IMPACTS OF RIDESOURCING – LYFT AND UBER – ON TRANSPORTATION

INCLUDING VMT, MODE REPLACEMENT, PARKING, AND TRAVEL BEHAVIOR

by

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A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Civil Engineering Program

2017

ProQuest Number: 10265243

ProQuest 10265243

This thesis for the Doctor of Philosophy degree by

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Date: May 13, 2017

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Replacement, Parking, and Travel Behavior

Thesis directed by Associate Professor Wesley E. Marshall.

ABSTRACT

The transportation sector is currently experiencing a disruption with the introduction
and evolution of technology and transportation services such as bikesharing, carsharing, on-
demand ridesourcing (e.g. Lyft, Uber), and microtransit (e.g. Bridj, Chariot). As these new
layers of technology-based transportation options begin to flourish, it is important to
understand how they affect our transportation systems and society. This doctoral dissertation
analyzes the impacts of ridesourcing on several areas of transportation including: efficiency
in terms of distance – Vehicles Miles Traveled (VMT) versus Passenger Miles Traveled
(PMT) – and travel times, mode replacement, VMT increase, parking, transportation equity,
and travel behavior. Realizing the difficulty in obtaining data directly from Lyft and Uber,
this research employs an innovative approach by the author becoming an independent
contractor to drive for both companies; this allowed the author to gain access to exclusive
data and real-time passenger feedback. The datasets include actual travel attributes – such as
times, distances, and earnings – from 416 rides (Lyft, UberX, LyftLine, and UberPool), and
travel behavior and socio-demographics from 311 passenger interviews. This dissertation
estimates a low ridesourcing efficiency rate compared to other modes, mix of modes
replacement, overall increase in VMT, decrease in parking demand, low wages (i.e. net
earnings) for drivers, travel behavior changes for users, as well as relationships between

modality style, trip purpose, and stated reasons for mode replacement. These results give us

insights into the impacts of ridesourcing on several key aspects of transportation. This, in

turn, will help cities and transportation organizations better account for ridesourcing in their

planning and engineering processes (e.g. travel demand models) as well as policy decisions.

The form and content of this abstract are approved. I recommend its publication.

Approved: Wesley E. Marshall

DEDICATION

I dedicate this work to my wife Gusty. She has been a constant supporter, contributor, and has carried a lot of weight in our lives. Without her, this project would not have been possible.

To my boys, Tomás and Andrés, who are my everyday inspiration.

To my parents, who instilled in me the unmeasurable value of education and have supported me unconditionally in all aspects of my life.

ACKNOWLEDGMENTS

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LIST OF ABBREVIATIONS

DTT   Drive to Transit

ETA   Estimated Time of Arrival

HOV   High Occupancy Vehicles

Hr   Hour

IRB   Institutional Review Board

MAX.   Maximum

MIN.   Minimum

MINS   Minutes

MPH   Miles per Hour

O-D   Origin-Destination

PMT   Passenger Miles Traveled

Q#   Question Number

SOV   Single Occupancy Vehicle

St. Dev.   Standard Deviation

TDM   Transportation Demand Management

TNC   Transportation Network Company

U.S.   United States of America

VMT   Vehicle Miles Traveled

WP   With-Passenger

WPMT   With-Passenger Miles Traveled

WTT   Walk to Transit

CHAPTER I

INTRODUCTION

Evolving transportation services such as bikesharing, carsharing, ridesharing, on-demand ridesourcing (e.g. Lyft, Uber), and microtransit (e.g. Bridj) are becoming increasingly popular all over the world. Many factors – including social networks, real-time information, and mobile technology – allow passengers and drivers to connect through mobile smartphone applications (i.e. apps). In turn, this has led to the creation and popularization of technology companies offering app-based on-demand transportation platforms. As these new layers of technology-based transportation options begin to flourish, it is important to understand how they compete and interact with more traditional modes. Beyond travel behavior, these tools and evolving transportation services can also significantly impact our transportation systems, society, and the environment; yet, very little data is known and the academic research is minimum to understand and measure the impacts of these services regarding outcomes such as vehicle miles traveled (VMT), mode replacement, parking, equity, and travel behavior.

Providing a more diverse array of travel options should theoretically reduce car dependence and lower parking demand; however, there remain unresolved questions about what cities actually gain (or lose) in terms of sustainability-related outcomes including efficiency, congestion, carbon emissions, and transportation equity issues. Even when replacing single occupancy vehicle (SOV) trips, there are negative effects. For example with VMT, there are additional miles traveled by the ridesourcing driver – before passenger pick-up or after passenger drop-off – over and above the actual trip the passenger would have driven in the first place (Cramer & Krueger, 2016; Henao & Marshall, in press). There is also

a theoretical saturation point where higher ridesourcing supply than demand leaves many drivers circulating without riders, which can cause unnecessary VMT, congestion, environmental issues, and other problems that are not yet documented with these new technology-based modal options.

While there is widespread information online regarding companies such as Uber and Lyft, the academic literature on ridesourcing is extremely limited due to the lack of open data on these services. Obtaining data for independent academic research from Lyft and Uber is extremely difficult (Bialick, 2015a; Levitt, 2016) and even when these companies agree to share data, the data is often not adequate for research purposes (Vaccaro, 2016). These private companies cite customers' privacy protection and business competitiveness for their lack of data sharing, but perhaps they do to avoid showing the potential negative impacts in our transportation system. City officials and transit advocates have expressed concerns about the lack of open data and potential problems with ridesourcing such as congestion, competition with public transportation, and equity issues (Flegenheimer & Fitzsimmons, 2015; Grabar, 2016; Rodriguez, 2016)

Without appropriate data, measuring impacts is not possible; and even when such data is available, investigating short-term and long-term impacts of ridesourcing on travel behavior – such as the travel modes replaced by ridesourcing and why people shifted from a previous mode – remains extremely difficult. There are still limitations with regard to measuring new trips that may not have occurred before (i.e. induced travel), modality resources (e.g. car ownership), and modality style (e.g. car-oriented) of users as well as multimodality (i.e. availability of several modes) and intermodality (i.e. combination of various modes for a single trip or mixed-modes). This combination of problems makes

analyzing the impact of these services on the overall transportation system exceedingly difficult.

Due to the complexity of this topic, this dissertation first proposes a comprehensive framework aimed at starting the conversation on the type of data that needs to be collected, the questions that researchers need to be asking, and pointing out issues that might arise with conventional research methods. For example, if we ask someone that does not own a car what they would have done without Lyft/Uber for a specific trip, they might answer transit. In theory, the ridesourcing trip is classified as a negative environmental impact. However, a more comprehensive research framework might reveal that the decision not to own a car in the first place was made in part due to the availability of Lyft/Uber. Considering such long-term car ownership decisions would now expose the ridesourcing trip as a positive environmental benefit.

Beyond looking at the travel modes replaced by ridesourcing, the framework also includes insights from individuals on the process of why a specific mode was selected over the alternatives. For example, what is the role of travel time, travel cost, parking, and other factors in the decision making process? Such insight would help provide researchers with the ability to investigate the impact of ridesourcing on a region or city in terms of VMT and parking demand. It may also facilitate studies across different geographical areas (e.g. urban vs. suburban, city size, density, etc.) where we could find differing impacts in different contexts. In other words, could ridesourcing have, for example, positive impacts in more suburban areas and negative impacts in more urban areas? Or could the contrary be true? The intent is to provide a framework that will allow such questions to be explored, and then to carry out the research.

The overall goal of this dissertation is to start filling the gap in the academic literature and help researchers study the effects of evolving services such as ridesourcing and start measuring these impacts on transportation. This, in turn, will help cities and transportation organizations better account for the impacts of evolving transportation services in their policies, transportation planning, and engineering processes.

Specific Aims

The specific aims and key contributions of this research are that I will build upon the existing literature on evolving transportation services by:

1. Developing a comprehensive research framework to study ridesourcing

2. Collecting unique and interrelated datasets of ridesourcing drivers and passengers

3. Developing a ridesourcing survey for passengers seeking Institutional Review Board (IRB) approval

4. Measuring travel distances, times, earnings, and its efficiencies from the driver perspective

5. Measuring the VMT and parking demand impacts of ridesourcing services

6. Investigating travel behavior changes by assessing what travel modes are replaced by these evolving transportation services; and evaluating the factors associated with why people shifted from their previous travel modes and for what trip purposes.

7. Developing a framework for a mode choice model that would allow for integrating ridesourcing services into regional travel models.

Study Organization

This dissertation is organized into eleven chapters. Chapter II provides a background for ridesourcing including a history and overview of Lyft and Uber. Chapter III (Literature Review) overviews the topic of evolving transportation services and covers the limited research in this area. In order to better understand how to do research on ridesourcing services, the first step is to develop a comprehensive research framework. Thus, Chapter IV is devoted to this, and includes research methods, city choice, and data collected for its application in this dissertation. Chapter V presents the data. The first three objectives are addressed in Chapter IV and V. Objective four is addressed in Chapter VI (Driver Perspective: Travel Times, Distances, and Earnings), the fifth objective in Chapters VII (VMT Impacts) and VIII (Parking Impacts), and the sixth in Chapter IX (Travel Behavior Changes). Chapter IX is a summary of results and Chapter X1 finalizes this dissertation with overall conclusions, recommendations, and future research. Assisting the reader and for better organization, each of the four paper chapters (Chapters VI through IX) includes its own detail section on literature review, specific data and analysis, chapter results, and chapter conclusions for each detail topic.

CHAPTER II

BACKGROUND

While Lyft and Uber in their current form are mostly known for their regular Lyft and UberX services, and carpool options: LyftLine and UberPool, they offer other options and have evolved from a variety of services in their history (Figure II.I). For example, 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 previously co-founded Zimride, a true rideshare platform created to connect drivers and passengers through social networking. Green and Zimmer started Zimride in 2007 and sold it to Enterprise Holding 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, a couple of years after it started with UberCab. LyftLine and UberPool services started in 2014 but are only available in certain metropolitan cities (Lyft Blog, 2016; Uber Newsroom, 2014, 2016). For example, Figure II.II shows the cities where LyftLine was in service or about to launch as of April 2016 (including Denver).

As of the summer 2016, Uber was already in 450 cities globally, and completed two billion trips in its life span. One billion rides were completed in six years, while the same number of rides were completed in six months (Somerville, 2016). Uber's estimated valuation continues to grow and currently is at $62.6 billion, making it the most valuable transportation company in the world; and currently, without owning any vehicle, infrastructure, or having to hire drivers as employees. Lyft operates exclusively in the U.S. and is valued at approximately $5.5. billion dollars (B. Salomon, 2016).
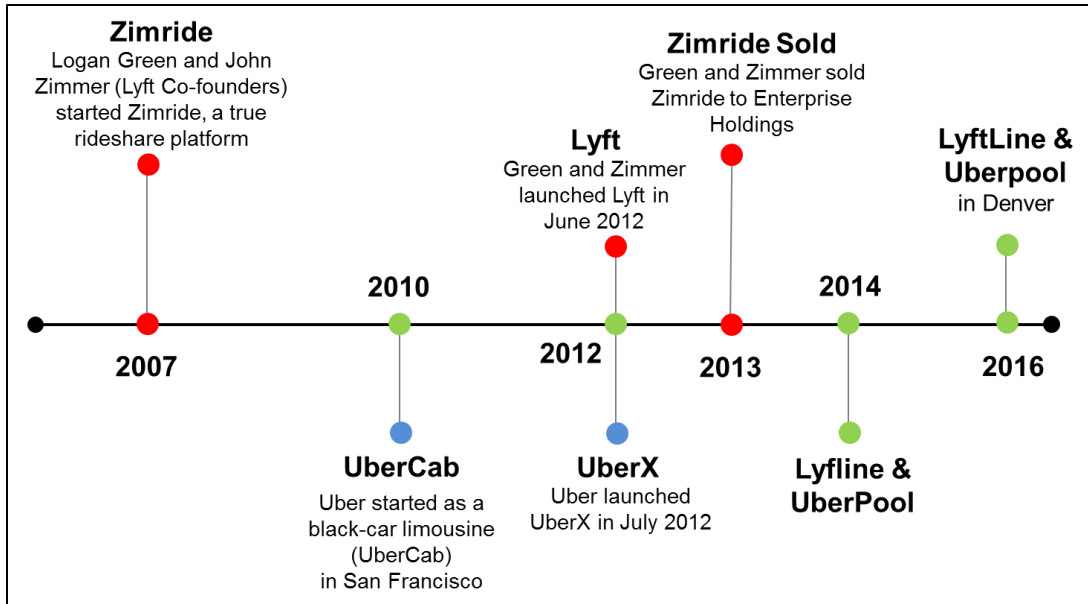
Figure II.I. Lyft and Uber Timeline
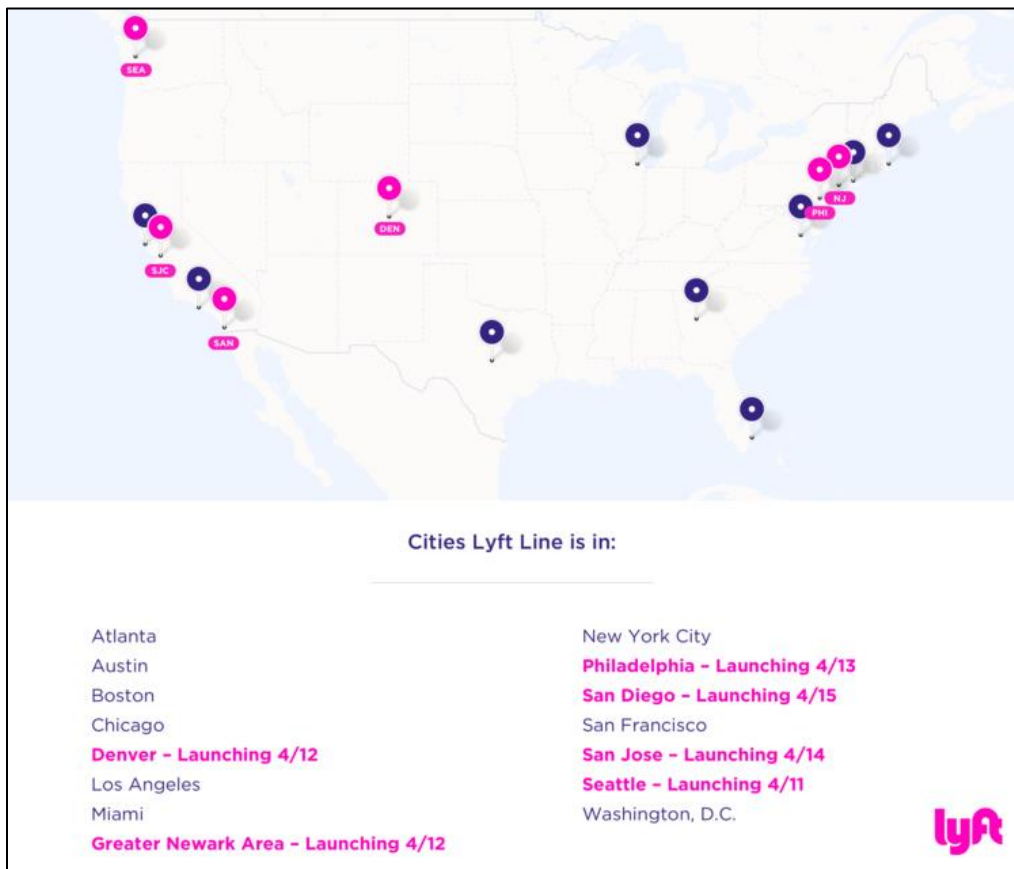
Figure II.II. LyftLine serving cities

(Source: Lyft Blog, *"Five Days. Six Cities. A Lyft Line First"*, April 5, 2016)

One of the latest news releases shows that Lyft is giving rides at a rate of 17 million U.S. rides per month. It is estimated that Lyft has around 20% of the market share, making Uber the ridesourcing company with the highest volume in the U.S. These numbers show the magnitude of Lyft and Uber and their influence on the way people get around. Uber and Lyft path has not been worry free. They have to constantly deal with different situations such as regulations, protests, and lawsuits from taxi companies, city officials, and drivers claiming employment rights. They also have taken advantages of the terminology in their marketing strategies.

The terminology of new and evolving transportation services can be confusing and sometimes ill defined by the transportation sector. Intentionally or unintentionally, many accredited people and companies use the terminology incorrectly, which can mislead public perception and general use of the services. A recent example is the misused word 'ridesharing' when referring to ridesourcing companies in their original form (Goddin, 2014). 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 a defined term. Some of the names include: "Transportation Network Companies (TNCs)", "ride-hailing", "ride-booking", "ride-matching", "on-demand-rides", "app-based rides". In an attempt to be consistent with previous academic research (Rayle, Dai, Chan, Cervero, & Shaheen, 2016) and to allow for possible future variations of such schemes to be housed under the same header, this study

uses the term "ridesourcing". The definition of ridesourcing is the sourcing of rides from a

for-fare driver pool accessible through an app-based platform.

CHAPTER III

LITERATURE REVIEW

Lyft and Uber are disrupting urban transportation systems and competing with more traditional modes (i.e. car, taxi, transit, walk, and bike), but a minimal number of U.S. cities has been able to account the impacts of ridesourcing (DuPuis, Martin, & Rainwater, 2015). The introduction of these services has implications for travel behavior and mode shift, as well as impacts on the overall transportation system.

Other services such as bikesharing and carsharing are continuously evolving and increasing users in cities across the globe (S. Shaheen & Cohen, 2012; S. Shaheen, Guzman, & Zhang, 2010). In addition, while the academic literature on carsharing and bikesharing systems has provided insights about these systems' user characteristics (e.g. socio-economic demographics, preferences, etc.) and transportation impacts (e.g. car ownership, car use, VMT, reductions of cars on the network, and mode share), the literature on ridesourcing remains very limited.

While there is abundant information online regarding companies such as Lyft and Uber, the academic literature on ridesourcing is very limited, in part due to their novelty and lack of open data on these services. Due to the ridesourcing history, evolution, and similarity to other services, the few academic studies on this topic compared ridesourcing mostly to the taxi industry and ridesharing services (Anderson, 2014; Cramer & Krueger, 2016; Rayle et al., 2016).

Rayle et al. (2016) did a research study comparing ridesourcing and traditional taxis in San Francisco using an intercept survey in spring 2014. The findings from this study indicated that compared to the overall San Francisco population, ridesourcing users tend to

be a lot younger, have higher incomes, have lower car ownership, and frequently travel with companions. This study also shows that compared to taxis, ridesourcing customers experienced shorter waiting times. Participants in this study said that ridesourcing both substitute and complement public transit, walking, and biking; and 8% of survey respondents stated that they would not have traveled (i.e. induced travel effect) if ridesourcing services were not available.

More recently, the Shared-Use Mobility Center investigated the relationship between public transportation and shared modes, including bikesharing, carsharing, and ridesourcing 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 spent less on transportation. It also shows that shared modes complement public transportation (Murphy, 2016).

Regarding literature not currently published in academia, the website FiveThirtyEight has published a few articles regarding ridesourcing companies using data acquired via a Freedom of Information Act request. The articles show that in New York, Uber is taking rides away from taxis and generally covers a larger area (Bialik, Flowers, Fischer-Baum, & Mehta, 2015; Fischer-Baum & Bialik, 2015). In another article, FiveThirtyEight argues that for Uber to be worth its $50 billion valuation, it has to complement and attract customers that normally use public transportation. This last article also used data on median income levels by census tract and residential pick up rates showing that lower incomes experienced fewer pickups (Silver & Fischer-Baum, 2015). The article compared general travel cost (using basic assumptions) of public transit, Uber, and the cost to own a car; arguing that Uber in combination with high use (around 65% to 85%) of public transportation can be significantly

cheaper than car ownership. Overall, the articles suggested that Uber is affecting mode choice, intermodality, and travel costs (that could in turn affect mode choice).

Since the literature in ridesourcing is extremely limited, is important to review the literature on a similar service that has evolved over the last few years and contains more in-depth studies. This is useful in helping understand ridesourcing and for helping design this newer strand of transportation research.

Carsharing systems provide a fleet of shared vehicles for short-term use where members pay in time increments of minutes or hours. Currently, there are several carsharing models including the following variations: round-trip or one-way (i.e. point-to-point), station-based or free-floating, and peer-to-peer.

Round-trip station-based carsharing is the oldest and most established system, where users need to return the vehicle at the same fixed station it was checked out. Round-trip carsharing started in Europe as early as the 1940s, but more successful programs did not began operating until the mid-1990s (S. Shaheen & Cohen, 2007). While most carsharing research is based on the traditional station-based round-trip carsharing system, the last few years have seen a surge in one-way carsharing research. The first services without any fixed vehicle stations – Car2go by Daimler and DriveNow by BMW – started in 2009 and 2011, respectively (Firnkorn, 2012). As of October of 2014, approximately 4.8 million individuals are members of carsharing programs worldwide with a total fleet of 104,000 vehicles (Shaheen and Cohen, 2014).

There have been a number of studies aiming to evaluate carsharing impacts, but the results are not clear with respect to the effects resulting from changes in the launch of a carsharing system. This is probably due to difficulties with respect to data availability,

timelines, confounding effects, as well as research design and methodologies (Firnkorn, 2012; Graham-Rowe, Skippon, Gardner, & Abraham, 2011; J Kopp, Gerike, & Axhausen, 2013; Johanna Kopp, Gerike, & Axhausen, 2015; Le Vine, Adamou, & Polak, 2014; Stopher & Greaves, 2007). Numerous carsharing studies focus on determining impacts on transportation, land use, environmental, and social benefits with some mixed results in certain areas and clear evidence on others. As regards to this dissertation, carsharing research on travel behavior can be classified and quantified in the following areas:

Socio-demographics for carsharing users and non-users: Studies suggest that carsharing users do not usually represent the overall population with regard to socio-economics, demographics, and travel behavior characteristics. Carsharing users tend to be younger, with higher levels of education and income, and live in denser areas with better access to public transportation. Carsharing users also tend to have higher public transit, walking, and biking mode shares and lower car usage compared to the general population (Cervero & Tsai, 2004; J Kopp et al., 2013; Johanna Kopp et al., 2015; Martin, Shaheen, & Lidicker, 2010; Sioui, Morency, & Trépanier, 2012).

Car ownership: Studies revealed that car ownership for carsharing members is lower than the general population and non-members. Empirical evidence has also shown a reduction in private vehicle ownership after joining a carsharing program by getting rid of a vehicle owned or foregoing vehicle purchase (Cervero & Tsai, 2004; Meijkamp, 1998; S. A. Shaheen, Cohen, & Chung, 2009; Steininger, Vogl, & Zettl, 1996). For example, a study on City Carshare in San Francisco indicated that a higher share of members reduced car ownership as compared to a control group of non-members, approximately 29% versus 8%. Two-thirds of members also said they refrain from purchasing a vehicle as compared to 39%

of non-members (Cervero & Tsai, 2004). Another study based on a survey in 2010 of members of Communauto, a Montreal carsharing company, concluded that members of the carsharing service have approximately 30% lower car usage compared to the level of those that own a vehicle (Sioui et al., 2012). Another study showed that the average number of vehicles per household dropped from 0.47 to 0.24 (Martin et al., 2010).

Car use and vehicle miles traveled (VMT): A large study across North America on round-trip car share subscribers revealed that while most members drive more with carsharing, the minority that drive less are driving less by a higher order of magnitude, which leads to less driving overall. In this study, VMT declined by 27%, and when including those that decided not purchase a vehicle in the first place, it was a 43% reduction (Martin et al., 2010; S. A. Shaheen et al., 2009). The first year of City Carshare operation in San Francisco suggested an increase in motorized travel for members (Cervero, 2003); however, in the second year of operation, the daily VMT reduced slightly for members and increased for non-members (Cervero & Tsai, 2004).

Reduction of cars on the transportation network: Based on several carsharing reports in the U.S., carsharing helps remove an aggregate of 9 to 23 vehicles from the road (including both shed autos and foregone car purchases) per shared-use vehicle from the transportation network (Lane, 2005; S. A. Shaheen et al., 2009). For example, Cervero and Tsai (2004) estimated that a carsharing fleet of 74 in San Francisco removed approximately 500 vehicles from the streets, equivalent to 6.8 private vehicle per carsharing vehicle. Similarly, a study from Philadelphia found that each PhillyCarShare vehicle replaced an average of 23 private vehicles, 11 vehicles from members giving up a car and 12 vehicles from not acquiring one in the first place (Lane, 2005).

Mode share: Studies on station-based carsharing suggest that some of its members change travel behavior towards public transportation and non-motorized modes, while others do the opposite by reducing transit, walking and biking usage; overall, however, most people tend to increase public transit and non-motorized modal use (E. Martin & S. Shaheen, 2011). A study of Ulm, Germany using two different methods reported that after the introduction of a point-to-point carsharing service, members shift modes and reduce the usage of all other modes of transportation including private cars, public transportation, and non-motorized travel (Firnkorn, 2012). Carsharing research on both round-trip and point-to-point carsharing concluded that point-to-point is a substitute for public transport while round-trip carsharing is a complement (Le Vine, Lee-Gosselin, Sivakumar, & Polak, 2014).

Many of the studies on carsharing research rely on sample surveys to gather information on members demographics, current usage of the carsharing service, and prior-to-joining carsharing travel behavior information (Lane, 2005; E. Martin & S. Shaheen, 2011; Martin et al., 2010; E. W. Martin & S. A. Shaheen, 2011). While these studies provide a basic idea on socio-economic demographics and travel behavior patterns at the aggregate level, they are inconclusive on the effects of carsharing because they fail to control for several factors that could affect the results (such as predisposition characteristics of people joining a carsharing system) or by not comparing the study population with a control group. From all the carsharing studies, only a few include a statistical control group in their methodology. Control groups, either on longitudinal or cross-sectional research, allow to correct for some confounding effects that otherwise would be difficult to distinguish from effect results. The best example of the use of control groups is the study over time by Cervero, Golub, and Nee (2007) on City Carshare in San Francisco. After two years of

service, VMT for carsharing members decreased, but it decreased even further for non-members; so relative to the control group, VMT for members increased. Another example is the research study by Johanna Kopp et al. (2015), where they used a reference group of non-carsharing users using an online and app based travel dairy, MyMobility, to collect individual trips over a 7-day period. This was a relatively well-designed study (with respect to survey instruments, methodology, and clearly stated limitations) of a free-floating carsharing service. The study also implemented a multimodal index by analyzing the distribution of transportation modes of carsharing for users and non-users, and stating future research needs to disentangle the effects of joining a carsharing service on mobility behavior, which this dissertation aims to find.

Although studies that use control groups are considered to have a better statistical methodological research design, there are still some problems to overcome such as confounding biases resulting from carsharing members' self-selection and arbitrary choice of non-member sampling that could potentially misrepresent the population. Concerning this dissertation, using latent classes will help understand the modality style of individuals using carsharing in relation to the same classes from the general population. Per the literature review, carsharing members tend to have a more sustainable modality style as compared to the general population, including higher use of non-motorized transportation and lower frequency of private car use. In this case, the fair comparison would be to calculate the difference against non-members that have a multimodal travel behavior.

Another way to compare, track, and measure the impacts of carsharing is using the research design implemented by Firnkorn (2012) using Car2go data. Firnkorn used the following two approaches to triangulate toward the impact of carsharing on travel behavior:

i) hypothetical travel behavior at present without Car2go; and ii) past mobility travel behavior on top of current behavior with Car2go. Details on the survey methods and methodology from this study are applicable to this dissertation. However, the author states that the two measurement techniques should theoretically have produced the exact same results if they were completely independent. In reality, a person's behavior pre-carsharing could easily be different to what that person would do today without carsharing.

The results from the few ridesourcing studies were similar to carsharing studies suggesting that carsharing users do not usually represent the overall population with regard to socio-economics, demographics, and travel behavior characteristics and users tend to be younger, with higher levels of education and income, and live in denser areas with better access to public transportation. Members also have different mobility resources with fewer cars per households, higher levels of bike ownership and public transportation passes, as well as higher transit, walking, and biking mode shares compared to the general population.

The current carsharing, and ridesourcing literature offers a general idea of the socio-economic demographics and insights into travel behavior impacts at the aggregate level, but there is no clear understanding at the individual level on the actual motivations why a user chooses a mode over the alternatives. For example from the previous studies, there is no investigation on the role of travel time, travel cost, or convenience (e.g. parking) on the utility and mode choice of travel demand models. There is also no implementation of modality style on the effects of carsharing on travel behavior. The changes cannot clearly be attributed to carsharing or ridesourcing without knowing the members behavior prior to joining a new service (e.g. car-oriented or multimodal) and controlling for the factors that influence travel behavior over time such as individual and household characteristics, location

choice, or transportation resources. This dissertation aims to address these problems by implementing a methodology that focuses on a more comprehensive examination of ridesourcing effects on individual travel behavior and overall impacts on the transportation system.

As seen in this overall literature review section, independent research on ridesourcing remains very limited. Each chapter covering specific topics (Chapter VI through Chapter IX) includes a more detail review and related literature to each theme.

CHAPTER IV

RESEARCH METHODS

The first step in understanding the impacts of ridesourcing is to develop a framework to guide the research and fill the important gaps in the literature. With Dr. Wesley Marshall, we co-authored the book chapter – "A Framework for Understanding the Impacts of Transportation" – recently published in the book "*Disrupting Mobility: Impacts of Sharing Economy and Innovative Transportation on Cities*" (Henao & Marshall, 2017). This study lays-out the research framework needed to investigate ridesourcing impacts in transportation, emphasizing the need to employ a combination of travel attributes (e.g. travel times), revealed-behavior data, and stated-response data structures.

Many transportation planners and engineers dream of having ridesourcing data to analyze and make transportation decisions. While it would be nice to have access to this data, we still have not seen any examples of data sharing from these companies for independent academic research. Realizing the difficulty obtaining data directly from Lyft and Uber, I decided to become an independent contractor and drive for both companies; this allowed me to gain access to exclusive data and real-time passenger feedback.

I signed-up to drive for both companies in early 2015, initially doing exploratory analysis to determine how viable this methodology would be for collecting data. After the initial test rides, I decided to continue in this direction by developing the research framework and the passenger survey. I then sought IRB approval and applied for research funding.

There are two interconnected datasets on the data collection: "driver dataset" and "passenger dataset". The first is the 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 the information gathered by surveying passengers during the actual rides (i.e. "passenger dataset"). Since I would be surveying passengers, I needed to obtain IRB approval to conduct this research. In the spring of 2016, I submitted a research proposal to the Colorado Multiple Institutional Review Board (COMIRB), obtaining IRB approval to interview passengers (COMIRB Protocol 16-0773, Exception APP001-3).

Driving for Lyft/Uber and Driver Dataset

I conducted my data collection using a sedan vehicle – 2015 Honda Civic – and a smartphone – iPhone 5s – to drive as an independent-contract for both Lyft and Uber (Figure IV.I). The main apps in the smartphone used for this research were "Lyft", "Uber-driver Partner", "GoogleMaps", and "My Tracks" (Figure IV.II). GoogleMaps and MyTracks helped me to track and record ridesourcing travel data. Passengers completed the online survey using their own smartphone or via a tablet device, Samsung Galaxy Tab A, that I provided.
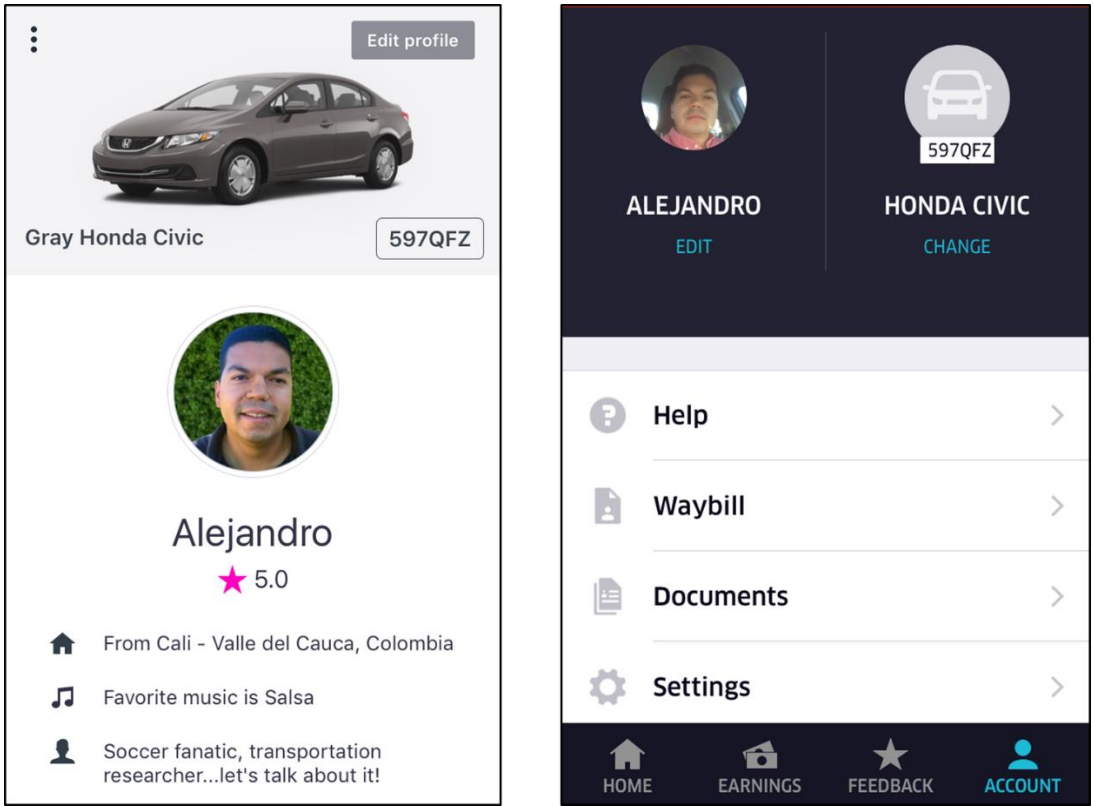
Figure IV.I. Lyft and Uber Driver Profiles
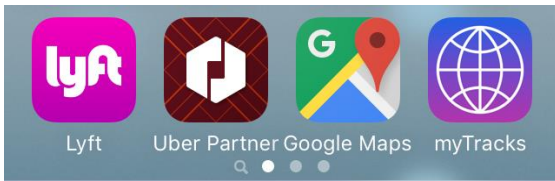
Figure IV.II. Smartphone Apps

I used the data collection form presented in Figure IV.III to help guide the travel

attributes data collection process for the "driver dataset". The ridesourcing driver data

includes information for each ride such as date and time of the day, weather, pick-up and

drop-off locations, driver earnings, and times and distances broken down by

"waiting/cruising for a ride", "en-route to passenger", "waiting for passenger", and "actual

ride". When I was done with driving for the day, I then recorded the "end of shift" travel time

and distance, as shown in Figure IV.III. Additionally, I collected information about parking; including "cruising to park" time and cost to determine parking difficulty at destination. Chapter VI includes a more detail description of each segment for the driving travel times and distances.

For the origin and destination locations, I collected the closest cross-streets, rather than the address, to maintain confidentiality. As mentioned previously, I used "Google Maps" and "myTracks" GPS apps to track times, distances, and locations, which allowed me to double-check the data recorded.

Figure IV.III. Driver Data Collection Form

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Driving Strategy and Passenger Survey

On a typical driving day, I turned on both Lyft and Uber apps and waited until a passenger requested a ride. To be conservative, I generally minimized unnecessary driving; thus, I accepted most of the requests unless there were problems with the app or the pick-up location was more than 15 miles away from the driver location (again, this is to minimize driving without a passenger). Once the ride was accepted, I turned off the driving mode for the other service. For example, if it was a Lyft request, the Uber driver mode was turned-off; or vice versa. Then, I traveled to the pick-up passenger location and waited until the passenger got into the car to travel to the desired destination.

I, as a driver, invited passengers to participate in a short survey about ridesourcing both verbally and with signs in the car (Figure IV.IV). The car sign reads: "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 on a tablet provided by me, the driver, or use their own device by going to a pre-defined website. In some cases, I conducted a verbal interview with the passenger that covered all the questions included in the survey. I waited until the ride was over to take notes and record the interview. Once the ride ended at the destination location, I turned on the other app and waited for a new passenger request. Once the passenger got out of the car, I tried to find the closest parking space available with the intent to record parking data, and again, to minimize cruising distance without a passenger in the car. Driving for both Lyft and Uber helped minimize the waiting times and cruising distance. For example, there were occasions where new requests came in even before I finished parking. I did all of the data collection by myself

to eliminate bias between drivers, to control travel without a passenger (i.e. deadheading minimization), to reduce surveyor errors, and to ensure data quality.

Figure IV.IV. Car Sign for Passenger Survey

The passenger survey 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 ridesourcing 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).

All survey questions are included in Appendix A. Chapter V, about data, as well as Chapters VII, VIII, and IX include a more detailed description of the survey questions in this dissertation.

Study Area

While Lyft and Uber originated in what they considered an unregulated space, Colorado was the first state in the U.S. to legislatively authorize Lyft and Uber services to operate with a bill signed by Governor John Hickenlooper in June 2014 (Vuong, 2014). This helped make Denver and the surrounding cities an innovative and welcoming location for these evolving transportation services. The Denver metropolitan region comprises a variety of places, covering both urban and suburban areas. For example, it contains very urban places like Union Station in downtown Denver, as well as low-density areas such as those surrounding the Denver International Airport (DIA), located about 24 miles north-east of Union Station. This metropolitan area also includes a college town like Boulder and suburban cities like Westminster or Broomfield in between Denver and Boulder. This diversity of characteristics (e.g. density, race diversity, income levels) makes the Denver region an ideal place to study ridesourcing.

Another positive factor in the research design was the randomness of the passenger destinations. As the driver, I did not know where each ride would end up; thus, I drove all over the study area and visited many of the places previously described. The only location

that I had control over is where I turned on the app at the beginning of the shift. Thus, I

varied my starting location.

CHAPTER V

DATA

Since I signed-up for Lyft and Uber in 2015 – including the rides in exploratory

analysis – I gave around 500 rides, transporting over 650 passengers. This dissertation

includes 416 rides for the "driver dataset" and 311 surveys for the "passenger dataset"

collected over a period of 14 weeks mostly during the fall 2016. The flowchart in Figure V.I

shows the datasets' description to help guide the two types of interconnected datasets.
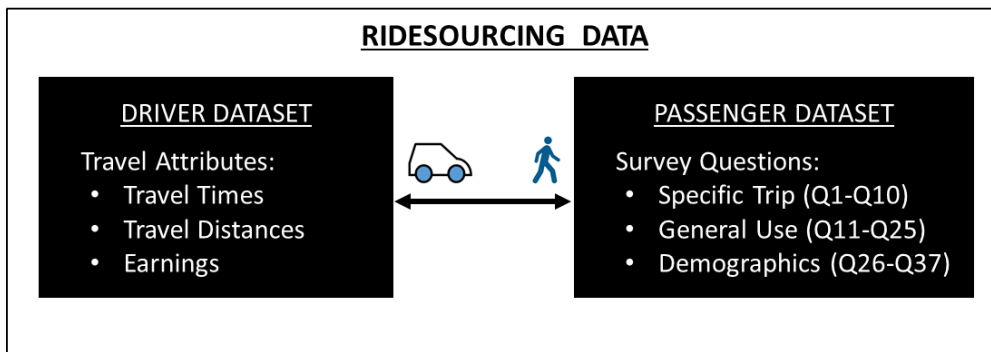
Figure V.I. Ridesourcing Data

Driver Dataset

The distribution of the 416 rides for the different services was:

- 198 regular Lyft rides

- 164 UberX rides

- 39 LyftLine rides

- 15 UberPool rides

For this dissertation, I drove a total of 4,950.7 miles, spent a total of 15,529 minutes

(or 258 hours and 49 minutes) working as a driver, and earned a total of $4,062.08, including

tips. More details on the summary statistics for travel times, travel distances, and earnings can be found in Chapter VI (Table VI-I & Table VI-IV).

Passenger Dataset

As stated before, the passenger dataset from 311 surveys include three types of questions. I analyzed responses to specific trip questions and general ridesourcing usage in Chapters VII through IX. To give the reader an idea of the origin and destination (O-D) combinations, I created the O-D matrix shown in Table V-I. Of all O-D combinations, the three most common were from "Home" to "Work", from "Home" to "Going out/Social" and from "Going out/Social" to "Home". Originally, there were many more responses for "Other – Write in" but with further analysis, I disaggregated this category and included those with common origin and destination. They are "Hotel/Airbnb" and "Family/Friend".

Table V-I. Origin - Destination (O-D) Matrix

DESTINATION / ORIGIN	Home	Work	School	Shopping/ Errands	Going Out/ Social	Airport	Hotel/ Airbnb	Family/ Friend	Other	Totals
Home	2	36	16	7	34	18	0	4	12	129
Work	21	8	1	1	1	2	6	0	1	41
School	5	0	0	3	0	0	0	2	0	10
Shopping/Errands	11	1	0	3	1	0	0	0	0	16
Going Out/Social	30	1	0	3	10	0	3	3	1	51
Airport	3	0	0	0	0	0	2	0	0	5
Hotel/Airbnb	0	2	0	0	7	4	0	0	4	17
Family/Friend	10	1	0	0	1	1	3	1	2	19
Other	8	3	0	2	2	1	3	1	3	23
Totals	90	52	17	19	56	26	17	11	23	311

Table V-II provides description statistics from all 311 passengers surveyed. Comparing the summary statistics to the Denver population, the sample seems very representative of the population. Previous studies have shown that the ridesourcing

population (and carsharing) does not usually replicate the area they represent with higher incomes, low minority representation, and younger users (Murphy, 2016; Rayle et al., 2016). The authors from these research papers suggest that these services mostly serve certain populations but I believe is mostly due to the location of the intercept surveys. My research has the advantage of being random by design since I did not know the passengers' destination location. Thus, allowing this study to cover a larger area and include populations that are usually not represented in this type of studies. The sample has a very close split of male-female population. Passengers were mostly younger adults but compared to other studies, I had higher participation from persons of ages 55 to 64, and 65+ years old people. While two thirds of the sample stated being of white race, I obtained representation from different races and ethnicities. In contrast to previous studies, income is better distributed between different ranges, and not very far from the Denver population.

Table V-II. Demographics of Ridesourcing Passengers

	Ridesourcing Responses	(%)	Denver Population[a] (%)		Ridesourcing Responses	(%)	Denver Population[a] (%)
Gender				**Marital Status**			
Female	145	46.9%	50.0%	Single or never married	185	62.7%	41.7%
Male	162	52.4%	50.0%	Married or in a family relationship	80	27.1%	39.2%
Prefer not to answer	2	0.6%		Separated, divorced, or widow	28	9.5%	19.1%
n	309			Other	2	0.7%	
				n	295		
Residency							
Local Resident	254	82.2%	--	**Household size**[b]			
Visitor	55	17.8%	--	1	65	22.3%	--
n	309			2	129	44.2%	--
				3	56	19.2%	--
Age				4	30	10.3%	--
18-24[b]	78	25.2%	10.0%	5+	12	4.1%	--
25-34	132	42.7%	21.8%	n	292		
35-44	56	18.1%	15.4%				
45-54	30	9.7%	11.7%	**Children in household**			
55-64	7	2.3%	10.5%	Yes	47	20.5%	25.1%
65+	6	1.9%	10.7%	No	182	79.5%	74.9%
n	309			n	229		
Race/Etchnicity				**Education**			
Asian	24	7.8%	3.5%	Less than High School	9	3.0%	13.9%
Black/African American	16	5.2%	9.4%	Graduated high school or equiv.	49	16.5%	17.7%
Hispanic or Latino	39	12.7%	30.9%	Some college, no degree	58	19.5%	18.3%
White	206	66.9%	53.1%	Associate or Bachelor's degree	124	41.8%	32.5%
Other	16	5.2%	3.1%	Advanced degree (Master's, PhD)	57	19.2%	17.6%
Prefer not to answer	7	2.3%		n	297		
n	308						
				Employment Status			
Household Income[c]				Working (Full-time or Part-Time)	246	81.7%	70.9%
$30K or less	34	11.5%	28.3%	Volunteer	1	0.3%	--
$31K - $45K	56	18.9%	14.0%	Unemployed	15	5.0%	6.3%
$46K - $60K	58	19.6%	11.1%	Retired	8	2.7%	--
$61K - $75K	30	10.1%	10.0%	N/A	31	10.3%	--
$76 - $100K	40	13.5%	11.9%	n	301		
Over $100K	50	16.9%	24.9%				
Prefer not to answer	28	9.5%	--	**Student Status**			
n	296			Student (Full-time or Part-time)	70	23.3%	34.2%
				Not currently a student	230	76.7%	65.8%
				n	300		

[a] 2011-2015 ACS 5-Year Estimates, Denver County

[b] Age 1st Range is 15 - 24 for ACS

[c] Income Range for ACS slighly different

CHAPTER VI

DRIVER PERSPECTIVE: TRAVEL TIMES, DISTANCES, AND EARNINGS

This chapter focuses on three very important aspects of ridesourcing from the driver perspective: travel times, distances, and earnings. For this study, I used the driver dataset including 416 rides from Lyft, UberX, LyftLine, and UberPool. When driving for Lyft and Uber, travel times were measured in minutes and travel distances in miles starting with the length from "app log-in" to "ride request/acceptance", from "ride request/acceptance" to pick-up", waiting for passenger (time only), and from passenger "pick-up" to "drop-off". The length from "pick-up" to "drop-off" will be referred as "with-a-passenger (WP) ride" for the rest of the study. These four measurements were recorded for each new ride, and at the end of the shift, lengths from "drop-off" to "app log-out" and/or "end destination" were measured. This involves the commute at the end of the shift. Note that during the period that data was gathered, Uber and Lyft introduced an option to set a destination filter. This option allows the driver to set a destination filtering the ride requests that go along the same route.

I estimated ridesourcing efficiency rates based on WP rides versus total times and distances. Based on the distance efficiency, I also calculated total VMT per 100 with-passenger miles traveled (WPMT), which helps to determine the additional VMT or deadheading experienced in our transportation system due to ridesourcing. Total ridesourcing travel time and distances also allow me to calculate the gross earnings per hour and per mile. Finally, I estimated ridesourcing driving expenses and net earnings per hour and per mile.

This study starts to fill a gap in the literature by studying the effects of ridesourcing on transportation from the driver perspective. My aim is to help cities and regional transportation organizations better account for the impact of technology and evolving

transportation services such as Lyft and Uber in their transportation planning and engineering

processes and have a clearer picture of the actual gross earnings, expenses, and net earnings

for ridesourcing drivers. In this chapter's concluding section, I consider improvements to the

current ridesourcing services in terms of increasing efficiency to reduce VMT, due to

deadheading and wasted time, and provide higher earnings for ridesourcing drivers.

Chapter Related Literature

While most of the studies mentioned on Chapter III (Murphy, 2016; Rayle et al.,

2016) focus mainly on the ridesourcing passengers, there are only a few articles that focus on

the driver side.

Ridesourcing has been mainly compared with taxis. There has been a lot of resistance

and controversy with the introduction of ridesourcing since they disrupted the industry,

competing and taking away many customers from taxis. Both services are similar in the fact

that drivers transport passengers for a fee, but there are many differences including

technology innovation, labor market differences, and government regulations. In terms of

driving and time efficiency of ridesourcing and taxi services, Cramer and Krueger (2016)

compared the capacity utilization rate of UberX drivers against taxi drivers in a few U.S.

cities. Using the aggregated data across all drivers available for both cities, the findings show

that the percent of work hours with a passenger ranges from 32.0% to 49.5% for taxis, and

46.1% to 54.3% for UberX. The mileage-based capacity utilization measure (i.e. percent of

miles driven with a passenger) from the same study was calculated at 39.1% to 40.7% for

taxis, and 55.2% to 64.2% for UberX. The main limitation of Cramer and Krueger's study

was the exclusion of mileage and times drivers have to travel from the point of log-out to the

end location (i.e. commute home), which overestimates their capacity utilization rate.

The media has put a lot of attention in the income for Lyft and Uber drivers. A Wall Street Journal article in 2013 stated that a typical Uber driver takes in more than $100,000 a year in gross sales (MacMillan, 2013). After this income estimation was questioned, Uber reduced this income characterization and more recently advertise that its drivers earn up to $35 an hour (same as Lyft advertisement). Based on data from October 2014, a study commissioned by Uber found that UberX drivers were grossing around $17.40 an hour for 20 market cities as a whole (Hall & Krueger, 2015). They also reported taxi drivers and chauffeurs wages of around $12.90 an hour based on the Occupational Employment Statistics survey. The main difference is that Uber's driver-partners, who are independent contractors, are not reimbursed for driving expenses, in contrast to taxi drivers, who are usually employees. The Uber hourly wage calculated in the Hall & Krueger's study was based in 2014, when rates were higher than in 2015 or 2016, and did not include the time drivers have to travel from the point of log-out to the end location, same as previously described for the article by Cramer and Krueger (2016).

A recent online article published by BuzzFeed News based on leaked internal data from Uber reported that Uber drivers earn $12.70 an hour in Detroit, $14.18 an hour in Houston, and $16.89 an hour in Denver before expenses (O'Donovan & Singer-Vine, 2016). The article also estimates driver's expenses, but I find the assumptions and methodology very poor since it underestimates the depreciation cost by using a $16,000 car value, overestimates the lifetime expectancy of an average automobile to 250,000 miles, and uses a low gas cost of $1.75 per gallon. It is also not clear about the insurance, maintenance, and miscellaneous costs associated with driving. It is important to note again that these calculations also do not include the commute time and distance for drivers (from the point of log-out to the end

location). By not including this additional time and expenses, the reported earnings per hour could be severely overestimated.

This study is the first research that independently analyzes data from the driver perspective using both Lyft and Uber trips, including all the additional travel distances, additional times, and actual gross, expenses, and net earnings per hour and per mile incurred by Lyft/Uber drivers.

Chapter Data and Analysis

I used a total of 416 rides – 108 rides pre-IRB and 308 with IRB approval – for this study. For each ride, the information of interest includes: the service the ride was requested from (Lyft, LyftLine, UberX, or UberPool), travel times, travel distances, and earnings including tips. The data analysis process began by calculating the breakdown of travel times and travel distances for each ride (Figure VI.I & Figure VI.II):

- t_1 = time a driver has to wait until a new ride request

- d_1 = travel distance cruising for a ride (if the driver decides to park and wait until a new request, this distance is zero or close to zero)

- t_2 = travel time from "ride request/acceptance" to "passenger pick-up" (i.e. en-route to passenger) or estimated time of arrival (ETA)

- d_2 = travel distance from "ride request/acceptance" to "passenger pick-up" (i.e. en-route to passenger)

- t_3 = waiting for passenger time once at pick-up location

- t_4 = travel time from passenger "pick-up" to "drop-off", or WP time

- d_3 = travel distance from passenger "pick-up" to "drop-off", or WPMT
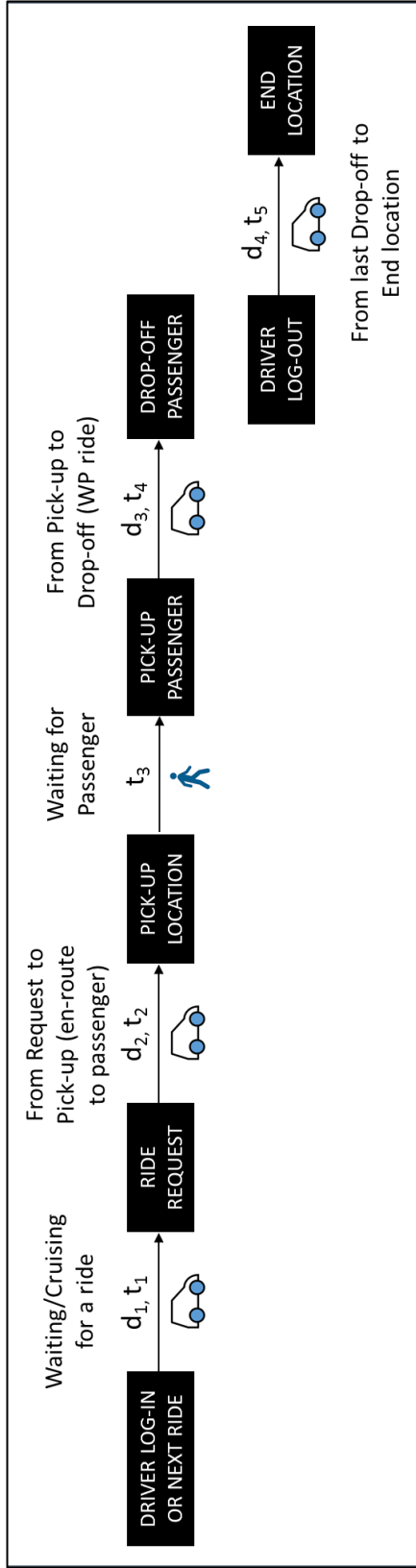
Figure VI.I. Travel Distances and Times of a Lyft/Uber Driver
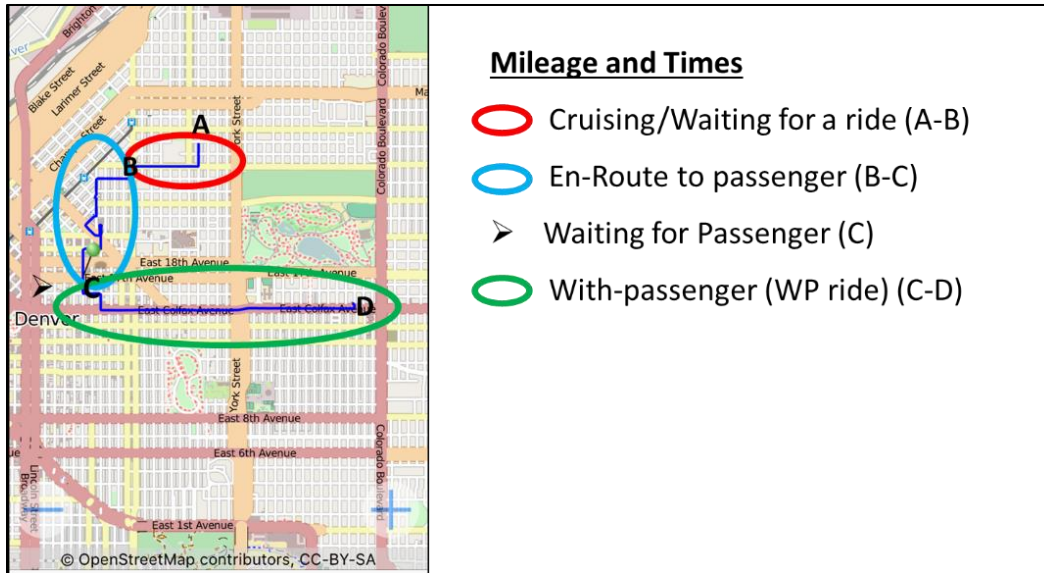
Figure VI.II. GPS Tracking of a Lyft/Uber Ride

In addition to the previous travel times and distances, drivers have to travel to their end locations and commute home once they drop-off the last passenger and are finished with the shift. The commute at end is also illustrated in Figure VI.I and includes:

- t_5 = travel time from "drop-off" to "app log-out" plus travel time from "app log-out" to driver "end location"

- d_4 = travel distance from "drop-off" to "app log-out" plus travel distance from "app log-out" to driver "end location"

Travel Distances and Times

The ridesourcing driving time and distance per shift are calculated by the following equations:

$$t_{shift} = \left[\sum (t_1 + t_2 + t_3 + t_4)\right] + t_5$$

$$d_{shift} = \left[\sum (d_1 + d_2 + d_3)\right] + d_4$$

For this study, the total ridesourcing driving time is:

$$t_T = \sum t_{shift} = \sum t_1 + \sum t_2 + \sum t_3 + \sum t_4 + \sum t_5$$

And the total ridesourcing driving distance is:

$$d_T = \sum d_{shift} = \sum d_1 + \sum d_2 + \sum d_3 + \sum d_4$$

In terms of VMT and WPMT, the total ridesourcing driving distance can be expressed as follows:

$$VMT_T = \sum d_1 + \sum d_2 + WPMT_T + \sum d_4$$

$$VMT_T = WPMT_T + \left[\sum d_1 + \sum d_2 + \sum d_4\right]$$

$$VMT_T = WPMT_T + Additional\ VMT$$

Ridesourcing Efficiency Rate

To determine the time efficiency rate, I compared the sum of WP times ($\sum t_4$) against total times (t_T):

$$Time\ Ridesourcing\ Efficiency = \frac{\sum t_4}{t_T}$$

And the sum of WPMT travel distances ($\sum d_3$) against total travel distances (d_T) for the mileage efficiency rate:

$$Mileage\ Ridesourcing\ Efficiency = \frac{\sum d_3}{d_T} = \frac{WPMT_T}{VMT_T}$$

Based on the total VMT equation: $VMT_T = WPMT_T + Additional\ VMT$, the

additional percent of WPMT is:

$$\frac{Additional\ VMT}{WPMT_T} = \frac{VMT_T}{WPMT_T} - 1$$

Finally, I calculated the total driving miles for every 100 miles transporting

passengers (100 WPMT), as follows:

$$Total\ Miles\ per\ 100\ \text{WPMT} = \frac{100 * VMT_T}{WPMT_T}$$

Ridesourcing Earnings

I calculated driver gross earnings per hour and per mile using total earnings divided

by the corresponding travel time or travel distance. For example, the gross earnings for all

416 rides was calculated by adding all driver earnings and divided by total time and total

mileage, as per the following equations:

$$Gross\ Earnings\left(^{\$}/_{hr}\right) = \frac{\sum Driver\ Earnings\ (incl.\ tip)}{t_T}$$

$$Gross\ Earnings\left(^{\$}/_{mile}\right) = \frac{\sum Driver\ Earnings\ (incl.\ tip)}{d_T}$$

I also calculated three different scenarios to account for the broad range of expenses

drivers might incur. The expense rate and calculations are explained in more detail on the

results section. After discounting expenses, I estimated the net earnings per hour for all rides,

for Lyft-only rides, for Uber-only rides, including before and after tips.

Chapter Results

Using the median travel times and distances summary statistics (Table VI-I) from the dataset, a representative day for a ridesourcing driver would be as the following description. The Lyft/Uber driver logs-on both apps; he/she tries to minimize the cruising distance (0.2 miles) but has to wait 7.5 minutes (mins) until he/she gets a request. Once the driver accepts the request, he/she spends approximately 5.0 minutes traveling 1.0 miles to the passenger pick-up location. Then, the driver has to wait 1.0 minutes for the passenger to board the car and start the actual ride. The median time and distance of the actual WP ride is 11.5 mins and 3.6 miles, traveling at an average speed of 28.8 miles per hour (based on a total of 6,106 minutes and 2929.9 miles). After the passenger is drop-off, the driver starts the process again waiting for a new ride request but minimizing unnecessary driving. When the driver is done for the day, he/she travels to the desired end location, commuting around 12.0 miles in 20.0 minutes (based on median values of 65 commuting trips or shifts). When the sum of all commuting times and distances are equally distributed to all rides, the median total driving time per ride is 32.8 minutes (average of 37.3 mins) and the median total driving distance per ride is 8.3 miles (average of 11.9 miles).

Following this dataset summary statistics, I divided the chapter results section into two subsections covering ridesourcing efficiency rates (time and distance) and earnings (gross and net earnings after expenses).

Table VII-I. Travel Times and Distances Summary Statistics
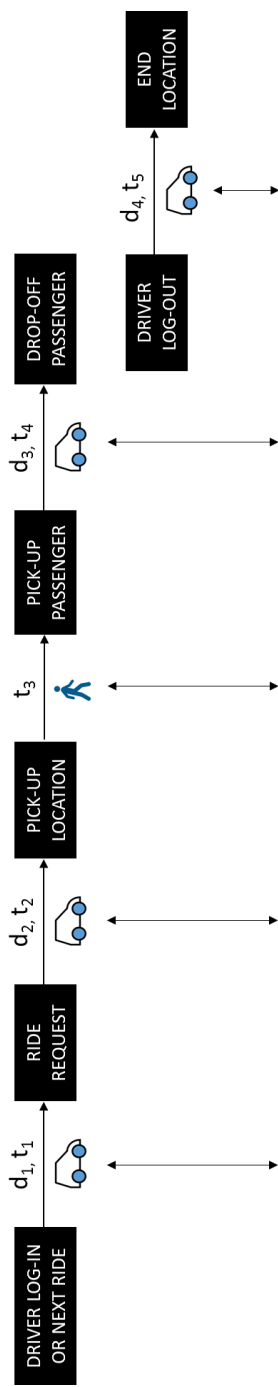
		Waiting/Cruising for a ride	From Request to Pick-up (en-route to passenger)	Waiting for Passenger	From Pick-up to Drop-off (WP ride)	From last Drop-off to End Location	Totals (t_T & d_T)
Time (minutes)	Total (Σt)	4,965.00	2,511.00	531.00	6,106.00	1,416.00	15,529.00
	Mean	11.94	6.04	1.28	14.68	21.78*	37.33
	St. Dev.	15.46	3.65	2.10	10.04	12.27*	20.30
	Median	7.50	5.00	1.00	11.50	20.00*	32.83
Distance (miles)	Total (Σd)	635.91	600.56		2,929.94	784.29	4,950.69
	Mean	1.53	1.44		7.04	12.07*	11.90
	St. Dev.	3.94	1.44		8.60	7.43*	10.37
	Median	0.20	1.00		3.55	12.00*	8.30
Average mph			14.35		28.79	33.23	19.13

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

* Commute based on 65 shifts

Ridesourcing Efficiency Rate

The time efficiency rate of a ridesourcing driver based on the time a passenger is in the car and total time from driver log-in to log-out (not accounting for the commute at the end of the shift) is 41.3%, meaning that I, as a driver, during my shift hours spent more time without a passenger than with one in the car. For example, if in a shift, I was working for five hours, I only spent just over two hours with passengers in the car, due to all the time spent waiting for a ride, going to pick-up the passenger, and waiting for the passengers once I was at the pick-up locations. When accounting for commuting time at end of shift, the time efficiency rate drops to 39.3% of total time (t_T) (Table VI-II). Based on distance, the ridesourcing mileage efficiency rate – without and with commute at end – is 65.4% and 59.2%, respectively. The total ridesourcing driving mileage per every 100 WPMT is 169.0. In other words, Lyft and Uber drivers travel an additional 69.0 miles in deadheading for every 100 miles they are with passengers.

Table VI-II. Time and Distance Efficiency

	WP Ride (Σd_3 & Σt_4)	Total minus Commute at End	Efficiency: WP/(Total minus Commute at End)	Totals (t_T & d_T)	Overall Efficiency (WP/Total)	Additional Percent of WPMT	VMT per 100-WPMT
Time (minutes)	6,106.0	14,767.0	41.3%	15,529.0	39.3%		
Distance (miles)	2,929.9	4,482.9	65.4%	4,950.7	59.2%	69.0%	169.0

Ridesourcing Earnings

The rates that passengers pay for Lyft and Uber fluctuates, but traditionally, they have been lowered over time. The percent that Lyft and Uber pay their drivers has also lowered over time going from paying 80% initially (20% commission to Lyft/Uber) to 75% nowadays (25% commission to Lyft/Uber). Table VI-III presents the Lyft/Uber fares and commission rates applicable to this study. Table VI-IV shows the total amount paid by passengers, driver earnings, and the actual Lyft and Uber commission, before and after tips. Earnings include prime and guarantee bonus per hour but does not include initial sign-up bonuses. All monetary values are in 2016 U.S. dollars.

Table VI-III. Lyft/Uber Fares and Driver Commission

	Passenger Cost*					To Driver**	Lyft/Uber Commision**
	Lyft/Uber Service Fee	Base Fare	Cost per Minute Fare	Cost per Mile Fare	Minimum Paid by Passenger (Fee + Fare)		
Lyft	$2.10	$0.50	$0.12	$1.01	$7.10	80% Fare + 100% Tips	100% Service Fee + 20% Fare
UberX	$1.95	$0.75	$0.13	$1.00	$6.95		

* Rates as of Fall 2016 in U.S. dollars. Rates varied and have been lowered over time

** 20% Commision when first signed-up in 2014. Newer drivers pay a higher commision (25% or more)

Table VI-IV. Passenger Cost, Driver Earnings, and Actual Commission

	Passenger Cost		To Driver			To Lyft/Uber	
	Total Paid (before tip)	Total Cost per WP Mile (before tip)	Total Earned (before tips)	Tips	Total Earned (with tips)	Actual Commision (before tip)	Actual Comission (after tip)
Lyft (n=237)	$2,934.58	$1.87	$2,059.25	$276.00	$2,335.25	29.8%	27.3%
Uber (n=179)	$2,505.62	$1.84	$1,687.83	$39.00	$1,726.83	32.6%	32.1%
All Trips (n=416)	$5,440.20	$1.86	$3,747.08	$315.00	$4,062.08	31.1%	29.4%

* Earnings include prime and guarantee bonus per hour but does not include initial sign-up bonus.

** Earnings in Year 2016 U.S. dollars

Gross Earnings

The dataset shows that if only the time and distance drivers spent with a passenger (WP) is taken into account; Lyft/Uber drivers would be making around $40 per hour or $1.39 per mile. However, there is more to account for within the overall work shift. After including all times and travel distances, gross earnings turn out to be $15.69 per hour or $0.82 per mile (Table VI-V).

Table VI-V. Gross Earnings

	Gross Earnings based on WP	Gross Earnings based in Total minus Commute	Gross Earnings based in Totals (t_T & d_T)
$/hr	$39.92	$16.50	$15.69
$/mile	$1.39	$0.91	$0.82

n=416. Earnings include tips (Year 2016 U.S. dollars)

Disaggregating by ridesourcing company, I found differences between Uber and Lyft earnings (Table VI-VI), with tips playing an important role in the differences. The small amount of Uber tips was from a few passengers giving tips in cash since Uber does not facilitate tipping on its app.

Table VI-VI. Gross Earnings – Lyft compared to Uber

	Gross Earnings (before tip) ($/hr)	Gross Earnings (with tip) ($/hr)	Gross Earnings (before tip) ($/mile)	Gross Earnings (with tip) ($/mile)
Lyft (n=237)	$14.38	$16.31	$0.77	$0.87
Uber (n=179)	$14.60	$14.93	$0.75	$0.76
All Trips (n=416)	$14.48	$15.69	$0.76	$0.82

* Earnings based in Totals (t_T & d_T)

** Earnings in Year 2016 U.S. dollars

<u>Expenses</u>

There many variables and rates that go into calculating personal car expenses such as ownership costs (e.g. depreciation, finance charges, 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, and the risk of crash or injury). The expenses also depend on the value of your car, driving mileage, and whether or not you own a car already and/or have already paid for some of these expenses. To account for the broad range of possibilities, I characterize three different expense scenarios (Table VI-VII.) covering all types of drivers, from occasionally part-time drivers to full-time drivers. In the basic added cost, I assume a range of driving hours of 1-15 hrs/week and around 11,000 miles per year. The next scenario included most of the drivers with 16-49hrs/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. Ridesourcing drivers are supposed to upgrade their car insurance to be properly insured with ridesourcing but a few drivers probably do, risking that an insurance company would not pay a claim if a person was driving for Lyft/Uber. For this first scenario, I assumed most ownership cost – such as insurance – as a sunk cost that drivers pay regardless of whether a person drives for a ridesourcing company or not; in other words, it is not considered an additional expense. 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 ridesourcing drivers (51% of drivers) based on Uber data published by Hall and Krueger (2015). Since drivers in this scenario experience higher timing and mileage, I included costs associated with owning a car and increased the other values according to the mileage per year. I used assumptions based on AAA 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, I used the 2016 U.S. standard mileage rate determined by the federal government of 54.0 cents per mile. The average mileage rate based on the previous three scenarios is calculated at $0.41 per mile. The corresponded cost per hour is based on the average of 19.1 mph from Table VI-I.

Table VI-VII. Ridesourcing 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)	Average Mileage Rate
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*	**$0.41**
$/hr	$5.34	$7.60	$10.31	**$7.75**

Assumptions: Car value: $18,000; Lifetime mileage: 150,000; Work: 50 weeks/year; Gas price: $2.40/galon (Average in 2015); Gas efficiency: 26 MPG; Maintenance: 5.36 cents/mile; Miscellaneous include car wash & cleaning, mobile device & data fees, parking & traffic violations, risk of crash or injury
* 2016 U.S. Federal Standard Mileage Rate

Ridesourcing drivers are probably excited to think they are making $40 per hour, or even $16/hr but would be disappointed to learn that, after accounting for expenses, the average hourly rate, including tips, is $7.94 (not even minimum wage in Colorado) as shown in Table VI-VIII. This net earning wage could be even lower because of the higher commission rate of 80% – versus 75% of newer driver – and relatively conservative expense estimates.

The net earning rate per mileage is between $0.28 and $0.54, with an average of $0.41; meaning drivers' gross earnings are cut in half after expenses. With these numbers, if a driver work 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.

Table VI-VIII. Net Earnings (Gross Earnings minus Expenses)

	Net Earnings	
	Range (Low to High)	**Average**
$/hr	$5.38 - $10.36	$7.94
$/mile	$0.28 - $0.54	$0.41

n=416. Earnings include tips (Year 2016 U.S. dollars)

When disaggregating by ridesourcing company and including tips, the Uber net earning rate is $7.18 per hour, and Lyft is $8.56/hr (Table VI-IX). Tips makes a significant difference on living wages for Lyft drivers with around $1.93/hr and accounting for a 29.1% increase of net earnings, while is only $0.33/hr (4.9%) for Uber.

Table VI-IX. Net Earnings – Lyft compared to Uber

	Net Earnings (before tip) ($/hr)	Net Earnings (with tip) ($/hr)	Tip Percent
Lyft (n=237)	$6.63	$8.56	29.1%
Uber (n=179)	$6.85	$7.18	4.9%
All Trips (n=416)	$6.73	$7.94	18.1%

* Earnings based in Totals (t_T & d_T)

** Earnings in Year 2016 U.S. dollars

Chapter Conclusions

The time efficiency rate without taking into account commuting at the end of the shift is 41.3%. This time efficiency rate is lower than the capacity utilization rate of 46-54% in a previous study (Cramer & Krueger, 2016). Accounting for the commute at the end, the overall time efficiency rate drops to 39.3%, meaning that drivers spent more time without a passenger than with one in their car. The main implication for this result is the reduction on earnings per time ($/hour) since ridesourcing drivers have to spend time waiting for a passenger request, traveling to a pick-up destination, waiting for the passenger once at the pick-up location, and commuting time at the end of the shift.

The efficiency rate in terms of WPMT versus total mileage without including commute distance is 65.4%. The mileage efficiency rate for this study is higher than the 61.0% utilization rate calculated by Cramer and Krueger (2016). I attribute this difference to the research design; which minimized the cruising for a ride request, did not accepting rides when the distance to pick-up a passenger was too long, and used conservative commute

distances at end of shifts. When including all distances, the mileage efficiency rate drops to 59.2%, but I believe the real mileage efficiency rate is even lower. Even with this conservative calculation, drivers have to travel 69 extra miles in deadheading for every 100 miles originally from WPMT.

There has been a lot of uncertainty regarding how much money a Lyft/Uber driver makes. What is widely known is the difference between what passenger pay and what Lyft/Uber drivers are paid. The Lyft/Uber fare per mile is around $1, but when we take into account all fees and divided by the WP time, passengers pay around $1.86 per mile (Table VI-3 & Table VI-4). When I became a Lyft and Uber driver, I signed-up with a commission rate of 80-20 (80% of fare for driver and 20% for Lyft/Uber), which is used for this study (newer drivers get even lower rates at 75% of fares). When the booking fee is taking into account, the commission rate before tips for all rides is 31.1%. When tips are taking into account and separated by company, the Uber commission is higher (32.1%) than the Lyft commission (27.3%), suggesting that drivers earn better driving for Lyft.

This is the first study to incorporate commute times and distances into earning calculations, but even without accounting for the commute time of the driver to or from their home, the gross earnings drops to less than $16.50/hour. This is a conservative high number since the commission rate received was at the high-end, I was driving for both Lyft and Uber minimizing waiting for a ride times, and I minimized unnecessary driving whenever possible. As a comparison, a recent Buzzfeed article reported that an Uber driver in Denver makes $16.89/hour (O'Donovan & Singer-Vine, 2016), but they overestimated this hourly earning with some of the assumptions used in calculating driver expenses.

Using all the data from the 416 rides and including all times and distances, the gross earnings for this study equals to $15.69/hour, which might seems like a good hourly rate, but many drivers do not realize the expenses incurred by driving. The expenses varied from our conservative calculations using very basic added cost of $0.28 per mile to the standard 2016 mileage rate of $0.54 per mile, so in reality ridesourcing drivers make between $5.38 and $10.36 per hour, with an average of $7.94/hr before taxes.

Uber net earnings before tips ($6.85/hr) is slightly higher that Lyft earnings ($6.63/hr) but completely change when tips are taken into account. Net earnings with tips included are $8.56/hr for Lyft versus $7.18/hr for Uber. Lyft tips in net earnings equals to a 29.1% increase and plays a critical component in the ridesourcing driving economy. Uber could easily add a tipping option in their app to allow passengers add a tip in their credit card bill if they wish. This choice would help increase drivers' earnings, but Uber has thus far refused to implement this option.

Uber and Lyft depend on the driver-partners labor market. They incentivize new drivers with bonuses and referrals, but their retention rate is not very good. According to Hall and Krueger (2015), 89% of Uber driver-partners stay active after one month, 70% after six months, and around 50% after a year. One of the reasons for this may be the realization of driving expenses and costs incurred by driving. For example, a taxi driver who makes $12/hour might think that they can make a lot more driving for Uber ($40/hr or $16/hr). However, they may soon realize that, after accounting for expenses, it is not nearly as profitable as expected and are actually not even making minimum wage at about less than $8/hour.

Based on the results from this study, I have several recommendations to create more efficiency by reducing the amount of time and distances ridesourcing drivers have to travel and earn wages that are more decent. Cities authorizing ridesourcing services and companies such as Lyft and Uber should:

- Suggest drivers to minimize the amount of miles they drive without a passenger

- Balance the driver network better by directing certain drivers to their closest prime rate zones instead of generalizing without specific guidance

- Balance the supply of drivers better, especially when passenger demand is not high. This would minimize VMT from drivers circulating around.

- Allow drivers to create ride zones so they do not end up far away from their desired location. Also, expand the destination filter option so rides can be matched along certain routes or destinations and not just at the end of the shift (during the study period, Lyft and Uber started an option for drivers to put a destination filter but the option has not been very effective). Lyft and Uber have stated that they want to reduce the inefficiency of empty seats as one of their desired goals so ridesourcing could function like a carpooling app where all drivers set their destination and find passengers along the way.

- Not match drivers when the passengers pick-up location is far from the driver location or compensate drivers for these scenarios (I, as a driver, have seen requests from locations more than 30 minutes or 20 miles away).

- Concerning earnings, Lyft and Uber could always pay their independent-contractors better by paying drivers on the service fee (which goes 100% to Lyft/Uber), increasing passenger fees, increasing the driver commission fee,

providing better incentives, or covering some of the expenses. Thus far, these companies seem to be moving in the other direction by increasing the Lyft/Uber cut from 20% to 25% or higher, lowering passenger rates (mileage and time), and increasing the service fee (which is not shared with the drivers). Uber also has not shown any desire to allow an option to tip in their app, which is the number one request from drivers.

The main limitation to this study is the trip sample size and diversification of drivers. Drivers might have different work strategies such as searching for prime areas, have a desired location in mind, cruising unlimitedly until they get a ride request, or limiting driving without a passenger as much as possible by parking right after a passenger is dropped off. I minimized the distance traveled without a passenger for the results to be conservative. The study is also limited to the Denver metropolitan area so the Lyft/Uber costs and earnings are based on this area.

This is the first independent study to use Lyft and Uber data exclusively to drivers. The results provide insight into the impacts of ridesourcing into travel times, travel distances, and the labor economy of Lyft/Uber independent contractors. This research starts to fill a gap in the academic literature by identifying, measuring, and disentangling the impacts of ridesourcing on very important aspects of transportation. I hope this study helps cities and regional organizations better account for the impacts of ridesourcing on travel time and mileage efficiency, as well as inform the ridesourcing labor market on the complicated issues of earnings and expenses.

CHAPTER VII

VMT IMPACTS

Most of my life I have lived in two cities: Cali in Colombia and Denver in the U.S. These cities differ quite dramatically in their economies, demographics, employment, culture, etc. Regarding transportation, they are also very different in terms of land use, transportation services offered, mode share, car ownership, work force, etc. For example, the mode share of private vehicles in Cali is 10% (Cali Cómo Vamos, 2015) versus around 79% in Denver (U.S. Census Bureau, 2015)

Growing up in Colombia, I lived a completely different transportation experience than my current one. My parents owned one car to be shared by the five members of my family. My travel behavior was truly multimodal; I would take public transportation, carpool, walk, or bike. Occasionally, I would take a taxi to get around the city. Thinking back, one of the things that influenced me the most was the large amount of taxis and their effect in congestion. Still nowadays, Cali experiences many impacts from taxis circulating around (Figure VII.I) and getting in line outside the airport, hospitals, malls, bus terminals, and other public places (Figure VII.II). The taxi impact experienced is very clear since in Cali taxis are yellow and represent 7% of total mode share (Cali Cómo Vamos, 2015). This suggests a 0.7 (around 7 to 10) relationship when taxi mode share is compared to private vehicles mode share. The estimate of mode share for taxis in Denver (combined with motorcycle or other non-traditional means) is only 1% (U.S. Census Bureau, 2015), representing a 0.01 (around 1 to 79) ratio of taxi versus private vehicles.

Figure VII.I. Taxis in Cali, Colombia (Source: ElPais.com.co)
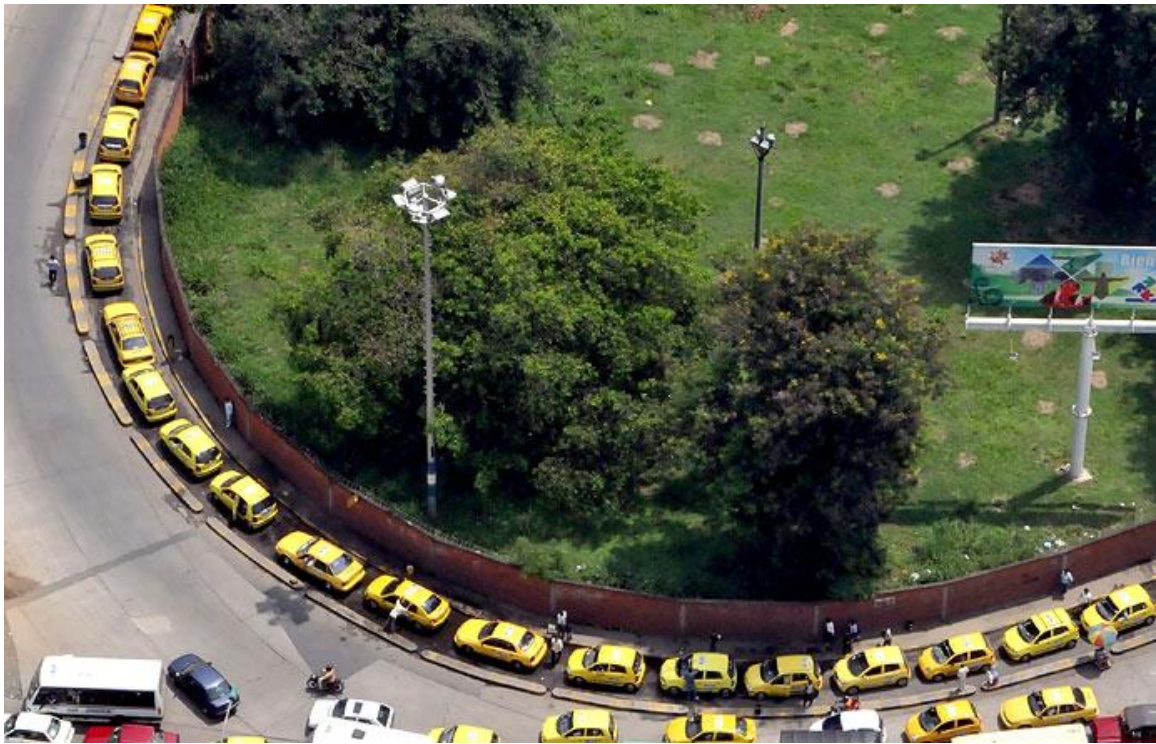
Figure VII.II. Taxi Tracks in Cali, Colombia (Source: ElPais.com.co)

This experience is relevant to ridesourcing since very little is known about the contribution that Lyft and Uber provides to the efficiency and impacts of our transportation systems. When people use private vehicles to operate for Lyft and Uber, we might not realize the impacts in city streets since most only carry a barely visible logo sticker.

Cities, regions, and transportation organizations usually set up goals to reduce congestion, environmental impacts, and equity issues. A general term used for housing strategies to aim for more efficient use of transportation resources is Transportation Demand Management (TDM). Some of these goals are in terms of measuring and tracking mode share, passenger miles traveled (PMT), and VMT.

In an effort to contribute to the conversation, this study chapter aims to analyze the mode share replacement occurring with ridesourcing, measure the efficiency ratio of PMT/VMT and VMT/PMT, compare VMT before and after ridesourcing, and estimate the extra VMT generated in the U.S. from Lyft and Uber.

Chapter Related Literature

Transportation organizations across the globe are trying to solve transportation problems by setting strategic goals to reduce SOV or increase the mode share of sustainable modes of transportation including transit, walking, and biking. A few reports and studies have shown that cities have successfully met some of these goals through a variety of strategies, including TDM efforts – such as congestion fees, tollways, high occupancy vehicle (HOV) lanes to carpool/increase vehicle occupancy, parking management, transit passes – as well as infrastructure investments and policy changes (Bialick, 2015b; Henao et al., 2015; Kaffashi et al., 2016; Steele, 2010).

The problem with ridesourcing is that when organizations are trying to set up goals in regards to mode shift and prioritizing certain modes, they do not know the real impacts and efficiency of services like Uber and Lyft. Shall organizations support ridesourcing and encourage its services to a higher use? What modes are they replacing? What is the PMT/VMT or PMT/VMT ratios compared to other modes? How would the transportation system benefit if ridesourcing was replacing modes that are more efficient? For example, we know that it will never be better than biking, walking, or transit since VMT for theses modes is zero or close to zero, but how does it compare to the SOV PMT/VMT ratio of 1.0, or taxis being around 0.40 (Cramer & Krueger, 2016)?

The few studies that look into mode share changes and VMT impacts analyze the data at the aggregate level and do not make a distinction about the magnitude and directional shifts occurring within all modes. This study chapter aims to start filling this gap in the literature by looking in more detail the mode replacement, as well as PMT and VMT changes, and find out the place where ridesourcing stands in terms of efficiency compared to other modes of transportation.

Chapter Data and Analysis

For this research, I used the information containing both the information collected by driving and the corresponding passenger survey information, for a total of 311 passenger surveys during 308 rides. The information gathered by driving is the same as the data collected in chapter VI, except the focus on this chapter is on distance and does not include times nor earnings. I also include information on the number of passenger for each ride. 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?" (Figure VII.III). 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

- Other

After reviewing the "other" responses, I created three new categories; including two categories for "get a ride" and "car rental". Seventeen passengers responded either "Lyft" during the Uber ride or "Uber" during the Lyft ride. These passengers probably did not read the question carefully, or they use Lyft/Uber as their main mode of transportation and did not think of other replacement mode. For these passengers, I created the "other ridesourcing" category.

Q5. For this trip, how would you have traveled if Lyft/Uber wasn't an option?

Carpool (drive) 3.2%
Other, 1.6%
Car rental, 4.2%
Get a ride, 4.5%
Other ridesourcing 5.5%
Carpool (ride) 6.1%
Taxi 9.6%
Bike or Walk...
Public transportation 22.2%
Drive alone 19.0%
Wouldn't have traveled, 12.2%
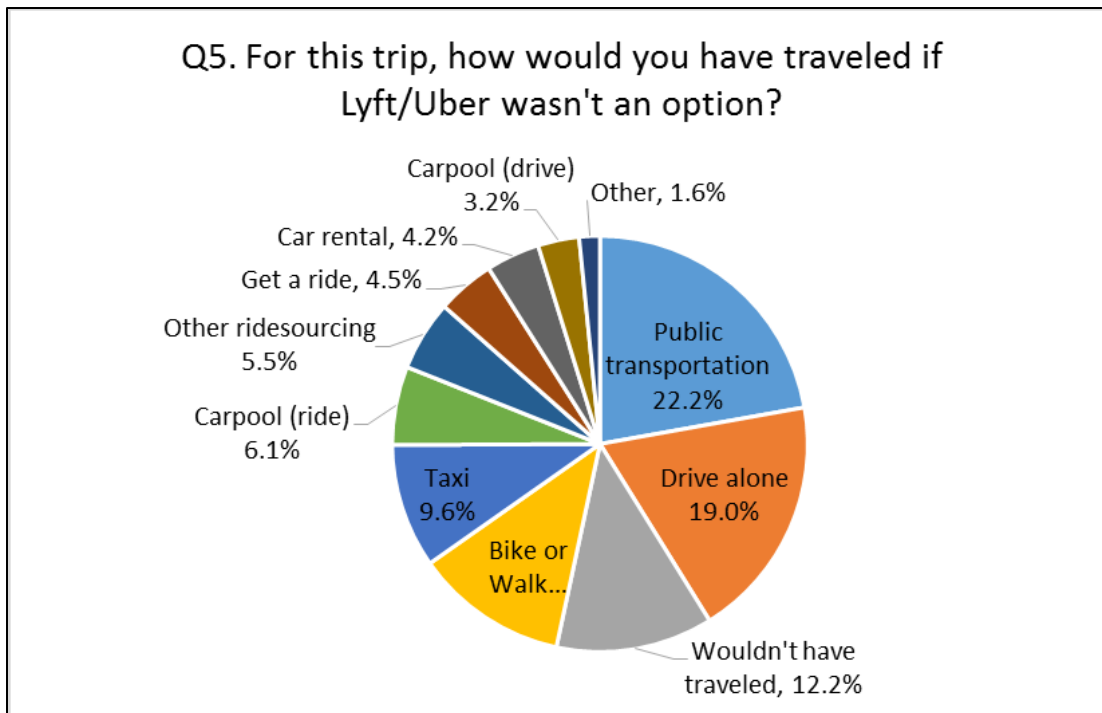
Figure VII.III. Mode Replacement (Q5)

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, with the intent to make a fair comparison (Q6). For this study, I also included the question on whether or not the passenger was using Lyft/Uber for the entire length of the trip (origin to final destination), or he/she was making a connection to another mode of transportation (Q9), and which mode of transportation (Q10). Finally, I included the survey question 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)

- Number of people carpooling if passenger would have carpooled (Q6)

- Connection with another mode of transportation (Q9 & Q10)

- Own or have access to a personal car (Q19).

For the twenty-nine passengers that would have carpooled, the number of people that would have carpooled together is between two and four people with an average of 2.59 people per trip (Q6). Regarding connection with another mode of transportation, 94.50% of the passengers stated that they were using Lyft/Uber for the entire trip, and only 5.50% were using another mode of transportation in connection with Lyft/Uber (Q9). Moreover, 187 people out of 291, or 64.3%, responded to question Q19 by stating that they own or have access to a personal car.

Based on the data previously described and the VMT for each mode replaced, I proceeded to calculate the Replaced VMT (or VMT_{BEFORE}) and passenger miles traveled (PMT) based on travel behavior prior to Lyft and Uber were in place, as follows:

- VMT Replaced for "wouldn't have traveled" is 0

- VMT Replaced for "bike or walk" is 0

- VMT Replaced for "car rental" is the same as WPMT

- VMT Replaced for "carpool (drive)" is the same as WPMT

- VMT Replaced for "carpool (ride)" is given by the following formula:

  $VMT = WPMT \times \left(\frac{\# \ Passengers \ for \ Ride}{\# \ People \ what \ would \ have \ Carpooled} \right)$, which is the same as

  WPMT for most rides

- VMT Replaced for "driving" is the same as WPMT

- VMT Replaced for "get a ride" is equal to two times (2x) WPMT. This is the case when someone else (e.g. parent or spouse) would have driven the passenger from origin to destination (O-D) and go back to origin incurring in a round-trip doubling the miles of the original O-D trip.

- VMT Replaced for "other ridesourcing" is the same as ridesourcing VMT

- VMT Replaced for "public transportation" is zero 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 Replaced for "taxi" is equal to 2.5 times (2.5x) WPMT based on the taxi distance efficiency of around 40% (Cramer & Krueger, 2016). I used the same ridesourcing VMT for trips to the airport.

- If the ride included a connection, the previous distance replaced is based on total VMT & 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 Replaced is equal to two times (2x) the total distance (WPMT plus the train distance) because the person taking the passenger would have travel all the way to the airport and back.

The Ridesourcing VMT (or VMT_{AFTER}) was calculated using the same methodology as Chapter VI, where all distances – with and without a passenger – are taken into account.

Then, I calculated PMT/VMT and VMT/PMT ratios for before (VMT Replaced) and after (Ridesourcing VMT) to understand the efficiency of PMT/VMT, and how much VMT is put into the transportation system per PMT before and after ridesourcing. Finally, in order to understand the additional VMT put into the system because of ridesourcing, I calculated the ratio of VMT$_{AFTER}$ versus VMT$_{BEFORE}$ for every mode replaced and overall.

Chapter Results

The total Ridesourcing VMT in this analysis was 3,617.7 miles while VMT Replaced was 1,959.6 miles, and PMT was 2,200.0 miles. The average passenger travels a mean distance of 7.14 miles (median distance of 3.50 miles) ranging from 0.5 miles to 49.10 miles. See summary statistics in Table VII-I. for more details.

Table VII-I. PMT, VMT Replaced, and Ridesourcing VMT

	PMT	VMT Replaced or VMT$_{BEFORE}$	Ridesourcing VMT or VMT$_{AFTER}$
Total (Σd)	2200.03	1959.58	3617.68
Mean	7.14	6.30	11.75
St. Dev.	8.83	10.97	10.24
Median	3.50	1.82	7.56
Min.	0.50	0.00	2.54
Max.	49.10	57.00	54.59

Rides=308 (Lyft: 128, LyftLine: 36, UberX:131, UberPool: 13)

PMT/VMT Efficiency

The before travel behavior based on the replaced mode was 112.3% efficient in terms of how much PMT per VMT would have happened if Lyft or Uber were not available, meaning that

all the modes replaced were transporting passengers at a rate of 112.3 miles for every 100 VMT. With the introduction of ridesourcing, the PMT/VMT efficiency dropped to 60.8%, meaning that the miles passengers travel is less than the vehicles miles at a rate of only 60.8 PMT for every 100 VMT from Lyft and Uber. This equates to a -51.5% net change or 45.8% percent reduction (Table VII-II.).

VMT/PMT Ratio

Using the same numbers but inverting the numerator and dominator, I calculated the before and after VMT/PMT ratios. If Lyft/Uber were not available, the before travel behavior scenario would have been 0.89 VMT per every 1.0 PMT (Table VII-III), meaning that all the modes replaced were transporting more passengers miles than vehicles miles. With the introduction of ridesourcing, the VMT_{AFTER}/PMT ratio went up to a value of 1.64 meaning that now with Lyft and Uber the VMT is 1.64 miles for every 1.0 PMT (Table VII-III). This value is very similar to the calculation of 1.69 from chapter VI.

VMT before and after

The total (Σd) and median distances of PMT, VMT Replaced, and Ridesourcing VMT for each mode replaced and total are presented in Table VII-III. The last column of this table shows the VMT_{AFTER} / VMT_{BEFORE} ratio for every mode and total, with an overall ratio of 184.6%, meaning an overall increase of 84.6% in VMT.

Table VII-II. PMT/VMT, before and after

PMT	VMT Replaced or VMT$_{BEFORE}$	Ridesourcing VMT or VMT$_{AFTER}$	Efficiency Replaced $\frac{PMT}{VMT_{BEFORE}}$	Ridesourcing Efficiency $\frac{PMT}{VMT_{AFTER}}$	Net Change Ridesourcing Efficiency minus Replaced Efficiency	Percent Change Net Change / Efficiency Replaced
	Total (Σd)					
2,200.03	1,959.58	3,617.68	112.3%	60.8%	-51.5%	-45.8%

Table VII-III. VMT by Mode Replacement, before and after

Mode Replaced	n	PMT Total (Σd)	PMT Median	VMT Replaced or VMT$_{BEFORE}$ Total (Σd)	VMT Replaced or VMT$_{BEFORE}$ Median	Ridesourcing VMT or VMT$_{AFTER}$ Total (Σd)	Ridesourcing VMT or VMT$_{AFTER}$ Median	$\dfrac{VMT_{BEFORE}}{PMT}$	$\dfrac{VMT_{AFTER}}{PMT}$	$\dfrac{VMT_{AFTER}}{VMT_{BEFORE}}$
Public transportation	69	419.6	3.50	27.2	0.00	768.9	7.54	0.065	1.832	2826.7%
Drive alone	59	661.3	5.17	661.2	5.17	935.5	10.97	1.000	1.415	141.5%
Wouldn't have traveled	38	194.0	3.67	0.0	0.00	370.2	8.00	0.000	1.908	∞
Bike or Walk	37	74.3	1.65	0.0	0.00	195.9	4.95	0.000	2.638	∞
Taxi	30	364.2	5.77	639.5	14.41	568.3	10.74	1.756	1.560	88.9%
Carpool (ride)	19	132.1	3.87	82.2	1.82	227.7	7.64	0.622	1.724	277.1%
Other ridesourcing	17	52.8	3.00	143.3	7.58	143.3	7.58	2.713	2.713	100.0%
Get a ride	14	132.6	5.67	265.3	11.33	140.5	9.75	2.001	1.060	53.0%
Car rental	13	54.6	3.71	54.6	3.50	119.7	6.52	1.000	2.191	219.1%
Carpool (drive)	10	77.1	2.74	77.1	2.74	93.6	5.51	1.000	1.215	121.5%
Other	5	37.5	2.55	9.2	2.28	54.1	6.09	0.244	1.441	589.8%
Total	311	2200.0	3.50	1959.6	1.82	3617.7	7.56	0.891	1.644	**184.6%**

Legend:

Worst VMT	
Better VMT	
Overall	

Chapter Conclusions

This study chapter shows that, overall, ridesourcing VMT is approximately 184.6% of what would have been without Lyft/Uber, which has significant implications for our cities in terms of congestion and environmental concerns. Ridesourcing provides more mobility – 12.2% of passengers stated that they "wouldn't have traveled" – but affects the efficiency of transporting passengers versus vehicles going from a PMT/VMT efficiency of 112.3% to 60.8% (VMT/PMT ratio of 0.89 to 1.64). The worst VMT changes come from passengers that would have used public transportation or active transportation. The problem is that for these modes, the transportation system was previously experiencing zero or close-to-zero VMT, but now with ridesourcing we end up with some of the worst VMT_{AFTER}/PMT ratios. The main explanatory reason is that these are short distance trips and ridesourcing is less efficient with these trips. For example – as shown in Table VII-III – the median distance for "bike or walk" is 1.65 miles and the ridesourcing VMT median is 4.95, which equates to 2.6 times the PMT. The transportation system experiences better VMT efficiency when the replacing mode is "taxi" or "get a ride", since the efficiency rate of ridesourcing is better than taxis or people chauffeuring family or friends. In addition, one of the things to notice on the data is that many of the Lyft/Uber trips that were replacing "get a ride" were actually connection trips to transit so the VMT_{AFTER} is minimal compared to the total VMT_{BEFORE} that a person would have done. For example, if a person rides a Lyft/Uber for 4 miles to a transit station and then, rides the train for 20 miles; the replaced VMT is 48 miles ($48 = 2 \times [4 + 24]$).

In an attempt to have a more general idea of the impacts of Lyft and Uber, I look at some published data on the rides that Lyft and Uber have given so far. This summer, Uber

reported that its second billion rides were completed during six months (the first billion was reached in six years) (Somerville, 2016). While Uber operates globally, Lyft is only in the U.S., so I looked at numbers exclusively for the U.S. According to several news articles and based on a statement from Lyft co-founder and president John Zimmer, Lyft does around 17 million rides per month in the U.S., and compared to Uber, their market share of total is around 20% (Buhr, 2016; Kokalitcheva, 2016). Using these numbers, Lyft and Uber gives around 1 billion rides per year in the U.S. If the results for this dissertation held true for the entire country, the impacts of ridesourcing on VMT would be around 5.5 billion extra miles per year in the U.S.; since the VMT_{BEFORE} (or replaced) would have been 6.4 billion per year, and VMT_{AFTER} (or Ridesourcing) would be close to 12 billion miles per year from total Lyft/Uber VMT. See Table VII-IV for calculations and more details.

Lyft and Uber have changed travel behavior for many people and they are becoming more popular, but cities and transportation professionals that have expressed concerns over the potential negative implications of ridesourcing have valid points. There should be better policies and regulations in place for ridesourcing companies to operate in a way that would allow our transportation system to function in a more efficient way, but it seems that the opposite is occurring as shown in this chapter study.

Table VII-IV. Extra VMT per year in the U.S. due to Lyft/Uber

Lyft and Uber rides per year in the U.S.	1,000,000,000.00
$t_{T\ mean} = (\Sigma d)/ride$ (Table IV.1)	11.90
VMT_{AFTER} = Rides per year * 11.90	11,900,707,268.24
VMT_{AFTER}/VMT_{BEFORE} (Table V.3)	1.85
$VMT_{BEFORE} = VMT_{AFTER} / 1.85$	6,446,228,741.23
$VMT_{EXTRA} = VMT_{AFTER} - VMT_{BEFORE}$	5,454,478,527.02

CHAPTER VIII

PARKING IMPACTS

This parking study is one component of a broader research strand that analyzes the impacts of ridesourcing on transportation. As seen in previous chapters, there are negative impacts as it relates to VMT since a ridesourcing driver travels additional miles well above the actual passenger O-D trip. This becomes worse if the passenger is shifting from a mode other than SOV, such as carpooling, transit, biking, or walking. Ridesourcing could also have positive impacts such as parking as more people can access destinations without requiring an accompanying parking space. In turn, this could facilitate reduced parking supply and help alleviate congestion problems that might come from vehicles cruising around searching for parking. On the other hand, parking difficulty and cost is an important TDM strategy that transportation professionals use to deter driving, which might influence people's decisions to use Lyft/Uber when parking supply is limited and/or expensive. In terms of travel behavior, ridesourcing could also serve as a transition in travel behavior change, car ownership, and long-term modality styles as people shift from an auto-oriented lifestyle towards becoming more of a multimodal traveler. However, this has not yet been adequately studied. Therefore, this research aims to evaluate the impacts of ridesourcing on parking by looking at the trips that otherwise would have needed parking (e.g. if passengers would have driven their own car, renting a vehicle, or carpooling) and investigate specific origins and destinations (e.g. airport, sporting events, special events, bars/night-life, park and ride locations). This study also seek to shed light on understanding parking – in terms of issues such as supply and price – as a reason of someone using Lyft/Uber instead of driving.

Chapter Data and Analysis

For this study, I used the dataset of 311 samples containing both the information collected by driving and the corresponding passenger surveys. The information of interest for this section is on the origins and destinations, trip purposes, and parking-related questions including driving mode replacement and parking as a stated reason to use ridesourcing instead of another mode. I analyzed the dataset for both the specific trip and for general travel behavior questions.

Chapter Results

I divided the results section in three subsections to explore:

- Parking demand by exploring the trips where ridesourcing replaced driving

- Locations – origin & destination (O-D Matrix) – with trip purpose, and connection with other modes (e.g. park and rides)

- Parking difficulty as a reason to choose ridesourcing over other modes.

Each subsection includes results from the specific Lyft/Uber ride as well as answers from the general travel behavior survey questions.

Parking Demand

Specific Trip

Since parking, theoretically, is only needed for driving trips; I decided to look in more detail at the mode replacement distribution and pay closer attention to the trips that would have involved driving – such as drive alone, carpool (drive), car rental, and carsharing – to start understanding potential changes in parking demand.

In terms of replacing driving trips with ridesourcing, we should exercise 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 final destination. In other words, a passenger might have still driven and parked but ridesourcing 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 cheaper. Then, she/he requested a Lyft/Uber ride to reach the final destination, thus benefiting from cost and time savings of a shorter ridesourcing trip. This has both positive and negative implications for transportation. Within this section, I analyzed the specific trip answers to the question "For this trip, how would you have traveled if Lyft/Uber wasn't an option?" (Q5) under two conditions: i) the mode replaced is one of the driving option; and ii) driving is not part of the connection trip (Q9 & Q10). Figure VIII.I illustrates the percentage of respondents that otherwise would have driven and needed a parking location, with a result of 26.4% (82 O-D trips) of all respondents.
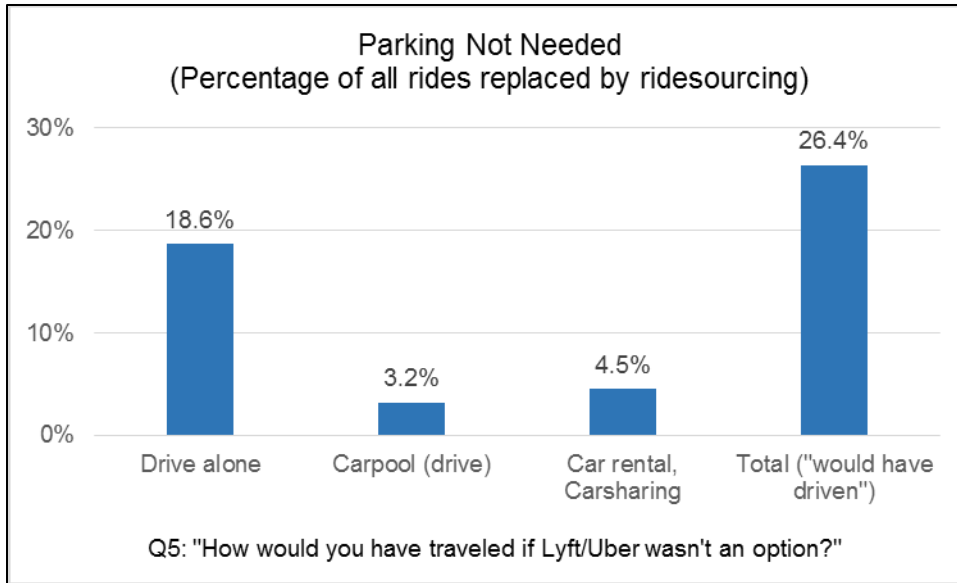
Figure VIII.I. Ridesourcing Replacing Driving Trips (Parking)

General Use

In the general questions section of the survey, I asked passengers about travel behavior changes for different modes (Q25), "For the next few questions, complete the sentence based on your travel today compared to the past". The question of interest about parking is "Because of ridesourcing, I drive…" with the option to respond "a lot less", "a bit less", "about same", "a bit more", or "a lot more". Figure VIII.II provides the results with a third of participants – 14.3% plus 19.9% – stating that they drive a lot 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 seven passengers (2.4%) responded to this question with "a bit more" and a "lot more". Based on my experience and interactions with the passengers, this might be explained under two scenarios. The first one is that passengers share a vehicle with others in their household; the other household drivers begin relying more on

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ridesourcing, which facilitates greater vehicle availability and more driving for the

respondent. The second explanation is that passengers are also ridesourcing drivers, which

turned out to be the case for three of the survey respondents.
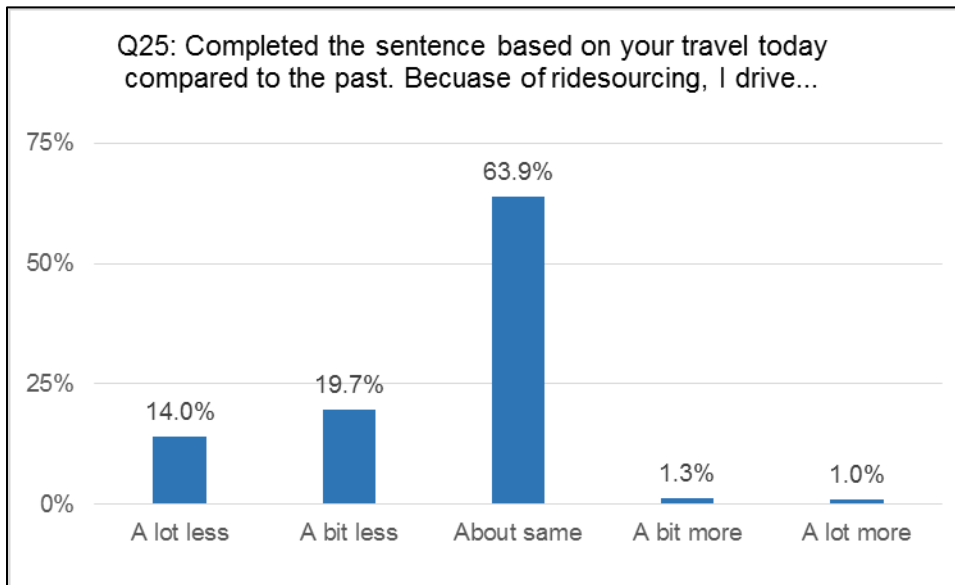
Figure VIII.II. Travel Behavior Change (Driving today compared to the past)

Locations, Trip Purpose, and Connectivity to Transit Stations

Specific Trip

Data in Chapter V includes the O-D matrix (Table V-I) for all the rides in the study

that contains both the driver and passenger datasets. In order to understand the trips that

influence parking – those that otherwise would have driven as described in the previous

subsection – I created an O-D matrix (Table VIII-I) exclusively for the Lyft/Uber rides that

replaced driving showing the locations that could potentially reduce parking supply. The

most common origin and destination locations were "home" and places that people "go out

for social trips". The third common location was work trips with an even number of origins

and destinations. "Airport" was also a common destination in the dataset, with 14 trips most of them originating at passengers' homes.

Table VIII-I. O-D Matrix (Driving Trips Replaced)

DESTINATION / ORIGIN	Home	Work	School	Shopping/ Errands	Going Out/ Social	Airport	Hotel/ Airbnb	Family/ Friend	Other	Totals
Home	0	5	1	1	19	13	0	1	2	42
Work	2	2	1	0	0	0	4	0	1	10
School	1	0	0	0	0	0	0	1	0	2
Shopping/Errands	1	0	0	0	0	0	0	0	0	1
Going Out/Social	8	0	0	0	2	0	0	2	1	13
Airport	0	0	0	0	0	0	1	0	0	1
Hotel/Airbnb	0	2	0	0	0	0	0	0	2	4
Family/Friend	2	0	0	0	1	0	1	0	0	4
Other	1	1	0	0	0	1	2	0	0	5
Totals	15	10	2	1	22	14	8	4	6	82

General Use

In order to understand travel behavior changes in general, I created Figure VIII.III showing the distribution of trip purpose for all respondents, and for the 101 passengers that stated driving either "a lot less" or "a bit less" in question Q13. As the figure shows, social trips (i.e. go out) is the number one trip purpose for all respondents as well as those ridesourcing users that are driving less.
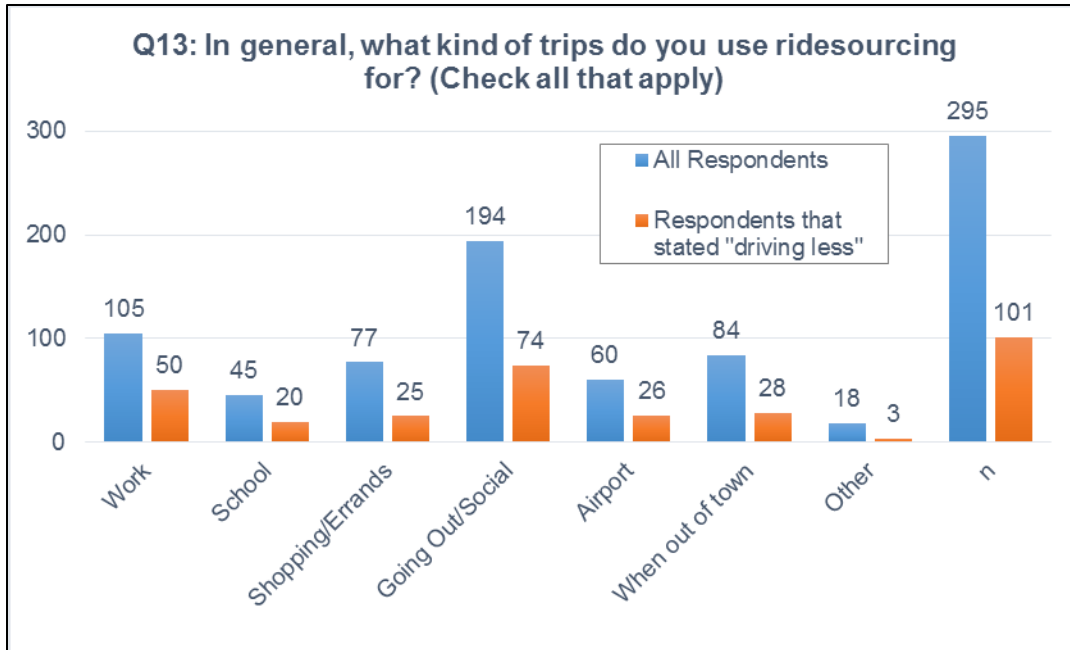
Figure VIII.III. Ridesourcing Trip Purpose (All respondents and those "Driving less")

Connectivity to Transit Stations

Ridesourcing advocates state that these services are solving many of the issues with connecting to public transportation (i.e. the last mile). In order to explore this topic further, I recorded trips with transit stop locations as the origin or destination. The passenger survey also included questions in regards to connectivity – Q9 & Q10 as described in Chapter VII for the specific trip, and for general use with Q22: "Have you ever used another mode of transportation in addition to Lyft/Uber for a single trip? For example, using Lyft/Uber to/from a bus station", Q23 asks: "How often have you used other modes of transportation in addition to Lyft/Uber for a single trip?" and Q24: "Please write all the modes of transportation you have used in addition to Lyft/Uber for a single trip:" Table VIII-II includes the results for the specific trip and general use whenever passengers were replacing driving modes or were connecting to bus or rail at a transit station.

Table VIII-II. Connectivity to Transit Stations

Q9. Ride connecting with other mode (n=311)		
No	294	94.5%
Yes	17	5.5%
If yes, number of rides replacing driving and connecting to transit	3	1.0%
Q22. Have you ever connected with other mode? (n=293)		
No	233	79.5%
Yes	60	20.5%
If yes, number of passenger that stated driving less and public transportation (e.g. bus, rail) as the connection mode	21	7.2%

Parking as a stated reason to choose Ridesourcing

This subsection analyzes parking as a reason for someone to use ridesourcing over other modes, both for the specific trips and for general use.

Specific Trip

Passengers stated the main reason that led them to choose Lyft/Uber over other options (Q8) for the actual O-D ride. Figure VIII.IV includes the percentage for each reason including for all passengers, as well as those that "would have driven if ridesourcing was not available". "Parking is difficult/expensive" is highlighted in the responses as one of the reasons to choose ridesourcing.

Figure VIII.IV. Main reason for choosing Lyft/Uber for Actual Ride

over other options?

Category	Passengers that "would have driven"	All rides
Going out/drinking	36.6%	20.6%
Don't have a car available	17.1%	19.0%
Time (e.g. in a rush)	2.4%	17.0%
Parking is difficult/expensive	19.5%	8.0%
Cost	8.5%	7.4%
Can't drive (no license, DUI, injury)	0.0%	4.8%
Weather	2.4%	3.9%
Public transportation not available	0.0%	3.9%
Carrying something	0.0%	2.6%
Tired/Feeling sick	0.0%	2.6%
Able to do something while riding	3.7%	1.9%
Other	9.8%	8.4%

Similar to the previous subsection, question Q17 ask the main reasons to choose ridesourcing over other modes, allowing respondents to check up to three reasons. In addition to this question, I used the driving frequency question Q21 to create Figure VIII.V. I selected the top five reasons from the dataset per driving frequency. In this graph, I highlighted parking again to show the clear relationship between high frequency of driving and parking. Parking is the second most important reason for frequent drivers to choose ridesourcing.
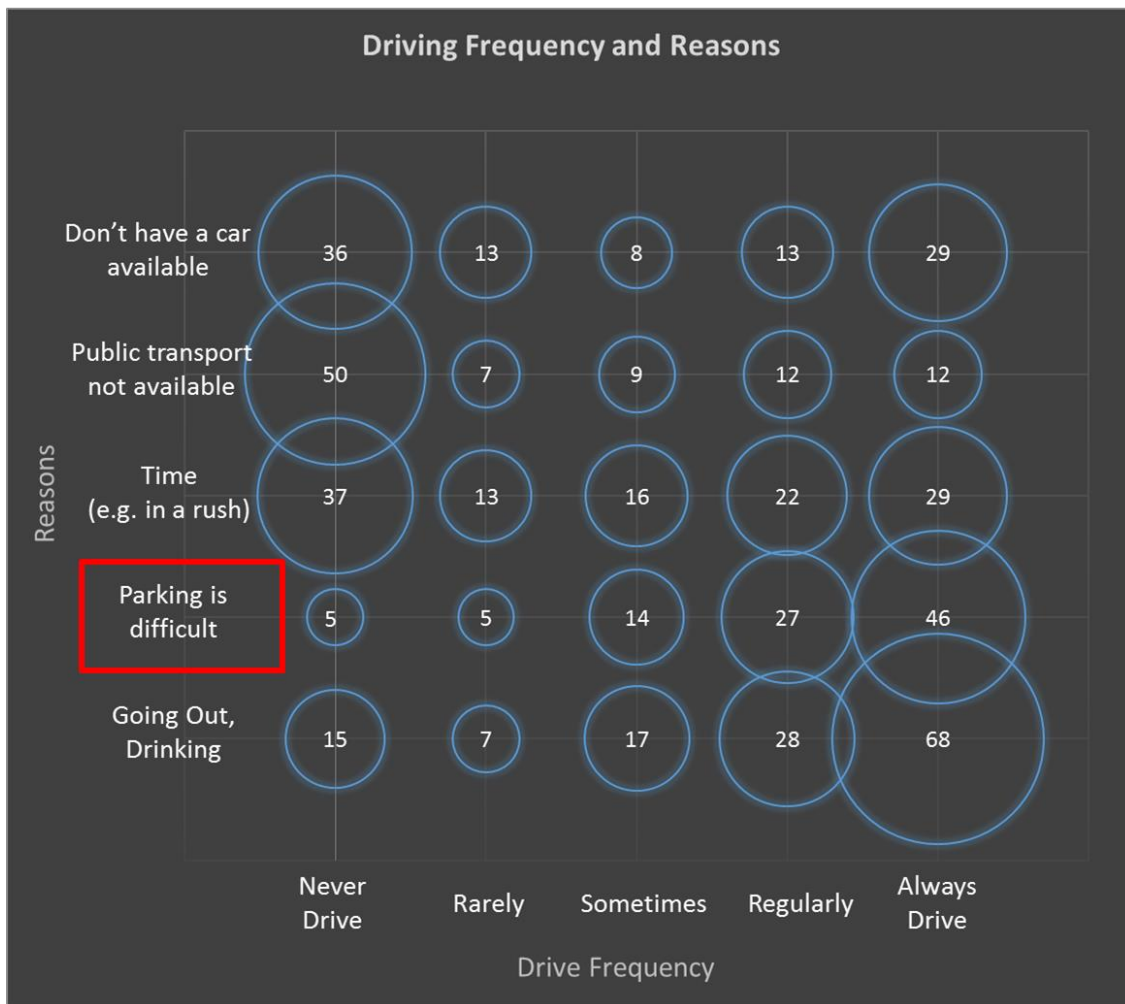
Figure VIII.V. Driving Frequency and Trip Purpose

Chapter Conclusions

With evolving transportation services and the promise of autonomous vehicles, changes in the transportation industry are creating a window of opportunity to help dissolve the car-dependency and automobile focus of transportation infrastructure in the U.S. and around the globe. Thus, this study aims at investigating the reciprocal influence of an evolving transportation service – ridesourcing – in terms of a very important transportation infrastructure – parking – so we can model, design, and build future transportation infrastructure.

I conducted a cross analysis to compare specific Lyft/Uber rides and general travel behavior for three inter-related parking topics. First, I looked at mode replacement finding that a third of all Lyft/Uber rides were replacing trips that would have needed parking.

Then, I looked in more detail at the origin and destination locations, travel behavior changes, trip purpose, and connectivity to the transit system. The results show that passengers that usually drive ("always drive" and "regularly") are using ridesourcing mostly to go to the "airport", "when out of town", and for "going out/social trips". Thus, parking capacity could be reduced at these types of locations (e.g. airport, bars, and stadiums). With respect to connection to the transit system, very few Lyft/Uber rides were used with this purpose in mind.

Finally, I analyzed parking as a stated reason for using ridesourcing, showing that for the specific trip, parking difficulty/cost is the fourth most cited reason for all trips, and the second most cited reason for trips replacing driving. For general use, the passengers that drive the most ("always drive" and "regularly") stated that "parking is difficult/expensive" as the second most cited reason why they chose ridesourcing over other modes.

The results from this chapter suggest that thanks to ridesourcing, we could easily decrease the parking supply because of two reasons: ridesourcing is replacing driving trips and parking is one of the main reasons people choose not to drive in the first place. Thus, parking can be used as a TDM tool to influence travel behavior. The less parking provided, the less driving desired, especially when people have choices to shift to other modes of transportation.

Continuation of this positive cycle would facilitate decreasing car dependency. In the future, autonomous ridesourcing vehicles would enable us to continue this trend more rapidly. In preparation for this drastic change, we should adapt the current transportation infrastructure to reduce parking stock and make room for more desirable land uses, especially in urban areas where land is costly. For example, we could eliminate parking minimums in the generation rate manual so developers build less parking spaces and more building amenities. They should offer residents different transportation options and plan to re-accommodate parking spaces for future use. Similarly, common destinations such as the airport or hot spot areas for social activity (e.g. restaurants, bars, stadiums, and nightlife) shall remove parking spaces or design future buildings with less parking capacity. In turn, this could facilitate more livable and desirable places to walk, bike, and take public transportation.

CHAPTER IX

TRAVEL BEHAVIOR CHANGES

Ideally, mode choice models are run and tested with robust data containing information regarding travel activities (e.g. mode of transportation, frequency, time of days, etc.) and specific individual characteristics (e.g. socio-demographics, transportation resources, land use, travel behavior style, etc.) from a random population sample. While I do not have the necessary data for a traditional mode choice model, I can investigate the most probable mode replacement for each individual, and explore the variables and reasons influencing travel behavior change from previous modes of transportation after the introduction and evolution of ridesourcing. Thus, this study chapter has three main objectives:

1. Collect the data necessary for integrating ridesourcing services into a research framework to help current travel models move past their simplistic focus on traditional modes of transportation (i.e. car, transit, walk, and bike);

2. Use ridesourcing as a shock into the system to evaluate changes in travel behavior as well as relationships between travel behavior, trip purpose, and stated reasons for mode replacement; and

3. Identify and analyze components from the framework such as modality styles.

The term "modality style" is defined as "*a certain travel mode or set of travel modes that an individual habitually uses*" by Vij, Carrel, and Walker (2013). The concept is derived from empirical studies on higher-level orientations, lifestyles or "mobility style", both in short-term decisions and long-term choices, which counters the conventional assumption that people choose a mode independently for every trip.

Conceptually, this dissertation builds upon the existing body of literature on the influence of ridesourcing on modality style, mode replacement, and travel behavior. Methodologically, this work contributes to the understanding of modality styles, changes to modality styles with the introduction of additional transportation options – ridesourcing in this case – and the influence of modality styles on travel behavior. More generally, this dissertation contributes to the body of knowledge considering transportation planning and future travel demand models. Ultimately, this dissertation sheds light on the travel behavior impacts of ridesourcing with the current trends we are experiencing in our transportation systems to better inform urban planners, policy makers, and transportation engineers.

Chapter Literature Review

Understanding travel behavior and the related decision-making is a very complex area of study. One of the most common ways to rationalize and forecast travel behavior and decisions is through travel demand models. One of the issues with travel demand models is that the outcomes are dependent on the assumptions used in the model, and traditionally, travel demand models assume that an individual is fully aware of the range of transportation options so that the choice is based on utility maximization theory. Utility maximization derived from economic theory assigns a utility value for each transportation alternative and assumes that the mode with the highest utility value will be chosen. While this theory is well established in economics, it contains some limitations. Calculating the actual utility of any good is very complex and typically contains several attributes that are not realistic to measure in many scenarios such as inhibited values, attitudes, perception, and beliefs that could relate to ingrained lifestyles and deeply established habits for certain modes. Individuals adopt different patterns of consumption behavior, not only based on utilitarian needs, but also

because they express self-identity, leading to a person making a choice as a result of how to act and who to be (Giddens, 1991).

Transportation researchers have studied links between lifestyles and travel behavior since early 1980s by classifying groups that depend on the time spent at different activities, weekly travel patterns, or travel expenditures (Kitamura, 2009; Pas, 1988; I. Salomon & Ben-Akiva, 1983). More recently, the literature evaluated the effects on transportation choice by the influence of a person's mobility decisions including land use (Handy, Cao, & Mokhtarian, 2005; Kitamura, Mokhtarian, & Laidet, 1997; Krizek & Waddell, 2002) and mobility resources (e.g. automobile ownership, bicycle ownership, public transportation pass) (Choo & Mokhtarian, 2004; Vredin Johansson, Heldt, & Johansson, 2006). Specific to carsharing, recent studies suggest that carsharing members have different mobility resources compared to the representative population, with fewer cars per households and higher levels of bike ownership and public transportation passes. In general, carsharing seems to broaden the mix of transportation modes and increase the distribution of transportation modes, including intermodality (mixed-modes) and multimodality (Johanna Kopp et al., 2015; Le Vine, Lee-Gosselin, et al., 2014).

In an attempt to capture modality styles and their influence on mode choice decisions, Vij et al. (2013) developed a model framework within the context of travel demand models using the Latent Class Choice Model (LCCMs). LCCM models were first developed in the field of marketing sciences (Kamakura & Russell, 1989) and include two components: a class membership model; and a class-specific choice model. LCCM is seen as a solution to the black box of correlation structure from the continuous mixture distribution in most widely known travel demand models (Walker & Ben-Akiva, 2011).

This dissertation uses the framework by Vij et al. (2013) as a foundation to incorporate ridesourcing into modality styles and mode choice modeling. The proposed framework facilitates the analysis of the three objectives in this part of the dissertation by looking at the full datasets and paying special attention to the passengers' stated responses regarding travel behavior in general and socio-demographic characteristics. Utilization of the full dataset is needed to disentangle the effects of using ridesourcing on travel behavior by controlling for factors such as modality resources and modality styles – auto-oriented (i.e. drivers), multimodal, or non-drivers – of passengers prior to start using ridesourcing services.

Chapter Data and Analysis

For this study, I used the dataset containing all 311 passenger surveys – same as Chapters VII and VIII – and adapted the previously described travel demand framework (Figure IX.I) to use in this dissertation.
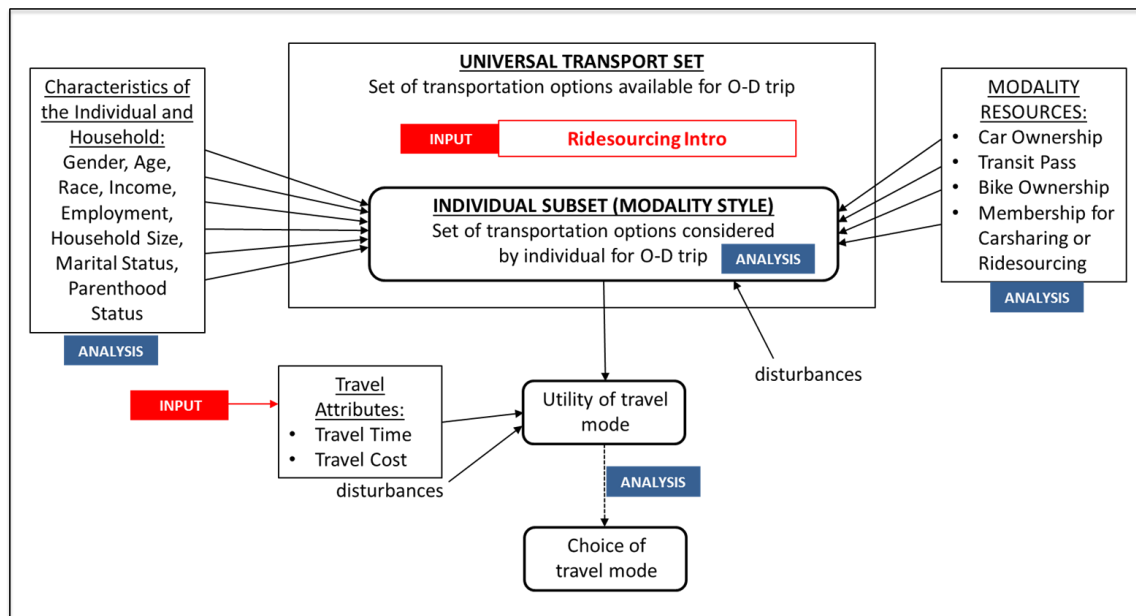

Figure IX.I. Travel Demand Framework to Study Ridesourcing

The framework shows that for a given origin-destination pair and time, there is a "universal transportation set" of mode options available. From this universal set, there is an "individual subset" comprised of the transportation options from the universal set minus the discarded options by the individual. Individuals discard certain transportation options due to perceptions, values, habits, preferences, experience, or because they might not be aware of the existence of a transportation service. Below the individual subset, there is the "utility of travel mode," which is the evaluation of each travel mode contained in the subset. The person then chooses a travel mode from the subset based on the utility evaluation. This is done for every given origin-destination pair and time; so every person has a group of individual subsets given the situation.

The group of individual subsets is analogous to what Vij et al. (2013) define as modality style in their model framework. In this dissertation, I identified four different classes of modality styles:

- Driver or car-oriented: if the individual stated driving as the main mode of transportation

- Multimodal: if individuals use several modes of transportation

- Non-driver or multimodal without car: if the individual rarely, if ever, drives

- Bi-style: if the individual assumes a combination of any of the three previous modality styles.

To my knowledge, this dissertation is the first study to introduce a bi-style modality classification, which hypothesizes that an individual may adopt two completely different modality styles according to several factors and attributes of travel. For example, a person could normally act as a multimodal traveler, but for trips transporting a child, the person

would only consider the car. In this case, the person is bi-style (first: multimodal; then: car-oriented). Similarly, a person that normally only considers the car as the mode of transportation might behave differently for leisure trips (e.g. going out to eat or drink). This person's classification is bi-style (first: car-oriented; then: multimodal without car). Previous studies on carsharing systems provide indirect insights into the bi-modality style topic, with the distribution of journey purposes per mode showing that individuals use personal cars, taxi, and carsharing differently depending on the type of journey (Le Vine, Lee-Gosselin, et al., 2014). Another insight is the potential effect of ridesourcing on drunk driving crash reduction (Jones, 2015), which implies that people may be using these services more often for leisure trips but not necessarily for other purposes. The bi-modality style classification is an important distinction because it allows travel demand modes to explain travel behavior better. Accordingly, we could create better policies and more effective planning to influence modal shifts away from SOV.

The modality style classification is sensitive to the group of individual subsets; therefore, I established time limits to determine modality style classifications for a specific time period. Once a period is determined, I measured changes in modality style due to specific inputs. An individual could potentially change modality style with the introduction of several factors: i) changes in characteristics of the individual and households (e.g. income or expenditures, employment status, marital status, parenthood status); ii) changes in location (e.g. home, work, or school); iii) changes in infrastructure or services (e.g. improvement on certain mode infrastructure, evolving transportation services); or iv) changes in mobility resources (e.g. personal cars, bicycles, public transportation pass, carsharing membership, or ridesourcing membership). For this dissertation, I surveyed passengers once but the survey

included questions specific to the current trip as well as more general questions regarding travel behavior changes due to the introduction of ridesourcing. Establishing travel behavior prior to the introduction of Lyft/Uber and controlling for explanatory factors (e.g. the person recently moved from out of town, the passenger cannot drive anymore due to DUI or illness) is key to understanding travel behavior.

The key questions for data analysis in this chapter are:

- Mode frequency (Q21), where passengers stated how often they use each mode of transportation. The multiple choice options were never, rarely (special occasions, monthly), sometimes (~ 1-2 times per week), regularly (at least 3 times per week), and always.

- Travel Behavior, based on question Q25: "For the next few questions, complete the sentence based on your travel today compared to the past", and followed by the following subsections sentences:

   o Because of ridesourcing, I go to places…

   o Because of ridesourcing, I drive…

   o Because of ridesourcing, I use public transportation…

   o Because of ridesourcing, I bike or walk…

   o Because of ridesourcing, I take taxis

   With the options to answer: "A lot less", "A bit less", "About same", "A bit more", or "A lot more".

- Change in resources (Q19): "Do you (or your household) own fewer cars because of ridesourcing?" with "Yes" or "No" answer options.

- Besides questions on mode frequency and travel behavior changes, I reevaluated several other questions such as trip purpose (Q13) and stated reasons (Q17) from the previous chapters.

In the last question, I recorded passenger's emails for a possible follow-up study, Q38: "In the future, we would like to do a follow-up study on ridesourcing travel changes. If it's OK for us to contact you about a future study, please share your email address".

Chapter Results

I organized this chapter result section in three sub-sections. The first one presents mode frequency and travel behavior changes. The second part investigates relationships between frequency of use, trip purpose, and stated reasons. The last subsection analyzes modality styles.

Mode Frequency and Travel Behavior Changes

Figure IX.II presents frequency of use per mode of transportation. About half of ridesourcing users stated that they "always" or "regularly" drive alone. In contrast, only 0.7% of passengers use taxi always or regularly. Carpool, public transportation, and bike/walk modes have a more evenly frequency of use distribution.

Q21: Thinking about your typical week travel, how often do you?
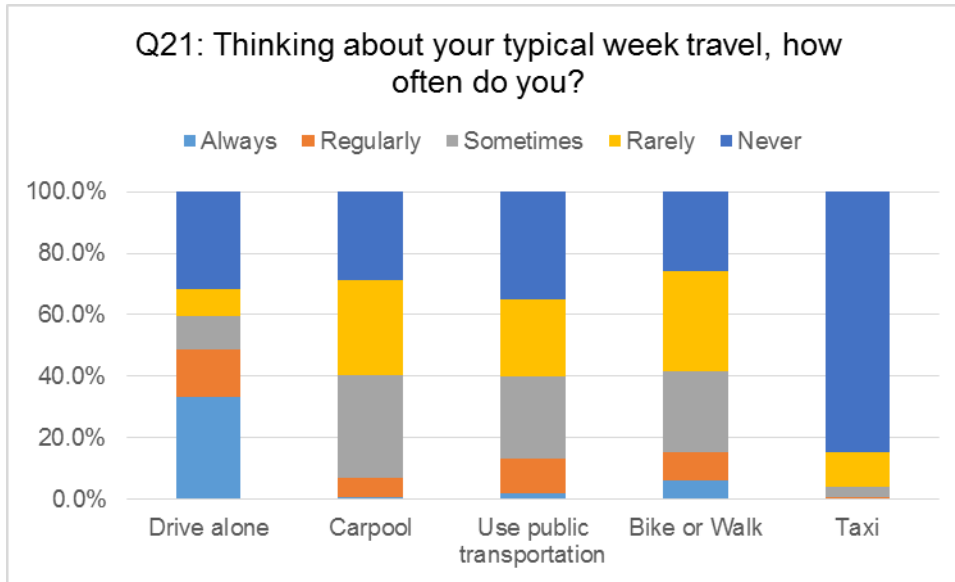
Mode Frequency (n=292)	Never	Rarely	Sometimes	Regularly	Always
Drive alone	92	26	32	45	97
	31.5%	8.9%	11.0%	15.4%	33.2%
Carpool	84	90	98	18	2
	28.8%	30.8%	33.6%	6.2%	0.7%
Use public transportation	102	73	78	33	6
	34.9%	25.0%	26.7%	11.3%	2.1%
Bike or Walk	75	96	77	26	18
	25.7%	32.9%	26.4%	8.9%	6.2%
Taxi	248	33	9	2	0
	84.9%	11.3%	3.1%	0.7%	0.0%

Figure IX.II. Mode Frequency

I collected information on travel behavior changes for five different categories – new trips, drive, public transportation, bike/walk, and taxis – which allow me to measure and compare the magnitude of change for each mode. For example, Figure IX.III shows driving change versus public transportation change.
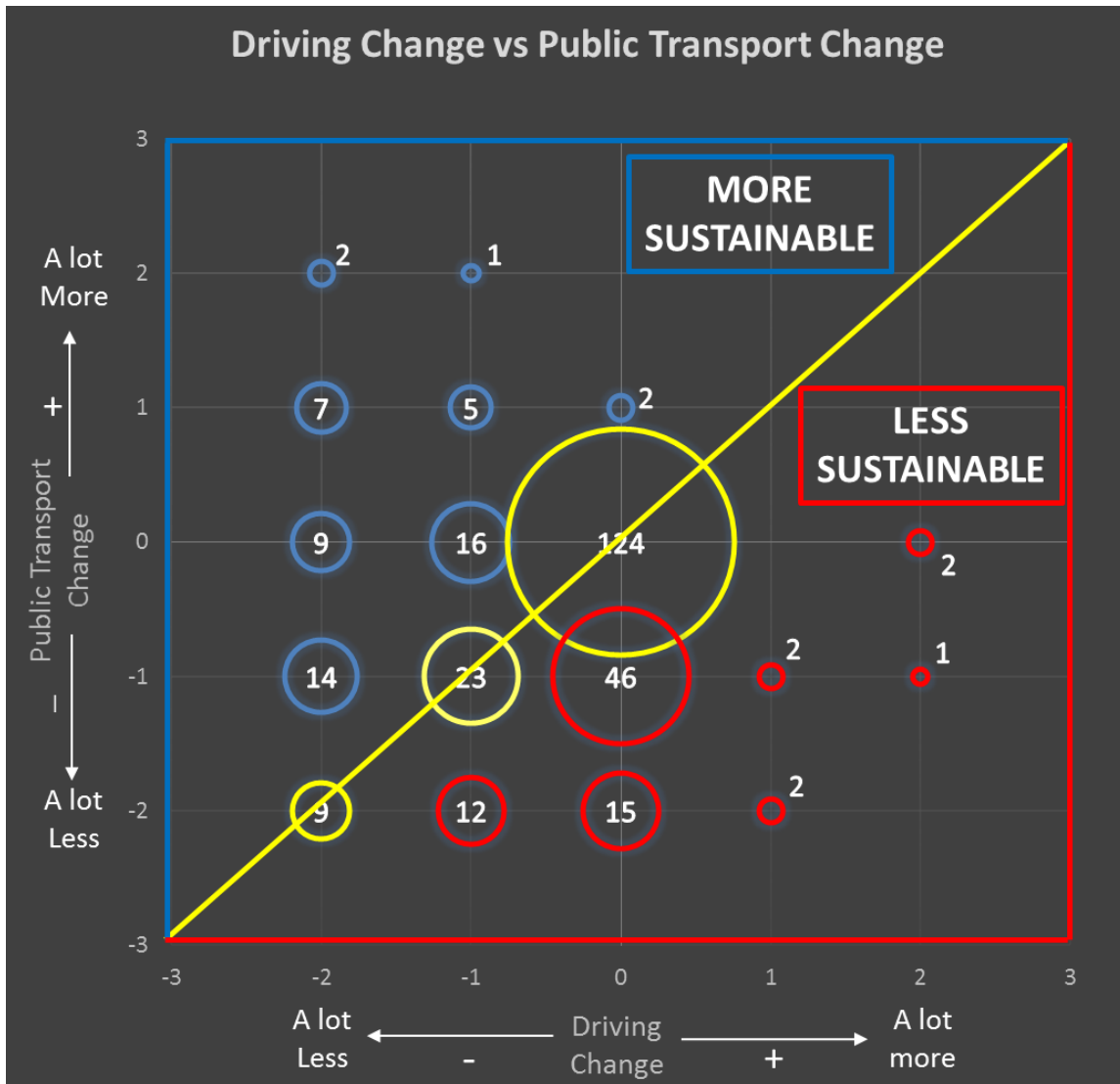
Figure IX.III. Travel Behavior Changes, Driving & Public Transportation

The three yellow circles in Figure IX.III have the same magnitude of change for driving and public transportation. The triangle covering the area in quadrant IV is labeled as "less sustainable" (red zone) since the magnitude of change for public transportation is worse than the magnitude of change for driving, and triangle around quadrant I is label as "more sustainable" since the opposite occurs (blue zone). For example, a positive change occurred when public transportation use increased and driving use decreased due to ridesourcing. The

figure shows that the majority of users did not change travel behavior, and there are more negative changes (red) than positive changes (blue).

Relationships between Drive Frequency and Other Variables

Drive Frequency and Trip Purpose

There are some clear relationships between drive frequency and trip purpose. Passengers that drive the most – regularly and always – are using ridesourcing to go out for social trips, going to the airport, and/or when they are out of town (Figure IX.IV). In contrast, passengers that never drive are using ridesourcing to go to work and/or school.
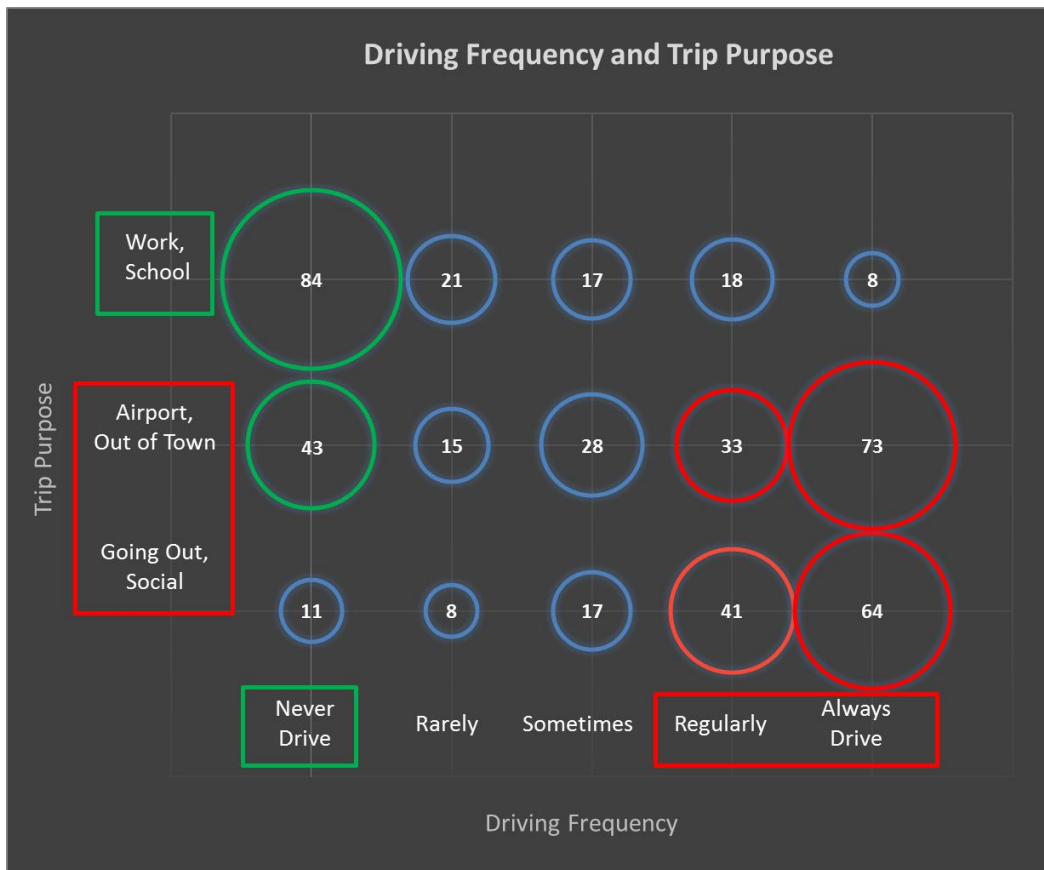

Figure IX.IV. Driving Frequency and Trip Purpose

I first explored stated reason on why passengers use ridesourcing in chapter VIII on parking. Further analysis on the topic shows that car-dependents are replacing driving trips mainly because they are consuming alcohol and/or because they find parking difficult and/or expensive. On the other hand, non-drivers use ridesourcing because they do not have a car available, public transportation is not great, and/or time constraints (e.g. passengers are in a rush to get somewhere), as shown in Figure IX.V.
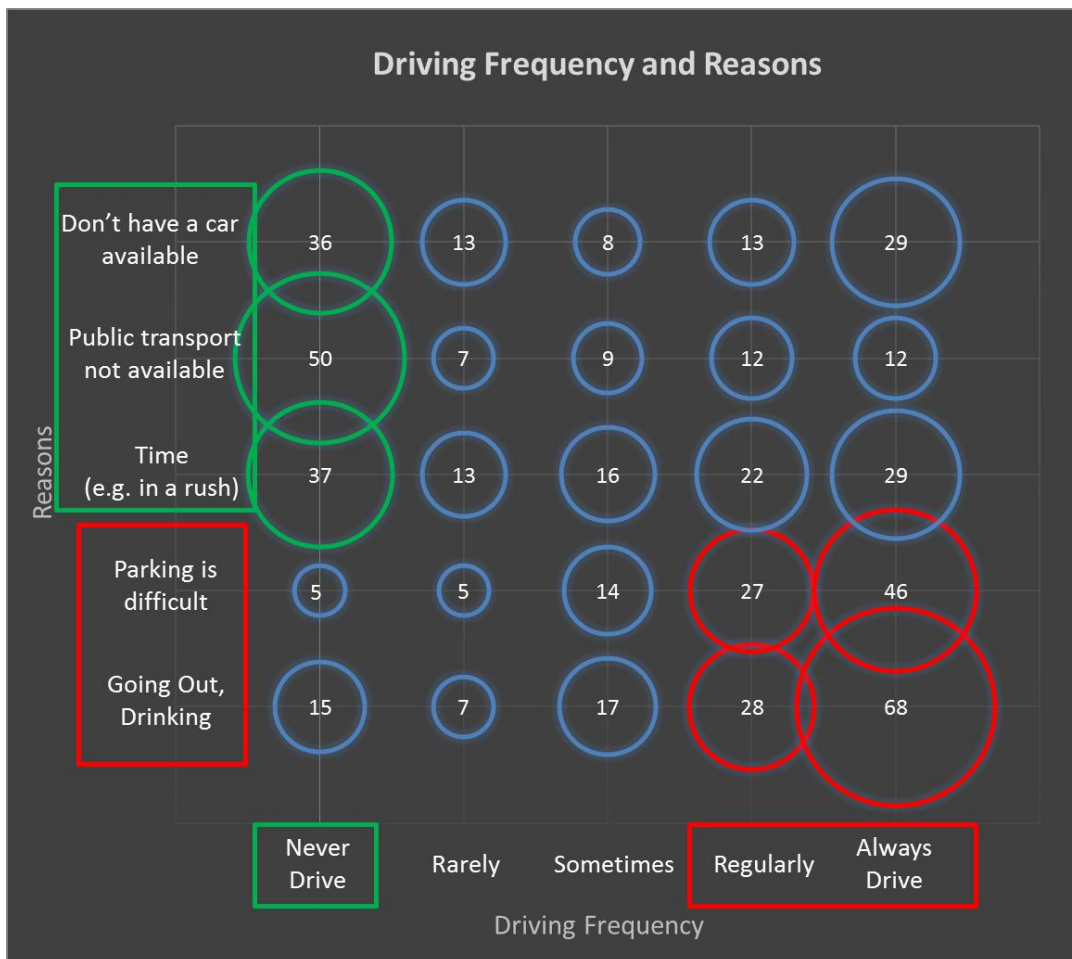

Figure IX.V. Driving Frequency and Stated Reasons

Modality Styles

Based on use frequency for different transportation modes (Q21), I was able to identify three modality style classes – 111 drivers, 64 multimodal passengers, and 117 non-drivers – as the research methodology suggested (Figure IX.VI). Then, I explored the "drivers" group in more detail based on the introduction of ridesourcing (Q11), frequency of ridesourcing use (Q14), and travel behavior change due to ridesourcing (Q15). I was able to identify a fourth modality style classification – bi-style – comprised of typical drivers that use ridesourcing only for rarely or special occasions such as going out to eat or drink and/or when out of town. Table IX.I presents summary results for questions Q11, Q14, and Q15, showing the bi-modality group comprised of 49 passengers.
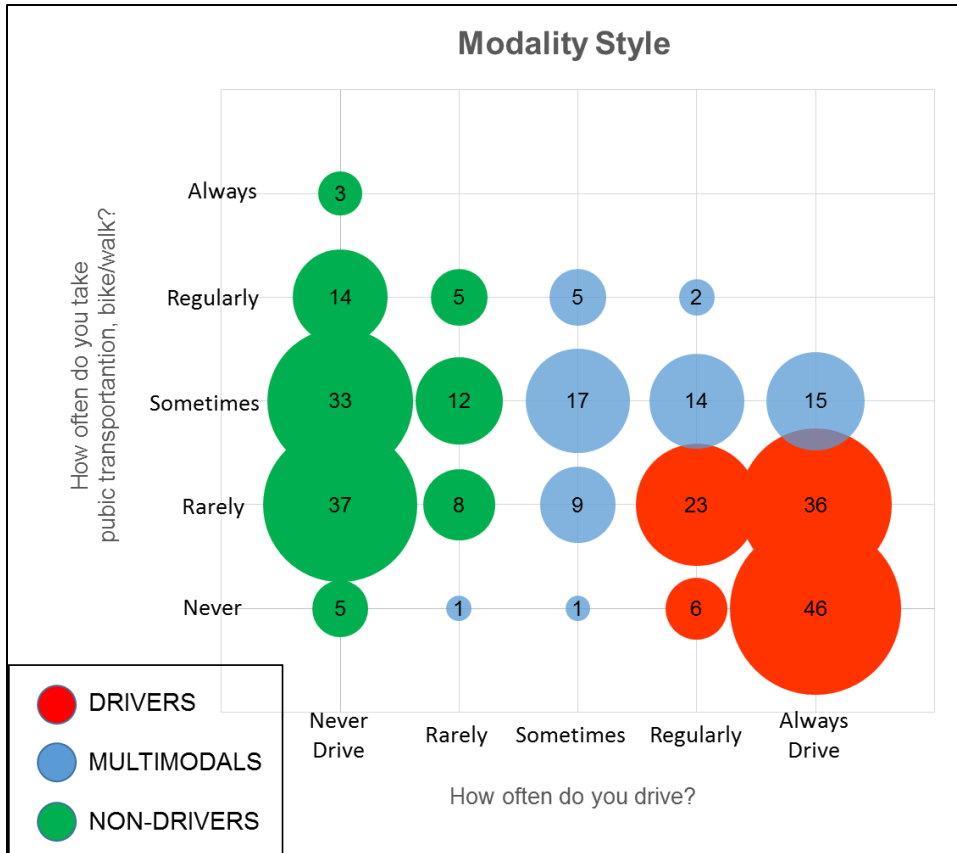
Figure IX.VI. Modality Style Classification

Table IX-I. Bi-modality Style Classification

Q11. How long have you been using ridesourcing?

This is my first week	14	4.7%
A few weeks	43	14.4%
A few months	97	32.6%
1 year or more	144	48.3%
n	298	

Q14. Typically, how often do you use ridesourcing?

	All Passengers		Modality Style: Drivers	
Never	11	3.7%	8	7.2%
Rarely (special occasions, monthly)	78	26.4%	51	45.9%
Sometimes (~ 1-2 times/week)	113	38.2%	41	36.9%
Regularly (at least 3 times/week)	67	22.6%	9	8.1%
Always (Daily)	27	9.1%	2	1.8%
n	296		111	

Q15. Have you changed your travel habits because of ridesourcing?

Yes, a lot	29	9.8%
Yes, some	93	31.3%
No	175	58.9%
n	297	

Chapter Conclusions

In this study chapter, I identified mode use profiles of ridesourcing passengers, showing that most passengers are on the "always" or "never" drive categories. Then, I investigated the magnitude of change for driving and public transportation modes to determine if the direction in which travel behavior is occurring is more or less sustainable. The data shows that most travel behavior stays unchanged, but for those changing modes, more people are replacing public transportation than driving (i.e. the magnitude of change for public transportation is more negative than the magnitude of change for driving). With regards to trip purpose, this study finds that most drivers use ridesourcing to go out for social trips, going to/from the airport, and/or when out of town with the main reasons being

"drinking alcohol" and/or "finding parking difficult". Non-drivers are using ridesourcing mostly to commute to work or go to school with the main reasons being "not having a car available", "public transportation not being available or poor service", and "time" (e.g. in a rush).

Finally, I conclude this chapter study identifying four modality style groups. The existing literature identified three classifications of ridesourcing passengers: drivers, multimodals, and non-drivers. With further analysis, I identified a fourth class, the bi-modality style, including those that vary between two or more different modality systems depending on the type of trip.

CHAPTER X

OVERALL RESULTS

The overall result section for this dissertation is divided in four main parts: results

from the driver dataset, VMT, parking, and travel behavior.

Driver Dataset

Ridesourcing Times and Distances

The overall time efficiency rate for this study, accounting for commute time at the

end of the shift, is 39.3%.

The efficiency rate in terms of WPMT versus total mileage is 59.2%. The overall

efficiency rate could be even lower since, by research design, I minimized the cruising for a

ride request, did not accept rides required long travel distances for passenger pick-up, and

used conservative commute distances at the end of shifts.

Even with this conservative rate, drivers have to travel 69 extra miles in deadheading

for every 100 miles originally from WPMT.

Ridesourcing Earnings

Including all times and distances, the gross earnings for this study equals to

$15.69/hour, which might seems like a good hourly rate, but this does not include expenses. I

estimated expenses to be between $0.28 per mile to the U.S. Federal Standard 2016 mileage

rate of $0.54 per mile, so in reality, ridesourcing drivers make between $5.38 and $10.36 per

hour, with an average of $7.94/hr (including tips).

Uber net earnings is slightly higher that Lyft earnings but completely change when

tips are taking into account. Lyft tips in net earning equates to a 29.1% increase. Uber could

easily add a tipping option on their app to allow passengers add a tip in their credit card bill if they wish; this choice would increase drivers' earnings, but Uber has thus far refused to implement this option.

VMT

Ridesourcing provides more mobility (12.2% of passengers stated that they "wouldn't have traveled") but affects the efficiency of transporting passenger versus vehicles going from a PMT/VMT efficiency of 112.3% to 60.8%.

Overall, ridesourcing increases VMT by 185%, which has significant implications for our cities in terms of congestion and environmental concerns.

If the results for this dissertation held true for the entire country, the VMT impact of ridesourcing would be around 5.5 billion extra miles per year in the U.S. We need more empirical studies that would help understand the magnitude of VMT impact.

Parking

Ridesourcing allows parking supply to decrease. At the same time, many passengers stated that parking is one of the main reasons for passengers with high drive frequency to use ridesourcing instead of driving. Continuing with this cycle of reducing parking supply will help decrease car dependency.

Travel Behavior

Based on modality style, I identified four groups of modality styles for ridesourcing users: drivers, multimodals, non-drivers, and bi-modal style based on trip purpose.

For typical drivers, ridesourcing is mostly replacing social trips (e.g. go out), to/from airport, and when out of town. Drivers stated drinking/avoid driving and parking as the main

reasons not to drive. For typical non-drivers, ridesourcing is replacing work and school trips with the main reason being that public transportation is not available.

CHAPTER XI

SUMMARY CONCLUSIONS AND FUTURE WORK

Ridesourcing has quickly become a very popular service that is successfully competing and interacting with other modes of transportation. This dissertation had several objectives in mind. First, this dissertation established a data collection methodology and gathered ridesourcing data to investigate ridesourcing impacts. Then, the dissertation measured ridesourcing efficiency in terms of times and distances (VMT and PMT), and evaluated VMT impacts of ridesourcing by analyzing before-and-after scenarios. After investigating the labor market economy for ridesourcing drivers, I investigated parking impacts and opportunities to calibrate parking generation rates and reduce car dependency. Finally, this dissertation explored travel behavior and its implications on future travel demand models.

I hope this research helps cities and transportation organizations better understand the impacts of ridesourcing on several aspects of transportation. For example, transit agencies that are contemplating removal of bus services in certain areas can use these results – in terms of ridership and PMT/VMT efficiency – to help them look at the issue in more detail. This will help inform them as to what they gain or lose in terms of replacing or connecting transit with ridesourcing. As this dissertation shows, transportation officials also need to be cautious regarding the positive and negative outcomes of ridesourcing. One of the most important results from this dissertation is the realization that ridesourcing in the current form is only more efficient in terms of transportation passengers with VMT than two other modes, taxis and if getting a ride. We might think that shifting all drivers to ridesourcing would be a positive change, but in reality, that might not be the case. For example, a driver needing to go

five miles to his/her destination would put in the transportation system five miles (5 VMT); if that same person is taking a Lyft or Uber instead, he/she would be still move five miles, but the ridesourcing driver would be adding approximately nine miles (9 VMT) to the transportation system. This is even worse if walking or bicycling are the replaced modes since such modes do not add VMT to the transportation system. Ridesourcing efficiency is even worse with shorter trips since a driver might be circulating and driving a few miles – for example 3 or 4 miles – only to be transporting a passenger for a shorter distance – for example 1 or 2 miles –. The same occurs with public transportation and carpooling, modes that are more efficient than ridesourcing.

Looking at the positive aspects, ridesourcing provides a positive utility to many costumers by increasing their mobility and/or ease of mind when it comes to avoid drinking and driving and resolving parking. Concerning parking, ridesourcing decreases the need for parking supply. At the same time, many passengers stated that parking is one of the main reasons to use ridesourcing instead of driving. Continuing this positive cycle would help decrease car dependency.

Potential positive effects into reducing VMT and increasing ridesourcing efficiency may come with newer services such as LyftLine and UberPool, which are true ridesharing platforms; thus far, these services has not been proven to be effective. Passengers that use these services are usually less car-dependent and multimodal compared to the general population. New members willing to try these service might be only doing so for two reasons; one, that the ride is way below the regular cost; and two, that the probability of finding a match during the ride is low. Academic research has mathematically proven using algorithms that on-demand high-capacity ride-sharing is doable and provides positive effects

in terms of efficiency (Alonso-Mora, Samaranayake, Wallar, Frazzoli, & Rus, 2017), but we need more research on travel behavior and social sciences to determine the willingness to share in our cities. This conversation will become more relevant with autonomous vehicles coming in the near future. The other issue with LyftLine and UberPool is that drivers make even lower wages with these services since they spent more time picking up and dropping off several customers.

This study does not come without limitations. The main limitation is the trip sample size relative to the overall number of rides these companies provide. Doing the data collection by myself is also both a limitation and an advantage. It is a limitation because I am not taking into account different driver strategies but an advantage since I was able to control the amount of driving and design the research with conservative estimations. However, we need more empirical studies like this one to gather independent datasets and help narrow down the numbers calculated in this dissertation. At the same time, the transportation sector should demand that ridesourcing companies share data in order to operate in our cities.

I plan to continue doing ridesourcing research as it relates to travel demand models. Modelers need these types of data to include newer services in their travel demand plans, as well as calibrate better inputs for newer services such as autonomous vehicles.

This research starts to fill several gaps in the literature regarding ridesourcing services. My ultimate goal is to help cities and transportation organizations better account for the impacts of technology and evolving transportation services in their policies, planning, and engineering processes. I would also hope to contribute to the conversation on how ridesourcing companies can help better achieve sustainable transportation goals including

more VMT efficiency, better interconnectivity and integration with active modes of transportation, equity, and safety for both users and drivers.

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