MOUNTAIN-PLAINS CONSORTIUM

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Impacts of Ridesourcing on VMT, Parking Demand, Transportation Equity, and Travel Behavior

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16. Abstract

Ride-haling such as Uber and Lyft are changing the ways people travel and is critical to forecasting mode choice demands and providing adequate infrastructure. Despite widespread claims that these services help reduce driving and the need for parking, there is little research on these topics. This research project uses ethnographic methods – complemented with passenger surveys where one of the authors drove for Uber and Lyft in the Denver, Colorado, region – to collect quantitative and qualitative data on ride-hailing and analyze the impacts of ride-hailing on deadheading, vehicle occupancy, mode replacement, vehicle miles traveled (VMT), and parking. The dataset includes actual travel attributes from 416 ride-hailing rides – Lyft, UberX, LyftLine, and UberPool – and travel behavior and socio-demographics from 311 passenger surveys.

Section one focuses on changes in driving. The conservative (lower end) percentage of deadheading miles from ride-hailing is 40.8%. The average vehicle occupancy is 1.4 passengers per ride, while the distance weighted vehicle occupancy is 1.3 without accounting for deadheading and 0.8 when accounting deadheading. When accounting for mode replacement and issues such as driver deadheading, we estimate that ride-hailing leads to approximately 83.5% more VMT than would have been driven had ride-hailing not existed.

Section two examines relationships between parking time and parking cost. This includes building a classification tree-based model to predict the replaced driving trips as a function of car ownership, destination land type, parking stress, and demographics. The results suggest that: i) ride-hailing is replacing driving trips and could reduce parking demand, particularly at land uses such as stadiums, airports, restaurants, and bars; ii) parking stress is one of the main reasons our respondents chose not to drive themselves in the first place; and iii) our respondents are generally willing to pay more for reduced parking time and distance. Conversely, parking supply, time, and cost can all influence travel behavior and the use of ride-hailing.

Section three investigates the economic opportunity that ride-hailing companies provide to drivers. Companies such as Uber and Lyft constantly promote potential earnings on the order of \$25–\$35 per hour. Yet, the advertised earnings do not account for factors such as time spent without passengers, the need to travel back-and-forth between areas of low and high ridership, driver residential location, or driving expenses. This section assesses driver earnings and estimate gross wages averaging \$15.57 per hour. Given three common expense scenarios, we estimate net hourly wages ranging between \$5.72 and \$10.46 per hour.

Although our data collection is specific to the Denver region, this report provides insight into potential benefits and disadvantages of ride-hailing.

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Disclaimer

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Ride-haling such as Uber and Lyft is changing the way people travel and is critical to forecasting mode choice demands and providing adequate infrastructure. Despite widespread claims that these services help reduce driving and the need for parking, little research exists on these topics. This research project uses ethnographic methods complemented with passenger surveys where one of the authors drove for Uber and Lyft in the Denver, Colorado, region to collect quantitative and qualitative data on ride-hailing. It also uses the methods to analyze the impacts of ride-hailing on deadheading, vehicle occupancy, mode replacement, vehicle miles traveled (VMT), and parking. The dataset includes actual travel attributes from 416 ride-hailing rides — Lyft, UberX, LyftLine, and UberPool — and travel behavior and socio-demographics from 311 passenger surveys.

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1. INTRODUCTION

The main services provided by companies like Uber around the globe, Lyft in the United States, Cabify in South America, or Didi in China can be called ride-hailing, ride-sourcing, or transportation network companies (TNCs). As ride-hailing continues to grow, the importance of understanding its impacts becomes more critical. City officials and transit advocates have expressed concerns about the lack of open data and potential problems with ride-hailing such as congestion, competition with public transportation, and equity issues (Flegenheimer & Fitzsimmons, 2015; Grabar, 2016; Rodriguez, 2016). The first gap this study aims to fill is around the lack, need, and difficulty to obtain data (Bialick, 2015; Levitt, 2016). The second gap in the literature we aim to fill is to provide a basic of ride-hailing impacts including deadheading, vehicle occupancy, car ownership, mode substitution, and changes in vehicle miles travel (VMT).

To do so, one author collected data by serving as an independent-contractor driving for Uber and Lyft. This quasi-natural experiment was designed to look specifically at the impacts of ride-hailing and includes two inter-related datasets: i) the "driver dataset" and ii) the "passenger dataset." With these novel datasets, we estimated the impact of ride-hailing on deadheading, vehicle occupancy, mode replacement, and impacts on transportation efficiency by measuring passenger miles traveled (PMT) versus VMT, and comparing VMT with and without ride-hailing. We believe that this research will help stress the importance of data and has already proven to be helpful for cities and transportation agencies in new strategies for data collection (CommonWealth, 2018). This research could also serve as a window of opportunity to understand impacts of future autonomous vehicles (AVs).

The next section provides a background for ride-hailing including a history and overview of Uber and Lyft, followed by a literature review on research in this area. We then covered the quasi-natural experiment, data collection and research methods before presenting the analysis and results. We concluded with recommendations, limitations, and suggestions for future research.

2. BACKGROUND

Many factors — including social networks, real-time information, and mobile technology — allow passengers and drivers to connect through mobile smartphone applications (i.e. apps). This technology led to the creation and popularization of app-based on-demand transportation platforms such as Uber and Lyft. These companies in their current form are mostly known for their regular UberX and Lyft services and their carpool options: LyftLine and UberPool. Uber started as a black-car limousine service called UberCab launched in San Francisco in 2010 (McAlone, 2015), while Lyft co-founders Logan Green and John Zimmer co-founded Zimride in 2007, a true rideshare platform created to connect drivers and passengers through social networking (Green and Zimmer sold Zimride to Enterprise Holdings in July 2013) (Lawler, 2014). While Lyft was launched in June 2012 with its original regular Lyft service, Uber did not unveil its regular UberX service until July 2012. The LyftLine and UberPool carpool options started in 2014 but are only available in certain metropolitan cities (Lyft Blog, 2016; Uber Newsroom, 2014, 2016).

As of early 2018, Uber was already operating in over 600 cities across 78 countries, while Lyft was in over 300 U.S. cities and expanded outside of the United States for the first time by launching in Toronto, Canada, in November 2017. Uber completed its first billion rides in six years, while the second billion rides were completed in just six months (Somerville, 2016). It then took Uber only 10 months to add three more billion more and reach a total of five billion rides by May 2017 (Holt, Macdonald, & Gore-Coty, 2017). Uber's estimated valuation was around $50 billion in early 2018 (Boland, 2018), while the latest funding round values Lyft at $11 billion (Fiegerman, 2017; Loizos, 2017). The valuations put these TNCs as the most valuable transportation companies in the United States despite little in the way of transportation infrastructure, vehicle ownership, or even having to hire drivers as employees. However, both Uber and Lyft are investing and teaming up with vehicle manufacturers for autonomous vehicles technology (Hawkins, 2017a, 2017b; Isaac, 2017; Scrutton, 2016) and might have their own fleets of vehicles in the future.

The number of rides and valuation numbers show the magnitude of Uber and Lyft and their influence on the way people get around. Their path, however, has not been worry free. They constantly deal with situations regarding regulations, protests, and lawsuits from taxi companies, city officials, and drivers claiming employment rights. They also have taken advantage of the terminology in their marketing strategies. The terminology of new and evolving transportation services can be confusing and sometimes incorrectly used, which can mislead public perception and general use of the services. An example is the misused word "ridesharing" when referring to ride-hailing companies in their original form (Goddin, 2014). However, a ridesharing trip should, in theory, carry two or more passengers; yet, most ride-hailing trips only carry one passenger per trip. Some of the other names include: Transportation Network Companies (TNCs), ride-hailing, ride-sourcing, ride-booking, ride-matching, on-demand-rides, and app-based rides. TNCs originated as the legal term for regulation purposes; ride-sourcing has been used in academic publications; and ride-hailing has been used in more recent academic publications and media articles. The Associated Press Stylebook in January 2015 presented an update on the topic:

> "*Ride-hailing services such as Uber or Lyft let people use smartphone apps to book and pay for a private car service or in some cases, a taxi. They may also be called ride-booking services. Do not use ride-sharing*" (Warzel, 2015).

While there seems to be a consensus that these services are not ridesharing, there is still no clearly defined term. To correct and use the right terminology, be consistent with more recent academic and media publications, and capture a larger audience, we are using the term ride-hailing for this report.

3. LITERATURE REVIEW

Early academic studies on this topic compared ride-hailing mainly to the taxi industry and ridesharing services (Anderson, 2014; Cramer & Krueger, 2016; Rayle, Dai, Chan, Cervero, & Shaheen, 2016). Rayle et al. (2016) compared ride-hailing services with traditional taxis in San Francisco using an intercept survey in spring 2014. Findings from this study indicated that ride-hailing users tend to be younger, have higher incomes and lower car ownership, and frequently travel with companions more than the general San Francisco population. This study also showed that compared to taxis, customers experienced shorter waiting times. Participants in this study said that ride-hailing substitutes and complements public transit, walking, and biking; moreover, 8% of survey respondents stated that they would not have traveled if ride-hailing services were not available (i.e. induced travel effect). The website FiveThirtyEight.com also published a few non-peer reviewed articles regarding ride-hailing using data acquired via a Freedom of Information Act request. They showed that in New York City, most of the mode substitution for Uber comes from taxis (Bialik, Flowers, Fischer-Baum, & Mehta, 2015; Fischer-Baum & Bialik, 2015; Silver & Fischer-Baum, 2015).

In terms of driving efficiency, Cramer and Krueger (2016) compared the capacity utilization rate of UberX drivers against taxi drivers in a few U.S. cities. Using aggregated data across all drivers available for both cities, findings suggest that mileage-based capacity utilization measure (i.e. percent of miles driven with a passenger) was calculated at 39.1% to 40.7% for taxis, and 55.2% to 64.2% for UberX. The main limitation of the Cramer and Krueger's study is that the Uber data only included the time and distance when drivers have the app on. They excluded other segments such as the mileage and time drivers must travel from origin to point of log-in and from the point of log-out to the end location, which would overestimate their capacity utilization rate.

Regarding literature focusing more on the overall impact to the transportation system, a non-peer reviewed report from the Shared-Use Mobility Center investigated the relationship between public transportation and shared modes, including bikesharing, carsharing, and ride-hailing in seven U.S. cities. This report found that the higher the use of shared modes, the more likely people use public transportation, own fewer cars, and spend less on transportation. This report also showed that shared modes complement public transportation (Murphy, 2016). These statements should be analyzed in more detail since these correlations do not necessarily mean causation. Do users of services like Uber and Lyft also use public transportation at higher rates and own fewer cars? Or could it be that people who use public transportation and own fewer cars are more likely to add Uber and Lyft to their transportation menu of options?

Researchers from the University of Michigan, Texas A&M, and Columbia University surveyed people in Austin, Texas, to examine how their habits changed after Uber and Lyft left the city due to a local law change regarding driver fingerprinting and background checks. After Uber and Lyft ceased operation, they found that 41% of respondents shifted to a personal vehicle while 3% shifted to public transit. Additionally, 9% of respondents stated that they purchased a vehicle after the TNCs left (Hampshire, Simek, Fabusuyi, Di, & Chen, 2017). More recently, a report from the University of California Davis presented results from a targeted email survey of over 4,000 adults in major U.S. metropolitan areas, showing that 21% of adults personally use ride-hailing services. Of those ride-hailing users, 39% were substituting driving, 15% public transportation, 23% bike or walk, and 22% would not have made the trip (Clewlow & Mishra, 2017).

Still, the literature on ride-hailing remains limited, in part due to their relative novelty and lack of open data. Thus, it is difficult for municipalities, states, and transportation agencies to know whether they should be encouraging or prioritizing these options. This study aims to begin filling these gaps by looking in more detail at deadheading, vehicle occupancy, car ownership, mode replacement, VMT changes, and find the place where ride-hailing stands in terms of efficiency compared to other modes.

4. QUASI-NATURAL EXPERIMENT

The first step to understanding impacts of ride-hailing was to develop a framework to guide the research and fill important gaps in the literature. This framework lays out the data and research needed to investigate ride-hailing, emphasizing the need to employ a combination of travel attributes (e.g. travel times), revealed-behavior data, and stated-response data structures (Henao & Marshall, 2017). Realizing the difficulty obtaining data directly from Uber and Lyft and finding the lack of ride-hailing research, we sought to gain access to exclusive driver data and real-time passenger feedback by signing-up and driving for these companies. We submitted a research proposal to the Colorado Multiple Institutional Review Board (COMIRB) and obtained IRB approval to interview passengers (COMIRB Protocol 16-0773, Exception APP001-3) in spring 2016 (Henao, 2017).

There are two interconnected datasets on the data collection: "driver dataset" and "passenger dataset." The first is exclusive data that Lyft/Uber drivers can obtain by giving rides to passengers. This "driver dataset" contains information about travel attributes from actual trips including date, time of the day, origin and destination (O-D) locations, travel times, travel distances, passenger cost, and driver earnings. The second dataset is information gathered by surveying passengers during the actual rides (i.e. "passenger dataset"), similar to the traditional on-board survey developed by transit organizations.

We conducted the data collection using a sedan vehicle (2015 Honda Civic) and a smartphone (iPhone 5s). The main apps in the smartphone used for this research were "Lyft," "Uber-driver Partner," "GoogleMaps," and "My Tracks." GoogleMaps and MyTracks GPS apps helped tracking and recording ride-hailing travel data.

4.1 Driving Strategy

Based on previous research (Anderson, 2014) and extensive conversations with ride-hailing drivers, there are three main driving strategies: i) circulate around until you get an app request (similar to traditional taxis); ii) strategically locate to increase the chance of getting a request (e.g. drive to downtown areas, hotels, or airports); and iii) minimize driving by parking immediately after a ride is finished. Most ride-haling drivers use a combination of these strategies. The driver-author also used a combination of these strategies, with an emphasis on the parking strategy since it is the most conservative option in terms of minimizing deadheading (i.e. driving without a passenger).

On a typical driving day, for instance, the driver-author turned on Uber and Lyft apps and waited until a passenger requested a ride. To be consistent with our conservative strategy, unnecessary driving was minimized by not picking-up passengers if the location was more than 15 miles away from the driver location at request, by parking as soon as possible after a passenger was dropped, and using conservative commute distances at the end of the shift (we did not include commuting at the start of the shift). Once the ride was accepted, driving mode was turned off for the other service. For example, if it was a Lyft request, the Uber driver mode was turned off, or vice versa. Then, the driver traveled to the passenger pick-up location and drove the passenger to the desired destination.

Once the ride ended at the destination location, the other app was turned on to wait for a new passenger request. Once the passenger left the car, the driver-author tried to find the closest parking space available with intent to minimize cruising distance without a passenger. For this study, we also kept in mind the rationale of what a passenger would have done if he/she was driving and needed to park (e.g. free parking, on-street metered parking, and garage parking under some circumstances). We recorded the cruising-to-park time and distance using the same methodology with the GPS-based apps.

Driving shifts ranged from as low as two hours to as high as nine hours. All seven days and times (24-hour period) were covered during the study period, but higher number of rides came during high demand times such as Friday and Saturday nights, representing typical ride-hailing services. Driving for both Uber and Lyft helped minimize the waiting times and cruising distances since the chances of getting a request from either service increased. It is also common that ride-hailing drivers work for both Uber and Lyft. For example, there were occasions where new requests came in even before finishing parking. We decided to complete all data collection by the driver-author to eliminate bias between drivers, to control travel without a passenger (i.e. deadheading minimization), to reduce surveyor errors, and to ensure data quality.

4.2 Passenger Survey

The driver-author invited passengers to participate in a short survey about ride-hailing verbally and with signs in the car, reading:

> *"Hi rider, I am a grad student doing research on transportation. Would you help me by doing a short survey (~6 minutes) about this ride? You can use my tablet or go to this link www.ride-survey.com. Thank you!"*

As the sign indicated, passengers had the option to take the survey using their own device or via a provided tablet device. Details of the survey are included in the Data section.

4.3 Study Area

The Denver metropolitan region comprises a variety of contexts, covering urban and suburban areas. For example, it contains urban places such as the area around Union Station in downtown Denver and low-density areas such as those surrounding the Denver International Airport (DIA), located about 24 miles northeast of Union Station. The Denver metropolitan region also includes Boulder, a college town, and suburban cities like Westminster, Broomfield, and Castle Rock. This diversity of characteristics (e.g. density, race diversity, income levels) makes the Denver region a good place to study ride-hailing.

Our sample was random by design since the driver-author did not know where each ride would end; this entailed driving all over the study area and providing transportation to passengers across a wide variety of socio-economic and socio-demographic characteristics. The only location we had control over is where the app was turned on at the beginning of the shift. Thus, we varied the starting location from urban to suburban areas.

While Uber and Lyft originated in what is considered an unregulated space, Colorado was also the first state in the United States to authorize Uber and Lyft services to operate with a bill signed by Governor Hickenlooper in June 2014 (Vuong, 2014).

5. DATA

This study includes 416 ride-hailing trips – 198 regular Lyft, 164 UberX, 39 LyftLine, and 15 UberPool – for the “driver dataset” and 311 surveys for the “passenger dataset,” collected over a period of 14 weeks during fall 2016.

5.1 Driver Dataset

The “driver dataset” contains several pieces of information for each ride including date, time, weather, pick-up/drop-off location, passenger cost, driver earnings, travel times, distances, and parking information. Figure 5.1 presents mileage for all 416 passenger O-D rides, and the remaining data derived from this dataset is the focus of the results section.

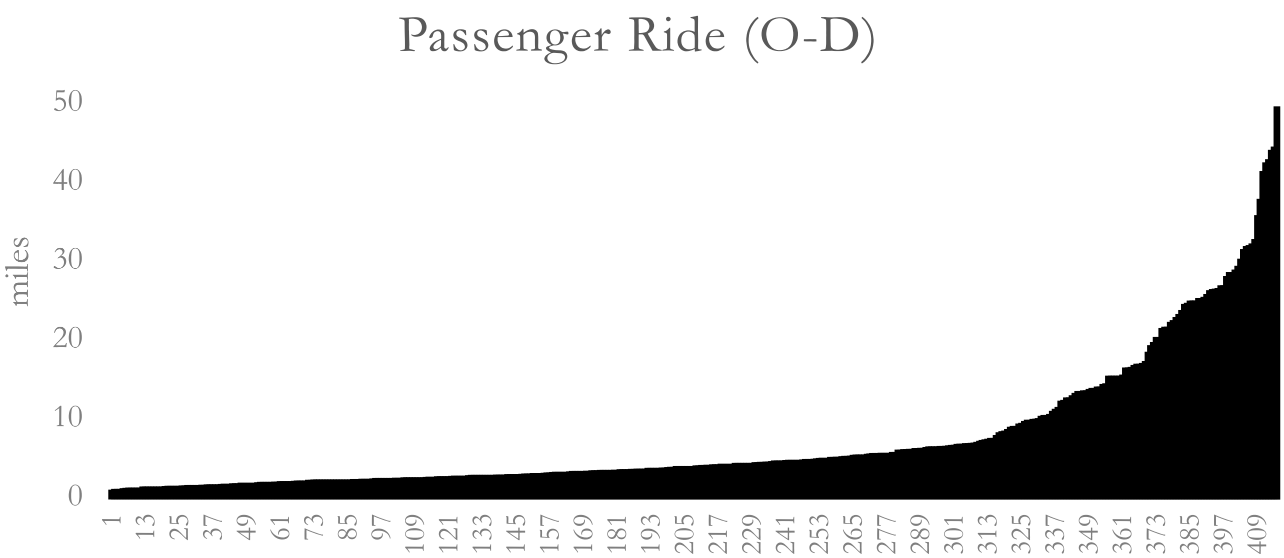


Figure 5.1 Ride-hailing Rides (n = 416)

5.2 Passenger Dataset

The 311-survey passenger dataset included three groups of questions:

Specific Trip Questions (Q1 – Q10):
The first section asks passengers questions regarding the specific Lyft/Uber ride and includes questions such as trip purpose, travel mode replacement, and reasons to shift from a previous mode.

General Use Questions (Q11 – Q25):
The second part of the survey covers broader questions about travel behavior in general such as modality resources (e.g. car ownership, transit pass, etc.), general ride-hailing use, frequency of use for different modes, travel behavior changes, and more general trip purposes and reasons.

Demographic Questions (Q26 – Q37):

The third section of the survey includes questions regarding characteristics of the individual and household (i.e. socio-economic demographics).

Table 5.1 provides descriptive statistics from passengers' survey answers. Previous studies have shown that ride-hailing (and carsharing) users do not usually represent the larger population in terms of income, age, and ethnicity (Murphy, 2016; Rayle et al., 2016). The authors from these papers suggest that these services mostly serve certain populations. Comparing the summary statistics of this study to the Denver population, our study results somewhat agree with these previous studies but are slightly more aligned with the representative populations than the existing literature. Different from previous studies — where researchers used intercept surveys at specific locations or online — our research has the advantage of being random by design since the passengers' destination location is unknown. Thus, this study covered a larger area and included populations that may not be represented in the existing literature. The sample has a close split of male-female population. Passengers were mostly younger adults, but compared to other studies, we had higher participation from elderly people. While two-thirds of the sample were white, we had representation from various races and ethnicities. In contrast to previous studies, income and education demographics were also better distributed between different ranges, although still skewed towards higher income and higher education levels compared to the Denver population. Clearly these services are mostly used by single or never-married individuals, and people working full-time or part-time.

Table 5.1 Demographics of Ride-hailing Passengers

		Survey Responses		Denver
Gender (n = 309)	Female	145	46.9%	50.0%
	Male	162	52.4%	50.0%
	Prefer not to answer	2	0.6%	-
Resident (n = 309)	Local Resident	254	82.2%	-
	Visitor	55	17.8%	-
Age (n = 309)	18-24	78	25.2%	10.0%
	25-34	132	42.7%	21.8%
	35-44	56	18.1%	15.4%
	45-54	30	9.7%	11.7%
	55-64	7	2.3%	10.5%
	65+	6	1.9%	10.7%
Race/Ethnicity (n = 308)	Asian	24	7.8%	3.5%
	Black/African Americ	16	5.2%	9.4%
	Hispanic or Latino	39	12.7%	30.9%
	White	206	66.9%	53.1%
	Other	16	5.2%	3.1%
	Prefer not to answer	7	2.3%	-
Household Income (n = 296)	$30K or less	34	11.5%	28.3%
	$31K - $45K	56	18.9%	14.0%
	$46K - $60K	58	19.6%	11.1%
	$61K - $75K	30	10.1%	10.0%
	$76 - $100K	40	13.5%	11.9%
	Over $100K	50	16.9%	24.9%
	Prefer not to answer	28	9.5%	-

		Survey Responses		Denver
Marital Status (n = 295)	Single or never married	185	62.7%	41.7%
	Married	80	27.1%	39.2%
	Separated, divorced, or widow	28	9.5%	19.1%
	Other	2	0.7%	-
Household Size (n = 292)	Household Size of 1	65	22.3%	-
	Household Size of 2	129	44.2%	-
	Household Size of 3	56	19.2%	-
	Household Size of 4	30	10.3%	-
	Household Size of 5+	12	4.1%	-
Children (n = 229)	Children in Household	47	20.5%	25.1%
	No Children in Household	182	79.5%	74.9%
Education (n = 297)	Less than High School	9	3.0%	13.9%
	Graduated high school or equiv.	49	16.5%	17.7%
	Some college, no degree	58	19.5%	18.3%
	Associate or Bachelor's degree	124	41.8%	32.5%
	Advanced degree (Master's, PhD	57	19.2%	17.6%
Employment (n = 301)	Working (Full-time or Part-Time	246	81.7%	70.9%
	Volunteer	1	0.3%	-
	Unemployed	15	5.0%	6.3%
	Retired	8	2.7%	-
	Not Applicable	31	10.3%	-
Student (n = 300)	Student (Full-time or Part-time)	70	23.3%	34.2%
	Not currently a student	230	76.7%	65.8%

Notes:

Denver data is from 2011-2015 ACS 5-Year estimates

First age category for ACS is 15 to 24 years old

Income ranges for ACS differ slightly from survey

6. METHODOLOGY

This section is divided has subsections that cover the specific methodology to calculate deadheading, vehicle occupancy, and VMT changes with mode replacement.

6.1 Deadheading

The term deadheading is mostly used for the taxi and trucking industry and refers to distance traveled without passengers or freight. Exclusive to ride-hailing, there are four specific segments of deadheading: commuting from driver residence; cruising for a ride (this is the most commonly known form of deadheading); from dispatch to pick-up location (we propose to name this new form of deadheading, exclusive to ride-hailing, overheading); and commuting at end of shift. Figures 6.1 and 6.2 illustrate these four segments, in addition to the actual passenger ride, for a total of five segments.

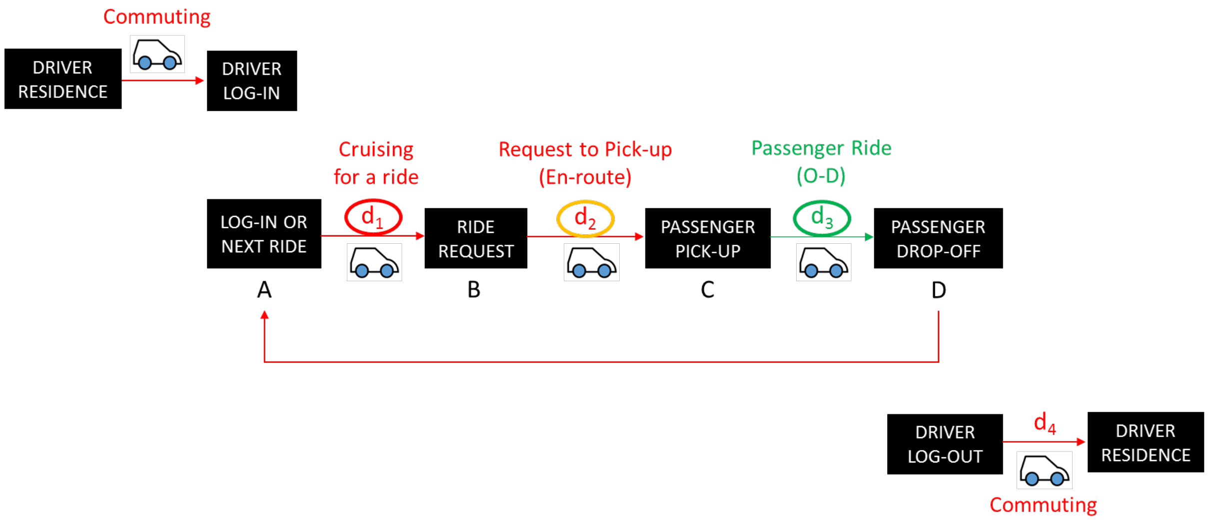


Figure 6.1 Travel Segments of a Lyft/Uber Driver

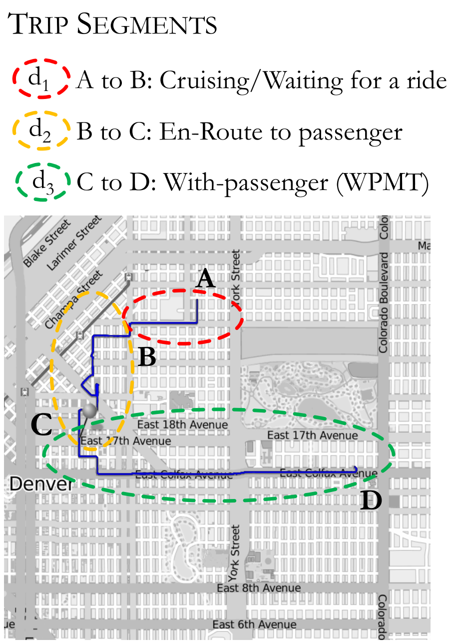


Figure 6.2 GPS Tracking of a Lyft/Uber Ride

The total ride-hailing driving distance (VMT_R) is calculated by equation (1) where for each shift *i* and ride *j*, we have:

$$VMT_R = \sum_{i=1}^{n}\left(\sum_{j=1}^{m}\left[d_{1(\mathrm{i,j})} + d_{2(\mathrm{i,j})} + d_{3(\mathrm{i,j})}\right] + d_{4(\mathrm{i})}\right) \qquad (1)$$

where *m* is the last ride of each shift *i*; *n* is the last shift, d_1 is the miles cruising for a ride; d_2 is the "overheading" miles; d_3 is miles for the O-D ride; and d_4 is commute miles at end of shift.

Equation (1) can also be expressed as:

$$VMT_R = \sum_{i=1}^{n}\sum_{j=1}^{m} d_{1(\mathrm{i,j})} + \sum_{i=1}^{n}\sum_{j=1}^{m} d_{2(\mathrm{i,j})} + \sum_{i=1}^{n}\sum_{j=1}^{m} d_{3(\mathrm{i,j})} + \sum_{i=1}^{n} d_4 \qquad (2)$$

In terms of passenger O-D rides and deadheading, the total driving distances is expressed as:

$$VMT_R = \mathrm{OD} + deadheading \qquad (3)$$

where:

$$\mathrm{OD} = \sum_{i=1}^{n}\sum_{j=1}^{m} d_{3(\mathrm{i,j})} \qquad (4)$$

$$\mathrm{Deadheading} = \left(\sum_{i=1}^{n}\sum_{j=1}^{m} d_{1(\mathrm{i,j})} + \sum_{i=1}^{n}\sum_{j=1}^{m} d_{2(\mathrm{i,j})} + \sum_{i=1}^{n} d_4\right) \qquad (5)$$

We estimated the ride-hailing deadheading percentage by comparing deadheading versus VMT_R, as follows:

$$Deadheading\ Percentage = \frac{Deadheading}{VMT_R} \qquad (6)$$

Finally, we calculated the ratio of "deadheading without commuting" and O-D to estimate the amount of deadheading (no commute) occurring per vehicle miles traveled with passengers (O-D) as:

$$Deadheading\ (no\ commute)\ rate\ \ per\ O-D = \frac{\left(\sum_{i=1}^{n}\sum_{j=1}^{m} d_{1(\mathrm{i,j})} + \sum_{i=1}^{n}\sum_{j=1}^{m} d_{2(\mathrm{i,j})}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{m} d_{3(\mathrm{i,j})}} \qquad (7)$$

6.2 Vehicle Occupancy

For every ride-hailing trip, we recorded the vehicle occupancy defined as the number of passengers in the vehicle for each ride, ranging from one to four. For the deadheading segments, the vehicle occupancy equals zero. We calculated the average vehicle occupancy based on total rides and the distance weighted average, with and without deadheading.

6.3 Combining the Driver and Passenger Datasets

Both interconnected datasets — driver and passenger — are necessary to compare with- and without-ride-hailing scenarios. For example,e in the without scenario, we need to know what passengers would have done without ride-hailing; thus, the question of interest from the passenger survey is Q5: *"For this trip, how would you have traveled if Lyft/Uber wasn't an option?"* The survey response options to the multiple choice question were: *"wouldn't have traveled; drive alone; carpool (drive); carpool (ride); public transportation; bike or walk; taxi; and other."* After reviewing the "*other*" responses, we created new categories including "*get a ride*" and "*car rental.*" If the passenger response to question Q5 was carpool, the survey was designed to ask the number of people that the passenger would have carpooled with (Q6), with the intent to make a fair comparison. For this study, we included a question on whether the passenger was using Lyft/Uber for the entire length of the trip (origin to destination), or if he/she was making a connection to another mode of transportation (Q9), and if so, to which mode of transportation (Q10). Finally, we included survey questions about car ownership/access (Q19). In summary, the information of interest for each ride includes:

- Date of ride
- Time at request
- The service the ride was requested from: Lyft, LyftLine, UberX, or UberPool
- Travel distances
- Number of passengers
- Trip Mode replaced (Q5)
- If passenger would have carpooled, the number of people carpooling (Q6)
- Connection with another mode of transportation (Q9 & Q10)
- Own or have access to a personal car (Q19)

Based on the data previously described, including the mode replaced and travel behavior if Uber and Lyft were not in place, we calculated passenger miles traveled (PMT) and replaced VMT (or $VMT_{WITHOUT}$), as follows:

- $VMT_{WITHOUT}$ for "*wouldn't have traveled*" is 0
- $VMT_{WITHOUT}$ for "*bike or walk*" is 0
- $VMT_{WITHOUT}$ for "*car rental*" is the same as the VMT from the origin to the destination (O-D) plus parking distance
- $VMT_{WITHOUT}$ for "*carpool (drive)*" is the same as O-D VMT plus parking distance
- $VMT_{WITHOUT}$ for "*carpool (ride)*" is calculated based on O-D VMT, the number of passengers in the ride, and the number of people that they stated would have carpooled with to
- $VMT_{WITHOUT}$ for "*driving*" is the same as O-D VMT plus parking distance
- $VMT_{WITHOUT}$ for "*get a ride*" is equal to two times the O-D VMT. This is the case when someone else (e.g. parent, spouse, or friend) would have driven the passenger from the origin to the destination and then gone back to origin, thus incurring in a round-trip doubling of miles from the original O-D trip.
- $VMT_{WITHOUT}$ for "*other ride-hailing*" is the same as ride-hailing VMT_R
- $VMT_{WITHOUT}$ for "*public transportation*" is 0 for walk-to-transit (WTT) and 3.4 miles for drive-to-transit (DTT). The selection of WTT and DTT rides were based on ride distance, answer to connection mode (Q9 & Q10), answer to car access (Q19), percentage of WTT and DTT based on data from a previous study in the Denver area (Marshall & Henao, 2015), and DTT distance based on another paper in the study area (Truong & Marshall, 2014).
- $VMT_{WITHOUT}$ for "*taxi*" is equal to 2.5 times O-D VMT based on the taxi distance efficiency of around 40% (Cramer & Krueger, 2016). We used the same ride-hailing VMT for trips to the airport.
- If the ride included a connection, the previous distance replaced is based on total VMT and PMT. For example, if a passenger was dropped-off at a transit station to ride a train to the airport, and the mode replaced was "*get a ride,*" the $VMT_{WITHOUT}$ is equal to two times the total distance (O-D VMT plus the train distance) because the person taking the passenger would have traveled all the way to the airport and back.

Ride-hailing VMT (or VMT_R) was calculated using all distances with and without a passenger as described in equation (1) or (2). Then, we calculated PMT/VMT ratios for before and after rides-hailing scenarios to understand the efficiency (Equation 8) of moving people (PMT) versus moving vehicles (VMT). Finally, to understand the additional VMT put into the system because of ride-hailing, we calculated the ratio of VMT_R versus $VMT_{WITHOUT}$ (Equation 9) for every mode replaced and overall.

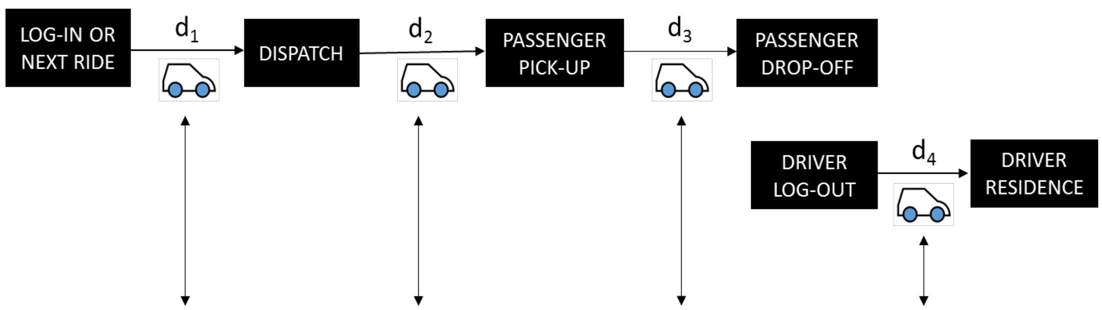
$$PMT\ per\ VMT\ Efficiency = \frac{PMT}{\mathrm{VMT}} \qquad (8)$$

$$VMT\ Ratio = \frac{Ridehailing\ VMT}{Replaced\ VMT} = \frac{VMT_R}{VMT_{WITHOUT}} \qquad (9)$$

7. RESULTS

The total ride-hailing VMT (VMT_R) distance based on all 416 rides was 4,951 total miles driven. Using the mean and median travel distances summary statistics (Table 7.1) from the datasets, a representative day from the sample would be as follows. The driver-author logs-on both apps, trying to minimize cruising for a ride (mean: 1.5 miles, median: 0.2 miles) until getting a passenger request. Once the driver accepts the request, he travels approximately 1.4 miles (median: 1.0 miles) from the dispatch location to the passenger pick-up location (i.e. overheading). The average distance for a passenger ride (or O-D) is 7.0 miles (median: 3.6 miles). After the passenger is dropped-off, the driver starts the process again by waiting for a new ride request but also by minimizing unnecessary driving. When the driver is done for the day, he travels to the desired end location, commuting and average of around 12 miles (based on 65 commuting trips or shifts).

Table 7.1 Ride-hailing Distance Summary Statistics



		Cruising for a ride	Dispatch to Pick-up (Overheading)	Passenger Ride (O-D)	Commute at End	Total VMT_R
Distance (miles)	Total (S_t)	635.9	600.6	2,929.9	784.3	4,950.7
	Mean	1.5	1.4	7.0	12.1*	
	St. Dev.	3.9	1.4	8.6	7.4*	
	Median	0.2	1.0	3.6	12.0*	

n = 416 (Lyft, 198; LyftLine, 39; UberX, 164; UberPool, 15)

*Commute based on 65 shifts

7.1 Deadheading

For this study, the conservative (low end) deadheading percentage of ride-hailing (without commuting at beginning of shift) equals to 40.8% (25.0% from "cruising" plus "overheading," and 15.8% from commuting at end). This means that for every 100 miles with a passenger, a ride-hailing driver travels an additional 69 deadheading miles without a passenger. Previous to this study, the only ride-hailing data and study available was the one by Cramer and Krueger (2016), where they calculated a utilization rate of 64.2% for Los Angeles and 55.2% for Seattle, which equates to 35.8% to 44.8% in deadheading. Since they only had data for when the Uber app was on, they missed information such as the commuting distance at the end of shifts. Recently, a dataset of over 1.49 million O-D trips was made available by RideAustin, a non-profit ride-hailing company in Austin, Texas, on the website Data.World for a 10-month period (June 2016 to April 2017). Using conservative estimates, the deadheading percentage for

RideAustin equates to 49% (31% from "cruising" plus "overheading", and 18% from commuting). Another recent study is the San Francisco TNC Today report (Castiglione et al., 2017), where researchers at the Northeastern University (Chen, Mislove, & Wilson, 2015) used the Uber and Lyft API to develop a research method to track vehicles. They estimated 20.3% deadheading for intra-city trips. Unfortunately, they incorrectly calculated this number: i) by not including "overheading" in the deadheading, and ii) by adding this "overheading" distance to the passenger O-D rides. They also excluded trips starting or ending outside of the city core such as going to and from the airport and did not account for commuting at the beginning or end of shifts. More recently, the Rocky Mountain Institute (RMI) published an article online (RMI Outlet, 2018) using data from Lyft for San Francisco, New York, and Chicago. Although the post is not very clear about their calculation methods and analysis, one of the figures provides insights into the relationship between deadheading from "cruising" plus "overheading" and VMT with passengers (or the O-D distance).

Since the studies by Cramer and Krueger and RMI do not include commuting in their calculations, we decided to calculate the deadheading rate of "cruising plus overheading" (no commuting) per 1.0 "VMT with passengers" (or O-D), as defined in Equation 7, for the sake of comparison. Table 7.2 presents these results.

Table 7.2 Deadheading Rate per Vehicle Mile Traveled with Passengers

	Cruising for a ride + Dispatch to Pick-up (Overheading)
Cramer and Krueger (2016)	0.56 - 0.81
RideAustin (2017)	0.61
RMI (2018)	0.46 - 0.67
This Study	0.42

Because we minimized cruising for a ride request, did not accept rides when the distance to pick-up a passenger was too long, and used conservative commute distances at end of shifts, our deadheading rate calculation is lower than the other studies. Even with this conservative calculation, ride-hailing drivers tend to travel 69.0 extra miles in deadheading (42.2 miles from "cruising and overheading" and 26.8 miles from commuting) for every 100 miles with a passenger.

7.2 Vehicle Occupancy

Including all 416 rides, the average vehicle occupancy was 1.36 passengers per ride (Figure 7.1). When we consider the VMT with passengers per vehicle occupancy, the distance weighted vehicle occupancy equates to 1.31 passengers per ride without including deadheading (Figure 7.2). When we include deadheading, the distance weighted vehicle occupancy becomes 0.8 passengers per vehicle (Figure 7.3), which is lower than a SOV trip.

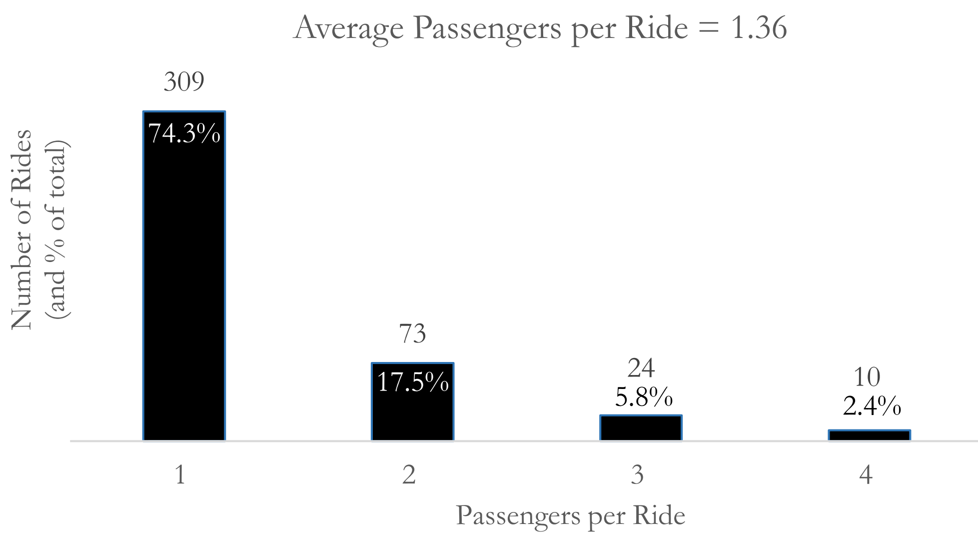


Figure 7.1 Ride-hailing Vehicle Occupancy (n = 416)

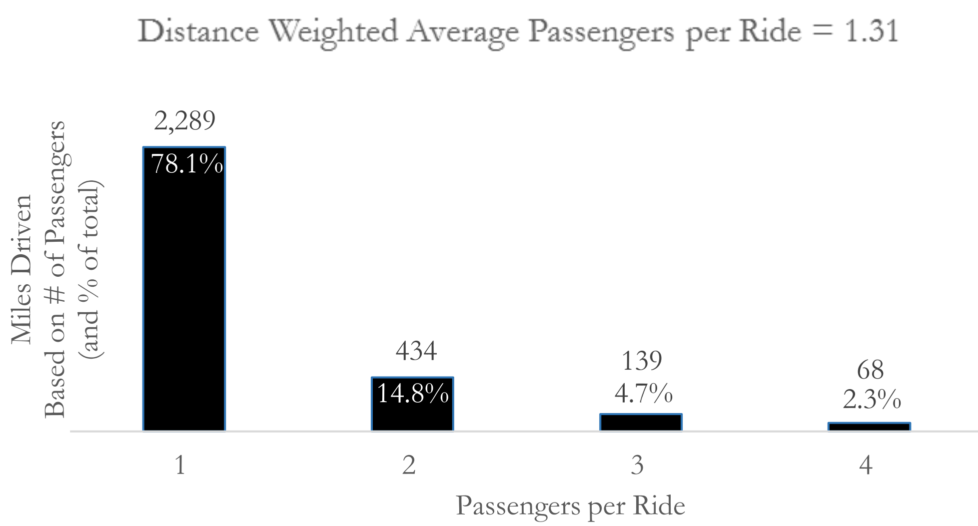


Figure 7.2 VMT with passengers per Vehicle Occupancy (n = 2,930)

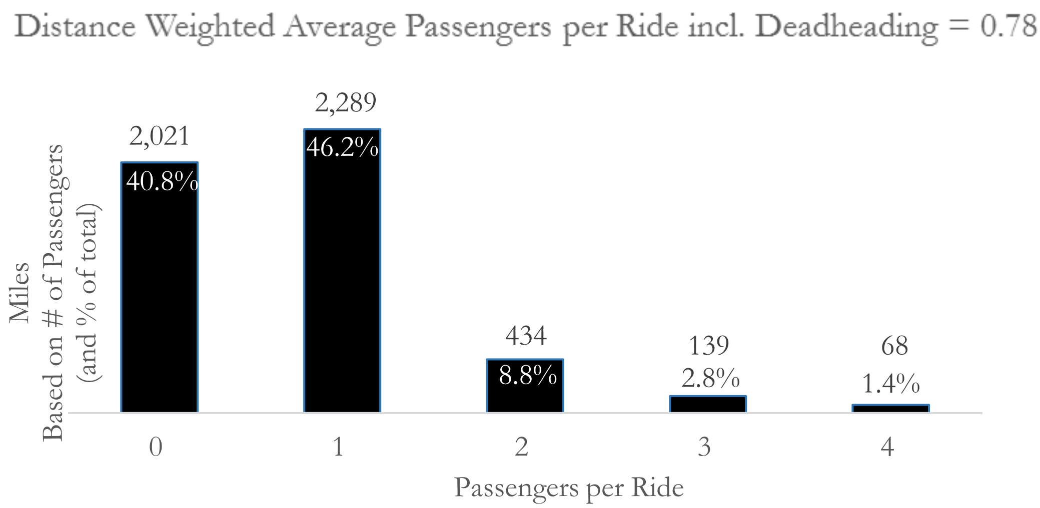


Figure 7.3 VMT per Vehicle Occupancy (n = 4,951)

7.3 Pooling Ride-Hailing: UberPool and LyftLine

Fifty-four requests were either from UberPool or Lyftline services, representing about 13.0% of all requests. From those 54 requests, only eight (or 14.8%) received a matching ride. This last fact is important to note because when Uber or Lyft representatives mention statistics on these services, they do not differentiate between requests and actual matches. They have stated that requests for these pooled services represent between 20%–40% of total ride-hailing requests, but they have not clarified the rate of actual matches.

7.4 Car Ownership

Reductions in car ownership could potentially represent one of the biggest benefits of ride-hailing services. While causation between ride-hailing and car ownership rates is difficult to discern, approximately 13% of respondents report owning fewer cars due to the availability of ride-hailing. Our results suggest that only 60% of our ride-hailing passengers own their own car, which is significantly lower than average for the Denver region. However, approximately half who do not own a car still report having access to a car. Table 7.3 tests for demographic differences between passengers that own a car and those who do not. Ride-hailing passengers who owned a car tended to be older, more educated, wealthier, and were more likely to be white and married with children. They were also less likely to be a student and more likely to be from out of town.

While demographic differences related to car ownership with ride-hailing passengers were expected, Table 7.4 considers how these two groups used ride-hailing services differently. Ride-hailing passengers who do not own a car used ride-hailing an average of 3.4 times per month as compared to 2.5 times per month for those that own a car. However, they also used ride-hailing for significantly shorter trips (4.6-mile average) than ride-hailing passengers that own a car (8.2-mile average). Figure 7.4 depicts the trip mileage of each group. We also found that ride-hailing passengers who do not own a car are significantly more likely to use ride-hailing to replace public transit while those who own a car are more likely to replace driving alone. The next sub-section delves further into this mode replacement issue further to understand how ride-hailing impacts VMT.

Table 7.3 Demographic Differences between Ride-Hailing Passengers by Car Ownership

	Car mean	No-car mean	t-stat	df	p-value
Gender (female)	0.48	0.45	0.502	305	0.3082
Age	2.52	1.89	5.043	307	**<0.0001**
Race/Ethnicity (white)	0.75	0.58	3.288	299	**0.0006**
Marital status (single)	0.53	0.78	-4.458	293	**<0.0001**
Household size	2.24	2.40	-1.252	290	0.1059
Children	0.28	0.09	3.658	227	**0.0002**
Education	3.99	2.90	3.658	295	**<0.0001**
Employment	0.94	0.85	2.651	268	**0.0042**
Income	4.10	2.53	8.181	266	**<0.0001**
Local Resident	0.76	0.92	-3.680	307	**0.0001**
Student	0.13	0.40	-5.643	298	**<0.0001**

Table 7.4 Ride-hailing Use Differences between Ride-Hailing Passengers by Car Ownership

	All mean	Car mean	No-car mean	t-stat	df	p-value
Ride-hailing frequency	2.83	2.50	3.40	5.043	307	**<0.0001**
Ride distance (miles)	6.79	8.23	4.63	3.690	309	**<0.0001**
Drive alone replaced	0.19	0.31	0.01	7.161	309	**<0.0001**
Public transportation replaced	0.22	0.14	0.35	-4.438	309	**<0.0001**

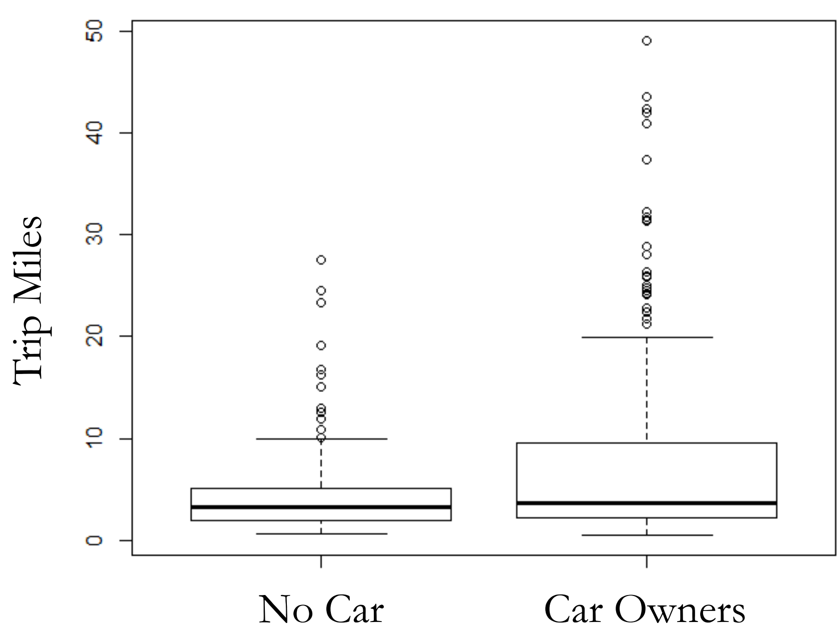


Figure 7.4 Box and Whisker Plots Comparing Ride-Hailing Trip Mileage by Car Ownership

7.5 Mode Replacement

Figure 7.5 depicts the mode replacement results. For instance, 19% of ride-hailing trips would have been single-occupancy vehicle trips while 34% would have been either walking, biking, or transit. Also, more than 12% of ride-hailing rides would not have been taken had Uber and Lyft not existed.

Regarding connections with other modes of transportation, 94.5% of passengers stated that they were using Lyft or Uber for the entire trip, and only 5.5% were using another mode of transportation in connection with the specific Lyft or Uber ride (Q9). Moreover, 187 people out of 291, or 64.3%, responded to question Q19 stating that they own or have access to a personal car.

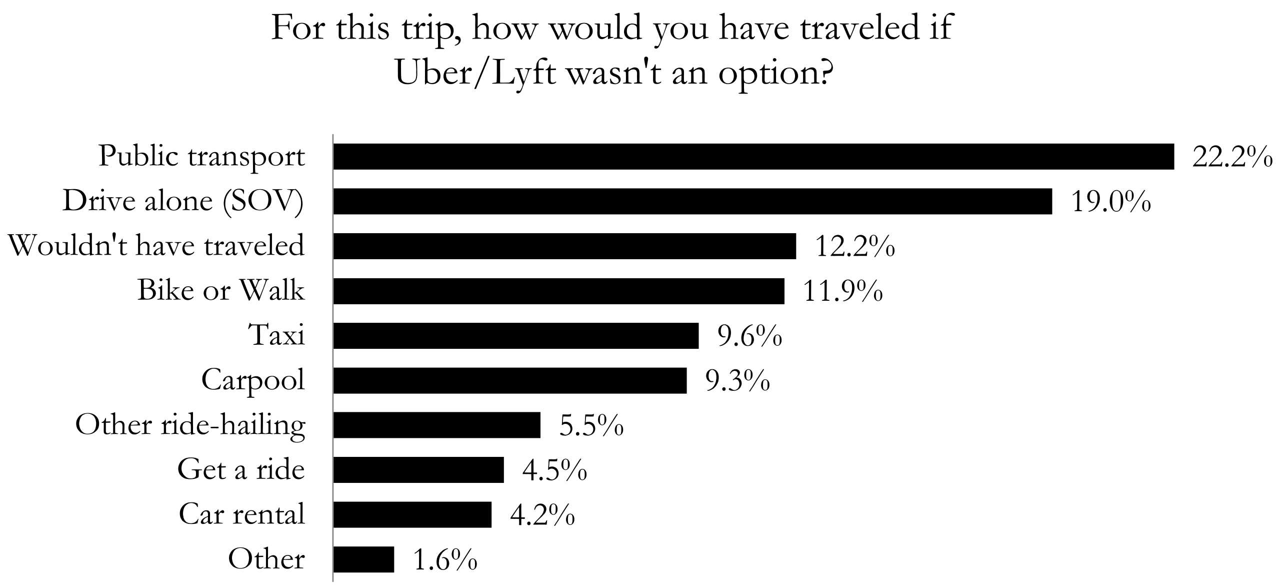


Figure 7.5 Mode Replacement

7.6 Passenger Miles Traveled (PMT) and Vehicle Miles Traveled (VMT) Efficiency

Looking exclusively at rides that included at least one passenger survey, the ride-hailing VMT distance (VMT_R) in this analysis was 3,618 miles, while PMT was 2,200 miles. The average passenger surveyed traveled a mean distance of 7.1 miles (median: 3.5 miles) with a range from 0.5 miles to 49.1 miles. Based on the mode replaced and the calculations discussed above, the replaced VMT ($VMT_{WITHOUT}$) would have been approximately 1,972 miles. This suggests that the ride-hailing passengers would have put 1,972 VMT into the system if Uber/Lyft did not exist. With Uber/Lyft, they now put 3,618 VMT into the system. The before travel behavior based on the replaced mode was 111.6% efficient in terms of how much PMT (2,200 miles) per VMT (1,972 miles) would have happened if Lyft or Uber were not available, meaning that all the modes replaced were transporting passengers at a rate of 111.6 miles for every 100 vehicle miles. With the introduction of ride-hailing, the PMT/VMT efficiency dropped to 60.8%, meaning that the miles passengers travel is lower than the vehicles miles at a rate of only 60.8 PMT for every 100 VMT from Lyft/Uber. This equates to a 45.8% percent reduction.

7.7 VMT Change

Table 7.5 presents the total, mean, and median distances of PMT and the total and mean distances for $VMT_{WITHOUT}$ and Ride-hailing VMT_R for each mode replaced and total. The last column of this table shows the percent change in VMT for every mode and the total. Overall, our results suggest that ride-hailing adds approximately 83.5% more VMT to the system than if these services did not exist.

Table 7.5 Before-and-After VMT by Mode Replacement

Mode Replaced	n	Ride-Hailing Passenger Miles Traveled			Replaced VMT		Total Ride-Hailing VMT		$\frac{Ridehailing\ VMT}{Replaced\ VMT}$	% Change in VMT
		Total	Mean	Median	Total	Mean	Total	Mean		
Public transportation	69	419.6	6.1	3.5	27.2	0.4	768.9	11.1	28.27	2726.7%
Drive alone (SOV)	59	661.3	11.2	5.2	670.4	11.4	935.5	15.9	1.40	39.6%
Wouldn't have traveled	38	194.0	5.1	3.7	0.0	0.0	370.2	9.7	-	-
Bike or Walk	37	74.3	2.0	1.7	0.0	0.0	195.9	5.3	-	-
Taxi	30	364.2	12.1	5.8	639.5	21.3	568.3	18.9	0.89	-11.1%
Carpool (ride)	19	132.1	7.0	3.9	82.2	4.3	227.7	12.0	2.77	177.1%
Other ride-hailing	17	52.8	3.1	3.0	143.3	8.4	143.3	8.4	1.00	0.0%
Get a ride	14	132.6	9.5	5.7	265.3	18.9	140.5	10.0	0.53	-47.0%
Car rental	13	54.6	4.2	3.7	55.4	4.3	119.7	9.2	2.16	115.9%
Carpool (drive)	10	77.1	7.7	2.7	79.2	7.9	93.6	9.4	1.18	18.3%
Other	5	37.5	7.5	2.6	9.2	1.8	54.1	10.8	5.90	489.8%
Total	311	2,200.0	7.1	3.5	1,971.7	0.9	3,617.7	11.6	1.83	83.5%

8. CONCLUSIONS

Ride-hailing has quickly become a popular service successfully competing and interacting with other modes of transportation, but due to the lack of open data, research on this topic is scarce. We use an innovative research methodology to gather interconnected driver and passenger datasets with a quasi-natural experiment. To our knowledge, this is the first independent study that uses Uber and Lyft data from both the driver- and passenger- perspectives to assess several impacts of ride-hailing on transportation including deadheading, vehicle occupancy, mode replacement, analyze PMT/VMT efficiency, and measure VMT impacts by exploring without- and with- ride-hailing scenarios.

While ride-hailing provides mobility and convenience, our results suggest that ride-hailing adds a significant amount of VMT (+83.5%) to the system when accounting for deadheading, induced travel, and substitution of more sustainable modes.

For all 416 ride-hailing trips, we found that deadheading accounts for 69.0 extra miles for every 100 miles with passengers (or O-D). Compared to private driving trips — and even accounting for the extra mileage cruising for parking at the destination — the ride-hailing VMT is significantly higher to what would have been driven without Lyft/Uber. For example, a single-occupancy vehicle (SOV) traveler who needs to go five miles to his/her destination would add approximately 5.1 miles (accounting for parking distance) to the transportation system (+5.1 VMT); if that same person is taking a Lyft or Uber instead, he/she would still travel five miles, but the ride-hailing driver might add nine total miles to the transportation system (+9 VMT). It is obviously concerning that ride-hailing — when accounting for deadheading — seems less efficient than driving alone. Such results should be investigated in other contexts and may have significant implications for our cities in terms of congestion and environmental concerns.

In terms of vehicle occupancy, while the average passenger per ride was between 1.3 and 1.4, it is concerning that when accounting for deadheading miles, the distance weighted average passenger occupancy drops down to approximately 0.8, which is less than a single-occupancy vehicle (1.0). Ride-hailing passengers tended to have lower car ownerships rates that average. Those who did not own a car tended to use ride-hailing services more frequency, but for shorter trips. For this study, a combined 34.1% of our ride-hailing passengers would have taken transit, walked, or bicycled. While mode substitution rates from more sustainable modes were significantly higher for ride-hailing passengers that did not own a car, car ownership and mode substitution is a complicated issue in need of further inquiry. For instance, if someone owns a car and uses ride-hailing, then it is relatively easy for them to tell us what mode is being replaced. When someone who does not own a car uses ride-hailing, the short-term thinking may be that the trip is replacing walking, biking, or transit. Still, they may have made the long-term decision not to own a car, at least in part, due to the availability of ride-hailing services. It is worth noting that 13% of our respondants report owning fewer cars due to ridesourcing. The reported mode substitution rates, however, remain based on their stated response to the question, "How would you have traveled if Lyft/Uber wasn't an option?" These modal shifts represent an indication of how ride-hailing affect the efficiency of transporting passengers versus vehicles, going from a PMT/VMT efficiency of 111.6% to 60.8%. In fact, ride-hailing, in its current form, is only more efficient — in terms of transportation passengers per VMT — than two other modes: "taxis" and "getting a ride."

This study does not come without limitations. The main limitation is the trip sample size relative to the overall number of rides that Uber and Lyft provide. Secondly, our data is limited to one metropolitan area and not necessarily generalizable to other regions. Luckily, more recent datasets have proven to complement our analysis. In terms of data collection, our singular driver-author approach is both a limitation and an advantage. It is a limitation because drivers have different work strategies such as searching for prime areas, having a desired location in mind, cruising unlimitedly until getting a ride request, or limiting driving without a passenger as much as possible by parking right after a passenger is dropped off. At the same time, our methods are an advantage since we were able to control the amount of driving, and in turn, design the research with conservative estimations. Future studies should also consider how these results might differ depending upon the context. For instance, there may be less deadheading in urban areas where ride requests may be more frequent and closer together. At the same time, ride-hailing may prove to help people connect to transit in more suburban locations.

Cities can use the results from this research to look at this issue in more detail and realize what they might gain or lose. However, we believe that much more research — especially with the newer and truer sharing services such as LyftLine and UberPool — is needed on these critical topics of vehicle occupancy, mode replacement, and VMT. Unfortunately, such research cannot be done without appropriate data, and the approach we took in this report is not easily replicable at larger scales. Thus, cities authorizing ride-hailing companies such as Uber and Lyft should demand data sharing agreements for research purposes. Such research is needed before we start encouraging or prioritizing the use of these services (e.g. curb space and parking priorities, transit agencies contemplating removal/replacement of bus services in certain areas, subsidizing Lyft/Uber rides, etc.). Positive outcomes should come when car ownership is being reduced and the modes being replaced are SOV, taxis, or getting a ride instead of more sustainable modes like transit, walking, or biking.

This research begins to fill a gap in the academic literature by identifying, measuring, and disentangling ride-hailing data to help us better understand the impacts of ride-hailing on important aspects of the transportation system, including deadheading, vehicle occupancy, mode replacement, efficiency, and VMT. We hope this study helps cities and transportation organizations better account for the impacts of ride-hailing in their policies, planning, and engineering processes. We also hope to contribute to the conversation as to how ride-hailing companies can help better achieve sustainable transportation goals such as mode shifts away from SOV into transit, walking, and biking, better VMT efficiency, improved interconnectivity and integration with active modes of transportation, equity, and safety for users and drivers.

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PART 2: The Impact of Ride-Hailing on Parking (and Vice Versa)

10. INTRODUCTION

This section focuses on the impacts of ride-hailing on parking, looking at the bi-directional relationship between these two topics. In other words, does ride-hailing contribute to changes in parking demand? On the other hand, how does parking stress (i.e., availability, time, and cost) deter driving trips and encourage ride-hailing use? If ride-hailing replaces driving trips, we should theoretically reduce parking supply, as more people can access destinations without requiring an accompanying parking space. In turn, this could facilitate re-allocating parking infrastructure to other needs and land uses.

Obtaining data for independent academic research from ride-hailing companies such as Uber and Lyft is extremely difficult (Levitt, 2016). Even when these companies agree to share data, the data often is not adequate for research purposes (Vaccaro, 2016) or does not contain the required information to answer even the most basic research questions. For this study, one of the authors collected data by serving as an independent-contractor driving for both Uber and Lyft. This type of research combines ethnography with additional elements — interviews and technology-based data —to facilitate quantitative and qualitative analysis.

We designed the study to look specifically at ride-hailing trips that otherwise would have needed parking (e.g. if passengers would have driven their own car or renting a vehicle). For instance, our on-board passenger survey asked passengers about: i) driving mode replacement in terms of what mode they would have used if not for Uber or Lyft, and ii) parking as a stated reason to use ride-hailing instead of another mode. After dropping off the passenger, the driver pretended he needed to park to estimate "cruising to park" time, parking cost, and the estimated walking time from the parking spot to the final destination. This combination of data allowed us to assess the relative shift in parking demand and the contribution of parking as a reason of why someone decides to use ride-hailing.

This chapter is divided into the following five sections: literature review, data, methods, results, and discussion/conclusions. The literature review section contains previous research studies relevant to ride-hailing and parking. In the data section, we describe in more detail the study design and data collection. The methods section explains the classification tree-model analysis. We follow with the results section and finalize the chapter with conclusions and a discussion of the bi-directional implications of ride-hailing and parking in the context of transportation and land use.

11. LITERATURE REVIEW

Despite a lack of open data, we are beginning to see an increase in academic research related to ride-hailing services. For this study, we focus on literature specific to ride-hailing and parking-related outcomes. Since parking is affected when ride-hailing replaces driving, we also consider how passengers are choosing this service as a new means of travel and what transportation modes are being replaced. We then review the literature on parking availability, time, and cost with respect to predicting (encouraging or deterring) driving mode choice.

We used ethnography as the main data collection method to examine travel behavior of the population using ride-hailing in the Denver metro area. Ethnography, as the representation of empirical data on humans, has been explored thoroughly in biological, social, and cultural studies from anthropology, and more recently has become widely used in social science (Brewer, 2000; Lewis, 2015). While the main method of ethnography studies is participant observation, ethnographers also conduct interviews and surveys (O'Reilly, 2012). While ethnographic studies are not common in transportation science, they offer valuable insights for understanding phenomena by researchers delving and studying a topic from the insight perspective. Specific to our research, we learned about ride-hailing from the driver interacting with passengers and collecting quantitative and qualitative data. Such data would have been difficult to acquire without becoming a driver for Uber and Lyft.

Regarding ride-hailing research, one of the first case studies looking at passenger travel behavior changes used an intercept survey to compare taxis, transit, and ride-hailing services in San Francisco (Rayle, Dai, Chan, Cervero, & Shaheen, 2016). While this study was conducted at an early stage of ride-hailing entrance in 2014, participants stated that ride-hailing substitutes and complements public transit, walking, and biking. Overall, 7% of survey respondents stated that they would have driven, and 8% would not have traveled (i.e. induced travel effect) if ride-hailing services were not available.

A case study in Austin, Texas, surveyed people to examine how their habits changed after Uber and Lyft left the city due to a local law change requiring driver fingerprinting and background checks. After Uber and Lyft ceased operation, researchers found that 41% of respondents shifted to a personal vehicle while 3% shifted to public transit. Additionally, 9% of respondents stated that they purchased a vehicle after the ride-hailing companies left (Hampshire, Simek, Fabusuyi, Di, & Chen, 2017).

More recently, a report surveying over 4,000 adults in major U.S. metropolitan areas found that 21% of adults personally use ride-hailing services. Of those ride-hailing users, 39% were substituting driving, 15% public transportation, 23% bike or walk, and 22% would not have made the trip (Clewlow & Mishra, 2017). More relevant to this study, the same report found that 37% of urban ride-hailing users cite parking issues as their top reason to do so. Second on the list was avoiding driving when drinking (33% of ride-hailing users).

Regarding parking, several studies suggest that parking availability (Guo, 2013; Weinberger, 2012; Weinberger, Seaman, & Johnson, 2009) and cost (Hess, 2001; Willson & Shoup, 1990; Wilson, 1992) are significantly associated with car ownership and mode choice. The higher the parking supply and the lower the cost to park, the higher the chance of someone owning a car and/or choosing to drive as the mode of transportation. Parking also poses a problem in terms of cruising for a parking space at destination locations and the related traffic congestion (Brooke, Ison, & Quddus, 2014; Shoup, 2006).

Recent studies suggest that parking revenues have been declining due to the increased in ride-hailing use in urban areas and for special destinations/events (Morris, 2018; Steele, 2018). Airports are also experiencing a similar trend with changes in ground transportation revenue from parking and other services (Mandle & Box, 2017; Zipkin, 2017). More recently, a study of medium to major airports found that parking revenues peaked one to two years after ride-hailing companies started their service, and a steady decline in parking revenues has followed since then (Henao, Sperling, Garikapati, Hou, & Young, 2018). This has caused some airports to reconsider parking needs. Developers are similarly beginning to rethink parking, and transportation professionals continue to suggest a future decline in parking demand as new services and automated vehicles come into place.

While ride-hailing may negatively impact deadheading (drivers circulating around without passengers), vehicle miles traveled, congestion, and substituting from more sustainable modes such as walking, biking, and public transportation (Clewlow & Mishra, 2017) [Redacted for blind review], a positive impact might be found in parking. Parking, with respect to ride-hailing, presents an opportunity to: i) lower parking generation rates, ii) reduce zoning requirements or eliminate minimums with some land uses, and iii) replace parking spaces with different land uses and economic development opportunities. Ride-hailing and parking could also reduce car ownership and reduce personal driving.

The literature on ride-hailing remains limited in part due to the novelty and lack of open data on these services. Thus, it is difficult for cities and transportation agencies to know what to do when it comes to emerging services such as ride-hailing. This study aims to begin filling this gap in the literature by looking in more detail at changes with respect to parking.

12. DATA

Realizing the lack of available data from companies such as Uber and Lyft, we decided to collect the data by one of us signing up as a driver for both companies. By doing this, we gained access to exclusive data and interacted directly with passengers. To our knowledge, this is the first independent research that implements an ethnographic approach for ride-hailing data collection.

Data was collected in the Denver metropolitan area with a research proposal to interview passengers approved by the Colorado Multiple Institutional Review Board (COMIRB Protocol 16-0773, Exception APP001-3). The Denver metropolitan region includes a contexts covering urban and suburban areas. This diversity of characteristics (e.g., density, race diversity, income levels, etc.) makes the Denver region a good place to study ride-hailing. Our sample is also random by design since the driver-author did not know where each ride would end. It entailed driving all over the study area and providing transportation to passengers across a wide variety of socio-economic and socio-demographic characteristics. The only location we had control over is where the app was turned on at the beginning of the shift. Thus, we varied the starting location from urban to suburban areas across the metropolitan region. We decided to conduct all data collection ourselves to eliminate bias between drivers, control travel without a passenger (i.e. deadheading minimization), reduce surveyor errors, and ensure data quality.

We conducted data collection using a sedan vehicle (2015 Honda Civic) and a smartphone (iPhone 5s). The main apps in the smartphone used for this research were “Lyft,” “Uber-driver Partner.” “GoogleMaps,” and “My Tracks” (Figure 12.1). GoogleMaps and MyTracks GPS apps helped tracking and recording ride-hailing travel data. For the origin and destination locations, we collected the closest cross streets, rather than the actual address, to maintain confidentiality. Driving shifts ranged from as low as two hours to as high as nine hours. All seven days and times (24-hour period) were covered during the study period, but a higher number of rides came during high demand times such as Friday and Saturday nights, representing typical ride-hailing services.

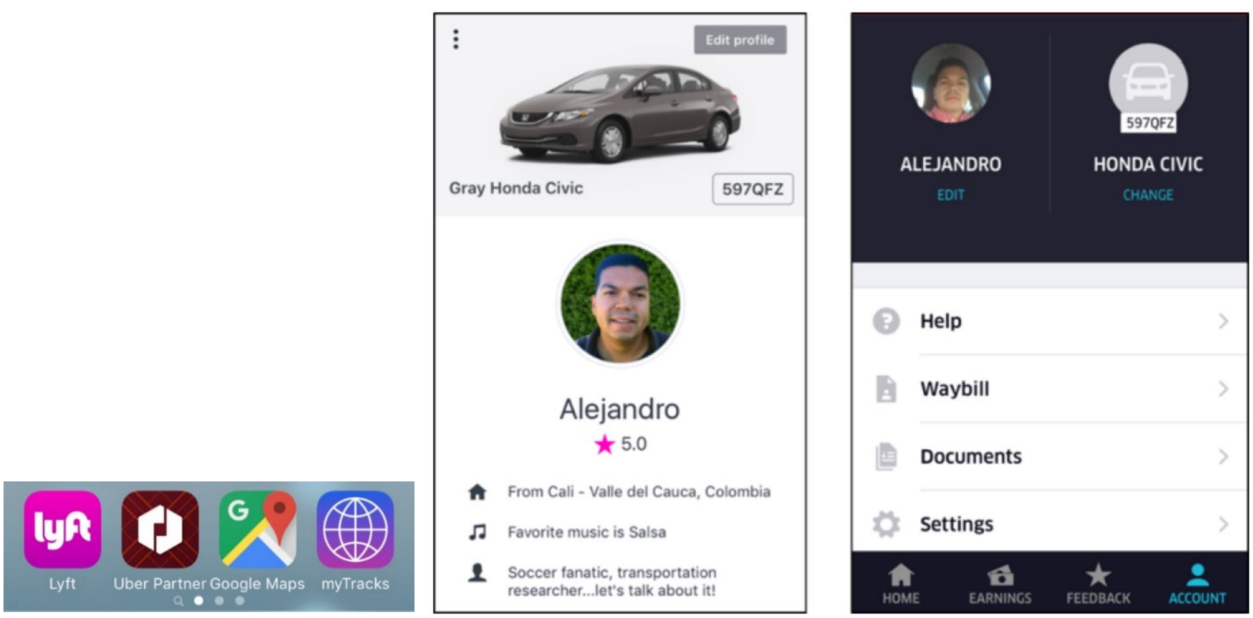

Figure 12.1 Lyft and Uber Driver Profiles and Smartphone Apps

We ended up with two inter-connected datasets: i) the ride-hailing driver dataset, and ii) the ride-hailing passenger dataset. The first is the exclusive data that Uber/Lyft drivers can obtain by giving rides to passengers. This "driver dataset" contains information with GPS tracking of date, time of day, travel times, and travel distance (e.g., origin-destination rides). We also collected additional data relevant to parking, including the cost, time, and distance it would take to find a parking space after passenger drop-off. We based the parking location as a combination of different passenger rationalities (e.g. free parking, on-street metered parking, and garage parking in special destinations such as stadiums or airports). We recorded the cruising to park time and distance using the same GPS-based methodology. For the walking time and distance to final destination, we input the coordinate locations for parking and final destination (i.e. ride-hailing passenger drop-off) in Google Maps and recorded the estimated walking time and distance. We then described the destination type as high urban (e.g., central business district or CBD), general urban, suburban, or special event (e.g., airport, university campus, or stadium).

The "passenger dataset" contains information gathered by surveying passengers during the actual rides. On a typical day, the driver-author turned on both ride-hailing apps and waited until a passenger requested a ride. Once a passenger was on board during the ride, he/she was invited to participate in a short survey about ride-hailing verbally and with signs in the car that read:

> *"Hi rider, I am a grad student doing research on transportation. Would you help me by doing a short survey (~6 minutes) about this ride? You can use my tablet or go to this link www.ride-survey.com. Thank you!"*

As the sign indicates, passengers had the option to take the survey using their own device or via a tablet device that was provided. In some cases, the driver-author conducted verbal interviews. Once the ride ended at the destination location, the other app was turned on to wait for a new passenger request. Once the passenger left the car, the driver-author tried to find the closest parking space available with the intent to minimize cruising distance without a passenger.

The passenger survey included three groups of questions:

Specific Trip Questions

The first section asks passengers questions regarding the specific Uber/Lyft ride and includes questions such as trip purpose, travel mode replacement, and reasons to shift from a previous mode.

General Use Questions

The second part of the survey covers broader questions about travel behavior in general such as modality resources (e.g. car ownership, transit pass, etc.), general ride-hailing use, frequency of use for different modes, travel behavior changes, and more general reasons.

Demographic Questions

The third section of the survey includes questions regarding characteristics of the individual and household (i.e. socio-economic demographics).

Table 12.1 depicts the demographics of our ride-hailing passengers. Comparing the summary statistics of this study to the overall Denver population, our respondents show a close gender split, higher representation from younger adults (ages 18-34, +28%) that are single or never married (+21.4%), of white race (+15.3%), with mid household incomes ($46K – $60K, +10.5%), and higher education levels (some college or higher, +12.1%). In contrast, our respondents exhibited lower representation from older populations (age 55+, -22%), married (-11.9%), of Hispanic or Latin race (-17.9%), with lower incomes ($30K or less, -15.6%), and lower education levels (high school or less, -12.1%). Our sample shows that 17.8% of passengers were from out of town.

The existing literature suggests that ride-hailing (and carsharing) users do not usually represent the general population in terms of income, age, and ethnicity (Murphy, 2016; Rayle et al., 2016). The authors from these papers suggest that these services mostly serve certain populations. Although the ride-hailing passengers from our study skewed towards certain demographics as compared to the overall Denver population, we had higher participation from some subgroups as compared to the existing literature. For example, age, income and education were better distributed across a wider range than found in previous studies. Different from previous studies — where researchers used intercept surveys at specific locations or online — our research has the advantage of being random by design since the passengers' destination location is unknown.

We collected data over a period of 14 weeks during fall 2016. Our dataset includes 311 responses over the course of 308 rides (during three rides, more than one passenger took the survey). The survey response rate was 87.5%.

Table 12.1 Demographics of Ride-hailing Passengers

		Survey Responses		Denver
Gender (n = 307)	Female	145	47.2%	50.0%
	Male	162	52.8%	50.0%
Resident (n = 309)	Local Resident	254	82.2%	-
	Visitor	55	17.8%	-
Age (n = 309)	18-24	78	25.2%	12.5%
	25-34	132	42.7%	27.2%
	35-44	56	18.1%	19.2%
	45-54	30	9.7%	14.6%
	55-64	7	2.3%	13.1%
	65+	6	1.9%	13.4%
Race/Ethnicity (n = 301)	Asian	24	8.0%	3.5%
	Black/African American	16	5.3%	9.4%
	Hispanic or Latino	39	13.0%	30.9%
	White	206	68.4%	53.1%
	Other	16	5.3%	3.1%
Household Income (n = 268)	$30K or less	34	12.7%	28.3%
	$31K - $45K	56	20.9%	14.0%
	$46K - $60K	58	21.6%	11.1%
	$61K - $75K	30	11.2%	10.0%
	$76 - $100K	40	14.9%	11.9%
	Over $100K	50	18.7%	24.9%
				-

		Survey Responses		Denver
Marital Status (n = 293)	Single or never married	185	63.1%	41.7%
	Married	80	27.3%	39.2%
	Separated, divorced, or widow	28	9.6%	19.1%
Household Size (n = 292)	Household Size of 1	65	22.3%	-
	Household Size of 2	129	44.2%	-
	Household Size of 3	56	19.2%	-
	Household Size of 4	30	10.3%	-
	Household Size of 5+	12	4.1%	-
Children (n = 229)	Children in Household	47	20.5%	25.1%
	No Children in Household	182	79.5%	74.9%
Education (n = 297)	Less than High School	9	3.0%	13.9%
	Graduated high school or equiv.	49	16.5%	17.7%
	Some college, no degree	58	19.5%	18.3%
	Associate or Bachelor's degree	124	41.8%	32.5%
	Advanced degree (Master's, PhD)	57	19.2%	17.6%
Employment (n = 261)	Working (Full-time or Part-Time)	246	94.3%	91.8%
	Unemployed	15	5.7%	8.2%
Student (n = 300)	Student (Full-time or Part-time)	70	23.3%	34.2%
	Not currently a student	230	76.7%	65.8%

Notes:

Denver data is based on 2011-2015 ACS 5-Year estimates
First age category for ACS is 15 to 24 years old
Income ranges for ACS differ slightly from survey

13. METHODS

We examine the parking dataset using descriptive statistics and perform a one-way ANOVA test to analyze the difference in parking time means for three different groups. We then explore the relationship between parking time and parking cost for ride-hailing trips replacing driving. Lastly, we build a classification tree-based model to evaluate how ride-hailing influences parking demand (i.e., replacement of driving) and attempt to identify the variables that influence travel shifts.

13.1 Tree-Based Model

The classification tree-based model first assesses how mode replacement is affected from a set of variables in three areas: modality resources (e.g. car ownership), travel attributes (e.g. destination type, parking stress), and demographics (e.g. age). This analysis can help determine the level of importance and relationship between each variable and the outcome. The pruned categorical tree provides a visual representation with the categorical dependent variable at the root and the corresponding relative importance and associated threshold values at the top.

We used the classification and regression trees (CART) statistical method since it facilitated breaking down the predictor space into several regions based on the relationship of each group with the dependent variable of interest (Breiman, Friedman, Stone, & Olshen, 1984). The model first groups the predictors using a specific method, such as simple average, and then it determines the true relation between the predictors, or covariates, and the variable of interest — ride-hailing replacing driving modes for this study — in each of the groups in the tree. Since our response variable is categorical, the model used for this study is called a classification tree-based model.

Finally, we "pruned" the tree to limit the size of the tree and avoid data over-fit by removing the least important splits based on deviance criterion and mean squared error. CART has the advantage of capturing and ordering the predictor variables based on relationship with the outcome while providing a graphical representation of these interactions. CART is used widely in several areas including environmental, construction, engineering, and computer science fields (Suchetana, Rajagopalan, & Silverstein, 2017).

13.1.1 Categorical Dependent Variable

The dependent variable in the model is the mode being replaced by ride-hailing. We created categorical values for this variable based on answers to question Q5 (Figure 14.1) from the passenger survey: "For this trip, how would you have traveled if Lyft/Uber wasn't an option?" The survey response options to the multiple choice question were then grouped into three categories: "replaced mode requiring parking," "replaced mode not requiring parking," or "new trip."

13.1.2 Driver Dataset Predictor Variables

The following variables from the "driver dataset" were considered in the model:

- Parking time: continuous
- Parking cost: continuous
- Destination type: categorical (high urban, general urban, suburban, or special event)

13.1.3 Passenger Dataset Predictor Variables

The following variables from the "passenger dataset" were included in the model:

- Car ownership: binary variable (yes, no)
- Trip purpose: categorical (discrete, non-discrete, or airport)
- Parking as a reason to take ride-hailing instead of driving. Binary (yes, no)
- Demographics: age (1 through 6 based on age levels), gender (male, female), income (1 through 6 based on levels)

We combined three parking variables (parking time, parking cost, and parking) as a reason to form a new predictor variable called "parking stress" with numerical levels from 0 to 4. To do this, we first converted the three variables as follows:

- Parking time: if parking time was 0, the new value is 0; if parking time was higher than 0 but lower or equal to 7, the new value is 1; and if parking time was higher than 7, the new value is 2.
- Parking time: if parking cost was 0, the new value is 0; and if parking cost was higher than 0, the new value is 1.
- Parking as a reason: if parking as a reason was "no", the new value is 0; and if parking as a reason was "yes", the new value is 1.

We used the statistical R program to perform our analysis (Team, 2014), including the appropriate packages such as the "tree" and "prune.tree" packages that help fit categorical trees (Ripley, 2005). We started our model with the three categories previously described from the "mode replaced by ride-hailing" dependent variable using the specific trip dataset.

14. RESULTS

This section is divided in four main subsections. First, we explore parking demand by analyzing driving trips being replaced with ride-hailing. Second, we assess parking as a reason to choose ride-hailing over other modes. These two subsections include results from the specific Uber/Lyft rides as well as the respondents' overall travel behavior. Third, we present results from the parking time and parking cost analysis. Last, we present results of the classification tree-based model.

14.1 Parking Demand

To better understand how parking demand might be impacted by ride-hailing, we explored driving trips that ride-hailing was replacing for the specific origin to destination (O-D) ride and in a more general context.

14.1.1 Parking Demand: Specific Trip

Since vehicle parking, theoretically, is only needed for driving trips, we decided to look in more detail at the mode replacement distribution and pay close attention to trips that would involve driving — such as drive alone or single occupancy vehicle (SOV), car rental, carpool (drive), and carsharing — to start understanding potential changes in parking demand.

In terms of replacing driving trips with ride-hailing, we exercised some caution since, in some cases, the trip replaced might have been only a part of the trip with the intent to avoid parking at the destination. A passenger might have still driven and parked, but ride-hailing allowed him/her to do so in a different location. For example, parking downtown might be limited and expensive, so a passenger decides to drive to a location — as close as possible to the destination — where parking is more abundant and/or free/cheaper. They then requested an Uber/Lyft ride to reach the final destination, thus benefiting from cost and time savings of a shorter ride-hailing trip. This has positive and negative implications for transportation. In this section, we analyzed the specific ride with the question, "*For this trip, how would you have traveled if Uber/Lyft wasn't an option?*" under two conditions: i) the mode replaced is one of the driving options; and ii) driving is not part of a connection trip. Figure 14.1 illustrates that 26.4% of all respondents would otherwise have driven and needed a parking location.

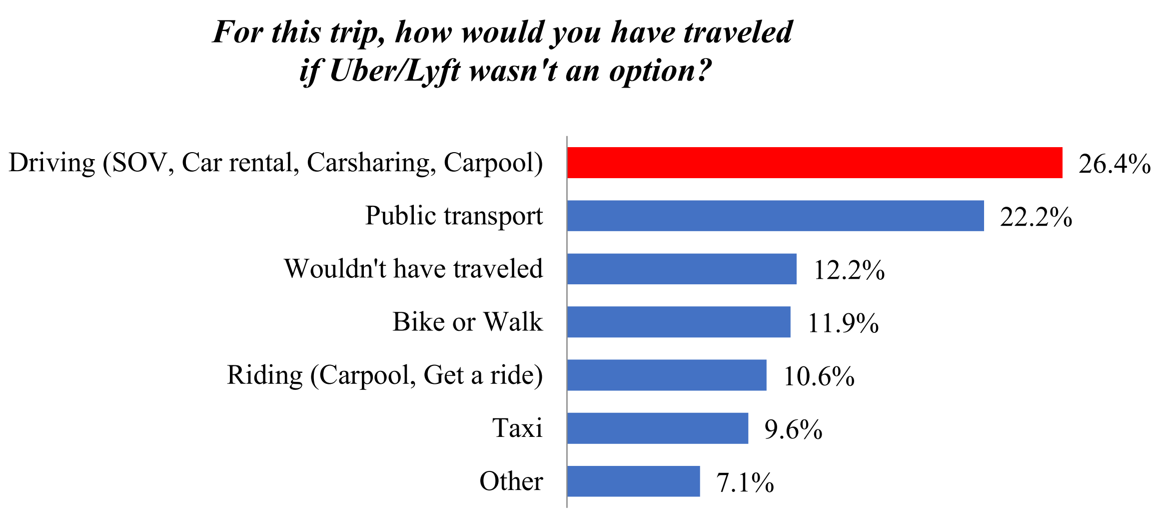

Figure 14.1 Ride-hailing Replacing Driving Trips (n = 311)

Figure 14.2 represents the origin and destination locations for the specific ride-hailing trips. The outer circle represents the total of origins plus destinations; the corresponding color connecting one place over the other represents the ride-hailing trips originating at that location type. For example, the red color on the ring represents 32 total trips to/from restaurants, and the connections red lines represent 14 of the 32 originating there (keeping in mind that a few trips were from a restaurant/bar to another restaurant/bar).

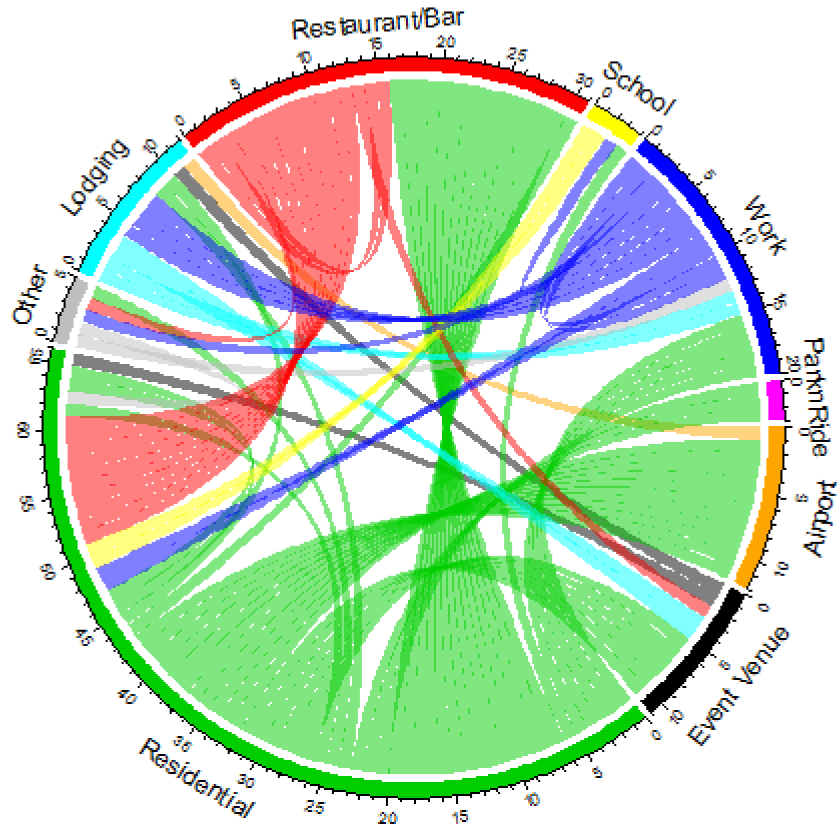

Figure 14.2 Origins and Destination for Ride-hailing Replacing Driving Trips (n = 82 to 82)

14.1.2 Parking Demand: General Use

Beyond looking at specific trips that would have needed parking, we considered the passengers' responses regarding travel behavior changes for different modes with the following question: "*Complete the sentence based on your travel today compared to the past.*" The specific section of interest about parking is: "*Because of ride-hailing, I drive…*" with the response options: *"a lot less," "a bit less," "about same," "a bit more," or "a lot more."*

Figure 14.3 shows that about one-third of participants stated that they drive less — 13.5% said a lot less and 19.0% said a bit less — which has implications for reduction in parking demand and slightly higher than the percentage of respondents to the specific trip replacement question. It was not expected that passengers would increase their driving, but 2.3% of respondents said, "*a bit more*" or a "*lot more.*" Based on our experiences of interacting with passengers, this is explained as a handful of survey respondents are also ride-hailing drivers themselves.

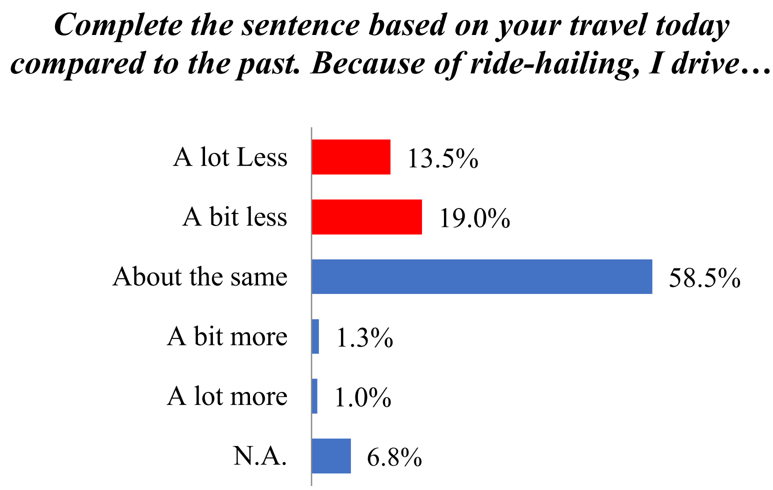

Figure 14.3 Ride-hailing and Driving Behavior Change (n = 311)

14.2 Parking Difficulty as a Reason to Choose Ride-Hailing

This subsection analyzes parking as a reason for someone to use ride-hailing over other modes of transportation, both for specific O-D ride-hailing trips and for general use.

14.2.1 Parking Difficulty: Specific Trip

Passengers stated the main reason that led them to choose Uber/Lyft over other options for their ride that day. Figure 14.4 presents the percentages for those passengers that "would have driven if ride-hailing was not available." "Parking" is highlighted in the responses as the second top reason in choosing ride-hailing over driving.

Exploring further on the type of trip including origin and destination locations, four out of five trips with a reason of going out and/or drinking was to an event venue (e.g. stadium), a restaurant, or a bar. For the trips stating parking as the main reason, about half were to the airport and a third again to an event venue, restaurant, or bar. Passengers responding "Don't have a car available" were travelers from out of town and passengers whose vehicle was getting repaired. Passengers stating that the cost of their ride-hailing trip would be reimbursed were either traveling to/from the airport or visitors from out of town.

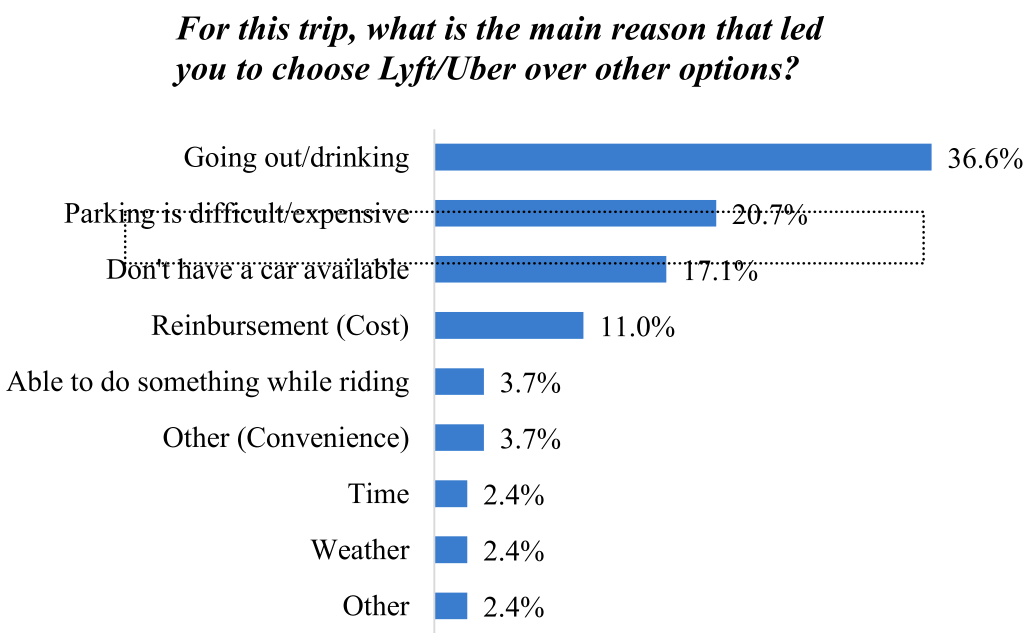

Figure 14.4 Percentage of 'Passengers that would have Driven' identifying the Main Reason to Choose Ride-hailing (n = 82)

14.2.2 Parking Difficulty: General Use

Complementing the main reason of using ride-hailing for the specific rides, we evaluated parking difficulty for the passengers' general travel behavior. We look specifically at the survey question: "*In general, what are the main reasons you choose ride-hailing over other modes? (check up to 3 reasons).*" About one-third of respondents selected parking as one of the main reasons to use ride-hailing over other modes (Figure 14.5).

Since parking is related to driving behavior, we examined the same dataset based on the driving frequency of the passengers. To better understand the results, we selected the top five reasons from the dataset based on driving frequency, as shown in Table 14.1.

In this table, we observed correlations between driving frequency and reasons choosing ride-hailing instead of the previous mode. High frequency drivers tend to use ride-hailing mostly when they are going out for social activities (i.e. avoid driving after drinking) and/or when they feel parking is difficult. Time — including travel savings and time use — while it was barely identified as a main reason for the specific trip (only 2.4%, Figure 14.4), it was heavily cited on general behavior when choosing up to three reasons, thus acting as a secondary or complementary factor. Reasons such as cost (including reimbursement) and not having a car available (e.g. out of town travel, issues with the vehicle), which were identified on previous specific trip analysis, were also mid-level indicators as to the general reasons why people shift from driving to ride-hailing. "Public transportation not being available" has low representation for high frequency drivers but was the most frequent reason cited by passengers that normally do not drive.

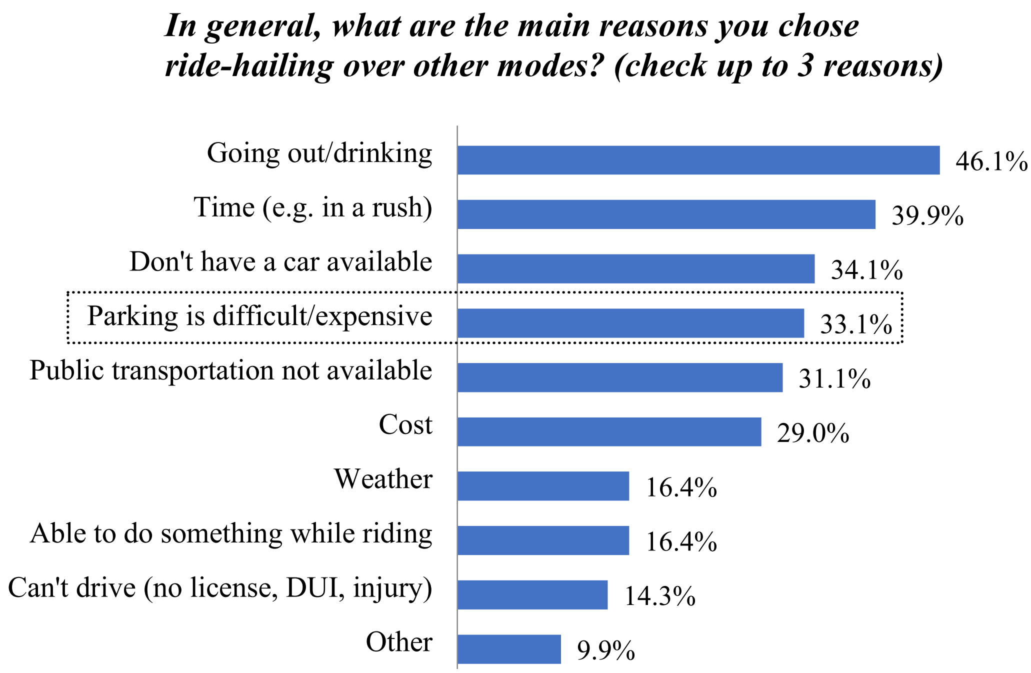

Figure 14.5 Percentage of All Respondents identifying Reasons to Choose Ride-hailing

Table 14.1 Reasons to Choose Ride-hailing and Driving Frequency

	Driving Frequency				
Reasons to use ride-hailing	Always drive	Regularly	Sometimes	Rarely	Never drive
Going out, drinking	68	28	17	7	15
Parking is difficult	46	27	14	5	5
Time	29	22	16	13	37
Cost (including Reinbursement)	31	19	7	5	25
Don't have a car available	29	13	8	13	36
Able to do something while riding	16	9	9	4	10
Public transportation not available	12	12	9	7	50

14.3 Parking Time, Parking Cost, and Time/Cost Relationships

This subsection analyzes parking time, parking cost, and the relationship between time savings and cost for those passengers shifting from driving to ride-hailing. We first present descriptive statistics on these variables and then results comparing cost and time for passengers shifting from driving to ride-hailing with parking as the main reason.

14.3.1 Parking Times

Table 14.2 presents summary statistics for the 311 observations on parking times including: i) cruising for parking, and ii) walking to final destination. For most rides, we experienced less than 30 seconds of additional times for parking and walking to the final destination, but the additional total time can be up to 29 minutes with a mean time of 3.4 minutes.

Table 14.2 Parking Time Summary Statistics (in minutes)

	Cruising to Park	Walking to Destination	Additional Time for Parking
Mean	1.2	2.2	3.4
St. Dev.	2.0	4.3	6.1
Min	0.0	0.0	0.0
Max	11.0	20.0	29.0

Figure 14.6 presents the distribution of additional time for parking for those that took at least one minute. Most of the rides with a total of 15 or more minutes to park were experienced at Denver International Airport (DIA), university campus, or event venues (e.g. stadium, theater).

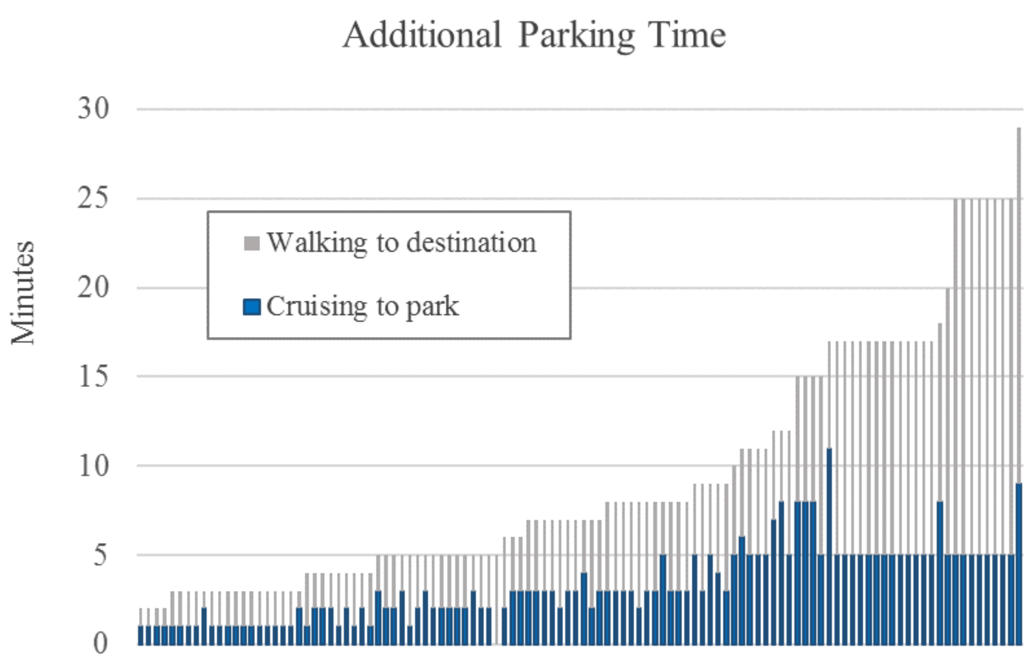

Figure 14.6 Additional Parking Time if Driving

We use a one-way ANOVA test with post-hoc Tukey HSD to compare the "additional parking time if driving" mean of the three sub-groups based on the mode being replaced. The ANOVA results show a statistically significant difference in parking time for two out of the three sub-groups

The first post-hoc Tukey HDS compares the difference in the time it takes to park and walk to the destination for those stating they were replacing a driving trip and those stating they were replacing another mode, with a significant difference. Compared to "other mode" replaced, ride-hailing trips that replaced a driving trip would have taken, on average, 2.6 minutes longer to park and walk to the destination.

The second comparison looks at those stating they are replacing a driving trip against those stating they would not have taken the trip at all. This also results in a statistically significant difference of 3.8 minutes longer for those replacing the driving trip.

The last ANOVA, comparing those that stated they were replacing a mode other than driving against those that would not have taken the trip, did not result in a significant difference.

Table 14.3 Tukey Simultaneous Tests for Differences of Means (parking time per mode replaced)

	Parking Time Difference	95% C.I.	Adjusted p-value
Replaced Driving vs. Replaced Other Mode	2.61	(0.77, 4.44)	**0.0026**
Replaced Driving vs. Induced Trip	3.80	(1.06, 6.53)	**0.0034**
Replaced Other Mode vs. Induced Trip	-1.19	(-3.68, 1.30)	0.4991

14.3.2 Parking Cost

Parking cost was not high for most of the rides (Figure 14.7). High parking cost was only experienced at DIA, universities, special events (e.g. sports, concerts), and private parking in the CBD.

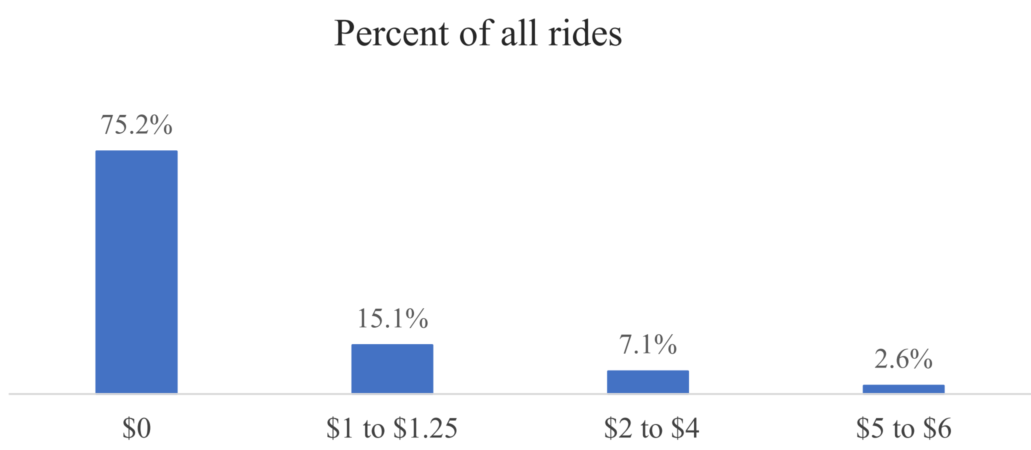

Figure 14.7 Parking Cost

14.3.3 Additional Cost and Time Gains: Willingness to pay?

When passengers shift from mode A to mode B, they gain and lose certain utility. Since time and cost are two of the most important predictors on mode choice, we decided to evaluate these two variables for trips that would have been by car. We use travel times and cost for ride-hailing rides versus hypothetical driving trips. We exclude trips where passengers stated a strong reason and would have unbalanced the results; these include going out/drinking, visitors not having a car available, and trips to the airport (since many trips can be travel-reimbursed and we did not have information on how long passengers were going to be out of town to determine total parking cost). For ride-hailing travel time, we use data collected on waiting for ride-hailing plus on-board time; for driving travel times, we use driving time plus parking times. For cost, we have detailed information on total ride-hailing fare; for driving, we estimate cost per mile driven, using $0.54 per mile based on the U.S. federal standard mileage rate in 2016, summed with parking cost. Assuming unbiased decision-making, we would expect to see little shift from driving to ride-hailing when parking time and parking cost is low; on the other hand, we would expect to see large shifts when parking time and parking cost is high. If parking time and parking cost are going in different directions, then we are uncertain. Figure 14.8 presents boxplots comparing travel time and cost for driving versus ride-hailing for trips shifting from driving to ride-hailing, showing that passengers pay more to save time. While all travel times are not the same (e.g., driving time, on-board time, waiting time, and/or parking time), these results might give us insight into the potential expense passengers are willing to pay to save parking time.

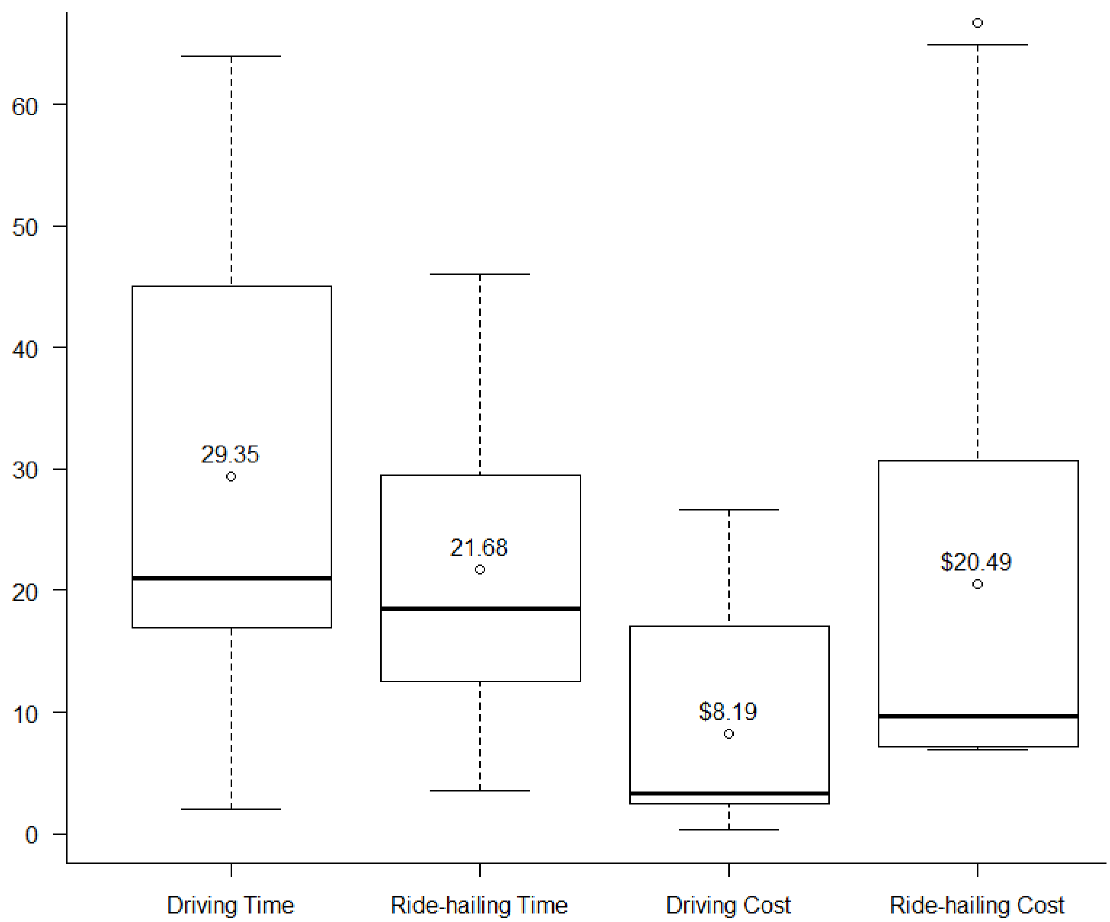

Figure 14.8 Travel Times and Monetary Cost, Ride-hailing over Driving (n = 17)

14.4 Tree-Based Model

The final tree-based model includes the dependent variables “mode replacing parking” as a binary “yes” or “no” and the following five predictors: “car ownership (car)”; “destination type (destype)”; “parking stress (pstress)”; “age (age)”; and “gender (gender).” The age ordinal value is distributed as follows: 1 for “18 to 24 years old”; 2 for “25 to 34 years old”; 3 for “35 to 44 years old”; and 4 for “45 years old or older.” Figure 14.9 presents the visual representation of the best classification tree-based model after pruning the tree.

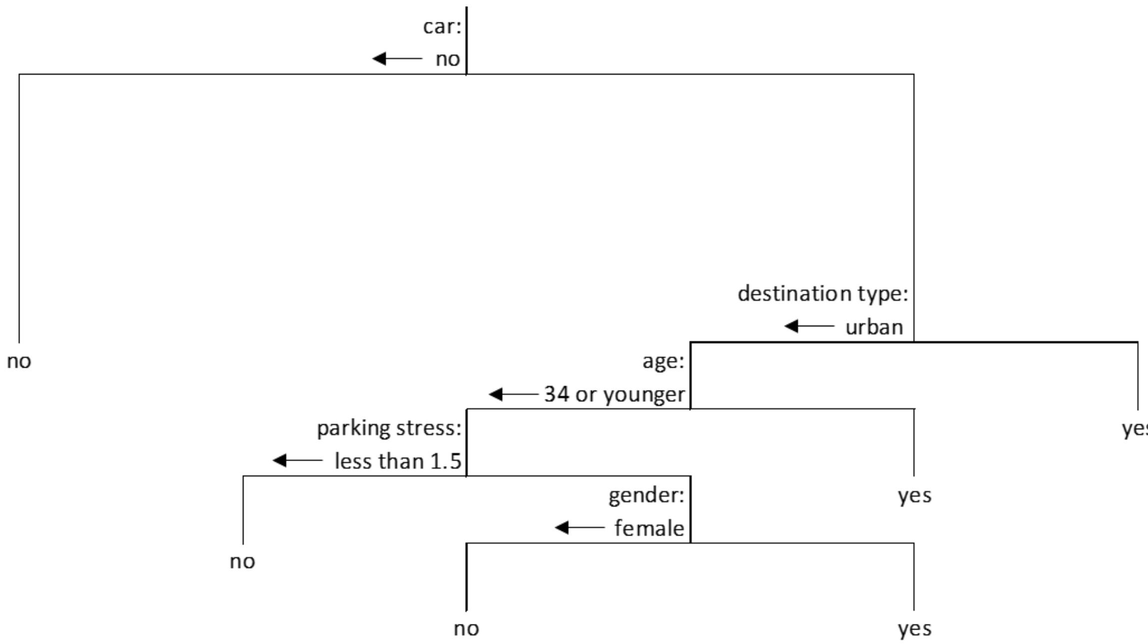

Figure 14.9 Best Classification Tree Model of Ride-Hailing Replacing Modes Requiring Parking with Car Ownership, Destination Type, Stress Level, Age, and Gender

The final prune tree contains 268 observations of 5 variables with 6 nodes, and a model accuracy of 0.74. The highest level predictor is whether a passenger owns a car or not. For those passengers not owning a car, the mode replaced is non-driving (e.g. transit, walking, or biking). Destination type is the second level predictor, showing, for example, that a person owning a car and going to a suburban or special destination would have driven. Following car ownership and destination type is age. If a person owns a car, is going to an urban place, and is 35 years old or older, they are most likely to drive. However, if they are 34 or younger, it would depend on our fourth and fifth predictors: parking stress and gender. For female passengers that are 34 years old or younger, own a car, and are going to an urban destination, a parking stress level of 2 or more might represent the reason why they would take ride-hailing instead of driving.

This model helps shed light on driving trips being replaced by ride-hailing — particularly with respect to the subsequent parking issues — and the relationship with the predictors. Take, for example, a passenger data subset in which passengers answer: “Do you (or your household) own fewer cars because of ride-hailing?” For the 311 passengers surveyed, 12.5%, or 39 people, stated yes. Of those 39 passengers, 18 still had access to a car. Our tree-based model predicts 13 driving trips replaced (33.3% of the 39 passenger). If all those 39 passengers would have had access to a car, our model would have predicted 25 replaced driving trips (64.1% of the 39 passengers).

15. DISCUSSION AND CONCLUSIONS

Emerging transportation services such as ride-hailing might be creating a window of opportunity to help dissolve individualized car-dependency and the transportation infrastructure centered around this pattern, particularly parking. Thus, this study aims to investigate the reciprocal influence of an evolving transportation service — ride-hailing — in terms of an important transportation topic — parking — so we can better model, design, and build future infrastructure.

First, we looked at parking demand by analyzing the transportation modes being replaced by Lyft/Uber. Results suggest that 26.4% of Uber/Lyft riders would have driven and needed a parking space if these ride-hailing services did not exist. Also, about a third of respondents stated that they are driving less when asked about general travel behavior. The most common places for ride-hailing replacing driving trips are restaurant/bars, working trips to the CBD, airport, lodging, and event venues. Second, we analyzed parking as a stated reason for using ride-hailing, showing that for the specific surveyed trip and with their more general usage, parking difficulty (e.g., availability, additional time, and cost) is the second most cited reason for trips replacing driving. We then investigated the relationship between parking time and parking cost. While time spent and monetary cost between driving versus ride-hailing is not exclusively parking-related, we were able to analyze in more detail the rides where passengers stated parking as the main reason, excluding trips that might bias the decision. When individually considering the costs of driving and ride-hailing, we found that passengers, on average, spent more money on a ride-hailing trip that would not necessitate cruising for parking and walking to the final destination. This could provide insight into right pricing parking structures to better manage parking demand and supply, which would in turn, increase the traveler experience without incurring negative externalities. Finally, we presented the best fit classification tree-model with our data, showing that car ownership, destination type, parking stress level, age, and gender are factors contributing to reducing the modes requiring parking with the use of ride-hailing services. Trip purpose and income were not significant in our model.

When passengers shift away from driving, cities might gain space from people not needing to park, but they still need to manage where and how people get pick-up/drop off with ride-hailing. Besides passengers, they need to manage ride-hailing drivers (including parking for ride-hailing drivers). The experience as a ride-hailing driver shows that passenger pick-up/drop-off can be stressful with safety concerns, customer experience, and drivers/passengers being able to find each other. Stress is higher when the origin or destination is in dense urban areas such as the CBD and/or places at university campuses/stadiums that do not provide adequate curb space. For example, during some rides, passengers wanted to get out of the car in areas that could compromise their own safety or the safety of others (e.g., wanting to get off at the bike lane, at a red light, etc.). On one hand, drivers want to do the right thing and not allow passengers to dangerously disembark; on the other hand, they know that passengers could get upset if they were not allowed to leave and then give a bad rating. Proper infrastructure and communication between city enforcement and ride-hailing companies could alleviate some of these issues.

The main limitation of our study is the trip sample size relative to the overall number of rides that Uber and Lyft provide. Another limitation is that our case study focuses on Denver and the surrounding areas, and might not be applicable to other metropolitan regions. Despite our study limitations, we learned many lessons for future research. For example, ride-hailing is dynamic and could provide different infrastructure use at different times (e.g. parking during the day, and pick-up/drop-off at night). Further exploration on travel cost and travel times is important for mode choice, including different values for separate travel times (waiting, on-board, driving, parking). Other future potential research include value on curb space access to incentivize sharing/carpool behaviors and/or willingness to pay for riding alone; and parking needs for ride-hailing drivers based on driving strategy in-between rides (park and wait, travel to places with potentially high demand and wait, cruise around)

While total taxi and ride-hailing passenger miles in the United States is less than 1% of total vehicle miles traveled (U.S. Department of Transportation, 2017), the percentage is much higher for specific destinations in urban areas such as restaurant/bars, airports, CBD, lodging, event venues). With this study, we find evidence that cities might want to examine transportation infrastructure (e.g., parking, ride-hailing pick-ups/drop-off space, built environment that encourages other non-vehicular modes) and adaptation strategies (e.g. pricing to deal with supply and demand) to provide a better travel experience for all and aiming at specific city goals (e.g. increase walking, biking, and public transit use, and/or higher vehicle occupancy). Similarly, parking requirements and parking supply for specific developments such as bars, restaurants, event venues, and airports should be re-evaluated so that we can design buildings with lower parking capacity in the future, particularly at stadiums, restaurants, and bars.

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PART 3: An Analysis of the Individual Economics of Ride-Hailing: Passenger Costs & Driver Earnings

17. INTRODUCTION

Ride-hailing — as the service provided by Transportation Network Companies (TNCs) — has been called an economists' dream (Levitt, 2016). It tests some of the most basic economic theories of demand (i.e. passengers) and supply (i.e. drivers). On the passenger side, ride-hailing offers a convenient, technology-based mobility option. Riders do not need to own a car, worry about parking, or even know how to drive. This can save time and effort, all in a mode that is similar, but typically less expensive, than traditional taxis. On the driver's side, ride-haling provides a convenient way to make money. With promises of high wages and flexible hours (see Figure 17.1), the growth of the industry is not surprising. Ride-hailing growth has also not shown any signs of plateauing with both drivers and passengers constantly signing-up and using these services on a regular basis. While the share numbers of ride-hailing for the United States might seem small compared to the overall vehicles miles traveled (U.S. Department of Transportation, 2017), its percentage reaches double digits in urban areas with high density (Castiglione et al., 2017) and at airports (Henao, Sperling, Garikapati, Hou, & Young, 2018).

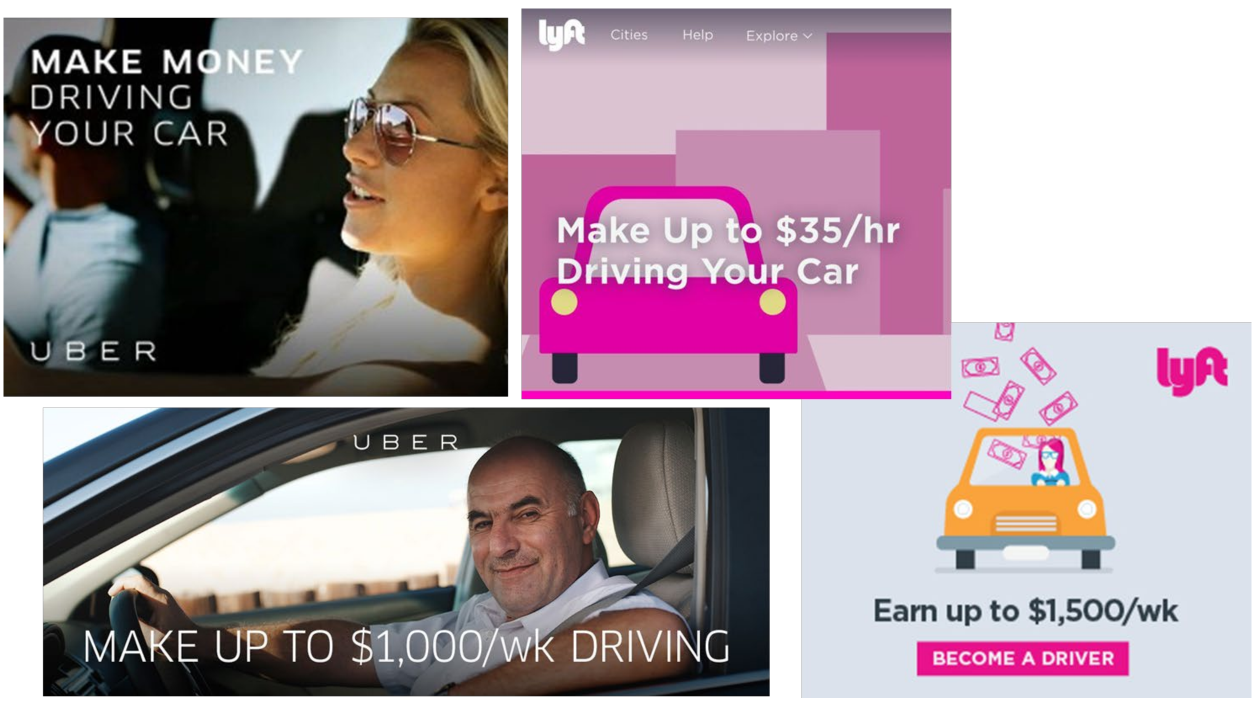

Figure 17.1 Lyft and Uber Driver Advertisements

With Uber considering an IPO in 2019, Wall Street banks estimates their valuation at $120 billion (Hoffman, Bensinger, & Farrell, 2018). This is more than double Honda, GM, Ford, or Tesla and more than four times Fiat Chrysler (Blumenthal, 2018). Lyft is not far behind with a valuation of more than $15 billion as of June 2018 (Farrell & Bensinger, 2018). With such high valuations, one might assume these companies are highly profitable with millions of drivers making great incomes — or at least a decent earning wage — but profitability and driver earnings remain questionable. Uber and Lyft need to constantly recruit drivers to keep up with growing passenger demand and an inability to retain drivers. A study co-authored by an Uber employee and an Uber consultant using Uber data found that only half of its Uber-driver partners stay active after a year (J. V. Hall & Krueger, 2015), and a report from SherpaShare — an app platform for ride-hailing drivers — surveyed 963 drivers and found that turnover rates for Uber and Lyft was notably high, with about only 35% of drivers remaining active for more than six months, and only 20% of drivers for more than 12 months (SherpaShare, 2015). More recently, the six-month attrition rate for Uber shows to be 68.1% (Cook, Diamond, Hall, List, & Oyer, 2018), which is similar to the SherpaShare report.

While there are different motivations for drivers to sign-up for ride-hailing, the main motivation is income (J. V. Hall & Krueger, 2015; SherpaShare, 2015). And when it comes to Uber and Lyft, driver income has become a hot topic. For instance, a 2013 Wall Street Journal article stated that a typical Uber driver takes in more than $100,000 a year in gross sales (MacMillan, 2013). After this estimate was questioned, TNCs reduced this income characterization to around $25–$35 per hour. The previously referenced study by J. V. Hall and Krueger (2015) shows that in 2014, Uber drivers grossed approximately $17.40 an hour across 20 of the highly-population, early adopter cities. A more recent study, co-authored by Uber economists, had access to Uber data for 1.87 million drivers across 196 cities (Cook et al., 2018). Focusing on the gender wage gap, they also provided overall estimated gross hourly earnings of $15.80 (although the study misleads readers by stating $21.07 per hour while neglecting the ~25% service fee that Uber charges its drivers). One issue with the studies using Uber data is that the ride-hailing wage rates only includes the times when the Uber app is turned on; this ignore times where drivers are traveling at the beginning/end of shift or driving (with the app-off) to reposition to areas with high ridership. As a comparison, SherpaShare survey respondents working 21 to 25 hours a week collected in average $1,376 monthly before expenses for an hourly rate of about $15 per hour (SherpaShare, 2015). Another survey of around 1,000 drivers from a blog called the “Rideshare Guy 2017 report” estimates hourly earnings of $15.68 (Campbell, 2017). Early in 2018, there was a controversy over an MIT working paper entitled “The Economics of Ride-Hailing” where researchers used ride-hailing driver survey responses acquired via that blog to estimate median net earnings of $3.37 per hour (S. M. Zoepf, Chen, Adu, & Pozo, 2018). Uber’s chief economist criticized the report (J. Hall, 2018), and the report even garnered a response from Uber CEO, Dara Khosrowshashi, who tweeted: “MIT = Mathematically Incompetent Theories.” MIT admitted fault and revised their estimations, finding the median profit to be on the order of $8.55/hour and $10/hour (S. Zoepf, 2018). This example shows the delicacy and importance of this topic.

This chapter seeks to investigate the individual economics of ride-hailing by assessing the monetary cost per mile for passengers and the monetary earnings per hour for drivers. Understanding actual costs per mile for passengers would help with transportation demand models by providing inputs, calibrating these models, and forecasting future demand. It will also help to understand future projections on car ownership and cost per mile in future automated vehicles, which are currently forecasted at $0.15 to $1.00 per mile ((Bösch, Becker, Becker, & Axhausen, 2018). This study also seeks to provide clarity and answer the question of how much ride-hailing passengers pay per mile as well as how much drivers earn per hour with a detailed breakdown of gross earnings, expenses, and net earnings by using primary data collected by one of the authors as an Uber and Lyft independent contractor. The next sections detail our dataset and methods before we then present results and discuss the topic in more detail with recommendations and policy suggestions on what could be done with these issues.

18. DATA

Realizing the difficulty in obtaining data directly from TNCs, one of the authors signed up to drive for Uber and Lyft and conduct an ethnographic experiment while gaining access to exclusive data and real-time passenger feedback. We submitted a research proposal to the Colorado Multiple Institutional Review Board (COMIRB) and obtained IRB approval in spring 2016 (COMIRB Protocol 16-0773, Exception APP001-3). Extensive work was performed prior, during, and after data collection to record and validate detailed information on ride-hailing. For example, the Uber and Lyft driver apps contain information on each ride, reporting pick-up and drop-off locations and time (HH:MM), ride mileage distance, ride duration time, and earnings. We also collected GPS locations, times, and distances using two additional apps (Google Maps and MyTracks) to validate TNC information. Through this process, we found a few errors on the TNC apps (mostly due to connectivity); these errors were confirmed by the companies after we reported our findings. More details on the data collection, including the survey instrument and a detailed methodology, can be found in previous publications (Henao, 2017; Henao & Marshall, 2018).

Driving shifts ranged from as low as two hours to as high as nine hours, and while this included all days of the week and most times of day, most driving came during high demand times such as Friday and Saturday nights, representing typical ride-hailing services. Driving for Uber and Lyft helped minimize the waiting times and cruising distances since the chances of getting a request from either service increased (it is also common that ride-hailing drivers work for Uber and Lyft). For example, there were occasions where new requests came in even before finishing parking. We decided to do all the data collection by the driver-author to eliminate bias between drivers, to control travel without a passenger (i.e. deadheading minimization), to reduce surveyor errors, and to ensure data quality.

The final sample includes 416 rides (Lyft, UberX, LyftLine, and UberPool) from 69 shifts with unique and detailed information on how much passengers paid (including fare, tolls and fees, and tips) and driver earning (including mileage, times, surcharge, tolls, fees, and gratuity).

From the total paid by passengers, a percentage goes to the driver with the remaining going to TNCs and minimal cost to cover toll roads and airport fees. The amount that Lyft and Uber pay their drivers is mostly based on the percentage offered at the time of signing the contract. While the percentage rate for this study is 80% to the driver (20% commission to the TNC), most drivers have a 75% rate (25% commission to the TNC). Uber increased its service fee from 20% to 25% in September 2015; however, drivers who joined before then were grandfathered in (Cook et al., 2018). This percentage rate is only applicable to the passenger fare (base, per minute, per mile, surcharge) since drivers do not receive any commission from the TNC fee, toll roads, and/or other fees. In times of high demand, ride-hailing companies use surge pricing (Uber) or Prime Time (Lyft) to entice more drivers onto the road and help ensure that the supply can accommodate demand. We encountered surge multipliers in 7.2% of our rides, and they ranged from 1.25 to 2.0. Some routes (such as toll roads) or destinations (such as airports) also incur an additional fee. For example, the pick-up or drop-off fee at Denver International Airport is $2.15. The driver offered passengers to take the toll road with the mutual understanding that the customer pay the fee, which only occurred in a handful of rides. Drivers do not receive any commission on the toll or airport fees. Sometimes, TNCs also offer driver incentives (e.g. guarantee bonus per hour) to work at certain times for a minimum number of rides or a minimum acceptance rate. Monetary incentives offered to the driver-author are reflected in this study.

So overall, a TNC driver typically gets paid as an independent contractor based on: i) commission percentage offered at the time of sign-in, ii) passenger fare based on city, mileage distance, time duration, and surcharge multiplier at specific times and locations, and iii) voluntary tips. Additional monetary bonuses are given based on targeted incentives with number of rides given and acceptance rate. After each ride ended, passengers had the option to provide a voluntary tip (all of which would go to the driver). At the time of our data collection, riders could tip in the Lyft app, but Uber did not provide that option until July 2017 (some Uber passengers tipped our driver in cash). Thus, our Uber data likely underrepresents tips that a driver might currently earn (although it is worth pointing out that our driver's commission is 5% higher than most current drivers). Our overall dataset shows that 7.8% of driver earnings come from tips, but the subset for Lyft tips shows that it accounts for 11.8%.

Percentage distribution of payment is presented in Figure 18.1 showing percentage to driver (before tip), tip, and TNC/Toll/Fees. Gross revenues are usually calculated as the total income per number of working hours (Uber estimates based on when the app is on). Net income would include the cost incurred in driver expenses. All monetary values are in 2016 U.S. dollars.

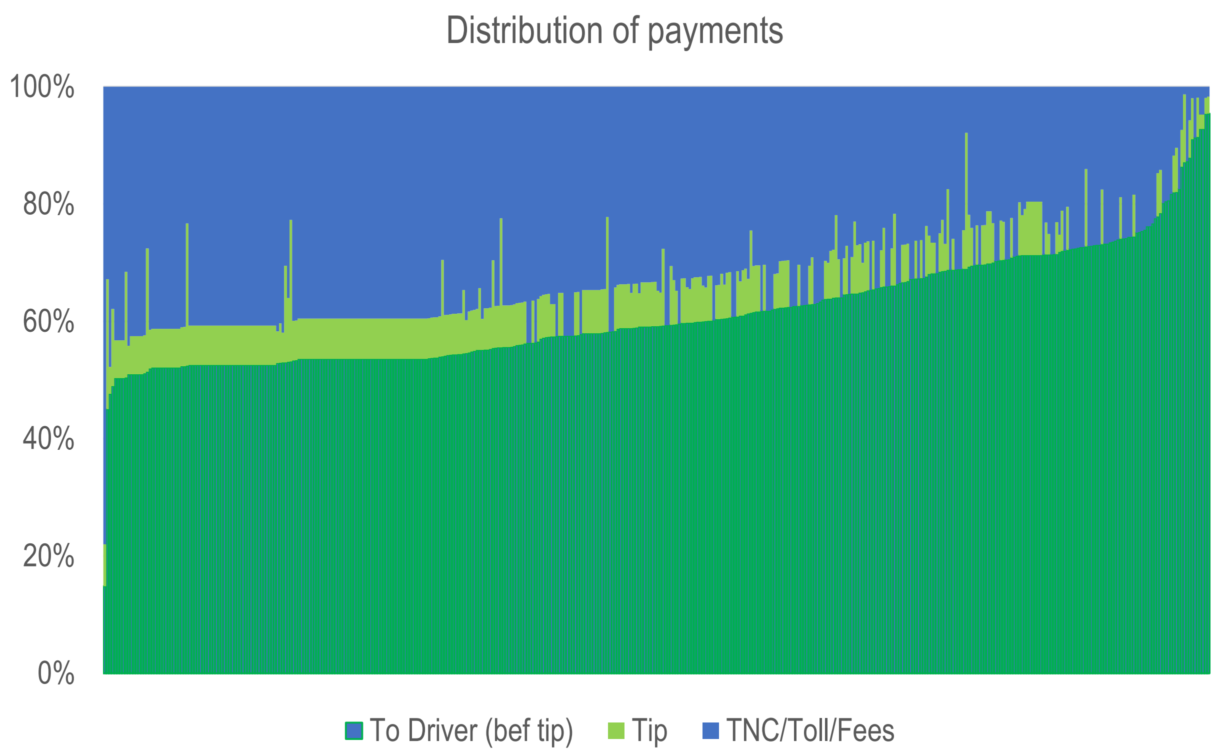

Figure 18.1 Distribution of TNC Payments from Passengers

19. METHODS

19.1 Driver Gross Earnings per Hour

As previously discussed, several factors affect driver earnings. Thus, the variation in ride distance, time of day, driver percentage, tips, surcharge, incentives, etc. in our detailed dataset provide us the opportunity to estimate 416 different hourly wages (i.e. gross earnings). The time used to estimate wages is based on working time with passengers and without passengers — including cruising, over-heading (time from dispatch to pick-up), waiting, and traveling at the beginning/end of shift, as presented in Figure 19.1. Our study does not include the time spent traveling at the beginning of each shift since we designed the ethnographic research to vary the starting location (and time) among different geographical typologies on the metropolitan area (e.g., suburbs, central business district, college campus). The travel at end of shift (time and distance) was distributed randomly using mean and standard deviation after distributing the 69 shifts among the number of rides per shift. For each ride (either from Uber or Lyft), we know the total monetary value corresponding to the driver (including tips) and the time in minutes from end-of-previous ride to end-of-assigned ride (i.e., cruising + over-heading + waiting at pick-up + ride + fraction of travel at end of shift).

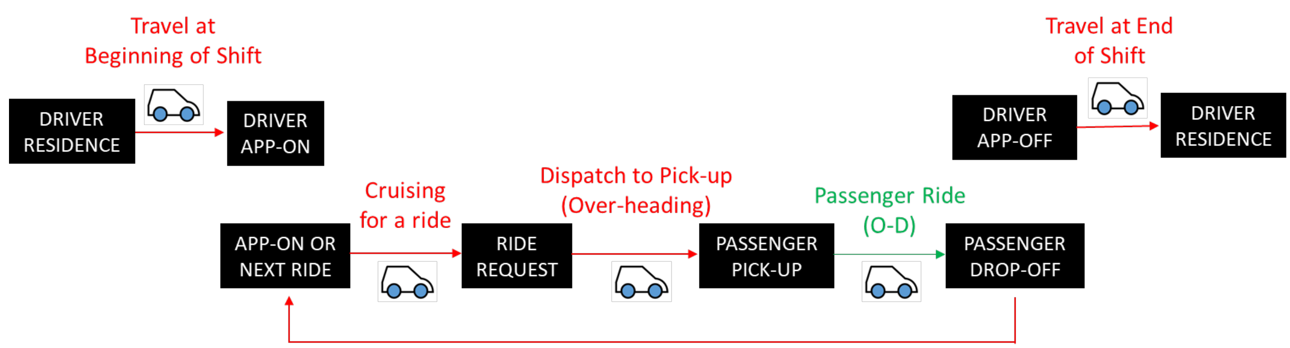

Figure 19.1 Travel Segments of a Ride-hailing Driver

The variation in times and driving strategies between minimize deadheading (i.e. driving without a passenger), driving to strategic locations for high demand, and circulating around until getting an app request simulates different drivers in the ride-hailing network (Henao & Marshall, 2018). Table 19.1 presents statistics on average speeds for all segments (from end-of-previous ride to end of actual ride) and "number of rides – passenger trips – per hour" rate.

Table 19.1 Speed and Rides per hour (n = 416)

	Speed (mph) for all segments	**Rides per hour**
Mean	18.25	1.97
s.d	8.82	0.86
Median	16.22	1.88

19.2 Driver Expenses and Net Earnings per Hour

Several factors affect driver expenses, including ownership or lease cost (e.g. finance, depreciation, license, insurance, registration, taxes) and operating costs (e.g. gas, maintenance, miscellaneous upkeep such as car washes and cleaning, mobile device and data fees, parking and traffic violations, risk of crash or injury). Expenses also depend on car value, driving mileage, and whether you own a car already and/or have already paid off some of these expenses. To account for the broad range of possibilities, we characterized three different expense scenarios (Table 19.2) covering different types of drivers, from occasionally part-time drivers to full-time drivers. In the basic added cost scenario, we assumed a range of driving hours of 1–15 hours/week and around 11,000 miles per year. The next scenario included most of the drivers with 16–49 hours/week and around 33,000 miles per year, and the last scenario is based on the U.S. Federal Standard Mileage Rate.

The first cost scenario assumes that a driver already owns a car and has paid off basic ownership expenditures. Thus, we assumed most ownership costs are a sunk cost that drivers pay regardless of whether a person drives for ride-hailing or not; in other words, they are not considered an additional expense[1]. This scenario also includes conservative values for depreciation, maintenance, and other miscellaneous expenses. The cost expense for this scenario is $0.28 per mile.

The next scenario represents the majority of ride-hailing drivers based on estimation from previous studies (J. V. Hall & Krueger, 2015; SherpaShare, 2015). Since drivers in this scenario experience higher timing and mileage, we included costs associated with owning a car and increased other values according to the mileage per year. We used assumptions based on American Automobile Association rates (AAA, 2015) and other sources but still trend toward the conservative end of the expense spectrum. In this scenario, expenses equal to $0.40 per mile.

In the third scenario, we used the 2016 U.S. standard mileage rate determined by Internal Revenue Service of $0.54 cents per mile, which is based on an annual study of all the fixed and variable costs of owning and operating a car (including vehicle depreciation).

We then applied these rates to each of the 416 scenarios to discount driver expenses based on driving mileage (with and without passengers) to determine the net hourly wage. Expenses in driving mileage without a passenger is as important as mileage with passengers, since for every 100 miles carrying passengers, Uber and Lyft drivers travel an additional 69 miles without a passenger (Henao & Marshall, 2018).

[1] Most insurance companies require that ride-hailing drivers upgrade their insurance policy, and our driver did so. However, the popular press suggests that many drivers do not and put themselves at risk should an incident occur when they were driving for a ride-hailing company.

Table 19.2 Ride-hailing Expenses

Item	Basic Added Cost 1-15hr/week, ~11k miles/year	Most Drivers 16-49hr/week, ~33K miles/year	U.S. Federal Standard Mileage Rate (2016)
Ownership			
Depreciation	$1,320.00	$3,960.00	
Finance Charge	-	$500.00	
License, Registration & Tax	-	$350.00	
Insurance	-	$1,500.00	
Operating			
Gas	$1,015.38	$3,046.15	
Maintenance	$589.60	$1,768.80	
Miscellaneous	$150.00	$2,000.00	
Total	$3,074.98	$13,124.95	
$/mile	$0.28	$0.40	0.54*

20. RESULTS

20.1 Passenger Costs per Mile

A ride-hailing fare is typically divided into the following costs: TNC base fee, per mile fee, per minute fee, surcharge multiplier at specific times and locations, toll roads, specific location fee (e.g. airport and city), and voluntary tip. More recently, Uber and Lyft have implemented an up-front cost, but the price structure still follows the same principle. The rates that passengers pay for Lyft and Uber fluctuate based on city and market, but traditionally, they have been consistent over time. Table 20.1 presents the Lyft and UberX rates applicable to this study (Denver in 2016). As a price comparison, the website http://uberestimate.com provides estimates for Uber rates in different cities.

Table 20.1 Uber and Lyft Cost to Passengers (Denver, 2016)

	TNC fee	Base fare	Cost per minute fare	Cost per mile fare	Minimum paid by passenger	Gratuity	Other
Lyft	$2.10	$0.50	$0.12	$1.01	$7.10	yes	surcharge, toll road, airport fee
UberX	$1.95	$0.75	$0.13	$1.00	$6.95	not in app	

Figure 20.1 presents the total passenger costs per mile (after accounting for all fares and fees) and cumulative distribution of all rides based on distance (secondary y-axis). The trendline formula follows a power function ($y = 5.37x^{-0.49}$) with a cost of $5.37 per mile for a 1-mile trip, and $1.00/mile for a 31.5-miles trip. The median distance is 3.55 miles and median cost is $2.50/mile (mean statistics are: 7.04 miles and $3.19/mile). A clear distinction from previous assumptions in travel demand models is that the cost per mile for passenger varies based on the trip distance given the set cost of specific fares/fees.

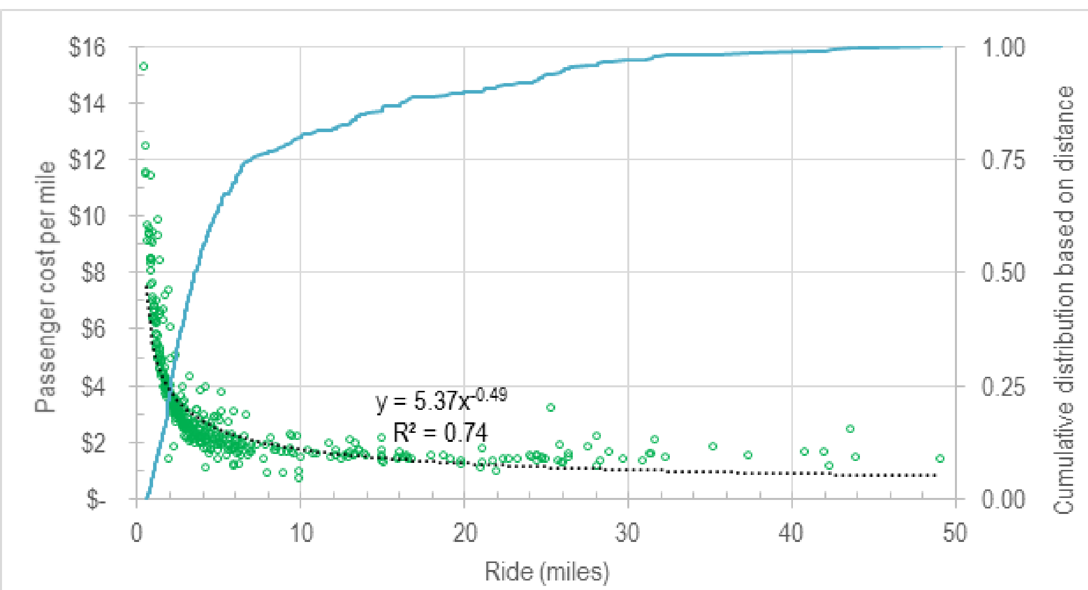

Figure 20.1 TNC Passenger Cost and Cumulative distribution (based on distance)

20.2 Driver Gross Earnings per Hour

In terms of driver gross earnings, we first compared gross earnings for "time spent working" versus overall "time spent driving." The green line in Figure 20.2 represents the distribution of hourly wages based on gross earnings (including tips) based on time spent driving both with and without passengers. Since the location of the last passenger drop-off is unknown, we included the end of shift travel time in this calculation. An extreme example of this is the story of an Uber driver that drove an NFL player from Chicago, IL, to Buffalo, NY (Mays, 2017). After dropping the player off at training camp, the Uber driver had to drive 540 miles back to Chicago. While this time spent driving would probably not be considered time spent working by a ride-hailing company, it would be considered so by the driver. We excluded the beginning of shift travel time, per our research design. Also, a set commute is typically not considered to be time spent working in most jobs.

The blue line represents the distribution of earnings (including tips) based on just the time spent with a passenger and the time spent over-heading (time spent from accepting the request until passenger pick-up). We hypothesize that the blue line might be the number that ride-hailing companies promote in terms of potential driver earnings while the green line represents a more realistic estimate of gross hourly earnings. The average gross earnings, including tips, for the under-estimated time (blue line) is $25.01 per hour (with a median of $22.13/hour) and more realistic average gross earnings (green line) is $15.57 per hour (with a median of $12.99/hour). These statistical means are comparable to the total gross earnings for all 416 rides of $4,068.08 divided by the working times (9,148 minutes from "dispatch to passenger drop-off" and 15,529 minutes for "time spent driving") for an equivalent rate of $26.68 and $15.72, respectively.

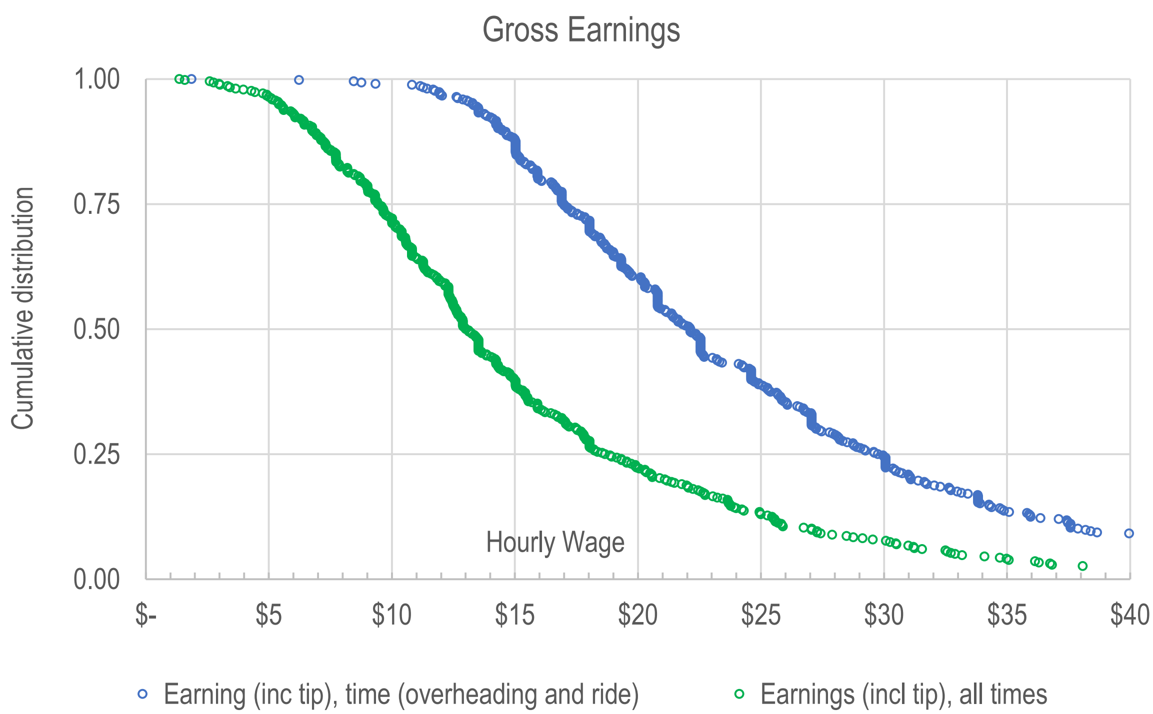

Figure 20.2 Cumulative Distribution of Gross Earnings Hourly Wage (n = 416)

20.3 Driver Net Earnings per Hour

Using three different scenarios of expenses per mile ($0.28, $0.40, $0.54), as described in the Methods section, we calculated net hourly wages (Figure 20.3) based on the specific driving mileage (with and without passengers) for each of the 416 scenarios. Some scenarios would be efficient by earning high gross earnings with minimal driving expenses but only a fraction of drivers could experience this (only 7% would experience $15 or higher net hourly wage). In contrast, 8% would actually lose money (i.e., make $0 or less per hour).

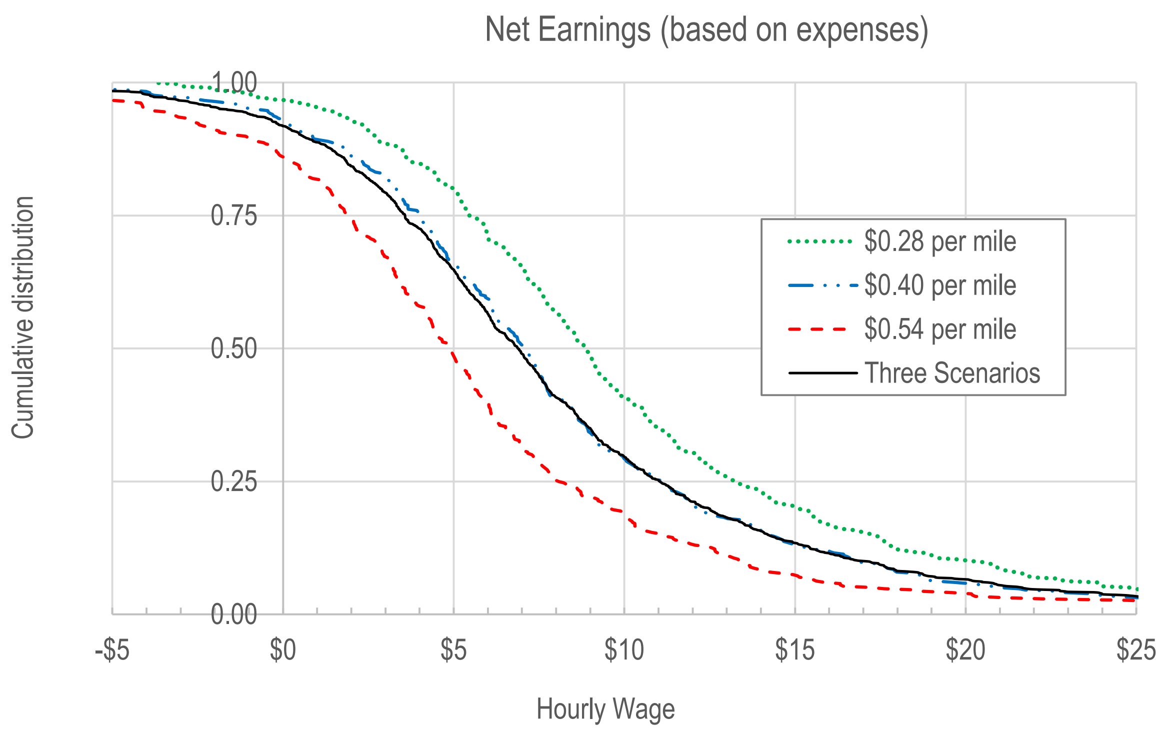

Figure 20.3 Cumulative Distribution of Net Earnings Hourly Wage (n = 416)

Ride-hailing drivers are probably excited to think they can make $35 per hour, or even $25/hour, but would be disappointed to learn that, after accounting for expenses, the average hourly wage is $8.15 (not even minimum wage in Colorado) as shown in Table 20.2. These net earnings could be higher with increased tipping that is now available in the Uber app but lower due to the higher commission rate of 80% for our driver versus 75% for newer drivers. For a driver working full-time (40 hours a week, 50 weeks a year) driving over 40,000 miles a year, the annual net income would be around $16,000. These net numbers are all pre-tax earnings.

As a reference for the taxi and limousine services, the Bureau of Labor Statistics shows that the Occupational Employment and Wages hourly mean for taxi and limousine service in May 2017 is $13.68 (U.S. Bureau of Labor Statistics, 2017). An important distinction between ride-hailing and professional chauffeurs is that ride-hailing drivers tend to own their own vehicles and are considered independent contractor; this means that they are not reimbursed for driving expenses. While some taxi drivers also own their vehicles, they are more likely to be classified as employees and receive benefits and/or expense reimbursement.

Table 20.2 Summary Statistics (Gross and Net Earnings) (n = 416)

	Gross Earnings (n=416)	Net Earnings ($0.28 per mile) (n=416)	Net Earnings ($0.40 per mile) (n=416)	Net Earnings ($0.54 per mile) (n=416)	Average Net Earnings (n=1,248)
Mean	$15.57	$10.46	$8.28	$5.72	$8.15
s.d	9.96	8.45	7.95	7.52	8.21
Min	$1.37	-$3.80	-$7.54	-$12.75	-$12.75
1st Quarter	$9.43	$5.46	$4.03	$1.87	$3.57
Median	$12.99	$8.87	$7.05	$4.91	$6.88
3rd Quarter	$18.58	$13.20	$11.04	$8.01	$11.04
Max	$89.70	$74.82	$68.44	$61.00	$74.82

20.4 Waiting or Cruising for the Next Ride?

One of the most interesting dilemmas that drivers face is what to do once a ride ended: Do they try to find a parking spot and wait until next request? Do they start circulating around as traditional cabs? Or do they try to go to specific locations with high demand? This all depends on many factors, including driver strategy, experience, market, and times, but aiming at helping understand the dynamics of waiting versus cruising times, we explore scenarios based on the results from our dataset and analysis. On one hand, driving low distances and waiting for the next request results in lower expenses for the driver, but it might take longer to get that new request. On the other hand, driving to specific places could lower the waiting times for a new request but involve additional driving expenses. Figure 20.4 presents the hourly wage based on the minutes per hour either waiting or cruising (average speed of 25 mph) and using driving expenses at a rate of $0.40 per mile.

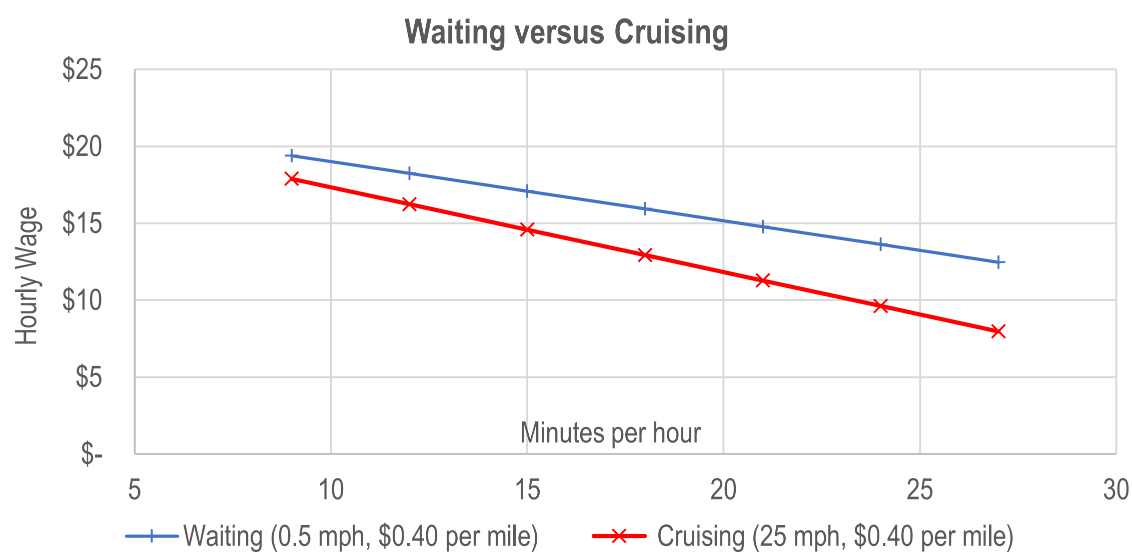

Figure 20.4 In-between Rides: Waiting versus Cruising

Drivers could make the same hourly wage by either waiting or cruising. The equivalent waiting time versus cruising time is presented in Figure 20.5, with a relationship (slope) of 0.70. For example, driver A “waiting” (or speeding at a very low rate of 0.5 mph) for 20 minutes (y-axis) could be making the same money (approximately $15 per hour) as driver B, who cruises at 25 mph for 14 minutes until the next ride (x-axis). In the same comparison, if driver B gets a ride in less than 14 minutes, he/she would be making more money than driver A; but if driver B cruises longer than 14 minutes, then his/her hourly wage is lower than driver A. This is relevant as cruising represents congestion and also influences wages for drivers. Another typical scenario is at airports, where drivers sometimes drop-off a customer there but do not immediately find a new passenger. Then, they are faced with the dilemma of waiting at the airport or driving back to the city for the next ride. In some cases, waiting up to 60 minutes at the airport could be better than driving all the way back to a specific location, since the driver waiting at the airport does not incur additional expenses, and the next ride is typically a long-distance trip.

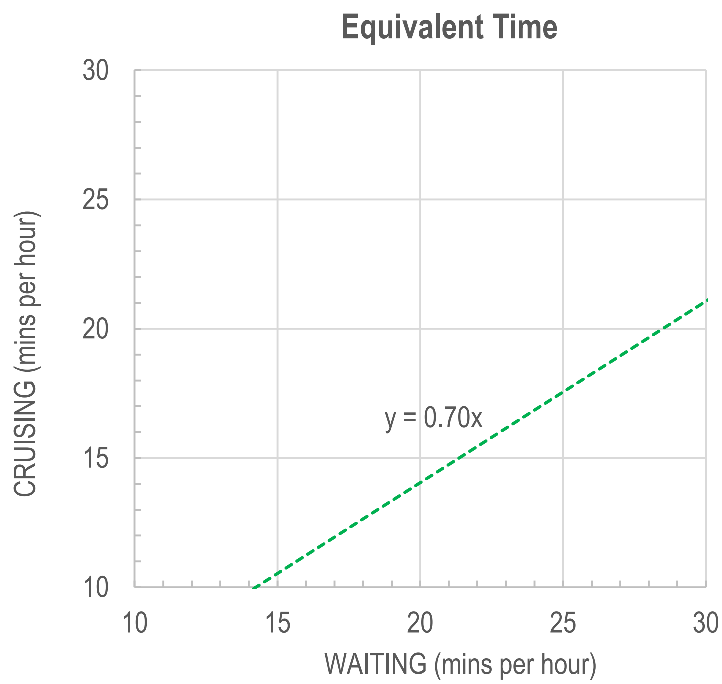

Figure 20.5 Waiting versus Cruising Equivalent Time

21. DISCUSSION

There has been widespread misunderstanding regarding passenger cost and driver earnings with ride-hailing services such as Uber and Lyft. Our study main limitation is that our dataset comes from a single driver in the Denver region for year 2016, but given our unique and detailed data, we were able to account for variations in market rates, driver commissions, gratuity, number of rides per shift, and distances/times with/without a passenger. For example, our sample compensates for lower Uber gratuity with a higher driver commission rate. Our study can also be adjusted for other cities based on TNC rates published on online websites such as http://uberestimate.com or national cost of living indexes.

Passenger cost per mile is important to understand, as it is used as input values in travel demand models incorporating ride-hailing, taxis, and future modes. Our results show that the cost per mile for a passenger suggests a power law function (contrary to a general assumptions of a set cost per mile regardless of trip distance) with lower cost per mile for longer rides (passengers pay in average $2.50 per mile with a median of $3.19 per mile after considering total fare, tolls, fees, gratuity, and travel distance). This cost does not include value of the passenger's time.

While the commission split for certain fares is 75% to 80% to the driver, when taking into account all fees paid by passengers, the payment is typically distributed as 67% to the driver (including gratuity) and 33% to the ride-hailing service. Using each of our 416 rides as different hourly wage scenarios, we found the gross earnings average to be $15.57/hour (median: $12.99/hour). However, based on three driving expense scenarios per mile ($0.28, $0.40, $0.54), we found the mean to be $8.15 per hour (median $6.88/hour) with a mean range of $5.72 and $10.46 per hour.

We hint at the dilemma of waiting versus cruising by explaining that cruising represents a driver expense. Most drivers receive higher net earnings by waiting rather than cruising, unless cruising is likely to cut at least 30% off waiting time. From a city and region's perspective, drivers waiting rather than cruising is preferred, as it reduces congestion by minimizing deadheading.

Uber and Lyft depend on the driver-partners labor market. They incentivize new drivers with bonuses and referrals, but their retention rate tends to be low. It is important to notice that other motivations besides income might be weighing into this decision (e.g., flexible hours, a means to car ownership, etc.), but one of the reasons for high turnover of drivers may be the eventual realization of driving expenses and thus, lower than advertised income. For example, a person who makes $12 per hour in an hourly wage job might think that they can make more driving for Uber or Lyft (such as advertised values of $35/hour). However, they may soon realize that – once accounting for expenses – it is not as profitable as once thought and may not even reach minimum wage. Cities like New York are starting to realize this issue and have initiated measurements to help drivers (O'Brien, 2018). However, detail research on gross earnings, driver expenses, and net earnings is necessary to help cities make this type of decisions.

Based on the results from this study, it is important that Uber and Lyft clarify to their potential drivers more realistic numbers on gross and net hourly wages. Drivers can make more money by driving at certain times (e.g. surcharge or prime times), providing great customer service reflected in gratuity, and/or aiming at specific incentives. Drivers can also spend less money on driving depending on the type of car (e.g., fuel efficient or electric vehicles), and driving strategies (e.g., minimize deadheading in-between rides, increase the number of rides per shift).

Based on the results of this study, we offer select recommendations:

- Better management of driver supply based on passenger demand, including specific and targeted network areas and drivers. Similar to how ride-hailing companies attempts to balance high passenger demand with low driver supply (Castillo, Knoepfle, & Weyl, 2017), should be given to times of low passenger demand and high driver supply.
- Better information to drivers to minimize deadheading, especially for circulating around in-between rides. For example, instead of a waiting queue at airports based on number of drivers, the companies can provide estimating waiting times.
- Increase driver compensation by increasing passenger fees, increasing commission rates for drivers, providing better incentives, and/or help defray some of the driving expenses such as recent opportunities in three U.S. cities (Hawkins, 2018), or partnering with third-party companies such as Maven (Hawkins, 2018).
- Automatically match driver start and end desired location and time with the first few rides and last few rides per shift to avoid additional driving times without passengers at beginning and end of shift.

Thus far, these companies seem to be moving in the other direction by increasing the TNC commission, lowering passenger rates (mileage and time), and increasing the TNC service fee, which is not shared with the drivers.

Based on this chapter and previous ride-hailing research (Henao & Marshall, 2018), there is a clear common negative impact that everyone should be aiming to reduce/eliminate: deadheading. It is bad for drivers, as it represents more driving expenses, and is bad for cities and the general public, as it means congestion. What can be done? We suggest a general policy with transportation fees in a per-mile basis discounted by vehicle occupancy, starting with a fee for any driving without passengers. Setting this in place would help everyone in the industry — TNCs, ride-hailing drivers, cities, passengers, the general public — work together towards the same goal of providing a more efficient transportation system. A later goal might be to apply this structured fee to any mode of transportation — including private cars, public transportation, taxis, and even future automated vehicles – under the same general policy (fees per mile discounted by vehicle occupancy) with zero passengers as the starting/highest fee. With the current passenger cost per mile versus forecasted estimations, there is plenty of room to include this type of fee and pay the true cost of transportation.

22. CONCLUSIONS

The results of this chapter show that the total cost per mile to ride-hailing passengers varies per ride distance, which could help travel demand modelers adjust current and future projections in their models.

In terms of driver earnings, there are significant differences between the income that Uber and Lyft advertised their drivers versus more realistic earnings — both before and after driving expenses — which in many cases do not even meet minimum wage. Cruising for a ride represents a significant driver expense suggesting that drivers might be making more money waiting for the next ride than cruising around. In general terms, we identify a general policy which implements a per-mile driving fee discounted by vehicle occupancy starting with a zero-passenger per-mile fee, which could get everyone on board working towards the same goal of minimizing deadheading/congestion and provide a more efficient transport system.

The results of this study provide insight into the passenger and driver economics of ride-hailing companies. Equity — and decent wages — for millions of drivers is at the core of this topic, and we hope that this study helps inform current and potential drivers (and the regulating transportation and labor entities) on the complicated issues of earnings and expenses in the shared, gig economy.

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