Title

What Makes Travelers Use Ridehailing? Exploring the Latent Constructs behind the Adoption and Frequency of Use of Ridehailing Services, and Their Impacts on the Use of Other Travel Modes

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Publication Date

2018-06-30

What Makes Travelers Use Ridehailing? Exploring the Latent Constructs behind the Adoption and Frequency of Use of Ridehailing Services, and Their Impacts on the Use of Other Travel Modes

By

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DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

Doctor of Philosophy

in

Transportation Technology & Policy

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA
DAVIS

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2018

ABSTRACT

Emerging transportation Emerging transportation services are quickly changing the way individuals travel by expanding the set of transportation alternatives available for a trip, allowing for more flexibility in travel schedules and providing access to transportation without incurring the costs of auto ownership. One of the most rapidly growing shared-mobility services are ridehailing services, such as those offered by Uber and Lyft in the U.S. market. In this dissertation, I investigate the factors affecting the adoption and frequency of ridehailing services and the impacts that these services have on different components of travel behavior using California Millennials Dataset, a rich dataset was collected in fall 2015 with a comprehensive online survey administered to a sample of 2400 California residents, including millennials (i.e. young adults born between 1981 and 1997) and members of the preceding Generation X (i.e. middle-aged adults born between 1965 and 1980).

To investigate the factors that affect the adoption of ridehailing, I estimate several models that help assess the role of individual characteristics and residential location in affecting these choices. The results of two binary logit models confirmed that highly educated, older millennials are more likely to use on-demand ride services than other groups. I also find that greater land-use mix and regional accessibility by car are associated with greater likelihood of adopting on-demand ride services. Respondents who report higher numbers of long-distance business trips and have a higher share of long-distance trips made by plane are also more likely to have used these services, as are frequent users of smartphone transportation-related apps, and those who have previously used taxi and carsharing services. Among various attitudinal factors that were investigated, individuals with stronger pro-environmental, technology-embracing, and variety-seeking attitudes are more inclined to ridehailing.

Further, I expand my analyses of the factors affecting the adoption of ridehailing through the estimation of a latent-class adoption model that captures the heterogeneity in individuals' tastes and preferences. Users of ridehailing can be grouped into three well-defined latent classes, based on their individual and household characteristics, lifestyles and stage in life. The three distinct classes are: (1) a class that is largely composed of more highly-educated, independent (i.e. who have already established their household) millennials, who has the highest adoption rate. The adoption of ridehailing services for the members of this class is influenced by the frequency of long-distance leisure and business-related trips made by non-car modes. The adoption of ridehailing among the members of this group is higher if they live in high-quality transit neighborhoods. (2) The second highest adoption rate is observed among the members of the class that is mainly composed of affluent individuals living with their families who are either dependent millennials or older members of Generation X. The frequency of use of smartphone apps and the share of long-distance leisure trips made by plane affect the adoption of ridehailing for the members of this class. The members of this class also tend to adopt ridehailing if they live in neighborhoods with higher land-use mix and if they have used taxi services within the past 12 months. The lowest adoption rate is observed among the members of the class, comprising the least affluent individuals with the lowest level of education. The members of this class are more likely to live in rural neighborhoods and they rarely use ridehailing. The adoption of ridehailing among the members of this class is affected by household income, the frequency of long-distance non-car business trip, transit accessibility as well as the use of taxi and of carsharing.

I estimate an ordered probit model with sample selection and a zero-inflated ordered probit model with correlated error terms to explore the impacts of various explanatory variables on the frequency of use of Uber/Lyft. The results show that sociodemographic variables are important predictors of service adoption but do not explain much of the variation in the frequency of use. Land use mix and activity density respectively decrease and increase the frequency of ridehailing. The results also confirm that individuals who frequently use smartphone apps (e.g. to select a route or check traffic) are more likely to adopt ridehailing and use it more often. This is also true for long-distance travelers, in particular, those who frequently travel by plane. Individuals with higher willingness to pay to reduce their travel time use ridehailing more often. Those with stronger preferences to own a personal vehicle and those with stronger concerns about the safety/security of ridehailing are less likely to be frequent users.

Finally, I conduct a number of exploratory analyses to investigate the factors that limit or encourage the use of single-user ridehailing services and the potential impacts that these services have on other modes of travel. I find that Uber/Lyft users are more responsive to waiting time and ease of arranging rides than other travelers. Both users and non-users rate their preference towards private vehicle ownership and usage as the strongest limiting factor to the use of these technology-based services. I find that the use of ridehailing tends to reduce the amount of driving made by both frequent and non-frequent users. It also substitutes for some trips that would have otherwise been made by transit or active modes, more so among frequent users, younger individuals, those who live in zero-/lower-vehicle households, and those who are more multimodal.

The findings from this dissertation provide a starting point for efforts to forecast the adoption and frequency of use of ridehailing services, improve the understanding of how ridehailing as the spearhead of other emerging trends in transportation (e.g. automation and electrification) will transform future transportation and help inform policy decisions designed to increase transportation sustainability.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to people helping me in my PhD journey and making this dissertation possible.

Without any questions, I would like to start with my advisors. Special mention goes to my advisor and mentor, Dr. Giovanni Circella, for his valuable guidance, scholarly inputs and consistent encouragement throughout my research work. Dr. Circella, thank you for your continuous support and for letting me fulfill my dream pursuing my diverse, interdisciplinary interests. Similarly, I would like to thank prof. Susan Handy, who graciously accepted to work with me when I admitted to the UC Davis in 2013. Since then, she has patiently mentored me and introduced me to the world of transportation planning and travel behavior. Thank you, Susan, and I look forward to continued collaboration in the years to come.

Thank you to the members of my doctoral dissertation committee, without whom I could not have made it this far. I have had a great fortune to have Professor Patricia Mokhtarian in my doctoral dissertation committee. I would like to thank Prof. Mokhtarian, with whom it has been an honor and a pleasure to work. I thank her for sharing her in-depth statistical modeling knowledge, and her valuable feedback on the dissertation as a whole as well as on specific papers and helping to get them in shape for publication. I also would like to express my deepest appreciation to Prof. Daniel Sperling for his encouragement and his insightful comments on the policy implications of my research.

I also gratefully acknowledge the numerous sources from which this dissertation and research have been funded, including The National Center for Sustainable Transportation (NCST) for the Dissertation Fellowship and the Student Exchange Program; California Department of Transportation and USDOT for their support of university-based research in transportation and funding the data collection; the Sustainable Technology Energy Pathways (STEPS) Program of the University of California, Davis for additional financial support for the data collection; Toyota and Nissan for their Corporate Affiliate Fellowship. I would also like to thank all the friends and colleagues at University of California, Davis and Georgia Institute of Technology who have made the process a whole lot more enjoyable and who contributed to different stage of this research project.

I also want to acknowledge the support from the staff of Institute of Transportation Studies. Specifically, Annemarie Schaaf, the Graduate Program Coordinator, for her unfailing support and her perseverance in resolving administrative and financial issues faced by the students including me. Others who supported me in my journey include Lauren Iacobucci, Helen Barr, Natalie Ruiz and UC Davis IT personnel.

Finally, thank to my amazing family, who provide me with more love, support and friendship then I would otherwise think possible. Most of all, I am fully indebted to my wife, Tina, for her unwavering love and for encouragement, and willingness to go on academic adventures with me. To my parents and my sister, whose love and guidance are with me in whatever I pursue and for being my ultimate role model.

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LIST OF ACRONYMS AND ABBREVIATIONS

AIC	Akaike's Information Criterion
ANOVA	Analysis of Variance
BART	Bay Area Rapid Transit
BIC	Bayesian Information Criterion
Caltrans	California Department of Transportation
CNT	Center for Neighborhood Technology
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
GDP	Gross Domestic Products
Gen X	Generation X
GHG	Greenhouse Gas
HH	Household
ICLV	Integrated Choice and Latent Variable
ICT	Information and Communication Technology
IPF	Iterative Proportional fitting
ML	Maximum Likelihood
MPO	Metropolitan Planning Organization
MSA	Metropolitan Statistical Areas
MTC	Metropolitan Transportation Commission
NCST	National Center for Sustainable Transportation
OPSS	Ordered Probit with Sample Selection
PCA	Principal Component Analysis
QML	Quasi-maximum likelihood
SACOG	Sacramento Area Council of Government
SacRT	Sacramento Regional Transit
SANDAG	San Diego Association of Government
SCAG	Southern California Area of Government
SFCTA	San Francisco County Transportation Agency
STEPS	The Sustainable Technology Energy Pathways
TCRP	Transit Cooperative Research Program
TNC	Transportation Network Companies
U.S.	United States
USD	United States Dollar
USDOT	United States Department of Transportation
VMD	Vehicle Miles Driven
VMT	Vehicle Miles Traveled
ZIOP	Zero-inflated Ordered Probit
ZIOPC	Zero-inflated Ordered Probit with Correlated Error terms

1. INTRODUCTION

Transportation is changing quickly. The increased availability of location data and the continuously-increasing number of smartphone applications, together with other information and communication technologies (e.g. telecommuting, e-commerce), are transforming transportation supply and demand in many ways. New technologies and reinvented business models increasingly allow separating the access to transportation services from the fixed cost of auto ownership by providing unique opportunities for the introduction and extensive deployment of a wide range of new transportation services. Among other innovations, new shared-mobility services can affect travel behavior in multiple ways, e.g. through increasing the number of available options for a trip, reducing travel uncertainty, and providing easier access to a vehicle (or a car ride) also to those individuals that live in households that do not own a car.

The range and availability of shared-mobility services are continuously evolving as the market introduces new services and related smartphone apps. As noted by Shaheen et al. (2016a), emerging mobility services can be distinguished based on their underlying type of service and business models. Table 1.1 provides a list of emerging shared-mobility services by type and the variations of these services in terms of service and business models. As shown in Table 1.1, shared-mobility services range from carsharing, including fleet-based round-trip and one-way services such as Zipcar and Car2Go, respectively, or peer-to-peer services such as Turo, to ridesharing services, including dynamic carpooling such as Carma, ridehailing services such as Uber and Lyft, microtransit services such as Via, and bikesharing. The availability of each of these new shared-mobility services varies across different cities and regions (Shaheen et al. 2016a; Hallock and Inglis 2015). Similarly, it is expected that the range and nature of these new shared services will evolve even faster with the introduction of autonomous and connected vehicles in the near future (Sperling et al. 2018).

Table 1.1– Shared-Mobility Services by Type, Service and Business Model

Service Type	**Service Model**	**Business Model**
Carsharing	• Round-trip One-way • Free floating/ Station-based	• Fleet-based (Public / Private) • Community-based • Peer-to-peer
Bikesharing/Scooter Sharing	• Round-trip/ One-way • Docked-based/ GPS-based	• Fleet-based (Public / Private) • Peer-to-peer
Dynamic Carpooling	• Vanpooling / Carpooling • Short-distance/ Long-distance • On-demand/ Pre-arranged	• Public-private Partnership • Peer-to-peer
Ridehailing	• Single-user / Pooling • On-demand/ Pre-arranged	• Private (For Hire-services) • (in some case) Subsidized by Public
Microtransit	• Fixed/ Flexible Route • On-demand/ Flexible Scheduling	• Public-private Partnership

While the proportion of total trips made with these services is still rather small, the popularity of shared-mobility is expected to increase as these services become more common, potentially causing large effects on future travel patterns. The impacts of shared-mobility services may vary significantly depending on the types of services that are available, the local context in which the services are provided, the characteristics of the users, and the differences among various segments of the population. For example, researchers have found mixed, even contradictory, results about the impact of carsharing on public transit: Firnkorn and Müller (2011) as well as Costain et al. (2012) showed that carsharing can complement the use of public transit, while Le Vine et al. (2014) observed that one-way carsharing is mainly used in place of public transportation. Similarly, researchers found that bikesharing programs may increase transit use for those living on the urban periphery, where access to public transportation by walking is limited, but decrease transit use for individuals in the urban core (Buck et al. 2013, Martin and Shaheen 2014).

Ridehailing is one of the most rapidly growing forms of shared-mobility services. These services are also known as on-demand ride services, or transportation network companies (TNCs), such as Uber and Lyft in the U.S. market, Didi Chuxing in China, Ola in India, or Grab in South Asian countries. Uber and Lyft, the major providers of these services in the U.S. market, launched their popular services UberX and Lyft Classic, which directly compete with local taxi services, in summer 2012. These services enable users to request a ride, track the progress of their drivers in real time, pay for the ride, and rate their experience using a smartphone application. None of these technology-based features had been widely available to regular taxi users before the introduction of ridehailing services. Uber and Lyft have grown tremendously over a short time, by expanding into different cities and neighborhood types of the U.S. and by diversifying their services. For example, to increase vehicle occupancy and provide more affordable rides, Uber and Lyft launched their pooled services UberPOOL and Lyft Line, respectively, in the fall of 2014. These services offer a ride to several distinct users in the same vehicle matching them based on their similar routes. They provide pooled ride services at a lower cost than conventional on-demand ride services by allowing drivers to pick up and drop off multiple passengers during the same trip. These pooling services are priced up to 50% lower, which increases their appeal to price-sensitive travelers. As of December 2017, Uber had expanded its operation to more than 700 cities (across about 80 countries). Lyft operates mainly in the U.S. market, providing rides in more than 300 cities (Shaheen et al. 2018). However, the share of pooling services in this market is still limited: both Uber and Lyft provide pooled services in about 15 cities in the U.S. market, accounting for a total of 905 million trips (as cited in Shaheen et al. 2018).

The availability and popularity of ridehailing services are quickly growing in different geographic areas and neighborhood types, but evidence on adoption rates, factors affecting their use, and the potential effects of these services on the use of other modes is still limited. Ridehailing services can (a) provide flexible alternatives to driving; (b) offer first- and last-mile access to public transportation, increasing public transportation efficiency and convenience; (c) provide a ride home outside the hours of operation of public transit, or at a time in which traveling by transit and/or accessing/egressing transit stops may be considered unsafe; and (d) increase the attractiveness and feasibility of living in a zero-/lower vehicle household (Hallock and Inglis 2015, Shaheen et al. 2018, Taylor et al. 2015, Circella et al. 2016a; Circella et al. 2018). On the other hand, ridehailing may generate additional trips, inducing additional demand for travel (as a result of the increased transportation accessibility and reduced travel costs) and reduce public transit ridership especially in places where the quality of public transit services is low.

The goal of this dissertation is to investigate the factors affecting the use of ridehailing and explore the different rationales of individual users for adoption, the circumstances under which travelers use these services more often, the factors that limit the use of these services, and the impacts that the use of these services has on other components of travel behavior. I analyze data from the California Millennials Dataset, a rich dataset collected in fall 2015 as the first round of data collection in a panel study investigating emerging travel patterns and adoption of technology in California. In this first round of data collection, a comprehensive online survey was designed and administered to a sample of more than 2400 residents of California, including both members of the millennial generation (18 to 34 years old in 2015) and the previous Generation X (middle-age adults, 35 to 50 years old in 2015). The survey collected a wealth of information that focused, among other topics, on the awareness, adoption, and frequency of use of modern technologies and new shared-mobility services, and many factors that are potentially behind their use.

1.1 Conceptual Model

Various theoretical frameworks can explain the adoption and frequency of use of shared-mobility services, including the Theory of Planned Behavior, the Theory of Reasoned Action, the Technology Acceptance Model, and Innovation Diffusion Theory. Adoption of new shared-mobility services is not a simple decision process and is contingent on a series of circumstances and other decisions made at the individual and household levels over various time horizons. For example, the use of ridehailing could be conditional on long-term decisions such as whether or not to own a car or acquire a driver's license, as well as even longer-term decisions about where to live, work, and the choice of individual lifestyles.

Travel-related choices reflect complex decision processes that have been studied from the perspective of different disciplines, including economics, sociology, geography, and psychology. Researchers have addressed the complexity of travel behaviors mainly by applying three main approaches: (1) Rationalist approaches, where analysts assume that travelers behave in accordance with the theory of rational behavior and choose the alternative that has the highest utility in their choice set; (2) Socio-geographical approaches, which assume that demand for traveling is derived from the need to participate in an activity that is distributed in time and space; (3) Socio-psychological approaches, which explain travel related decisions based on an individual’s attitudes and preferences (Witte et al. 2014). According to Handy (2005), socio-geographical approaches describe travel behavior’s mechanisms, whereas socio-psychological approaches determine the factors influencing travel behavior. The integration of various theories becomes more important as the complexity in individual’s decision-making process increases. For example, El Zarwi et al. (2017) estimated a latent-class choice model to identify different classes of new shared-mobility adopters based on Innovation Diffusion Theory and integrated it with a network effect model (destination choice model) to quantify the network impacts associated with the adoption of these services. The authors later used this framework to forecast the adoption of one-way carsharing using time-series data for a major city in the United States.

In this study, I follow the theoretical framework proposed by Van Acker et al. (2010), who outlined transportation-related decision-making mechanisms as a series of hierarchical decisions made by individuals to meet their needs and preferred lifestyles. In another word, this theory of travel behavior assumes that travel behavior is derived from locational and activity behavior, while concepts such as lifestyles, perceptions, attitudes, preferences, and habits directly mediate/influence travel behavior. In this framework, lifestyle is considered a higher-level orientation that impacts all other individual’s decisions and choices, including mode choice and the decision as to whether to use certain transportation services.

According to social scientists, lifestyle is a higher-level orientation that impacts individual’s decisions and choices. In 1984, Bourdieu (as cited in Van Acker et al. 2010) defined lifestyle as a pattern of behavior that demonstrates the social position of the individuals, which can be measured by the amount and composition of capital (e.g. economic, cultural, and social capitals). Socio-economic variables were traditionally used to define individuals’ lifestyle; however, this relationship is influenced by intermediate variables such as opportunities and constraints provided by time budget, income, cognitive skills and status consideration (Van Acker et al. 2010). Ganzeboom (1988, as cited in Van Acker et al. 2010) used a three-dimensional indicator to define individual lifestyles, including economic dimension, cultural dimension and stage in life. The author also noted that lifestyles can influence beliefs, attitudes and interests (specific to individuals) and can also be expressed by observable patterns in individual's behaviors. Lifestyles are manifested in individual behavior including his/her locational behavior, activity behavior and travel behavior (Van Acker et al. 2010). Kitamura (2009) defined lifestyles as a measure of time use and activity patterns as well as values and behavioral orientation. Based on the former definition, individuals' lifestyles may change in response to changes in the environment or stage in life, while a lifestyle as a behavioral orientation may influence this adaptation process. "Lifestyle" as a value and behavioral orientation explains the motivation behind individual's decision-making mechanisms.

The impact of lifestyles on travel choices is irrefutable. Salomon and Ben-Akiva (1983) quantified the impact of lifestyles on travel behavior for the first time, defining lifestyle as "a pattern of behavior under constrained resources which conforms to the orientations an individual has toward three major life decisions" (Salomon and Ben-Akiva 1983, p. 624). In their study, the authors defined the three major life decisions: the formation of the household, participation in the labor force, and orientation toward leisure. Since then, a wide range of studies has quantified the impact of individuals' lifestyles on different components of travel behavior, including mode choice (Kitamura et al. 1997; Lanzendorf 2002; Vredin Johansson et al. 2006; Vij et al. 2013), vehicle type choice (Choo and Mokhtarian 2004; Bolduc et al. 2008), residential location (Walker and Li 2007), and activity participation (Ory and Mokhtarian 2009).

Even though the literature is converging to a formal definition of lifestyle either as a typology of behavior or as latent factors motivating behavioral patterns, researchers have not reached consensus, yet, on the methods that can be employed to measure individuals' lifestyles. Van Acker (2015) illustrated three major approaches that have been used to measure lifestyles. The first approach is known as the *socioeconomic and demographic lifestyle* approach, where various objective socioeconomic and demographic characteristics as well as the stage of life are used to characterize individual or household lifestyles. In the second approach, researchers characterized lifestyles based on attitudes toward various topics (most importantly attitudes toward family, work and leisure), personality traits and related motives. This approach is known as the *sociographic* approach. Van Acker described the third approach, the *mechanistic lifestyle* approach, as a method which focuses on individual behavioral patterns. In this study, I characterize individual lifestyles based on their socioeconomic and demographic attributes, using Ganzeboom's three-dimensional indicators (1988, as cited in Van Acker et al. 2010), which measure an individual's economic, cultural and stage-in-life dimensions.

In addition to traditional factors that affect travel behavior, such as sociodemographic variables, characteristics of the built environment, and alternative-specific attributes (e.g. level of service, in the case of mode choice), other complex unobserved factors may impact an individual's transportation-related decisions. In other words, the process by which individuals decide about transportation-related choices is not observable but may be explained by variables beyond tradition modal and individual attributes. McFadden (2001) and Ben-Akiva et al. (2002) argued that traditional choice models should be expanded to incorporate the other important factors that influence the decision-making process, including perceptions, information processing, cognitive processes, external constraints, prior experiences, motivations, attitudes, and preferences.

This theory of travel behavior classifies these influential factors (mediators) as reasoned and unreasoned forces. Using the Theory of Planned Behavior, the Theory of Reasoned Action, and the Theory of Repeated Behavior, Van Acker et al (2010) showed that initial behavior depends on relevant attitudes, perceptions and beliefs (reasoned influence), while repeated behaviors are mainly influenced by habits rather than attitudes (unreasoned influence). In this context, perceptions refer to the way urban form, activity, and travel characteristics are considered, whereas attitudes include an evaluation of these characteristics. Van Acker et al. (2010) also argued that reasoned and unreasoned influences can be affected by individual's lifestyle; for example, an adventurous lifestyle is associated with more unreasoned behavior, whereas behaviors of family-oriented lifestyle can be explained more by reasoned influences.

A valid criticism of this theory is the lack of association between reasoned and unreasoned influences (for example, a person who habitually drives may express stronger pro-automobile attitudes and preferences), which partially could be explained by the trade-off between attitudes and habits in the prediction of travel behavior (Bamberg et al. 2003). In response to this criticism, van Acker et al. (2010) noted that their theory of travel behavior is designed to explain an individual's daily travel behavior, and not the relationships between reasoned and unreasoned influences. In addition, habitual and spontaneous behaviors are not only influenced by the individual's lifestyle, but also by the locational, travel and activity opportunities. As an illustration, a person who lives in a high-density area with high level of transit accessibility may travel more spontaneously by public transportation compared to a person who lives in a suburban area with lower level of transit accessibility.

As discussed by Sallis et al. (2006), a transdisciplinary approach requires multilevel research (and interventions) to combine the concepts and methods of multiple disciplines operating at different levels of the system. According to the ecological model, employed in several public health studies, a wide range of influences should be taken into account at multiple levels (settings) to understand the relationship between different factors affecting individual's travel behavior (e.g. personal, inter-personal, built environment). The theory of travel behavior deals with these multiple levels of analysis, ranging from micro, to intermediate, to macro levels, by placing the model within (1) the social-environment/interpersonal level, which refers to the influence of the social network of family, friends and colleagues on individual's behavior; and (2) the spatial-environment, which refers to the community level of influence such as neighborhood/built environment characteristics.

The conceptual model that is used for this research is adapted from the Van Acker et al theory of travel behavior (as shown in Figure 1.1). As shown in Figure 1.1, I define lifestyles based on the *socioeconomic and demographic lifestyle* approach, using the group of variables proposed by Ganzeboom's, including an individual's economic, cultural and stage in life dimensions.

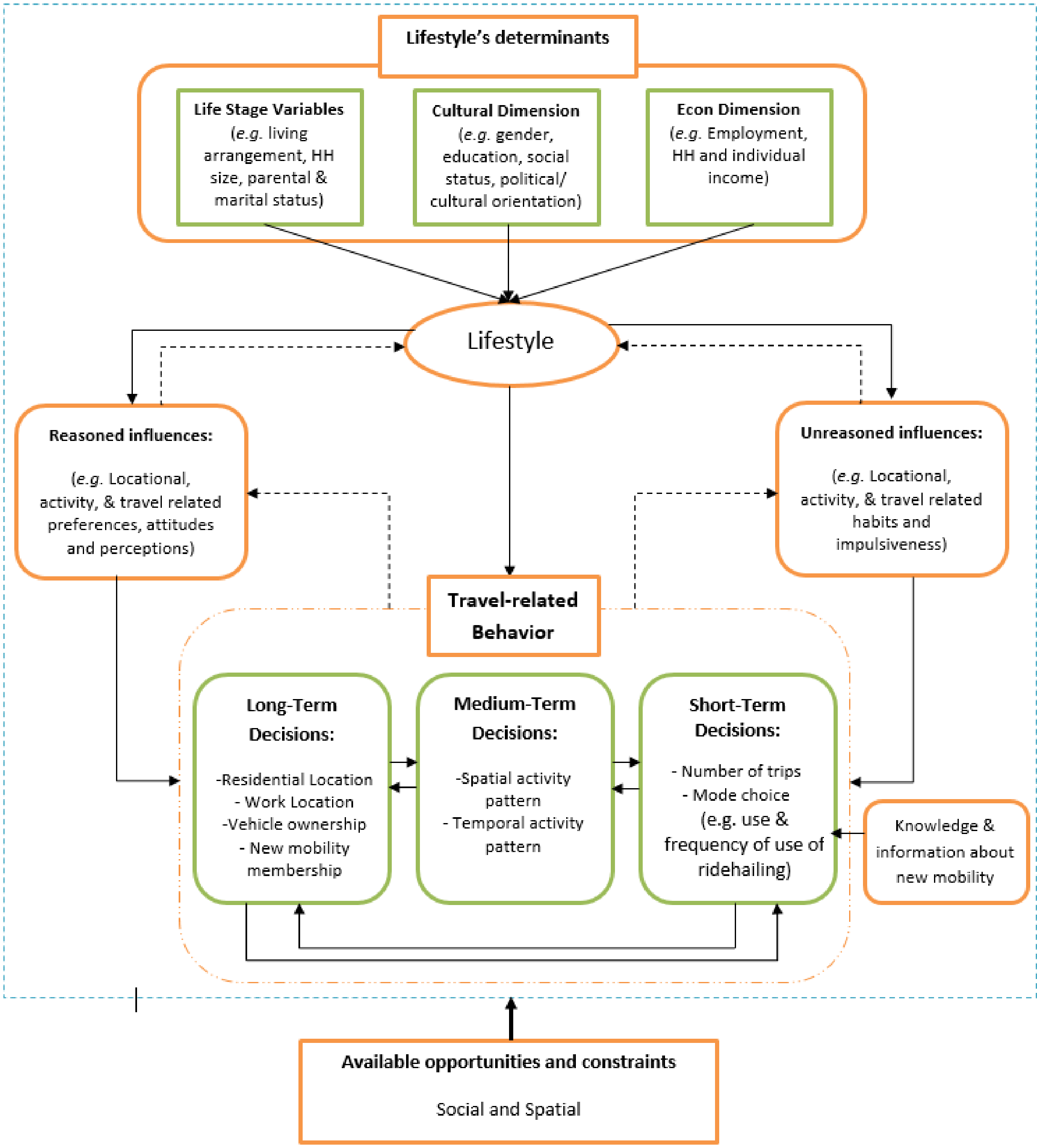

Figure 1.1 – Conceptual Framework (Source: Adapted from the Theory of Travel Behavior, van Acker et al. 2010)

1.2 Outline

This dissertation is organized around four self-contained chapters (Chapters 3 to 6), which are tailored to address questions about adoption, frequency of use, and the potential impacts of ridehailing services on other components of travel behavior. Chapter 3 and Chapter 4 address (1) How are shared-mobility services (including carsharing, ridehailing and bikesharing) used in California? (2) What factors drive the use of ridehailing services? and (3) Under what circumstances are individuals are more likely to use Uber and Lyft?

In Chapter 5, I answer the following questions: (1) How does the frequency of use of ridehailing vary across different segments of the population? (2) Which built environment characteristics have the highest impact on the use of ridehailing? and (3) Under what circumstances do millennials and the members of the preceding Generation X use Uber/Lyft more often? This is followed by answers to questions about the factors limiting/encouraging the use of ridehailing services, and the impacts of these services on other components of travel behavior in Chapter 6.

Since all four chapters are about ridehailing services, I aggregate and discuss the most recent literature about these services in greater depth and breadth in Chapter 2. Additionally, I provide an overall conclusion and discuss the key findings and the policy implications of the four chapters as cohesive whole in Chapter 7.

2. LITERATURE REVIEW

The transportation system in the United States as well as other countries is going through an era of rapid transformation, including the disruption of long-standing patterns and the emergence of new ones. Total vehicle mile traveled (VMT) in the U.S. and other developed countries at least temporarily "peaked" and began to decline in the 2000s before VMT growth started to recover around 2013 to reach new record highs between 2016 and 2018. This flattening of VMT growth, sometimes referred to as "peak car," and the factors affecting it have been discussed in many previous publications (e.g. Garceau et al. 2014; Circella et al. 2016b; Goodwin and Van Dender 2013; Kuhnimhof et al. 2013; McDonald 2015; Bastian et al. 2016; Rohr et al. 2017). Sivak (2014) studied changes in vehicle ownership level in the U.S. between 2005 and 2012 and showed that the percentage of zero-vehicle households increased from 8.7% to 9.2% during this period, even though the total number of trips by private vehicle in the country continued to rise. The author further expanded this study by looking at the variation in this proportion among the 30 largest U.S. cities and found that the percentage of zero-vehicle households increased in 21 of the 30 studied cities (Sivak 2014). Despite the continued reliance on private cars, at least some segments of the population are apparently becoming more multimodal (Buehler and Hamre 2014). For example, Rohr et al. (2017) noted that the rate of VMT per driver dropped much more among millennials during the period 2001-2009, while only a modest change was observed for the other age groups in the same period.

The combination of information and communication technology (ICT) and the so-called sharing and/or gig economy has contributed to the emergence of new transportation services, (Shaheen et al. 2016b) and has influenced individual travel pattern. Modern technologies increase the success rate and the potential market for emerging transportation services by improving the convenience of arranging travel or making a reservation, providing online pay-for-service methods, collecting and disseminating online customer feedback, and offering better platforms for the efficient and dynamic management of resources (Taylor et al. 2015). People are more open to the use of ICT and the adoption of technology-enabled transportation alternatives, such as new shared-mobility services. These disruptive trends, including the increase in the adoption of ICT and new shared-mobility services, might also be confounded with other factors affecting travel patterns, including generational differences, changes in household compositions and lifestyles, and the temporary changes associated with the recession that began in 2008. For example, it is not clear whether the increase in the percentage of zero-vehicle households will slow or even reverse now that the economic recession has ended, or whether other factors will sustain it.

The rapid growth in the use of ridehailing services exemplifies these factors. Uber and Lyft, the two largest providers of ridehailing service in the U.S. market, launched their so-far most popular offerings, UberX and Lyft Classic, in direct competition with local taxi services, in July 2012. Didi, Grab, and Ola are the other major providers of ridehailing services serving mainly the markets in China, South Asian countries, and India, respectively. While ridehailing services are similar to traditional taxicabs with respect to their cost schemes and vehicle miles traveled per trip (Schaller 2017), their attractions mean they constitute another (appealing) choice for travelers (Taylor et al. 2015). They are already transforming transportation by separating access to transportation (and automobility) from the fixed cost of auto ownership and increasing the attractiveness and feasibility of living in a zero-/lower vehicle household.

Uber and Lyft (and other similar app-based operators) have grown tremendously over a short time, by expanding into different areas of the U.S. and diversifying services (including introducing shared/pooled ridehailing services such as UberPOOL and Lyft Line). As of November 2017, Uber operated in more than 700 cities (expanded into about 80 countries); Lyft operates mainly in the U.S. market, providing rides in more than 300 cities (Shaheen et al. 2018). As the popularity and availability of ridehailing services increases, their impacts on different components of travel behaviors becomes less negligible: A recent study in San Francisco found that Uber and Lyft served 15% (170,000 trips per day) of all trips inside the city on a typical weekday (SFCTA 2017), accounting for 20% of intra-city vehicle miles traveled (VMT) and 6.5% of total VMT including both intra- and inter-city trips. The role of ridehailing services will likely increase as these services gain in popularity in smaller cities and suburban neighborhoods (Wang 2017) and as society transitions toward a future dominated by *autonomous vehicles* and *mobility as a service*. Transportation researchers so far have had limited ability to assess the factors affecting the use of these services and their impacts, mainly due to a dearth of data about the users themselves and the way they use ridehailing, as well as the high level of uncertainty over the evolution and eventual maturation of these services. Differences in the local contexts in which these services are provided add to the complexity.

To date, knowledge of the characteristics of the users of ridehailing services and the potential impacts that these services have on other components of travel behavior and other travel modes is limited. One of the primary limitations on research in this area is the lack of reliable operator data on users, scale and performance of ridehailing services. Much of the existing knowledge about these services is based on descriptive statistics, disseminated by the popular media. Overall, the behavioral studies about ridehailing services follow one of these two distinct paths: (1) studies that investigate the factors associated with the adoption and frequency of the use of on-demand ride services; and (2) studies that discuss the potential impacts of on-demand ride services on components of travel behavior, such as mode choice, vehicle ownership, and activity patterns.

Adoption and frequency of use of ridehailing services vary significantly among different segments of the population: previous research about the early adopters of other shared-mobility services that were introduced to the market earlier than ridehailing services (services such as carsharing, bikesharing) showed that early adopters of these new shared-mobility services tended to be younger, highly-educated and multimodal individuals who lived in urban neighborhoods and in households with a lower-than-average number of vehicles per household driver (Cervero 2003; Katzev 2003; Buck et al. 2013; Circella et al. 2016a; Shaheen et al. 2012).

In a study of users of ridehailing services, Rayle et al. (2014) found that the majority of Uber and Lyft users are young adults who have a rather high level of education, own fewer vehicles and travel more frequently with companions compared to older cohorts. As discussed in Chapter 3 (and in Alemi et al. 2017), I observed similar trends among the early adopters of ridehailing services and showed that the adoption of ridehailing is higher among better-educated and higher income older millennials (i.e. individuals between the age of 25-34 years old at the time of the data collection in 2015) who predominantly live in urban neighborhoods. These findings are also confirmed in other related studies including Circella et al. (2018), Taylor et al. (2015), Feigon and Murphy (2016), Feigon and Murphy (2018), Clewlow and Mishra (2017), and PEW research center (2016). Younger people (i.e., millennials) use new shared-mobility services more frequently than older adults, possibly due to their familiarity with ICT applications in general, and/or because of differences from older cohorts in terms of travel behavior and residential location. In addition, millennials own fewer cars, drive less, and use non-motorized means of transportation more often (Blumenberg et al. 2016; Kuhnimhof et al. 2012; Frändberg and Vilhelmson 2011) compared to older segments of the population. These differences in travel behavior might be the result of a combination of differences in lifestyles, attitudes, and familiarity with modern technologies (as suggested by McDonald, 2015), as well as the recessionary economic conditions which tended to hit early-career millennials harder than older cohorts. The fact that millennials more often live in central urban areas with mixed land uses and housing types (BRS 2013) could influence their likelihood of using shared-mobility services.

Among other socio-economics and demographic factors, I found that individuals who work and study have the highest adoption rates compared to non-workers and those who either only work or only study (Alemi et al. 2017). Higher adoption levels were also found among individuals who live in households without kids, and among individuals of non-Hispanic origin. In Chapter 4, I employed a latent class choice model to better understand the factors affecting the use of ridehailing services, thorough controlling for individuals taste heterogeneity and variations (see Alemi et al. under review, for more details). In this chapter, I identified three latent classes based on individuals' lifestyles and their stage in life, and showed that the class that is largely composed of higher educated independent millennials (i.e. millennials who have already established their own households) has the highest adoption rate, while adoption of these services reaches to its lowest point among the members of the class that is largely composed of the least affluent individuals with the lowest level of education.

Adoption and frequency of use of ridehailing services are also higher among business travelers: according to Certify, a travel expense management company, the use of ridehailing services has surpassed the use of taxicabs among business travelers in the second quarter of 2015 (Certify 2015, as cited in Taylor et al. 2015). The main reasons for this change could be the relatively lower fares of these services and their better availability compared to regular taxi services. Business travelers usually have higher willingness to pay for door-to-door transportation services and are more likely to be in situations where they have limited access to their own car (when away from home) than other groups of travelers.

The role of the built environment on the adoption and frequency of ridehailing services is undeniable. Among various built environment characteristics, neighborhood type, land use mix, regional auto accessibility and public transit availability (and quality) can affect the adoption of ridehailing (Alemi et al. 2017; Alemi et al. under review; Rayle et al. 2014; Circella et al. 2018). With respect to personal traits, Alemi et al. (2017) showed that those having greater familiarity with and use of modern technologies in connection with transportation (such as the use of smartphone apps for transportation purposes, and the use of carsharing), frequent long-distance trips (for both business and leisure purposes) and stronger *pro-environmental policies*, *technology embracing*, and *variety seeking* attitudes (Alemi et al. 2017) are more likely to adopt these services.

Future adoption rates and the use of ridehailing will likely depend on a number of factors, including the availability and accessibility of these services and other travel alternatives, individuals' perceptions of convenience and reliability, and residential location choices. Another important question would be the eventual permanence of the observed travel patterns: will current users continue to use these services with the same frequency as they transition to later stages of life and as the rise in the population of urban millennials slows down and millennials eventually begin to move back to the suburbs (Myer 2016)? In order to help answer this and other related questions, it is important to better understand variations in the factors that affect the travel decisions of different population segments and better incorporate individual taste heterogeneity into travel demand forecasting models.

Few studies have investigated the factors affecting the frequency of using ridehailing services. A recent study by the Pew Research Center (2016) found that out of the 15% of respondents in their sample who reported that they have used ridehailing (N=4,787), only 3% and 12% reported that they have used these services on a daily and weekly basis, respectively. The research confirmed that younger adults tend to use on-demand ride services more frequently. In another study, Feigon and Murphy (2016) showed that the most frequent users of ridehailing live in middle-income households (annual incomes of $50 to 75K). Both studies noted that frequent Uber/Lyft users are more likely to live in households with a lower-than-average number of vehicles per driver and tend to rely more on other means of transportation, including public transit or active modes. However, the extent to which the adoption of ridehailing *causes* such changes is not clear. This leads to the second category of studies, which investigates the impacts that ridehailing services may have on different components of travel behavior.

Research on the overall impacts that ridehailing services have on other components of travel behavior is growing but is still preliminary in nature mainly due to the lack of longitudinal data or robust analytical approaches that capture the causal relationships among the use of ridehailing services and different components of travel behavior. Most of the existing studies in this area, to date, are based on either descriptive statistics of the self-reported behavioral changes, or other coarse proxy variables such as Google trend data that is used to measure the intensity of use of Uber/Lyft. Further, many of the existing studies report the aggregated results and ignore the potential heterogeneity associated with use and the impacts of ridehailing services on other means of transportation without controlling for the effects of various confounders/covariates. Other relevant issues with these studies are the use of convenience sampling approaches or non-representative samples (e.g. samples from large metropolitans leaving out those living in smaller metro areas or suburban/rural neighborhoods). Thus, it is often difficult to extrapolate the findings from these studies to generalize them to the entire population. Additional difficulties associated with these studies include the eventual maturation of ridehailing services and their impacts over time (longer term). Despite these limitations, the current literature sheds some light on the effects of ridehailing on different components of travel behavior.

Among different Uber/Lyft impacts, ridehailing may affect activity patterns, mode choice, vehicle miles traveled, and vehicle ownership. Recent studies show that the impact of ridehailing services on other means of transportation varies based on the type of services available, the local context, and the characteristics of the users (Taylor et al. 2015; Circella et al. 2016a). For example, Rayle et al. (2014) indicated that about 40% of Uber/Lyft users in San Francisco reported that they reduced their driving due to the adoption of ridehailing services. In previous related research based on the analysis of the same dataset that is used for the analysis presented in this dissertation, Alemi et al. (2017) showed that about 30% and 50% of both millennials and Generation X would have driven a car and would have taken a taxi, respectively, in the absence of Uber/Lyft. Another example is the natural experiment in Austin, Texas, imposed by the temporary halting of Uber and Lyft, which revealed similar patterns: due to the suspension of Uber/Lyft services in Austin during 2016 about 80% of Uber/Lyft users reported that they replaced their Uber/Lyft trips by personal vehicles or other ridehailing services provided by other local/regional companies (Hampshire et al. 2017).

Although ridehailing is an attractive alternative to driving (at least for some trip purposes), the extent to which ridehailing can affect Vehicle Miles Traveled (VMT) is not yet clear. Whether or not ridesharing adds to VMT depends on the balance of competing forces. On one hand, these services divert non-driving trips to driving mode, add new types of VMT which is known as dead-head. On the other hand, these services reduce personal vehicle dependency and cruising for parking. Henao (2017) evaluated the changes in total VMT by providing a ride to more than 300 Uber and Lyft riders in Denver, Colorado. The author found that total VMT can increase by as much as 85%, accounting for all factors affecting the total VMT, including the dead-heads and the potential substitution or complementary effects associated with the use of this mode. Similarly, Schaller (2017) reported that the use of Uber/Lyft has contributed to a 3.5% increase in VMT citywide in New York and a 7% increase in VMT in Manhattan, western Queens, and Western Brooklyn in 2016.

Depending on local circumstances, ridehailing users may use the services as a substitute for or as a complement to the use of public transit, a million-dollar question that has received much attention from the media and the public. Ridehailing may increase the use of transit services by solving the first/last-mile issue and also by providing a ride during hours when transit services operate infrequently, if at all (Circella et al. 2016a; Taylor et al. 2016). Researchers from the Shared-Use Mobility Center found that frequent Uber/Lyft users are more likely to be multimodal and use public transit more often, possibly due to the correlation of both behaviors with other intermediate variables such as low car ownership or a residential location in a more accessible location (Feigon and Murphy 2016). The same study reported that the majority of Uber/Lyft trips are made between 10 pm to 4 am, when public transit runs very infrequently, suggesting a complementary effect is at work (Feigon and Murphy 2016). In another study, Hall et al. (2017) modeled the differences in transit ridership before and after Uber's entry for 24 month-window and concluded that when Uber arrives in Metropolitan Statistical Areas (MSAs) transit ridership does not change that much, but as this service becomes more common transit ridership increases. The authors showed that this complementary effect varies by the population lives in an MSA, type of transit service, and the transit pre-existing ridership.

At the other extreme of the spectrum, recent drops in public transit ridership may signal that TNCs have replaced some trips that would have been otherwise made by public transit. For example, the Bay Area Rapid Transit (BART) system lost about 6.5% and 4.5% of riders to San Francisco and Oakland airports, respectively, over the past two years, while Uber and Lyft ridership to these airports increased substantially during that period (Cabanatuan, 2017). The Sacramento Regional Transit (SacRT) system is another example of a transit service that continuously loses ridership, while (not coincidentally) the number of drivers of on-demand ride service companies continues to increase in this area (Bizjak 2017). Rayle et al. (2016) and Henao (2017) reported, respectively, that about 30% and 22% of Uber/Lyft users would have traveled by transit if these services had not been available for the last trip that they made with these services. As discussed in Chapter 3, I analyzed this substitution pattern by age group and found that the magnitude of the substitution effect is more than double among millennials compared to older cohorts, confirming that this multimodal generation is expanding its mobility choice set (Alemi et al. 2017). It should be noted, though, that millennials, on average, use public transit more often than older adults (therefore, they have more space to make this type of adjustments).

Babar and Burtch (2017) and Clewlow and Mishra (2017) looked at the impact of ridehailing on public transit by type of service. Babar and Burtch (2017) classified transit services by their right of way and the distance of each type of service and then evaluated the impact of Uber's entry across time and locations. The authors found that Uber's entry is associated with a 1.05% decline in the use of city bus (a short-haul service that share the right of way with other motorized mode), a 2.59% increase in the use of subway (a short-haul service with its own right of way), and a 7.24% growth in the use of commuter rail (a long-haul service with its own right of way). Similarly, Clewlow and Mishra (2017) showed that ridehailing tends to substitute for 6% and 3% of the trips that would have been otherwise made by bus and light rail, respectively, and tends to increase the use of commuter rail by 3%. Among other factors, the quality of public transit services, total travel time (including both in vehicle travel time and waiting time) and the reliability of ridehailing services seem to fuel this substitution/complementary pattern (Feigon and Murphy 2018; Babar and Burtch 2017).

Manville et al. (2018) analyzed the factors that affect the decline in transit ridership in Southern California Area of Government (SCAG) region and found that the relationship between ridehailing and transit use is far from conclusive. The authors concluded that ridehailing services do not appear to be a major contributing factor to transit ridership decline in the SCAG region, simply due to the timing (the decline in per capita transit use started in 2007, while ridehailing services began serving the SCAG region in large way in 2012), the cost of services compared to transit services, and substantial differences between the profile of ridehailing users and those who use public transit frequently. Another clue is the pattern of using ridehailing services: according to Transit Cooperative Research Program (TCRP) report 195 (2018) and TCRP report 188 (2016) the heaviest use of ridehailing services across the six main U.S. metropolitans (including Chicago, Los Angeles, San Francisco, Seattle, Nashville, and Washington) took place during evening hours and on weekends when transit operates infrequently.

Uber/Lyft are used for shorter trips. Data from ridehailing operators in five U.S. metro showed that average Uber/Lyft trips are between 2-4 miles (Feigon and Murphy 2018), confirming the potential impacts that ridehailing services may have on non-motorized mode (i.e. walking and biking). Little is known about the impact of this door-to-door service on walking and biking, but it is expected that Uber/Lyft affect this mode in both directions. As discussed in Chapter 3 and Alemi et al. (2017), I showed that about 25% of millennials and 12% of Gen Xers who used ridehailing services would have walked or biked in the absence of these services. The same study reported that the use of ridehailing services can also increase biking and walking for some individuals, but in much smaller magnitude. Similarly, Henao showed that out of 311 respondents about 12% of them would have walked or biked if Uber/Lyft had not been available for their last trip by these services. In another study, Hampshire et al. (2017) found that the suspension of Uber/Lyft led to a small increase (about 2.5%) in the use of non-motorized modes, suggesting the substitution effect of ridehailing on walking and biking is prevalent.

Evidence suggests that ridehailing affects vehicle ownership (a medium-long term decision that household members made). A recent Reuters/Ipsos opinion poll revealed that about 10% of the Uber/Lyft users plan to dispose of their vehicles and turn to ridehailing services as their primary means of travel (Henderson 2017). Hampshire et al. (2017) found that about 17% of Uber/Lyft users either purchased a vehicle or were seriously considering purchasing a vehicle due to the suspension of Uber/Lyft in Austin, Texas. Decisions about changes in the level of vehicle ownership are complex and can emerge from a range of factors and circumstances (Clark et al. 2016), including major life events, residential location, attitudes toward a car (instrument vs. affective attitudes), disrupting technologies and trends (e.g. shared-mobility, telecommuting, and use of social media), individuals lifestyle, differences between current and desired level of car ownership as well as other exogenous stimuli (e.g. habits and changes in the cost of vehicle ownership). Cost is also important. A recent study showed that the use of ridehailing, which on average costs about $2 per miles (Walker and Johnson 2016), would be economically preferable to own a vehicle for about 25% of Americans if they account for the true cost of vehicle ownership (Davidson and Webber 2017). Experts expect a sharp increase in this percentage as the cost of ridehailing services decreases in a future dominated by autonomous vehicles (to less than $1 per mile).

None of the studies above could explore (let alone, confirm) the causal relationships among the use of on-demand ride services and vehicle ownership and different components of travel behavior, including travel multimodality, vehicle ownership, and VMT. Further, the extent to which the adoption of ridehailing services *causes* an increase or decrease in the use of other means of transportation in particular, transit and/or non-motorized mode, is not yet clear. Studies to date leave open the possibility that both of those conditions are caused by other variables such as residential location, age/stage in lifecycle, or vehicle ownership. Longitudinal data would provide a unique opportunity to study the impacts of ridehailing and the maturation of this service as well as other emerging trends, and would provide a unique opportunity to disentangle the complex relationships behind the formation of travel behavior over time (e.g. modifications in the use of shared-mobility and their impacts on vehicle ownership) among the various segments of the population. Further, the potential changes of ridehailing services on different components of travel behavior and vehicle ownership are likely to accelerate with the introduction of new services, such as pooled ridehailing. For example, UberPOOL/Lyft Line may draw some riders from transit if their fares fall low enough compared to transit fares. The introduction of autonomous vehicles will almost certainly lead to other substantial changes: a recent study by the Boston Consulting Group (2017) suggested that about 25% of miles driven by private vehicles in the U.S. could be replaced by 2030 by shared autonomous vehicles as this mode will offer similar transportation characteristics at the lowest-cost in larger cities.

Finally, there is no doubt that the changes in total VMT and individual travel behavior (from auto-ownership to modal shift) can create a number of societal and economic challenges (e.g. expedite gentrification and dividedness) as well as opportunities (e.g. improve equity, and decrease traffic fatalities) and can amplify or attenuate various negative transportation-related externalities, including traffic congestion, greenhouse gas emissions, and cruising for parking. For example, Henao (2017) reported that about 19.5% of Uber/Lyft riders used ridehailing to avoid the difficulty of searching and paying for parking. The largest impact of ridehailing on parking is expected to occur at event centers (e.g. stadium, concert), airports, and dense urban neighborhoods, where parking costs and search time become substantially prohibitive. Indeed, Cortright (2016) showed that the growth in the use of Uber/Lyft is highly correlated with higher parking rates. A reduction in VMT associated with parking and cruising can potentially affect traffic congestion and the associated emissions. On the other hand, the induced demand for traveling, the cruising of vacant ridehailing vehicles or their occupancy of a parking space while waiting for a passenger can generate additional demand and worsen traffic conditions. More research is required to better understand the impact of ridehailing services on traffic congestion and parking.

3. WHAT INFLUENCES TRAVELERS TO USE UBER/LYFT? EXPLORING THE FACTORS AFFECTING THE ADOPTION OF RIDEHAILING SERVICES IN CALIFORNIA?

3.1 Abstract

On-demand ride services, such as those offered by Uber and Lyft, are transforming transportation supply and demand in many ways. As the popularity and visibility of Uber/Lyft grow, an understanding of the factors affecting the use of these services becomes more important. In this chapter, I investigate the factors affecting the adoption of on-demand ride services among millennials (i.e. young adults born between 1981 and 1997), and members of the preceding Generation X (i.e. middle-aged adults born between 1965 and 1980) in California. I estimate binary logit models of the adoption of Uber/Lyft with and without the inclusion of attitudinal variables, using the California Millennials Dataset (N = 1975). The results are consistent across models: I find that highly educated, older millennials are more likely to use on-demand ride services than other groups. I also find that greater land-use mix and regional accessibility by car are associated with greater likelihood of adopting on-demand ride services. Respondents who report higher numbers of long-distance business trips and have a higher share of long-distance trips made by plane are also more likely to have used these services, as are frequent users of smartphone transportation-related apps, and those who have previously used taxi and carsharing services. Among various attitudinal factors that were investigated, individuals with stronger pro-environmental, technology-embracing, and variety-seeking attitudes are more inclined to ridehailing. These findings provide a starting point for efforts to forecast the adoption of on-demand services and their impacts on overall travel patterns across various regions and sociodemographics.

3.2 Introduction

Transportation is changing at a fast pace. Information and communication technologies, which among other roles facilitate the availability of locational data and smartphone applications (apps), provide unique opportunities for the introduction and widespread deployment of new transportation services. Among these technology-enabled options, modern shared-mobility services merge the advantages of mobile communications and instant reservations with the principles of the so-called sharing economy. In doing so, they separate access to transportation services from the fixed costs of auto ownership and provide cheaper options compared to driving one's own car for large groups of travelers (Davidson and Webber, 2017). These technology-enabled services can affect travel behavior in multiple ways, such as by increasing the number of available options for a trip, reducing travel uncertainty, and potentially replacing the use of other travel modes.

The range and availability of shared-mobility services are continuously evolving as the market introduces new services and related smartphone apps. Shared-mobility services range from *carsharing* services, including *fleet-based round-trip* and *one-way services* such as Zipcar and Car2Go or *peer-to-peer services* such as Turo, to *ridesharing* services, including *dynamic carpooling* such as Carma and *on-demand ride services* such as Uber and Lyft, to *bikesharing* services (Shaheen et al. 2016b). Reviewing the availability of 11 technology-enabled transportation services in 70 U.S. cities, Hallock and Inglis (2015) found that 19 U.S. cities (with a combined population of 28 million) already had access (at the time of that study) to nearly all new mobility options included in the study. In addition, 35 other cities had access to most emerging transportation options (but not all), leaving only 16 of the 70 cities where few technology-enabled transportation options were available.

One of the most rapidly growing – and controversial – forms of shared-mobility services is on-demand ride services, also known as ridehailing, ridesourcing, or transportation network companies (TNCs), such as Uber and Lyft in the U.S. market. A recent study of on-demand ride services showed that the share of total trips made with Uber and Lyft can exceed 15% (170,000 trips per day) of all trips inside the city of San Francisco on a typical weekday (SFCTA 2017), equivalent to 20% of total vehicle miles traveled (VMT) inside the city of San Francisco, and 6.5% of total VMT including both intra- and inter-city trips. If these services continue to grow in availability and popularity, as investors and others widely expect them to do, the implications for future travel patterns are substantial.

Transportation researchers so far have had a limited ability to assess the potential impacts associated with the growth in the use of on-demand ride services. One reason is the dearth of data about users themselves, the ways they use ridehailing services, and the changes in travel behavior that ridehailing use produces. Another reason is the high level of uncertainty over the evolution and eventual maturation of on-demand ride services. A third reason is the heterogeneity in the potential impacts owing to differences in the local context and the characteristics of the users. Without a clear understanding of how these services will be changing travel patterns, policymakers and transportation planners face a significant challenge in their efforts to move the transportation system toward goals for sustainability, equity, and safety.

The goal of this study is to investigate the factors affecting the use of on-demand ride services and the circumstances under which individuals are more likely to adopt these services. In particular, this study plans to address the following questions: (1) Is the adoption of on-demand ride services consistent across different segments of the population, and if not, how does the use of ridehailing services vary? (2) How does the adoption of on-demand ride services vary with respect to built environment variables after controlling for socio-demographics? (3) Do the early adopters have different attitudes than those who have not yet used these services? The answers to these questions can help policymakers and transportation planners to anticipate changes in travel demand over time and to better plan for the future.

To address these questions, I analyze data from the California Millennials Dataset. I collected these data in fall 2015 as a part of a larger research project investigating emerging travel patterns and residential location decisions among selected segments of the population. A sample of more than 2400 residents of California, including both members of the millennial generation (18 to 34 years old in 2015) and the preceding Generation X (middle-age adults, 35 to 50 years old in 2015), completed a comprehensive online survey. The survey collected a wealth of information on, among other topics, the awareness, adoption, and frequency of shared-mobility services and the many factors that are potentially behind their use.

The remainder of this chapter is organized as follows: after a brief literature review in Section 3.3, Section 3.4 discusses the data collection and methods of analysis. Then, Section 3.5 discusses the estimation of two binary choice models and the model results, followed by a discussion of the impact of on-demand ride services on the use of other modes of transportation in Section 3.6. Finally, conclusions and perspectives for future research are presented in Section.

3.3 Literature Review

Transportation in the United States is going through an era of rapid transformation, including the disruption of long-standing patterns and the emergence of new ones. Among other trends, total vehicle miles-traveled (VMT) and the total number of privately owned vehicles have started to rise again in the U.S. after a steady decrease in the mid-2000s (FHWA 2017). The percentage of zero-vehicle households also increased during the period, even as the total number of trips by private vehicle in the country continued to rise (Sivak 2014). Despite the continued reliance on private cars, at least some segments of the population are apparently becoming more multimodal (Buehler and Hamre 2014). In general, people are more open to the use of information and communication technologies (ICT) and the adoption of technology-enabled transportation alternatives, such as new shared-mobility services. On the other hand, the impacts of many of these emerging trends are confounded with other factors affecting travel patterns, including generational differences, changes in household compositions and lifestyles, and the temporary changes associated with the recession that began in 2008. For example, it is not clear whether the increase in the percentage of zero-vehicle households will slow or even reverse now that the economic recession has ended, or whether other factors will sustain it.

The combination of ICT and the so-called sharing economy has contributed to the emergence of new transportation services, thanks to increased online connectivity and associated changes in individual lifestyles (Shaheen et al. 2016b). Modern technologies increase the success rate and the potential market for emerging transportation services by improving the convenience of arranging travel or making a reservation, providing online pay-for-service methods, collecting and disseminating online customer feedback, and offering better platforms for the efficient and dynamic management of resources (Taylor et al. 2015).

The rise of on-demand ride services exemplifies these factors. Uber and Lyft, the two largest providers of ridehailing service, launched their so-far most popular offerings, UberX and Lyft Classic, in direct competition with local taxi services, in July 2012. Ridehailing services are similar to taxi services in that they connect travelers requesting a ride with the network of available drivers – in the former case through a smartphone application, whereas in the latter case (historically) through a human dispatcher. They are different from dynamic ridesharing services such as Carma in the U.S. or BlaBlaCar in Europe – whose drivers only offer rides to other travelers along the route of a trip the driver would be taking anyway – because Uber/Lyft drivers chauffeur passengers to their destination independently from the drivers' own mobility needs. In fall 2014, Uber and Lyft launched their ride-pooling services, UberPOOL and Lyft Line, in San Francisco and few other markets, serving as a carpooling application by providing travelers with the opportunity to decrease the travel fare by sharing a ride with other users (Mcbride 2015). The availability and popularity of on-demand ride services are growing quickly: according to new statistics released on November 2016, Uber and Lyft operate in more 500 cities, with pooled services available only in selected large cities and metropolitan areas, such as San Francisco, San Diego, and Seattle.[1]

To date, knowledge of the characteristics of the users of on-demand ride services and the potential impacts that these services have on other components of travel behavior and other travel modes is limited. Much of the existing knowledge about these services is anecdotal, disseminated by the popular media. This is particularly true for studies about the potential impacts of these services. Overall, the behavioral studies about shared-mobility services follow one of these two distinct paths: (1) studies that investigate the factors associated with the adoption and frequency of the use of on-demand ride services; and (2) studies that discuss the potential impacts of on-demand ride services on components of travel behavior, such as mode choice, vehicle ownership, and activity patterns. The goal of this study is to investigate the factors affecting the adoption of on-demand ride services and provides insights into the impact that the adoption of these services has on the use of other means of transportation.

[1] https://uberexpansion.com/lyft-vs-uber-side-by-side-comparison/ (last accessed on April 9, 2018)

Previous research about the early adopters of shared-mobility services (e.g. carsharing, bikesharing and on-demand ride services) showed that the early adopters tend to be more highly-educated young adults who live in urban areas (Rayle et al. 2014; Taylor et al. 2015; Buck et al. 2013; Circella et al. 2016a). In a study of users of on-demand ride services, Rayle et al. (2014) found that the majority of Uber and Lyft users are young adults who have a rather high level of education, own fewer vehicles and travel more frequently with companions compared to older cohorts. Younger people (i.e., millennials) use these services more frequently than older adults, possibly due to their familiarity with ICT applications in general, and/or because of differences from older cohorts in terms of travel behavior and residential location. Millennials own fewer cars, drive less and use non-motorized means of transportation more often (Blumenberg et al. 2016; Kuhnimhof et al. 2012; Frändberg and Vilhelmson 2011) compared to older segments of the population. These differences in travel behavior might be the result of a combination of differences in lifestyles, attitudes, and familiarity with modern technologies (as suggested by McDonald, 2015), as well as the recessionary economic conditions which tended to hit early-career millennials harder than older cohorts. The fact that millennials more often live in central urban areas with mixed land uses and housing types (BRS 2013) could influence their likelihood of using shared-mobility services.

Another group of Uber/Lyft users comprises business travelers. According to Certify, a travel expense management company, the use of on-demand ride services has surpassed the use of taxicabs among business travelers in the second quarter of 2015 (Certify 2015, as cited in Taylor et al. 2015). The main reasons for this change could be the relatively lower fares of these services and their better availability compared to regular taxi services. Business travelers usually have higher willingness to pay for door-to-door transportation services and are more likely to be in situations where they have limited access to their own car (when away from home) than other groups of travelers.

Apart from some major cities, where most ridehailing trips are made, the mode share for these services still remains rather small. However, as on-demand ride services become increasingly common in many parts of the country, future adoption rates and the impact of the adoption of these services on the use of other modes will depend on a number of factors. These include individual perceptions of convenience and reliability, residential location choice, and availability of other travel alternatives. Another important question is whether current users will continue to use these services with the same frequency as they transition to later stages of life and move to other residential locations (Taylor et al. 2015).

Despite the growing numbers of scientific papers and research projects that explore the factors affecting the adoption of on-demand ride services, research on the overall impacts that these services have on other components of travel behavior is still limited, largely due to the lack of longitudinal data or robust analytical approaches that can disentangle the causal relationships among the use of on-demand ride services and different components of travel behavior in cross-sectional datasets. Most studies, to date, have relied on descriptive statistics. Other important limitations on the understanding of the way Uber/Lyft impact travel behavior relate to the evolving nature of these services and the maturation of their effects over time.

Recent studies indicate that the impact of shared-mobility services on other means of transportation may vary based on the type of services available, the local context, and the characteristics of the users (Taylor et al. 2015; Circella et al. 2016a). For example, 40% of TNC users in San Francisco reported that they reduced their driving due to the adoption of on-demand ride services (Rayle et al. 2014). Further, depending on local circumstances, travelers may use on-demand ride services as a substitute for or as a complement to the use of public transit. The Feigon and Murphy (2016) administered a survey among 4,500 users of shared-mobility services, revealing that frequent users of shared-mobility also tend to be frequent users of public transit and multimodal travelers. Some of this relationship may be due to the correlation of both behaviors with third-party variables such as low car ownership or living in more accessible locations, and thus it does not imply causality. The same study found that the majority of the trips made by on-demand ride services occurred between 10 pm and 4 am, when public transit either runs very infrequently or does not run at all. This finding suggests a complementarity effect. On the other hand, public transit may be losing riders as the share of ridehailing services increases: a study of seven large U.S. metro areas showed that these services tend to substitute for 6% and 3% of the trips that would have been otherwise made by bus and light rail, respectively (Clewlow and Mishra 2017). Still, it is not yet clear the extent to which the adoption of shared-mobility services *causes* an increase (for example) in transit use, as opposed to both of those conditions being caused by other variables such as residential location, age/stage in lifecycle, and vehicle ownership.

This chapter helps to fill this research gap. Compared to other studies, the distinctive contribution of this study lies in its investigation of the factors that affect the use of on-demand ride services through the estimation of adoption models (in addition to analysis of the descriptive statistics generally used) that simultaneously account for the roles of socio-demographics, characteristics of the built environment, technology adoption, individual lifestyles and personal attitudes on the use of Uber and Lyft among millennials and the members of Generation X.

In my conceptual framework, I hypothesize that individuals will use ridehailing services if these services meet their needs better than other travel options, where these needs include travel time, cost, comfort, safety, convenience, or other qualities. I do not directly assess the relative utility of ridehailing and other options in my analysis, but rather assume that the utility of ridehailing to individuals depends on their socio-economic characteristics, the characteristics of their residential location, their familiarity with ICT, and their attitudes and preferences. I expect that younger individuals, higher income and higher educated people will be more likely to adopt ridehailing services. Similarly, I expect that the adoption rate will be higher among those who live in cities and large metropolitan areas, where Uber/Lyft are ubiquitous. I also believe that individuals with stronger attitudes towards the environment and the adoption of technology and those with lower affective and symbolic attitudes towards (owning) cars will be more likely to adopt these services. Further, I seek to determine under what other circumstances the utility of adopting on-demand ride services increases. For example, I expect long-distance (business) travelers to be more likely to use these services as they provide convenient access to/from the airport.

3.4 Data Collection and Methodology

3.4.1 The California Millennials Dataset

The California Millennials Dataset was collected in fall 2015 as part of an on-going research project investigating emerging travel patterns and residential location decisions among selected segments of the population. To conduct the project, our research group designed and administered an online survey to a sample of more than 2400 residents of California recruited through an online opinion panel. The sample included 1400 millennials, i.e. young adults 18 to 34 years old in 2015, and 1000 members of the preceding Generation X, i.e. middle-aged adults between 35 and 50 years old. Our research group employed a quota sampling approach to ensure that a sufficient number of respondents were included from each of six main geographic regions of California and from three neighborhood types (urban, suburban, and rural). The six regions were defined as (1) the California Central Valley (those parts not otherwise covered); (2) Sacramento, following the boundaries of the Sacramento Area Council of Governments (SACOG); (3) San Diego, following the boundaries of the San Diego Association of Governments (SANDAG); (4) Greater Los Angeles, following the boundaries of the Southern California Association of Governments (SCAG); (5) the San Francisco Bay Area, following the boundaries of the Metropolitan Transportation Commission (MTC); and (6) the rest of Northern California and Others, comprising the remaining mountain, coastal and rural regions in the state. Our research group also set targets for five socio-demographic characteristics while recruiting the sample: gender, age, household income, race and ethnicity, and the presence of children in the household. A combination of cell weighting and iterative proportional fitting (IPF) raking were employed to correct for non-representativeness of the sample on various pertinent traits, including age group, neighborhood type, region, race, ethnicity, presence of children in the household, household income, student/employment status, and gender.

A total of 5,466 invitations were sent out, and 3,018 complete cases were collected. The high response rate of 46.3% is not surprising considering the data collection method used for this project, and the higher propensity of opinion panel members to respond to survey invitations. It is important to note potential concerns with the use of opinion panels. In addition to self-selection bias, which affects most of the studies that use surveys as a main method for data collection, one of the major concerns about the use of an online panel is non-coverage bias (also known as non-/under-representation bias). The concern is that the members of the online opinion panel may not be (fully) representative of the larger population. Studies show that several groups of individuals are more likely to be excluded from online panels than others. For example, elderly women with low educational attainment and people without access to the internet are more likely to be excluded from online panels (e.g., Blasius and Brandt 2010), although the former group is not a segment addressed by the present analysis. A quota sampling approach were used to ensure that enough respondents are recruited in each group; however, as also discussed by Blasius and Brandt (2010), quota sampling does not completely resolve this issue given the infeasibility of defining large numbers of categories for the quotas. In this study, I believe that defining quotas based on different regions and neighborhood types as well as five socio-demographic characteristics does a reasonable job of controlling for non-coverage bias. Further, whatever remaining sampling bias(es) may still affect the data, it is reasonable to expect them to affect both age groups in a similar way, thus maintaining the validity of the comparisons between millennials and older adults in the study.

The survey collected information in many categories: individual attitudes and preferences; lifestyles; use of ICT and adoption of online social media; residential location and living arrangements; commuting and other travel patterns; auto ownership; awareness, adoption and frequency of use of several types of shared-mobility services; major life events that happened in the past three years; future expectations, aspirations and propensity to purchase and use a private vehicle versus other means of travel; and sociodemographic traits.

The survey asked respondents to report their level of agreement with 66 attitudinal statements on a 5-point Likert-type scale from “Strongly disagree” to “Strongly agree.” These questions measured individual attitudes and preferences related to a number of general and transportation-related latent constructs including land use preferences, environmental concerns, adoption of technology, government role, travel preferences, car ownership, and others, that were identified in previous studies as important influences on travel behavior. After data cleaning and preprocessing, I performed a principal axis factor analysis with an oblique rotation which reduced the dimensionality from 66 statements to 17 factors and 10 remaining single statements that identified main attitudinal constructs (for additional details, see Table 3.7 in appendix A, Circella et al. 2016a, and Circella et al. 2017a).

The California Millennials Dataset is a relevant sample for this study, as millennials and members of Generation X are believed to comprise the majority of the early adopters of Uber and Lyft. In the survey, respondents were asked to indicate whether they are already familiar with various types of emerging shared-mobility services, if these services are available in the area where they live, and what services they have already used. For those services used by respondents, they were asked to report how often they use them. The emerging transportation services included in the study were *fleet-based carsharing* (e.g. Zipcar or Car2go), *peer-to-peer carsharing* (e.g. Turo), *on-demand ride services* (e.g. Uber or Lyft), *dynamic carpooling* (e.g. Zimride or Carma), *peer-to-peer carpooling* (usually arranged via online platform such as Facebook or Craigslist) and *bikesharing*. In addition to the adoption rate and frequency of use, the survey asked users of on-demand ride services to rate the importance of a set of factors in affecting their use of these services. For the last trip made with Uber and/or Lyft, respondents were also asked to report (1) how the use of these services affected their use of other means of transportation, and (2) what they would have done if these services had not been available. After excluding severely incomplete, inconsistent or unreliable cases, a final dataset that included approximately 1975 valid cases was used for this study. For detailed information on the data collection process, the content of the survey, and the exact language used for these questions, see Circella et al. 2016a and Circella et al. 2017a).

3.4.2 Analysis

Various factors could influence the adoption of on-demand ride services, such as individual and household socio-demographic characteristics, or the characteristics of a trip. However, most of the existing studies on this subject are dominated by descriptive statistics, and therefore have limited ability to disentangle the contribution of various groups of variables to explaining choices. In this chapter, I explore what factors increase the utility of adopting on-demand ride services and under what circumstances individuals are more likely to use these services. I examine the relationship between the adoption of on-demand ride services and individual lifestyles and personal attitudes, while controlling for the impact of socio-demographics and built environmental variables. I estimate two binary logit models of the adoption of on-demand ride services. The first model includes three groups of variables, controlling for socio-demographics, individual lifestyles, and built environment characteristics. The second model is a modified version of the first one with the addition of individual attitudes.

The dependent variable is binary: a value of 1 for this variable indicates that the respondent has (already) used on-demand ride services. Figure 3.1 shows the distribution of users and non-users of such services by age group (millennials vs. members of the preceding Generation X) in the weighted sample. As shown in this figure, larger shares of millennials have adopted on-demand ride services (31.8%) compared to members of the older cohort (21.3%). To create the dependent variable for the model estimation, I grouped all individuals who reported having used such services in their hometown, away from home, or in both locations, and classified them as “users”. Those who have heard about these services but have not used them yet and those who reported that they have not heard about these services were classified as “non-users”. Table 3.2 summarizes the key attributes of the individuals who have used these services, who have heard but not used yet, and who have not heard about these services, respectively.

To identify the factors that affect the use of on-demand ride services, I first looked at the differences between users and non-users in the distribution of potential explanatory variables. I selected variables to include in the models by conducting a series of descriptive analyses using one-way analysis of variance (ANOVA) or chi-squared tests to identify variables that differed significantly between the two groups and that were also conceptually meaningful. Table 3.1 defines, and Table 3.2 reports the descriptive statistics of the weighted explanatory variables that are included in the final binary logit models (Table 3.8, in Appendix B, reports the same descriptive statistics for the unweighted dataset). I divided these explanatory variables into four main groups and tested different variable transformations in each group to identify the variables most closely associated with the use of Uber/Lyft. The four groups of variables are as follows:

Socio-demographics: I expect that adoption of on-demand ride services varies across different segments of the population and by other socio-demographic attributes. I controlled for the impacts of demographics including a dummy variable for sex (female); age (a categorical variable representing *younger millennials,* between 18 and 24 years old, *older millennials,* ages 25 to 34, *younger generation Xers,* between 35 and 41 years old, and *older generation Xers,* ages 42 to 50); household income (with the range *$0-40K* of annual household income classified as low income, *$40-100K* as medium income, and *$100K or more* as high income); employment and student status; a dummy variable for non-Hispanic origin ethnicity; and the highest attained educational level (I defined individuals with a bachelor’s degree or more as highly-educated individuals).

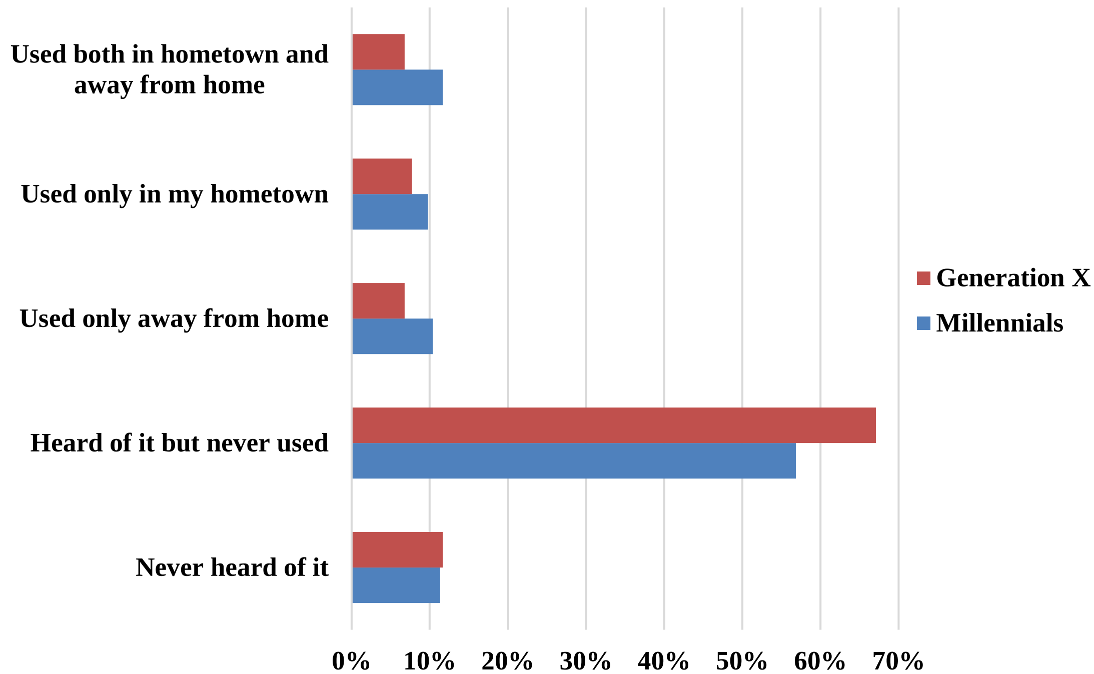

Figure 3.1 – Awareness and Use of On-demand Rides by Age Group (Weighted Sample, $N_{Millennials}$=1022, $N_{Gen\ X}$ = 945)

Geographic region and built environment: This group of variables includes information on the geographic region where the respondent lives and additional built environment variables that were imported from other datasets. Controlling for the impact of the characteristics of the built environment on the adoption of on-demand ride services is important, as these services are not equally available across all California regions and all neighborhood types. As part of this study, our research group geocoded the reported home address for each individual in the dataset and classified the residential neighborhood type as predominantly urban, suburban or rural, using the typology defined in Salon (2015).[2] Figure 3.2 maps the distribution of the users in different

[2] Salon (2015) classifies U.S. census tracts into five neighborhood types using information on local land use and transportation characteristics. For the purposes of this study, I further aggregated those five neighborhood types into three predominant neighborhood types: *central city* and *urban* were both classified as *urban*, and *rural in urban* and *rural* were classified as *rural*.

regions of California and neighborhood types. To capture spatial heterogeneity and test the impact of other built environment variables such as land use mix, network connectivity, population density, and regional accessibility on the adoption of on-demand ride services, I integrated the dataset with additional data extracted from the U.S. Environmental Protection Agency (EPA) Smart Location Dataset,[3] based on the respondent's geocoded home location.

Table 3.1 – Description of Key Variables

Variable Name	Description
Dependent Variable	
Adoption of on-demand ride services	1= Have used on-demand ride services before; 0=Have heard of these services but have never used them, or have not heard of these services
Explanatory Variables	
Socio-demographics	
Age	
Younger Millennials	1= Individual 18-24 years old; 0=Else
Older Millennials	1= Individual 25-34 years old; 0=Else
Younger Gen X	1= Individual 35-41 years old; 0=Else
Older Gen X	1= Individual 42-50 years old; 0=Else
Presence of Children in the Household	1= Household with child(ren); 0= Household without children
Household Income	
Low	1= Annual household income of 0-39,999 USD; 0=Else
Medium	1= Annual household income of 40,000-99,999 USD; 0=Else
High	1= Annual household income of 100,000 or more USD; 0=Else
Employment Status	1= Work as full time or part time employee; 0= Else
Student Status	1= Full time or part time student; 0=Not student
High Education Level	1= High education (with at least Bachelor's degree); 0=Else
Non-Hispanic Ethnicity	1= Non-Hispanic origin; 0=Hispanic origin
Sex (Female)	1= Female; 0=Else
Geographic Region and Built Environment	
Region	
Central Valley	1= Home address is located in Central Valley; 0=Else
Northern California and Others	1= Home address is located in Northern California or Other area; 0=Else;
Sacramento	1= Home address is located in Sacramento area; 0=Else
San Diego	1= Home address is located in San Diego area; 0=Else
Greater Los Angeles	1= Home address is located in Los Angeles area; 0=Else
San Francisco Bay Area	1= Home address is located in San Francisco area; 0=Else

[3] The EPA Smart Location Dataset provides various statistical and deterministic built environment indicators, estimated at the Census block group level, which were matched to the respondent's residential location based on the geocoded location of the self-reported street address (https://www.epa.gov/SMARTGROWTH/SMART-LOCATION-MAPPING).

Neighborhood Type (Geocoded Home Address)	
Urban	1= Respondent lives in urban/central city neighborhood; 0=Else
Suburban	1= Respondent lives in suburban neighborhood; 0=Else
Rural	1= Respondent lives in rural/rural in urban neighborhood; 0=Else
Land Use Mix	A continuous variable between 0 and 1 (where higher values mean a more diverse mix), showing 8-tier employment entropy (denominator set to observed employment types in the Census Block Group), obtained from the EPA Smart Location Dataset
Destination Accessibility	A continuous variable between 0 and 1 (where higher values mean greater auto accessibility), showing the Regional Auto Centrality Index, obtained from the EPA Smart Location Dataset
Lifestyles and Use of Technology	
Use of Social Media (Facebook)	
Lower frequency	1= Checks Facebook less than once a day; 0=Else
Higher frequency	1= Checks Facebook at least once or multiple times a day; 0=Else
Use of Taxi	1= Has used taxi before; 0=Else[1]
Use of Carsharing Services	1= Has used any type of carsharing services (including peer-to-peer carsharing and fleet-based carsharing) before; 0=Else
Use of Smartphone (see Table 4.3 for details)	
To Determine Destination and Route	Standardized principal component scores measuring frequency of using smartphone to determine destination and route
For Mode Choice	Standardized principal component scores measuring frequency of using smartphone to choose specific mode(s) and check transit time
Frequency of Long-Distance Business Travel (Log-Transformed)	Continuous variable showing the log of the total number of long-distance trips made for business purposes during the past 12 months
Share of Total Long-Distance Travel by Plane	Continuous variable showing the share of total long-distance trips made by plane during the past 12 months
Personal Attitudes (see Table 4.4 for details)	
Technology Embracing	Standardized Bartlett factor score measuring attitudes towards the adoption of technology
Variety Seeking	Standardized Bartlett factor score measuring attitudes towards seeking variety in life
Pro-Environmental Policies	Standardized Bartlett factor score measuring pro-environmental policy attitudes

[1] I excluded cases who reported never having heard of taxi services, as likely being frivolous respondents

Lifestyles and use of technology: This group of variables accounts for individuals' lifestyles and propensity to use social media (i.e., Facebook), ICT and other technological applications (in general, or to access transportation-related services), as well as the frequency of long-distance travel by purpose (business vs. leisure/personal) and by mode (e.g., car, plane, intercity bus and train). The literature has discussed the role of some of these variables in the context of non-transportation sharing economy services, e.g. their relationships with the use of peer-to-peer lodging services provided by Airbnb. For example, those who are more familiar with the use of technology more often search for (or share) information online, and those who are more active on Facebook or other online social media are more inclined to use Airbnb (Latitude 2010). I hypothesize that these individuals are also more likely to use shared-mobility services. Several variables in California Millennials Dataset measured the use of smartphones for different purposes. To reduce the dimensionality of the smartphone-related variables, I performed principal component analysis. Table 3.3 reports the two principal components and their associated variables. My hypothesis is that the familiarity with and use of smartphone in connection to transportation and the use of other emerging transportation services (e.g., carsharing, bikesharing) can affect the adoption of on-demand ride services, as technology-oriented users that already benefit from the use of other shared-mobility services might be more inclined also to adopt on-demand ride services.

Personal attitudes: Testing the impacts of individual attitudes on the adoption of technological transportation services such as those provided by Uber and Lyft is an important addition. This was possible using the information available in this dataset, whereas attitudinal variables are not commonly available in other datasets available for travel behavior research (such as those collected with national and most regional household travel surveys). As discussed earlier, in this study I estimated two models: the first model only accounts for the first three groups of variables, while the second also includes individual attitudes using the standardized Bartlett factor scores that were computed through a factor analysis of the original attitudinal variables included in the dataset. Among the 17 factors that were extracted, the *Technology Embracing*, *Variety Seeking*, and *Pro-Environmental Policies* factors had significant effects on the adoption of shared-mobility services and were included in the final model. Table 3.4 provides more details on the three factor scores that were included in the final model and the attitudinal statements loading on each of them.

Table 3.2 – Distribution of Key Explanatory Attributes by Use of On-demand Ride Services (Weighted Sample, N=1967)

Explanatory Variables	Users [N=526]		Heard of but Never Used [N=1215]		Never Heard of [N=226]	
	Count	Col. %	Count	Col. %	Count	Col. %
Socio-demographics						
Age						
Younger Millennials	92	17.49%	250	20.59%	58	25.78%
Older Millennials	233	44.30%	331	27.27%	58	25.78%
Younger Gen X	116	22.05%	314	25.86%	46	20.44%
Older Gen X	85	16.16%	319	26.28%	63	28.00%
Presence of Children in the Household						
Yes	248	47.15%	645	53.13%	125	55.31%
No	278	52.85%	569	46.87%	101	44.69%
Household Income [N=1831]						
Low ($0-40K)	108	21.51%	306	27.15%	109	50.46%
Medium ($40-100K)	180	35.86%	482	42.77%	62	28.70%
High ($100K+)	214	42.63%	339	30.08%	45	20.83%
Employment Status						
Employed	470	89.52%	949	78.11%	165	73.01%
Not Employed	55	10.48%	266	21.89%	61	26.99%
Student Status						
Student	127	24.10%	215	17.71%	60	26.55%
Not Student	400	75.90%	999	82.29%	166	73.45%
Education Level						
Bachelor's Degree or Higher	341	64.83%	547	45.28%	58	25.78%
Associate Degree or Below	185	35.17%	661	54.72%	167	74.22%
Ethnicity						
Hispanic Origin	182	34.60%	490	40.36%	118	52.21%
Non-Hispanic Origin	344	65.40%	724	59.64%	108	47.79%
Sex						
Female	282	53.61%	602	49.55%	124	54.87%
Male	244	46.39%	613	50.45%	102	45.13%
Geographic Region and Built Environment						
Region						
Central Valley	30	5.70%	211	17.38%	60	26.67%
Northern California and Others	3	0.57%	27	2.22%	12	5.33%
Sacramento	21	3.99%	75	6.18%	14	6.22%
San Diego	57	10.84%	108	8.90%	10	4.44%
Greater Los Angeles	295	56.08%	531	43.74%	94	41.78%
San Francisco Bay Area	120	22.81%	262	21.58%	35	15.56%
Neighborhood Type (Geocoded Home Address)						
Urban	220	41.82%	279	22.98%	27	11.94%
Suburban	241	45.82%	568	46.79%	95	42.04%
Rural	65	12.36%	367	30.23%	104	46.02%

Land Use Mix (8-Tier Employment Entropy)						
Mean *(Std. Deviation)*	0.64 *(0.23)*		0.59 *(0.28)*		0.60 *(0.27)*	
Destination Accessibility (Regional Centrality Index by Auto)						
Mean *(Std. Deviation)*	0.57 *(0.20)*		0.51 *(0.22)*		0.50 *(0.25)*	
Lifestyles and Use of Technology						
Use of Social Media (Facebook)						
Lower Frequency	137	26.05%	461	37.94%	77	34.22%
Higher Frequency	389	73.95%	754	62.06%	148	65.78%
Use of Taxi						
Used Taxi Before	367	71.54%	438	36.93%	59	35.54%
Never Used Taxi Before	146	28.46%	748	63.07%	107	64.46%
Use of Carsharing Services						
Used Carsharing Services Before	93	17.71%	18	1.48%	8	3.56%
Never Used Carsharing Services	432	82.29%	1197	98.52%	217	96.44%
PCA Score: Use of Smart Phone to Determine Destination and Route [N=1961]						
Mean *(Std. Deviation)*	0.49 *(0.75)*		-0.16 *(0.99)*		-0.28 *(1.16)*	
PCA Score: Use of Smart Phone for Mode Choice [N=1961]						
Mean *(Std. Deviation)*	0.39 *(1.04)*		-0.16 *(0.92)*		-0.10 *(1.04)*	
Frequency of Long-Distance Business Travel (Log-Transformed) [N=1936]						
Mean *(Std. Deviation)*	0.50 *(0.54)*		0.26 *(0.44)*		0.38 *(0.52)*	
Share of Total Long-Distance Travel with Plane [N=1924]						
Mean *(Std. Deviation)*	0.34 *(0.32)*		0.18 *(0.29)*		0.10 *(0.23)*	
Personal Attitudes						
Factor Score: Technology Embracing [N=1965]						
Mean *(Std. Deviation)*	0.42 *(0.90)*		-0.01 *(0.97)*		-0.08*(0.99)*	
Factor Score: Variety Seeking [N=1965]						
Mean *(Std. Deviation)*	0.39 *(0.88)*		-0.03 *(0.97)*		-0.13*(1.08)*	
Factor Score: Pro-Environmental Policies [N=1965]						
Mean *(Std. Deviation)*	0.46 *(1.15)*		-0.04 *(1.02)*		-0.13*(1.01)*	

Table 3.3 – Principal Component Loadings of Use of Smartphone in Relation to Transportation

Principal Components and Associated Variables	Loadings from Pattern Matrix
Frequency of use of smartphone to determine destination and route	
Navigate in real time (e.g. using Google Maps or other Navigation Services)	0.88
Learn how to get to a new place	0.83
Identify possible destinations (e.g. restaurant, etc.)	0.81
Check traffic to plan my route or departure time	0.75
Frequency of use of smartphone for mode choice	
Check when a bus or train will be arriving	0.97
Decide which means of transportation, or combination of means, to use	0.86

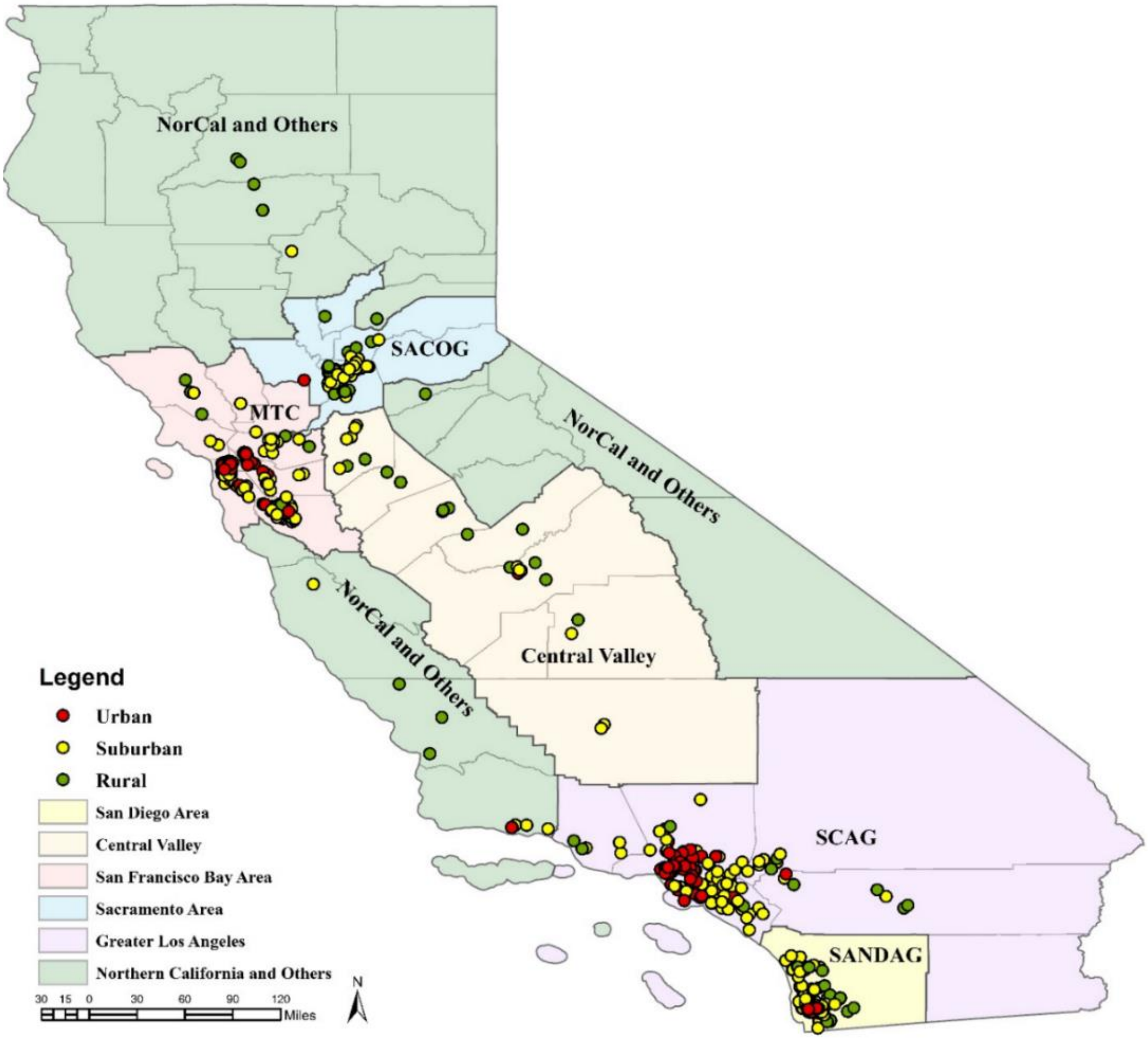

Figure 3.2 – Distribution of the Uber/Lyft Users by Region and Neighborhood Type

Incorporating attitudinal variables into a choice model is an important way to improve the model's ability to explain behavior. The exclusion of attitudinal variables may reduce the explanatory power of the model and may confound the effect of the included explanatory variables on the adoption of on-demand ride services, wrongly attributing the influence of attitudes to other variables in the model (as discussed in the next section). Thus, neglecting attitudinal variables may lead to omitted variable biases if these variables are correlated with the included independent variables. However, the inclusion of attitudinal variables into a choice model in the form of separately estimated factor scores may introduce some measurement bias because answers to attitudinal questions are not direct measures of attitudes but rather functions of underlying latent attitudes. Although the approach followed in the present chapter is a practical way to include attitudes in the model estimation, while retaining simplicity in the model estimation and interpretability of the results, in future phases of the project I plan to use attitudinal indicators as outcomes of latent explanatory variables in the adoption model. This requires a model specification that embeds joint models of revealed (stated) choice(s) and the response to attitudinal statements through latent variables, i.e. a hybrid choice model (Ben-Akiva et al. 2002; Bolduc et al. 2005). Nevertheless, the practicality of Integrated Choice and Latent Variable (ICLV) models have been questioned by researchers (Chorus and Kroesen, 2014). Further, Vij and Walker (2016) showed that an ICLV model can in many cases be reduced to a choice model without latent variables that fits the choice data at least as well as the original ICLV model from which it was obtained. Further, neither of the discussed approaches (i.e. the joint and separate estimation of attitudinal factors in the choice model) can account for the eventual reverse causality and/or bi-directional causality between choice and attitudes. This, particularly, becomes very important if the use (or non-use) of ridehailing over time affects attitudes towards these services, or if personal attitudes simultaneously affect the adoption of ridehailing and at the same time are affected by the adoption of the service.

As indicated in Table 3.2, the adoption of on-demand ride services is higher among older millennials and those whose education includes a bachelor's degree or higher. About 38% of older millennials reported that they have used on-demand ride services, while the adoption rate is lower among younger millennials and the members of Generation X. I also find a higher adoption rate for individuals who live in high-income households and those with higher levels of education. Similarly, urban dwellers are more likely than others to use these services. With respect to technology adoption, I find that users of on-demand ride services are frequent users of transportation-related smartphone applications and technology-enabled transportation services, while those who have heard about on-demand ride services but never used them, or those who have not heard about these services, are less frequent users of these smartphone-based services. The average scores of all three attitudinal factors are positive among the users of on-demand ride services and higher than for the two groups of non-users, reflecting more positive attitudes toward technology adoption, variety in life and pro-environmental policies.

Table 3.4 – Relevant Factors and their Strongly-Loading Attitudinal Statements

Factors and Most Strongly-Associated Attitudinal Statements	**Loadings from Pattern Matrix**
Pro-environmental Policies	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.938
We should raise the price of gasoline to provide funding for better public transportation.	0.844
The government should put restrictions on car travel in order to reduce congestion.	0.344
Variety Seeking	
I like trying things that are new and different.	0.605
I have a strong interest in traveling to other countries.	0.406
Technology Embracing	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.623
Getting around is easier than ever with my smartphone.	0.517
Learning how to use new technologies is often frustrating.	-0.333
Technology creates at least as many problems as it does solutions.	-0.293

In other model specifications, not shown in this chapter, I included an additional group of explanatory variables measuring the self-reported expected changes in individual travel behavior, such as the expected changes in the use of various transportation modes during the next three years, and the propensity to sell or replace one or more household vehicle(s). The results showed that users of on-demand ride services tend to expect to travel by train and active modes more often and to use a car less often in the next three years, and they are less likely to increase the number of cars in their household. However, I excluded these variables from the final models, even though they had statistically significant coefficients, because of their likely endogenous nature, which would therefore bias the coefficient estimates. For example, a recent Reuters/Ipsos opinion poll reveals that about 10% of the users of on-demand ride services plan to dispose of their vehicles and turn to on-demand ride services as their primary means of travel (Henderson 2017), supporting the supposition that the decision to sell a household vehicle in the medium-term future could well be an effect rather than a cause of the adoption of shared-mobility services.

3.5 Modeling the Adoption of On-Demand Ride Services

Table 3.5 presents the final models of on-demand ride services adoption (user versus non-user) without and with attitudinal variables. The first model, without attitudinal variables, is largely consistent with the results from previous studies based on descriptive statistics, and with my expectations. In the second model, the three attitudinal factors discussed above proved to be significant.

3.5.1 Model of On-Demand Ride Services Adoption – Without Attitudes

The first model shows that the likelihood of adopting on-demand ride services is higher among well-educated individuals (individuals with a bachelor’s or higher degree) and those who live in higher-income households, compared to lower-educated individuals or those who live in lower/medium-income households. The same is true for older millennials, i.e. individuals between 25 and 34 years old. These results are consistent with previous studies; for example, Rayle et al. (2014) showed that higher-educated individuals are more likely to use on-demand ride services. In my first model, being a student or worker increases the likelihood of using on-demand ride services; I find the highest adoption rate among individuals who both work and study. In early models that I estimated, the presence of children in the household was significant;

however, the magnitude of the impact of this variable diminishes after including other variables, and the variable was found not to have statistically significant effects in the final model. In addition, I find that the adoption of on-demand ride services is higher among females and individuals of non-Hispanic origin.

The results show that living in the major California metropolitan areas increases the likelihood of using on-demand ride services compared to regions where on-demand ride services are less common. Land-use mix and regional auto accessibility measures also have significant impacts on the use of on-demand ride services: the probability of adopting these services increases as those two measures increase, and this relationship holds also after controlling for the impact of other built environment variables.

Variables related to technology adoption and use are also significant, as hypothesized. Individuals who actively use social media (i.e., those who use Facebook at least once a day) and who use their smartphone more frequently in regard to their daily travel (e.g. to decide which means of transportation to use or to check when the bus arrives) are more likely to use ridehailing. The same is also true for individuals who reported that they have already used carsharing (including both peer-to-peer and fleet-based carsharing services) in the past. This confirms that the degree of familiarity with modern technologies and their adoption in daily life is associated with the adoption of on-demand ride services. Users who are high adopters of technology, or who live in areas where all these services are available, tend to adopt many of them as a bundle, as part of a modern “technology-oriented” lifestyle.

The final model without attitudes shows that those individuals who travel more frequently for business purposes are more inclined to adopt ridehailing. In fact, business travelers are more likely to be in situations where they do not have access to their own car. Adoption is higher for those who make a higher share of long-distance trips by plane, suggesting the popularity of these services for traveling to and from airports.

3.5.2 Model of On-Demand Ride Services Adoption – With Attitudes

To test for the impact of individual attitudes and preferences on the adoption of on-demand ride services, I incorporate factor scores as explanatory variables in the adoption model. I find that the rate of adoption of on-demand ride services is significantly higher among individuals with more positive factor scores for technology embracing, pro-environmental policies, and seeking variety in life. These findings are consistent with the expectations about ridehailing users. Interestingly, none of the other attitudes that I tested, including factors measuring attitudes toward (1) car use and ownership (e.g. "car as a tool" and "must own a car"); (2) multitasking while commuting; and (3) mode choice were significant. I speculate that I will see more statistically significant attitudinal variations between users and non-users when analyzing the frequency of use of on-demand ride services (rather than simply their adoption as I do in this chapter).

As shown in Table 3.5, the inclusion of attitudinal variables improves the goodness of fit of the model but has only a small impact on the coefficients and statistical significance of the variables included in the model, consistent with the low correlations between these factor scores and other variables used in the final model. The small impact indicates that the attitudinal variables mostly add independent explanatory power not captured by other variables.

Table 3.5 – Estimation Results for Weighted Binary Logit Model of the Adoption of On-demand Ride Services (N=1,702)

Variable	Model without Attitudinal Variables		Model with Attitudinal Variables	
	Estimates (P-values)	Robust Std. Error	Estimates (P-values)	Robust Std. Error
Intercept	-6.92 *(0.00)*	0.61	-6.91 *(0.00)*	0.64
Age [Reference=Older Millennials]				
Younger Millennials	0.75 (0.05)	0.36	0.52 (0.18)	0.38
Older Millennials	0.95 (0.00)	0.27	0.85 (0.00)	0.27
Younger Gen X	0.22 (0.43)	0.28	0.07 (0.80)	0.28
Sex				
Female	0.5 (0.01)	0.19	0.6 (0.01)	0.20
Household Income and Education Interaction [Reference= Low/Medium Income and Low Education Individuals]				
High Income Household and High Education Individual	0.98 (0.00)	0.28	0.81 (0.01)	0.28
High Income Household and Low Education Individual	0.99 (0.00)	0.31	0.99 (0.00)	0.32
Low/Medium Income Household and High Education Individuals	0.64 (0.01)	0.22	0.73 (0.00)	0.23
Student and Employment Status [Reference= Neither Work nor Study]				
Work and Study	1.51 (0.00)	0.36	1.27 (0.00)	0.36
Work Only	0.74 (0.01)	0.27	0.61 (0.04)	0.28
Study Only	1.04 (0.02)	0.43	0.70 (0.15)	0.48
Ethnicity [Reference=Non-Hispanic Origin]				
Hispanic Origin	-0.49 (0.03)	0.21	-0.53 (0.02)	0.21
Region [Reference= Central Valley, Northern California and Others]				
San Francisco Bay Area	0.73 (0.03)	0.31	0.71 (0.03)	0.31
San Diego	1.36 (0.00)	0.31	1.44 (0.00)	0.32
Greater Los Angeles	1.31 (0.00)	0.29	1.35 (0.00)	0.29
Sacramento	0.52 (0.14)	0.35	0.62 (0.09)	0.35
Land Use Mix				
8-Tier Employment Entropy	1.03 (0.01)	0.34	1.06 (0.01)	0.37
Regional Accessibility				
Regional Centrality by Auto	1.53 (0.00)	0.45	1.64 (0.00)	0.45
Use of Smartphone (PCA score)				
For mode choice	0.42 (0.00)	0.10	0.27 (0.01)	0.10
Use of Taxi Services				
Have used taxi services before	1.18 (0.00)	0.20	1.06 (0.00)	0.20
Use of Carsharing Services [Reference = Have not Used Carsharing Services]				
Have used carsharing before	2.04 (0.00)	0.36	2.25 (0.00)	0.39
Use of Social Media (Facebook) [Reference = Did not Use It Daily]				
Used it at least once a day	0.41 (0.06)	0.21	0.38 (0.08)	0.21
Long-Distance Travel				
Total number of long-distance business trips (log transformed)	0.50 (0.02)	0.19	0.39 (0.05)	0.19
Share of total long-distance trips by air	1.02 (0.00)	0.30	0.94 (0.00)	0.30
Individual Attitudes (Factor Scores)				
Variety Seeking	-	-	0.32 (0.01)	0.11
Technology Embracing	-	-	0.63 (0.00)	0.10
Pro-Environmental Policies	-	-	0.38 (0.00)	0.10
Model Log Likelihood (BIC)	-698.55 (1575.65)		-645.96 (1492.78)	
$\bar{\rho}^2_{constant-based}$ ($\bar{\rho}^2_{equally\ likely-based}$)	0.26 (0.36)		0.31 (0.41)	

Note: P-values are reported in parentheses and are based on the robust standard errors, used to control for heteroscedasticity that might exist.

The inclusion of the attitudinal variables reduces the magnitude of the estimated coefficients for the age group-related variables: this is a sign that some of the apparent impacts of age and generation on the adoption of on-demand ride services are more properly explained by the personal attitudes of the individuals. Because these attitudes are correlated with age, when I do not control for attitudes, the effects of individual attitudes are attributed to the age group variables. Further, since individual attitudes are not perfectly correlated with age, it is desirable to distinguish the separate roles of age and attitudes, as only the second model is able to do. In addition, the inclusion of the attitudinal variables diminishes the impact of technology adoption variables (including the use of smartphones in relation to transportation and the use of social media). This confirms that technology savviness can be party explained by technology-related attitudinal factors (and that the "true" impact of technology-embracing attitudes is attributed to the adoption of technology options when I do not control for individual attitudes).

3.6 Frequency of Use of Ridehailing and Impact on the Use of Other Travel Modes

How the use of on-demand ride services affects other components of travel behavior, and in particular the use of other means of transportation, is a critical question for understanding the environmental, economic and equity effects of these services. As shown in Figure 3.3, the majority of Uber and Lyft users solicits on-demand ride services only occasionally (less than once a month). Millennials tend to use on-demand ride services with higher frequency compared to the older cohorts. Interestingly, about 10% of both groups report they have used these services in the past, but they do not use them anymore. This may indicate dissatisfaction with prior use, or a change in circumstances that has made usage less accessible or desirable.

Table 3.6 shows how users of ridehailing differ with respect to their sociodemographic traits and the geographic location of their residence. I find that frequent users of on-demand ride services (those who reported that they have used these services at least on a weekly basis) are mainly from the Bay Area and Los Angeles regions and are more likely to live in urban neighborhoods. About half of frequent users of these services are between 25 and 34 years old and are more likely to live in low-/medium-income households. Interestingly, I find that a larger percentage of frequent ridehailing users live in zero-vehicle households, compared to non-frequent users. However, it is not clear whether the current number of vehicles in the household is a cause of the higher usage of these services, or an effect of their adoption (e.g. ridehailing users might decide to dispose of a vehicle, as they can fulfil their mobility needs with these services). The cross-sectional nature of the dataset does not allow exploring this topic in more detail, though in future stages of the research (when longitudinal data will become available in this panel study) I plan to investigate this topic.

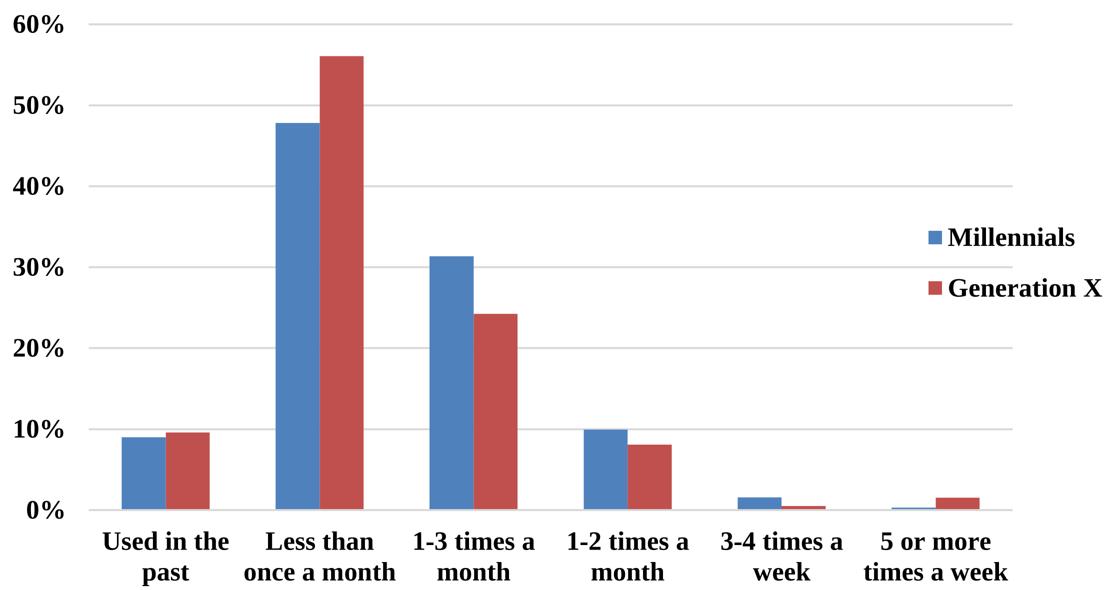

Figure 3.3 – Frequency of Using On-demand Ride Services (Weighted Sample, $N_{Millennials}$=322, $N_{Gen\ X}$ =198)

Table 3.6 – Distribution of Key Explanatory Attributes by Frequency of Use of On-demand Ride Services (Weighted Sample, N=1961)

Explanatory Variables	Did not Use or Used in the Past [N=1491]		Used it Less than Once a Month [N=265]		Used it 1-3 Times a Month [N=148]		Used it at Least 1-2 Times a Week [N=57]	
	Count	Col. %	Count	Col. %	Count	Col. %	Count	Col. %
Age								
Younger Millennials	321	21.53%	41	15.47%	27	18.24%	11	19.30%
Older Millennials	406	27.23%	113	42.64%	74	50.00%	27	47.37%
Younger Gen X	373	25.02%	60	22.64%	28	18.92%	12	21.05%
Older Gen X	391	26.22%	51	19.25%	19	12.84%	7	12.28%
Household Income [N=1831]								
Low ($0-40K)	429	30.95%	43	16.86%	33	23.40%	17	29.82%
Medium ($40-100K)	561	40.48%	89	34.90%	50	35.46%	24	42.11%
High ($100K+)	396	28.57%	123	48.24%	58	41.13%	16	28.07%
Education Level								
Bachelor's Degree or Higher	628	42.35%	190	71.70%	82	55.03%	41	70.69%
Associate Degree or Below	855	57.65%	75	28.30%	67	44.97%	17	29.31%
Region								
Central Valley	279	18.71%	11	4.17%	9	6.04%	0	0.00%
Northern California	40	2.68%	2	0.76%	1	0.67%	0	0.00%
Sacramento	92	6.17%	10	3.79%	4	2.68%	2	3.45%
San Diego	125	8.38%	26	9.85%	20	13.42%	5	8.62%
Greater Los Angeles	647	43.39%	149	56.44%	81	54.36%	42	72.41%
San Francisco Bay Area	308	20.66%	66	25.00%	34	22.82%	9	15.52%
Neighborhood Type (Geocoded Home Address)								
Urban	328	22.00%	79	29.92%	69	46.31%	49	84.48%
Suburban	685	45.94%	150	56.82%	61	40.94%	7	12.07%
Rural	478	32.06%	35	13.26%	19	12.75%	2	3.45%

In addition, I asked users of these services two questions about how the use of on-demand ride services has affected their use of other means of transportation. The first question asked the effect that the most recent trip made by Uber/Lyft had on the use of other means of transportation. The second question asked how the respondent would have made that trip (if at all) if these services had not been available. The results are reported in Figure 4 and Figure 5, respectively. As shown in Figure 4, the use of on-demand ride services tends to reduce the amount of driving done by most users, but it also substitutes, to a non-trivial extent, for some trips that would have otherwise been made by transit or active modes. This is more true for millennials, who are less likely to own their own car and are thus more dependent on transit and active modes than older cohorts. Of course, it should be pointed out that any driving being saved by the respondent is essentially being transferred to the Uber/Lyft driver, more (to the extent that the Uber/Lyft driver cruises or deadheads between rides) or less (to the extent that the on-demand ride is shared with others or time spent looking for parking is avoided).

I also asked respondents to report the mode(s) with which they would have traveled if Uber or Lyft had not been available for the last trip made with these services. As indicated in Figure 5, the majority reported that they would have hailed a taxi in the absence of these services. This finding is not surprising, and it confirms the competition between on-demand ride services and taxicabs, a situation that has led to controversy in many countries regarding the introduction and regulation of these services. On-demand ride services target a wider user market than taxis by offering services at lower (and more predictable) costs with shorter waiting times and easier hailing and payment.

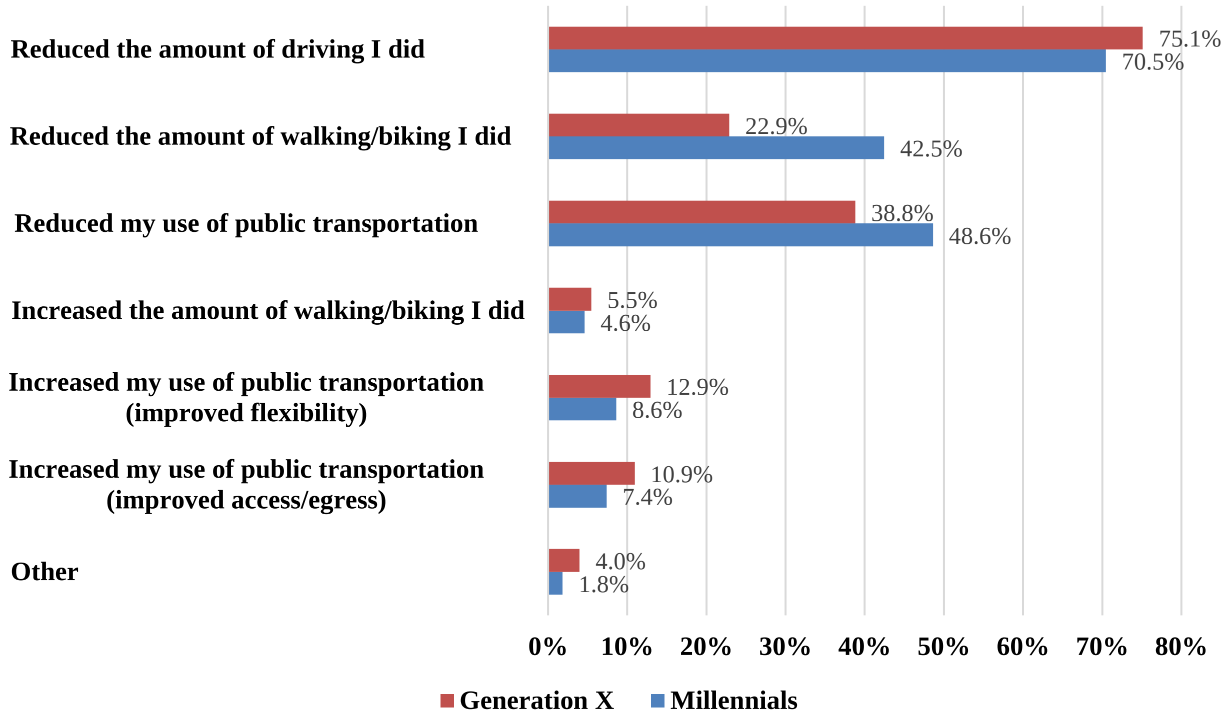

Figure 3.4 – The Impact of Uber/Lyft on Other Means of Transportation by Age Group (Weighted Sample, $N_{Millennials}$=325, $N_{Gen\ X}$ =201, multiple answers allowed for each respondent)

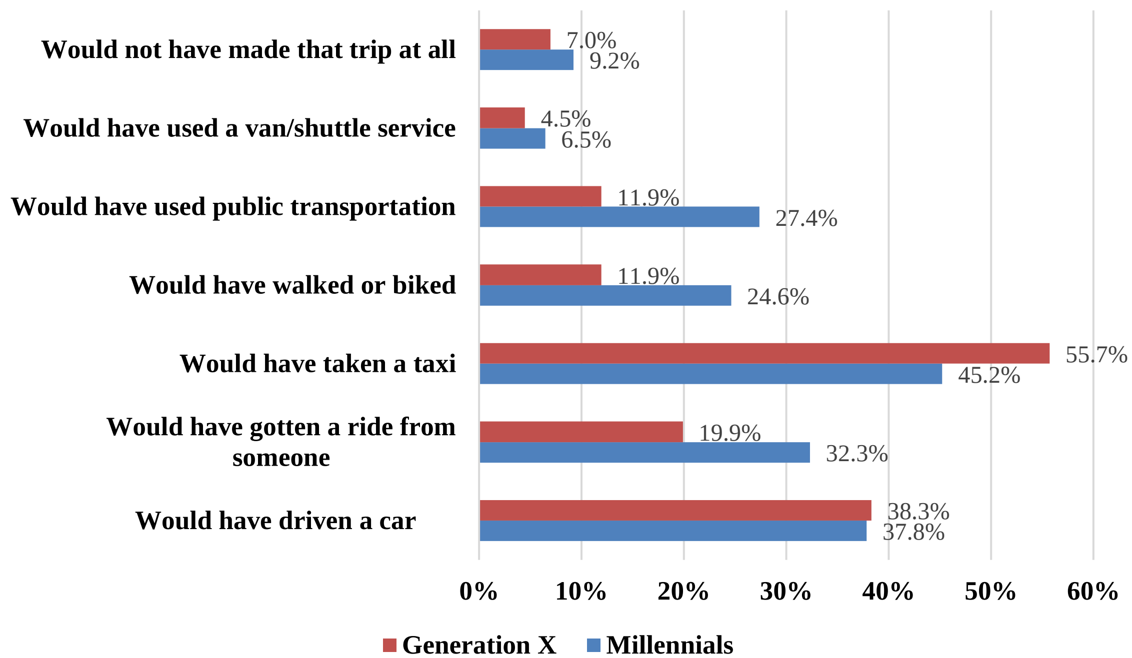

Figure 3.5 – How Users Would Have Traveled in the Absence of Uber/Lyft by Age Group (Weighted Sample, $N_{Millennials}$=302, $N_{Gen\ X}$ =164, multiple answers allowed for each respondent)

Figure 3.4 and Figure 3.5 exhibit similar patterns, such as higher shares of millennials reporting reductions in walking/biking and transit use than for Gen Xers. A close comparison of the two figures is revealing, however. Strictly speaking, the same people who reported that they would have walked/biked or used public transportation if not for Uber/Lyft (Figure 3.5) should also have reported that Uber/Lyft reduced their walking/biking or public transportation use (Figure 3.4). Instead, for both of these mode categories and across both cohorts, I see substantially lower shares in Figure 3.4 than in Figure 3.5.[4] I speculate that these logical inconsistencies are a result of the differences in question format, the multiple answers allowed for each question, and the fact that many users might end up reporting a reduction in some modes (e.g. they walk less because of the use of Uber) as the impact of the substitution with a *third* mode (e.g. users who switch from using public transit to Uber *do* reduce their use of public transit and also the amount of walking they do to/from public transit stations). Further, in Figure 3.5, respondents were asked to consider a counterfactual: "what would you have done if Uber/Lyft had not been available?" To answer this question, they must "think backward" and *hypothetically* "change the past", whereas to respond in Figure 3.4 ("how did Uber/Lyft affect your use of other modes?", they must "think forward" about the *consequences* of an action *actually taken*. Of course, accurately picturing the consequences still requires comparison to the counterfactual, but it seems plausible to conjecture that the forward-oriented question format evokes that comparison in a more instinctive fashion.

[4] The situation for reducing driving is more complex, because some respondents could conceivably have answered "Reduced the amount of driving I did" with taking a taxi or being a car passenger in mind, since those options were not presented in the first question. The combined shares of people (92% of Gen Xers, 84% of millennials) responding "would have driven a car", "would have taken a taxi", "would have used a van/shuttle service", or "would have gotten a ride from someone" in Figure 3.5 is higher in each cohort than the shares (72% Gen Xers, 69% of millennials) responding "Reduced the amount of driving I did" in Figure 3.4, suggesting that at least some of these respondents reported a reduction in "driving" to more generally refer to a reduction in "car use".

3.7 Conclusions and Discussion

In this study, I investigated the factors that affect the adoption of on-demand ride services such as Uber and Lyft among millennials and members of the preceding Generation X, using data collected in California during fall 2015. This study is different from previous ones in using multivariate analysis to investigate the joint and separate influence of multiple factors affecting the adoption of on-demand ride services. Availability of Uber and Lyft as well as the share of trips made by these services are continuously growing: even though Uber and Lyft do not share information about their market and characteristics of their users, information disseminated online suggests that the number of cities where these services are available at least doubled from 2015 to 2016. I expect that these services will continue to grow until they become available throughout the U.S. The role of on-demand services will likely increase still more as society transitions toward a future dominated by autonomous vehicles. Accordingly, planners and policymakers have a strong interest in improving their understanding of the factors affecting the use of these services and the potential impacts that these services have on travel behavior.

I estimated two binary logit models to quantify the relationships between the use of on-demand ride services and several groups of explanatory variables including individual lifestyles, the adoption of various forms of technology, the characteristics of the built environment where an individual lives, and individual attitudes and preferences, while controlling for key socio-demographic traits. The results from this study confirm that younger, better-educated individuals and individuals of non-Hispanic origin are more likely to adopt on-demand ride services. I also find that increased land-use mix and regional auto accessibility increase the likelihood of using on-demand ride services. The same is true for individuals with “technology-oriented” lifestyles: the degree of familiarity with modern technologies and their adoption in daily life is associated with a higher likelihood of adopting ridehailing. Further, the adoption of on-demand ride services is more likely for individuals who make more long-distance business trips and for those who travel more by plane.

I also find that individuals who reported that they are using their car less frequently compared to the past (i.e. 2012) and those who plan to replace or dispose of at least one of their household's vehicles are more likely to use on-demand ride services. While these findings provide information on potentially relevant relationships of interest to planners (for their implications regarding future travel demand), these variables were not included in the final models due to potential endogeneity biases. The directionality of the relationships with these variables is an important question that should be addressed in future stages of the research. In fact, the direction of these relationships could be reversed, or bi-directional, meaning that the use of on-demand ride services leads to these changes, or these behavioral shifts and the use of on-demand ride services could both be influenced by other intermediate variables. The nature of this complex relationship is analogous to the issue of residential self-selection (Cao, Mokhtarian and Handy 2009). Someone might choose to adopt on-demand ride services as a consequence of their car-ownership and use (e.g. those who do not own enough vehicles in the household might use these services to satisfy their mobility needs), or might decide to reduce their vehicle ownership and use as a result of the adoption of these technological transportation options. I plan to investigate this topic in future steps of the research through alternative modeling approaches and specifications.

This study found that the initial single-user versions of ridehailing services tend to reduce the amount of driving among both frequent and non-frequent users, and substitutes for some trips that would have otherwise been made by transit or active modes. The substitution effect is found to be stronger among the frequent users of Uber/Lyft, who are more likely to live in zero-/lower vehicle households and are more multimodal. Thus, the net VMT impacts of single-user services are uncertain, given that reduced trips are offset to an uncertain extent by reduced transit trips and some deadheading by Uber/Lyft drivers. Hence, the public benefits of single-user demand-responsive services are still uncertain.

Moving forward, there will be an increasing need to coordinate policymaking and incentives in order to harvest the potential benefits of these services while reducing the negative effects. The greatest public benefits would be achieved by promoting the pooling version of these services. However, information about factors affecting the use of pooling services is still limited. Another challenging issue is transit. As discussed above, single-traveler services inevitably divert some passengers from transit, undermining the use of public services. On a positive note, on-demand ride services can be integrated with public transit to provide better overall service, in particular by providing rides during the hours public transit does not run very frequently or by solving the first and last mile issues. Even though this study and others provide some insight on this phenomenon, the effects that on-demand ride services may have on the use of other modes are still uncertain due to large variability across demographic groups, transit service levels, and other factors.

During the next stages of the research, I plan to expand and address some of the limitations of this analysis (a) through the inclusion of attitudes as latent rather than manifest variables using a hybrid choice model, and (b) by incorporating preference heterogeneity and taste variation (as latent classes) into the choice model. This will allow us to, respectively, avoid measurement biases in modeling the impact of individual attitudes on the use of on-demand ride services and to better account for differences in the importance of various factors among different groups of individuals. I also plan to investigate the factors affecting the frequency of use of on-demand ride services, because the binary models that I developed in this chapter group frequent and non-frequent users of these services together. It is expected that different factors and circumstances affect the frequency of use of on-demand ride services. In addition, to address the issue of self-selection in the context of using on-demand ride services, I plan to explore/test different causality structures (two unidirectional and one bidirectional), and compare the magnitudes of the marginal effects of each endogenous variable to understand the nature of the relationships between the adoption of ridehailing and other behavioral changes.

3.8 Acknowledgements

This study was funded by the National Center for Sustainable Transportation (NCST), which receives funding from the USDOT and Caltrans through the University Transportation Centers program. The first author also received financial support through an NCST dissertation fellowship. The authors would like to thank Caltrans, the NCST and USDOT, for their support of university-based research in transportation. The Sustainable Technology Energy Pathways (STEPS) Program of the University of California, Davis provided additional financial support for the data collection. The authors wish to thank Lew Fulton, Rosaria Berliner and Kate Tiedeman who contributed to the survey design and data collection, and Yongsung Lee who assisted in the data preparation.

3.9 Appendices

3.9.1 Appendix A

Table 3.7 – Factors and their Attitudinal Statement Loadings

Attitudinal Statements	Loadings from Pattern Matrix
Pro-environmental Policies	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.938
We should raise the price of gasoline to provide funding for better public transportation.	0.844
The government should put restrictions on car travel in order to reduce congestion.	0.344
Variety Seeking	
I like trying things that are new and different.	0.605
I have a strong interest in traveling to other countries.	0.406
Technology Embracing	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.623
Getting around is easier than ever with my smartphone.	0.517
Learning how to use new technologies is often frustrating.	-0.333
Technology creates as least as many problems as it does solutions.	0.293
Traditional Shopper	
I prefer to shop in a store rather than online.	0.997
I enjoy shopping online.	-0.418
Pro-exercise	
The importance of exercise is overrated.	0.824
Getting regular exercise is very important to me.	-0.586
Pleasant Commute	
My commute is stressful.	-0.800
My commute is generally pleasant.	0.689
Traffic congestion is a major problem for me personally.	-0.545
The time I spend commuting is generally wasted time.	-0.501
Getting stuck in traffic does not bother me that much.	0.306
Pro-suburban	
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to.	0.761
I prefer to live close to transit even if it means I will have a smaller home and live in a more crowded area.	-0.690
I like the idea of living somewhere with large yards and lots of space between homes.	0.429
I like the idea of having different types of businesses (such as stores, offices, restaurants, banks, library) mixed in with the homes in my neighborhood.	-0.351
Responsive to Environment and Cost of Travel	
The environmental impacts of the various means of transportation affect the choices I make	0.731
I am committed to using a less polluting means of transportation as much as possible	0.591
The price of fuel affects the choices I make about my daily travel	0.532
To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle	0.381
Established in Life	
I am already well-established in my field of work.	0.698
I am still trying to figure out my career (e.g. what I want to do, where I will end up).	-0.638
I am generally satisfied with my life.	0.382
Long-term Urbanite	
I picture myself living long-term in a suburban setting	-0.808
A house in the suburbs is the best place for kids to grow up.	-0.570
I picture myself living long-term in an urban setting	0.321
Must Own a Car	
I definitely want to own a car	0.716

I am fine with not owning a car, as long as I can use or rent one any time I need it	-0.488
Materialistic	
I would/do enjoy having a lot of luxury things.	0.417
I prefer to minimize the material goods I possess.	-0.402
I like to be among the first people to have the latest technology.	0.394
For me, a lot of the fun of having something nice is showing It off.	0.387
To me, owning a car is a symbol of success	0.299
Climate Change Concern	
Greenhouse gases from human activities are creating major problems.	0.791
Any climate change that may be occurring is part of a natural cycle.	-0.662
It is pointless for me to try too hard to be more environmentally friendly because I am just one person.	-0.315
Monochronic	
It's best to finish one project before starting another.	0.513
I like to juggle two or more activities at the same time.	-0.346
Time and Mode Constrained	
My schedule makes it hard or impossible for me to use public transportation.	0.578
I am too busy to do many things I'd like to do.	0.442
Most of the time, I have no reasonable alternative to driving	0.398
Pro-social	
Social media (e.g. Facebook) makes my life more interesting.	0.502
People are generally trustworthy.	0.426
I enjoy the social aspects of shopping in stores.	0.325
Car as a Tool	
The functionality of a car is more important to me than its brand	0.580
To me, a car is just a way to get from place to place	0.478

Note: loadings <0.29 are omitted.

3.9.2 Appendix B

Table 3.8 – Distribution of Key Explanatory Attributes (Unweighted Sample)

Explanatory Variables	**Users [N=472]**		**Heard But Never Used [N=1243]**		**Never Heard [N=251]**	
	Count	**Col. %**	**Count**	**Col. %**	**Count**	**Col. %**
Socio-demographics						
Age [N=1966]						
Younger Millennials	70	14.83%	219	17.62%	45	17.93%
Older Millennials	233	49.36%	419	33.71%	86	34.26%
Younger Gen X	101	21.40%	286	23.01%	57	22.71%
Older Gen X	68	14.41%	319	25.66%	63	25.10%
Presence of Children in the Household [N=1966]						
Yes	198	58.05%	641	51.57%	140	55.78%
No	274	41.95%	602	48.43%	111	44.22%
Household Income [N=1831]						
Low ($0-40K)	101	22.54%	334	29.04%	122	52.36%
Medium ($40-100K)	209	46.65%	586	50.96%	87	37.34%
High ($100K+)	138	30.80%	230	20.00%	24	10.30%
Employment Status [N=1966]						
Employed	376	79.66%	781	62.83%	136	54.18%
Not Employed	96	20.34%	462	37.17%	115	45.82%
Student Status [N=1966]						
Student	106	22.46%	213	17.14%	47	18.73%
Not Student	366	77.54%	1030	82.86%	204	81.27%
Education Level [N=1958]						
Bachelor's Degree or Higher	306	64.83%	519	41.96%	50	20.08%
Associate Degree or Below	166	35.17%	718	58.04%	199	79.92%
Ethnicity [N=1966]						
Hispanic Origin	91	19.28%	304	24.46%	71	28.29%
Non-Hispanic Origin	381	80.72%	939	75.54%	180	71.71%
Sex [N=1966]						
Female	275	58.26%	736	59.21%	148	58.96%
Male	197	41.74%	507	40.79%	103	41.04%
Geographic Regions and Built Environment						
Region [N=1966]						
Central Valley	26	5.51%	180	14.48%	50	19.92%
Northern California	17	3.60%	111	8.93%	54	21.51%
Sacramento	52	11.02%	186	14.96%	41	16.33%
San Diego	103	21.82%	198	15.93%	18	7.17%
Greater Los Angeles	143	30.30%	296	23.81%	51	20.32%
San Francisco Bay Area	131	27.75%	272	21.88%	37	14.74%
Neighborhood Type (Geocoded Home Address) [N=1966]						
Urban	164	34.74%	196	15.77%	19	7.57%
Suburban	234	49.58%	617	49.64%	111	44.22%
Rural	74	15.68%	430	34.59%	121	48.21%
Land Use Mix (8-Tier Employment Entropy) [N=1966]						
Mean *(Std. Deviation)*	0.64 *(0.24)*		0.59 *(0.29)*		0.61*(0.28)*	
Destination Accessibility (Regional Centrality Index by Auto) [N=1966]						
Mean *(Std. Deviation)*	0.59 *(0.21)*		0.51 *(0.23)*		0.51*(0.26)*	
Lifestyles and Use of Technology:						
Use of Social Media (Facebook) [N=1966]						
Lower Frequency	119	25.21%	458	36.85%	84	33.47%
Higher Frequency	353	74.79%	758	63.15%	167	66.53%

Use of Taxi [N=1863]						
Used Taxi Before	325	71.59%	463	38.08%	73	37.82%
Never Used Taxi Before	129	28.41%	753	61.92%	120	62.18%
Use of Carsharing Services [N=1961]						
Used Carsharing Services Before	79	16.74%	22	1.77%	6	2.39%
Never Used Carsharing Services	393	83.26%	1221	98.23%	245	97.61%
PCA Score: Use of Smart Phone to Determine Destination and Route [N=1961]						
Mean *(Std. Deviation)*	0.35 *(0.79)*		-0.25 *(1.01)*		-0.50 *(1.15)*	
PCA Score: Use of Smart Phone for Mode Choice [N=1961]						
Mean *(Std. Deviation)*	0.28 *(1.02)*		-0.21 *(0.91)*		-0.26 *(0.94)*	
Frequency of Long-Distance Business Travel (Log-Transformed) [N=1936]						
Mean *(Std. Deviation)*	0.42 *(0.51)*		0.21 *(0.41)*		0.31 *(0.48)*	
Share of Total Long-Distance Travel with Plane [N=1924]						
Mean *(Std. Deviation)*	0.32 *(0.32)*		0.15 *(0.27)*		0.07 *(0.18)*	
Personal Attitudes:						
Factor Score: Technology Embracing [N=1965]						
Mean *(Std. Deviation)*	0.41 *(1.14)*		-0.08 *(1.26)*		-0.35 *(1.26)*	
Factor Score: Variety Seeking [N=1965]						
Mean *(Std. Deviation)*	0.41 *(1.11)*		-0.11 *(1.27)*		-0.26 *(1.44)*	
Factor Score: Pro-Environmental Policies [N=1965]						
Mean *(Std. Deviation)*	0.33 *(1.12)*		-0.10 *(1.02)*		-0.17 *(0.97)*	
Factor Score: Multi-tasking [N=1965]						
Mean *(Std. Deviation)*	0.10 *(1.33)*		-0.05 *(1.41)*		-0.41 *(1.42)*	

4. EXPLORING THE LATENT CONSTRUCTS BEHIND THE USE OF RIDEHAILING SERVICE IN CALIFORNIA

4.1 Abstract

Emerging transportation Emerging transportation services are quickly changing the way individuals travel by expanding the set of transportation alternatives available for a trip, allowing for more flexibility in travel schedules and providing access to transportation without incurring the costs of auto ownership. Among the most controversial and rapidly growing shared-mobility services are ridehailing services, such as those offered by Uber and Lyft in the U.S. market. In this Chapter, I investigate the factors affecting the adoption of ridehailing through the estimation of a latent-class adoption model that captures the heterogeneity in individuals' tastes and preferences, focusing on members of the millennial generation and the preceding Generation X. I present a 3-class adoption model that provides better goodness of fit and interpretability of the classes compared to other model specifications that were tested. The three distinct classes are: (1) a class that is largely composed of more highly-educated, independent (i.e. who have already established their household) millennials, who has the highest adoption rate. Among other factors, the adoption of ridehailing services for the members of this class is influenced by the frequency of long-distance leisure and business-related trips made by non-car modes. The adoption of ridehailing among the members of this group is higher if they live in high-quality transit neighborhoods. (2) The second highest adoption rate is observed among the members of the class that is mainly composed of affluent individuals living with their families who are either dependent millennials or older members of Generation X. The frequency of use of transportation-related smartphone apps and the share of long-distance leisure trips made by plane affect the adoption of ridehailing for the members of this class. The members of this class also

tend to adopt ridehailing if they live in neighborhoods with higher land-use mix and if they have used taxi services within the past 12 months. Finally, the lowest adoption rate is observed among the members of the last class, comprising the least affluent individuals with the lowest level of education. The members of this class are more likely to live in rural neighborhoods and they rarely use ridehailing. The adoption of ridehailing among the members of this class is affected by household income, the frequency of long-distance non-car business trip, transit accessibility as well as the use of taxi and of carsharing.

4.2 Introduction

The increased availability of locational data and the continuously increasing number of smartphone apps, together with other information and communication technology (ICT) solutions, are transforming transportation supply and demand in many ways. These new technology-enabled transportation services substantially increase the flexibility of travel choices and the access to transportation services without the fixed cost of auto ownership. New shared-mobility services range from *carsharing* to *ride-sharing* services, including *dynamic carpooling* such as Carma and *ridehailing* services such as Uber and Lyft, as well as *bikesharing* services (Shaheen et al. 2016a). The range and availability of these transportation services are continuously growing and are expected to evolve even faster with the introduction of autonomous and connected vehicles (Sperling et al. 2018).

One of the rapidly growing forms of shared-mobility services is ridehailing (also known as on-demand ride services, ridesourcing, transportation network companies, or TNCs) such as Uber and Lyft in the U.S. market. Ridehailing services provide rides to passengers in a manner similar to traditional taxi cabs, but they differ from taxi cabs in that passengers can only request a ride via their smartphone app. The app connects travelers to a network of available drivers, who are recruited from among non-professional drivers, who can enroll to drive, if desired, only for a limited amount of time using their own vehicles (e.g. part-time drivers who have another job during the rest of the day). Ridehailing drivers “chauffer” passengers to their final destination in exchange for monetary compensation. Thus, they provide a service which is more similar to a taxi than to other dynamic ridesharing services, such as Carma, which only offer rides to passengers along (or with only short deviations from) a driver’s main route and/or to the same final destination.

The availability and visibility of ridehailing have grown quickly: a recent study of ridehailing services showed that the share of total trips made with Uber and Lyft can exceed 15% (170,000 trips per day) of all trips inside the city of San Francisco on a typical weekday (SFCTA 2017), which is equivalent to 20% of total vehicle miles traveled (VMT) inside the city of San Francisco, and 6.5% of total VMT including both intra- and inter-city trips. If these services continue to grow in availability and popularity, the implications for future travel patterns are substantial. Thus, understanding the factors that affect the adoption of Uber and Lyft is an important topic in transportation research with important implications for planning and policy making.

It is also critical to understand how the use of ridehailing affects activity patterns and schedules, the use of other means of transportation, vehicle ownership, vehicle miles traveled and the associated greenhouse gas (GHG) and pollutant emissions. Transportation researchers (so far) have had a limited ability to understand the potential impacts associated with the growth in the use of the these services, largely due to (1) the dearth of data about users, the nature of their use, and the changes in travel behavior that ridehailing causes; (2) uncertainty over the evolution and eventual maturation of the use of Uber/Lyft and related impacts, and (3) heterogeneity in the potential impacts owing to differences in the local contexts and the characteristics of the users. Without a clear understanding of how these services are changing travel patterns, policy makers and transportation planners face a significant challenge in pursuing the goals of designing a more sustainable, equitable, and safe transportation system.

This chapter builds on a study of the factors that affect the adoption of ridehailing and further expands my investigation of the impacts of these factors through the estimation of a latent-class model. The latent-class adoption model is an extension of the previous binary logit adoption models (for more details, see Alemi et al. 2017). The latent-class adoption model allows us to capture variation in individuals' tastes, preferences, lifestyles, and sensitivities (Gopinath 1995), by simultaneously grouping individuals into latent classes and estimating how the adoption of ridehailing services is influenced by the various groups of factors that are studied and how choice processes differ by class. While in my previous paper (Alemi et al., 2017) no segmentation was introduced in the models, in this Chapter I identify three well-defined latent classes of users. The analysis of the class sizes, of the variables affecting the likelihood of an individual to belong to a certain class (membership model), and of the variables that affect the adoption of ridehailing for the members of each class (outcome model) contributes to improving the understanding of how sociodemographic traits, built environment variables, lifestyles, and individual and household characteristics lead to the adoption of these services. In this analysis, I use data from the 2015 California Millennials Dataset, a rich source of information on attitudes, lifestyles, travel patterns and the characteristics of the built environmental in the place of residence for members of the millennial generation and the preceding Generation X in California.

The remainder of this chapter is organized as follows: after a brief literature review in Section 4.3, Section 4.4 discusses the data collection and methods of analysis. Then, Section 4.5 discusses the estimation of a latent-class adoption model that investigates the impact of various factors on the adoption of ridehailing. Finally, conclusions and perspectives for future research are presented in Section 4.6.

4.3 Literature Review

Transportation in the United States as well as in other countries is going through an era of rapid transformation. The previously steady growth in the amount of personal driving was temporarily interrupted in the first decade of the new century. Total vehicle mile traveled (VMT) in the U.S. and other developed countries at least temporarily "peaked" and began to decline before VMT growth started to recover around 2013 to reach new record highs between 2016 and 2018. This trend, which is also referred to as (at least temporary) "Peak Car" and the factors affecting it have been discussed in many previous publications (e.g. Garceau et al. 2014; Circella et al. 2016a; Goodwin and Van Dender 2013; Kuhnimhof et al. 2013; McDonald 2015; Bastian et al. 2016; Rohr et al. 2017). The majority of these studies show that the decline in automobile use was stronger among young adults (millennials) who tend to live in more urban areas and are less dependent on car use. For example, Rohr et al. (2017) denoted that the rate of VMT per driver dropped much more among millennials during the period 2001-2009, while only a very modest change was observed for the other age groups in the same period.

Millennials are increasingly reported to have different lifestyles, travel behavior, and preferences from other age groups (Rohr et al. 2017; McDonald 2015; Circella et al. 2017a; Garikapati et al. 2016). For example, they often postpone the time they obtain a driver's license, choose to live in urban locations and not to own a car, and use alternative means of transportation more often (Rohr et al. 2017; Circella et al. 2017b; Blumenberg et al. 2012; Kuhnimhof et al. 2012; Frändberg and Vilhelmson 2011). Several explanations have been proposed to explain these patterns and the differences between the choices of millennials and the members of preceding generations, including the recent economic recession, differences in familiarity with modern technologies (as suggested by McDonald, 2015), differences in individual attitudes and preferences (Circella et al 2017b; Rohr et al. 2017), the emergence of technology-enabled transportation services, and differences in residential location (BRS, 2013).

A contributing factor is certainly the emergence of new shared-mobility services, which are expected to impact travel behavior and transportation choices of the members of all generations. One of the most rapidly growing types of shared-mobility services is ridehailing. Uber and Lyft, the major providers of these services in the U.S. market, launched their flagship services UberX and Lyft Classic in summer 2012 directly competing with local taxi services. To increase vehicle occupancy and provide more affordable rides, these companies launched UberPOOL and Lyft Line, respectively, in the fall of 2014. These services offer a ride to several distinct passengers in the same vehicle matching them based on their similar routes. They provide pooled ride services at a lower cost than conventional ridehailing options by allowing drivers to pick up and drop off multiple passengers during the same trip. These pooling services are priced up to 50% lower, which increases their appeal to price-sensitive travelers. Ridehailing companies have quickly extended the availability of their services to all major metropolitan areas across the country. As of November 2017, Uber operates in more than 700 cities and has expanded into about 80 countries, while Lyft operates mainly in the U.S. market providing rides in more than 300 cities (Shaheen et al. 2018).

Despite many anecdotal articles in the media on the adoption of these services, research on the users of ridehailing services and the overall impacts that these services have on other components of travel behavior is still limited. Overall, studies on ridehailing follow one of these two distinctive directions: (1) studies that investigate the adoption and frequency of use of ridehailing; and (2) studies that discuss the impacts of ridehailing on travel patterns and other components of travel behavior, e.g. mode choice, vehicle ownership, and activity patterns.

Previous research about the early adopters of carsharing and bikesharing (i.e. other shared-mobility services that were introduced to the market earlier than ridehailing) showed that early adopters of shared-mobility services tend to be younger, highly-educated and multimodal individuals who live in urban neighborhoods and in the households with a lower-than-average number of vehicles per household driver (Cervero 2003; Katzev 2003; Buck et al. 2013; Circella et al. 2016a; Shaheen et al. 2012). In a related study (Alemi et al. 2017; Circella et al. 2018), I estimated an adoption model of ridehailing, showing that the adoption of ridehailing is higher among better-educated and higher income older millennials (i.e. individuals between the age of 25-34 years old at the time of the data collection in 2015) who predominantly live in urban neighborhoods. These findings are consistent with the results of other related studies based on the analysis of descriptive statistics (e.g. Rayle et al. 2014; Taylor et al. 2015; Feigon and Murphy 2016; PEW research center 2016). Among other socio-demographic factors, I found that individuals who work and study have the highest adoption rate compared to non-workers and those who either only work or only study. Higher adoption levels were also found among individuals who live in households without kids, and among individuals of non-Hispanic origin (Alemi et al. 2017). The results discussed in previous chapter and Alemi et al. (2017) also confirmed the role of the built environment on the adoption rate of ridehailing: higher land-use mix and regional accessibility by car is associated with a higher probability of using ridehailing. Similarly, the degree of familiarity with and the use of modern technologies (such as the use of smartphones in relation to transportation, and the use of other emerging transportation services) are associated with higher adoption of ridehailing. With respect to individual attitudes, I found that those with stronger pro-environmental, technology-embracing, and variety-seeking attitudes are more likely to use Uber/Lyft (Alemi et al. 2017).

Future adoption rates and the usage of ridehailing will likely depend on a number of factors, including the availability and accessibility of these services and other travel alternatives, individuals' perceptions of convenience and reliability, and residential location choices. Another important question would be the eventual permanence of the observed travel patterns: will current users continue to use these services with the same frequency as they transition to later stages of life and as the rise in the population of urban millennials slows down and millennials eventually begin to move back to the suburbs (Myer 2016)? In order to help answer this and other related questions, it is important to better understand the factors that affect the travel decisions of each group of individuals and better incorporate individuals taste heterogeneity into travel demand forecasting models. This is one of the goals of the current chapter.

There are various theoretical frameworks that can explain the adoption of new shared-mobility services, including the Theory of Planned Behavior, the Theory of Reasoned Action, the Technology Acceptance Model, and the Innovation Diffusion Theory. However, the adoption of new shared-mobility services is not a simple decision process and is contingent on a series of circumstances and other decisions made at the individual and household levels over various time horizons. The integration of various theories becomes more important as the complexity in individual's decision-making process increases. For example, El Zarwi et al. (2017) estimated a latent-class choice model to identify different classes of shared mobility adopters based on the Innovation Diffusion Theory and integrated it with a network effect model (destination choice model) to quantify the network impacts associated with the adoption of these services. The authors later used this framework to forecast the adoption of one-way carsharing using time-series data for a major city in the United States. In this study, I follow the theoretical framework proposed by Van Acker et al. (2010), who outlined transportation-related decision-making mechanisms as a series of hierarchical decisions made by individuals to meet their preferred lifestyles. Thus, lifestyle is considered a higher-level orientation that impacts all other individual's decisions and choices, including mode choice and the decision on whether to use certain transportation services.

Kitamura (2009) defined lifestyles as a measure of time use and activity patterns as well as values and behavioral orientation. Based on the former definition, individuals' lifestyles may change in response to changes in the environment or stage in life, whereas a lifestyle as a behavioral orientation may influence this adaptation process. "Lifestyle" as a value and behavioral orientation explains the motivation behind individual's decision-making mechanism. The impact of lifestyles on travel choices is irrefutable. Salomon and Ben-Akiva (1983) quantified the impact of lifestyles on travel behavior for the first time, defining lifestyle as "a pattern of behavior under constrained resources which conforms to the orientations an individual has toward three major life decisions" (Salomon and Ben-Akiva 1983, p. 624). In their study, the authors defined the three major life decisions: the formation of the household, participation in the labor force, and orientation toward leisure. Since then, a wide range of studies has quantified the impact of individuals' lifestyles on different components of travel behavior, including mode choice (Kitamura et al. 1997; Lanzendorf 2002; Vredin Johansson et al. 2006; Vij et al. 2014), vehicle type choice (Choo and Mokhtarian 2004; Bolduc et al. 2008), residential location (Walker and Li 2007), and activity participation (Ory and Mokhtarian 2009).

Even though the literature is converging to a formal definition of lifestyle either as a typology of behavior or as latent factors motivating behavioral patterns, there is no consensus, yet, on the methods that can be employed to measure individuals' lifestyles. Van Acker (2015) illustrated three major approaches that have been used to measure lifestyles. The first approach is known as the socioeconomic and demographic lifestyle approach, where various objective socioeconomic and demographic characteristics as well as the stage of life are used to characterize individual or household lifestyles. In the second approach, researchers characterized lifestyles based on attitudes toward various topics (most importantly attitudes toward family, work and leisure), personality traits and related motives. This approach is known as the sociographic approach. Van Acker described the third approach, the mechanistic lifestyle approach, as a method which focuses on individual behavioral patterns. In this study, I characterize individual lifestyles based on their socioeconomic and demographic attributes, using Ganzeboom's three-dimensional indicators (1988, as cited in Van Acker et al. 2010), which measure an individual's economic, cultural and stage in life dimensions.

The focus of this chapter is both on modeling individual lifestyles and on better understanding the factors affecting the adoption of ridehailing services (while controlling for variation in individual lifestyles). I do this through a stochastic segmentation of individuals based on their sociodemographic attributes, so that those who put similar weight on the various factors influencing their decision on whether to use ridehailing services are grouped together. The estimation of a latent-class adoption model allows the joint estimation of the adoption of ridehailing (behavior) as well as the latent classification of respondents with respect to their sociodemographic attributes and built environment characteristics. The joint estimation of latent-class choice models combines the socio-economic and mechanistic lifestyle approaches, which can be further extended through including attitudes as latent variables in the model. Thus, this approach is preferable over other aggregated adoption and diffusion models that may result in "badly judged marketing decisions" or in targeting the wrong people, particularly in the context of fast-moving ICT-based innovations (cf. De Marez and Verleye, 2004). Instead, the use of diffusion models would make more sense for the analysis of longitudinal data, where researchers can take into account the temporal dimensions of the adoption process (as reflected in the form of innovators and imitators, or early adopters, early majority, late majority, etc.) over time.

4.4 Data Collection and Methodology

4.4.1 The California Millennials Dataset

The data used in this study was collected in fall 2015, as part of research project that investigates emerging travel patterns and residential location decisions among the members of Generation Y or millennials (i.e. young adults born between 1981 and 1997) and the members of the preceding Generation X (i.e. middle-aged adults born between 1965 and 1980). As a part of this large research effort, our research group designed and administered an online survey to a sample of 1,191 millennials and 964 members of the Generation X who were selected with a quota sampling approach from six major regions of California and three neighborhood types (urban, suburban, and rural). The six regions were defined as (1) the California Central Valley; (2) Sacramento, following the boundaries of the Sacramento Area Council of Governments (SACOG); (3) San Diego, following the boundaries of the San Diego Association of Governments (SANDAG); (4) Greater Los Angeles, following the boundaries of the Southern California Association of Governments (SCAG); (5) the San Francisco Bay Area, following the boundaries of the Metropolitan Transportation Commission (MTC); and (6) the rest of Northern California and Others, comprising the remaining mountain, coastal and rural regions in the state. In addition, various sociodemographic targets were employed to ensure that the sample adequately represented the characteristics of California residents with respect to age, income, race and ethnicity, sex, and presence of children in the household.

A total of 5,466 invitations were sent out, and 3,018 complete cases were collected. The high response rate of 46.3% is not surprising considering the data collection method used for this project, and the higher propensity of opinion panel members to respond to survey invitations. It is important to note potential concerns with the use of opinion panels. In addition to self-selection bias, which affects most of the studies that use surveys as a main method for data collection, one of the major concerns about the use of an online panel is non-coverage bias (also known as non-/under-representativeness bias). The concern is that the members of the online opinion panel may not be (fully) representative of the population. Studies show that several groups of individuals are more likely to be excluded from online panels than others. For example, elderly women with low educational attainment and people without access to the internet are more likely to be excluded from online panels (e.g., Blasius and Brandt 2010). In this study, our research group used a quota sampling approach to recruit participants and ensure that enough respondents are recruited among each group; however, as also discussed by Blasius and Brandt (2010), quota sampling does not completely resolve this issue given the infeasibility of defining large numbers of categories for the quotas. In this study, I believe that defining quotas based on different regions and neighborhood types as well as five socio-demographic characteristics reduce the non-coverage bias.

To compensate for the effect of the quota sampling (which was designed to oversample the cases live in lower-population areas) and to correct for the remaining non-response and non-convergence biases, a combination of cell weighting and iterative proportional fitting (IPF) raking were employed. The weights were developed based on age, neighborhood type, region, race, ethnicity, presence of children in the household, household income, occupation (i.e. student and employment status), and gender. Further, to improve the distribution of the sample weights, in particular, to reduce excessively large sampling variance, our research group decided to trim extreme weights, which only changed the weights of a handful number of cases.

The survey collected information on individual attitudes and preferences; lifestyles; use of ICT and adoption of online social media; residential location and living arrangements; commuting and other travel patterns; auto ownership; awareness, adoption and frequency of use of several types of shared-mobility services; major life events that happened in the past three years; future expectations, aspirations and propensity to purchase and use a private vehicle versus other means of travel; and sociodemographic traits. In the emerging transportation section of the survey, respondents were asked about their familiarity with and the use of several types of emerging transportation services in their home town or while traveling. The emerging transportation services included in the study were *fleet-based carsharing* (e.g. Zipcar or Car2go), *peer-to-peer carsharing* (e.g. Turo), *ridehailing services* (e.g. Uber or Lyft), *dynamic carpooling* (e.g. Zimride or Carma), *peer-to-peer carpooling* (usually arranged via online platforms such as Facebook or Craigslist) and *bikesharing*. In addition to familiarity with and adoption of emerging services, users of ridehailing services were asked to rate the importance of different factors in affecting their use of ridehailing services, how the use of these services impacted their use of other means of transportation, and what they would have done if these services had not been available for their last trip they made by Uber or Lyft. For detailed information on the data collection, the content of the survey, and the exact language used for these questions, see Circella et al. (2016a).

4.4.2 Dependent Variable

Although I also collected various pieces of information on the adoption, the place of use, and the frequency of use of ridehailing services, in this study I mainly focus on the factors and circumstances that are associated with the adoption of ridehailing services. The dependent variable of interest is a binary variable that shows whether a respondent has ever used ridehailing services or not. Figure 4.1 shows the distribution of users and non-users of ridehailing services by age group (millennials vs. the members of the preceding Generation X). As shown in this figure, larger shares of millennials have adopted ridehailing services (28.3%) compared to the older cohorts (18.8%). To create the binary dependent variable, I grouped all individuals who reported that they have used ridehailing services regardless of the location where they used these services and classified them as “users”. Those who have heard about these services but have not used them yet were classified as “non-users”. I excluded from the modeling portion of this study the individuals who reported that they have not heard about Uber and Lyft, since this group of individuals is the smallest one in size, and the individuals in this group are expected to behave differently once they become familiar with the service.

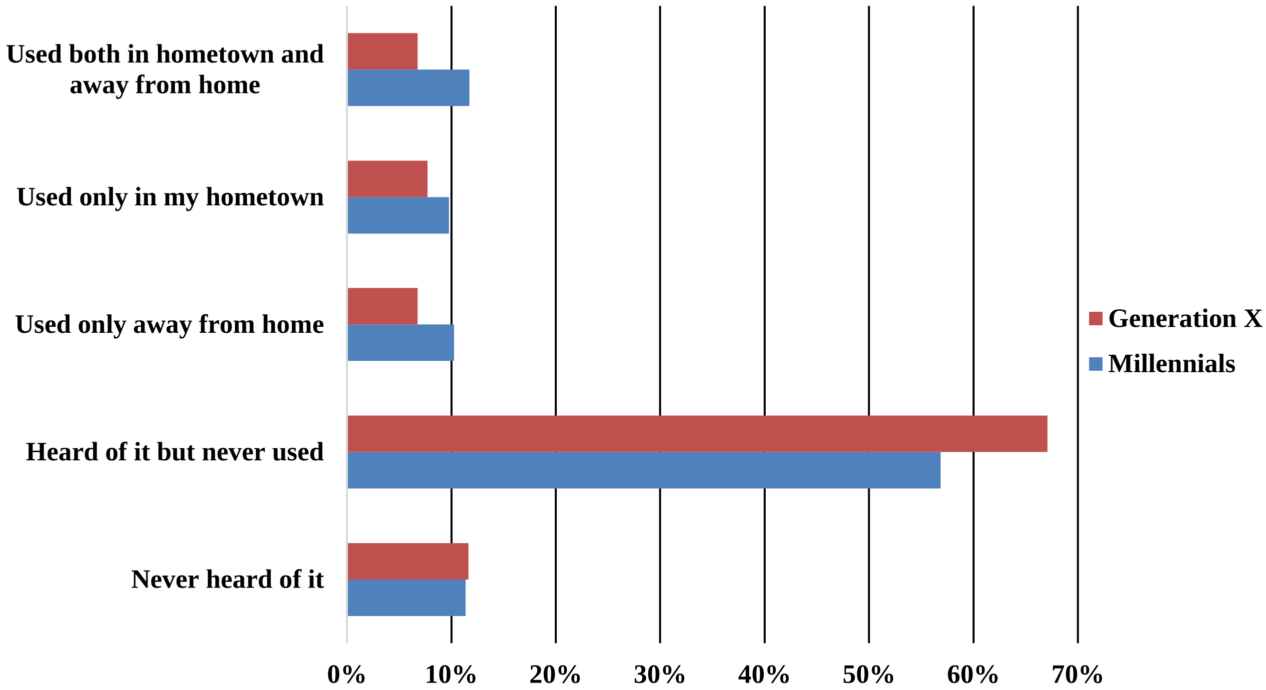

Figure 4.1 – Awareness and Use of Ridehailing (e.g. Uber and Lyft) by Age Group ($N_{Millennials}$=1022, $N_{Gen\ X}$ = 945; Weighted Sample)

4.4.3 Independent Variables

I carefully reviewed the existing literature on the adoption and use of shared-mobility services, sharing economy, and lifestyles to identify the key explanatory variables to include in the model. I divide the explanatory variables available in the California Millennials Dataset and that were included in the model estimation into the four main categories described below:

Socio-economic and demographic variables: The first group includes socio-economic and demographic variables. According to Ganzeboom's (1988, as cited in Van Acker et al. 2010) three-dimensional indicators, I tested the impact of an extensive list of sociodemographic variables on the adoption of ridehailing services such as age, household structure, educational background, stage of life, ethnicity, household income, employment and student status. Table 4.1 presents the distribution of all relevant socio-demographic variables that were included in the final model specification (including those that were used as inactive covariates) grouped by users and non-users of ridehailing services.

Built environmental variables: Controlling for the impact of the built environment on the adoption of ridehailing services is important, since these services are not equally available across various California regions and neighborhood types. Further, differences in land use characteristics may lead to higher adoption rates among individuals who live in specific regions, e.g. as an effect of differences in the travel patterns of the residents of these areas or the availability of travel alternatives. This group of variables includes geographic regions and the characteristics of the neighborhood where the respondent lives; neighborhoods were classified as predominantly urban, suburban or rural, using the geocoded home address and the neighborhood typology defined in Salon (2015)[5]. In addition, to capture spatial heterogeneity and to test the impacts of other built environmental variables such as land-use mix, network connectivity, population density, and accessibility by different modes on the adoption of ridehailing services, I integrated the dataset with additional data extracted from the U.S. Environmental Protection Agency (EPA) Smart Location Dataset, Walkscore.com and the Center for Neighborhood Technology (CNT)'s AllTransit metrics, based on the geocoded residential location of the respondents (for more details, see Circella et al., 2017). Table 4.1 shows the distribution of the built environmental variables that are used in the final model.

Technology adoption and use of social media: The third group of variables controls for an individual's adoption of technology and propensity to use social media, ICT, and other technological solutions (in general, or specifically to access transportation-related services). In

[5] Salon (2015) classifies U.S. census tracts into five neighborhood types using information on local land use and transportation characteristics. For the purposes of this study, I further aggregated those five neighborhood types into three predominant neighborhood types: central city and urban were both classified as *urban*, and rural in urban and rural were classified as *rural*.

the survey, respondents were asked to report their frequency of use of different online social media (e.g. Facebook, Instagram and Snapchat), the frequency of use of smartphone applications to book transportation services, purchase tickets, check traffic conditions, or decide what mode of transportation to use, as well as frequency of e-shopping, adopting telecommuting, etc. I also performed principal component analysis with oblique rotation to reduce the dimensionality of the variables related to the use of smartphones, extracting two main components. Table 4.2 reports smartphone-related variables loading on each of the two factors that were extracted. I also tested the impact of an individual's familiarity with and use of other emerging transportation services (e.g. carsharing and bikesharing) on the adoption of ridehailing services. My hypothesis is that the familiarity and use of other emerging transportation services (that were introduced before Uber and Lyft) can affect the adoption of ridehailing services, as technology-oriented users that already benefit from the use of other shared-mobility services might be more inclined also to adopt ridehailing services.

Long distance travel and number of vehicles in the households: A detailed information on each individual's travel behavior were collected in the California Millennials Dataset, which includes the number of long-distance trips, by purpose and by mode, they made during the past twelve months, and the number of vehicles and number of drivers in the household. The information captured by these variables can be important in explaining the adoption of ridehailing services as these services increasingly become a popular mode to travel to/from airports or other transportation terminals (e.g. intercity train or bus stations), a less expensive option (compared to taxi-cabs) for business-related travel, and reliable (even cheaper) option for low-/zero-vehicle-owning households. The distributions of these variables by user and non-user are presented in Table 4.1.

Table 4.1 – Distribution of Key Explanatory Variables by Use of Ridehailing

Variable Name	Description	Users [N=526]	Non-Users [N=1215]
Socio-economic and Demographics: Stage of Life			
Age and Stage of Life			
Younger Dependent Millennials	18-24 years old, lives with parents and does not live with partner	33 (6.3%)	124 (10.2%)
Younger Independent Millennials	18-24 years old, does not live with parents, or lives with partner and parents	59 (11.2%)	126 (10.4%)
Older Dependent Millennials	25-34 years old, lives with parents and does not live with partner	26 (4.9%)	66 (5.4%)
Older Independent Millennials	25-34 years old, does not live with parents, or lives with partner and parents	208 (39.5%)	266 (21.9%)
Younger Gen X	35-41 years old	116 (22.0%)	314 (25.8%)
Older Gen X	42-50 years old	85 (16.1%)	319 (26.3%)
Presence of Children in the Household			
Yes	Lives in a household with child(ren)	248 (47.1%)	645 (53.1%)
No	Lives in a household without child(ren)	278 (52.9%)	569 (46.9%)
Marital Status			
Married	Married	262 (50.2%)	605 (50.4%)
Not Married	Single or in a committed relationship but not married yet	260 (49.8%)	596 (49.6%)
Socio-economic and Demographics: Income and Employment			
Household Income			
Very Low	Annual household income of 0-19,999 USD	35 (7.0%)	94 (8.4%)
Low	Annual household income of 20-39,999 USD	73 (14.5%)	211 (18.8%)
Medium	Annual household income of 40,000-79,999 USD	121 (24.1%)	372 (33.1%)
High	Annual household income of 80,000-119,999 USD	114 (22.7%)	232 (20.6%)
Very High	Annual household income of 120,000 USD or more	159 (31.7%)	216 (19.2%)
Employment & Student Status			
Work Only	Works only	371 (70.4%)	822 (67.7%)
Study Only	Goes to school only	27 (5.1%)	89 (7.3%)
Work and Study	Works and studies	100 (19.0%)	127 (10.5%)
Not Work and Study	Does not work nor study	29 (5.5%)	177 (14.6%)
Socio-economic and Demographics: Education			
Education			
High Education	Bachelor’s degree or higher	341 (64.8%)	547 (45.3%)
Lowe Education	Lower than Bachelor’s degree	185 (35.2%)	661 (54.7%)
Built Environment			
Neighborhood Type (Geocoded)			
Urban	Lives in urban neighborhood	220 (41.8%)	279 (23%)
Suburban	Lives in suburban neighborhood	241 (45.8%)	568 (46.8%)
Rural	Lives in rural neighborhood	65 (12.4%)	367 (30.2%)
Region			
Northern Region	Lives in *MTC* or *SACOG* area	141 (26.8%)	337 (27.8%)
Southern Region	Lives in *SCAG* or *SANDOG* area	352 (66.9%)	639 (52.6%)
Other	Lives in *Central Valley* or *Northern California or Others*	33 (6.3%)	238 (19.6%)
Land Use Mix	A continuous variable between 0 and 1 (where higher values mean a more diverse mix), measuring employment and household entropy, obtained from the U.S. EPA Smart Location Dataset	0.61 (0.25)	0.56 (0.29)

Transit Performance Index	A continuous variable between 0 and 10 (where higher values mean a more accessible and higher quality transit), measuring overall transit score as a composite index of connectivity, access to land area and jobs, and frequency of service, obtained from the CNT AllTransit dataset	6.73 (2.53)	5.37 (2.82)
Technology Adoption and Use of Social Media			
Use of Smartphone			
To Determine Destination and Route	Standardized principal component scores measuring the frequency of using a smartphone to determine trip destination and route	0.49 (0.75)	-0.16 (0.99)
For Mode Choice	Standardized principal component scores measuring the frequency of using a smartphone to choose specific mode(s) and check transit time	0.39 (1.04)	-0.16 (0.92)
Use of Other Emerging Transportation Services			
Used Carsharing Before	Used carsharing (including fleet-based carsharing and/or peer-to-peer carsharing)	93 (17.7%)	18 (1.5%)
Has not Use Carsharing Before	Never used carsharing (including fleet-based carsharing and/or peer-to-peer carsharing)	432 (82.3%)	1197 (98.5%)
Travel Related Behavior and Decisions			
Use of Other On-demand Services			
Used Taxi Before	Used taxi before	367 (71.5%)	438 (36.9%)
Has not used Taxi Before	Never used taxi before	146 (28.5%)	748 (63.1%)
Long Distance Travel			
Frequency of Long Distance Business Travel by Non-car Mode	Total number of long-distance business trips made by plane, train and inner-city bus in the last 12 months (log transformed)	0.72 (0.92)	0.21 (0.52)
Frequency of Long Distance Leisure Travel by Plane	Total number of long-distance leisure trips made by plane in the last 12 months (log transformed)	0.78 (0.69)	0.33 (0.52)
Household Vehicles per Driver			
Zero-vehicle Household	Household with 0 vehicles or 0 drivers [6]	25 (4.9%)	56 (4.7%)
Vehicle-deficient Household	Household with more than 0 but less than 1 vehicle per household driver	45 (8.8%)	140 (11.8%)
Vehicle-sufficient Household	Household with 1 or more vehicles per household driver	456 (88.9%)	1019 (85.9%)

Note: The mean and the standard deviation (in parentheses) are presented for the continuous variables

Despite the availability of a rich array of attitudes, collected through 66 attitudinal statements included in the survey, I did not use them in the model that is presented. As discussed by various scholars (Ben-Akiva et al. 2002; Bolduc et al. 2005), the inclusion of attitudinal variables into a choice model either singly or in the form of factor scores may introduce some measurement bias. In fact, answers to attitudinal questions are functions of underlying latent attitudes. In future

[6] The households with zero drivers were also included as the zero-vehicle household in household vehicles per driver variable.

developments of the project I plan to include attitudinal indicators as outcomes of latent explanatory variables in the adoption model, which requires the joint estimation of revealed choice(s) and the response to attitudinal statements.

Table 4.2 – Principal Component Loadings of Use of Smartphone in Relation to Transportation

Principal Components and Associated Variables	**Loadings from Pattern Matrix**
Frequency of use of smartphone to determine destination and route	
Navigate in real time (e.g. using Google Maps or other Navigation Services)	0.88
Learn how to get to a new place	0.84
Identify possible destinations (e.g. restaurant, etc.)	0.82
Check traffic to plan my route or departure time	0.75
Frequency of use of smartphone for mode choice	
Check when a bus or train will be arriving	0.97
Decide which means of transportation, or combination of means, to use	0.86

4.4.4 Analysis

To better understand the factors affecting the adoption of ridehailing services, while accounting for variation in individuals' lifestyles, I apply discrete mixture models, and in particular latent class choice models, as the most appropriate model. The latent class choice model captures both unobserved and observed heterogeneity by grouping decision makers into discrete classes that are not immediately identifiable from the data (Walker and Ben-Akiva, 2002) without requiring an analyst to make prior unwarranted assumptions about the distributional parameters or number of clusters (Greene and Hensher, 2003). Latent class choice models comprise two models: (1) the class membership model and (2) the class-specific choice model. In this chapter, the latent classes represent the variations in individual lifestyles (determined with a socio-economic lifestyle approach), whereas the factors affecting the adoption of ridehailing services are tested in the class-specific choice models of the adoption of Uber/Lyft. Latent class choice models simultaneously group individuals with similar lifestyles and estimate how different lifestyles could impact the process of adoption of ridehailing services. This model can capture underlying, unobservable discrete segmentation along with heterogeneity in the adoption of ridehailing services such that people with different lifestyles exhibit different adoption rates and are allowed to be influenced by different variables in the choice model.

The probability of adoption or non-adoption is based on a binary logit formulation that transforms the utility specification into probabilities. As shown below, U_{in}^{s} denotes the utility of adoption (i=1, if the individual reported that he/she has used ridehailing) and non-adoption (i=0 if the individual has not used these services) for the individual n, given that the person belongs to the latent class s:

$$U_{in}^{s} = V(X_{in};\, \beta^{s}) + \varepsilon_{in}^{s}$$

Where V is the systematic utility function that estimates the general utility as a function of explanatory variables X_{in}, the unknown class-specific parameters β^{s} , and a class-specific random disturbance term for i and n. Hence, the complete probability of the individual n to adopt ridehailing services, denoted as $P_n(i)$, can be written as:

$$P_n(i) = \sum_{s \epsilon S} P_n(i|s)\, P_n(s)$$

Where $P_n(i|s)$ is the probability of adoption of ridehailing services for each individual n, conditional on the class s to which he or she belongs to, and $P_n(s)$ is the probability of individual n to belong to class s.

I estimate the latent-class adoption model on the weighted sample to control for non-response bias and adjust for any imbalances in the sample, failure to control for which usually leads to an estimation of inconsistent and biased coefficients. As discussed by Vermunt and Magidson (2007), there are various methods to deal with sampling weights in latent-class models. One of the methods to deal with sampling weights is the two-step approach: in this approach sampling weights are used to adjust latent-class sizes and correct covariate effects, after the model is estimated on the unweighted dataset. The unweighted analysis may yield more stable estimates (compared to the other two approaches discussed below) for the parameters used to determine the latent classes but yields biased class sizes and covariate effects (Vermunt and Magidson, 2005). The biases in covariate effects are corrected in the second step of the procedure, while the class sizes remain biased. Another method to control for sampling weights is the quasi-maximum likelihood approach (also known as pseudo-maximum likelihood). In this approach, the model parameters are estimated on the weighted cases using quasi-maximum likelihood estimators (QMLE). Cameron and Trivedi (2005) noted that the asymptotic properties of the QMLE is similar to that for the maximum likelihood estimator, with two problems: (1) QMLE is centered around θ^* (the pseudo true value) due to a misspecified log-likelihood function that results from a wrong density function, instead of the true value of the parameter (θ); and (2) it is not possible to use the Information Matrix equality and therefore the resulting statistical tests are invalid. Even though quasi-maximum likelihood gives the correct parameter estimates, this approach is often criticized because the goodness-of-fit tests and other Maximum Likelihood (ML)-related criteria (e.g. Akaike Information Criterion or Bayesian Information Criterion) may not be valid/reliable. In particular, the goodness-of-fit test measures will no longer be valid, if the Pearson and likelihood-ratio tests are computed by comparing the estimated frequencies with the weighted observations because sampling weights distort data such that these statistics are no longer distributed as χ^2 (Vermont and Magidson 2007). To address the issues associated with the use of quasi-maximum likelihood approach, Vermont and Magidson (2007) proposed to incorporate the inverse of cell-specific sampling weights as a term (usually as an offset) in the final model. This approach is an extension of maximum likelihood estimation with sampling weights in the log-linear model (a special case of Harberman's model). However, this approach works well when the number of indicators is small. In this study, I employed both the two-step and quasi-maximum likelihood methods to determine the number of classes (as shown in Table 4.3), as the former approach provides more reliable ML-based goodness-of-fit measures and the latter one provides unbiased class sizes and estimates.

4.5 Model Estimation and Validation

One of the most critical steps in latent class choice modeling is the determination of the number of latent classes. To determine the number of classes, I first estimated the best model that could be estimated for each distinct number of classes. Then, after identifying the most important variables that affect class membership and adoption of the services, I re-estimated the same models maintaining the specification fixed and testing different numbers of classes, in order to assess the models' goodness of fit, interpretability of classes and classification errors. A summary of the model results is shown in Table 4.3. I presented the results of both the two-step weighting and the quasi-maximum likelihood approaches because of the reasons discussed above. In this table, in addition to the Bayesian Information Criterion (BIC) and the Rho-squared, I also include the Akaike Information Criterion 3 (AIC3), which is the modified version of the Akaike's Information Criterion (AIC) with a penalty factor of three rather than the traditional value of two.[7] Andrews and Currim (2003) showed that in most cases the AIC3 has the highest segment retention success rate compared to other statistics. I also present classification errors in Table 4.3, to provide information on how well the observed choices and

[7] AIC3 is estimated using this formula AIC3 = -2logL + 3npar

covariates can predict the latent classes. For more detailed information about how these measures are estimated, see Vermunt and Magidson (2005).

Table 4.3 – Summary of Model Estimation Results for Both Quasi-maximum Likelihood and Two-step Methods

Number of Classes	**2**	**3**	**4**	**5**
Number of Parameters	35	61	87	113
BIC $_{QML}$	1549.11	1586.11	1677.52	1770.67
BIC $_{two\text{-}step}$	1579.63	1654.31	1785.53	1888.43
AIC3 $_{QML}$	1397.11	1321.20	1299.70	1279.93
AIC3$_{two\text{-}step}$	1427.64	1438.40	1407.71	1397.70
Rho-squared $_{QML}$	0.50	0.56	0.68	0.82
Rho-squared $_{two\text{-}step}$	0.63	0.53	0.57	0.66
Classification Error $_{QML}$	0.05	0.03	0.06	0.14
Classification Error $_{two\text{-}step}$	0.16	0.05	0.06	0.09

Note: (1) To deal with the sampling weights, I present the results of both QML (Quasi Maximum Likelihood) and the two-step approaches. (2) The reported rho-squared for each column is based on the corresponding equally-likely model.

I selected the 3-class model as the best model for this study, due to a combination of performance (goodness of fit and classification error) and interpretability of the results in terms of lifestyle segmentation and class-specific choice model. In the next sections, I first discuss the results of the class membership model and then discuss the results of the class-specific adoption model.

4.5.1 Class Membership Model

The class membership model (including individual coefficients and corresponding t-ratio) and distribution of active covariates in each of the three classes are presented in Table 4.4. I employ a random utility multinomial logit model to predict the probability that individuals belong to each of the three classes (indicated as P_{ns}). To compute class-specific values for active and inactive covariates I used the weighted average of each covariate across the sample, where the weights are the probabilities P_{ns} that case n belongs to class s. This function can be expressed as shown in the equation below for both active and inactive covariates:

$$X_{js} = \frac{\sum_n P_{ns} * X_{nj}}{\sum_n P_{ns}}$$

Where X_{js} is the weighted average of a covariate in class s (j= 1 for the desired category of the categorical covariate X; 0=else). In the above equation the class membership probabilities P_{ns} can be prior (i.e. the probability that individual n belongs to class s is estimated only based on the variables used in the membership model) or posterior (i.e. where the additional information offered by the knowledge of the adoption of Uber/Lyft is incorporated in the class membership probabilities). I estimated the distribution of active and several inactive covariates using both prior and posterior class membership probabilities, but only present (in Table 4.4) the distribution of each covariates using the prior class membership probability. The overall pattern between the two set of covariates was similar but not identical. As discussed by Kim and Mokhtarian (2018), using prior membership is much more reasonable, in particular, when the purpose of the model is to predict the choice variable, the information about which is not provided.

The explanatory variables (covariates) that include in the class-membership model comprise socio-economic, demographic and neighborhood type variables that are expected to affect individual's lifestyles. As indicated in Table 4.4, approximately 38%, 34% and 28% of respondents are assigned to Class 1, Class 2, and Class 3, respectively. The results of the class membership model show that individuals in Class 1 tend to have the lowest education level and live in the least affluent households compared to the members of the other two classes. This class has the highest share of younger members of the Generation X and has a large share of individuals who do not work or study. The members of Class 2 tend to be more affluent and are usually *dependent* millennials (e.g. young adults that still live with their family of origin) or older members of Generation X. Members of this class tend to only work or only study, which is consistent with other attributes such as age distribution and household composition of this class. *Independent* millennials (i.e. those not living with their parents) are grouped mainly in Class 3: members of this class are usually not married and tend to live in a medium-income household. This class has the highest number of individuals who both work and study at the same time. Examining the residential neighborhood parameters, I found that both Class 2 and Class 3 include large shares of urban and suburban dwellers, while Class 3 has the highest proportion of rural dwellers.

Further, to better understand the profile of each of the three classes, I expand my investigation to other inactive covariates (i.e. variables not included in the class membership model), including gender, ethnicity, the presence of children in the household, and the ratio of household vehicles per driver. The results show that differences among classes with respect to the ratio of household vehicles per driver and individual's ethnicity are not significant. I also find that the share of female respondents is slightly higher in Class 1 compared to the other two classes. Another noticeable pattern is the distribution of presence of children in the household among the members of each of three classes: About 68% of the members of Class 3 live in the household without any children –consistent with the other attributes of the members of this class– while this rate decreases to 50% and 43% among the members of Class 2 and Class 1, respectively.

Table 4.4 – Results of the Class Membership Model (N=1,545; Weighted dataset)

	Class 1 (38%)	Class 2 (34%)	Class 3 (28%)	Distribution across Classes		
	Coefficients (t-ratio)	Coefficients (t-ratio)	Coefficients (t-ratio)	Class 1	Class 2	Class 3
Age and Stage of Life						
Younger Dependent Millennials	0.87 (1.06)	-0.92 (-1.76)	0.04 (0.06)	7%	9%	7%
Younger Independent Millennials	-4.83 (-6.42)	-0.63 (-1.56)	5.47 (7.42)	7%	11%	11%
Older Dependent Millennials	0.31 (0.32)	5.77 (7.12)	-6.08 (-5.05)	3%	13%	3%
Older Independent Millennials	-5.44 (-7.97)	-3.37 (-6.21)	8.80 (8.93)	25%	22%	58%
Younger Gen X	1.65 (1.53)	-4.64 (-5.79)	2.99 (3.86)	30%	15%	19%
Older Gen X	7.44 (8.6)	3.79 (4.76)	-11.23 (-9.16)	29%	31%	2%
Marital Status						
Married	5.52 (7.21)	0.86 (2.29)	-6.38 (-8.07)	61%	48%	32%
Not Married	-5.52 (-7.21)	-0.86 (-2.29)	6.38 (8.07)	39%	52%	68%
Household Income						
Very Low (Less than 20k)	13.48 (7.24)	2.72 (3.06)	-16.2 (-7.93)	17%	8%	2%
Low (20-40k)	3.80 (4.06)	-6.51 (-7.62)	2.71 (3.55)	24%	4%	18%
Medium (40-80k)	-0.22 (-0.42)	-3.78 (-6.39)	4.00 (5.15)	46%	18%	45%
High (80-120k)	-8.94 (-5.91)	5.93 (6.87)	3.01 (3.28)	7%	47%	13%
Very High (More than 120k)	-8.12 (-6.49)	1.64 (2.66)	6.48 (7.10)	7%	23%	22%
Employment & Student Status						
Does not Work nor Study	4.47 (5.85)	2.45 (3.58)	-6.92 (-5.62)	36%	23%	4%
Studies Only	2.64 (3.3)	5.24 (6.06)	-7.88 (-5.29)	8%	14%	1%
Works Only	2.25 (4.41)	-0.62 (-1.47)	-1.62 (-2.59)	52%	59%	64%
Works and Studies	-9.36 (-8.3)	-7.07 (-7.33)	16.42 (8.89)	3%	3%	32%
Education						
High (Bachelor's Degree or Higher)	-4.61 (-8.61)	-2.48 (-5.33)	7.08 (8.12)	30%	54%	74%
Low (Lower than Bachelor's Degree)	4.61 (8.61)	2.48 (5.33)	-7.08 (-8.12)	70%	46%	26%
Neighborhood Type						
Urban	-6.09 (-6.27)	1.88 (3.17)	4.22 (6.05)	7%	33%	31%
Suburban	-4.10 (-7.06)	-1.72 (-3.92)	5.83 (8.36)	40%	52%	62%
Rural	10.20 (8.35)	-0.15 (-0.21)	-10.04 (-8.60)	53%	14%	6%
Constant	4.97 (6.24)	6.83 (7.87)	-11.80 (-7.34)			

Note: Italicized coefficients and t-ratios are significant at 95% confidence interval level; Effect coding was used for categorical variables.

4.5.2 Class-specific Adoption Model

The adoption of ridehailing varies significantly across the classes. Members of Class 3, which largely comprises independent millennials and higher-educated individuals, have the highest rate of adoption, with an adoption rate of 48%, meaning that 48% of the members of this class had used Uber/Lyft at the time of the survey. The second highest adoption rate (30%) belongs to the members of Class 2. The members of this class tend to live in more affluent households and are more likely to be younger dependent millennials or older members of Generation X. The lowest rate of adoption rate (only 13%) is associated with members of Class 1, i.e. lower educated individuals who predominantly live in lower-income households and are more likely to neither work nor study.

Table 4.5 shows the parameter estimates of the class-specific adoption models. Class-dependent parameters show how the impacts of some variables vary across classes. Looking at the magnitude and direction of each class-specific coefficient, I find that adoption rate among the members of Class 1, the class with the lowest adoption rate, is greater if the members of this class have participated in a carsharing program and have used taxi services before. Further, the members of Class 1 are more likely to adopt ridehailing service if they have made more long-distance trips for business purposes by plane, train and inner-city bus in the last 12 months. The adoption of Uber/Lyft for the members of this class is also found to depend on the economic conditions of the household: the probability of adoption of on-demand ride services increases if the members of Class 1 live in households with annual income of $60,000[8] or higher.

The members of Class 2 tend to use ridehailing if they have traveled more by plane (e.g. they use ridehailing service to go to/from an airport) in the last 12 months for leisure purposes. I also find that the adoption of ridehailing services among the member of Class 2 increases as the transportation-related use of smartphones (i.e. use of smartphone apps to determine the route and destination) increases. The same is true if the members of Class 2 have used taxi services before. Interestingly, the members of Class 2 are less likely to adopt ridehailing services if their

[8] This approximately corresponds to the California median household income in 2015.

household earns more than the median household income in California (i.e. $60,000 or higher), showing the potential impact that household income may have on multimodality and the use of emerging transportation services. Specifically, I find that for the members of this class, higher income is usually associated with higher access to vehicle ownership (measured in terms of higher number of vehicles per driver), which in turn (and together with other potential covariates, e.g. residential location) is associated with a reduced likelihood of using these services. In addition, the impact of household income on the use of on-demand ride services among the members of Class 2 can be an indication of transient conditions such as age, student and work status.

The adoption of Uber/Lyft for the members of Class 3 –the class with the highest adoption rate– is more likely to be impacted by frequency of long-distance travel for both leisure and business purposes. Also, the members of Class 3 are more likely to use Uber/Lyft if they have frequently traveled by plane for leisure purposes and have traveled by plane, train, inner-city bus for business purposes. As also true for the members of Class1, I find that adoption of ridehailing increases if the members of this class have used carsharing and/or taxi before.

Table 4.5 – Class- dependent Choice Model Estimation Results (N=1,545; Weighted dataset)

Variables	Class 1		Class 2		Class 3	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Use of Other Emerging Transportation Services						
Used Carsharing before	0.94	**2.70**	0.04	0.11	3.23	**14.58**
Did not Use Carsharing before	-0.94	**-2.70**	-0.04	-0.11	-3.23	**-14.58**
Use of Taxi						
Used Taxi before	0.57	**3.20**	1.17	**5.95**	0.28	**1.66**
Did not Use Taxi before	-0.57	**-3.20**	-1.17	**-5.95**	-0.28	**-1.66**
Use of Smartphones						
To Determine Destination and Route (<75 Percentile)	0.08	0.36	-1.43	**-7.54**	0.26	1.42
To Determine Destination and Route (≥75 Percentile)	-0.08	-0.36	1.43	**7.54**	-0.26	-1.42
Built Environment						
Transit Performance Index (<75 Percentile)	-0.77	**-2.89**	0.78	**3.33**	-0.72	**-3.93**
Transit Performance Index (≥75 Percentile)	0.77	**2.89**	-0.78	**-3.33**	0.72	**3.93**
Land Use Mix (<50 Percentile)	0.29	1.61	-0.46	**-2.55**	0.24	1.46
Land Use Mix (≥50 Percentile)	-0.29	-1.61	0.46	**2.55**	-0.24	-1.46
Long Distance Travel						
Frequency of Long Distance Business Trips by Non-Car Modes (log-transformed)	2.65	**4.21**	0.45	0.63	1.54	**2.53**
Frequency of Long Distance Leisure Trips by Plane (log- transformed)	-0.44	-1.13	1.28	**3.44**	0.68	**2.20**
Household Income						
Less than 60k per year	-0.32	**-1.79**	1.05	**4.41**	-0.08	-0.46
More than 60k per year	0.32	**1.79**	-1.05	**-4.41**	0.08	0.46
Constant						
Users	-0.60	**-2.56**	-0.47	**-2.46**	1.24	**8.87**
Non-Users	0.60	**2.56**	0.47	**2.46**	-1.24	**-8.87**
	Class 1		**Class 2**		**Class 3**	
Adj Pseudo-R^2 (constant-only as base)	0.25		0.47		0.31	
Adj Pseudo-R^2 (equally-likely as base)	0.73		0.53		0.32	
Overall Adj Pseudo-R^2 (constant-only as base)			0.46			
Overall Adj Pseudo-R^2 (equally-likely as base)			0.56			

Note: Bold t-ratio are significant at 95% confidence interval level.

With respect to the built environment variables, members of both Class 1 and Class 3 are more likely to adopt ridehailing if they live in neighborhoods with higher transit performance scores (i.e. served by better-quality transit services). That said, the transit performance score measures the overall quality of transit as well as job accessibility by transit, which could be a proxy for other built environmental characteristics such as land use density, network density, regional centrality and walkability, due to the high correlations among many of these land-use measures. Interestingly, I find that living in more transit-accessible neighborhood reduces the adoption rate of Uber/Lyft among the members of Class 2. This association implies that the members of Class 2, which largely comprises of students and working parents, may rely more on transit or their own vehicles. Similarly, I find that the members of Class 2 are more likely to use ridehailing if they live in a neighborhood with more diverse land use, where the use of travel modes alternative to the use of cars is more attractive. In contrast, I observe a reverse effect (but not statistically significant) of the land-use mix variable on the adoption of Uber/Lyft among the members of Class 1 and 3. This could be associated with the socio-demographic characteristics and auto-availability among the member of these two classes. Due to lower auto-availability and lower household income, the members of Class 1 and 3 are more likely to be multimodal and rely on alternative means of transportation, if they live in highly accessible areas with higher quality transit. I further, tested the impact of regions on the adoption of ridehailing, to control for differences in the availability and visibility of ridehailing services. Ultimately, I excluded these variables as their estimated coefficients were not statistically significant in the final model.

The improvements in the overall and the class-specific rho-squared measures of goodness of fit achieved by adding only the constant (i.e. market share model) and by adding other parameters (i.e. full model) is shown at the bottom of Table 4.5. As indicated in this table, the final full model was able to explain the highest total proportion of information relative to the null model (the equally-likely base) for Class 1, the class with the lowest adoption rate. However, most of this improvement is associated with the role of the constant (market share model), as the shares of adopters and non-adopters for this class are highly unbalanced. In such cases, the market share model is already a large improvement compared to the equally-likely model, which would predict equal chances of adopting or not adopting ridehailing services for the members of this class. The large proportion of information explained by the addition of the explanatory variables, compared to the constant-only model, are obtained for both Class 2 and Class 3 models (in this case, on the contrary, the market share models are not that much better than the equally-likely models, as the shares in the sample are more balanced).

This study is limited in a number of ways: In this study I did not control for differences in individuals attitudes (which were found to have significant effects in the previous paper, cf. Alemi et al., 2017), inclusion of which requires a more sophisticated model. I plan to address this limitation by incorporating individual attitudes and preferences as latent variables in the model estimation. Another limiting factor is the absence of variables controlling for individual's willingness to pay for ridehailing (ideally by trip purpose), travel time, trip purpose and the cost of the trips made by Uber and Lyft. I expect this information to improve the explanatory power of my model significantly; however, this information is not available in the current dataset.

Further, the cross-sectional design of this study limits the ability to draw any causal inferences. In particular, I cannot make robust conclusion about the complex relationship between the use of ridehailing services and the use of other means of transportation (or other components of travel behavior). I also expect that the adoption of ridehailing and the role that different factors play changes over time as these services evolve. I plan to address some of these limitations through the analysis of a second set of data, which is being collected in Spring 2018, using a rotating panel structure. The analysis of the panel dataset obtained by combining the information collected in the two waves of data collection will provide a unique opportunity to better understand the changes in adoption of ridehailing over time and to disentangle the complex relationship between ridehailing adoption and other components of travel behavior, and in particular with eventual changes in vehicle ownership (a household-level medium-term decision) as the result of the adoption of shared mobility services.

4.5.3 Cross-validation

In this section, I present the result of the validation of the final model and discuss how well the final model is capable of predicting adoption of Uber and Lyft. I used validation technique to compare the results of several high-performance models that I estimated as a part of model estimation/selection. In the absence of a test dataset (i.e. out-of-sample data that can be used to test the accuracy of the models), the cross-validation of a model can provide valuable information about how well the model can be expected to perform on an independent dataset. In this chapter, I employ a k-fold cross-validation technique (k=10) by (1) randomly dividing the sample into k=10 groups of observations (based on uniform distribution); (2) training this model on k-1 groups; and then (3) computing the error rate based on the numbers of (in)correctly classified response in the hold-out group. I repeat this process ten times, each time using different groups of observations as test/validation set. The k-fold cross-validation is preferred over other resampling methods because, in addition to its computational advantages, this validation technique provides more accurate and unbiased estimates of test errors (for more information, cf. James et al. 2013; pages 183-184).

To estimate the error rate in each round of cross-validation, I created a success table, suggested by McFadden (2001), where the predicted share of each choice alternative is compared against the observed ones (this is equivalent to confusion matrix in the context of binary choices/classifiers). Success table can be estimated differently, in particular in the context of latent class choice model (Kim and Mokhtarian 2018). The variation in the estimation of success table stems from the decision about how to (1) incorporate the predicted probability of person n choose alternative i into the success table - this can be either incorporated (with *unit-weighted* cases, which is also known as *modal assignment* or *hard partitioning*) assigning each case to its highest-probability alternative (class), or (with *probability-weighted* cases, which is also known as *proportional assignment* or *soft partitioning*) using the probability that case n chooses alternative i to compute the success table; and (2) compute the class membership probability, which can be *prior*, where the probability of individual n to belong to class s is estimated only based on the variables used in the membership model, or *posterior*, where the information offered by the knowledge of the choice enriches the class membership probabilities. As suggested by Kim and Mokhtarian (2018) the probability-weighted method is preferred over the unit-weighted method, because the latter violates the rationale behind probabilistic choice modeling (Train 2009). Similarly, the prior class membership is found to be more preferable, because in most situations I do not have any information about the choice.

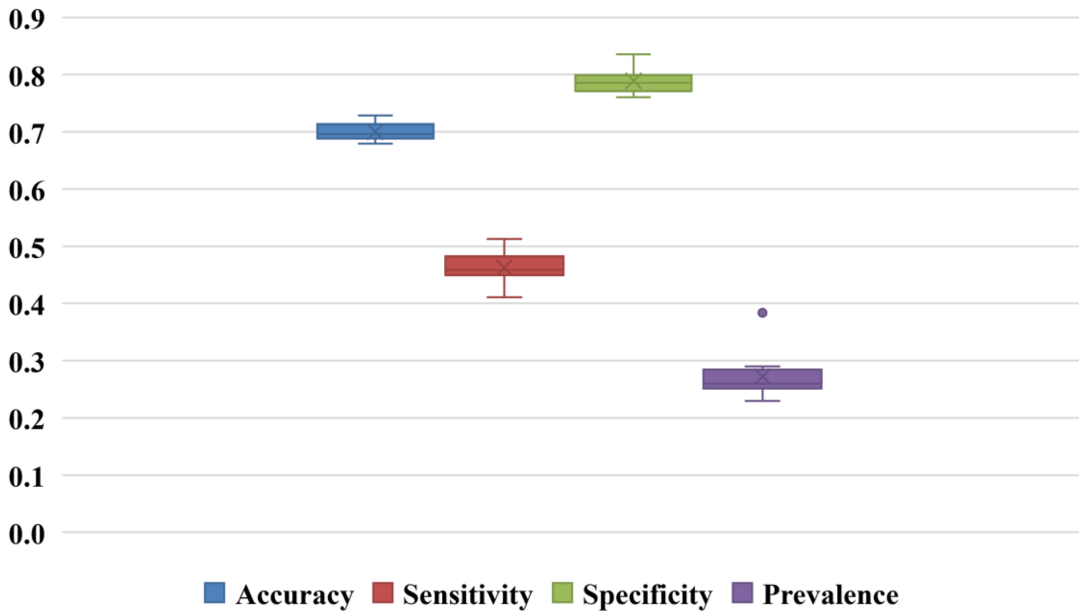

Figure 4.2 – Distribution of Confusion Matrix Indicators Estimated for 10-fold Cross-validation of Latent-class Adoption Model

Overall two types of error (misclassification) may occur in the context of binary choice (this can also be generalized to multiple choices), including incorrect assignment of users to non-user group and vice versa. In this chapter, for the reason discussed above I used prior class membership and probability weighted methods to evaluate the final model. Different measures can be used to evaluate the result of cross-validation, using success table (or confusion matrix). The most important indicator is the model's *accuracy*, which determines how often the model can predict users and non-users correctly. As shown in Figure 4.2, the average accuracy across the ten K-fold samples is about 0.70, with the minimum of 0.68 and maximum of 0.73. *Sensitivity* and *Specificity* are two other important indicators, measuring the proportion of Uber/Lyft users who are correctly identified, and the proportion of non-users who are correctly identified, respectively. As shown in Figure 4.2, on average 46% and 79% of the time the final model was successful in predicting users and non-users correctly. The lower sensitivity rate confirms that there are much more variations in the behavior of users of Uber/Lyft that cannot be (fully) explained by the final model. This is also consistent with the proportion of information explained by each of the class dependent models as shown at the bottom of Table 4.5. *Prevalence* is another indicator that indicates the share of Uber/Lyft users resampled for each round of model cross-validation. As shown in Figure 4.2, holding out cases based on the uniform distribution performs well in preserving the original distribution of users and non-users in the hold-out samples (with one exception as shown in Figure 4.2).

Other questions that require more investigation relate to the impact of different distributions of the dependent variables in the hold-out sample on the model's ability to predict and model the sensitivity to big changes in one or more variables in more extreme scenarios (e.g. Keane and Wolpin 2007 tried to improve their model's ability to forecast extreme changes using a non-random hold-out sample). Further, it is expected that the cross-validation method can enhance the model transferability over time or location (if the knowledge about the aggregate distribution of the dependent variable in the new context is available and if the elasticity/relationships among variables remain unchanged).

4.6 Conclusion and Discussion

In this study, I investigate the role of various factors in affecting the adoption of ridehailing services (such as Uber and Lyft) in California. I expand my previous research (discussed in Chapter 3 and Alemi et al. 2017) through the estimation of a latent-class choice model for ridehailing adoption that incorporates taste heterogeneity and is able to capture differences in adoption behavior across various groups of users. Based on the evaluation of the measures of goodness of fit and the interpretability of results, I found that a model with three latent classes is the most appropriate solution to describe these behavioral choices. The results of the latent class choice model show that the members of Class 3, which is largely composed of higher-educated independent millennials who are more likely to live in urban areas and in non-traditional households (either alone or with roommates) without any kids, tend to have the highest rate of adoption of ridehailing services. The adoption rates of the members of this class significantly increase as the rates of technology adoption and frequency of long-distance non-car travel increases (for both leisure and business purposes).

The second highest adoption rate is observed among the members of Class 2, the most affluent class including either dependent millennials or older Gen Xers who live with their families. I found that the technology adoption rate, use of taxi services, and the frequency of long-distance leisure trips made by plane affect the adoption of ridehailing among the members of this class. The members of Class 1 have the lowest adoption rate, which could be a reflection of the socio-economic status of these individuals and is also a result of the more rural locations where these individuals predominantly live. Class 3 is the least affluent and lowest-educated class of individuals; they are more likely to live in rural neighborhoods and more often do not work nor study. The adoption of ridehailing among the members of this class is affected by household income, the frequency of long-distance non-car business trips, transit accessibility as well as the use of taxi and carsharing.

The results of this study confirm that differences in the impacts of the variables affecting the adoption of ridehailing exist across various segments of the population. Several conclusions of relevance to transportation planning and policy making can be drawn. The model estimation results suggest that deploying different policies and marketing strategies can affect the rate of adoption of these services among various groups of individuals. This means that to harvest the potential societal benefits of ridehailing services, it will be important to better understand the impacts that ridehailing has across various segments of the population, and promote policies and incentives targeted to each segment that can help reduce the negative impacts associated with the use of these services (e.g. substitution of transit by these services or deadheads between rides).

I plan to extend this work in many directions, one of which is to expand this analysis through the inclusion of attitudinal variables as latent variables in the model estimation. In addition, in related analyses, I plan to expand the analysis of household's vehicle ownership: I found that the members of each class have significantly different propensities to modify their vehicle ownership, and the degree to which they would like to modify their vehicle ownership is correlated with the adoption of ridehailing services. I did not include a variable measuring this effect in the final model due to potential endogeneity biases, but I plan to further investigate it in future stages of the research. In fact, the direction of these relationships could be reversed, or could be bi-directional. For example, someone might choose to adopt ridehailing as a consequence of their car-ownership and use, or they might decide to reduce their vehicle ownership and use as a result of the adoption of these technological transportation options. The analysis of a second round of data collection (which is being collected in Spring 2018) will provide a unique opportunity to study the impacts of emerging technologies and trends with longitudinal data and will provide a unique opportunity to disentangle the complex relationships behind the formation of travel behavior over time (e.g. modifications in the use of shared mobility and their impacts on vehicle ownership) among the various segments of the population.

4.7 Acknowledgments

This study was funded by the National Center for Sustainable Transportation (NCST), which receives funding from the USDOT and Caltrans through the University Transportation Centers program. The first author also received financial support through an NCST dissertation fellowship. The authors would like to thank Caltrans, the NCST and USDOT, for their support of university-based research in transportation. The Sustainable Technology Energy Pathways (STEPS) Program of the University of California, Davis provided additional financial for the data collection. The authors wish to thank Lew Fulton, Rosaria Berliner and Kate Tiedeman who contributed to the survey design and data collection, and Yongsung Lee who assisted in the data preparation.

5. WHAT DRIVES THE USE OF RIDEHAILING IN CALIFORNIA? ORDERED PROBIT MODELS OF THE USAGE FREQUENCY OF UBER AND LYFT

5.1 Abstract

The availability of ridehailing services, such as those provided by Uber and Lyft in the U.S. market, as well as the share of trips made by these services, are continuously growing. Yet, the factors affecting the frequency of use of these services are not well understood. In this chapter, I investigate how the frequency of use of ridehailing varies across segments of the California population and under various circumstances. I analyze data from the California Millennials Dataset (N=1,975), collected in fall 2015 through an online survey administered to both millennials and members of the preceding Generation X. I estimate an ordered probit model with sample selection and a zero-inflated ordered probit model with correlated error terms to distinguish the factors affecting the frequency of use of ridehailing from those affecting the adoption of these services. The results are consistent across models: sociodemographic variables are important predictors of service adoption but do not explain much of the variation in the frequency of use. Land use mix and activity density respectively decrease and increase the frequency of ridehailing. The results also confirm that individuals who frequently use smartphone apps to manage other aspects of their travel (e.g. to select a route or check traffic) are more likely to adopt ridehailing and use it more often. This is also true for long-distance travelers, in particular, those who frequently travel by plane for leisure purposes. Individuals with higher willingness to pay to reduce their travel time use ridehailing more often. Those with stronger preferences to own a personal vehicle and those with stronger concerns about the safety/security of ridehailing are less likely to be frequent users. These results provide new

insights into the adoption and use of ridehailing that could help to inform planning and forecasting efforts.

5.2 Introduction

The rapid expansion of digital technology, and in particular the increased availability of locational data and smartphone applications, as well as the emergence of new technology-enabled transportation services, are transforming transportation demand and supply. New technologies and reinvented business models disentangle access to transportation services from the fixed cost of auto ownership by providing unique opportunities for the introduction and extensive deployment of a wide range of new transportation services. New mobility services range from *car-sharing*, including *fleet-based round-trip* and *one-way services* such as Zipcar and Car2Go, respectively, or *peer-to-peer services* such as Turo, to *ride-sharing services*, including *dynamic carpooling* such as Carma and *ridehailing services* such as Uber and Lyft, as well as *bike-sharing* services. The availability of each of these services is rapidly increasing, though it still varies considerably across different cities and regions (Shaheen et al. 2016, Hallock and Inglis 2015).

Ridehailing is one of the most rapidly growing forms of shared-mobility services. These services are also known as on-demand ride services, or transportation network companies (TNCs), such as Uber and Lyft in the U.S. market, Didi Chuxing in China, Ola in India, or Grab in South Asian countries. Uber and Lyft began offering their so-far most popular services, UberX and Lyft Classic, the services that directly compete with local taxi services, in summer 2012. These services enable users to request a ride, track the progress of their drivers in real time, pay for the ride, and rate their experience using their smartphone application; none of these technology-based features had been widely available to regular taxi users before ridehailing services. Uber and Lyft (and other similar app-based operators) have grown tremendously over a short time, by expanding into different areas of the U.S. and diversifying services (including introducing shared ridehailing services such as UberPOOL and Lyft Line). As of November 2017, Uber operates in more than 700 cities (expanded into about 80 countries), and Lyft operates mainly in the U.S. market, providing rides in more than 300 cities (Shaheen et al. 2018).

Ridehailing services still account for a small portion of mode share, but the increase in their popularity and visibility will likely bring larger effects on future transportation. For example, a recent study showed that the share of total trips made with Uber and Lyft accounts for approximately 15% (170,000 trips per day) of all trips inside the city of San Francisco on a typical weekday (SFCTA 2017). As Uber and Lyft become more visible in the city landscape, future use of these services and their impacts on the use of other transportation modes will likely depend on a number of factors, such as the availability and accessibility of the services and of other travel alternatives, and individuals' perceptions about their convenience, comfort, safety and reliability. Transportation researchers so far have had limited ability to assess the factors affecting the use of these services and their impacts, mainly due to a dearth of data about the users themselves and the way they use ridehailing, as well as the high level of uncertainty over the evolution and eventual maturation of these services. Differences in the local contexts in which these services are provided add to the complexity.

This study expands the previous work in this area by investigating the factors that affect the frequency of use of Uber and Lyft. This study addresses the following questions: (1) How does the frequency of use of ridehailing vary across different segments of the population? (2) Which built environment characteristics have the highest impact on the use of ridehailing? and

(3) Under what circumstances do millennials and the members of the preceding Generation X use Uber/Lyft more often? To address these questions, I analyze data from the 2015 California Millennials Dataset, a rich source of information on individual attitudes, lifestyles, travel patterns and the characteristics of the residential built environment for members of the millennial generation and Generation X. I estimate an Ordered Probit model with Sample Selection (OPSS) and a Zero-Inflated Ordered Probit model with Correlated error terms (ZIOPC) to investigate the factors affecting the frequency of use of ridehailing while controlling for the separate process that influences the adoption of these services. Most studies in this field are based on basic descriptive statistics, and to the authors' knowledge, this is the first application of statistical models to improve the understanding of the factors affecting both the adoption and frequency of use of ridehailing services.

The remainder of this chapter is organized as follows: after a brief literature review in Section 5.3, Section 5.4 discusses the data collection and methods of analysis. Then, Section 5.5 discusses the results of the ZIOPC and OPSS model estimation, followed by the conclusions and perspectives for future research in Section 5.6.

5.3 Literature Review

This study investigates the factors affecting the frequency of use of ridehailing, as one of the most rapidly-growing forms of shared-mobility services. Previous related studies available in the literature generally fall into two major categories: (1) those that investigate the factors affecting the adoption and frequency of use of ridehailing services; and (2) those that discuss the impacts of these services on other components of travel behavior, including vehicle ownership and the use of other means of transportation. Although the contribution of the present study lies in the first category, I briefly address studies relating to the second category as well.

In previous related studies, Alemi et al. (2017) and Alemi et al. (under review) found that better-educated and higher-income older millennials (i.e. individuals who were 25-34 years old in 2015) are more likely to adopt on-demand ride services. These results are largely consistent with the findings of studies based on descriptive statistics (e.g. Rayle et al. 2014; Taylor et al. 2015; Feigon and Murphy 2016; Pew Research Center 2016) and are logical in view of other attributes of millennials regarding their familiarity with and frequency of use of new technologies, vehicle ownership and their use of alternative modes. Millennials, who are sometimes described as “digital natives” due to their greater familiarity and comfort with the use of information/communication technology (ICT), more often live in zero-/lower-vehicle households, drive less and use non-motorized modes more often compared to older, “digital immigrant” (Prensky 2009) generations (Blumenberg et al. 2016; Kuhnimhof et al. 2012; Frändberg and Vilhelmson 2011; BRS 2013). Alemi et al. (2017) found that individuals who neither work nor study and individuals of Hispanic origin, among other demographic variables, are less likely to use on-demand ride services. The latent-class choice model that Alemi et al. (2017) estimated identified three classes based on individuals’ lifestyles and stage of life. The class that is largely composed of higher-educated independent millennials (i.e. those who have already established their own households) has the highest adoption rate, while adoption is lowest within the class that is largely composed of the least affluent individuals with the lowest level of education (Alemi et al. under review). Among various built environment characteristics, the authors also found that neighborhood type, land use mix, regional auto accessibility and public transit availability (and quality) impact the adoption of ridehailing (Alemi et al. 2017; Alemi et al. under review). With respect to personal traits, those having greater familiarity with and use of modern technologies in connection with transportation (such as the use of smartphone apps for transportation purposes, and the use of carsharing), frequent long-distance trips (for both business and leisure purposes) and stronger *pro-environmental policies*, *technology embracing*, and *variety seeking* attitudes (Alemi et al. 2017) are more likely to adopt these services.

Only a few studies have investigated the factors affecting the frequency of using on-demand ride services. A recent study by the Pew Research Center (2016) found that out of the 15% of respondents in their sample who reported that they have used ridehailing (N=4,787), only 3% and 12% reported that they have used these services on a daily and weekly basis, respectively. The research confirmed that younger adults tend to use on-demand ride services more frequently. In another study, Feigon and Murphy (2016) showed that the most frequent users of ridehailing live in middle-income households (annual incomes of $50 to 75K). Both studies noted that Uber/Lyft frequent users are more likely to live in households with a lower-than-average number of vehicles per driver, and tend to rely more on other means of transportation, including public transit or active modes. However, the extent to which the adoption of ridehailing causes such changes is not clear. This leads to the second category of studies.

Understanding the adoption and frequency of use of ridehailing is important, as these services may have substantial effects on different components of travel behavior. Research on the impacts of ridehailing services on other aspects of travel behavior is growing but is still limited, largely due to the lack of longitudinal data or robust analytical approaches that capture the causal relationships among the use of ridehailing services and different components of travel. Ridehailing can affect travel behavior in a number of ways, e.g. increasing the number of available options for a trip, providing a flexible alternative to driving, or enhancing public transportation efficiency through integrating first- and last-mile access/egress and providing rides when public transit is not safe/available (Shaheen et al. 2015; Shaheen et al. 2018; Taylor et al. 2015; Circella et al. 2016; Circella et al. 2018). For example, in one study about 40% of Uber/Lyft users in San Francisco reported that they reduced their driving due to the adoption of ridehailing (Rayle et al. 2014). Patrons of such services may also use them as a substitute for or as a complement to the use of public transit (Feigon and Murphy 2018; Clewlow and Mishra 2017; Hampshire et al. 2017; Babar and Burtch 2017). They may dispose of one or more of their vehicles and turn to ridehailing as their primary means of travel (Hampshire et al. 2017; Henderson 2017). Other technology-enabled transportation services, such as carsharing, may have similar effects on auto ownership (Roberts 2017; Mishra et al. 2017). To better understand the potential impacts of these services, researchers must test different causality structures, discussion of which is beyond the scope of this dissertation.

5.4 Data Collection and Methodology

5.4.1 The California Millennials Dataset

This study is part of a larger research endeavor aimed at investigating the travel behavior of millennials (i.e. young adults born between 1981 and 1997) and members of the preceding Generation X (i.e. middle-aged adults born between 1965 and 1980) in California, particularly their adoption of emerging transportation options. As part of this research, our research group designed a detailed online survey and administered it between September and December 2015 to a sample of more than 1,400 millennials and 1,000 Gen Xers, recruited from an online opinion panel, as the first stage of a longitudinal study of emerging transportation trends in California. Our research group used a quota sampling approach to sample respondents from three neighborhood types (urban, suburban, and rural) and the six major regions of California: (1) Sacramento, following the boundaries of the Sacramento Area Council of Governments (SACOG); (2) San Diego, following the boundaries of the San Diego Association of Governments (SANDAG); (3) Greater Los Angeles, following the boundaries of the Southern California Association of Governments (SCAG); (4) the San Francisco Bay Area, following the boundaries of the Metropolitan Transportation Commission (MTC); (5) the California Central Valley; and (6) the rest of Northern California and Others, comprising the remaining regions in the state. In addition, various sociodemographic targets were employed to ensure that the sample adequately represented the characteristics of California residents with respect to age, income, race and ethnicity, sex, and presence of children in the household.

Total number of 5,466 invitations were sent out, which yielded 3,018 complete cases. The propensity of the members of the opinion panel to respond to a survey invitation resulted in a response rate (46%) twice or more what is usually obtained in travel behavior surveys with other recruiting approaches. However, this higher response rate comes with the disadvantages of using an opinion panel, including higher self-selection bias, non-coverage bias (e.g. Blasius and Brandt 2010 show that elderly women with low educational attainment and people without access to the internet are less likely to be included in online panels), and the bias induced by professional respondents who answer the survey hastily and carelessly only to cash out the incentives associated with it. In this study, I believe that defining quotas based on different regions and neighborhood types as well as targets for five socio-demographic characteristics helps reduce the non-coverage bias. Further, I improved the quality of data by filtering out those who failed any trap questions imbedded in the California Millennials survey. As a result, after excluding severely incomplete, inconsistent, or unreliable cases, I used a final dataset of 1,975 valid cases for this study. For detailed information on the data collection process, the content of the survey, and the exact language used for the survey questions, see Circella et al. (2016) and Circella et al. (2017).

The survey collected information on the respondents' attitudes and preferences; lifestyles; use of ICT and adoption of online social media; residential location and living arrangements; commuting and other travel patterns; auto ownership; awareness, adoption, and frequency of use of several types of shared-mobility services; major life events that happened in the past three years; future expectations, aspirations and propensity to purchase and use a private vehicle versus other means of travel; and sociodemographic traits.

In the section of the survey on emerging transportation, respondents were asked to indicate whether they are already familiar with various types of new shared-mobility services, what services they have already used either in their hometown or while traveling, and how often they use them. The emerging transportation services included in the study were *fleet-based car-sharing* (e.g. Zipcar or Car2go), *peer-to-peer car-sharing* (e.g. Turo), *on-demand ride services* (e.g. Uber or Lyft), *dynamic carpooling* (e.g. Zimride or Carma), *peer-to-peer carpooling* (usually arranged via online platforms such as Facebook or Craigslist) and *bike-sharing*. Ridehailers were asked to rate the importance of different factors that encourage or limit their use of ridehailing, how the use of these services impacted their use of other means of transportation, and what they would have done for the last trip they made with Uber or Lyft if these services had not been available.

5.4.2 Dependent Variable: Frequency of Use of Ridehailing

The dependent variable of interest measures the frequency of use of ridehailing. Figure 5.1 presents the distribution of adoption and frequency of use of ridehailing services. As shown in

Figure 5.1, millennials are more likely than members of the older cohort to adopt ridehailing and tend to use these services more often.

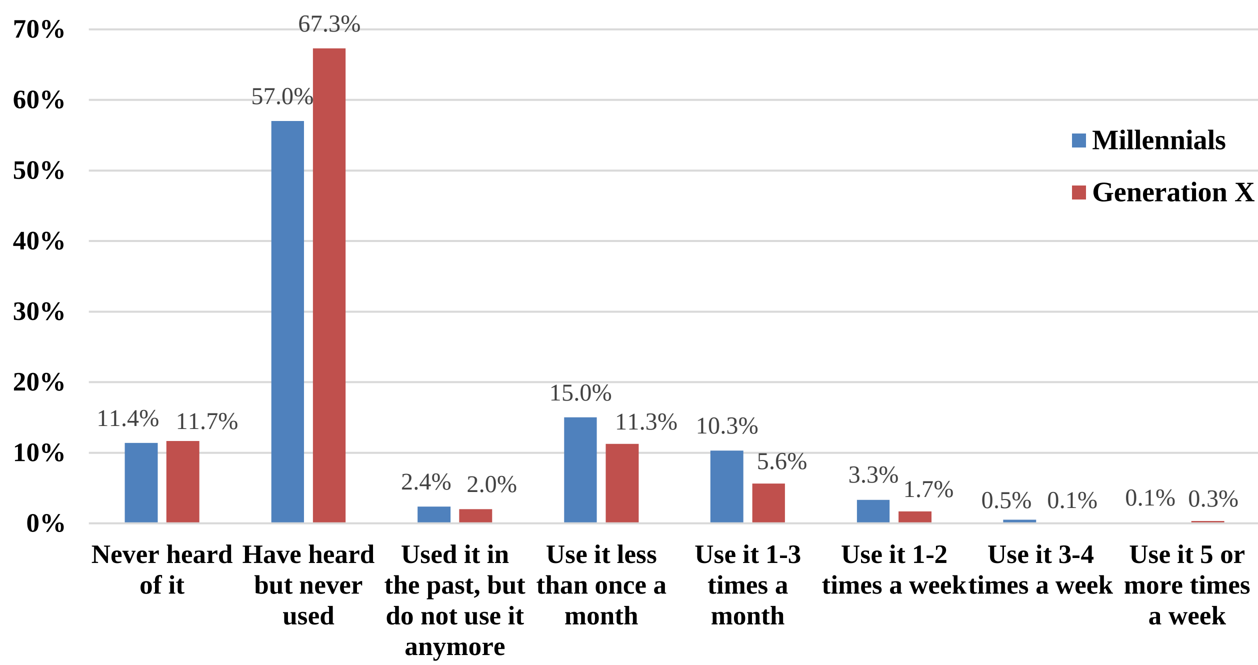

Figure 5.1 – Adoption and Frequency of Use of Uber and Lyft by Age Cohort ($N_{Millennials}$=1019, $N_{Gen\ X}$ = 942)

I grouped all individuals who used ridehailing at least once a month, including those who used it "5 or more times a week", "3-4 times a week", "1-2 times a week" and "1-3 times a month", into a "more frequent users" category. Those respondents who reported that they have used ridehailing "less than once a month" were classified as "infrequent users". For the purposes of the descriptive presentation, I grouped those who "have heard of but never used ridehailing" and those who "used the service in the past but do not use it anymore" into the category of "non-users/zero-frequency users" (although these cases will be separated in the models, as related in Section 5.4.4). The 11-12% of cases who have not heard about these services were excluded from the rest of the analysis, since I did not measure their perceptions of the factors that limit their use of ridehailing, variables which were used in the final model specifications.

Figure 5.2 presents the distribution of the adoption and frequency of use of Uber/Lyft by age cohort. Table 5.1 presents descriptive statistics for the key explanatory variables for the three groups of users/non-users that have been identified. As indicated in Figure 2, millennials tend to use ridehailing more frequently: about 17% and 16% of millennials reported using ridehailing respectively less than once a month or at least once a month, while the usage frequency of these services was lower among Gen Xers.

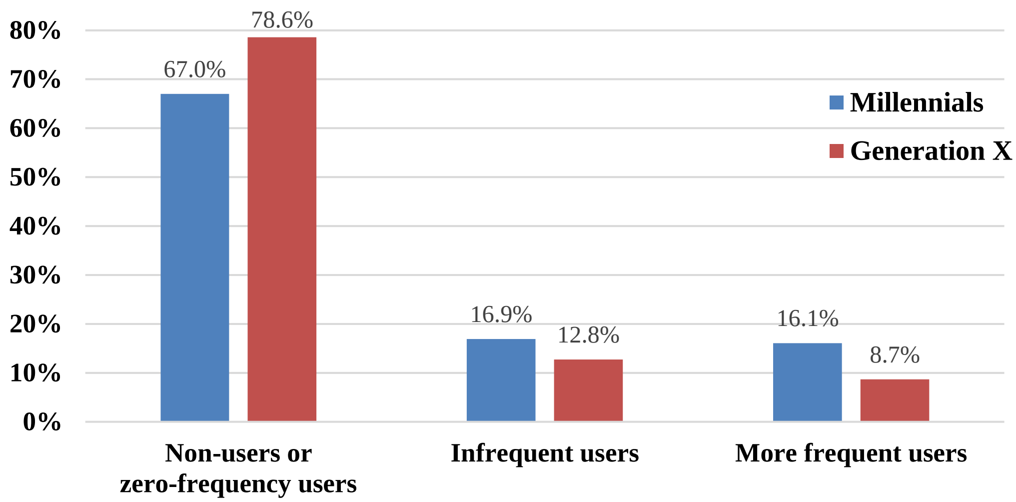

Figure 5.2 – Frequency of Use of Uber/Lyft by Age Cohort ($N_{Millennials}$=903, $N_{Gen\ X}$ = 831)

5.4.3 Explanatory Variables

Based on my previous investigation of the factors affecting the adoption of ridehailing and a carefully review of the existing literature on the frequency of use of other shared-mobility services, I divide the key explanatory variables used in the final models into six main groups. Table 5.1 summarizes the key attributes of the three groups of individuals who have heard about the services but never used it or used it before but do not plan to use it anymore (*non-users/zero-frequency users*), those who use them less than once a month (*infrequent users*), and those who use them at least once a month (*more frequent users*).

Sociodemographic Variables: I expect that the frequency of use of ridehailing varies across various segments of the population with different sociodemographics. I tested an extensive list of sociodemographic variables in the frequency models, including age and stage in life, income, student and work status, race and ethnicity, presence of children in the household, and educational background. Table 5.1 presents the description and the distribution of all relevant sociodemographic variables that are included in the final model specification.

Table 5.1 – Distribution of Key Explanatory Variables for Various Groups of Users/Non-users (N=1,639) [9]

Variable Name	Description	Non-users/zero-frequency users [N=1238] Count (Col.%)	Infrequent users [N=223] Count (Col.%)	More frequent users [N=178] Count (Col.%)
Socio-economic and Demographics - Stage in Life Dimension				
Age and Stage in Life				
Younger Dependent Millennials	18-24 years old, lives with parents and does not live with a partner	105 (8.7%)	11 (4.9%)	6 (3.4%)
Younger Independent Millennials	18-24 years old, does not live with parents, or lives with partner and parents	105 (8.7%)	17 (7.6%)	24 (13.5%)
Older Dependent Millennials	25-34 years old, lives with parents and does not live with a partner	76 (6.3%)	12 (5.4%)	9 (5.1%)
Older Independent Millennials	25-34 years old, does not live with parents, or lives with partner and parents	349 (28.8%)	96 (42.9%)	84 (47.2%)
Younger Gen X	35-41 years old	258 (21.3%)	52 (23.2%)	32 (18.0%)
Older Gen X	42-50 years old	318 (26.3%)	36 (16.1%)	23 (12.9%)
Presence of Children in the Household				
Yes	Lives in a household with child(ren)	640 (51.7%)	100 (44.8%)	68 (38.2%)
No	Live in a household without child(ren)	598 (48.3%)	123 (55.2%)	110 (61.8%)
Household Income and Individual Education				
Low/Med Income-Low Education	Less educated[1], annual household income of $0-99,999.	621 (50.2%)	54 (24.2%)	53 (29.8%)
Low/Med Income-High Education	More educated, annual household income of $0-99,999.	368 (29.7%)	87 (39.0%)	75 (42.1%)
High Income-Low Education	Less educated, annual household income of $100,000 or more	88 (7.1%)	18 (8.1%)	13 (7.3%)
High Income-High Education	More educated, annual household income of $100,000 or more	161 (13.0%)	64 (28.7%)	37 (20.8%)
Built Environment				
Neighborhood Type (Geocoded)				
Urban	Lives in urban neighborhood	205 (16.5%)	55 (24.7%)	85 (47.7%)
Suburban	Lives in suburban neighborhood	610 (49.3%)	134 (60.1%)	66 (37.1%)
Rural	Lives in rural neighborhood	423 (34.2%)	34 (15.2%)	27 (15.2%)
Region				
San Francisco	Lives in *MTC* area	268 (21.6%)	63 (28.3%)	48 (27.0%)
Sacramento	Lives in *SACOG* area	190 (15.3%)	24 (10.8%)	11 (6.2%)
Los Angeles	Lives in *SCAG* area	295 (23.8%)	73 (32.7%)	57 (32.0%)
San Diego	Lives in *SANDAG* area	203 (16.4%)	46 (20.6%)	45 (25.3%)

[9] I present the distribution of the key explanatory variables based on the sample size used for modeling the frequency of use of ridehailing services in Section 4. I excluded a total of 95 cases due to missing data on some of the key explanatory variables.

Other	Lives in *Central Valley* or *Rest of California and other* regions	282 (22.8%)	17 (7.6%)	17 (9.6%)
Land Use Mix[2]	A continuous variable between 0 and 1 (where higher values mean a more diverse mix), measuring the 8-employment type entropy in the Census Block Group, obtained from the U.S. EPA Smart Location Dataset	0.59 (0.28)	0.66 (0.23)	0.61 (0.26)
Land Use Density[2]	A standardized continuous variable (where higher values mean a higher activity density), showing gross employment and household density on unprotected land in the Census Block Group, obtained from the U.S. EPA Smart Location Dataset	-0.09 (0.75)	0.00 (0.21)	0.53 (1.87)
Technology Adoption and Use of Social Media				
Use of Smartphone[2]				
Apps to Determine Destination and Route	Standardized principal component score measuring the frequency of using smartphone apps to determine trip destination and route	-0.24 (1.01)	0.24 (0.76)	0.54 (0.73)
Apps to Determine Mode Choice	Standardized principal component score measuring the frequency of using smartphone apps to choose travel mode(s) and check transit time	-0.21 (0.92)	0.02 (0.94)	0.58 (1.00)
Use of Social Media				
Higher Frequency	Checks his/her Facebook once or multiple times a day	785 (63.4%)	166 (74.4%)	140 (78.7%)
Lower Frequency	Checks his/her Facebook less than once a day	453 (36.6%)	57 (25.6%)	38 (21.3%)
Use of Other Emerging Transportation Services				
Used Fleet-based Carsharing	Has used fleet-based carsharing services before (e.g. Zipcar, Car2GO)	19 (1.5%)	24 (10.8%)	38 (21.3%)
Never Used Fleet-based Carsharing	Has not used fleet-based carsharing services before (e.g. Zipcar, Car2GO)	1219 (98.5%)	199 (89.2%)	140 (78.7%)
Travel Related Behavior and Decisions				
Frequency of Use of Taxi				
Non-users	Never used taxi or used it in the past	959 (77.5%)	110 (49.3%)	74 (41.6%)
Low Frequency Taxi Users	Used taxi less than once a month	242 (19.5%)	105 (47.1%)	59 (33.1%)
High Frequency Taxi Users	Used taxi more than once a month	37 (3%)	8 (3.6%)	45 (25.3%)
Frequency of Long Distance Travel[2]				
Frequency of Long-distance Business Trips by Non-car Mode	Log-transformation of the count variable measuring the total number of long-distance business trips made by plane, train, and intercity bus in the last 12 months	0.08 (0.22)	0.19 (0.31)	0.35 (0.42)
Frequency of Long-distance Leisure Trips by Plane	Log-transformation of the count variable measuring the total number of long-distance leisure trips made by plane in the last 12 months	0.13 (0.21)	0.32 (0.28)	0.39 (0.32)
Household Vehicles per Driver				
Zero-vehicle Household	Household with 0 vehicles or 0 drivers	65 (5.3%)	10 (4.5%)	20 (11.2%)
Vehicle-deficient Household	Household with a number of vehicles per household driver between 0 and 1	120 (9.7%)	23 (10.3%)	13 (7.3%)
Vehicle-sufficient Household	Household with 1 or more vehicles per household driver	1053 (85.1%)	190 (85.2%)	145 (81.5%)
General Attitudes		**Mean (s.d.)**	**Mean (s.d.)**	**Mean (s.d.)**
Pay to Reduce Travel Time	Standardized single-item attitudinal construct, measuring individual's level of agreement with "*I would pay money to reduce my travel time*" statement.	-0.09 (0.99)	0.15 (0.95)	0.44 (0.97)
Variety Seeking	Standardized Bartlett factor score measuring attitudes towards seeking variety in life	-0.07 (1.00)	0.17 (0.80)	0.48 (0.88)
Technology Embracing	Standardized Bartlett factor score measuring attitudes towards the adoption of technology	0.06 (1.01)	0.29 (0.83)	0.46 (0.94)

Pro-Environmental Policies	Standardized Bartlett factor score measuring pro-environmental policy attitudes	-0.09 (0.97)	0.25 (1.01)	0.41 (1.12)
Perceptions of Attributes of Ridehailing Services				
Concern about Safety/Drivers	Standardized Bartlett factor score measuring the perceived concerns about safety and about the drivers of Uber/Lyft	0.20 (0.99)	-0.51 (0.87)	-0.56 (0.88)
Preference to Use Non-car Mode	Standardized Bartlett factor score measuring the perceived limiting effects on the use of Uber/Lyft associated with the preference to use non-car modes (e.g. transit, walk or bike)	0.08 (1.13)	-0.36 (0.83)	-0.09 (1.06)
Lack of knowledge about the Services	Standardized single-item construct, measuring the limiting effects on the use of Uber/Lyft of the lack of knowledge of these services	0.22 (1.02)	-0.47 (0.76)	-0.47 (0.84)
Preference to Use Own Vehicle	Standardized single-item construct, measuring the limiting effects on the use of Uber/Lyft of the "*preference to use/have my own vehicle*"	0.14 (0.97)	-0.11 (1.04)	-0.62 (0.93)

[1] By lower education I refer to individuals with less than a bachelor's degree, and by higher education I refer to individuals with a Bachelor's degree or higher.
[2] Mean and standard deviation (in parentheses) are presented for the continuous variables.

Built Environment Variables: Because on-demand ride services are not equally available across different neighborhood types and various regions, it is important to control for the impact of built environment variables. In addition, some land use characteristics might be more conducive to the use of these services where they are available. This group of variables includes (a) geographic regions; (b) the neighborhood type where the respondent lives (based on the geocoded home address), which I classified using Salon's (2015) neighborhood typologies;[10] and (c) other built environment characteristics that are extracted from additional data sources including the U.S. Environmental Protection Agency (EPA)'s Smart Location Dataset[11], the commercial website Walkscore.com, and the Center for Neighborhood Technology (CNT)'s AllTransit metrics (for more details, see Circella et al., 2017). The last group of variables

[10] Salon (2015) classifies U.S. census tracts into five neighborhood types using information on local land use and transportation characteristics. For the purposes of this study, I further aggregated those five neighborhood types into three predominant neighborhood types: *central city* and *urban* were both classified as *urban*, and *rural in urban* and *rural* were classified as *rural*.
[11] The EPA Smart Location Dataset provides various statistical and deterministic built environment indicators, estimated at the Census block group level, which were matched to the respondent's residential location based on the geocoded location of the self-reported street address (https://www.epa.gov/smartgrowth/smart-location-mapping, last accessed on March 20, 2018).

includes land use mix; network connectivity, population/job density, and accessibility by different transportation modes.

Technology Adoption and Use of Social Media: The third group of variables controls for an individual's propensity to use social media and other technological applications/devices (in general or specifically to access transportation-related services). As a part of this survey, our research group collected multiple arrays of information on the frequency of use of various online social media (e.g. Facebook, Instagram and Snapchat), the frequency of use of smartphone applications in general and to access transportation-related services, the frequency of use of e-shopping as well as the adoption and frequency of use of other shared-mobility services such as fleet-based carsharing (e.g. Zipcar/Car2Go). I performed a principal component analysis (PCA) with an oblique rotation to reduce the dimensionality of the variables related to the use of smartphones, extracting two main components. Table 5.2 reports the smartphone-related variables loading on each of the two factors that were extracted. My hypothesis is that the familiarity with and use of smartphones in connection with transportation as well as the use of other emerging transportation services (e.g., carsharing, bikesharing) can affect the frequency of use of Uber/Lyft.

Travel-Related Choices: The fourth group of variables controls for the potential impacts of various travel-related choices on the frequency of use of ridehailing. This group of variables comprises the frequency of long-distance travel by purpose (i.e. business and leisure) and by mode (including car, plane, intercity bus, and train), the frequency of use of taxi services, and the number of vehicles per household driver (i.e. household members with a driver's license). The information captured by these variables can be important in explaining the frequency of use of ridehailing. Other travel-related variables including trip and tour mode choice, travel multimodality, and intermodality were excluded from the analysis due to potential endogeneity bias (i.e. the directionality of the potential relationship between these variables and the frequency of use of ridehailing is unknown - disentangling this aspect would require a more nuanced analytical approach and is beyond the scope of this dissertation).

Table 5.2 – Principal Component Loadings of Use of Smartphone in Relation to Transportation

Principal Components and Associated Variables	Loadings from Pattern Matrix
Frequency of use of smartphone to determine destination and route	
Navigate in real time (e.g. using Google Maps or other Navigation Services)	0.88
Learn how to get to a new place	0.83
Identify possible destinations (e.g. restaurant, etc.)	0.81
Check traffic to plan my route or departure time	0.75
Frequency of use of smartphone for mode choice	
Check when a bus or train will be arriving	0.97
Decide which means of transportation, or combination of means, to use	0.86

General Attitudes: This group of variables tests the impacts of individual attitudes toward various general and transportation-related constructs as well as individual perceptions of the factors that limit or prevent the use of Uber/Lyft. I included standardized Bartlett factor scores computed from the original attitudinal variables with a factor analysis. I performed factor analysis to model the latent factors behind the observed variables (agreement with attitudinal included in the survey), and created standardized Bartlett factor scores computed from the original attitudinal variables. Among the 17 factors that were extracted in the factor analysis of the attitudinal variables, the *Technology Embracing*, *Variety Seeking* and *Pro-Environmental Policies* factors had significant effects in the final models. I also include a standardized single-item construct that did not load on any of the 17 factors. This single-item construct captures individuals' level of agreement with the statement "*I would pay money to reduce my travel time"*.

Perceptions of Attributes of Ridehailing Services: Those who used ridehailing and individuals who reported hearing about but not using ridehailing reported how strongly each factor affects their use of these services. I performed a factor analysis on these statements, producing four factors and three single-item constructs. From these, I include a factor capturing individual concerns about safety and drivers of ridehailing services, a factor capturing preferences for non-car modes (i.e. public transit or active modes), and two single-item constructs reflecting the lack of knowledge of/familiarity with Uber/Lyft and the preference to use/have a personal vehicle. Table 5.3 provides more details on the relevant factors and the statements loading on each of them.

Table 5.3 – Relevant Attitudinal Factors and their Strongly-Loading Statements

Factors and Most Strongly-Associated Statements	Loadings from Pattern Matrix
General Attitudes:	
Pro-environmental Policies	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.938
We should raise the price of gasoline to provide funding for better public transportation.	0.844
The government should put restrictions on car travel in order to reduce congestion.	0.344
Variety Seeking	
I like trying things that are new and different.	0.605
I have a strong interest in traveling to other countries.	0.406
Technology Embracing	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.623
Getting around is easier than ever with my smartphone.	0.517
Learning how to use new technologies is often frustrating.	-0.333
Technology creates at least as many problems as it does solutions.	-0.293
Perceptions of Attributes of Ridehailing:	
Concern about Safety/Drivers	
Concern about drivers	0.904
Concern about safety/comfort	0.893
Preference to Use Non-Car Modes	
Prefer to use public transit	0.838
Prefer to walk or bike	0.831

As shown in Table 5.1, frequent users of ridehailing services are more likely than occasional/infrequent users to be older independent millennials and live in a household without any children. With respect to the characteristics of the built environment, I find that more than half of the frequent Uber/Lyft users live in urban neighborhoods, and in areas with higher activity (employment and residential) density, whereas occasional users tend to be concentrated in suburban neighborhoods and less dense areas. I also find that frequent users of ridehailing are also regular users of transportation-related smartphone applications and technology-enabled transportation services, while infrequent ridehailers and non-users/zero frequency users are less frequent users of these services.

As shown in Table 5.1, about 7% of frequent ridehailing users live in zero-vehicle households, while this share shrinks to 3.5% and 4.5% among infrequent users and non-users/zero-frequency users, respectively. With respect to the attitudinal variables, frequent users have the lowest average score for the preference to use their own vehicles among the three groups. The magnitude of this score increases as the frequency of use of ridehailing decreases.

5.4.4 Methods

I employed two statistical approaches to investigate the factors that affect the frequency of use of ridehailing: Ordered Probit with Sample Selection, and Zero-Inflated Ordered Probit with Correlated Error Terms. These modeling approaches are based on different assumptions – however, the results from the estimation of the models are consistent with each other, confirming the robustness of the relationships among the variables that are studied. Below I discuss each model in more details.

Ordered Probit Model with Sample Selection: Sample-selection models may be considered the most appropriate method for modeling the frequency of using ridehailing, given that the frequency question was only asked from the individuals who used ridehailing. The exclusion of individuals who have not adopted ridehailing (yet) would artificially inflate the coefficients associated with the exogenous variables included in a frequency model (in the direction of the effects of adoption) if there are common unobserved factors that affect both the adoption and frequency of use of ridehailing. In this study, I use an extension of Heckman's selection model (1979), the Ordered Probit with Sample Selection (OPSS), to account for selectivity (i.e. the two-stage decision process driving the frequency variable, including first the decision to adopt ridehailing and then the frequency of use). Popuri and Bhat (2003) estimated a frequency model with adoption for the joint decision to adopt home-based telecommuting and the frequency of telecommuting. The authors showed that failure to correct for selection led to the estimation of inconsistent and biased coefficients.

In the OPSS model, I assume that the error terms of both equations (selection and frequency) follow a bivariate normal distribution. Thus, the probability that a person uses ridehailing and does so for a given frequency j can be written as the product of the adoption probability $Prob(y_0 = 1|x)$ and the frequency probability $Prob(y_1 = j|z, y_0 = 1)$, each of which has its own model:

$$Prob(y_0 = 1, y_1 = j\ |x, z) = Prob(y_0 = 1|x) * Prob(y_1 = j|z, y_0 = 1)$$

where y_0 represents the adoption (= 0 for those who have heard of but not used the services; = 1 for those who have used the services before), y_1 represents the frequency of use of ridehailing, and j takes on the values 0 for those individuals who reported that they used ridehailing only in the past but do not use it currently (i.e. zero-frequency users), 1 for infrequent users and 2 for more frequent users. Further, x and z refer to the explanatory variables respectively associated with adoption and frequency. With the assumption of joint normality of the error terms in the OPSS model, the associated probabilities can be estimated using a bivariate normal distribution.

Zero-Inflated Ordered Probit Model with Correlated Error Terms: The rationale behind the use of this model is that there are (at least) two types of people having zero frequency of use: those who will "never" be inclined to use the service (call them "permanent non-users"), and those who may have used it in the past or will use it in the future, but are not using it at present ("temporary non-users"). Some literature refers to the former group as "structural zeros", and to the latter group as "random zeros". The trouble is that I don't know how to distinguish these two groups, since I do not know who will become users in the future[12]. The Zero-Inflated Ordered Probit model with Correlated error terms (ZIOPC) is the natural approach to use when structural zeros cannot be distinguished from random zeros, as is the case here. The term "zero-inflated" refers to the fact that all non-zero-frequency categories include only users, but the zero-frequency category is "inflated" with the permanent non-users (structural zeros) as well as the temporary non-users (random zeros).

Harris and Zhao (2007) proposed a model to address zero-inflation in the context of ordered variables. The authors used a double-hurdle combination of a split probit model and ordered probit model, involving two equations: an inflation (zero-frequency) equation and an activity/frequency equation. According to Green and Hensher (2009, pp. 231-232), these two equations can respectively be written as:

$$Prob(y = 0|x, z) = Prob(y_0 = 0|x) + Prob(y_0 = 1|x) * Prob(y_1 = 0|z, y_0 = 1),$$
$$Prob(y = j|x, z) = Prob(y_0 = 1|x) * Prob(y_1 = j|z, y_0 = 1) \text{ for } j = 1,2$$

Where y, the only fully-observed dependent variable in the ZIOPC model, takes on the values 0, 1, and 2 and represents the frequency of using ridehailing (for both users and non-users). The y_0

[12] As mentioned in Section 5.4.2, in this particular sample I *can* identify *some* random non-users, namely those who formerly used the service but no longer do so – i.e., *past users*. However, because I cannot identify *all* random non-users (specifically, *future users*), the model does not treat those cases any differently from the other zero-frequency cases, for which (future) participation status is unknown.

adoption variable resembles its counterpart in the OPSS model, but there is a critical difference between its definition in that model versus in this one. For the OPSS model, y_0 is completely observable (known), taking on the value 1 for current and past users, and 0 for those who have never used ridehailing (not distinguishing between those who never will use it, and those who will do so in the future). For the ZIOPC model, by contrast, y_0 is now a partially-unobserved variable that indicates "ever user" status: $y_0 = 1$ for users (whether past, present, or future), and 0 only for permanent non-users. y_1 again represents the frequency of use of ridehailing, but here it is defined only for (past, present, or future) users (i.e. current users and temporary non-users): it takes on the value 0 for the temporary non-users (not all of whom are observable to be such), 1 for infrequent users and 2 for more frequent users.

In other words, if $y_1 > 0$ I know that $y_0 = 1$, but if $y_1 = 0$ I do not know (in general) whether $y_0 = 1$ or 0. What I do know is the observed y (the current frequency, which takes on the value 0 if the respondent is a permanent non-user or a temporary non-user, the latter category consisting of past and future users; 1 if a current infrequent user; 2 if a current more frequent user), and so with the equations above I can obtain the likelihood function for the observed sample, and find the values of the model parameters that maximize that likelihood. So the first (inflation) equation of the ZIOPC model represents the two ways in which y can be 0: the first term is the probability that a given case is a structural zero (a permanent non-user), and the second term is the probability that the case is a random zero (consisting of the probability that she is a user, times the probability she is a temporary non-user given that she is a user). Table 5.4 portrays the relationships among y_0 and y_1 of the two models, y, and the categories created from those presented to the survey respondent.

Table 5.4 – The Relationships among Model Dependent Variables and (Created) Survey Categories

Survey response category	User category	Frequency designation	Observed frequency	OPSS model		ZIOPC model	
			y (A/F)	y_0 (A)	y_1 (F)	y_0 (A)	y_1 (F)
Heard of, but never used	Permanent non-user	Structural zero	0	0	undef.	0	undef.
	Temporary non-user (future user)	Random zero	0	0	undef.	1	0
Used in past, but not now	Temporary non-user (past user)	Random zero	0	1	0	1	0
Infrequent user	Current user	Non-zero	1	1	1	1	1
More frequent user	Current user	Non-zero	2	1	2	1	2

Notes: (1) "A" means adoption; "F" means frequency; "undef." means undefined. (2) The dashed line between permanent non-users and future users represents the fact that I do not observe who belongs to each group. (3) Although I can separately identify past users, the ZIOPC model does not do so, as explained in footnote 4.

Harris and Zhao (2007) and Green and Hensher (2009) relaxed the assumption of independence of unobserved effects in the adoption/inflation and frequency equations by allowing the unobserved terms to be correlated in both equations (ZIOPC). In this study, I estimated the ZIOPC model, assuming that the error terms of both equations are jointly distributed following a bivariate normal distribution, and compared it to the ZIOP model, which requires independently distributed error terms.

5.5 Results

Table 5.5 presents the result of OPSS and ZIOPC models of the frequency of use of ridehailing (I also present the result of the ZIOP model in appendix A, to show how exclusion of the correlation between the error terms can lead to biased estimates). As shown in Table 5.5, the estimated coefficients from the OPSS model are largely consistent with those from the ZIOPC model, with some exceptions that are discussed in this section.

Sociodemographic variables significantly impact the adoption process. Independent millennials and better-educated individuals (i.e. individuals with a Bachelor's degree, or higher) are more likely to adopt ridehailing, largely consistent with findings from previous studies

(Rayle et al. 2014; Alemi et al. under review). Individuals who live in a household without any children are also more likely to adopt ridehailing. In contrast, I find that none of the sociodemographic variables influences the frequency of use of ridehailing.

The OPSS model shows that an increase in land use mix is associated with a decrease in the frequency of use of ridehailing, all else equal, possibly due to the use of other means of transportation (mainly active modes) facilitated by greater proximity to destinations within walking and biking distances. Another important built environment factor is the land use density: both the OPSS and ZIOPC models show that an increase in activity density (number of jobs and housing units per acre) leads to an increase in ridehailing frequency. To make sure that the different directions of the impact of land use density and land use mix is not an artifact of the models, I checked the correlation between these two variables and also estimated models with and without either of these two variables. The very low correlation between land use mix and activity density (= 0.064) and the negligible changes in the estimated coefficients confirm that these two built environment attributes impact ridehailing in opposite directions. Both the selection and inflation models show that the adoption of ridehailing services is higher among individuals who live in urban and suburban neighborhoods compared to those who live in rural neighborhoods, but these variables are not good indicators of ridehailing frequency.

The variable related to the use of smartphones in connection with transportation is significant in the OPSS model: the individuals who use their smartphone to access transportation-related services (e.g. to navigate in real time, learn how to get to new places, identify possible destinations and check traffic to plan route or departure time) more frequently are more likely to adopt ridehailing and to use it with higher frequency. Similarly, as confirmed by both OPSS and ZIOPC models, individuals who are more active on social media (e.g.

Facebook) tend to have higher adoption rates, consistent with the findings in the context of other non-transportation sharing-economy services, e.g. Airbnb (Latitude 2010).

I also test the impact of the use of other emerging transportation services on the adoption and frequency of ridehailing and find that individuals who have used fleet-based carsharing systems (e.g. Zipcar) are more likely to adopt ridehailing. In preliminary models, the use of carsharing negatively affected the frequency of ridehailing, suggesting a competition among the new shared-mobility services, a controversial topic that has been gaining attention in the popular media. The magnitude of the impact of carsharing on the dependent variables diminished after I included other variables, and the carsharing variable does not have statistically significant effects in the final model, possibly because few individuals reported that they frequently use carsharing.

Frequent taxi users (i.e. individuals who reported that they use taxi services at least once a month) are more likely to use Uber/Lyft frequently than non-frequent taxi users and non-users, according to the models. The ZIOPC model indicates that respondents who reported a higher number of long-distance leisure trips made by plane are more likely to adopt these services and to use them more frequently. Both models also confirm that the Uber/Lyft adoption rate is higher among individuals with a higher number of long-distance trips made by non-car mode for business purposes. This makes sense, given that business travelers are more likely to be in a situation where they do not have access to their own car. Preliminary models hinted that individuals who live in zero-vehicle households tend to use ridehailing more often; however, I excluded this variable from the final model as it was not statistically significant after the inclusion of other explanatory variables.

Among various attitudinal variables and perceived limitations on the use of ridehailing, concern about safety and drivers of ridehailing companies has the greatest impact on the frequency of use of these services. Both models confirm that concern about safety and drivers is associated with lower ridehailing frequency. The preference to use (have) one's own vehicle is another factor that can strongly limit ridehailing frequency: both the OPSS and ZIOPC models show that individuals who reported that they prefer to use (have) their own vehicles are less likely to use ridehailing frequently. Individuals with higher levels of agreement as to their willingness to pay to reduce their travel time (i.e. higher perceived value of time) tend to use Uber/Lyft more frequently. This variable was only significant in the ZIOPC model; the variable had statistically significant effects in early specifications of the OPSS model, but the magnitude, and significance, of the impact of this variable diminished after including other variables in the model, and the variable did not have statistically significant effects and was removed from the final OPSS model specification.

In addition to the impacts of attitudinal variables on ridehailing frequency, the adoption models in both OPSS and ZIOPC show that the rate of adoption of ridehailing is significantly higher among individuals with stronger attitudes on *technology embracing*, *pro-environmental policies*, and *seeking variety in life* dimensions. The models also show that lack of knowledge about ridehailing services and the preference to use public transportation or active modes can negatively affect the adoption of ridehailing.

Table 5.5 – Estimation Results of Sample Selection and Zero-inflated Ordered Probit Models with Correlated Error (N=1,639)

Variables	Ordered Probit with Sample Selection				Zero-inflated Ordered Probit Model with Correlated Error			
	Selection Model		Frequency Model		Inflation Model		Frequency Model	
	Estimates (P-values)	Std. Error	Estimates (P-values)	Std. Error	Estimates (P-values)	Std. Error	Estimates (P-values)	Std. Error
Age and Stage in Life								
Younger Dependent Millennials	0.29 (0.13)	0.19	--		0.32 (0.19)	0.24	--	
Younger Independent Millennials	0.49 *(0.00)*	0.16	--		0.67 *(0.00)*	0.22	--	

Older Dependent Millennials	0.43 *(0.02)*	0.19	--		0.49 *(0.05)*	0.25	--	
Older Independent Millennials	0.55 *(0.00)*	0.11	--		0.69 *(0.00)*	0.15	--	
Younger Gen X	0.20 (0.12)	0.13	--		0.21 (0.19)	0.16	--	
Household Income and Education Interaction								
Low/Medium Income Household and High Education Individuals	0.33 *(0.00)*	0.10	--		0.39 *(0.01)*	0.13	--	
High Income Household and Low Education Individual	0.33 *(0.04)*	0.16	--		0.31 (0.13)	0.20	--	
High Income Household and High Education Individual	0.25 *(0.05)*	0.13	--		0.27 (0.10)	0.16	--	
Presence of Children in the Household								
Household with Kid(s)	-0.22 *(0.01)*	0.08	--		-0.27 *(0.02)*	0.11	--	
Neighborhood Type (Geocoded)								
Urban	0.39 *(0.00)*	0.13	--		0.25 (0.14)	0.17	--	
Suburban	0.27 *(0.01)*	0.11	--		0.32 *(0.03)*	0.14	--	
Region								
San Francisco Bay Area	0.08 (0.60)	0.15	--		0.11 (0.55)	0.18	--	
Sacramento	0.15 (0.33)	0.16	--		0.12 (0.56)	0.20	--	
Greater Los Angeles	0.16 (0.26)	0.14	--		0.27 (0.15)	0.18	--	
San Diego	0.32 *(0.03)*	0.14	--		0.37 (0.06)	0.19	--	
Land Use Mix								
8-Tier Employment Entropy	--		-0.44 *(0.04)*	0.21	--		--	
Land Use Density								
Activity Density	--		0.16 *(0.01)*	0.06	--		0.17 *(0.02)*	0.07
Use of Smartphone								
Apps To Determine Destination and Route	0.19 *(0.00)*	0.05	0.20 *(0.02)*	0.08	0.26 *(0.00)*	0.06	--	
Use of Social Media (Facebook)								
High Frequency	0.25 *(0.01)*	0.09	--		0.34 *(0.01)*	0.12	--	
Use of Other Emerging Transportation Services								
Use of Fleet-based Carsharing	1.13 *(0.00)*	0.20	--		1.24 *(0.00)*	0.27	--	
Frequency of Using Taxi Services								
Used Less than Once a Month	0.39 *(0.00)*	0.09	--		0.61 *(0.00)*	0.14	--	
Used at Least Once a Month	0.46 *(0.01)*	0.17	1.24 *(0.00)*	0.23	0.12 (0.57)	0.22	1.61 *(0.00)*	0.26
Frequency of Long-distance Trips								
Frequency of Non-car Long-distance Business Trips	0.32 *(0.03)*	0.15	--		0.41 (*0.05)*	0.20	--	
Frequency of Long-distance Leisure Trips by Plane	0.99 *(0.00)*	0.17	--		0.79 *(0.01)*	0.30	0.60 *(0.05)*	0.29
General Attitudes								
Variety Seeking	0.15 *(0.00)*	0.05	--		0.16 *(0.01)*	0.06	--	
Technology Embracing	0.21 *(0.00)*	0.05	--		0.26 *(0.00)*	0.06	--	
Pro-Environmental Policies	0.14 *(0.00)*	0.04	--		0.13 *(0.02)*	0.05	--	
Pay to Reduce Travel Time	--		--		--		0.12 *(0.04)*	0.06
Perceptions of Attributes of Ridehailing								
Concern about Safety/Drivers	--		-0.16 *(0.02)*	0.07	--		-0.38 *(0.00)*	0.06
Preference to Use Non-car Mode	-0.18 *(0.00)*	0.04	--		-0.20 *(0.00)*	0.06	--	
Lack of Knowledge about the Services	-0.35 *(0.00)*	0.05	--		-0.32 *(0.00)*	0.07	--	

Preference to Use Own Vehicle	-0.14 *(0.00)*	0.04	-0.15 *(0.02)*	0.06	--		-0.26 *(0.00)*	0.06
Constant	-2.17 *(0.00)*	0.18	--		-1.85 *(0.00)*	0.29	--	
Threshold 0→1	--		-1.82 *(0.00)*	0.18	--		-0.31 (0.15)	0.21
Threshold 1→2	--		-0.09 (0.67)	0.20	--		0.86 *(0.00)*	0.20
Correlation Parameter (ρ)	-0.53 *(0.00)*				-0.59 *(0.00)*			
Final Model Loglikelihood	-965.22				-778.86			
AIC [BIC]	2006.43 [2211.70]				1631.71 [1831.58]			

Note: P-values are reported in parentheses; italicized P-values are significant at the 5% level.

The magnitude and significance of the correlation term ρ in the Sample Selection and Zero-inflation models indicate a very substantial and significant negative correlation between the unobserved factors affecting the adoption and frequency of use of ridehailing. I confirmed the significance of the correlation term by performing a likelihood ratio test of independence and Wald (t-)test (H_0: $\rho=0$). The significant negative correlation term indicates that some individual traits or other attributes that are not controlled for in the final OPSS and ZIOPC models impact ridehailing adoption and frequency in opposite directions.

5.6 Conclusion and Discussion

In this study, I expand my previous work on the adoption of ridehailing in California by investigating the factors that affect the frequency of use of ridehailing among millennials and Gen Xers, using data collected in California between September and December 2015. To account for differences in the behavioral processes of adoption and frequency of ridehailing, and to avoid biased model estimation, I employed two different approaches: an Ordered Probit model with Sample Selection (OPSS) and a Zero-Inflated Ordered Probit model with Correlated error terms (ZIOPC). The results of both models are largely consistent, with some exceptions related to the impact on ridehailing frequency of technology land use mix, and individual attitudes towards paying to reduce travel time, which are only significant in one of the two models.

The finding that sociodemographic variables are good predictors of the adoption of ridehailing but not of the frequency of use of these services is surprising. In this study, I use coarse frequency categories for modeling purposes (due to small sample sizes in some of the frequency categories) and believe that this coarse classification might mask some of the potential impacts that sociodemographics or other variables have on ridehailing frequency. The finding that land use mix and activity density impact the frequency of use of these services but in opposite directions is also notable, as is the finding that the impact of other built environment variables, including neighborhood types and geographic region, were only significant in the adoption model (i.e. selection or inflation model). The impacts of these two latter variables might have been masked due to the coarse classification of ridehailing frequency. Another potential explanation is the confounding effects of variables such as mobility/modality style (Vij et al. 2013) and factors affecting individuals' residential location. The finding that individuals who use a smartphone to determine trip destination and route and those who frequently travel by plane are more likely to adopt these technology-based services and to use them more frequently is consistent with expectations.

That individuals with a higher preference to use (have) their own vehicle and that those who evaluated the concern about safety and drivers as strongly limiting factors on the use of ridehailing are less likely to use Uber/Lyft is also to be expected. The finding that individuals with higher willingness to pay to reduce their travel (i.e. higher perceived value of time) are more likely to use ridehailing more often merits further exploration, given that ridehailing does not necessarily reduce travel, though it does enable travelers to make better use of their time. One possibility is that such individuals may be switching from modes having a lower quality of service (public transit, in many cases, but also driving, especially when parking is not easy to find) to more expensive but faster modes. The salience of safety/security concerns and personal-vehicle preference as limiting factors affecting ridehailing frequency suggests a promising future for these services, particularly if they can improve/maintain their current safety levels (by better monitoring drivers and the quality of their services), and (to approach the level of service of personal vehicles) reduce their prices and shorten waiting times. Pooling services (e.g. Lyft Line and UberPOOL) are the primary strategy to lower prices and represent an alignment of the public interest with business interests. However, more research on safety/security is required to better understand the needs of riders and match riders with the same needs in the same car (as is increasingly being done by pooled ridehailing services in large US metropolitan areas).

Moving forward, there will be increasing need to coordinate policymaking and incentives in order to harvest the potential benefits of these services, while reducing the negative effects. The greatest public benefits would come from pooling – reduced traffic congestion, road infrastructure costs, greenhouse gas emissions, and parking demand – which suggests that policymakers need better understanding of who might use pooling services and what incentives and policies would be most effective at encouraging them to do so. During the next stages of the research, I plan to expand and address some of the limitations of these analyses by incorporating preference heterogeneity and taste variation (as latent classes) into the zero-inflated ordered model. This will allow us to better account for heterogeneity in individual decision processes and to control the variation in individual tastes, preferences, lifestyles, choice sets and sensitivities. In addition, a second round of data collection (planned for spring 2018) will allow us to better understand the role that various factors have in affecting the adoption and frequency of ridehailing as the availability and visibility of these services increases and as an individual's mobility choice set expands to embrace new shared-mobility services.

5.7 Acknowledgment

This study was funded by the National Center for Sustainable Transportation (NCST), which receives funding from the USDOT and Caltrans through the University Transportation Centers program. The first author also received support through an NCST dissertation fellowship. The authors would like to thank Caltrans, the NCST and USDOT, for their support of university-based research in transportation.

5.8 Appendices

5.8.1 Appendix A

Table 5.6 – Estimation Results of Zero-inflated Ordered Probit (ZIOP) Model with Independent Error Terms (N=1,639)

Variables	Inflation Model		Frequency Model	
	Estimates (P-values)	**Std. Error**	**Estimates (P-values)**	**Std. Error**
Age and Stage of Life				
Younger Dependent Millennials	0.34 (0.22)	0.28	--	
Younger Independent Millennials	0.72 *(0.00)*	0.25	--	
Older Dependent Millennials	0.53 (0.07)	0.29	--	
Older Independent Millennials	0.77 *(0.00)*	0.17	--	
Younger Gen X	0.26 (0.15)	0.18	--	
Household Income and Education Interaction				
Low/Medium Income Household and High Education Individuals	0.44 *(0.00)*	0.15	--	
High Income Household and Low Education Individual	0.32 (0.17)	0.23	--	
High Income Household and High Education Individual	0.35 (0.07)	0.19	--	
Presence of Children in the Household				
Household with Kid(s)	-0.29 *(0.03)*	0.13	--	
Neighborhood Type (Geocoded)				
Urban	0.28 (0.13)	0.19	--	
Suburban	0.43 *(0.01)*	0.16	--	
Region				
San Francisco Bay Area	0.15 (0.48)	0.21	--	
Sacramento	0.20 (0.39)	0.21	--	
Greater Los Angeles	0.34 (0.10)	0.21	--	
San Diego	0.45 *(0.04)*	0.22	--	

Land Use Mix				
8-Tier Employment Entropy	--		--	
Land Use Density				
Standardized Activity Density	--		0.22 *(0.00)*	0.07
Use of Smartphone				
Apps To Determine Destination and Route	0.29 *(0.00)*	0.07	--	
Use of Social Media (Facebook)				
High Frequent	0.38 *(0.01)*	0.13	--	
Use of Other Emerging Transportation Services				
Used Fleet-based Carsharing	1.28 *(0.00)*	0.29	--	
Frequency of Using Taxi Services				
Used Less than Once a Month	0.76 *(0.00)*	0.16	--	
Used at Least Once a Month	0.32 (0.13)	0.21	1.70 *(0.00)*	0.26
Frequency of Long Distance Travel				
Frequency of Non-car Long Distance Business Travel	0.46 *(0.05)*	0.24	--	
Frequency of Long Distance Leisure Travel by Plane	0.86 *(0.00)*	0.28	0.91 *(0.00)*	0.24
General Attitudes				
Variety Seeking	0.17 *(0.02)*	0.07	--	
Technology Embracing	0.30 *(0.00)*	0.07	--	
Pro-Environmental Policies	0.13 *(0.03)*	0.06	--	
Pay to Reduce Travel Time	--		0.16 *(0.01)*	0.06
Perceptions of Attributes of Ridehailing				
Concern about Safety/Drivers	--		-0.40 *(0.00)*	0.06
Preference to Use Non-car Mode	-0.26 *(0.00)*	0.06	--	
Lack of Knowledge about the Services	-0.42 *(0.00)*	0.07	--	
Preference to Use Own Vehicle	-0.14 *(0.00)*	0.04	-0.30 *(0.00)*	0.06
Constant	-2.35 *(0.00)*	0.26	--	
Threshold 0→1	--		-0.06 (0.72)	0.17
Threshold 1→2	--		1.28 *(0.00)*	0.12
Correlation Parameter (ρ)		--		
Final Model Loglikelihood		-785.09		
AIC [BIC]		1642.19 [1836.85]		

Note: P-values are reported in parentheses; italicized P-values are significant at the 5% level.

6. EXPLORING THE FACTORS THAT LIMIT AND/OR ENCOURAGE THE USE OF UBER AND LYFT, AND THEIR IMPACTS ON THE USE OF OTHER TRAVEL MODES IN CALIFORNIA

6.1 Abstract

Ridehailing services such as those offered by Uber and Lyft (in the US market), one of the most rapidly growing forms of shared mobility, play an important role in the future of transportation. However, the factors that affect the adoption of these services, their impacts on other components of travel behavior, and the way these services can be integrated with other means of travel are not fully understood (and exploited) to date. In this chapter, I investigate the factors that limit or encourage the use of single-user ridehailing services such as Uber X and Lyft Classic in California, and the potential impacts that these services have on other modes of travel. I use data collected from a large travel behavior survey administered to a sample of millennials and members of the preceding Generation X. I find that millennials are more likely to adopt ridehailing and they tend to use these services more frequently. Uber/Lyft users are more responsive to waiting time and ease of arranging rides than other travelers. Both users and non-users rate their preference towards private vehicle ownership and usage as the strongest limiting factor to the use of these technology-based services – more so among non-users and infrequent riders who use these services less than once a month. I find that the use of ridehailing tends to reduce the amount of driving made by both frequent and non-frequent users. It also substitutes for some trips that would have otherwise been made by transit or active modes, more so among frequent users, younger individuals, those who live in zero-/lower-vehicle households, and those who are more multimodal. The study improves the understanding of how ridehailing as the spearhead of other emerging trends in transportation (e.g. automation and electrification) will

transform future transportation and it helps inform policy decisions designed to increase transportation sustainability.

6.2 Introduction

Transportation is changing at an unprecedented pace. The increased availability of locational data and ever-increasing numbers of smartphone applications, together with other information and communication technologies, are starting to transform transportation supply and demand in many ways. Among other effects, they provide opportunities for the introduction and massive deployment of a wide range of new transportation services and they make it easier to access mobility services without the fixed costs of vehicle ownership. New shared mobility services range from *carsharing*, including *fleet-based round-trip* and *one-way services* such as Zipcar and Car2Go or *peer-to-peer* services such as Turo, to *ridesharing* services, including *dynamic carpooling* such as Carma and *ridehailing* such as Uber and Lyft, as well as *bikesharing*.

Ridehailing services (also known as ride-sourcing, on-demand ride services or transportation network companies, or TNCs) are a rapidly growing form of shared-mobility services. Uber and Lyft, the major providers of these services in the U.S. market, launched their popular services UberX and Lyft Classic in summer 2012. Didi, Grab, and Ola are the other major providers of ridehailing services serving mainly the markets in China, South Asian countries, and India, respectively. These services provide “glorified taxicab” services that directly compete with local taxis in providing rides to passengers. Ridehailing smartphone apps connect travelers to a contracted pool of available drivers who own their vehicles. While ridehailing service are similar to traditional taxicabs with respect to their cost scheme and type of service (Schaller 2017), their easier access, lower costs and higher attractiveness increase have made them an increasing popular option for travelers (Taylor et al. 2015). They are transforming transportation by separating access to transportation (and automobility) from the fixed cost of auto ownership, and they can increase the attractiveness and feasibility of living in a zero-/lower vehicle household.

To increase vehicle occupancy and provide more affordable rides, Uber and Lyft launched their pooled services UberPOOl and Lyft Line, respectively, in the fall of 2014. These services offer a ride to several distinct passengers in the same vehicle matching them based on their similar routes. They provide pooled ride services at a lower cost than conventional on-demand ride services options by allowing drivers to pick up and drop off multiple passengers during the same trip. These pooling services are priced up to 50% lower, which increases their appeal among price-sensitive travelers. As of December 2017, both Uber and Lyft provide pooled services in more than 15 cities in the U.S. market, accounting for a total number of 905 million trips (as cited in Shaheen et al. 2018).

Pooled services increase the efficiency of the service and have the potential to reduce traffic congestion and greenhouse gas (GHG) emissions from transportation (compared to personal vehicles). According to a study conducted in the Toronto metropolitan area (CPCS 2017), increasing the automobile occupancy rate from 1.08 (current rate) to 1.20 would result in a gross cost saving of $3 million per day, without even considering reduced environmental and congestion externalities.[13] Still, the adoption of pooled TNC services may have positive, neutral of negative impacts, depending on what other modes of transportation the use of these services replaces and the extent to which the pooled services actually carry multiple passengers.

[13] The authors assumed that the average vehicle operating and infrastructure costs per vehicle kilometer traveled are $0.60.

The availability and popularity of on-demand ride services are quickly growing. Uber and Lyft the major providers of ridehailing services in the U.S. markets expand their markets substantially since 2012 (Shaheen et al. 2016, Shaheen et al. 2018): As of November 2017, Uber operates in 80 countries (in more than 700 cities) and Lyft provides services mainly in the U.S. markets (in more than 300 cities). Goldman Sachs (2017) reports that ridehailing delivered about 6 billion passenger trips in 2016 (with a mode share of less than 1%) in tier 1-2 cities (the 100 wealthiest cities in the world classified by total GDP) which is expected to grow to 30-83 billion passenger trips by 2030, depending on the proportion of mobility demand growth that can be met by ridehailing and the market penetration of these services. As the popularity and availability of ridehailing services increases, their impacts on various components of travel behaviors becomes less negligible: A recent study in San Francisco found that Uber and Lyft served 15% (170,000 trips per day) of all trips inside the city on a typical weekday (SFCTA 2017), accounting for 20% of intra-city vehicle miles traveled (VMT) and 6.5% of total VMT including both intra- and inter-city trips. The role of ridehailing will likely increase as these services gain in popularity in smaller cities and suburban neighborhoods (Wang 2017) and as society transitions toward a future dominated by autonomous vehicles and mobility as a service (Sperling et al. 2018). Planners and policymakers have a strong interest in improving their understanding of the potential impacts of ridehailing services on travel behavior, and the factors that increase or limit their use.

The goal of this chapter is to explore the factors that affect the adoption and frequency of use of ridehailing services, the limitations that prevent the use of these services, and the potential impacts that these services have on travel behavior and the use of other modes. I analyze data from a large survey of millennials and members of the preceding Generation X in California, and address policy issues related to increasing use of ridehailing services.

6.3 Literature Review

To date, there is limited knowledge on the characteristics of the users of ridehailing and the potential impacts that these services have on other components of travel behavior, such as the use of other means of transportation and vehicle ownership. One of the primary obstacles in this area is the lack of access to operator data on the users, and the scale and performance of ridehailing services. Much of the existing knowledge about these services is disseminated in narrative form by the popular media. Overall, studies about on-demand ride services follow one of these two distinctive directions: (1) studies that investigate the factors associated with the adoption and frequency of use of ridehailing; and (2) studies that discuss the potential impacts of ridehailing services on travel patterns and other components of travel behavior, vehicle ownership, mode choice and activity patterns.

The adoption and frequency of use of ridehailing may vary significantly among different segments of the population. As shown in previous chapters and in related analysis by Alemi et al. (2017) better-educated and higher-income older millennials are more likely to adopt on-demand ride services, and largely confirming the findings of the other studies based on descriptive statistics (e.g. Rayle et al. 2014; Taylor et al. 2015; Feigon and Murphy 2016; PEW research center 2016) and the results of the TCRP report 195 (2018), which looked at the distribution of key explanatory variables at zipcode level in five U.S. metro areas (including Chicago, Los Angeles, Seattle, Nashville and Washington) with high level of TNC activity. These findings seems consistent with other travel choices of millennials, who tend to more often live in zero-

/lower vehicle household, drive less and use non-motorized means of transportation mode more often than older cohorts at the same age (Blumenberg et al. 2016; Kuhnimhof et al. 2012; Frändberg and Vilhelmson 2011; BRS 2013), likely due to a combination of (a) generational differences in lifestyles and individual attitudes, (b) period effects and economic conditions and (c) stage in life cycle and residential location.

Alemi et al. (2017) also found that individuals who do not work nor study and individuals of Hispanic origin are less likely to use on-demand ride services. As shown in Chapter 4, I employed a latent-class choice model to better understand the factors affecting the use of on-demand ride services, thorough controlling for individuals taste heterogeneity and variations. I identified three latent classes based on individuals' lifestyles and their stage in life, and showed that the class that is largely composed of higher educated independent millennials (i.e. millennials who have already established their own households) has the highest adoption rate, while the adoption of ridehailing was the lowest among the members of the class that is largely composed of the least affluent individuals with the lowest level of education.

These studies confirmed the role of the built environmental on the adoption of ridehailing. The authors showed that living in an urban neighborhood is associated with higher Uber/Lyft adoption rate (Alemi et al. 2017). The authors also showed that, among other built environmental characteristics, land use mix, regional auto accessibility, and public transit availability and quality all impact the adoption of ridehailing. In addition, individuals with a higher degree of familiarity with the use of modern technologies in connection with transportation (e.g. use of a smartphone for transportation-related purposes, and/or use of carsharing), and frequent long-distance travelers are more likely to use ridehailing. This is also true for individuals with stronger attitudes toward pro-environmental policies, technology embracing, and variety seeking (Alemi et al. 2017).

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Planners are interested in understanding the degree to which current Uber/Lyft users will continue to use these services as they transition to later stages in life and as they move to other residential location (Taylor et al. 2015). Further, the emergence of other technology-enabled transportation services such as pooled ridehailing (i.e. UberPOOL and Lyft Line) and the future introduction of autonomous and connected vehicles raise questions about the eventual permanence of the observed travel patterns. How will shared mobility and other transportation technologies continue to further reshape transportation in future years?

Research on the overall impacts that ridehailing services have on other components of travel behavior is growing but is still in preliminary nature mainly due to limited availability of data and lack of robust approaches that can capture the causal relationship among the use of ridehailing and different components of travel behavior. Most of the existing studies in this area, to date, are based on either descriptive statistics of the self-reported behavioral changes, or other proxy variables such as Google trend data that are used to measure the intensity of use of Uber/Lyft. Further, many of the existing studies ignore the potential heterogeneity associated with the use and the impacts of ridehailing on other means of transportation among various groups of users, they do not control for the effects of various confounders/covariates and only report aggregated results (e.g. sample means for these variables). Other relevant issues with these studies are the use of convenience or other non-representative samples (e.g. studies developed on university students), and they mainly focus on large metropolitan areas, with little information collected, to date, among the residents of smaller cities or suburban/rural neighborhoods). Thus, it is often difficult to extrapolate the findings from these studies and generalize them to the entire population. Additional difficulties associated with these studies is the eventual maturation of ridehailing services and of their impacts over time. Hereon, I summarize the main findings from the available literature on the effects of ridehailing on various components of travel behavior.

The use of ridehailing may affect many transportation-related decisions, including e.g. activity patterns, mode choice, vehicle miles traveled, and vehicle ownership. Recent studies showed that the impacts of shared-mobility services on other means of transportation vary based on the local context and the characteristics of the users (Taylor et al. 2015; Circella et al. 2016a). For example, Rayle et al. (2014) indicated that about 40% of Uber/Lyft users in San Francisco reported that they reduced their driving due to the adoption of ridehailing. As shown in previous chapters and Alemi et al. (2017), I showed that about 30% and 50% of both millennials and Generation X, respectively, would have driven a car and/or would have taken a taxi in the absence of Uber/Lyft. Another example is the natural experiment in Austin, TX, which was imposed by the temporary halting of Uber and Lyft, which revealed similar patterns: due to the suspension of Uber/Lyft services in Austin during 2016 about 80% of Uber/Lyft users reported that they had replaced their Uber/Lyft trips with the use of personal vehicles or other ridehailing services provided by local companies (Hampshire et al. 2017).

Although ridehailing is an attractive alternative to driving (at least for some trip purposes), it is not yet clear the extent to which ridehailing affects vehicle miles traveled (VMT). Whether or not ridehailing increases total VMT depends on the balance of competing forces: on one hand, these services divert non-driving trips to driving mode, and add new types of VMT for dead-head repositioning of the vehicles. On the other hand, these services reduce personal vehicle dependency and cruising for parking. Henao (2017) evaluated the changes in total VMT by providing a ride to more than 300 Uber and Lyft riders in Denver, Colorado. The author found that total VMT increased by approximately 85%, when accounting for all factors including dead-heads and the potential substitution (or eventual complementary) effects on the use of other modes. Similarly, Schaller (2017) reported that in 2016 the use of Uber/Lyft contributed to a 3.5% increase in VMT in New York City and a 7% increase in Manhattan, western Queens, and Western Brooklyn.

Depending on local circumstances, ridehailing users may use the services as a substitute for or as a complement to the use of public transit - a million-dollar question that has received broad attention from the media and the public. Ridehailing may increase the use of transit services, by solving the first/last-mile issue and also providing a ride during hours where transit services operate infrequently, if at all (Circella et al. 2016; Taylor et al. 2016). Researchers from the Shared-Use Mobility Center found that frequent Uber/Lyft users are more likely to be multimodal and use public transit more often, possibly due to the correlation of both behaviors with other (intermediate) variables such as low car ownership or a residential location in a more accessible location (Feigon and Murphy 2016). The same study reported that the majority of Uber/Lyft trips are made between 10 pm to 4 am, when public transit runs very infrequently, suggesting a complementary effect is at work. In another study, Hall et al. (2017) modeled the differences in transit ridership before and after Uber's introduction in various Metropolitan Statistical Areas (MSAs) over a period of 24 months. They concluded that when Uber arrives in a new market transit ridership does not change that much, but as this service becomes more popular transit ridership increases. The authors showed that this complementary effect varies with the population that lives in an MSA, the type of transit services, and the transit pre-existing ridership.

At the other extreme of the spectrum, the recent drops in public transportation ridership signaled that TNCs might have replaced some trips that would have otherwise been made by public transportation. For example, BART ridership to the airports of San Francisco and Oakland decreased by 6.5% and 4.5%, respectively, over the past two years, while Uber and Lyft ridership to these destinations increased substantially during that same period (Cabanatuan, 2017). The Sacramento Regional Transit (SacRT) is another example of transit services that is continuing to lose ridership, while (not coincidentally) the number of drivers of on-demand ride service companies increases in this area (Bizjak 2017). Rayle et al. (2016) and Henao (2017) reported that about 30% and 22% of Uber/Lyft users would have traveled by transit if these services were not available for the last trip that they have made with these services. In my previous study, I further broke down the substitution patterns by age group and found that the magnitude of this substitution effect is more than double among millennials compared to their older cohorts, confirming how the more multimodal millennials continues to expand their set of mobility choices (Alemi et al., 2017). It should be noted, though, that millennials, on average, use public transit more often than older adults (therefore, they have more space to make this type of adjustments).

Babar and Burtch (2017) and Clewlow and Mishra (2017) looked at the impact of ridehailing on public transit by type of services. Babar and Burtch (2017) classified transit services by their right of way and the distance each type of service travels, and then evaluated the impacts of Uber's entry across time and locations. The authors found that Uber's entry is associated with 1.05% decline in the use of city buses (i.e. a short-haul service that share the right of way with other motorized mode), 2.59% increase in the use of subway (i.e. a short-haul service with its own right of way), and 7.24% growth in the use of commuter rail (i.e. a mid- to long-haul service with its own right of way). Similarly, Clewlow and Mishra (2017) showed that ridehailing tends to substitute for 6% and 3% of the trips that would have been otherwise made by bus and light rail, respectively, and tend to increase the use of commuter rail by 3%. Among various factors, the quality of transit services, total travel time (including both in vehicle travel time and waiting time) and the reliability of ridehailing services seem to fuel this substitution/ complementary pattern (Feigon and Murphy 2018; Babar and Burtch 2017).

Manville et al. (2018) analyzed the factors that affect the decline in transit ridership in the Southern California Area of Government (SCAG) and found that the relationship between ridehailing and transit use is far from conclusive. The authors concluded that ridehailing services do not appear to be a major contributing factor to the decline of transit ridership in the SCAG region, simply due to the timing of this decline (the decline in per capita transit use started in 2007, while ridehailing services began serving this region only in 2012), the higher cost of these services compared to transit, and the substantial differences between the profile of ridehailing users and those who use public transit frequently. Another important note should be made on the time of use of ridehailing services: according to the TCRP report 195 (2018) and TCRP report 188 (2016) the heaviest use of ridehailing across six main U.S. metropolitan regions (Chicago, Los Angeles, San Francisco, Seattle, Nashville, and Washington) takes place during the evening/ night hours and on weekends, when transit operates less frequently (if at all).

Uber and Lyft are used for short trips: data from the ridehailing operators in five U.S. metro areas showed that the average Uber/Lyft trips are between 2-4 miles (Feigon and Murphy 2018), confirming the potential impacts that ridehailing services may have on non-motorized mode (i.e. walking and biking). Little is known about the impact of this door-to-door service on walking and biking, but it is expected that Uber/Lyft might affect the adoption of this mode in either direction. In my previous study, I showed that about 25% of millennials and 12% of Gen Xers who used ridehailing would have walked or biked in the absence of these services (Alemi et al., 2017). The same study reported that the use of ridehailing services can also increase biking and walking for some individuals (e.g. if instead of driving for an entire trip/tour, the users walk on one leg, and return by Uber/Lyft, or walk for part of the trip, before catching a ride with these services), but in much smaller magnitude. Similarly, Henao showed that out of 311 respondents, about 12% of them would have walked or biked if Uber/Lyft was not available. In another study, Hampshire et al. (2017) found that the halting of Uber/Lyft can lead to a small increase (about 2.5%) in the use of non-motorized modes, suggesting that the substitution effect of ridehailing on walking and biking is prevalent.

With respect to the impact of ridehailing on vehicle ownership (a medium-long term decision that household members make), a recent Reuters/Ipsos opinion poll reveals that about 10% of the Uber/Lyft users plan to dispose of their vehicle(s) and turn to ridehailing as their primary means of travel (Henderson 2017). Hampshire et al. (2017) confirmed that about 17% of

Uber/Lyft users either purchased a vehicle or were seriously considering to purchase a vehicle due to halting of Uber/Lyft in Austin, Texas. The decision about changing the level of vehicle ownership is a complex household decision, which is affected by a range of factors and circumstances (Clark et al. 2016), including major life events, residential location, attitudes toward owning vs. using a car, the adoption of disrupting technologies and social trends (e.g. shared mobility, telecommuting, and use of social media), individual lifestyles, differences between current and desired level of car ownership as well as other exogenous stimuli (e.g. habits and changes in the cost of vehicle ownership). With respect to the cost, a recent study showed that the use of ridehailing, which on average costs about $2 per miles (Walker and Johnson 2016), would be a cheaper option than owning a vehicle for about 25% of Americans, if the true cost of vehicle ownership is accounted for (Davidson and Webber 2017). A very sharp increase in this percentage is expected with a decrease in the cost of accessing ridehailing services in a future dominated by autonomous vehicles (to less than $1 per mile).

None of the studies above could explore (let alone, confirm) the causal relationships among the use of on-demand ride services, vehicle ownership and other components of travel behavior, including travel multimodality, vehicle ownership and VMT. Further, it is not yet clear the extent to which the adoption of ridehailing causes an increase or decrease in the use of other means of transportation, in particular, transit and/or non-motorized mode, as opposed to both of those conditions being caused by other variables such as residential location, age/stage in lifecycle, and vehicle ownership. Further, it is reasonable to expect that any changes that the adoption of ridehailing prompts in various components of travel behavior and in vehicle ownership might be modified (amplified, eventually) with the introduction of new services such as pooled ridehailing. For example, pooled ridehailing services such as UberPOOL and Lyft Line may draw additional riders from transit if their fares fall low enough compared to transit fare. Further, the introduction of autonomous vehicles will lead to other substantial changes: a recent study by the Boston Consulting Group (2017) suggested that about 25% of the miles driven by private vehicles in the U.S. could be replaced by 2030 by shared autonomous vehicles, i.e. the mode that will offer transportation characteristics similar to today's TNCs at a lower cost in larger cities.

There is no doubt that the changes in total VMT and individuals' travel behavior (from auto-ownership to modal shift) can create a number of societal and economic challenges and opportunities (e.g. improve equity, expedite gentrification and dividedness, and decrease traffic fatalities) and can amplify or attenuate various negative transportation-related externalities, including traffic congestion and greenhouse gas emission (GHG). For example, Henao (2017) reported that about 19.5% of Uber/Lyft riders used ridehailing to avoid the difficulty of searching and paying for parking. The largest impact of ridehailing on parking is expected to occur at large event locations (e.g. stadium, concerts), as well as airports and dense urban neighborhoods, where parking costs and search time are often prohibitive. Cortrigh (2016) confirmed this issue and showed that the growth in the use of Uber/Lyft is highly correlated with higher parking rates. The reduction for parking demand and cruising for parking can ultimately affect traffic congestion and the associated emissions. On the other hand, cruising of vacant ridehailing vehicles or the use of parking space for these vehicles while they wait for a passenger can generate additional demand for parking and worsen traffic conditions. More research is required to better understand these impacts.

6.4 Data

The data used in this study was collected in fall 2015, as part of a research project that investigates emerging travel patterns and the residential location decisions among the members of Generation Y or millennials (i.e. young adults born between 1981 and 1997) and the members of the preceding Generation X (i.e. middle-aged adults born between 1965 and 1980). As a part of this large data collection, our research group designed and administered an online survey to a sample of 1,191 millennials and 964 members of the Generation X who were selected with a quota sampling approach from six major regions in California and three neighborhood types (urban, suburban, and rural). These six regions are (1) the California Central Valley; (2) Sacramento, following the boundaries of the Sacramento Area Council of Governments (SACOG); (3) San Diego, following the boundaries of the San Diego Association of Governments (SANDAG); (4) Greater Los Angeles, following the boundaries of the Southern California Association of Governments (SCAG); (5) the San Francisco Bay Area, following the boundaries of the Metropolitan Transportation Commission (MTC); and (6) the rest of Northern California and Others, where the remaining regions in California were grouped altogether. To reduce the non-representativeness of the sample, various targets for five socio-demographic characteristics were employed while recruiting the sample: gender, age, household income, race and ethnicity, and the presence of children in the household. A combination of cell weighting and iterative proportional fitting (IPF) raking were used to correct for any non-representativeness of the sample on various pertinent traits, including age group, neighborhood type, region, race, ethnicity, presence of children in the household, household income, student/employment status, and gender. See Circella et al. (2016a) and Circella et al. (2017) for detailed information about survey design and data processing.

The survey collected information on multitude arrays of individual attitudes and preferences; lifestyles; technology adoption and the use of social media; residential location and living arrangements; commute and non-commute related travel patterns; vehicle ownership; awareness, adoption and frequency of use of several types of shared-mobility services; factors that affect (e.g. increase or prevent) the use of Uber/Lyft; major life events that happened in the past three years; future expectations, aspirations and propensity to purchase and use a private vehicle versus other means of travel; and sociodemographic traits. The emerging transportation services included in the study were *fleet-based carsharing* (e.g. Zipcar or Car2go), *peer-to-peer carsharing* (e.g. Turo), *on-demand ride services* (e.g. Uber or Lyft), *dynamic carpooling* (e.g. Zimride or Carma), *peer-to-peer carpooling* (usually arranged via online platforms such as Facebook or Craigslist) and *bikesharing*.

As mentioned earlier, the goal of this chapter is to investigate the factors that limit or invigorate the use of ridehailing and the potential impacts of these services on other components of travel behavior. To do so, I first used the information reported by respondents on their familiarity with and use of various types of emerging shared-mobility services in their home town or while traveling. Those who reported that they have used any shared-mobility services, also reported their frequency of the use of them. In addition to the familiarity, adoption and frequency of use of emerging services, users of on-demand ride services were asked to rate the importance of different factors that affect their use of the services, how their adoption impacted their use of other means of transportation, and what they would have done if these services had not been available on their last trip they made by Uber or Lyft. Users and those who reported that are familiar with on-demand ride services but have not used these services yet also reported their evaluation of the importance of the factors that limit their use of on-demand ride services. I analyze these pieces of information in the remainder of this chapter. I perform all the analyses in this chapter using the weighted sample.

6.5 Adoption and Frequency of Use of Ridehailing Services

Figure 6.1 presents distribution of responses to two questions: (1) *familiarity with* and *adoption of* on-demand ride services (bigger pie); (2) *frequency of use* of on-demand ride services, which was only asked to those individuals who reported that they have used on-demand ride services before. As shown in Figure 6.1, about 26.5% of California millennials and Generation X reported that they have used ridehailing. However, the Uber/Lyft adoption rate is significantly higher among millennials (31.6%), while this rate drops to 19.4% for Generation X.

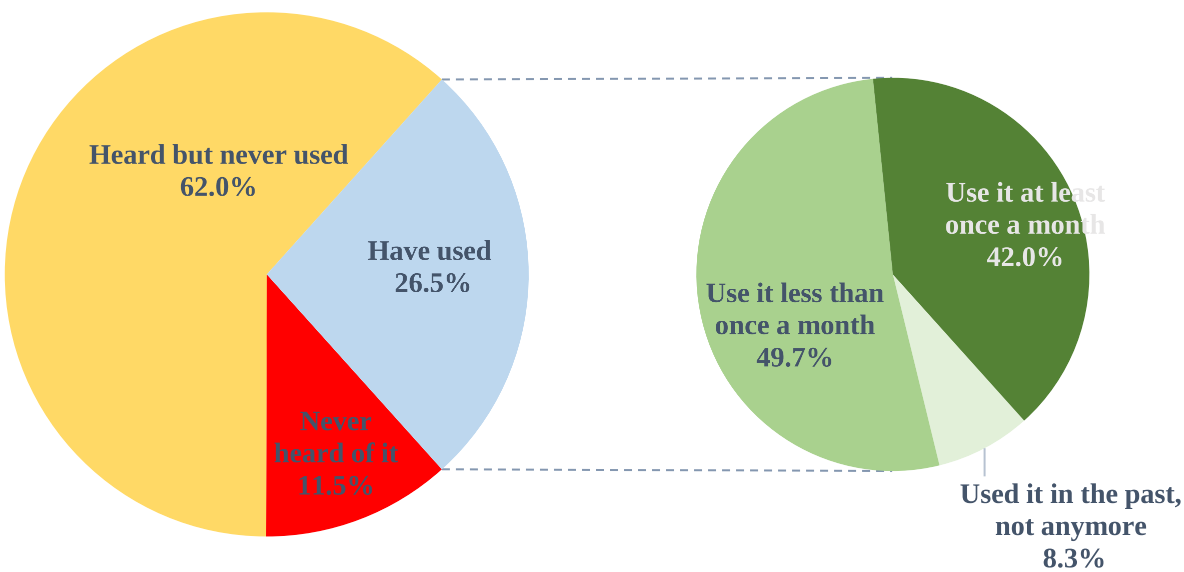


Figure 6.1 – Awareness, Adoption, and Frequency of Use of Ridehailing (N=1960, Weighted Sample)

As indicated in Figure 6.1, about 11.7% of the respondents (which is equivalent to 42.0% of Uber/Lyft users) reported that they use ridehailing at least once a month, and about 13.9% of the respondents (49.7% of users) reported that they use these services less than once a month, with the remaining 8.3% of those that have used ridehailing reporting that they have tried/used it at least once in the past, but do not actively use it anymore. Similar to the adoption rate, I found that millennials tend to use these transportation services more frequently: the percentage of users that use ridehailing at least once a month is 45.0% among millennials while only 36.9% of Gen Xers that are Uber/Lyft users use these services with such frequency. The 2.2% of respondents (8.3% of users) who report that they have used these services in the past but do not currently use them might signal dissatisfaction with prior use, or a change in circumstances that has made usage less accessible, or desirable. Or, more simply, this group of users might have tried the service at least once, perhaps in a specific location or under special circumstances, but ridehailing does not really match their usual mobility needs.

The geographic region, the neighborhood type and other characteristics of the built environment where the respondents live and work play an important role in the adoption and frequency of use of ridehailing. In the analysis of the 2015 California Millennials Dataset, I found that about 41.8% of urban dwellers used ridehailing, whereas this rate shrinks to 26.6% and 11.6% among suburban and rural dwellers, respectively. Further, I found that the adoption of on-demand ride services is higher among those who live in the major California regions, including San Francisco, Sacramento, Los Angeles and San Diego, and lower in all other areas. This is somehow not surprising, and it is consistent with the better quality of service, i.e. better availability and lower waiting time, that ridehailing companies provide in the urban neighborhoods of the major metropolitan areas of California.

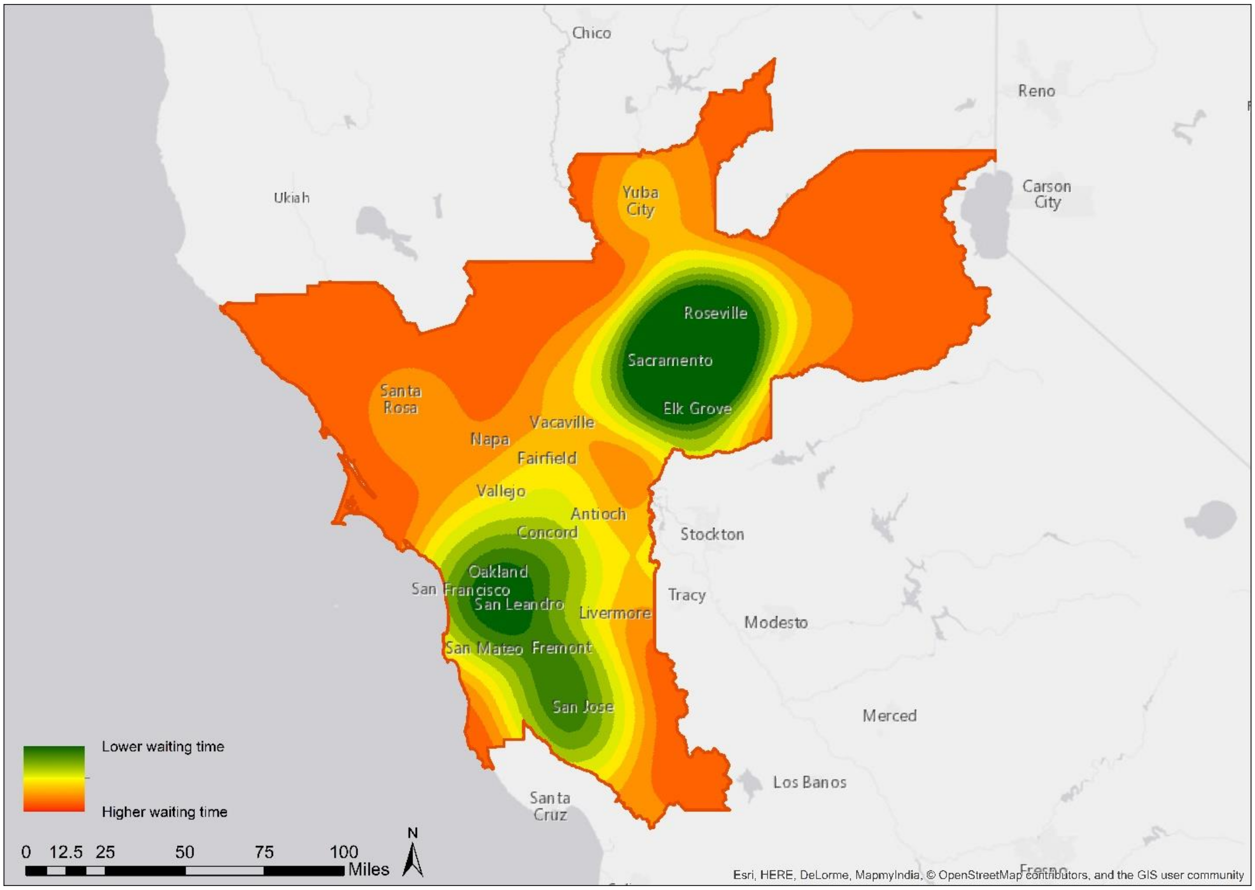


Figure 6.2 – Average Waiting Time for Uber X/Lyft Classic in San Francisco and Sacramento

Figure 6.2 and Figure 6.3 show the average waiting time for Uber X and Lyft Classic (the unshared or single-user ridehailing services provided by these companies) in northern California, i.e. the San Francisco and Sacramento regions, and southern California, i.e. Los Angeles and San Diego, respectively. The figures were built using information on the estimated waiting time (as provided by Uber and/or Lyft) at various times of the day during both weekdays and weekends in January and February 2017 using the survey respondents' geocoded home address as input –I mapped the average waiting time based on a kernel density distribution. The lowest average waiting times were observed in the central cores of cities of each of the four major California metropolitan planning organizations (MPO) areas, with the average waiting time increasing when moving to less central locations in each region. The average waiting time for Uber X and

Lyft Classic in the four major MPOs, at the time of measurement, ranged between 3.5 to 6 minutes in urban neighborhoods, 5 to 8 minutes in suburban areas, and 7.5 to 10.5 minutes in rural neighborhoods. The actual waiting times in these areas, though, may be higher than that, due to potential underestimation of the estimated waiting time by the Uber and Lyft smartphone apps. These findings are similar to the study by Hughes and MacKenzie (2016), who collected Uber X wait times in Greater Seattle, Washington area.

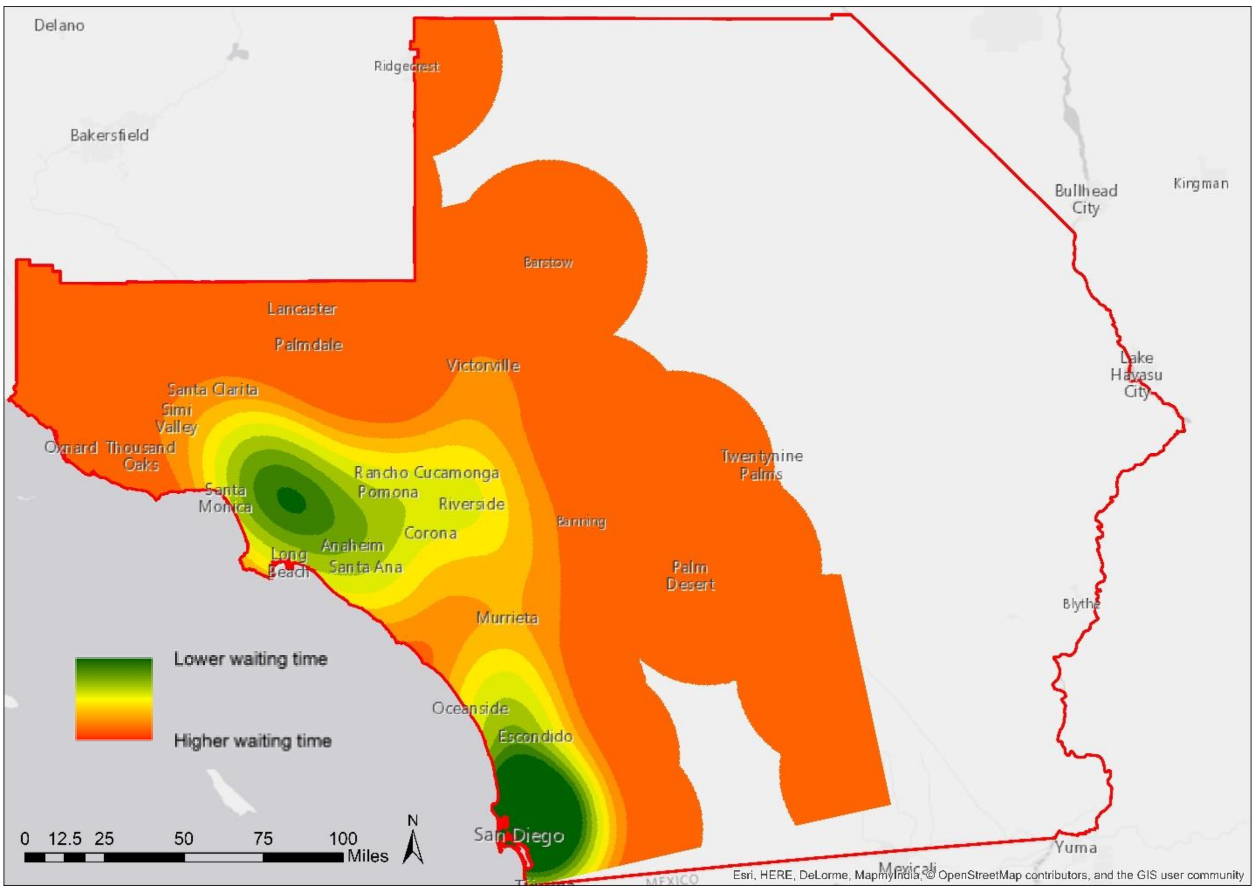


Figure 6.3 – Average Waiting Time for Uber X/Lyft Classic in Los Angeles and San Diego

I also find that increases in the order of 5-20% in the average waiting time are to be expected during peak hours in urban neighborhoods. The average waiting time remains unchanged or decreases slightly in suburban or rural neighborhoods during peak periods. The direction and magnitude of change in waiting time during weekends are mixed and vary across neighborhood types and regions of California, suggesting significant differences in the distribution of both supply (i.e. drivers) and demand on weekdays vs. weekends.

6.6 Factors Affecting the Use of Uber/Lyft

In the survey, respondents who use ridehailing were asked to evaluate the importance of a series of factors affecting their last trip made by Uber/Lyft, including the ease of payment, cost, ability to split fare, shorter waiting time, fastest way to get to destination, ease to hail a service, drivers (e.g. friendless or ability to speak the respondents' language), comfort/safety, reliability of services, difficulties with parking when driving their own car, the need to avoid drinking and driving, as well as the unavailability (limited availability) of other modes including public transit services, taxicabs, and personal vehicles. Figure 6.4 summarizes the factors that affect the use of Uber/Lyft. Users of ridehailing more often report being affected by the quality of the services, with two exceptions: avoiding the need (or cost) for parking and avoiding drinking and driving. More than 80% of the respondents reported that parking, including both difficulties in finding a parking space and the cost of parking, is a moderately to extremely important reason affecting their decision to use Uber/Lyft for their last trip they made using these services. I further looked at the breakdown of the "parking" motivation by neighborhood type and region, and found that urban and suburban dwellers, as well as those who live in large metro areas, in particular San Diego and the San Francisco Bay Area, are more likely to evaluate parking as an extremely important factor affecting their use of Uber/Lyft. About 60% of the respondents reported that they used ridehailing services to avoid driving under the influence.

Among the various characteristics of on-demand ride services, respondents put their highest emphasis on the waiting time, cost, ease to call a car, and drivers (including both friendliness and ability to communicate with riders) as the characteristics that seem most relevant to their choice of using the service. Further, I looked at the distribution of the importance of these factors among frequent users (i.e. those who used on-demand ride services at least once a month) and non-frequent users (i.e. those who used these services less than once a month). The largest discrepancy was observed in the importance of the availability of a personal vehicle: 25% of frequent users reported that the unavailability of a personal vehicle was an extremely important factor that affects their decision to use Uber/Lyft, while only 12% of non-frequent users considered this factor as extremely important, indicating some association between vehicle ownership and availability and the frequency of use of ridehailing. Among other factors, I found that the importance of ease of payment, the ability to split the fare and the unavailability of public transit are perceived rather differently between frequent and non-frequent users of the services: frequent users found these factors to be more important than non-frequent users did.

6.7 Limitation to the Adoption of Ridehailing

Both users of ridehailing services and those who reported that they have heard about the service but not used it yet were asked to evaluate the importance of the factors limiting or preventing their use of these services. **Error! Reference source not found.** summarizes the distribution of t hese factors by non-users, non-frequent (those who reported using ridehailing less than once a month) and frequent users (those who reported using ridehailing at least once a month). Among the factors limiting or preventing the use of ridehailing, both users and non-users ranked their preference to use their own vehicle as the most important one: about 25% of frequent users, 44% of non-frequent users and 56% of non-users reported that the preference to use their own vehicle strongly limits their use of ridehailing. Cost is another limiting factor that affects both users and non-users: about 28% of non-users, 21% of non-frequent users, and 18% of frequent users feel that the cost of the service strongly limits their use. I further look at the impact of this limiting factor by household income group and found that the members of the lower income groups are more likely to be strongly limited by the cost factor. This factor suggests a potential promising future for ridehailing if these services become are increasingly offered at lower cost, as it is already starting to happen with pooled services such as UberPOOL and Lyft Line in major metropolitan areas.

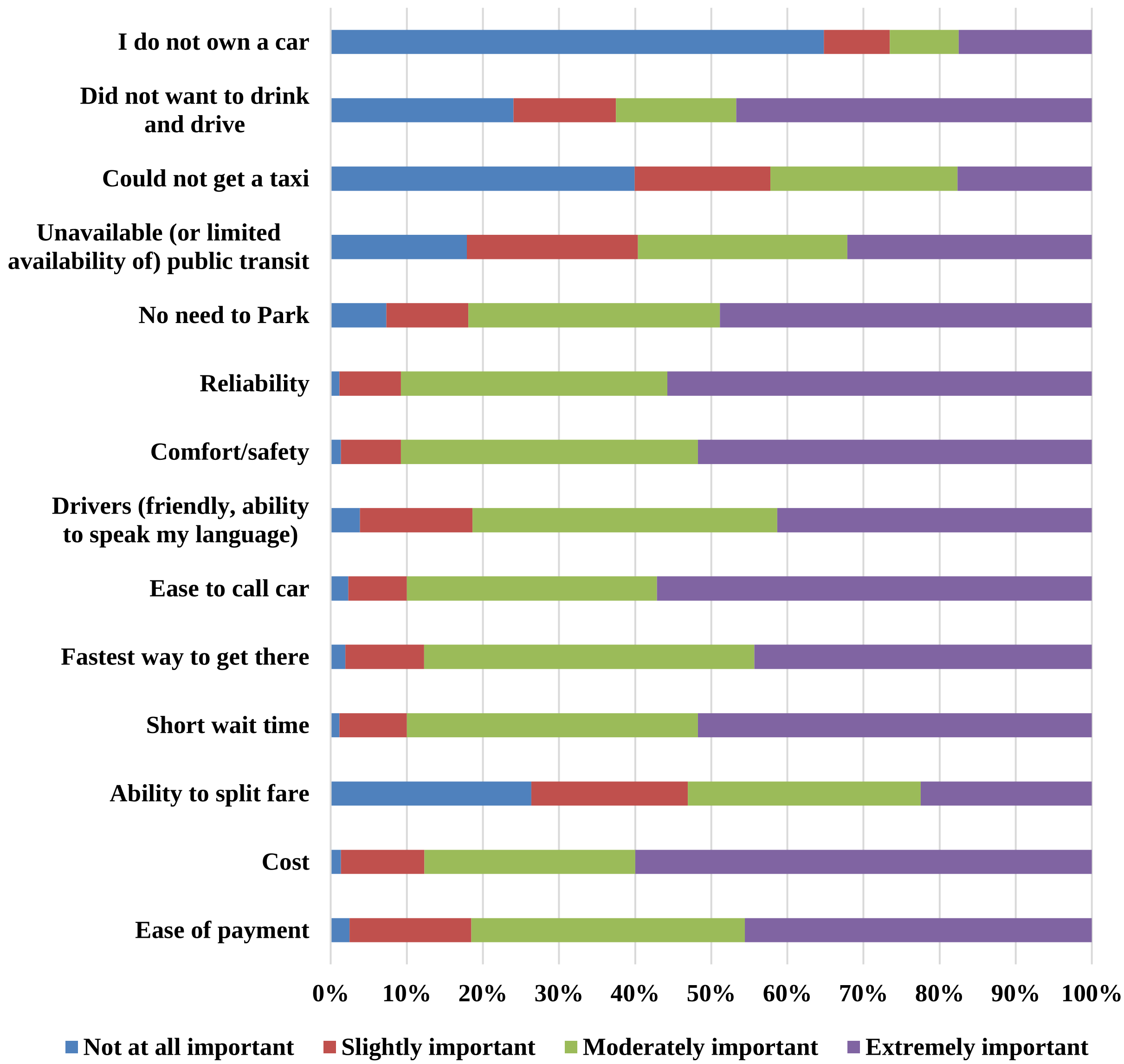
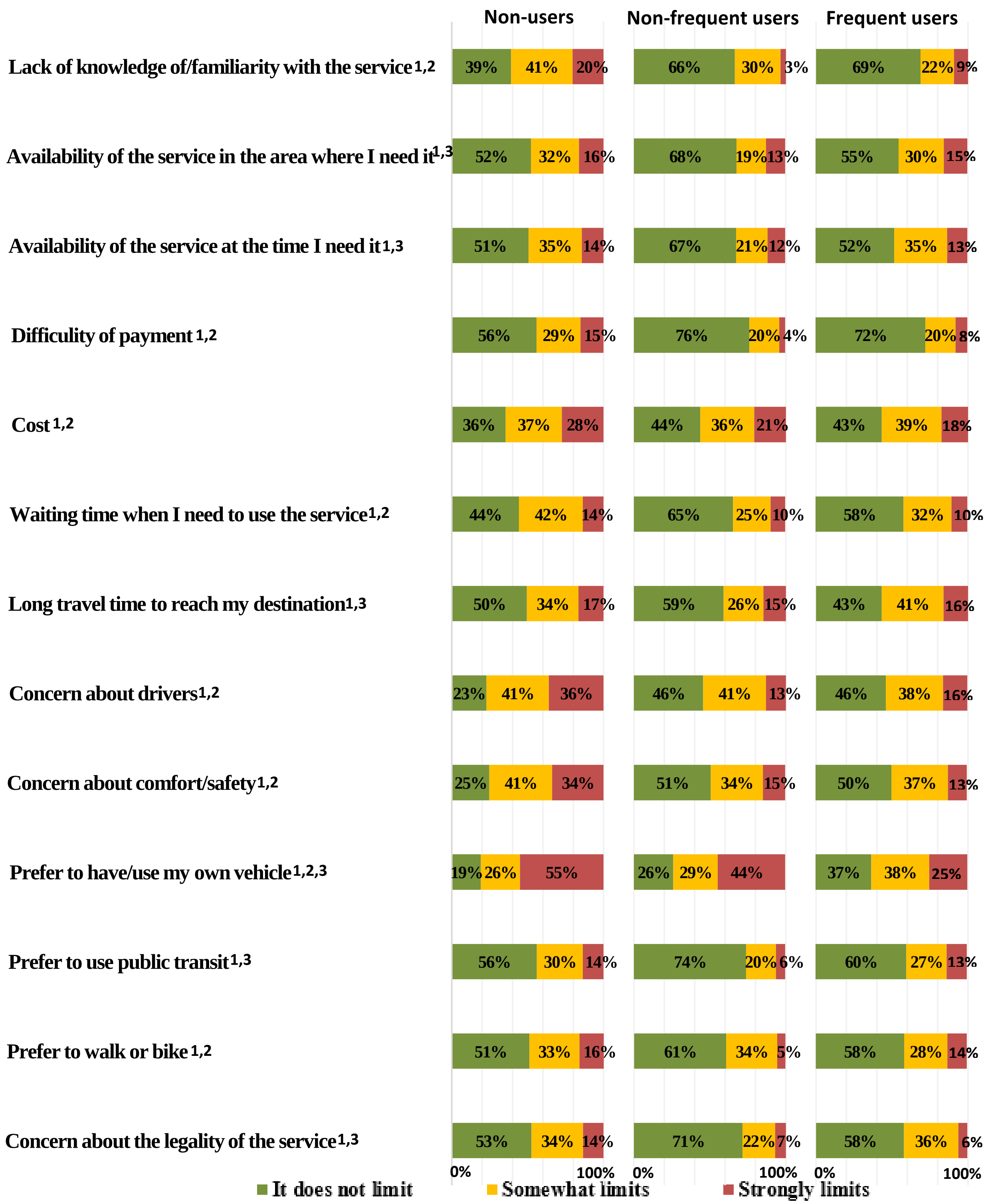


Figure 6.4 – Importance of Factors Affecting the Last Trip Made by Uber/Lyft (N=520, Weighted Sample)



Note: I performed the Mann-Whitney U test to compare the distribution of each variable across the two groups of users and a non-users: 1= differences are significant at the 5% level between non-users and non-frequent users; 2= differences are significant at the 5% level between non-users and frequent users; 3= differences are significant at 5% level between non-frequent and frequent users.

Figure 6.5 – Factors Limiting or Preventing the Use of Ridehailing ($N_{Non\text{-}users}$=1258, $N_{Infrequent\text{-}users}$ =259, $N_{Frequent\text{-}Users}$=218, Weighted Sample)

More than 1/3 of non-users reported that they are strongly concerned about the drivers (including both friendliness and ability to communicate with riders) and about the service comfort and safety. The importance of these two limiting factors shrinks to less than a half among non-frequent and frequent users, showing how the use of Uber/Lyft ride can affect their positive perception of the experience with these services –or potentially signaling self-selection of the more trustful users who are early adopters of these services. Interestingly, I find that the preference to use public transit limits the use of Uber/Lyft in a similar way among both non-users and frequent users (about 44% of non-users and 40% of frequent users reported that the preference to use public transit limits their use of ridehailing), although it is expected that the underlying reasons behind the impact of this factor may vary across these two groups.

6.8 Impact on the Use of Other Travel Modes

To explore the potential impacts that ridehailing services have on the use of other transportation modes, Uber/Lyft users were asked to report how the use of ridehailing affected their use of other means of transportation, through two questions:

1. One question asked how the most recent Uber/Lyft trip affected the use of other means of transportation; and
2. The second question asked how the respondent would have made that trip (if at all), if these services had not been available.

I discussed the distribution of the reported impacts of these services on the use of other means of travel, by age groups, in Chapter 3 and Alemi et al. (2017). The results show that the majority of both millennials and Gen Xers reduced their amount of driving because of the use of Uber/Lyft, among other impacts on the use of other modes.

In this section, I first present the changes in the use of other modes, by types of Uber/Lyft travelers, and then discuss the results of a latent class analysis that groups individuals by type of impacts of ridehailing on the use of other means of travel, which I estimated to better understand the heterogeneity in behavioral changes across different groups of Uber/Lyft users. Figure 6.6 presents the effects of the most recent trip made using Uber/Lyft on the use of other means of transportation among those who use Uber/Lyft at least once a month (frequent users) and those that do so less than once a month (non-frequent users). As shown in Figure 6.6, the use of on-demand ride services tends to reduce the amount of driving among both frequent and non-frequent Uber/Lyft users. Somewhat worrisome, the use of these services also substitutes for some trips that would have otherwise been made by transit or active modes. This is more common among frequent users of these services, those who live in zero-/lower vehicle households and those who are more multimodal.

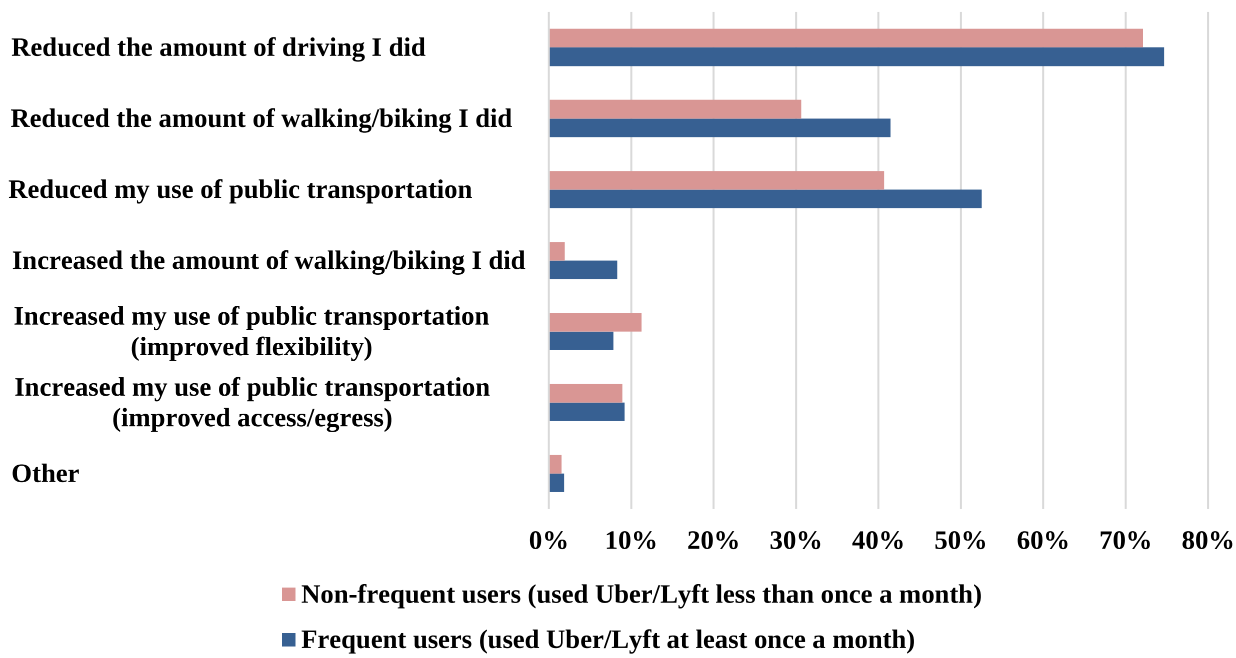


Figure 6.6 – The Impact of Last Uber/Lyft Trip on the Use of Other Means of Transportation among Frequent and Non-Frequent Uber/Lyft Users ($N_{Frequent\ users}$=217, $N_{Non\text{-}Frequent\ users}$ =258, Weighted Sample; Multiple Answers Allowed for Each Respondent)

Figure 6.7 shows how frequent and non-frequent Uber/Lyft users would have traveled if Uber or Lyft had not been available for the last trip made with these services. This second question provided additional options to respondents, including “would have gotten a ride from someone”, “would have taken a taxi” and “would have used a van or shuttle service”. In the first question, these options were not offered explicitly, so it is reasonable to assume that respondents might have selected “reduce the amount of driving” as a proxy for some of these options, too.

The majority of frequent and non-frequent users report that they would have hailed a taxi if Uber or Lyft was not available. This confirms the competition between these services and taxicabs in the cities’ landscapes. About 40% and 30% of non-frequent users reported that they would have driven a car or have gotten a ride from someone else, respectively. These shares become 37% and 23%, respectively, among frequent users of ridehailing services, confirming different car-dependencies and availability among frequent and non-frequent users. Again, something worrisome from the point of view of transportation sustainability, adoption of active travel and patronage for public transportation, a larger proportion of frequent Uber/Lyft users report that they would have used public transportation or active modes in the absence of Uber/Lyft. I also compared the availability of personal vehicles (as a ratio of the number of vehicles in the household to the number of household members with a driver’s license) among users and non-users and found that frequent users of ridehailing are more likely to live in zero-/lower vehicle households compared to non-frequent users or those who have not used these services. In addition, I found that the likelihood of being willing to reduce the number of households’ vehicles is higher among frequent users of ridehailing (results not shown, for brevity, but see Circella et al., 2018 for a full discussion of the topic) consistent with a recent opinion poll conducted by Reuters/Ipsos (Henderson 2017).

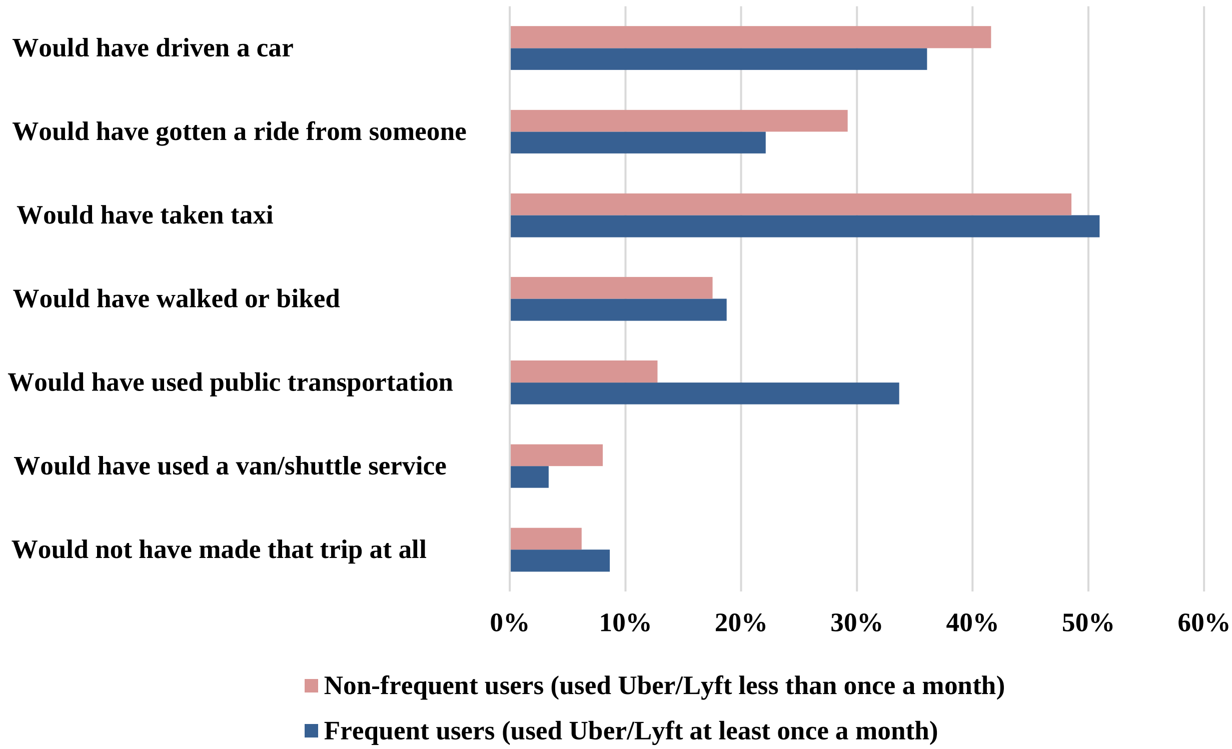


Figure 6.7 – How Users Would Have Traveled in the Absence of Uber/Lyft among Frequent and Non-frequent Uber/Lyft Users ($N_{\text{Frequent users}}$=208, $N_{\text{Non-Frequent users}}$ =274, Weighted Sample; Multiple Answers Allowed for Each Respondent)

The impacts of ridehailing vary among individuals and depend on other circumstances such as the frequency of use of other means of transportation, the trip purpose for which these services are used, the geographic context, and the availability of other travel modes. To better understand the variation in the impacts that these services had on the use of other travel modes, I estimated a latent-class analysis of the self-reported impacts on the use of other means of transportation associated with the latest trip by Uber/Lyft. As described by Collins and Lanza (2010), the latent-class analysis is a person-oriented approach (in oppose to variable-oriented approach, where the emphasis is on understanding the relationship among variables) that stochastically groups individuals who exhibit similar behavior/attributes. I expect that the latent-class analysis of self-reported behavioral changes provides more meaningful and scientifically interesting results against the noisy background compared to other existing approaches. I perform the latent-class analysis only on the self-reported impacts of the last Uber/Lyft trip, and exclude other active covariates from the model. Figure 6.8 summarizes the attributes of each latent class and shows how the use of ridehailing affects the use of other means of transportation for the members of each class.

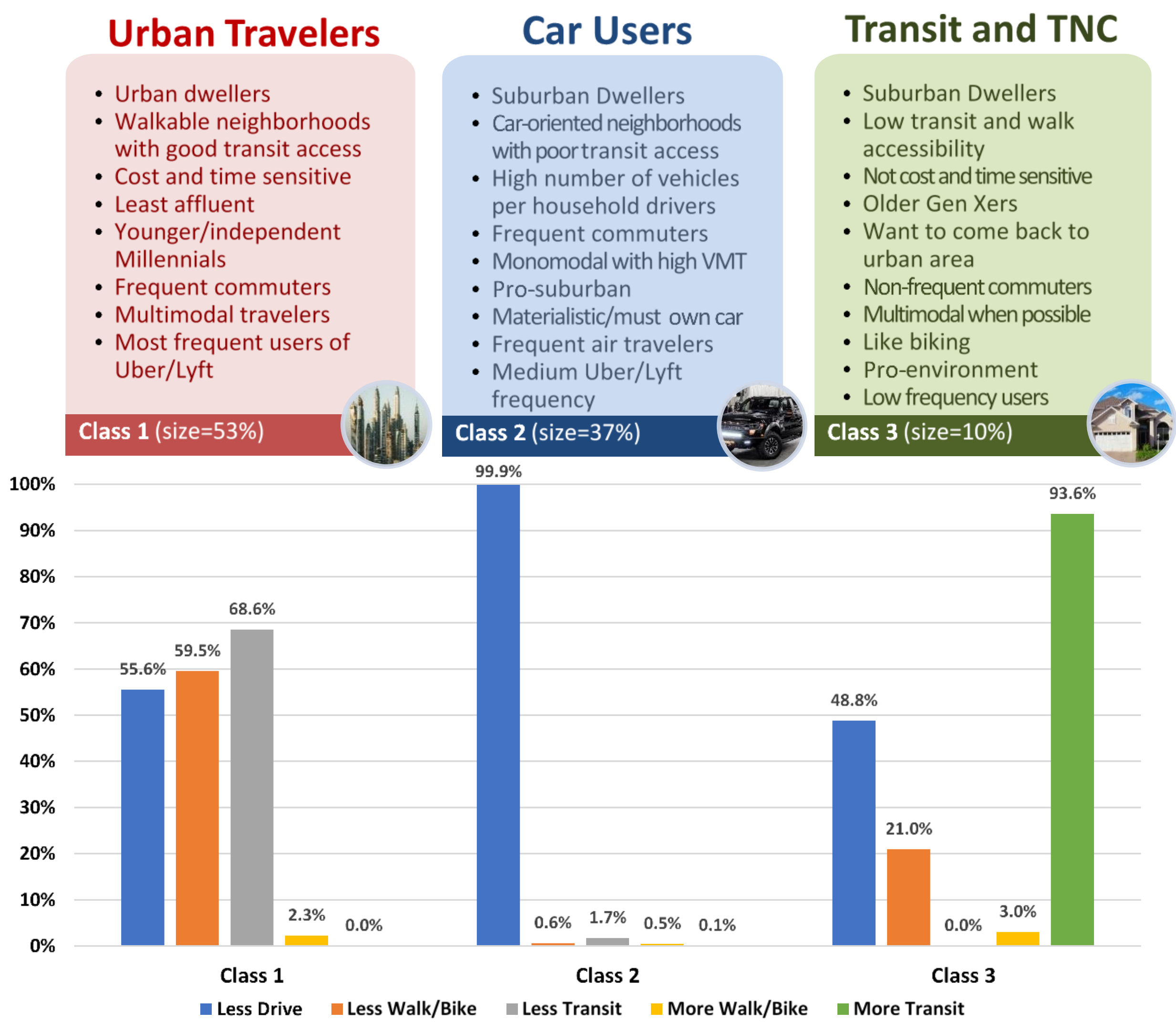


Figure 6.8 – Latent-Class Analysis of the Self-reported Behavioral Changes in the Use of Other Means of Transportation (N=482, Unweighted Sample; Multiple Answers Allowed for Each Respondent)

- *Class 1*: This class accounts for about 53% of the Uber/Lyft users in the dataset, the members of which are more likely to live in urban neighborhoods characterized by higher public transit access/connectivity and higher walkability. This class largely composes of younger adults and independent millennials, and cost- and time-sensitive individuals who travel frequently using a combination of multimodal alternatives. The members of this class tend to use ridehailing more frequently, compared to the members of the other two classes. As shown in Figure 6.8, the use of ridehailing reduces the use of personal vehicles, public transit and walking/biking among the members of this class. I expect that providing ridehailing at lower cost (e.g. through promoting pooling services) will bring the largest impact on the members of this class, who have the highest cost- and time-sensitivity.
- *Class 2*: This class accounts for 37% of the ridehailing users in the sample and predominantly comprises suburban dwellers who live in neighborhoods with very low transit access/connectivity. The members of this class live in households with the highest ratio of vehicles per household driver, drive for most trip purposes (i.e., they are monomodal) and, as a result, have the highest vehicle miles driven (VMD) in the sample. Consistent with their travel behavior, the members of this class report the strongest positive attitudes toward car ownership, use of personal vehicles, and residential locations in suburban neighborhoods. Uber/Lyft users in this class tend to use ridehailing with medium frequency, for reasons such as traveling to/from airports (the members of this class travel more often by plane than other users in the sample). The use of Uber/Lyft replaces the use of personal vehicles among the members of this class. Although the members of this class are not very cost sensitive, changes in the cost of driving and the

characteristics of the built environment in the residential and school/workplace might affect their use of ridehailing and ultimately the impacts that these services have on the use of other transportation modes.

- *Class 3*: Class 3 is the smallest class - it accounts for only 10% of Uber/Lyft users in the sample, and an even lower percentage of Uber/Lyft trips, due to the lower frequency of use – and it is largely composed of older members of Generation X and dependent millennials who live with their family of origin in suburban neighborhoods. The members of this class have the lowest sensitivity to cost and time factors. They do bike/walk or use public transit when possible (the members of this class are more attracted by the use of public transit) even if they often live in areas that are poorly served by public transportation, and report the strongest pro-environmental attitudes. Interestingly, this group of Uber/Lyft users often report they would like to move to more urban neighborhoods, which could be an indicator of their stage in life (e.g., empty nesters). The average frequency of use of ridehailing of the members of this class is the lowest in the entire sample. However, the use of ridehailing has the most desirable outcome in terms of sustainable transportation outcomes: the use of ridehailing increases the use of public transportation among the member of this class, through providing an access mode to connect to/from public transportation terminals or stations. Future policies that focus on the integration of ridehailing with public transit should focus on expanding the basis of users that can have such environmentally-beneficial effects of the use of ridehailing.

The latent-class analysis can be expanded in a number of ways, including (1) incorporating the impact of other confounders (e.g., key sociodemographics and built environmental variables) and (2) allowing for local dependencies (i.e., allowing the residual of the dependent variables to covary/be jointly distributed), to better capture heterogeneity in behaviors and better group users with similar patterns in the adoption of ridehailing and their impacts on the use of other modes.

Further, in future stages of this research, I will consider adopting more robust analytical approaches to analyze (and disentangle) causality structures behind the observed behaviors and, in particular, the heterogeneity in the direction in which these variables impact each other. In the next stage of the project, I plan to explore/test different causality structures.

6.9 Conclusions and Policy Implications

This chapter investigates the factors that limit and/or encourage the use of ridehailing, and the impacts that these new transportation services have on various components of travel behavior, and in particular on the use of other means of transportation. I find that young people (millennials) are more likely to use ridehailing, and ridehailing users are more likely to be influenced by service attributes that have been ignored by taxi service providers, such as shorter wait time, ease to call a car, and driver characteristics (both friendliness and ability to communicate with riders). Users are less affected by sparse service availability and the factors that limit their use of personal vehicle (e.g., insufficient number of vehicles in the household) and public transportation (e.g., limited availability of public transportation). Two exceptions include the difficulty of finding parking and the interest in avoiding drinking and driving.

Among the limiting factors, both users and non-users indicate that the preference to use their own vehicle is the most important factor limiting their use of on-demand ride services, although more studies are required to investigate the reason(s) for such preferences. The preference to have their own vehicles is stronger among non-users and users who use ridehailing less than once a month. The cost of service was also found to be an important contributing factor that limit the use of ridehailing. Another limiting factor that impacts both non-users and frequent users is the preference to use public transit. Those who perceive the preference to use public transit as a strongly limiting factor tend to use public transit on a more regular basis than other respondents in the sample, the reasons for which may stem from socio-demographic and lifestyle preferences.

The salience of cost and personal-vehicle preferences as limiting factors to the use of ridehailing suggests a promising future for ridehailing services – if these services can reduce their prices and travel time (including waiting times) and if they can provide more reliable and convenient alternatives to driving a personal vehicle. Lowering the cost of the service can be achieved in a number of ways: encouraging pooling services as oppose to single-user services, subsidizing ridehailing when it leads to positive societal benefits (e.g. an increase in public transit use), and through deploying automation and other innovative strategies.

Pooling is the primary strategy to reduce prices and is a case where the public interest aligns well with business interests. It is expected that the greatest public benefits would be achieved by promoting pooling services. Uber and Lyft executives widely assert that they are strongly committed to pooling services as a way to increase ridership, revenue and profits (Sperling et al. 2018, p189-196). Ridehailers can receive up to 50% discount on the fare for pooling services in return for longer travel time (including waiting times and/or longer in-vehicle time due to deviation from the route to pick-up/drop-off other riders) and compromising some of the convenience associated with using the single-user ridehailing services (e.g. privacy). More research is needed to determine the price elasticity among various groups of travelers and to understand individual’s willingness to share rides with strangers. As discussed by Sperling et al. (2018), public agencies can support pooling services in various forms, e.g. reducing the travel time through giving priority access and/or right of way to pooling services. Ridehailing service providers can also play an important role in promoting pooling services. For example, these companies can enhance the level of personal safety by better monitoring drivers and riders as well the quality of their services and improve their matching algorithms to match riders with similar needs and tastes in the same car.

Although lowering the cost of ridehailing services via pooling would affect social equity by enhancing the mobility of lower income household and disadvantageous communities, there is no guarantee that pooling services will flourish, especially outside dense urban neighborhoods, where these users often live. Local and regional agencies can consider partially or fully subsidizing ridehailing trips that increase transit ridership (directly or indirectly) and provide more affordable housing units in dense urban neighborhoods, using the additional developable space provided by relaxing minimum parking requirement that directly affect the housing costs.

The testing of public-private partnerships and additional experimental studies are required to better investigate the conditions under which ridehailing services lead to higher transit ridership, either as an access/egress mode or as a "guaranteed ride home" service, and to better understand the changes in individual behaviors if these transit-complementary trips are partly/fully subsidized. This subsidy can be offered directly for ridehailing trips that starts/ends at certain transit stops or trips within certain geo-fenced area, and through integrating the fare payment between first-/last-mile ridehailing services and transit trips, or can be offered indirectly such as tax credits or employer incentives. An example of indirect subsidy is the commuter benefits program in the San Francisco Bay Area (Senate Bill 1339), a program that encourages the employee to use some form of public transportation for commuting other than driving.

Vehicle automation, more intensive vehicle use, and vehicle right-sizing can reduce the operational costs and ultimately make ridehailing services much cheaper. As discussed by Walker and Johnson (2016) and Sperling et al. (2018) the cost of service can be reduced by half (to less than one US Dollars per passenger per mile) if ridehailing service providers deploy a fleet of fully automated vehicles. However, the future and the promised benefits of vehicle automation are far from certain, and more research is needed to fully understand the upcoming opportunities and challenges that will arise, and the interventions that will be required to ensure future transportation services move in the right direction. Intensive vehicle use spreads depreciation costs over many more miles, and vehicle right-sizing can efficiently manage vehicle use, conserve fuel/energy, reduce emissions, and save money on fuel/energy and maintenance. Both strategies can shrink the passenger-mile cost and ultimately increase the utility of using ridehailing. More research is needed to identify the most cost-effective vehicle use and management strategies which will likely vary depending on the local context in which these services are provided.

Providing more passenger loading zones instead of free on-street/off-street parking, giving priority to higher occupant vehicles, and more importantly getting the prices right for all transportation modes by considering all of their social and environmental costs can help transportation planners to better integrate ridehailing into the mobility ecosystem. The optimal strategy includes an incentive system to get more people into the same car and free up city's streets that lead to a more efficient public transit system and integrated biking and walking networks. The adoption of congestion pricing and the use of its revenues to fund public transit and pooling services, and other demand management strategies that discourage single/low-occupant vehicle use could be a boon in this era of rapid transformation.

With respect to potential impacts of ridehailing services, the public benefits of single-user demand-responsive services are uncertain. This study found that the initial single-user services tend to reduce the amount of driving among both frequent and non-frequent users, and they substitute for some trips that would have otherwise been made by transit or active modes. The substitution effect is stronger among the frequent users of Uber/Lyft, who are more likely to live in zero-/lower vehicle household and are more multimodal. Thus, the net VMT impacts of single-user services are uncertain, but most likely positive (i.e. the use of Uber X and Lyft Classic leads to higher total VMT) given the reduced transit trips and the deadheading of Uber/Lyft drivers while repositioning the vehicles between trips. Other studies also suggest that single-user services have a positive effect on VMT (Schaller 2017; Clewlow and Mishra 2017). To better understand the variation in the impacts that these services have on the use of other travel modes, I plan to develop more nuanced analyses that investigate the behavioral changes in more disaggregated way and follow these evolving changes and transformative trends over time through the collection of data over time.[14]

In terms of public benefits, the analysis of the data collected in this study found that frequent users of on-demand ride services are more willing to dispose one or more of their household's vehicle(s). If this trend is true and continues over time, the demand for parking spaces, at least in certain areas of cities, will decline. The reduction in parking demand will likely be stronger in dense urban neighborhoods and commercial areas where parking costs and parking search time discourage private car use. This might represent an opportunity for local governments to revise or even eliminate minimum parking requirements, i.e. requirements that discriminate the use of private vehicles against other modes, indirectly reduce accessibility by

[14] A second wave of data collection for this project is being carried out in spring 2018 (see Circella et al., 2018, for more details).

other modes, and increase development costs substantially. The conserved space and cost from the removal of minimum parking requirements can be dedicated to the development of more affordable infill housing units and other infrastructure such as greeneries, and bike and walk paths (Sperling et al. 2018). More study is required to better understand the direction of this relationship. In the next stage of this research I plan to better explore this topic by estimating joint models for the adoption of ridehailing services and other components of travel behavior, testing different causality structures (two unidirectional and one bidirectional), and comparing the magnitude of the marginal effects of each endogenous variable.

To harvest the potential benefit of ridehailing services, policy-making and incentives need to be coordinated to target each segment of the population while reducing the negative impacts associated with the use of these services (e.g. substitution of transit and deadheads between rides). The greatest public benefits would come from pooling –reduced traffic congestion, road infrastructure costs, greenhouse gas emissions, and parking demand –which suggests policymakers need better understandings of who might use pooling services and what incentives and policies would be most effective at encouraging them to do so. In the future follow-up study, I will be addressing these questions.

Perhaps more challenging is the issue of transit. Single-user ridehailing inevitably diverts some passengers from transit, undermining an important public service. This study and others provide some insights into this phenomenon, but the effects are still uncertain due to large variability across demographic groups, transit service levels, and other factors. More positively, though, shared mobility can be integrated with public transit to provide better overall service, with lower overall economic and environmental costs (especially since transit is often called upon to offer services in lightly populated areas that could be served at much lower cost by a variety of shared demand-responsive services). Many transit operators began partnering in 2016 with Uber, Lyft and others to reduce service costs and improve accessibility (Polzin and Sperling, 2018). In some case, they themselves are even offering demand-responsive services in vans and small buses (referred to as microtransit).

Public health could be another challenging issue. Among other impacts, ridehailing can contribute to higher pollutant emissions and lead to lack of physical activity, both of which are identified as common risk factors for many health issues. Deploying zero tailpipe emission vehicle would be needed to reduce GHG and other pollutant emissions and to remain on course to achieve GHG reduction targets. With respect to the impact of ridehailing on walking and bicycling, ridehailing provides a multifaceted experience for its users: on one hand, ridehailers may reduce their amount of walking and bicycling as the result of using this door-to-door services. For example, I found that about 40% and 30% of frequent and infrequent users, respectively, reported that they rode their bicycle or walked less because of the use of ridehailing. On the longer term, though, these services may increase the amount of walking and bicycling by reducing the reliance on private vehicle ownership. As a result, ridehailing (as well as other emerging transportation services such as carsharing and bikesharing) has been successful in shifting the fixed cost of ownership to variable costs that vary by trip distance and duration. This means that users of ridehailing are more likely to perceive the true cost of the available alternatives for their trips and are more likely to choose the most appropriate option (the means of transportation with the highest utility) on a trip by trip basis. The availability and integration of several transportation alternatives can fuel this paradigm shift and ultimately engage ridehailers in more active lifestyles. Recently, ridehailing providers has started to encourage users to walk/bike to major ridehailing hubs (known as hot spots) to meet other riders in return for a discounted fare, thus engaging users of pooled ridehailing in more active lifestyles. More research is needed to fully understand the complex relationship between the adoption of ridehailing and (the lack of) physical activity.

More studies are needed to help researchers and professionals understand the on-going transportation transformation and how to guide it to a better future. When driverless vehicles become available, the challenges of managing travel will become even more complicated. This increases the urgency for more research that can better understand travel behavior patterns and support policy making.

6.10 Acknowledgments

This study was funded by the National Center for Sustainable Transportation (NCST), which receives funding from the USDOT and Caltrans through the University Transportation Centers program. The first author also received financial support through an NCST dissertation fellowship. The authors would like to thank Caltrans, the NCST and USDOT, for their support of university-based research in transportation. The authors also wish to thank Susan Handy and Patricia L. Mokhtarian for their contribution to the different stages of this study.

7. CONCLUSION AND POLICY IMPLICATIONS

This dissertation provides insights into the factors that affect the adoption and frequency of use of shared-mobility services, such as Uber/Lyft, and discusses what factors limit or encourage their use. This research helps transportation planners and policymakers better understand how ridehailing services are transforming transportation; in particular, how ridehailing services affect the use of other modes of transportation. Without a clear understanding of how these services are and will be changing travel patterns, policymakers and transportation planners face a significant challenge in pursuing the goal of designing a more sustainable, equitable, and safe transportation system.

I analyzed a dataset that was collected with a detailed online survey in fall 2015 as the first round of data collection in a panel study of emerging transportation trends and adoption of technology in California. More than 2,000 respondents, including millennials (i.e., young adults born between 1981 and 1997) and members of Generation X (i.e., middle-aged adults born between 1965 and 1980), completed the survey. To understand the factors affecting the adoption of ridehailing services, first I estimated two binary logit models (with and without individuals attitudes) and later expanded my analyses to better account for the variation in individuals tastes and preferences through estimation of latent class adoption model. Similarly, I estimated a zero-inflated ordered probit model and an ordered probit model with sample selection to examine under what circumstances travelers use ridehailing more often. This is followed with a batch of exploratory analyses (including descriptive statistics and latent class model) that investigate the factors limit or encourage the use of ridehailing, and the impacts that the use of these services has on other components of travel behavior. Several limitations affect this study and its ability to generalize the results to the population of residents of California. The characteristics of shared mobility services and of their users are continuously evolving, thus increasing the uncertainty about the observed relationships. Further, the cross-sectional nature of this dataset limits the ability to assess causality in the observed behaviors.

The findings of this study are largely intuitive. The results show that better-educated individuals who live in predominantly urban areas are more likely to use ridehailing services, consistent with what previous studies have suggested based on descriptive statistics (Rayle et al. 2014, Taylor et al. 2015, Feigon and Murphy 2016). I find that the likelihood of using ridehailing is higher in areas with a higher level of land-use mix and regional auto accessibility. The adoption of on-demand ride services is also higher among individuals who make more long-distance trips (mainly by plane) and those with stronger pro-environmental, technology-embracing and adventure-seeking attitudes.

The results of the latent-class adoption model (discussed in Chapter 4), estimated to control for variation in individuals' preferences and behaviors, showed that adopters of ridehailing can be classified into three main classes. The first is a class largely composed of more highly educated, independent millennials with the highest adoption rate of Uber/Lyft. The class that is mainly composed of affluent individuals living with their families who are either dependent millennials or highly educated, older members of Generation X have the second highest adoption rate. The likelihood of using ridehailing increases with the number of long-distance airplane trips for the members of this class. Finally, the class that comprises the least affluent individuals with the lowest level of education or those who predominantly live in rural regions have the lowest adoption rate.

In Chapter 5, I present the results of my investigation of the factors affecting adoption and frequency of use of ridehailing services. This investigation showed that built environment variables explain more variation in the frequency of using ridehailing than do sociodemographic variables. Land-use mix and activity density contribute to, respectively, decreasing and increasing the frequency of use of on-demand ride services. Individuals with higher preference to use (have) their own vehicle and those who evaluated a concern about safety and drivers as strongly limiting factors on the use of ridehailing are less likely to use Uber/Lyft, consistent with my expectations. The finding that individuals with higher willingness to pay to reduce their travel (i.e. higher perceived value of time) are more likely to use ridehailing more often merits further exploration, given that ridehailing does not necessarily reduce travel, though it does enable travelers to make better use of their time.

As the popularity and availability of ridehailing services increase, their impacts on different components of travel behavior become less negligible. The public benefits of single-user demand-responsive services are uncertain. As discussed in Chapter 3 and Chapter 6, I found that the initial single-user services tend to reduce the amount of driving among both frequent and non-frequent users, but also substitutes for some trips that would have otherwise been made by transit or active modes. The substitution effect is stronger among the frequent users of Uber/Lyft, who are more likely to live in zero-/lower vehicle households and are more multimodal. Thus, the short-term net VMT impacts of single-user services are uncertain, given that reduced trips are offset to an uncertain extent by reduced transit trips and some deadheading by Uber/Lyft drivers, but evidence points to a likely increase in total VMT due to the use of single-user ridehailing. Other studies affirm that single-user services have a minor effect on VMT, possibly increasing it (Schaller 2017; Clewlow and Mishra 2017). To better understand the variation in the impacts that these services have on the use of other travel modes, I plan to develop more nuanced analyses that investigate the behavioral changes in a more disaggregated way and follow these evolving changes and transformative trends over time by collecting a second wave of data in the spring of 2018.

One apparent public benefit is that frequent users of ridehailing services are more willing to dispose of one or more of their household's vehicle(s), according to the findings presented in Chapter 3 and Chapter 6. If this trend is true and continues, households will have less demand for parking spaces. The reduction of parking demand is likely to be stronger in the dense urban neighborhoods and commercial areas, where parking cost and search time substantially deteriorate private car use. This would be an opportunity for local governments to revise or even eliminate minimum parking requirements, the requirements that privilege the use of private vehicles over other travel modes and substantially increase development costs (Donald Shoup, 1999). The space and cost conserved from the removal of minimum parking requirements can be dedicated to the development of more affordable infill housing units and other infrastructure such as greeneries, bike and walk paths (Sperling et al. 2018). A longitudinal study is required to better understand the direction of the relationship between changes in vehicle ownership and the use of ridehailing services, through testing different causality structures.

Perhaps more challenging is the issue of transit. Single-traveler services inevitably divert some passengers from transit, undermining an important public service. Chapter 3 and Chapter 6 in this dissertation and other studies provide some insight into this phenomenon, but the effects are still uncertain due to large variability across demographic groups, transit service levels, and other factors. More positively, though, shared mobility can be integrated with public transit to provide better overall service, with lower overall economic and environmental costs (especially since transit is often called upon to offer services in lightly populated areas that could be served at much lower cost by a variety of shared demand-responsive services). Many transit operators began partnering in 2016 with Uber, Lyft and others to reduce overall costs and improve accessibility (Polzin and Sperling, 2018); in some cases they themselves are even offering demand-responsive services in vans and small buses (referred to as microtransit).

Public health could be another challenging issue. Among other impacts, ridehailing can contribute to higher pollutant emissions and lead to more physical (in)activity, both of which are identified as the common risk factors for many health issues. Deploying zero tailpipe emission vehicles would be needed to reduce GHG and other pollutant emissions and to remain on course to achieve GHG targets. The impact of ridehailing services on walking and biking is uncertain. On one hand, ridehailers may reduce their amount of walking and biking as a result of using these door-to-door services. For example, I found that about 40% and 30% of frequent and infrequent users, respectively, reported that they have biked or walked less because of ridehailing services. On the other hand, these services may increase the amount of walking and biking by delinking car access and ownership. In this way, ridehailing services (as well as other emerging transportation services such as carsharing and bikesharing) have been successful in transforming the fixed cost of vehicle ownership to a variable cost that varies by trip distance and duration. This means that users of ridehailing services are more likely to perceive the true cost of the available alternatives for their trips and are more likely to choose the most appropriate mode (the mode with highest utility) on a trip-by-trip basis (assuming that policymakers get the prices right for all transportation modes by internalizing all of their social and environmental costs). The availability and integration of public transit with new shared-mobility services (such as bikesharing, and ridehailing) can fuel this paradigm shift and ultimately engage ridehailers in more active lifestyles. Further, ridehailing service providers can encourage users to walk or bike to major ridehailing hubs (also known as hot spots) in return for a discounted fare, thereby engaging ridehailers in more active lifestyles. More research is needed to fully understand the complex relationship between ridehailing services and physical (in)activity.

7.1 Pooling Is a Win-win Solution

To harvest the potential benefit of ridehailing services, public agencies must coordinate policies and incentives to target each *segment of the population* while reducing the negative impacts associated with the use of these services (e.g. substitution of transit by these services or deadheading between rides). It is expected that the greatest public benefits would be achieved by promoting the pooling services (e.g. UberPOOL and Lyft Line). Pooling services may have positive, neutral, or negative impacts, depending on what other modes of transportation the use of these services replaces and the extent to which the pooled services actually carry multiple passengers. The potential benefits may expand to myriad societal, environmental and economic benefits, such as reduced road infrastructure costs, greenhouse gas emissions, and parking demand. Uber and Lyft executives widely assert that they are strongly committed to pooling services as a way to increase ridership, revenue, and profits (Sperling et al. 2018, pp. 189-196). To achieve successful pooling services and thus to achieve the goal of sustainability, policymakers need a better understanding of who might use pooling services and what incentives and policies would be most effective at encouraging them to do so.

In examining the factors that limit or encourage the adoption of ridehailing services (as discussed in Chapter 6), I find that ridehailers are more likely to be influenced by service attributes that have been ignored by taxi service providers, such as shorter wait time, ease of calling a car, and driver characteristics (both friendliness and ability to communicate with riders). Users are less affected by sparse service availability and the factors that limit their use of personal vehicle (e.g., insufficient number of vehicles in the household) and public transportation (e.g., limited availability of public transportation). Two exceptions include the difficulty of finding parking and the desire to avoid drinking and driving. Both users and non-users rate the "prefer[ence] to have/use their own vehicle" as the factor most strongly limiting the adoption of these technology-enabled services. Not surprisingly, the preference to use their own vehicle is stronger among non-users and infrequent riders using these services less than once a month. The cost of service was also found to be an important limitation on the use of ridehailing services.

The salience of cost and personal-vehicle preference as limiting factors suggests a promising future for the pooled or single-user ridehailing services that might entail some positive societal benefits (including providing equal access to various segments of the population, or increasing transit ridership if it is used as an access/egress mode) – *if* these services can reduce their *prices* and *travel time,* including pickup/drop-off times and waiting times, and if they can provide a more *reliable* and *convenient* alternative to driving one's own personal vehicle. A combination of different strategies is required to achieve more *affordable* and *competitive-with-driving* service that offers high reliability and convenience.

Lowering the cost of service can be achieved in a number of ways: encouraging pooling services as opposed to single-user demand responsive services, subsidizing ridehailing when it leads to positive societal benefits (e.g. an increase in public transit use), automation, and other innovative strategies. Some of these cost-saving strategies may compromise convenience, travel time reliability and increase travel time. For example, pooled ridehailing services reduce travel cost in return for longer and less reliable travel time. To improve travel time reliability and maintain the travel time competitiveness of pooling services (compared to personal cars), a number of strategies can be employed, such as encouraging ridehailers to walk and bike to and from the nearest intersection (or hot spot) to (in some cases) shorten the delay associated with deviations from the main route, giving priority network access to pooling services, and discouraging “late show-up” behavior.

Pooling is the primary strategy to reduce prices and is a case where the public interest (i.e. promoting higher occupant vehicle use) seems to align well with business interests. From a business perspective, pooling services can be more profitable as these services maximize the utilization rate of the current (very expensive and labor intensive) services and can expand the ridehailing markets by targeting new segments of the population and new trip purposes. Ridehailers making use of pooling services can receive a discount of up to 50% on their fare in return for longer travel times (including waiting times and/or pickup/drop-off times), lower travel time reliability, and the loss of some of the convenience associated with using the single-user ridehailing services (e.g. privacy and safety). More research is needed to determine the price elasticity for various groups of travelers (preferably by trip purposes) and to understand individuals’ willingness to share rides with strangers. As discussed by Sperling et al. (2018), the public sector can support pooling services in various forms, for instance, by giving priority access and/or rights of way to pooling services as a way to lower travel time. Promoting flexible working hours is another strategy that can address the compromised travel time reliability among commuters.

Ridehailing service providers can also play an important role in promoting pooling services and reducing the negative consequences associated with the use of them. For example, these companies can enhance/maintain their current safety levels (by better monitoring drivers and riders as well the quality of their services) and improve their matching algorithms to match riders with the same needs in the same car. To provide a consistent and dependable travel time experience for riders, ridehailing companies can also incorporate a measure of travel time reliability into their matching algorithm. They can also restructure their pricing mechanism based on travel time reliability instead of/in addition to the likelihood of matching. A buffer index, for example, is an indicator of travel time reliability that measures the extra time travelers must add to their average travel time when planning to ensure on-time arrival (FHWA 2010). This means that ridehailing companies could provide more incentives (i.e. discount) for less reliable travel time (or may even define different classes of pooling services); for example, a ridehailer who has a buffer index of 60% would pay a different fare than a ridehailer with a buffer index of only 30%. As discussed earlier, to shorten the deviation from the main route and reduce pickup waiting times of pooling services, ridehailing companies could encourage passengers to walk/bike to/from nearby intersections (or other hot spots) and to discourage the "late show-up" behavior by educating riders and charging a waiting fee that can be credited back to both on-time riders and drivers. Unlike riders, drivers seem to benefit less from pooling services as the current pricing scheme is defined based on travel time and distance. Ridehailing companies would need to provide more (financial) benefits to drivers who are more willing to accept requests for pooled services, considering the added inconvenience per additional (group of) rider(s).

Promoting the pooling services is not an easy task. More than half of the U.S. population lives in low-density auto-oriented areas and in the suburban neighborhoods of cities (Berger et al. 2013). Suburban dwellers also drive more than urban residents. Kahn (2000) showed that suburban dwellers drove about 30% more than their urban counterparts. The low population density and higher car-dependency in suburban neighborhoods challenges the operational ability of pooling services, as these services require a critical mass of passengers and drivers to sustain themselves. One way to change the car-dependency culture in suburban neighborhoods is to provide a competitive-to-driving alternative or combinations of alternatives. This paradigm shift could take place if policymakers price driving based on its total negative externalities including both social and environmental impacts. Getting the prices right for all transportation modes can help transportation planners to better integrate ridehailing services into the mobility ecosystem. In fact, a combination of carrot and stick policies are required to encourage more people to use higher-occupancy vehicles and to discourage single/low-occupancy vehicle use and dependency. Decreases in single-occupant vehicle travel would free up space on city streets for a more efficient public transit system integrated with biking and walking networks, thereby encouraging further declines in driving. Additional strategies in this area could include (1) introducing congestion pricing on roads and using its revenues to support public transit, (2) solving the first and last mile problems for transit, (3) providing more passenger loading zones instead of free on-street/off-street parking, (4) giving more priority to higher-occupancy vehicles, and (5) other demand management strategies that could encourage the use of higher-occupancy vehicles (including pooling services) instead of single/low-occupancy vehicle use.

To promote the use of public transportation, local and regional agencies can partially or fully subsidize ridehailing trips, in particular those that increase transit ridership (directly or indirectly). Pilot projects evaluated using experimental designs are required to better investigate the conditions under which ridehailing services lead to higher transit ridership, either as an access or egress mode or as a “guaranteed ride home” service, and to better understand the changes in individual behavior that might occur if these transit-complementary trips were partly or fully subsidized. This subsidy could be offered directly for ridehailing trips that start or end at certain transit stops or trips within a certain geo-fenced area, or can be offered indirectly such as through a tax credit. An example of indirect subsidy is the commuter benefits program in San

Francisco Bay Area (Senate Bill 1339), a program that encourages the employee to use some form of public transportation for commuting by means other than driving. Cities and regional agencies could benefit from establishing an effective partnership with private entities (in particular, with shared-mobility service providers) to foster innovative strategies tailored to their context and better adapt to the rapid changes in their mobility ecosystem. To achieve effective public-private partnerships, the public would need to streamline some of the burdensome planning processes and also be more open to creative solutions. As discussed in Chapter 6, the impacts of new shared-mobility services vary depending on the local context in which these services are deployed; thus, there is not a one-size-fits-all solution that can address the challenges imposed by these new services.

Lowering the cost of ridehailing services via pooling would affect social equity by enhancing the mobility of lower-income households and disadvantaged communities. However, such households usually do not live in dense, central, urban neighborhoods. Pooling services may not flourish in other areas, as these services require a critical mass of riders and drivers to sustain. However, the paradigm shift could come more easily to the members of these communities due to their lower vehicle ownership: the members of lower-income households and disadvantaged communities are more likely to be multimodal and less reliant on personal vehicles due to lower vehicle ownership/availability (Titheridge et al. 2014; Zhao et al. 2013). Offering flexible, on-demand services at a lower cost point and subsidizing the first- and last-mile solutions can enhance the mobility of these groups while establishing a car-independent culture. Further, providing more affordable housing units in dense urban neighborhoods and enacting policies that slow down or prevent gentrification can be helpful. As discussed by Levy et al. (2006), retaining affordable housing or business units can be achieved through housing production strategies (e.g. establishing a trust fund or low-income housing tax credit, and inclusion of affordable housing in zoning ordinances), housing retention strategies (e.g. rent control, tax relief assistance), and asset building strategies (e.g. establishing individual development accounts and community land trusts).

Vehicle automation, more intensive vehicle use (meaning that the car is driven more miles in a given period of time and reaches its retirement age in fewer years), and right vehicle sizing (deploying a vehicle of the right size to accommodate the specific needs and tastes of the riders for that trip) have the potential to make ridehailing services much cheaper. As shown by Walker and Johnson (2016) and Sperling et al. (2018), the cost of service could decrease by half (to less than US$1 per passenger per mile) if ridehailing service providers were to deploy a fleet of fully automated vehicles. Intensive vehicle use spreads the depreciation cost of the vehicle over many more miles, and right vehicle sizing (or purpose-specific vehicle design) can efficiently manage vehicle use, conserve fuel/energy, reduce emissions, and save money on fuel/energy and maintenance. Both of these strategies can shrink the per-mile cost for passengers and ultimately increase the utility of ridehailing services. More research is needed to identify the most cost-effective vehicle use and management strategies, which vary depending on the local context in which these services are provided.

More studies are needed to help researchers and professionals understand the on-going transportation transformation and options for guiding it to a better future. When driverless vehicles become available, the challenges of managing travel will become even more complicated, enhancing the need for more research on travel behavior.

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