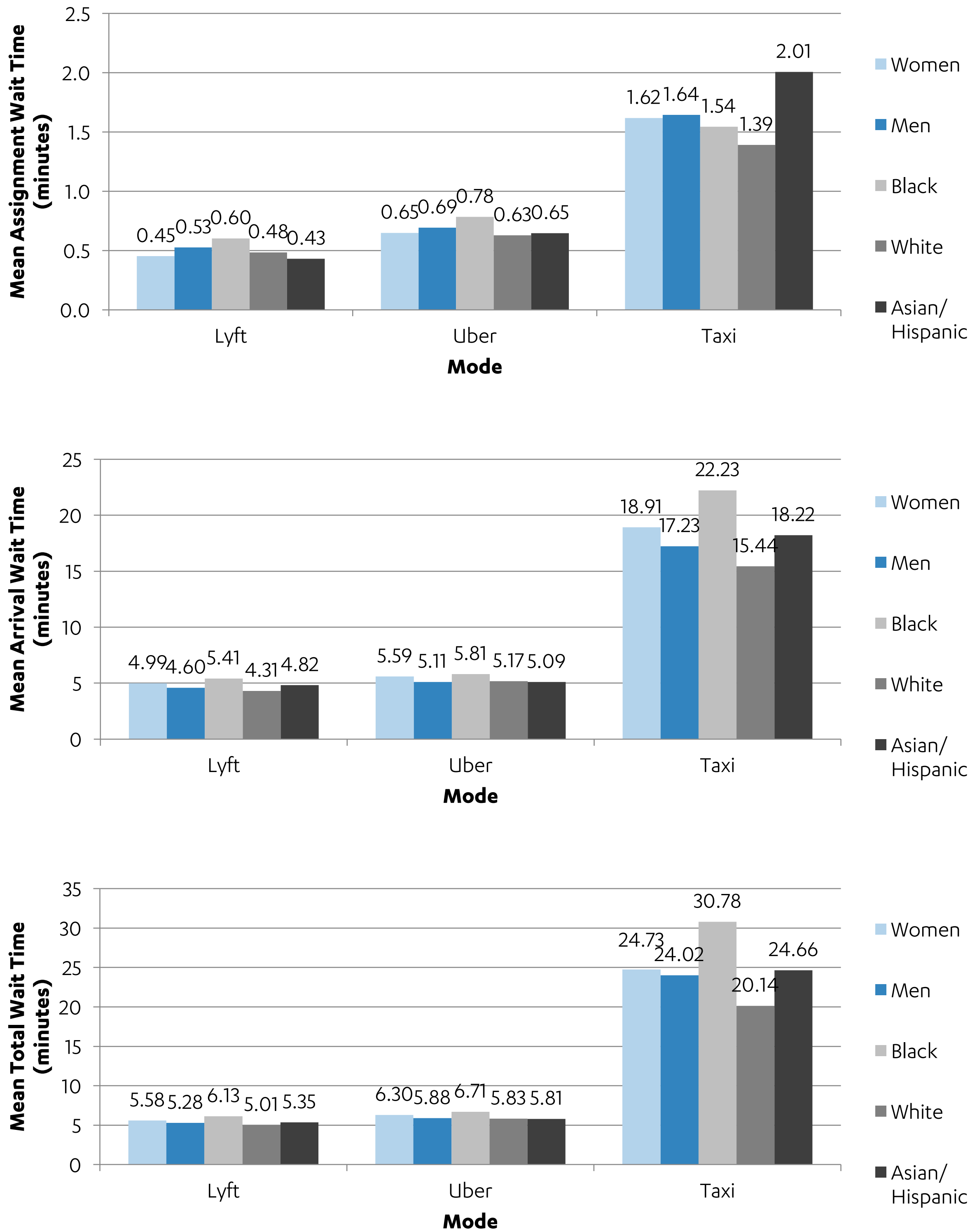
Error bars indicate 95% confidence intervals.

Cancellations translate into different rider experiences across services. For Lyft and Uber, cancellations are associated with longer wait times, as discussed in the following section; however, in 99.7 percent of "cancelled" Uber and Lyft trips, riders still reach their destinations. Taxi cancellations, by contrast, result in no pick up.

Wait Time

Figure 47 shows mean assignment, arrival, and total wait times by rider race, ethnicity, and gender. Overall, variation across rider characteristics appears smaller on ridehail than taxi services. Because some descriptive variations may be due to when riders took trips and which taxi companies they hailed, I controlled for both peak-hour trips and taxi company in a series of regression models. I present predicted outcomes for three wait time models in the following sections and include full model results in Appendix F.

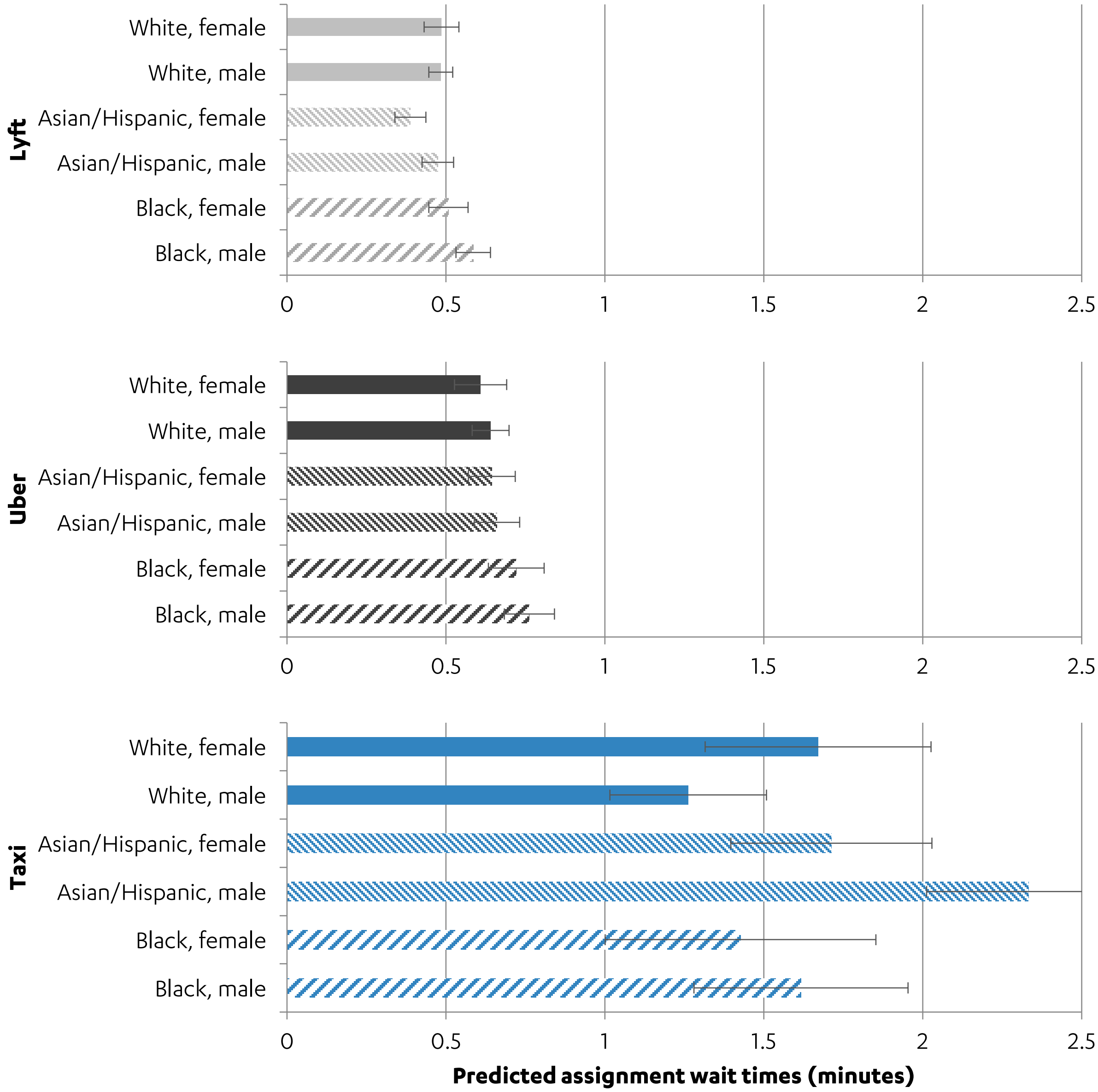
Figure 47. Wait Times by Services and Rider Races/Ethnicities



Assignment Wait Time

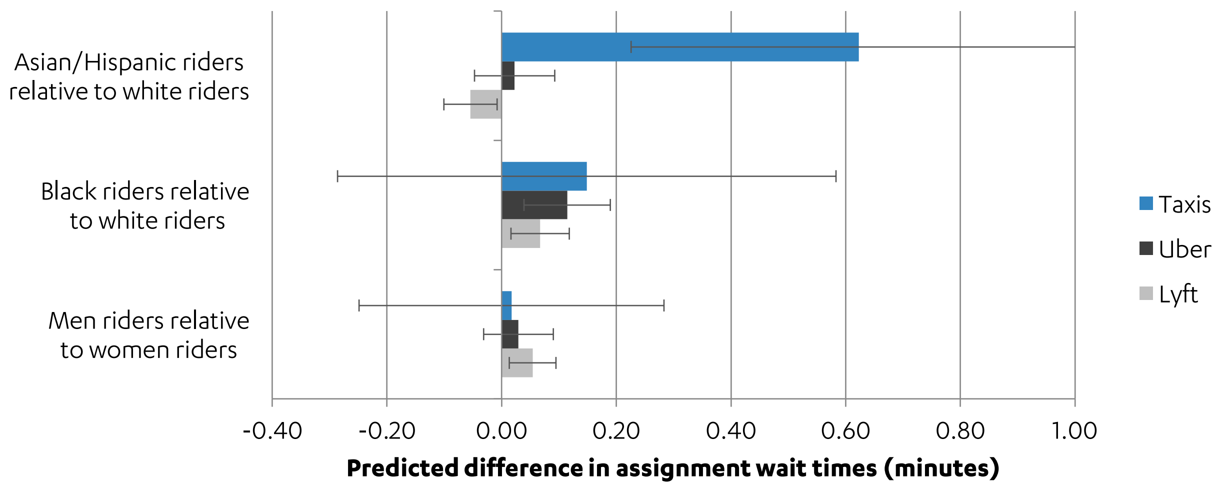
Figure 48 and Figure 49 show predicted assignment wait times by rider characteristics, controlling for peak periods and taxi company. I present full model results in Table 32 in Appendix F. Overall, differences in assignment wait times lend only moderate support to the hypothesis that discrimination occurs at the moment drivers learn of or infer rider characteristics. As hypothesized, black riders wait a statistically-longer time than white riders to be assigned to a Lyft driver. Unexpectedly, however, black riders also wait longer to be assigned to an Uber driver, and Asian and Hispanic riders wait longer for taxi dispatchers to confirm their hail requests. How differences in Uber and taxi assignment times manifest when all other factors are equal and drivers cannot infer rider characteristics prior to trip acceptance is uncertain and would require additional investigation. No differences in assignment wait time exist between men and women on Uber or taxis; with men waiting just two seconds longer than women on Lyft, the differences are also effectively zero.

Figure 48. Predicted Assignment Wait Times by Service and Rider Characteristics



Error bars indicate 95% confidence intervals.

Figure 49. Predicted Difference in Assignment Wait Times Across Services and Rider Race/Ethnicities



Error bars indicate 95% confidence intervals.

Like gender, differences in Uber and Lyft assignment wait times are statistically significant (i.e., they are not due to just chance), but effectively zero; black riders wait just four and seven seconds longer than white riders on Uber and Lyft, respectively. Figure 48 shows predicted assignment wait times by rider race, ethnicity, and gender, controlling for time of day and taxi company. The largest gaps between rider groups exist between white women and black men on Uber (10 seconds), between Asian/Hispanic women and black men on Lyft (12 seconds), and between white men and Asian/Hispanic men on taxis (1 minute 4 seconds).[66] While assignment time differences are unlikely noticed by ridehail users, the same cannot necessarily be said of taxis with a one-minute difference between white and Asian/Hispanic men. Assignment times contribute to total wait times, which are arguably the most important service quality to riders. I discuss total wait times by rider characteristics later in this chapter.

Arrival Wait Times

Controlling for rider characteristics, time of day, and taxi company, differences in arrival wait times are most strongly associated with time of day; drivers take between 40 seconds and 3 minutes 41

[66] While these time differences are small, they are larger when considering average assignment wait times, which are 29 seconds on Lyft, 41 seconds on Uber, and 1 minute 40 seconds on taxis.

seconds longer to arrive during rush hour, all else equal, as drivers navigate through congested streets. Riders also waited longer for Independent Cab Company taxis to arrive, possibly because the smaller company fleet—relative to United or LA Yellow Cab—means that fewer cars are available for dispatch or are farther away when called. I present full arrival time model results in Table 33 in Appendix F.

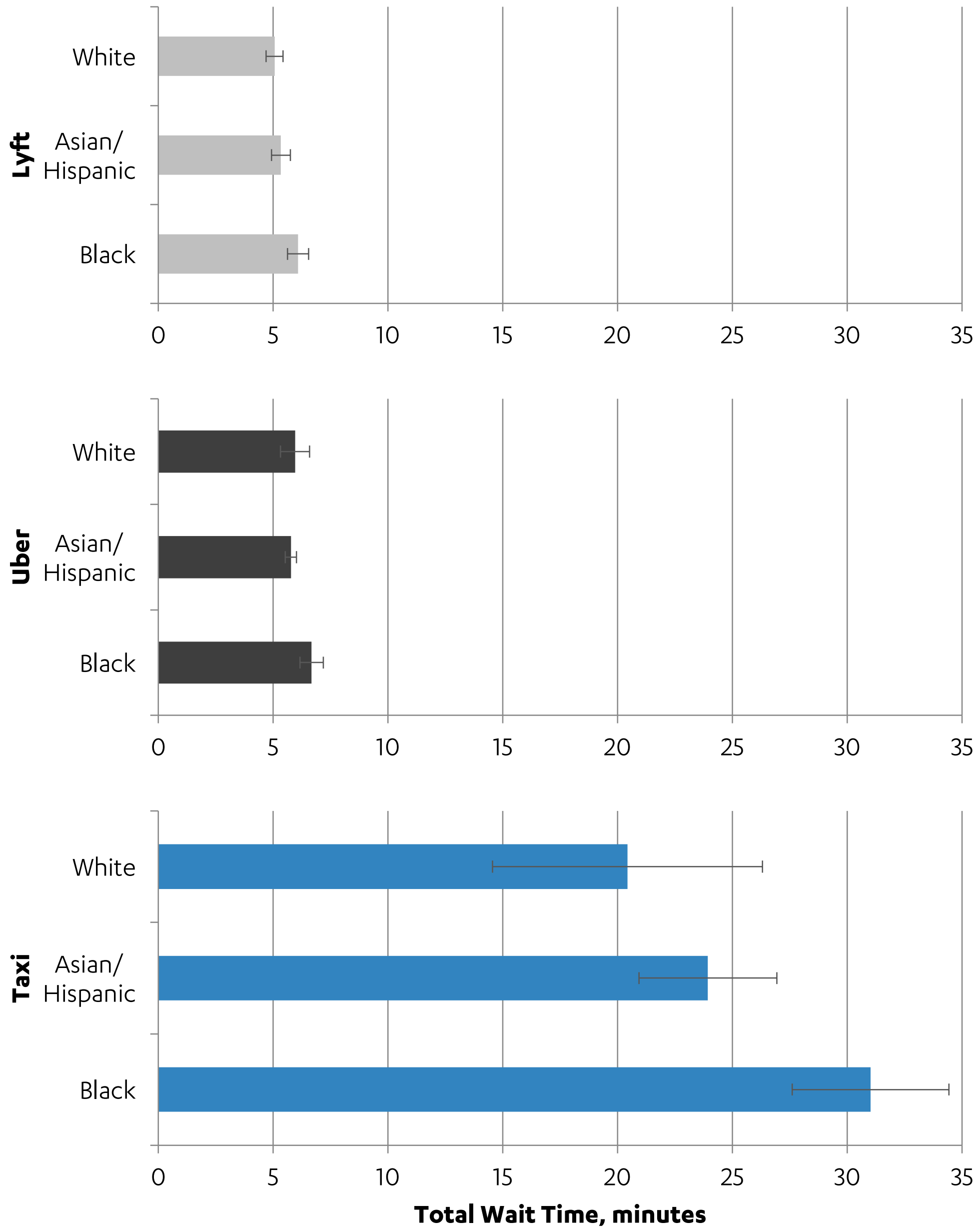
Total wait times are a combination of assignment and arrival wait times, plus any additional wait time incurred by a cancellation. Waiting to a vehicle to arrive constitutes the bulk (86%) of total wait time; as a result, arrival time is closely correlated (0.99, $p<0.01$) with total wait time. In addition, associations between rider characteristics and arrival wait time are likewise reflected in the total wait time mode. I therefore focus the remainder of the wait time discussion on total wait time.

Total Wait Times

Together, cancellations, assignment, and arrival wait times sum to the total time a rider spends waiting for a ride. Figure 50 and Figure 51 show total wait time predictions by rider characteristics and controlling for peak hour travel and taxi company. Figure 50 disaggregates predicted wait times by rider race/ethnicity alone, while Figure 51 further examines rider racial/ethnic groups by gender. I present full model results in Table 34 in Appendix F.

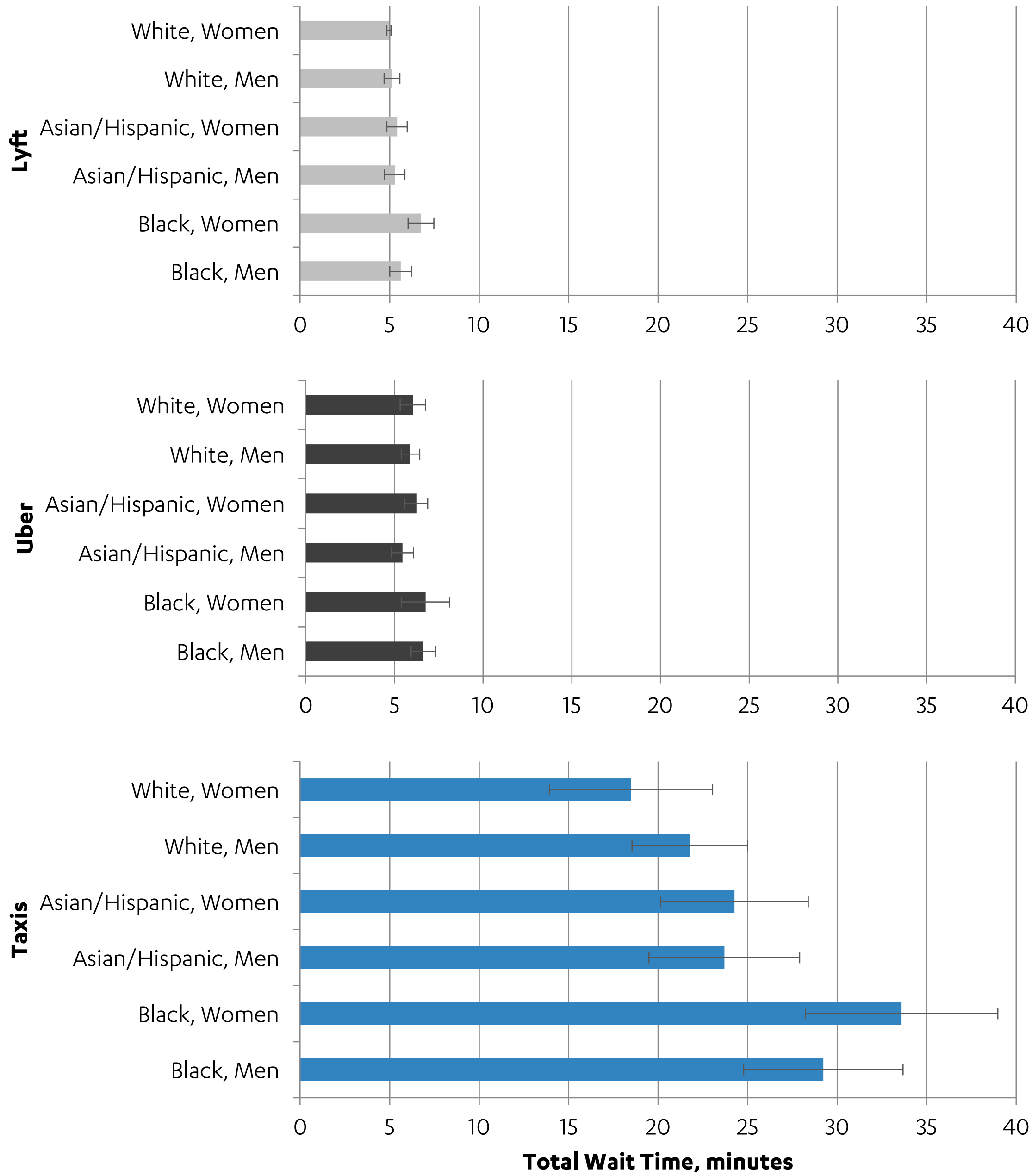
Overall, driver bias results in black (but not Asian or Hispanic) riders waiting longer than white riders on Lyft, Uber, and taxis. Differences between black and white riders are statistically significant on all three services, meaning that differences are unlikely due to chance. While black riders wait between 32 seconds and 1 minute 43 seconds longer than a white rider for Lyft car and between 11 seconds and 1 minute 30 seconds longer than a white rider for Uber, the starkest—and most meaningful—differences by rider race are on taxis. Black taxi riders wait between 6 minutes 14 seconds and 14 minutes 47 seconds longer than white riders, controlling for other factors; on average, black taxi riders wait 52 percent longer than white riders, all else equal.

Figure 50. Predicted Total Wait Times Across Services and Rider Race/Ethnicity



Error bars indicate 95% confidence intervals.

Figure 51. Predicted Total Wait Times Across Services and Rider Characteristics



Error bars indicate 95% confidence intervals.

Results demonstrate that while ridehailing has not eliminated driver biases, it has dramatically lower racial/ethnic service gaps compared to those still evidenced in taxi service. In addition, differences in hail methods across services suggest that discrimination occurs when drivers learn about or infer rider characteristics. These findings have implications for ridehail policy, which I discuss in Part III.

PART III: DISCUSSION OF RIDEHAIL EQUITY AND IMPLICATIONS FOR POLICY

Recap: Narrowing—But Not Erasing—the Mobility Gap

Taxi drivers have historically eschewed majority non-white neighborhoods (Hernandez 1992, LaMendola 1991, Spiegelman 2016) and unlawfully discriminated against riders based on their race, ethnicity, or gender (Belcher and Brown 2015, Wrigley 2013). While taxi regulators have long recognized these systematic failings, efforts to curb taxi discrimination and improve service in marginalized neighborhoods have proven largely unsuccessful. This raises the question of whether ridehailing services can improve car access, and do so equitability, where taxis have failed. This research suggests that at both the neighborhood and individual level, the answer is "yes."

Between September and November 2016, Lyft served neighborhoods home to 99.8 percent of the Los Angeles County population. While Lyft service and use is associated with the local built environment, the strong association between Lyft use and neighborhood household vehicle ownership suggests that Lyft is providing car access to neighborhoods and households where its substitute—the household car—is least available. Use frequency suggests that for most ridehail users, ridehail services fill the occasional modal gap or trip-specific need rather than fully replacing current travel modes. While 40 percent of users made less than one trip per month, a small share of avid ridehail users made the majority of all trips to, from, and within Los Angeles County. Consistent with a national survey that finds ridehail have are higher-income on average (Clewlow and Mishra 2017), ridehail users in Los Angeles live disproportionately in high-income neighborhoods relative to the broader population. While survey non-response rates may overestimate income differences in ridehail use (Holbrook, Krosnick, and Pfent 2007), together these studies suggest that ridehail adoption—i.e., people who have downloaded and use ridehail apps—is greater among high-income neighborhoods and travelers. However, adoption does not translate into trip frequency, and users living in low-income neighborhoods made more Lyft trips, all else equal. High ridehail use in low-income neighborhoods is more strongly associated with lower access to household cars than it is a function of income. Users living in low-income neighborhoods shared Lyft Line trips for a higher proportion of their trips compared to travelers living in higher-income neighborhoods. At the same time, less sharing occurred in racial and ethnically diverse neighborhoods; instead, similar to carpooling, people shared more in more homogenous neighborhoods (Charles and Kline 2006). In addition, significantly lower Lyft use in majority-Asian and Hispanic neighborhoods, even after controlling for median household income, car ownership, and built environment factors, suggests either that car access without ownership is already being met in these neighborhoods through carpooling or informal services, or that barriers to ridehailing remain.

At the individual level, I find that taxi drivers' discrimination against black riders is as present today as it was in audit studies conducted three decades ago (Ridley, Bayton, and Outtz 1989); while overall taxi service in my analysis was unreliable at best—nearly 20 percent of trips were cancelled and riders waited 24 minutes to be picked up on average—it was worst for black riders. I observed no meaningful differences among white, Asian, and Hispanic riders, suggesting that discrimination is particularly acute and common for black residents, as other research documents (Avery, McKay, and Wilson 2008, McLaughlin, Hatzenbuehler, and Keyes 2010, LaVeist, Rolley, and Diala 2003). Taxis failed to pick up black riders for more than one-quarter of their trip hails (26.3%), compared to about one-fifth of trips hailed by Asian and Hispanic rider (19.9%) and one-seventh (14.4%) of trips hailed by white riders. By contrast, ridehail services nearly eliminated the differences across rider characteristics. On taxis, black riders waited 52 percent longer (between about 6 and 15 minutes) than white riders; by comparison, black riders waited between 11 seconds and 1 minute 43 seconds longer for ridehail services than white riders. To put these differences in perspective: a black rider wanting to travel from the same location and at the same times as a white rider could expect to get picked up faster, on average, if she requested a ridehail trip *after* the white rider's taxi arrived than if she hailed a taxi trip at the same time as the white rider and waited for the taxi to arrive.

Ridehail Policy

In the following sections, I discuss implications of this research for ridehail policy and consider how policy and platform-level strategies can erase the remaining mobility gap and ensure equitable access to ridehailing, or other technology-enabled mobility services, in the future.

Access Across Space

For decades, taxi companies have delivered uneven geographies of service, typically underserving (or avoiding altogether) low-income neighborhoods and communities of color (Cohen 2015, Austin and Zegras 2012, Ridley, Bayton, and Outtz 1989, LaMendola 1991). By contrast, in my analysis Lyft provided trips in neighborhoods home to 99.8 percent of the Los Angeles population, and across a wide array of built environments. Areas with the highest Lyft trips per capita concentrated in high-density neighborhoods, regardless of income or racial/ethnic majority (see Chapters 4 and 5), suggesting that neighborhoods are not being refused service based on who lives there. Ridehailing achieved geographically ubiquitous service in part by eliminating two of the primary explanations for spatial inequities in the taxi industry.

First, unlike taxis, which tend to gather in places that they *think* riders will concentrate, ridehail apps *know* where riders are and match drivers to the nearest rider. In other words, ridehailing removes the guesswork for the passenger and, in particular, the driver. In addition, ridehailing can easily balance driver supply and rider demand by raising prices in certain areas to draw drivers to underserved neighborhoods. Once driver supply and rider demand are again balanced, prices return to equilibrium.

Second, many taxi drivers refuse to serve low-income neighborhoods or communities of color from fears about safety or concerns that they will not find a rider for the return trip (Cohen 2015, Hernandez 1992, King and Saldarriaga 2017a). Ridehailing changes these calculations in a number of ways. First, it removes a driver's ability to discriminate based on a destination; unlike dispatched taxis, which ask about the destination when the trip is requested, ridehail drivers with Lyft and Uber only learn the destination after they pick up a rider. Second, while dispatched taxis are only permitted to pick up riders in certain locations, resulting in frequent deadheading (King and Saldarriaga 2017a), ridehail drivers may pick up riders anywhere. In combination with the efficient matching process that connects nearby riders and drivers, ridehail drivers therefore may run lower risks of making empty return trips compared to taxis, which either lack the information or the permission to pick nearby riders up. Third, being an Uber or Lyft driver may be safer—or at least be perceived as safer—compared to being a taxi driver because both the driver and passenger have a digital record of the trip and reviews of one another. While ridehail drivers (and riders) still report incidents of assault (Levin 2017, Levenson and Allen 2016), being a taxi driver remains one of the most dangerous professions in the country, with homicide rates 60 times the national average (Mayhew 2000). Improved perceptions of safety may result from the entirely cashless operation (at least in the U.S.), star-ratings that vet drivers and riders, and navigation systems that make travel to and within unfamiliar neighborhoods easier.

While the spatial distribution of Lyft trips and use suggests that ridehailing extends reliable car access across space, equal service across space does not guarantee equitable access across riders. I discuss policies to combat discrimination and overcome individual barriers to access in the following sections.

Reducing Discrimination

As discussed in Chapter 7, rider discrimination was far lower on ridehail compared to taxi services. In this section, I discuss three ridehail innovations that help to explain why unlawful discrimination manifests less in the ridehail industry. These innovations hold lessons for future technology-enabled mobility services. In addition, I consider platform-specific and public sector interventions that may help to close the service gaps between riders entirely.[67]

[67] A fourth possibility is that taxi drivers themselves are more biased towards riders of certain races, ethnicities, or genders. However, as I found no evidence that driver identity affected bias towards riders across any service, I will not explore this possibility.

From Taxis to Ridehail: Innovations that Deter Discrimination

The first reason that discrimination may manifest less on ridehailing is the guaranteed cashless payment system. Although taxis accept credit cards, many taxi riders still pay with cash (Schneider 2015, King and Saldarriaga 2017b). Cash payments make drivers vulnerable to both robbery and fare evasion, and taxi drivers in this audit study specifically voiced fears of fare evasion, but *only* to black male riders (see Chapter 7). By contrast, fare evasion is impossible on ridehail services, which automatically charge one's credit or debit card after a trip is completed.

Ridehail ratings may also discourage discrimination. Picking up strangers in one's car involves inherent risk, and taxi drivers face elevated rates of personal injury, robbery, and death (Menéndez, Socias-Morales, and Daus 2017, Siegelman 1998). Unlike on taxis, ridehail drivers have some prior knowledge of riders through the rating system. Ratings essentially vet riders prior to pick up and can alert drivers of potentially problematic customers. In addition, drivers know that particularly troublesome riders are removed from the platform entirely (Rosenblat and Stark 2016, Rayle et al. 2016). Unlike on taxis, where drivers may have difficulty holding a disrespectful or even violent rider accountable, ridehail drivers can rate and issue complaints about riders, providing some recourse to poor rider behavior. Rider ratings may reduce proxy discrimination by drivers, who can use star ratings in lieu of observable traits to infer, for example, how safe or considerate a rider may be. One potential problem with star ratings, however, it that they too may discriminatory; I discuss this potential below in Future Research Directions.

Finally, greater (perceived or actual) driver accountability on ridehailing compared to taxis may deter discrimination. Auditors reported feeling that taxi drivers were not accountable for their actions. One auditor who attempted to file a complaint with a taxi company stated, "There's no accountability, I felt, with the taxis, 'cause you don't rate them. I tried calling them [the taxi company] and they didn't care." This rider is unlikely alone in encountering difficulties reporting complaints to taxi operators. For example, in 2015, out of millions of taxi trips, just 223 riders logged complaints with LADOT (Los Angeles Department of Transportation 2017b). Given rider experiences in this audit study, and reported dissatisfaction with taxi service in other cities (San Francisco Municipal Transportation Agency 2013), limited formal complaints likely reflects underreporting rather than high satisfaction with taxi service. By contrast, ridehail apps provide built-in driver accountability tools; riders can rate drivers and quickly file service complaints, including complaints of discrimination. Unlike taxis, auditors reported positive interactions with ridehail customer service.[68]

Closing the Gap on Ridehailing

While innovations have helped ridehailing dramatically shrink the service gap across rider demographics, interventions on both the supplier and public sector side can help close the gaps entirely. The first intervention is supply side: driver retraining. Much—albeit certainly not all—of racism today is "aversive," that is, a "subtle, often unintentional, form of bias" fueled by unconscious stereotyping and prejudice (Dovidio, Kawakami, and Gaertner 2000, 137, Burgess et al. 2007). Two common strategies can combat such biases. First, active retraining sessions targeting specific stereotypes can reduce peoples' reflexive categorization of others based on stereotypes (Dovidio, Kawakami, and Gaertner 2000, Kawakami et al. 2000). Second, because most averse racism is by people who do not *want* to be prejudiced, "it may be possible to capitalize on their good intentions" (Dovidio, Kawakami, and Gaertner 2000, 144). Techniques that raise people's awareness of the inconsistencies between their self-image, values, and behaviors, can cause people to confront their biases and align their behavior more consistently with their non-prejudiced beliefs (Dovido, Kawakami, and Gaertner 2000, Grube, Mayton, and Ball-Rokeach 1994, Altemeyer 1994). These examples from psychology suggest that retraining or, at a minimum, educational or information campaigns about racial stereotyping, can help to close the existing service gaps among riders.

[68] When asked about providing feedback to companies, one audit study rider stated, "Lyft was like the most helpful in their customer service", while another said, "So for Uber, it was amazing because I told them [about the complaint], and then immediately they responded, like less than two minutes."

Regardless of whether bias is conscious or unconscious, it is unlikely to be eradicated from the population entirely. Assuming biases will remain in the population for the foreseeable future, ridehail companies may institute four changes to deter drivers from acting on their biases: they may track discriminatory behavior, change *what* drivers see about riders, *when* drivers see rider information, or they may alter incentives for accepting and cancelling rides.

The most direct way to curb discrimination would be to identify discriminatory behavior and hold drivers accountable for their actions. Such an approach would require ridehail companies to collect rider demographics, which they currently do only sporadically (Lyft 2018a). Ridehail companies could track driver behaviors to determine if cancellations were biased against riders of certain races or ethnicities. Companies could then report biases to drivers, which may spur behavioral changes (Dovidio, Kawakami, and Gaertner 2000). Drivers who failed to alter their behaviors could be removed from the platform. Tracking driver discrimination over time could also be used to test the efficacy of other anti-discrimination policies.

In addition to holding drivers accountable for their actions, ridehail companies may also proactively deter discrimination by changing what information drivers see about riders and when they see it. Audit findings discussed in Chapter 7 revealed moderate support for discrimination occurring when drivers learn about or infer rider characteristics. Studies in economics suggest that making online transactions entirely anonymous erases discrimination (Doleac and Stein 2013, Morton, Zettelmeyer, and Silva-Risso 2003). These findings suggest that ridehail companies should eliminate or minimize the information that drivers receive about riders, or at the very least, delay that information until later in the trip. Lyft, for example, could remove rider photos from the hail process entirely to reduce the information that drivers have about riders to draw and act on bias. Of course, names, too, can still produce discriminatory results as this study and others found (Bertrand and Mullainathan 2004). One potential solution to this is for ridehail companies to allow riders (and potentially drivers) to use a pseudonym. A pseudonym may be attractive to riders who worry about discrimination or who wish to protect their privacy further. A small-scale pilot could test if pseudonyms reduced bias in ridehailing.

Ridehail companies, however, argue that photos and names create "digital trust profiles" to make riders and drivers feel secure (Dickey 2016). An alternative to removing photos and/or names could therefore be to show identifying information later in the trip, say, as a driver came within 100 feet of a rider. While star-ratings could still be communicated at the trip outset, delaying rider information until the moment before pickup may deter cancellations. At this point, both riders and drivers are invested in successfully completing the ride, having waited for and driven to one another.

Finally, in addition to what rider information drivers see or when they see it, ridehail companies could further incentivize high acceptance rates. For example, companies could provide bonuses or allow driver to recoup higher shares of fare revenues if they meet a 100 percent acceptance rate. Companies could also further deter cancellations by permitting fewer cancellations before a driver receives a "time out," requiring drivers to provide an explanation for why they cancelled a trip, tracking drivers who cancel frequently, or financially discouraging drivers from cancelling in ways inverse to the incentives enumerated above.

Particularly if ridehailing services become (or already are) subject to Title VI protections, the public sector must ensure that companies do not violate antidiscrimination or ADA laws. To do so, they may conduct periodic industry audits, as was done for this study. Alternatively, they should consider using abundant ridehail data to monitor and deter discrimination; I discuss data sharing considerations later in this chapter.

Access by Individuals

While Lyft trips in Los Angeles exhibit remarkable geographical diversity and serve neighborhoods home to nearly all Los Angeles County residents, findings suggest that barriers to access likely persist. Based on findings of who uses ridehailing and where they use it (Chapters 4 and 5), I focus this discussion on increasing ridehail access for 1) seniors and 2) travelers facing technological and banking barriers.

Expanding Access for Seniors

Findings discussed in Chapters 4 and 5 revealed a positive association between Lyft use and the share of neighborhood residents who are young (ages 15 to 34). While a rather blunt way to estimate the effects of age, findings, together with other survey research (Rayle et al. 2016, Henao 2017, Clewlow and Mishra 2017, Gehrke, Felix, and Reardon 2018), suggest that seniors use ridehailing less than other age groups. While lower use among seniors may partially reflect a general disinterest in these services (Shirgaokar 2018), technological and physical barriers likely impede use. In the following paragraphs, I discuss a number of private and public sector interventions to improve access to ridehail services for seniors. For a broader list of senior-specific policy interventions than I discuss here, see Shirgaokar (2018).

First, seniors face technological barriers to ridehailing, specifically, low-rates of smartphone ownership and a distrust of paying for services online (Shirgaokar 2018, FDIC 2016). Trends in smartphone ownership suggest that technological barriers are largely a cohort effect; in other words, technological barriers for seniors will become less prominent as Baby Boomers, many of whom already own smartphones, age (FDIC 2016). Although this cohort effect may wane over time, removing barriers for current seniors may enable them to age in place, increase their access to services, and improve their satisfaction with overall mobility options (Vivoda et al. 2018). A number of third-party platforms already offer potential solutions to technological barriers. Services such as RideWith24, GreatCall, and GoGoGrandparent all provide access to ridehail services without a smartphone. For example, GoGoGrandparent allows seniors to hail an Uber or Lyft from their home phone by pre-programming favorite destinations—assisted by friends of family if necessary—and using a call-back feature to alert riders when their vehicle arrives. GoGoGrandparent also offers telephone customer support and ride tracking for people to assist senior family members (GoGoGrandparent 2018). GreatCall offers an alternative model; through a 2016 partnership with Lyft, seniors can request a ride verbally through an operator for a small fee (GreatCall 2016). Cities and organizations can promote such third-party services, or set up partnerships directly with ridehail companies. For example, Lyft Concierge partners Lyft with local healthcare providers and businesses, who can then hail vehicles for patrons (Lyft 2018c). Senior housing developments, community centers, or public libraries could likewise adopt Lyft concierge to hail rides for residents without smartphones.

Second, many seniors have physical disabilities, and require assistance or medical devices in order to get around. Physical disabilities are an aging effect; unlike technological barriers, which will likely decline as tech-savvy Baby Boomers age, the need for disability-supportive services will remain. About 17 percent of adults 60 or older report a physical disability compared to less than five percent of adults under 60 (California Department of Transportation 2012). As a result, seniors are more likely to need an escort between the origin or destination door and vehicle. While many seniors say that they will rely on paratransit once they can no longer drive (Shirgaokar 2018), ridehail may offer a more flexible and lower-cost alternative. To provide full paratransit services, accommodate all physical needs, and to comply with Americans with Disabilities (ADA) requirements—particularly if ridehail companies take federal funding in first-last mile partnerships—ridehail companies will need to provide wheelchair-accessible vehicles (WAVs). Some cities fund WAVs through surcharges on regular taxi trips; the same could be done with ridehailing. Small surcharges across many rides, combined with public-subsidies like those that currently support traditional paratransit services, can help to fund ridehail WAV or contracted WAV services. Consolidating taxi and ridehail WAVs may help to provide sufficient funding and supply of vehicles that serve a diffuse population (Schaller 2016).

Technology and Banking Barriers to Access

In addition to an association between the share of young adults in a neighborhood and Lyft travel, I found that Lyft use is significantly lower in majority-Asian and majority-Hispanic neighborhoods, all else equal; I discussed a number of potential explanations for these findings in Chapter 5. In this section, I explore potential solutions to two barriers to access: the lack of a smartphone and/or bank account.

Creating ridehail access for travelers without smartphones involves solutions similar to those discussed above for seniors. Services such as GoGoGrandparent and GreatCall could easily be expanded to the broader population and Lyft Concierge or other community-ridehail partnerships could enable people to call ridehail vehicles from a variety of locations as previously discussed.

Unbanked individuals may also face barriers to ridehail access. While both Uber and Lyft allow prepaid cards, 12 percent of non-ridehail users still report not being able to pay cash as the largest deterrent to ridehailing (SharesPost 2018). Public sector solutions may help to bridge the gap between ridehail services and unbanked or cash-only households. As transit agencies seek to provide ridehail first-last mile solutions, they should consider how to do so in ways that eliminate the need for a credit or debit card. One option is for agencies to integrate ridehail services into pre-existing electronic fare payment systems. For example, Sound Transit Agency in Seattle plans to integrate the ridehail service Via with its ORCA transit cards as part of its Mobility on Demand sandbox pilot (Federal Transit Administration 2018b). During this pilot, transit users can use their ORCA card to pay directly for Via trips. A second option is to introduce electronic fare payment systems that support banking features, such as the Ventra card in Chicago. The Ventra card serves a dual role as MasterCard debit card and smart transit card. Cards can be loaded with cash at fare vending machines and balances are protected should the card be lost or stolen. Although the Ventra card is not formally integrated with ridehail services, the MasterCard debit feature allows households to pay for ridehail trips or other shared modes that require banking access, such as bikeshare.

Data Sharing

Finally, without data, cities will continue to struggle to understand where and when people use ridehailing, how it may be integrated with other modes, and how to promote more equitable ridehail access. While tempting, requesting huge quantities of disaggregate data from ridehail companies, unassociated with performance-specific aims, are unlikely to yield productive outcomes. Instead, in-line with broader understandings of performance-based equity planning (Karner 2016), data requests must be specific and connected to actionable performance metrics or mobility outcomes. While big data alone will not guarantee equitable service across neighborhoods or eliminate discrimination, new technologies can answer more questions, more reliably, and perhaps at lower costs than in the past. For example, in lieu of a physical audit as was done in this research, cities could require all-digital ridehail audits using wait times, cancellation rates, and rider characteristics; while ridehail companies do not regularly collect rider demographics, they do periodically collect rider information during annual reports and research collaborations, (Hall and Krueger 2015, Lyft 2018a). Using data attached to specific project evaluations or performance metrics can help to advance equitable access to ridehail and other innovative modes.

Future Research Directions

Many unknowns remain about ridehail services and how equitably they serve communities and travelers. I discuss three immediate research directions to promote equity and access in ridehailing.

First, while this audit study evaluated how services varied across individuals, it did not evaluate how service varied across space. Although I found no differences in wait times or cancellation rates between the two sites evaluated in this project (see Chapter 7), other researchers find both that estimated wait times (estimated by ridehail apps prior to hailing) vary by neighborhood characteristics (Hughes and MacKenzie 2016) and that estimated wait times diverge from *actual* wait times, particularly for black Uber riders (Ge et al. 2016). Additional research is needed to understand if and how actual wait times vary across space and if an interaction exists between neighborhood and individual characteristics. Such research could involve a physical industry audit or utilize ridehail data, as described in the previous section.

Second, barriers currently impede some travelers from accessing ridehail services; however, the types and prevalence of barriers remains unknown. Overcoming barriers is critical to ensure that ridehail services enhance mobility for all, not just some, travelers. Identifying and addressing barriers will become increasingly important as transit agencies partner with ridehail companies to provide first and last-mile services or replace transit routes entirely with subsidized ridehail services, such as in Pinellas Park, Florida (Brustein 2016).

Third, discrimination in ridehailing may extend beyond wait times and cancellation rates to ridehail star ratings. Understanding potential bias in star ratings is critical as they may affect wait times, cancellations, or motivate removal from the platform entirely. Previous research finds racial and gender biases in customer service satisfaction (Hekman et al. 2010, Snipes, Thomson, and Oswald 2006) and a lawsuit in Boston claims that ridehail star ratings may also be racially biased (Adams 2016). In conjunction with driver and/or rider surveys to ascertain individual characteristics, these questions could easily be answered by the data already collected by ridehail companies; alternatively, they may be answered by a combination of survey and audit methods.

Conclusion

Ridehailing extends reliable car access to groups and neighborhoods previously marginalized by limited access to private vehicles and expensive, unreliable taxi service. While ridehailing may represent a current solution to narrowing the mobility gap, it faces an uncertain future as—despite providing millions of rides—companies lose millions of dollars each year paying for driver incentives, promotional fares, and operating costs (Solomon 2016). Regardless, ridehailing offers broad lessons for the future innovative modes. While technologies can help to increase mobility across space and individuals, innovation alone will not solve all ills, and in particular stubbornly persistent racial/ethnic discrimination. Instead, planners and policymakers should view new technologies as opportunities to increase equity and enhance mobility for all, not just some, travelers.

APPENDICES

Appendix A. Robustness Testing for the Built Environment

I present three models with differing combinations of built environment variables to test for model fit and robustness. Each model includes two measures of parking supply (on and off-street parking spaces per square mile) adapted from Chester et al. (2015) to capture parking's influence on driving behavior (Weinberger, Seaman, and Johnson 2009, Weinberger 2012, Shoup 2011). The first model includes four additional density measures: population, employment, road network, and transit stop. The second model includes the sprawl index (Hamidi et al. 2015) plus a measure of transit stop density (Bureau of Transportation Statistics 2017). The sprawl index includes land use mix, street connectivity, and development density and higher index values indicate more compact and less sprawling areas. As the sprawl index itself does not include a measure of transit service, it is appropriate to include the additional measure in this model of the built environment. The final model uses a neighborhood typology developed by Voulgaris et al. (2017). The seven-type neighborhood typology created by Voulgaris et al. (2017) aims to capture potential threshold effects and multiple built environment and housing stock factors. The neighborhood typology includes three urban-type neighborhoods (Mixed-use, Old-urban, Urban residential), three suburban-type neighborhoods (Established suburb, Patchwork, New development), and one rural-type neighborhood.

Based on the Akaike and Bayesian information criteria (AIC/BIC), measuring the built environment using a combination of six density variables provides the best fit model. Importantly, the relationship between Lyft trips/trips per capita, the built environment, and socioeconomic characteristics remains steady regardless of model specification, suggesting robust associations between Lyft travel and the built environment. Full discussions of model results are presented in Chapter 4.

Dependent Variable: Number of Lyft Trips (ln)	**Density**			**Sprawl Index**			**Neighborhood Types**		
Built Environment	*Coef.*	*St. Error*	*Sig.*	*Coef.*	*St. Error*	*Sig.*	*Coef.*	*St. Error*	*Sig.*
Population Density (people/acre) (ln)	-0.115	0.027	**	-	-		-	-	
Employment Density (jobs/acre) (ln)	0.086	0.016	***	-	-		-	-	
Road Network Density	0.001	0.003	NS	-	-		-	-	
Transit Stop Density (stops/mile) (ln)	0.267	0.023	***	0.258	0.024	***	-	-	
Sprawl index	-	-		0.000	0.002	NS	-	-	
On-street parking (spaces/sq. mile) (ln)	0.021	0.035	NS	-0.081	0.031	NS	0.045	0.044	NS
Off-street parking (spaces/sq. mile) (ln)	0.075	0.026	***	0.097	0.026	***	0.133	0.039	***
Neighborhood Types									
Baseline: Established Suburban									
Mixed Use	-	-		-	-		0.846	0.130	***
Old Urban	-	-		-	-		0.688	0.082	***
Urban Residential	-	-		-	-		0.143	0.079	*
Patchwork	-	-		-	-		0.075	0.093	NS
New Development	-	-		-	-		-2.442	0.122	***
Rural	-	-		-	-		-1.917	0.245	***
Tract Socioeconomic Characteristics									
Neighborhood Income Group									
(Baseline: Middle)									
Low-Income	-0.135	0.054	**	-0.156	0.054	***	-0.462	0.084	***
High-Income	0.067	0.052	NS	0.114	0.052	**	0.384	0.076	***
Percent Zero Vehicle Households	2.005	0.254	***	2.005	0.254	***	2.471	0.384	***
Percent ages 15-34	2.561	0.231	***	2.671	0.238	***	1.893	0.336	***
Neighborhood Racial/Ethnic Majority									
(Baseline: No Majority)									
Asian	-0.396	0.079	***	-0.415	0.079	***	-0.188	0.119	NS
Black	0.376	0.111	***	0.388	0.111	***	0.746	0.173	***
Hispanic	-0.352	0.047	***	-0.367	0.047	***	-0.143	0.070	**
White	0.491	0.052	***	0.501	0.053	***	0.510	0.077	***
Tract Amenities & Land Use									
Number of Workers in Arts, Service, per sq. mile (ln)	0.171	0.014	***	0.193	0.014	***	0.217	0.019	***
Constant	6.283	0.125	***	6.237	0.179	***	6.246	0.170	***
AIC/BIC	4075/4164			4099/4177			6681/6783		
Adjusted R^2	0.543			0.534			0.505		

NS not significant, * p<0.1, ** p<0.05, *** p<0.01.

Appendix B. Five Densities Across Los Angeles County

Figure 52. Population Density, Los Angeles County

People per acre. Data source: Environmental Protection Agency (2014).

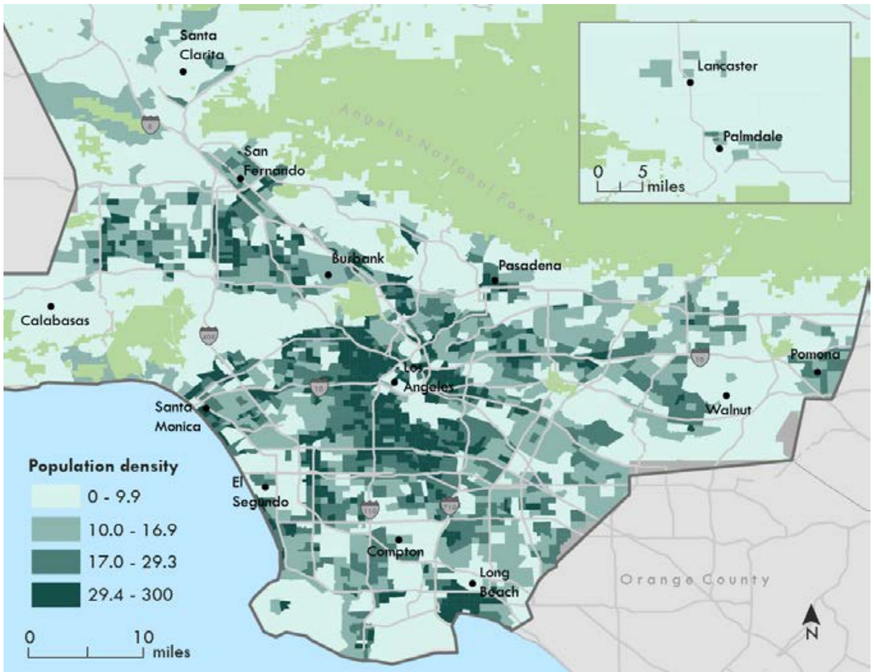


Figure 53. Employment Density, Los Angeles County

Jobs per acre. Data source: Environmental Protection Agency (2014).

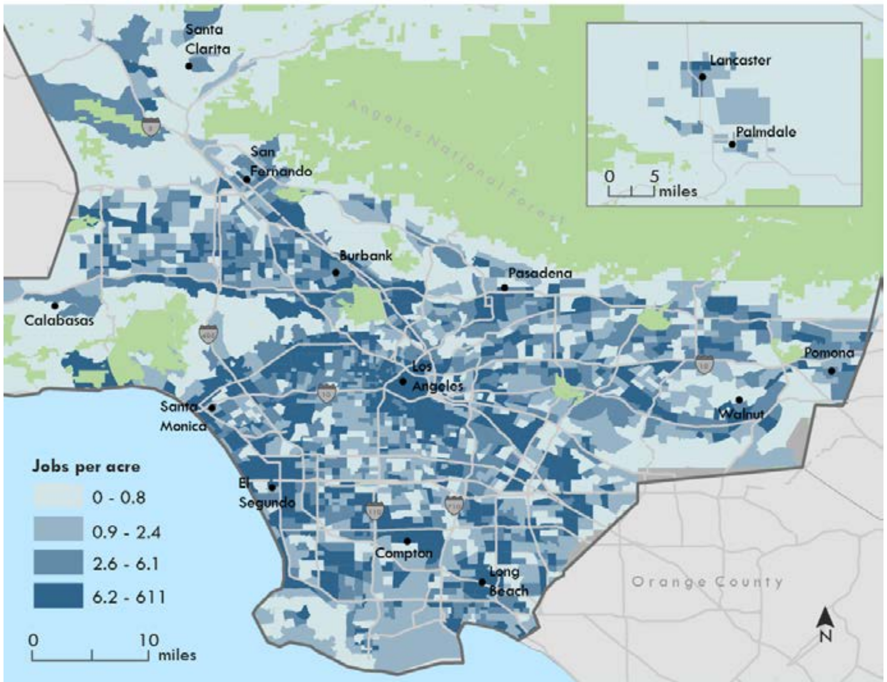


Figure 54. Road Network Density, Los Angeles County

Facility miles per square mile. Data source: Environmental Protection Agency (2014).

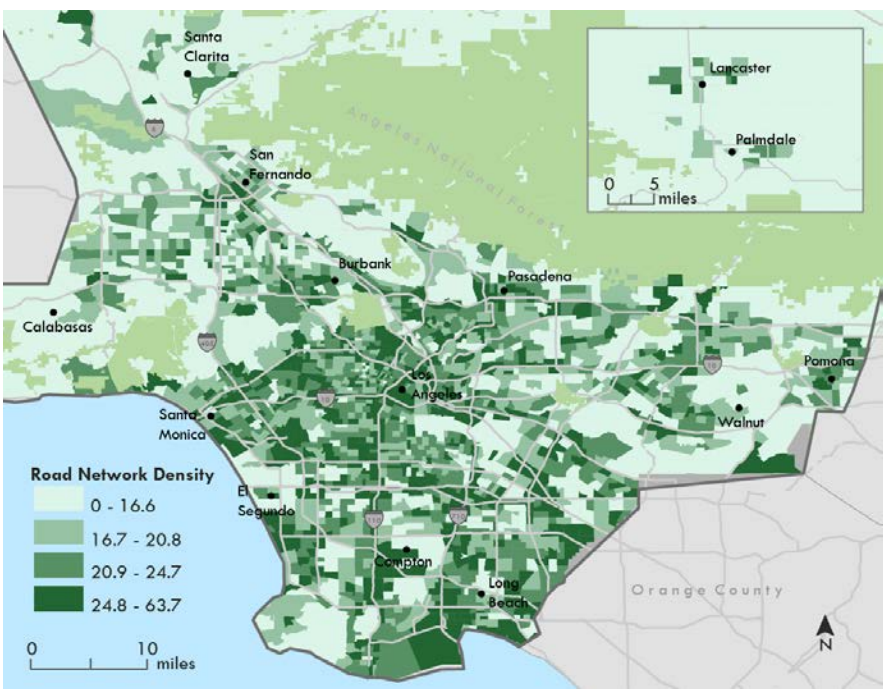


Figure 55. Off-street Parking, Los Angeles County

Data source: Chester et al. (2015).

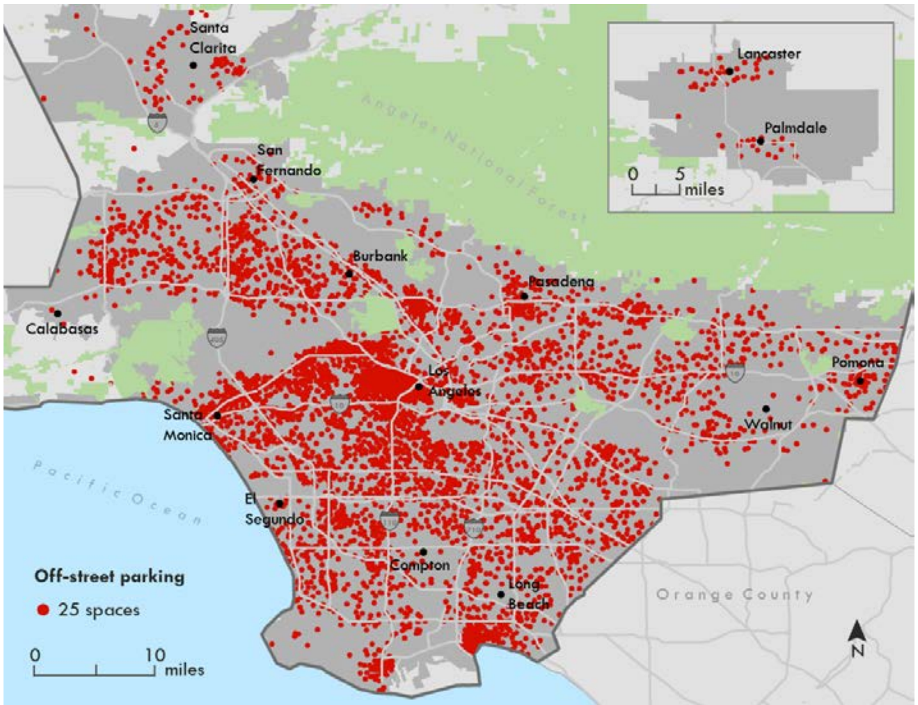
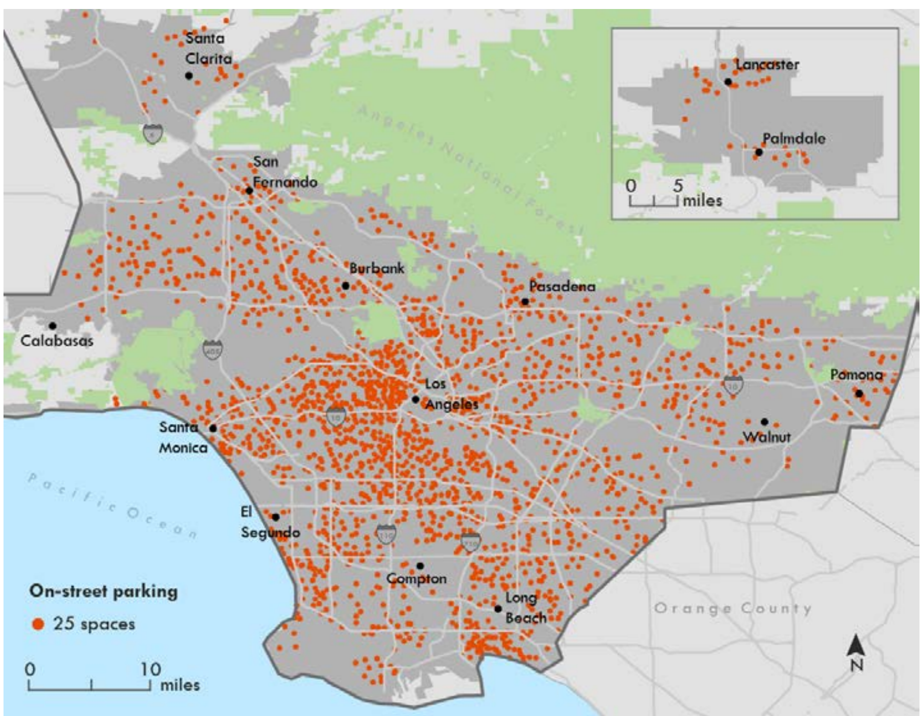


Figure 56. On-street Parking, Los Angeles County

Data source: Chester et al. (2015).



Appendix C. Lyft Trip Origin and Destination Counties

Nearly all Lyft users (99%) live somewhere in the United States, which is logical given that Lyft only began international operations in Toronto in November 2017. More than three-quarters (84%) of people who took a Lyft trip in Los Angeles County live in California, and the majority (69%) are Los Angeles County residents. Los Angeles County residents made 81 percent of all Lyft trips taken between September and November 2016. Domestic users who traveled on a Lyft in Los Angeles County hail from around the country, with a disproportionate share from western and neighboring states. Table 25 lists the share of Los Angles Lyft users who live in a state compared to the state's share of the U.S. population.

Table 25. State Share of Non-Resident Lyft Users vs. State's Share of U.S. Population

State	Share of Non-Resident Users	Share of U.S. Population	State	Share of Non-Resident Users	Share of U.S. Population
Alabama	0.2%	1.5%	Montana	0.1%	0.3%
Alaska	0.1%	0.2%	Nebraska	0.2%	0.6%
Arizona	2.7%	2.1%	Nevada	2.3%	0.9%
Arkansas	0.1%	0.9%	New Hampshire	0.1%	0.4%
California	50.4%	12.1%	New Jersey	2.0%	2.8%
Colorado	2.3%	1.7%	New Mexico	0.3%	0.6%
Connecticut	0.5%	1.1%	New York	6.8%	6.1%
Delaware	0.1%	0.3%	North Carolina	0.7%	3.1%
District of Columbia	0.6%	0.2%	Ohio	1.0%	3.6%
Florida	3.0%	6.4%	Oklahoma	0.2%	1.2%
Georgia	1.5%	3.2%	Oregon	1.8%	1.3%
Hawaii	0.6%	0.4%	Pennsylvania	1.5%	4.0%
Idaho	0.2%	0.5%	Rhode Island	0.1%	0.3%
Illinois	3.3%	4.0%	South Carolina	0.2%	1.5%
Indiana	0.5%	2.1%	South Dakota	0.0%	0.3%
Iowa	0.2%	1.0%	Tennessee	0.8%	2.1%
Kansas	0.2%	0.9%	Texas	4.2%	8.6%
Kentucky	0.3%	1.4%	Utah	0.7%	0.9%
Louisiana	0.4%	1.4%	Vermont	0.1%	0.2%
Maine	0.1%	0.4%	Virginia	1.1%	2.6%
Maryland	1.1%	1.9%	Washington	2.9%	2.3%
Massachusetts	1.7%	2.1%	West Virginia	0.0%	0.6%
Michigan	1.0%	3.1%	Wisconsin	0.4%	1.8%
Minnesota	0.8%	1.7%	Wyoming	0.1%	0.2%
Mississippi	0.1%	0.9%	*Total*	*100%*	*100%*
Missouri	0.5%	1.9%			

U.S. population source: U.S. Census (2016b).

Resident vs. Non-Resident Lyft Trips

Los Angeles County residents traveled quite differently on Lyft compared to non-residents. Unsurprisingly given that non-residents are likely only visiting Los Angeles, residents took on average twice as many trips (4 vs. 2) as non-resident users over the three-month study period. Table 26 shows that residents also took shorter and lower-priced trips on average, a higher-share of which were on Lyft Line.

Table 26. Trip Characteristics by Resident Status

	All Lyft Users		**Non-Residents**		**Residents**		
Trip Characteristics	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Sig.*
Trip Distance (miles)	9.6	7.5	11.6	7.5	8.7	7.5	***
Trip Price	$12.32	$9.58	$14.84	$11.25	$11.19	$8.75	***
Percent of Trips on Lyft Line	18%	0%	13%	0%	21%	0%	***
Trips per person	7.7	3.0	4.7	2.0	9.0	4.0	***
Sample size (N/n)	*828,616*		*257,501*		*571,115*		

Note: these are reported means and medians across Lyft users, not Lyft trips. Sig. indicates the statistical significance between non-resident and resident trip characteristics. NS not significant, *p<0.1, **p<0.05, ***p<0.01.

Appendix D. Airport Trips

Riders in Los Angeles took thousands of trips to each of Los Angeles County's three primary airports: Bob Hope Airport (BUR), Long Beach Airport (LGB), and Los Angeles International Airport (LAX). This appendix is organized into four sections: 1) identifying airport trips, characteristics of 2) inter- and 3) intra-county airport trips, and 4) comparing airport to non-airport trips.

Identifying Airport Trips

I identified airport trips as any trip that began or ended in a census tract containing one of the three largest airports in Los Angeles County. Because airports occupy unique census tracts (i.e., no people live in airport census tracts according to the 2011-2015 ACS), there is no potential for conflating people traveling to homes around the airport versus the airport itself.

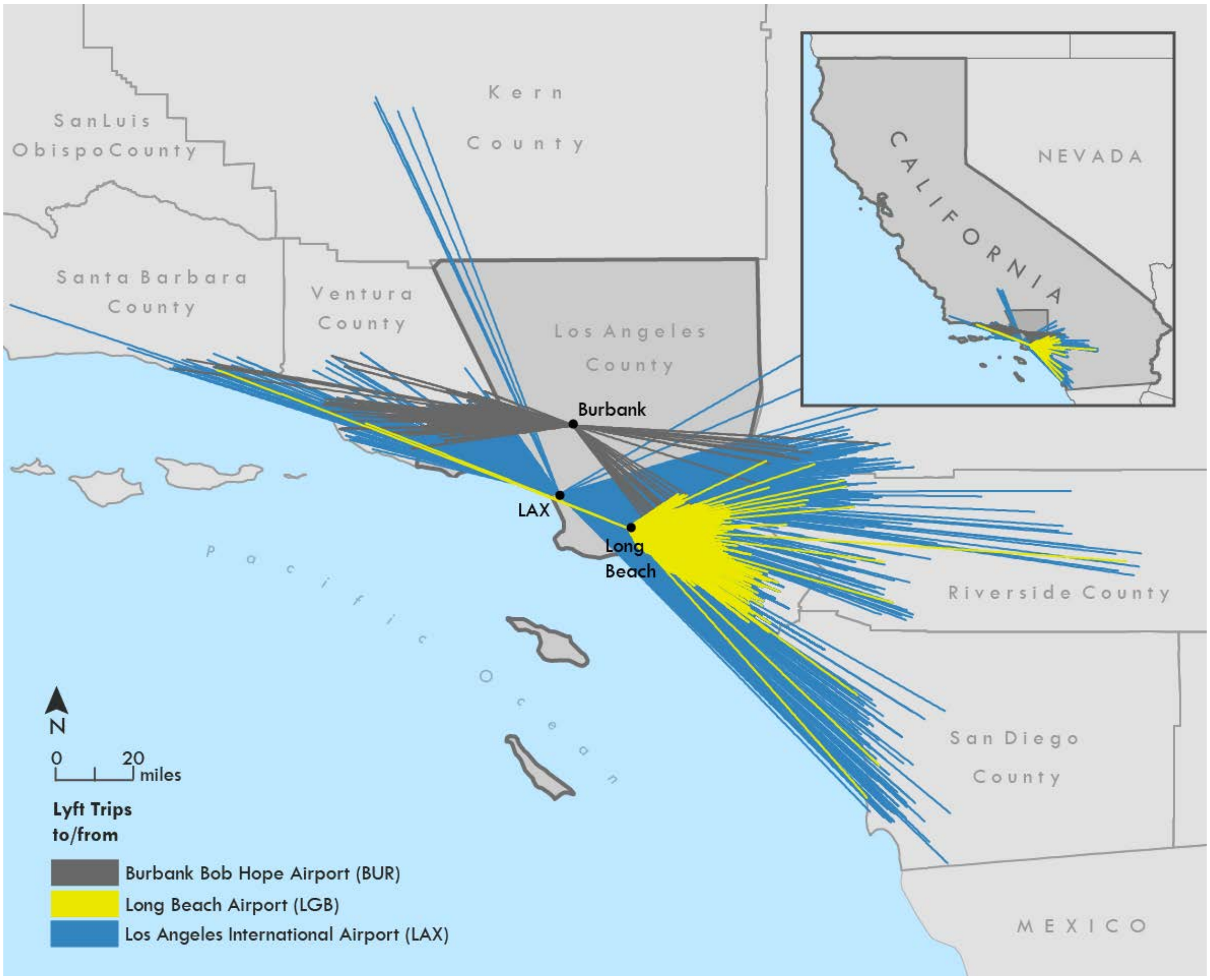
Inter-County Lyft Travel to Airports

Lyft travelers made nearly 83,000 inter-county trips (1.3% of total Lyft trips) between September and November 2016. Table 27 shows that, like intra-county trips, the majority of inter-county airport trips are to or from LAX. About 13 percent of inter-county trips ended or began at an airport compared to six percent of intra-county trips. Figure 57 shows the geography of these trips, which highlight the important role that the three Los Angeles airports—particularly LAX—play in connecting Southern Californians to air travel. Airport Lyft trips to Los Angeles' three major airports began and ended in seven surrounding counties: Kern, Orange, Riverside, San Diego, San Bernardino, Santa Barbara, and Ventura.

Table 27. Inter-County Lyft Trips to Los Angeles County Airports

	Number	**Share**
Number of Inter-county Trips	82,773	100%
Airport Trips	11,058	13.4%
Bob Hope (BUR)	310	0.4%
Long Beach Airport (LGB)	1,582	1.9%
Los Angeles International Airport (LAX)	9,166	11.1%

Figure 57. Inter-county Lyft Airport Trip Origin and Destinations



Intra-County Lyft Travel to Airports

About six percent of all Lyft trips taken within Los Angeles County (i.e., intra-county trips) either began or ended at one of Los Angeles' three largest airports. Non-residents make a higher share of their trips to or from the airport compared to residents: 12 percent of trips made by non-residents were to or from an airport compared to just four percent of Lyft trips made by county residents. While six (or even four) percent is perhaps surprisingly high, the share of Lyft trips that serve an airport falls directly between estimates from other cities (Rayle et al. 2016, Henao 2017).

Table 28 shows that the majority of Lyft trips (89%) served LAX, which is the second largest airport in the U.S. (after Atlanta) and the fourth largest in the world (Airports Council International

2016). In 2016, nearly 81 million people, or 92 percent of all air travelers in Los Angeles County, traveled through at LAX, generating tremendous amounts of ground traffic as airline passengers arrived and departed the airport. Lyft trips by airport are roughly in proportion to their share of air travelers.

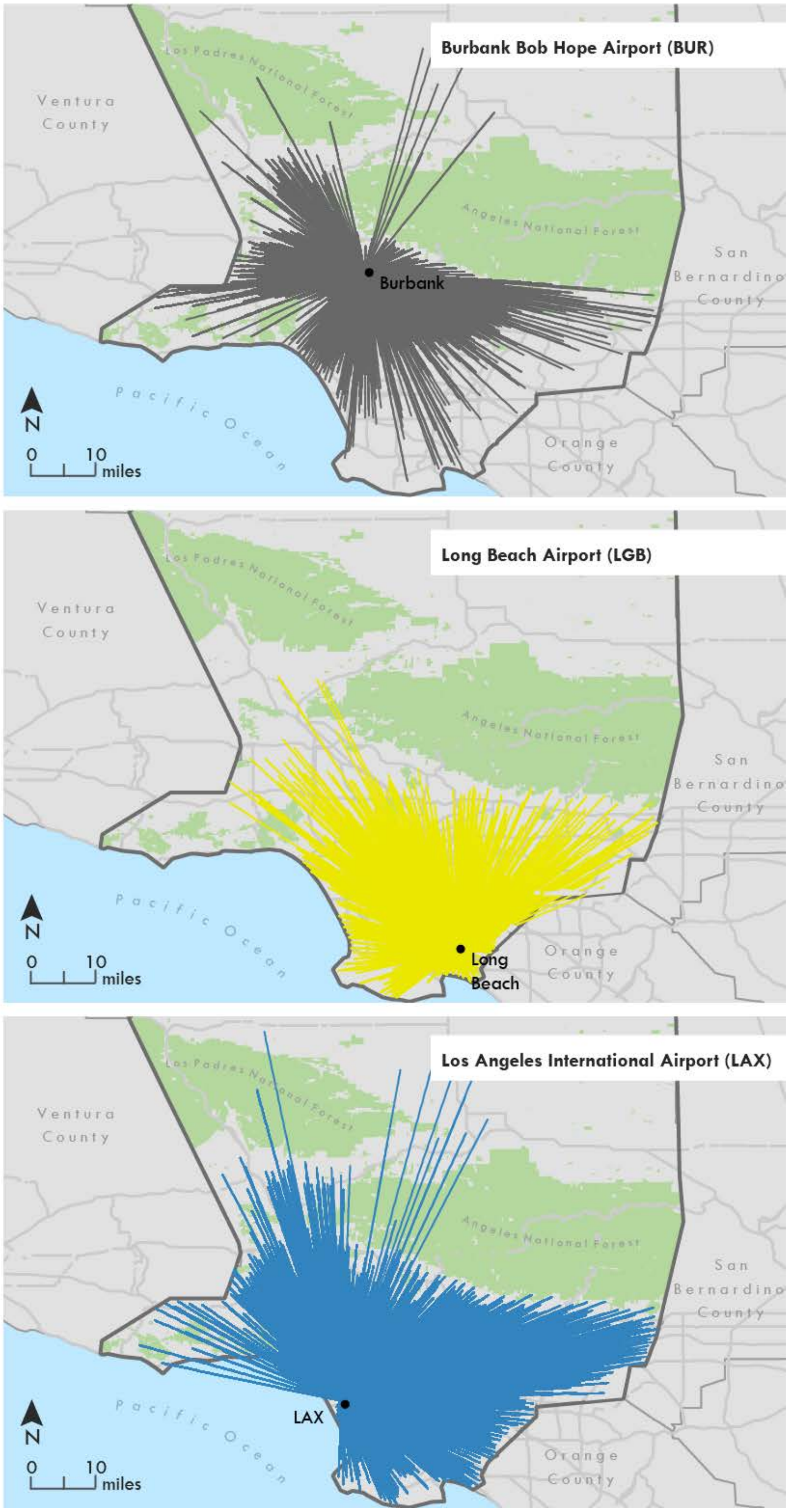
Table 28. Share of Lyft Trips by Airport

	Number	**Share of Trips**	**Share of Airport Trips**	**Share of Air Passengers[1]**
Total	*6,340,268*	*100%*		
Non-Airport Trips	5,945,807	93.8%		
Airport Trips/Passengers	394,461	6.2%	*100%*	*100%*
Bob Hope (BUR)	33,160	0.5%	8.4%	4.7%
Long Beach Airport (LGB)	11,153	0.2%	2.8%	3.2%
Los Angeles International Airport (LAX)	350,626	5.5%	88.9%	92.0%

[1]Sources: Burbank-Glendale-Pasadena Airport Authority (2016), Long Beach Airport (2016), Los Angeles World Airports (2016).

Trips serving the three airports originated from across the county; Figure 58 shows the flow of all trips that originated or ended at each of the three Los Angeles County airports. Unsurprisingly given its size, LAX has the strongest geographic pull, attracting Lyft trips from the far reaches of Los Angeles County. While Bob Hope and Long Beach airports have slightly smaller Lyft footprints than LAX, the airports nevertheless attract ridehail travelers from across the county.

Figure 58. Intra-county Lyft Trips to the County's Three Largest Airports



Comparing Airport and Non-Airport Lyft Trips

Table 29 shows that airport Lyft trips are significantly more expensive and longer distance compared to non-airport trips ($p<0.01$). The average airport trip is more than double the mean price and distance of a non-airport trip. Although differences between airport and non-airport trips appear stark, the inclusion or exclusion of airport trips from analysis does not alter overall patterns and findings presented in the body of this research.

Table 29. Lyft Airport vs. Non-Airport Trips

	Mean Price	Mean Distance	% Peak
Total	*$ 9.66*	*7.42*	*22.6%*
Non-Airport Trips	$ 9.02	6.89	22.6%
Airport Trips	$ 19.30	15.39	23.0%
Bob Hope (BUR)	$ 15.22	12.55	27.4%
Long Beach Airport (LGB)	$ 16.50	12.65	29.4%
Los Angeles International Airport (LAX)	$ 19.80	15.77	22.4%

In addition to being longer and more expensive, a disproportionate share of airport trips originate or end in high-income neighborhoods relative to their share of Lyft trips or county population plus jobs (see Table 26). This is perhaps unsurprising given that the elasticity of air travel is positive with respect to income (Mutti and Murai 1977).

Nearly half of all trips originated in majority white neighborhoods, which were the origin or destination for just over one-third (36%) of Lyft trips. Majority-Hispanic neighborhoods are the most underrepresented in airport trips; despite over one-quarter (28%) of trips originating or ending in a majority-Hispanic neighborhood, just 15 percent of Lyft airport trips served a majority-Hispanic neighborhood. These patterns likely reflect the positive relationship between income and air travel.

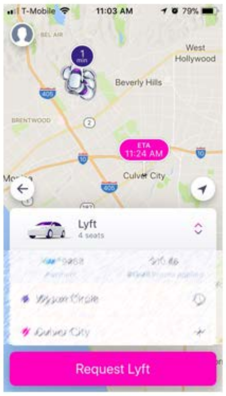
Table 30. Characteristics of Origin/Destination Neighborhoods, Airport vs. All Lyft Trips

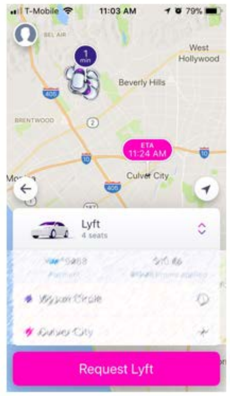
	Income			**Racial/Ethnic Majority Neighborhood**				
Share	*Low*	*Middle*	*High*	*Asian*	*Black*	*Hispanic*	*White*	*No Majority*
Total Trips	25.26%	46.37%	28.37%	7.16%	2.17%	27.67%	36.16%	26.84%
Airport Trips	15.71%	45.92%	38.37%	5.31%	2.37%	15.34%	49.49%	27.48%
Share of Los Angeles County Population + Jobs	22.13%	50.62%	27.25%	6.48%	2.08%	43.46%	24.77%	23.21%

Source: Environmental Protection Agency (2014).

Appendix E. Trip Data Collection Steps

Uber and Lyft, Not Cancelled

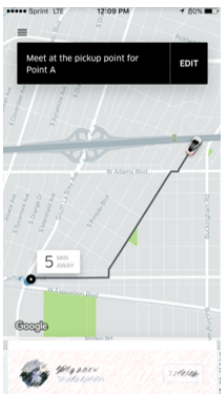




1 Enter origin & destination

2 Start stopwatch

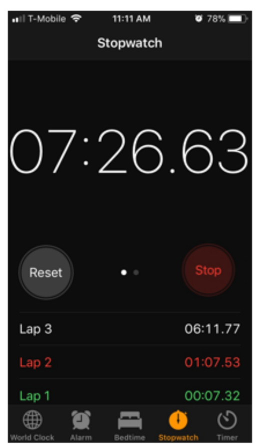
3 Hail/ request



4 When driver assigned, <u>Screenshot 1</u>

5 When driver assigned, <u>Timepoint 1</u>

6 Car arrives, <u>Timepoint 2</u>



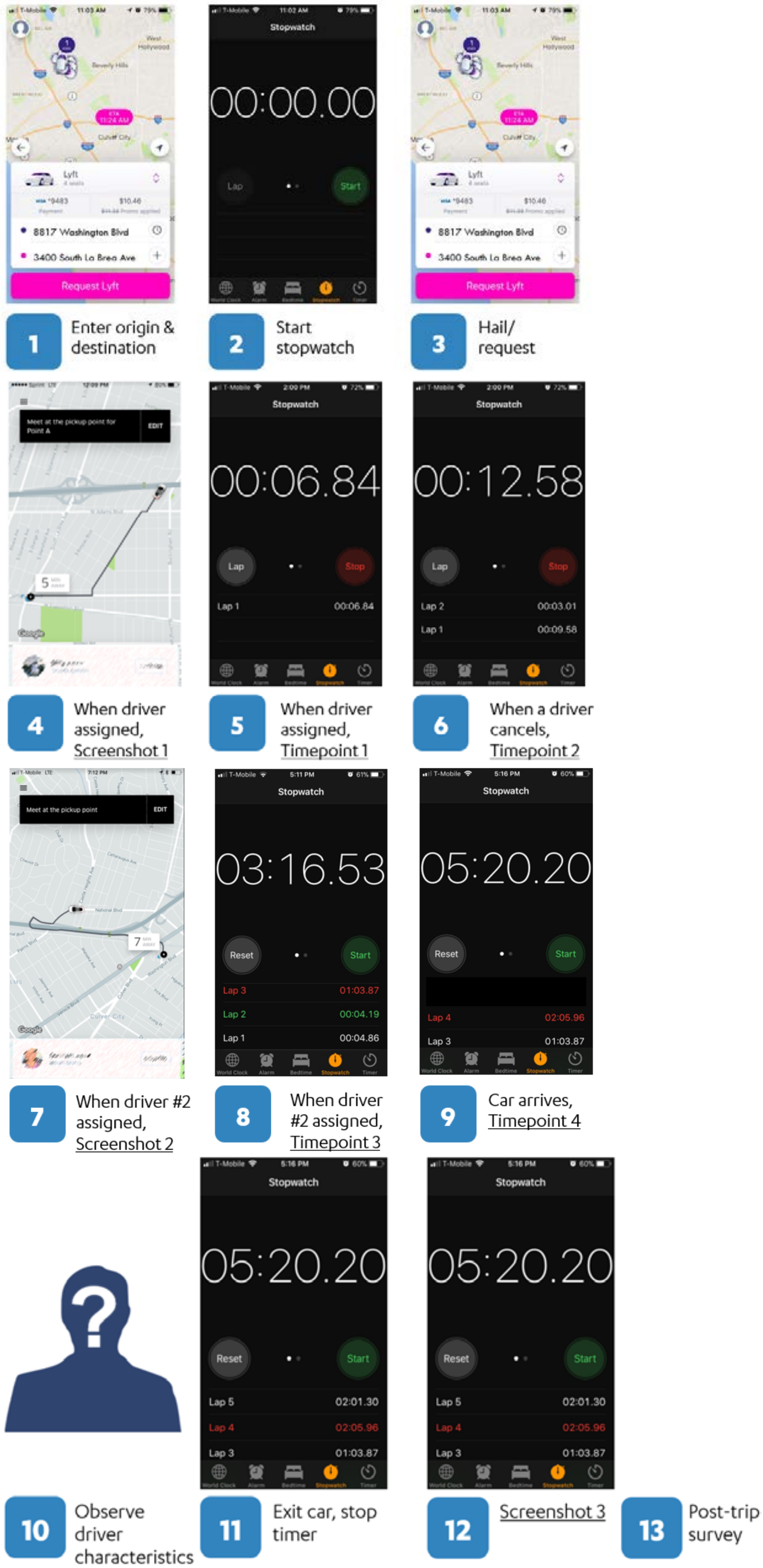
7 Observe driver characteristics

8 Exit car, stop timer

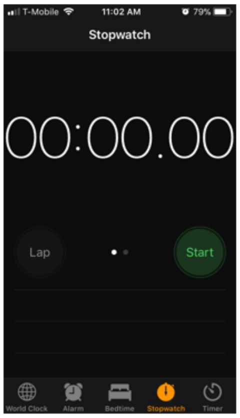
9 <u>Screenshot 2</u>

10 Post-trip survey

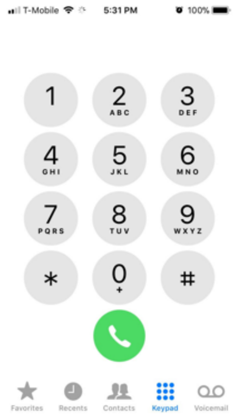
Uber and Lyft, Cancelled



Taxi



1 Start timer



2 Call cab company

Name
Address
Phone #
Etc.

3 Provide dispatcher info requested

4 Hang up phone, <u>Timepoint 1</u>

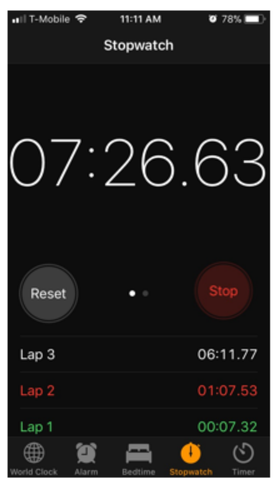
5 Car arrives, <u>Timepoint 2</u>

6 Observe driver characteristics

Pay
&
get a receipt

7 Arrive at destination

8 Exit car, stop timer



9 <u>Screenshot 1</u>

10 Post-trip survey

Appendix F. Unlawful Discrimination, Full Model Results

Table 31. Predictors of Trip Cancellations

	Lyft		**Uber**		**Taxi**	
	Coeff.	*Sig.*	*Coeff.*	*Sig.*	*Coeff.*	*Sig.*
Rider Race (Baseline: White)						
Black	0.38	NS	1.54	*	0.59	NS
	0.58		*0.83*		*0.39*	
Other	-0.09	NS	0.72	NS	0.27	NS
	0.64		*0.93*		*0.40*	
Rider Women (Yes)	-1.19	NS	0.69	NS	-0.61	NS
	1.08		*1.01*		*0.54*	
Black##Female	1.52	NS	-0.69	NS	0.50	NS
	1.26		*1.21*		*0.74*	
Other##Female	1.79	NS	-0.23	NS	0.34	NS
	1.26		*1.28*		*0.70*	
Taxi Company (Baseline: United)						
LA Yellow Cab	-		-		0.03	NS
					0.34	
Independent	-		-		0.45	NS
					0.31	
Peak Trip	0.68	NS	0.49	NS	1.15	***
	0.44		*0.54*		*0.31*	
Constant	-3.33	***	-4.43	***	-1.98	***
	0.40		*0.72*		*0.33*	

Logistic regression. NS not significant, *p<0.1, **p<0.05, ***p<0.01.
Standard Errors are italicized.

Table 32. Assignment Wait Times Across Services

	Lyft		**Uber**		**Taxi**	
	Coeff.	*Sig.*	*Coeff.*	*Sig.*	*Coeff.*	*Sig.*
Rider Race (Baseline: White)						
Black	0.10	***	0.11	**	0.38	*
	0.03		*0.05*		*0.22*	
Other	-0.01	NS	0.01	NS	1.05	***
	0.03		*0.05*		*0.21*	
Rider Women (Yes)	0.00	NS	-0.03	NS	0.41	*
	0.03		*0.05*		*0.22*	
Black##Female	-0.08	NS	-0.01	NS	-0.60	*
	0.05		*0.08*		*0.35*	
Other##Female	-0.09	*	0.02	NS	-1.03	**
	0.05		*0.07*		*0.32*	
Taxi Company (Baseline: United)						
LA Yellow Cab	-	-	-	-	-0.31	*
					0.16	
Independent	-	-	-	-	0.54	***
					0.16	
Peak Hour Trip (Yes)	0.01	NS	0.12	***	-0.13	NS
	0.03		*0.04*		*0.19*	
Constant	0.48	***	0.63	***	1.21	***
	0.02		*0.03*		*0.16*	

Linear Regression. NS not significant, *p<0.1, **p<0.05, ***p<0.01. ## indicates interaction. Peak hour trips are those for which a rider is picked up on a weekday between 4:00pm and 6:59pm. Standard Errors are italicized.

Table 33. Arrival Wait Time Model Results Across Services

	Lyft		**Uber**		**Taxi**	
	Coeff.	*Sig.*	*Coeff.*	*Sig.*	*Coeff.*	*Sig.*
Rider Race (Baseline: White)						
Black	0.43	NS	0.36	NS	3.91	*
	0.36		*0.42*		*2.25*	
Other	0.33	NS	-0.54	NS	1.38	NS
	0.35		*0.40*		*2.05*	
Rider Women (Yes)	-0.02	NS	0.18	NS	-0.54	NS
	0.37		*0.44*		*2.12*	
Black##Female	1.33	**	0.31	NS	7.17	**
	0.59		*0.67*		*3.56*	
Other##Female	0.24	NS	0.72	NS	1.72	NS
	0.53		*0.62*		*3.13*	
Taxi Company (Baseline: United)						
LA Yellow Cab	-	-	-	-	1.34	NS
					1.60	
Independent	-	-	-	-	9.67	***
					1.64	
Peak Hour Trip (Yes)	1.20	***	1.68	***	6.16	***
	0.31		*0.37*		*2.10*	
Constant	4.19	***	4.96	***	12.01	***
	0.21		*0.25*		*1.53*	

Linear Regression. NS not significant, *p<0.1, **p<0.05, ***p<0.01. ## indicates interaction. Peak hour trips are those for which a rider is picked up on a weekday between 4:00pm and 6:59pm. Standard Errors are italicized.

Table 34. Total Wait Time Model Results Across Services

	Lyft		Uber		Taxi	
	Coeff.	*Sig.*	*Coeff.*	*Sig.*	*Coeff.*	*Sig.*
Rider Race (Baseline: White)						
Black	0.49	NS	0.72	*	7.46	***
	0.39		*0.43*		*2.84*	
Other	0.15	NS	-0.45	NS	1.93	NS
	0.37		*0.41*		*2.70*	
Rider Women (Yes)	-0.12	NS	0.21	NS	-2.43	NS
	0.39		*0.45*		*2.86*	
Black##Female	1.31	**	0.00	NS	7.65	*
	0.63		*0.69*		*4.59*	
Other##Female	0.31	NS	0.65	NS	3.85	NS
	0.57		*0.64*		*4.14*	
Taxi Company (Baseline: United)						
LA Yellow Cab	-	-	-	-	0.90	NS
					2.12	
Independent	-	-	-	-	11.81	*
					2.10	
Peak Hour Trip (Yes)	1.32	***	1.77	***	9.07	NS
	0.33		*0.38*		*2.59*	
Constant	4.90	***	5.61	***	16.37	***
	0.23		*0.26*		*2.04*	

Linear Regression. NS not significant, *p<0.1, **p<0.05, ***p<0.01. ## indicates interaction. Peak hour trips are those for which a rider is picked up on a weekday between 4:00pm and 6:59pm. Standard Errors are italicized.

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