UC Davis
Research Reports

Title
Exploring the Relationships Among Travel Multimodality, Driving Behavior, Use of Ridehailing and Energy Consumption

Permalink
https://escholarship.org/uc/item/31v7z2vf

Authors
Circella, Giovanni
Lee, Yongsung
Alemi, Farzad

Publication Date
2019

Exploring the Relationships Among Travel Multimodality, Driving Behavior, Use of Ridehailing and Energy Consumption

Giovanni Circella, Georgia Institute of Technology

Yongsung Lee, Georgia Institute of Technology

Farzad Alemi, University of California, Davis

National Center for Sustainable Transportation

Georgia Tech | School of Civil and Environmental Engineering
College of Engineering

About the National Center for Sustainable Transportation

The National Center for Sustainable Transportation is a consortium of leading universities committed to advancing an environmentally sustainable transportation system through cutting-edge research, direct policy engagement, and education of our future leaders. Consortium members include: University of California, Davis; University of California, Riverside; University of Southern California; California State University, Long Beach; Georgia Institute of Technology; and University of Vermont. More information can be found at: ncst.ucdavis.edu.

U.S. Department of Transportation (USDOT) Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the United States Department of Transportation's University Transportation Centers program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Acknowledgments

NCST

Exploring the Relationships Among Travel Multimodality, Driving Behavior, Use of Ridehailing and Energy Consumption

A National Center for Sustainable Transportation Research Report

January 2019

Giovanni Circella, School of Civil and Environmental Engineering, Georgia Institute of Technology

Yongsung Lee, School of Civil and Environmental Engineering, Georgia Institute of Technology

Farzad Alemi, Institute of Transportation Studies, University of California, Davis

NCST

[page intentionally left blank]

TABLE OF CONTENTS

Exploring the Relationships Among Travel Multimodality, Driving Behavior, Use of Ridehailing and Energy Consumption

EXECUTIVE SUMMARY

In the last decade, advances in information and communication technologies and the introduction of the shared economy engendered new forms of transportation options and, in particular, shared mobility. Shared mobility services such as carsharing (*e.g.*, Zipcar and Car2go), dynamic ridesharing (*e.g.*, Carma), ridehailing (*e.g.*, Uber and Lyft), and bike/scooter sharing (*e.g.*, CitiBike, Jump Bike, Bird, and Lime) have gained growing popularity especially among subgroups in the population including college-educated or urban-oriented young adults (*e.g.*, millennials). These emerging transportation services have evolved at an unprecedented pace, and new business models and smartphone applications are frequently introduced to the market. However, their fast-changing nature and lack of relevant data have placed difficulties on research projects that aim to gain a better understanding of the adoption/use patterns of such emerging services, not to mention their impacts on various components of travel behavior and transportation policy and planning, and their related environmental impacts.

This report builds on an on-going research effort that investigates emerging mobility patterns and the adoption of new mobility services. In this report, we focus on the environmental impacts of various modality styles and the frequency of ridehailing use among a sample of millennials (*i.e.*, born from 1981 to 1997) and members of the preceding Generation X (*i.e.*, born from 1965 to 1980). The total sample for the analysis included in this report includes 1,785 individuals who participated in a survey administered in Fall 2015 in California. In this study, we focus on the vehicle miles traveled, the energy consumption and greenhouse gas (GHG) emissions for transportation purposes of various groups of travelers. We identify four latent classes in the sample based on the respondents' reported use of various travel modes: *drivers*, *active travelers*, *transit riders*, and *car passengers*. We further divide each latent class into three groups based on their reported frequency of ridehailing use: *non-users*, *occasional users* (who use ridehailing less than once a month), and *regular users* (who use it at least once a month). The energy consumption and GHG emissions associated with driving a personal vehicle and using ridehailing services are computed for the individuals in each of these groups (12 subgroups), and we discuss sociodemographics and economic characteristics, and travel-related and residential choices, of the individuals in each subgroup.

Research Questions

The study addresses the following main research questions:

- Which classifications (latent classes) best group individuals, based on their use of various travel modes and adoption of travel multimodality?

- How does the adoption of ridehailing relate to the use of other modes and travel multimodality of these individuals?

- What are the individual characteristics and mobility/residential choices of the members of each class?

- How does the distribution of the three ridehailing user groups (i.e., non-users, occasional users, and regular users) vary in the sample, as a whole and in each class?

- How do energy consumption and GHG emission differ by various subgroups of travelers?

Four Latent Classes of Modality Styles

We employ latent-class cluster analysis to identify latent (*i.e.*, underlying or not observable to researchers) classes in the sample, whose members share unique patterns in terms of use of various travel modes. This analysis estimates the *probability* of individuals to belong to a certain class, instead of deterministically assigning these individuals to one and only one class as it would be done using deterministic cluster analysis. With the probabilities as weights for individual cases, we explore the individual characteristics and choices for each of the four modality classes:

- *Drivers* (79.9%) are on average older, highly educated (*i.e.*, many members of this class have a Bachelor's or graduate degree), wealthier workers who typically have their own child(ren), and have higher vehicle ownership. About two thirds of them live in suburbs;

- *Active travelers* (7.9%), on average, live in a smaller household with fewer children and fewer household vehicles. Not surprisingly, more than 40% of them live in urban neighborhoods with better accessibility by non-motorized modes;

- *Transit riders* (6.3%), on average, are younger students, who have lower income, and are more likely to use ridehailing services than the other classes;

- *Car passengers* (5.9%) include many younger millennials (18-24) who still live with their parents, who often lack a valid driver's license and/or have worse access to personal vehicles. About 80% of this class lives in either suburban or rural neighborhoods.

Three Ridehailing User Groups in Each Latent Class

We further divide each modality class into three groups based on the individuals' reported use of ridehailing, and we examine any variation in individual characteristics and choices across the three ridehailing user groups identified within each modality class:

- Although the driver class is better educated and wealthier than the active traveler class as a whole, on average regular ridehailing users in the driver class tend to be less educated and have lower incomes than their counterparts in the active traveler class.

- Regular ridehailing users in the active traveler class are the wealthiest and most educated among all subgroups in the sample, signaling that their active travel style is more a results of individual choices than of economic constraints.

- Although their access to vehicles is quite low (0.6 cars/driver), the members of this subgroup drive 95 miles/week, on average, which is about two thirds of the weekly vehicle miles driven (VMD) of the driver class.

- Regular ridehailing users in the active traveler class present *unique* travel patterns, characterized by walking as the primary mode but driving a substantial number of miles in addition to their use of ridehailing. The unique lifestyle of these travelers includes high frequency of use of multiple travel modes, including ridehailing and personal cars.

Energy Consumption and GHG Emissions of the Twelve Subgroups of Travelers

With the information on the vehicles owned by the individuals in the sample, including make, model, and year of their primary vehicle, we compute the energy consumption (measured in gallons of gasoline per year) and GHG emissions associated with the use of personal vehicles, using information on fuel economy and conversion factors available from the US Environmental Protection Agency. We also estimate their environmental footprint from the use of ridehailing, using a set of assumptions about behavioral patterns of these users, together with data provided by a major US ridehailing company and information from the 2017 National Household Travel Survey (NHTS) on the distribution of trip distances for ridehailing trips.

- Not surprisingly, *drivers* present the highest energy consumption and GHG emissions from the use of their private vehicles, and their environmental footprint is not that much affected by their limited use of ridehailing.

- Not surprisingly, *active travelers* show the smallest energy consumption and GHG emission, on average; however, when accounting for trips made by ridehailing, regular ridehailing users in this group have fuel consumption and GHG emissions comparable to other groups.

- Among *transit riders* and *car passengers*, regular ridehailing users have even lower total energy consumption and GHG emissions from transportation than their non-user counterparts.

Study Limitations and Next Steps of the Research

This study presents the first application of a methodology that helps accounting for the energy consumption and GHG emissions from transportation, including both driving a private vehicle and using ridehailing, for various groups of travelers. However, it is important to stress that the results contained in this report do not allow us to establish relationships of causality between the adoption of certain modes and the environmental impacts of travel demand. Further, several limitations affect this analysis and the generalizability of the results to the population in California. First, we present a methodology that accounts for the fuel consumption of multiple travel modes, which goes beyond previous studies that mainly focused on the impacts of

personal vehicle driving. However, we do not account for other means of travel (e.g., carpooling with a family member or friend, riding public transportation, or long-distance travel by plane). Second, the characteristics of shared mobility and its users are continuously changing, and it is not clear to what extent the patterns observed in this dataset will continue to hold in future years. Third, a number of assumptions have been introduced in the computation of fuel consumption and GHG emissions from the use of ridehailing. Future extensions of the research based on the use of comprehensive data from official sources and ridehailing companies would improve the accuracy of the results.

Introduction

Shared mobility services are quickly reshaping transportation. These services, which combine the benefits of modern communication technologies with the principles of the sharing economy, provide access to a number of mobility options without entailing the costs of owning a vehicle. They can affect key factors influencing travel decisions including travel cost, convenience and security (Taylor et al., 2016). Over longer horizons, the adoption of these services can affect the level of auto ownership of a household, and impact daily schedules, lifestyles, and even residential location. Modern shared mobility services range from car-sharing services, including fleet-based services such as Zipcar or Car2Go and peer-to-peer services such as Turo, to ridesharing services, including dynamic carpooling such as Carma and on-demand ride services (also known as ridesourcing or transportation network companies, or TNCs) such as Uber and Lyft in the US market, and bikesharing services. The range of services, and their availability, is continuously evolving, with new services and smartphone apps that are frequently launched on the market.

Although the share of total trips made with shared mobility services is still rather small, the foreseeable increase in the popularity of these services is expected to significantly influence travel behavior in future years. By analyzing the 2017 National Household Travel Survey (NHTS) data, one study finds (Conway, Salon, & King, 2018) that on average, 0.5% of all trips are made using for-hire vehicles (e.g., ridehailing and traditional taxis), which approximately doubled the mode share for taxis in the previous NHTS data collection from 2009. Interestingly, this study also finds that about 10% of the 2017 NHTS sample has used ridehailing at least once in the month before the data collection. Early adopters of shared mobility services are found to be predominantly well-educated individuals who live in urban areas (Alemi, Circella, Handy, & Mokhtarian, 2018a, 2018b; Alemi, Circella, Mokhtarian, & Handy, *forthcoming*; Buck et al., 2013; Rayle, Dai, Chan, Cervero, & Shaheen, 2016; Taylor et al., 2016). The popularity of these services is in particular high among young adults (millennials), who are heavy users of ICT devices and are more open to the sharing economy. Millennials' changes in travel behavior are believed to be deeply affecting travel demand patterns (McDonald, 2015; Polzin, Chu, & Godfrey, 2014; Ralph, 2017). Millennials are found to have different lifestyles and travel behavior from the members of previous generations at the same stage in life: they tend to postpone the time they obtain a driver's license, often choose to live in urban locations and not to own a car, drive less if they own one, and use alternative means of travel more often (Blumenberg, Ralph, Smart, & Taylor, 2016; Blumenberg et al., 2012; Delbosc & Currie, 2013; Kuhnimhof et al., 2012; McDonald, 2015). Millennials' interests in urban lifestyles may influence their likelihood of using shared mobility services. Not surprisingly, millennials are more likely than older peers to use carsharing (Ballús-Armet, Shaheen, Clonts, & Weinzimmer, 2014; Zipcar, 2013), and form the majority of users of bikesharing (Buck et al., 2013) and on-demand ride services (Alemi, Circella, Handy, et al., 2018; Conway et al., 2018; Rayle et al., 2016).

To date, the factors contributing to the adoption of shared mobility services and the effects that the adoption of these services has on other components of travel behavior are still

somewhat unclear. The impacts of shared mobility services depend on the type of services that are provided, the local context in which the services are provided, the characteristics of the users, and differences among different segments of the population. Depending on the circumstances, shared mobility services, and ridehailing in particular, can provide flexible and cost-efficient alternatives to driving, and eventually offer the first and last mile access to transit, thus increasing public transportation efficiency and convenience; ridehailing companies can provide a ride home outside the hours of operation of public transit or at a time in which traveling by transit and/or walking to/from transit stops is considered unsafe; or conversely they can cannibalize public transportation in areas where their use mainly substitutes for the use of transit (Alemi, Circella, Handy, et al., 2018a; Circella & Alemi, 2018; Hall, Palsson, & Price, 2017; Hallock & Inglis, 2015; Shaheen, Chan, Bansal, & Cohen, 2015; Taylor et al., 2016).

Research results on the impacts of the adoption of shared mobility services, so far, have been mixed, and often tied to very narrow geographic areas: for example, Firnkorn and Müller (2011) and Costain, Ardron, and Habib (2012) showed that carsharing can complement the use of public transit, while Le Vine, Adamou, and Polak (2014) observed that one-way carsharing is often used in place of public transportation. Analyzing data on the use or ridehailing from seven selected US cities, Clewlow and Mishra (2017) found that the use of ridehailing tends to substitute 6% and 3% of the trips that would have been otherwise made by bus and light rail, respectively. Similarly, in previous analyses of the same dataset used for this project, the research team found that only a minority of users increased the use of public transit due to the increased mobility opportunities offered by ridehailing (e.g., accessing a transit station through the use of a TNC vehicle). Among most users, the adoption of ridehailing mainly replaces for the use of several other means of travel, including using a personal vehicle, riding public transit, walking and bicycling (Circella & Alemi, 2018).

Certainly, shared mobility services are quickly becoming part of the pool of travel options that users can access for completing their trips. These opportunities enrich the travel options in particular among urban residents and travelers more inclined to use multiple transportation options. A report from Feigon and Murphy (2016) highlighted that shared mobility users are more likely to be frequent users of public transit, own fewer cars, and spend less on transportation overall, though no conclusions could be drawn on the nature of the substitution effect associated with the use of these services. Similarly, Mishra, Clewlow, Mokhtarian, and Widaman (2015) found that vehicle holding among the members of carsharing programs is lower, while the proportion of transit, biking and walking trips are higher. In selected locations, TNCs have been proposed as an efficient way to provide transportation options in areas where the supply of local transit would be too expensive, or not justified by the local demand. The direction of causality of many of these relationships remains unclear: for example, do shared mobility users own fewer cars and drive less because they adopt shared mobility, or is the adoption of shared mobility the result of lower levels of auto ownership (e.g., increased competition for the use of a vehicle in the household) or of a residential location that favors specific lifestyles and mobility patterns?

In this research, we investigate how the use of ridehailing services relates to the adoption of other travel modes, and in particular to the adoption of multiple travel modes (*travel multimodality*), and propose an analytical approach that allows accounting for the fuel consumption and greenhouse gas (GHG) emissions associated with the travel patterns of individuals including both driving a personal vehicle and using ridehailing. The study does not attempt to establish relationships of causality between the adoption of ridehailing and the use of other modes, due to data limitations. Instead, it complements previous efforts in the literature to analyze the environmental impacts of various groups of travelers, through the application of a first attempt (to our knowledge) of an analytical approach that accounts also for the fuel consumption and GHG emissions associated with the use of ridehailing, in addition to the more well-established computation of the analogous impacts of driving a personally-owned vehicle.

In the study, we analyze a rich dataset collected in Fall 2015 as part of previous research funded by the National Center for Sustainable Transportation at UC Davis (hereafter, UC Davis NCST) and Caltrans. As part of the UC Davis NCST/Caltrans project, we designed a very detailed online survey that was administered to a sample of millennials and members of the preceding Generation X in California. The final sample includes information for 1,975 individuals. The dataset includes many variables of interest for the scope of this research, which were further integrated with land use and built environment variables available from other sources.

In this research, we use a latent class classification analysis (LCCA) approach to identify four main latent classes of travelers based on their use of various travel modes and degree of travel multimodality. We investigate the adoption of shared mobility services for the users in each class, and analyze their relationships with other components of travel demand and with individual and household characteristics of the individuals. We explore heterogeneity in travelers' behavior, with respect to the adoption of shared mobility and travel behavior. We further distinguish users in each latent class based on their frequency of use of ridehailing services, and classify them in non-users, occasional/infrequent users, and regular/frequent users. For each individual, we compute their average energy consumption and GHG emissions associated with their use of private vehicles. We then expand this analysis through proposing a novel approach to estimate approximate ranges of energy consumption and GHG emissions associated with the use of ridehailing services of each individual, which also account for the additional vehicle miles traveled (VMT) associated with deadheading to pick up/drop off passengers at their origins and destinations.

This study makes an important step towards the assessment of the environmental impacts associated with the travel patterns of various groups of travelers, including also ridehailing trips in addition to the average fuel consumption and GHG emissions associated with travelers' use of personal vehicles. Future stages of the analysis could further expand on this analysis, through incorporating the environmental impacts associated with the use of other modes (e.g., public transportation, and/or air travel, for long distance trips). The study also establishes a framework to account for the estimation of the environmental impacts of ridehailing use, using

information associated to the average fleet used to provide these services, and the additional components of travel (e.g., deadheading) associated with the use of these services. The study informs policy-making and planning processes on the environmental impacts associated with urban mobility patterns and can support the development of well-informed policies designed to reduce the overall impacts of transportation, e.g., through the electrification of personally-owned vehicles as well as TNC fleets, improvements in fuel economy standards, or incentives for the adoption of pooled ridehailing services, as a way to reduce total VMT in urban areas.

Literature Review

This section briefly summarizes some of the existing studies that have investigated the adoption of ridehailing and have examined the relationships between the use of these services and various components of travel behavior, including vehicle ownership, the use of public transit, and use of private vehicles (e.g., vehicle miles traveled/driven).

Ridehailing is one of the most rapidly growing – and controversial – forms of shared-mobility services. It includes services such as those provided by Uber and Lyft in the U.S. market (Didi, Grab, and Ola are the other major providers of ridehailing services mainly serving the markets of China, South Asian countries, and India, respectively). Ridehailing services are similar to taxi services in that they connect travelers requesting a ride with the network of available drivers through a smartphone application. They are different from dynamic ridesharing services such as Carma in the U.S. or BlaBlaCar in Europe, because drivers who participate in the latter only offer rides to other travelers (with similar destinations) along the route of a trip the driver would be taking anyway. Instead, ridehailing drivers "chauffeur" passengers to their destination, independently from the drivers' own travel needs.

The availability and popularity of these services are quickly growing. According to some estimates, the combined ridership of Uber, Lyft and taxis by the end of 2018 likely surpassed local bus ridership in the U.S., making them among the largest urban transportation providers (Schaller, 2018). However, to date, the factors affecting the use of these services and their impacts on the other components of travel behavior and vehicle ownership are still largely unexplored. In previous analysis of the same dataset that is used for this project, we found that better-educated or higher-income older millennials (i.e., age 25-34) are more likely to adopt ridehailing (Alemi, Circella, Handy, & Mokhtarian, 2018a, 2018b; Alemi, Circella, Mokhtarian, & Handy, *forthcoming*), in line with the findings from other studies (Feigon & Murphy, 2016; Rayle et al., 2016; Taylor et al., 2016). This seems also consistent with the other travel choices of the members of the millennial generation, who tend to more often live in zero-/lower-vehicle owning households, drive less, and use non-motorized means of transportation more often compared to the previous cohorts at the same age (Blumenberg et al., 2016; Frändberg & Vilhelmson, 2011; Kuhnimhof et al., 2012; McDonald, 2015), 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.

Ridehailing services expand the options available to travelers, and *allows* individuals to live with fewer or no household vehicles if they find getting a ride is more cost-efficient than traveling with their own vehicles. When individuals own a vehicle, they pay fixed (e.g., for purchase, insurance, and parking) and variable costs (e.g., for gasoline/electricity and maintenance). Regardless of the amount of use, they pay fixed costs. In comparison, the user of ridehailing pays fees that are designed to cover both the fixed and variable costs of ridehailing drivers. Since the user pays only a small portion of the fixed costs of ridehailing vehicles (and all variable costs) each time they get a ride, individuals with low demand for vehicle trips save money by traveling with ridehailing instead of owning a vehicle (Rodier, 2018). In this context, the

mobility needs, lifestyles, and personal attitudes of individuals are underlying factors that account for both the use of ridehailing and vehicle ownership. That is, to understand the true relationship of ridehailing and vehicle ownership, researchers need to employ multivariate analysis techniques that represent complex relationships surrounding ridehailing and vehicle ownership. To this date, we are not aware of such rigorous analysis in the literature.

Several studies in the literature, most of which are based on self-administered surveys and rely on self-reported information provided by the respondents, suggest that the use of ridehailing has a negative impact on vehicle ownership. Several studies in the ridehailing literature take a similar approach: asking survey respondents about any change in vehicle ownership as a result of using ridehailing. Clewlow and Mishra (2017) analyzed a sample of N=4,094 travelers recruited from seven major metropolitan areas in the U.S. Their study showed that about 9% of the subgroup of ridehailing users in their sample reported the disposal of one or more household vehicles after using ridehailing. Feigon and Murphy (2016) found that over 20% of their sample, a group of shared mobility users recruited through private shared mobility operators and transit agencies in 2015 (N=4,551), sold and did not replace their vehicles since they started using shared mobility services. Hampshire, Simek, Fabusuyi, Di, and Chen (2018) employed a natural experimental design in which the temporary suspension of Uber and Lyft from Austin, TX in May 2016 was treated as an exogenous shock. They examined the extent to which former users of Uber and Lyft added a vehicle after these ridehailing companies stopped serving Austinians. In their survey, 9% of their sample who used Uber/Lyft before the service suspension and kept the ridehailing apps on their smartphones by the time of the survey (November and December, 2016; N=1,214) answered that they purchased a vehicle after the suspension.

Several studies have investigated the relationships between the use of ridehailing and the use of other modes. Not surprisingly, the use of ridehailing is higher among (younger) multimodal travelers, who live in urban areas, and who have better transportation accessibility through a variety of travel options (Alemi, Circella, Handy, & Mokhtarian, 2018a, 2018b; Alemi, Circella, Mokhtarian, & Handy, 2018; Circella, Alemi, Tiedeman, Handy, & Mokhtarian, 2018; Conway et al., 2018; APTA, 2016) and often have lower levels of household vehicle ownership and car dependence (Mishra et al., 2015). However, the relationship between the use of these services and other travel modes is not clear. The adoption of 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 (Circella, 2017; Circella et al., 2018; Shaheen et al., 2015; Shaheen & Cohen, 2018; Taylor et al., 2016). Ridehailing can affect the demand for public transit with (at least) two counteracting mechanisms. First, ridehailing can be a *substitute* for the use of buses and trains because of its reliability, convenience, or often shorter travel time. Thus, some transit riders find the benefits of ridehailing outweigh its additional costs compared to public transit fares. Second, ridehailing *complements* public transit by helping transit riders overcome the geographic and temporal constraints of public transit. Geographically, ridehailing solves the first and last mile problem,

the case in which individuals live (or head to a destination) outside of transit catchment areas while not having effective ways to reach nearby transit facilities. Temporarily, ridehailing serves its riders outside of normal operating hours of public transit. Thus, individuals will rest assured that ridehailing is available for an inbound trip late night or early morning, if they ride a public transit during day time for an outbound trip (Alemi, Circella, Handy & Mokhtarian, 2018; Circella & Alemi, 2018; Taylor et al., 2016).

For the analysis of ridehailing and public transit, most studies employed surveys in which respondents were asked about the travel mode(s) that they would have used for the last trip they made with ridehailing if this service had not been available. Clewlow and Mishra (2017) found that approximately 15% of ridehailing users would have used rail transit; Alemi, Circella, Handy & Mokhtarian (2018a) estimate that 12 to 27% of ridehailing users would have traveled by public transit; Rayle et al. (2016) report that 33% of the ridehailing users in San Francisco would have used public transit. Studies also present evidence suggesting the complementary effect of ridehailing on public transit. In Clewlow and Mishra (2017), 3% of respondents told that they rode heavy rail transit more often since they started to use ridehailing, while riding light rail transit and buses less often. Alemi, Circella, and Sperling (2018) find that approximately 10% of respondents reported that ridehailing increased the use of public transit by improving access to or egress from transit Circella and Alemi (2018) developed a latent class analysis (LCA) of the impacts of the last Uber/Lyft trip on the use of other modes, and concluded that only a minority of ridehailing users (less than 10% of users in their sample, who account for an even lower percentage of ridehailing trips, as these are rather infrequent users) increased their use of public transit thanks to ridehailing. For the majority of other users, ridehailing substituted for the use of public transit, a personal vehicle, or walking and bicycling. Rayle et al. (2016) reported that only 5% of ridehailing users in their study used ridehailing to connect to/from public transit. Similarly, Henao (2017) found that 7% of his subsample, whose members traveled by ridehailing *and* other modes on a single tour, also used public transit. Very few aggregate level studies examine agency- or city-level transit ridership trends before and after the introduction of ridehailing services. Hall et al. (2017) find complementary effects larger than substitution effects from their transit agency level longitudinal study. In comparison, Sadowsky and Nelson (2017) suggest the competition among ridehailing companies may reduce the price of ridehailing. Thus, as more ridehailing companies enter a city, they tend to further substitute for public transit in terms of their net effects.

We expect various factors to account for the heterogeneity in the complementarity /substitution patterns between ridehailing and public transit, including individual, trip-specific, trip-end-specific, and transit-system characteristics. For example, Circella and Alemi (2018) examined the heterogeneity in substitution patterns of ridehailing services, which was present in the same data set of this report. The members of three latent classes identified in their study reported any change in their use of various travel modes as a result of using ridehailing. The largest group (53%), mostly urban millennials, reduced walking, biking, and riding public transit; the second largest group (37%), mostly suburban car-oriented mid-aged individuals, reducing driving personal vehicles; and the smaller group (10%), mostly suburbanites with travel

multimodality to limited extent, increased using public transit. At the aggregate level, the *net* effects of ridehailing on public transit or other travel modes will differ by city, metropolitan area, or public transit agency (Hall et al., 2017). To this date, the ridehailing literature lack studies that attempt to estimate the true effect of ridehailing in multivariate analysis settings.

Ridehailing is expected to affect the use of private vehicles either by substituting ridehailing for driving or by changing the time use and activity participation of individuals. For example, in the central business district of large cities, ridehailing is readily available while parking is expensive or burdensome and traffic is heavy. Thus, individuals may replace personal driving with ridehailing at least for certain trips (e.g., a business trip with colleagues from a workplace to a nearby destination in the same city). Also, with ridehailing services available, individuals may schedule social gatherings at night more often because they do not need to drive under influence when coming home late. That is, ridehailing is associated with their changes in time use and activity patterns (in this case, an increase in trip rates for a social purpose). This is also true for a household with limited access to vehicles (e.g., fewer vehicles than the number of household adults or drivers). Previously, household members had to plan the use of their vehicles in advance to meet the mobility needs of their members, and if necessary, some members needed to adjust their schedules. Now, with ridehailing available, the same household is given more flexibility in terms of time use and activity participation, which may decrease the use of personal vehicles (e.g., fewer carpooling or pickup/drop-off trips among the household members), but increase that of ridehailing vehicles (e.g., more separate trips by ridehailing). In brief, many possible mechanisms are at play. Also, the separate contribution of these mechanisms to the aggregate-level increase/decrease in private vehicle use (e.g., vehicle miles driven or VMD) is not clear, although the implication of ridehailing to system-wide total VMT appears obvious: a non-trivial amount of increases (Castiglione et al., 2016; Chen & Kockelman, 2016; Henao, 2017; Rodier, 2018) For example, 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. In another report (Schaller, 2018), he suggested that even pooled ridehailing services, such as UberPOOL and Lyft Line, which are increasingly available in large American cities, contribute to an increase in total VMT.

Whether ridehailing tends to increase or decrease the use of other modes, the purpose of the current study is to develop a flexible enough methodology that can account for the overall environmental impacts of the use of various modes of transportation among various groups of users. To do so, we study the adoption of travel multimodality among various groups of travelers in California, using latent class cluster analysis and identify various groups of travelers based on their travel multimodality patterns. We then use an analytical approach to estimate the average fuel consumption and GHG emissions associated with the use of both driving a personal vehicle and using ridehailing of the various groups of travelers. We focus on the fuel consumption and GHG emissions associated with the use of a private vehicle (e.g., associated with the vehicle miles driven by each individual) as well as the use of ridehailing services. To our knowledge, this is a novel approach that has not been proposed in the literature yet. It constitutes an intermediate step towards generating a more comprehensive approach to

account for the environmental externalities of all individual travel made by all travel modes. As such, it can serve as a basis for the evaluation of the environmental effects of travel behavior and the development of policies that can reduce the overall contribution of transportation to energy consumption and GHG emissions.

Data and Methodology

Data Collection

This study uses data from the California Millennials Dataset, which was collected with an online survey administered to a group of residents of California in Fall 2015. The goal of the survey was to collect detailed information that helps investigate the complex relationships behind the travel behavior and mobility/location choices of millennials and members of the preceding Generation X (i.e., Gen Xers). The survey collected a large amount of information from individuals throughout its eleven sections that focused on the following topics:

A. Individual attitudes and preferences
B. Use of online social media and adoption of technology
C. Residential location and living arrangements
D. Employment and work/study activities
E. Transportation mode perceptions
F. Current travel choices
G. Awareness, adoption, and frequency of use of emerging transportation services
H. Driver's license and vehicle ownership
I. Previous travel behavior and residential location
J. Expectations for future life events and mobility patterns
K. Sociodemographic traits

The dataset includes 1,975 cases (including both millennials and Gen Xers). These individuals were recruited via a commercial online opinion panel, i.e., they had voluntarily registered at some point to be members of the panel and regularly participate in various online surveys (e.g., marketing studies). The survey was administered using a quota sampling approach to collect sufficient cases across six regions of California and three neighborhood types (urban, suburban, and rural). Figure 1 summarizes the distribution of cases in the sample, by geographic region and neighborhood type. The dataset was collected as the first wave of data collection in a larger panel study of emerging transportation trends in California. This longitudinal study, which is designed with a rotating panel approach includes a second wave of data collection that is been completed in 2018. For more information on the survey design, survey administration, data cleaning and enriching, and previous analyses from this project, please refer to Circella et al. (2016); Circella et al. (2017); Circella et al. (2018).

The research team computed weights at the individual level to correct for the use of the quota sampling approach and to reduce the deviation from the distribution in the population of these two generations in California. For doing so, the team applied a combination of cell weights and the iterative proportional fitting (IPF) algorithm and used sociodemographic targets for gender, race and ethnicity, student/worker status, presence of children in the household, and

household income from the 2015 US Census American Community Survey 5-year estimate. The analyses included in this report are based on the use of the weighted dataset.
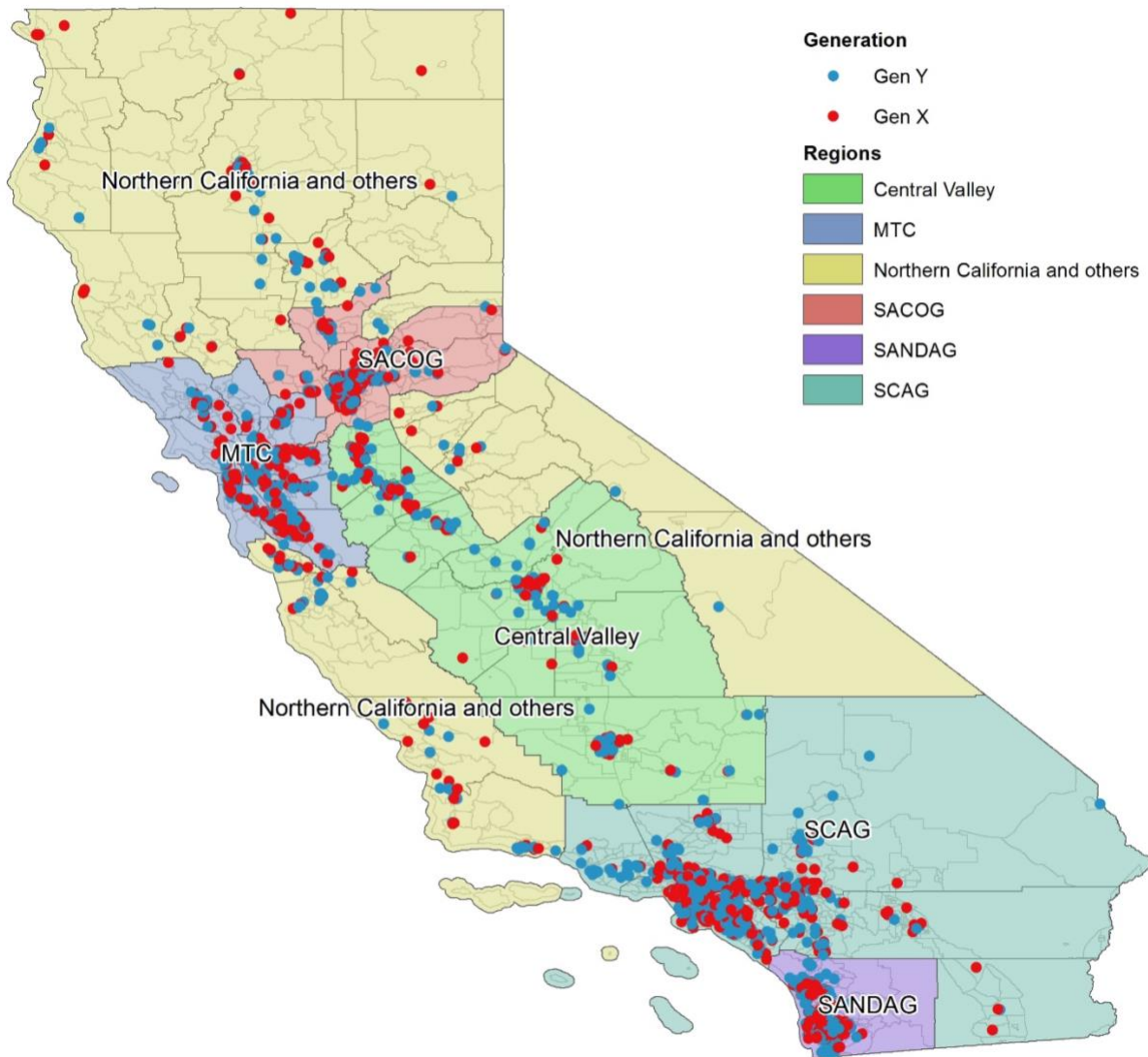
Figure 1. Distribution of Millennials and Gen Xers in the dataset, based on their geocoded residential addresses (Source: Circella et al., 2017)

Measuring Travel Multimodality

Travel multimodality refers to the use of various travel modes for a certain time period. Studies adopt several time periods for the definition of travel multimodality. For example, the use of multiple travel modes for a *single* tour (e.g., walk and ride a bus to a school and come home by ridehailing) is described as *intermodality*. Buehler and Hamre (2014) compared the varying shares of multimodal travelers in the 2001 and 2009 National Household Travel Surveys, defined by three time periods, such as on the survey day, in the last week, and in the last

month. They find the longer the time period gets, the larger the share of multimodal travelers become. Another dimension related to the identification of travel multimodality is the method with which to define multimodal travelers. Single measure approaches (e.g., % of trips made by non-motorized modes) are limited in that they do not take into account the nature of one's major travel mode (e.g., two individuals with 50% non-motorized modes, but one's main mode is driving while the other's main mode is carpooling) or the distribution of non-major modes (two individuals with 50% non-motorized modes, but one with balanced use of walking, biking, and public transit versus the other with only walking). Simple discrete measures (e.g., multimodal travelers defined as those with trips by walking, biking, or public transit at least once a week) are also problematic in that the threshold by which to define a traveler group is inherently arbitrary and does not guarantee the most heterogeneity in the sample of travelers.

In this context, we employ latent-class cluster analysis (LCCA) that identifies multiple groups of individuals in the sample based on indicators. The LCCA solution used in this study is a modified version of a previous analysis that focused on travel multimodality (Y. Lee, Circella, Mokhtarian, & Guhathakurta, 2018), which uses four groups of travel modes: *driving* a private vehicle, which includes also the use of motorcycles and carsharing vehicles; *carpooling*, which also includes getting a ride from ridehailing companies; riding *public transit*, which includes public bus, light rail, and heavy rail options; *active modes*, which includes walking, bicycling and skateboarding. We choose LCCA because it takes into account both the frequency and distribution of various travel modes. It also estimates the probability of an individual to belong to a certain latent class with distinctive mode use patterns. For more details on the use of LCCA and its advantages compared to other methods, and recent application to travel multimodality, please refer to Molin, Mokhtarian, and Kroesen (2016), Ralph (2017) and Y. Lee et al. (2018).

The California Millennials Dataset survey asks two questions on travel mode use, one for regular commuting trips to school or workplace and the other for all other trips such as those made for shopping, social, recreational, and leisure purposes. Individuals in the data reported the frequency of using each of 13 modes in a 7-point Likert-scale, from *no use* to *less than once a month* to *5 or more times a week*.[1] We converted the responses to from these frequency categories into a monthly frequency value. For example, 1-2 times a week was converted to 1.5/week * 4 weeks = 6 times a month. In addition, as mentioned above, we combined similar means of travel together, and grouped 13 travel options into four main travel modes: *driving*, *carpooling* (as a passenger), *public transit*, and *active modes*. In doing so, we combined trips for two purposes together because a previous study using the same dataset found that the mode use patterns for one purpose do not differ substantively from those for the other purpose (Lee et al., 2018). After testing with several a priori assumptions on the numbers of latent classes, we find that a four-class solution (without active covariates) best fit the data and identifies four latent classes with distinctive modality styles. The major travel modes for each of those latent

---

[1] The question for commuting trips also offered an option "Not available" that can be selected for those means of transportation that are not available for the home-work/school trip. This option was not included in the question for other trip purposes.

classes are driver (76.7%), active traveler (9.9%), car passenger (7.3%), and public transit ride (6.2%) (N=1,968 after the exclusion of incomplete cases).

Table 1. Latent-Class Cluster Analysis of Modality Styles (N=1,968, Unweighted)

	Driver (76.7%)	Active Traveler (9.9%)	Car Passenger (7.3%)	Transit Rider (6.2%)
Average Frequency of Trips per Month				
Driving	27.9	3.2	4.1	2.7
Carpooling	2.9	2.4	15.9	5.8
Public Transit	1.4	8.9	1.3	29.0
Active Modes	4.2	26.1	9.6	7.7
Share (Four cells in each column sum to 100%)				
% of driving	77%	8%	13%	6%
% of carpooling	8%	6%	51%	13%
% of public transit	4%	22%	4%	64%
% of active modes	11%	64%	31%	17%

* The columns are in a descending order (from left to right) by the size of latent classes in the sample of 1,968.

Computation of Energy Consumption and Greenhouse Gas (GHG) Emissions

In this report, we are interested in understanding the overall energy consumption and GHG emissions associated with the use of private vehicles, including both miles driven directly by the users and the additional contribution from ridehailing trips. Thus, we process information in the California Millennials Dataset to compute the fuel consumption and GHG emissions associated with individual' travel patterns. We obtain the fuel economy of the vehicles owned by the individuals in the California Millennials Dataset by matching their reported vehicle information (e.g., make, model, and year) with the information available from a US Department of Energy database (USEPA, 2018a).

After excluding cases with incomplete/inaccurate vehicle information, we compute the amount of fuel consumption and greenhouse gas (GHG) emissions for 1,795 individuals through the following steps.

1A. For the calculation of the gallon of gasoline consumed in a year[2], the self-reported weekly VMD and fuel economy of individuals enter Equation (1).

> (Annual gasoline consumption from driving)
> = (Self-reported weekly VMD) × (1/fuel economy) × (365/7 weeks)   **(1a)**

---

[2] We only use self-reported VMD in this step. Any long-distance trips that are not included in the reported weekly VMD are therefore not considered here, leading to a likely undestimation of total VMD for some travelers.

1B. For the GHG emissions from the use of personal vehicles, we assume that individuals drive *only* the vehicle that they reported in the survey *but no other vehicles.* Also, partial contribution to GHG emission through carpooling is not considered in Equation (1b).

(GHG from personal vehicles)
= (Annual gasoline consumption) × (conversion factor from gasoline to GHG)   **(1b)**

1C. The US EPA publishes a factor that converts the gallons of gasoline consumed from driving into GHG emissions (USEPA, 2018b)[3], and we use their factor for the conversion.

8,887 grams of CO_2/gallon of gasoline = 8.887 × 10-3 metric tons CO_2/gallon of gasoline **(1c)**

Now, to estimate a range of potential impacts of an individual's use of ridehailing on fuel consumption and GHG emissions, we propose the following approach. First, we compute the fuel consumption from ridehailing in Equation (2).

(Annual gasoline consumption from ridehailing)
= (ridehailing trip distance + deadheading distance)
× (1/fuel economy of ridehailing fleet)
× (frequency of using ridehailing/year)   **(2)**

2A. For the computation of the environmental impacts of ridehailing, the California Millennials Dataset contains information on the average frequency of trips made by ridehailing in a month. However, the dataset does not contain information about the distance of ridehailing trips. Thus, we extract this information from the 2017 National Household Travel Survey. We computed the trip distance at the 25th, 50th, and 75th percentiles by for-hire vehicle trips made by California residents (n=786 trips). We use the following values to estimate a range of environmental impacts by ridehailing.

25th percentile:	2.11725 miles/trip
50th percentile:	4.24650 miles/trip
75th percentile:	10.49175 miles/trip **(2a)**

2B. We use a set of factors that differ by the residential neighborhood where an individual lives to account for the additional miles due to deadheading and repositioning of vehicles to provide a ridehailing trip. We used information from Salon (2015), who classified all census tracts in California into five neighborhood types based on land use characteristics such as density, land-use mix, and street design patterns, in this step. In this report, we reclassify Salon's *central city* and *urban* neighborhoods as "urban" and the other three types (*suburban*, *rural-in-urban*, and *rural*) as "non-urban." Also, we assume that the deadheading miles depend on the residential neighborhoods of individuals, as an oversimplification for the application of this approach. Note

---

[3] Given that the two sources that the US EPA used for the calculation of the below factor were published in 2006 and 2010, the average conversion factor for all vehicles in California as of 2015 is likely to be smaller than the factor used in this study.

that the California Millennials Dataset did not ask whether individuals used ridehailing services in their neighborhoods or somewhere else. Thus, our approach is a somewhat rough approximation of the potential energy consumption and GHG emission from the use of ridehailing services: [4]

For urban residents:	0.5~2 miles/trip
For non-urban residents:	0.5~4 miles/trip **(2b)**

2C. We use confidential information obtained from a ridehailing company (Uber) to compute the average fuel economy of their vehicles. The company pulled data from a random sample of 5,000 trips made in July 2018 in the Los Angeles region using their app. These data were used to compute the average fuel economy of those vehicles using the trip distance of individual trips (i.e., passenger miles) as weights.

2D. For the annual frequency of using ridehailing services, the California Millennials Dataset identifies six categories of use of ridehailing services: *no use*, *did use it in the past but do not use it any more*, *use less than once a month*, *use 1-3 times a month*, *use 1-2 times a week*, *use 3-4 times a week*, and *use 5 or more times a week*. The first two categories are combined and treated as zero frequency per year in this analysis. The other categories are processed in the following way:

Less than once a month = 0.5 per month * 12 months = 6 per year
1-3 times a month = 2 per month * 12 months = 24 per year
1-2 times a week = 1.5 per week * 52.1428571429 weeks/year = 78.2 per year
3-4 times a week = 3.5 per week * 52.1428571429 weeks/year = 182.5 per year
5 or more times a week = 5 per week * 52.1428571429 weeks/year = 260.7 per year   **(2d)**

2E. For the GHG emissions from the use of ridehailing, we apply Equation (1b) and conversion factor in Equation (1c) to the annual fuel consumption from ridehailing in Equation (2).

(GHG from ridehailing)
= (Annual gasoline consumption from ridehailing from Equation (2))
× (conversion factor from gasoline to GHG)   **(2e)**

8,887 grams of CO_2/gallon of gasoline = 8.887 × 10-3 metric tons CO_2/gallon of gasoline **(2f)**

---

[4] In the 2018 data collection being completed as part of this project, more detailed information is obtained about the origins and destinations of the most recent trip made using ridehailing. The 2018 dataset also distinguish between trips made using ridehailing services such as Uber X and Lyft Classic from trips with pooled services such as UberPOOL and Lyft Line. In future extensions of this analysis, the differences between these types of services will be considered. Similarly, we plan to introduce a better estimation of the contribution of deadheading to total vehicle miles traveled, using data from the 2018 dataset and information obtained from ridehailing companies.

As the last step, we sum the fuel consumption and GHG emissions from two sources, driving and ridehailing, for the computation of the total environmental impacts from transportation.

For ridehailing non-users:

(fuel consumption) = (fuel consumption from driving)   *Equation (1a)*

(GHG emissions) = (GHG emissions from driving)   *Equation (1b)*

For occasional or regular ridehailing users:

(fuel consumption) = (fuel consumption from driving) + (fuel consumption from ridehailing)

Equation (1a) + Equation (2)

(GHG emissions) = (GHG emissions from driving) + (GHG emissions from ridehailing)

Equation (1b) + Equation (2e)

Results

Descriptive Statistics

First, before discussing the introduction of energy consumption and GHG emission from transportation, this section presents the sociodemographic and economic profile of individuals in various subgroups. In doing so, we first investigate the profile of each of the four modality latent classes, and further examine the profile of the three subgroups (non-users, occasional users, and regular users of ridehailing services) in each latent class. Table 1Table 2 shows the shares of the four modality latent classes in the final sample (N=1,785). We compute the shares by employing two weights, *both* the class probabilities from the latent class cluster analysis *and* the case-specific weights that correct for non-representativeness of the dataset.

Table 2. Share of Modality Latent Classes by the Use of Ridehailing (N=1,785, Weighted)

Modality class	Driver	Active Traveler	Transit Rider	Car passenger	Row sum
Share in the sample	79.9%	7.9%	6.3%	5.9%	
Count (weighted by class-specific probabilities and case weights)					
Non-users	1073	113	78	83	
Occasional users	214	11	11	11	
Regular users	140	17	23	11	
Share within each class (three cells in each column sum to 100%)					
Non-users	75.2%	80.2%	69.1%	79.0%	
Occasional users	15.0%	7.9%	10.1%	10.5%	
Regular users	9.8%	11.9%	20.8%	10.5%	
Share within each ridehailing group (four cells in each row sum to 100%)					
Non-users	79.7%	8.4%	5.8%	6.2%	
Occasional users	86.5%	4.5%	4.6%	4.5%	
Regular users	73.2%	8.8%	12.3%	5.8%	
Share in the sample (the below twelve cells sum to 100%)					
Non-users	60.1%	6.3%	4.4%	4.7%	75.4%
Occasional users	12.0%	0.6%	0.6%	0.6%	13.9%
Regular users	7.8%	0.9%	1.3%	0.6%	10.7%

Note: Rows present three groups defined by the level of ridehailing trips: non-users, occasional users (once per month), and regular users (at least once per month). The sample size is smaller than that in Table 1 by 190 because of cases with incomplete vehicle information, for which energy consumption and GHG emission cannot be computed.

Several patterns in Table 2 are worth mentioning. Not surprisingly, the driver class consists of approximately 80% of the final sample, and non-users is also a predominant group with the share of 75.4% (across all modality latent classes). Regarding the composition of the three ridehailing user groups within each latent class, in general non-users are the majority with at least about 70%. Interestingly, the share of regular users in each latent class differs to some

extent. Among drivers, regular users consist of only 9.8%, but regular users take more than 20% of the transit rider class. We find two explanations for this pattern. First, drivers can meet their travel demand by driving their vehicles, so they do not need/want to use ridehailing services very often. In comparison, the mobility of transit riders is often constrained by the temporal and geographic limit of transit services, so they may get rides from ridehailing to meet their *unmet* travel demand by public transit (e.g., ridehailing is complementary to the use of public transit, or in some cases it may be substitutive.). Second, individuals may choose a modality style for non-transportation reasons, for which they tend to travel by public transit and ridehailing while minimizing the use of personal vehicles. For example, those who prefer urban lifestyles (e.g., close proximity to restaurants, bars, and nightlife venues) find their urban neighborhoods do not support driving very much for reasons such as congestion and parking. If these urbanites usually move around within cities, public transit and ridehailing would suffice to meet most of their travel demand, if not all. Note that studies find that many of such urbanites are college-educated professionals living in cities (Baum-Snow & Hartley, 2016; Coutoure & Handbury, 2017; Kolko, 2016; H. Lee, 2018), who do not necessarily have tight budgets, but instead present consumption-oriented lifestyles. Thus, additional costs for ridehailing compared to public transit does not affect their mode choice much. Since the analysis in this report is based on a small sample (N=1,785) in California, we need more research and empirical evidence to see if the patterns present in the dataset is also found in other areas or at the national level.

Table 3 presents the sociodemographic/economic characteristics, and travel-related/neighborhood choices of individuals, computed for each of the four modality classes separately. It helps relate the chosen modality style of individuals to their various characteristics. Drivers are mostly older millennials and Gen Xers, highly educated, working instead of studying (many of them are professionals), and earning household income more than $100,000 per year. About half of them live with own children. Drivers have the highest vehicles per driver among the four latent classes and drive the longest miles per week in part because about two thirds of them live in suburban neighborhoods. On average, the members of active travelers live in cities more than the other latent classes. About 40% of transit riders study either full-time or part-time, and they make household incomes lower than $60,000 per year. As implied in Table 2, on average transit riders make the highest ridehailing trips than the members of the other latent classes. Car passengers consist of many young millennials in part because they live in a larger household and have limited access to vehicles (as a driver). Or, some of these young millennials might not have obtained a valid driver's license, which prevents them to travel as a driver. Thus, while 80% of them live in non-urban areas, where non-motorized travel modes are not feasible in most cases, their VMD is relatively small.

Table 3. Sociodemographic, Economic, and Travel-Related/Neighborhood Choices of Four Modality Classes (N=1,785, Weighted)

	Driver	Active Traveler	Transit Rider	Car Passenger
Share in the sample	79.90%	7.90%	6.30%	5.90%
Demographic group				
Young Millennials (18~24)	16%	26%	40%	**43%**
Older Millennials (25~34)	**33%**	30%	28%	26%
Young Gen Xers (35~44)	**32%**	28%	25%	19%
Older Gen Xers (45~50)	**19%**	16%	7%	12%
Female	52%	47%	49%	**57%**
Educational attainment				
Bachelor's degree	**37%**	26%	18%	22%
Graduate degree	**15%**	13%	12%	10%
Work/study status				
Worker	**85%**	67%	70%	56%
Professional workers	**25%**	15%	17%	13%
Student	18%	17%	**41%**	29%
Annual household income				
Up to 60k	42%	56%	**75%**	59%
60~100k	25%	24%	13%	**26%**
Greater than 100k	**34%**	20%	12%	15%
Living arrangement				
Household size	3.16	2.81	3.18	**3.50**
Presence of own children	**55%**	41%	39%	42%
# of children	**0.97**	0.69	0.68	0.79
Mobility choices and patterns				
Car/driver	**0.96**	0.70	0.70	0.77
Vehicle Miles Driven	**144**	37	35	48
# of Ridehailing/week	0.38	0.49	**1.15**	1.03
Residential neighborhood				
Urban	24%	**42%**	39%	20%
Suburban	68%	53%	55%	**70%**
Rural	8%	6%	5%	**10%**

Note: Bold indicates the largest value in each row.

Table 4 shows selected individual characteristics, divided further by the level of ridehailing use within each latent class. It reveals heterogeneity in the individual characteristics across ridehailing user groups within each latent class. Regarding educational attainment, the occasional and regular ridehailing users among active travelers are highly educated, even more so than their counterparts (i.e., occasional and regular ridehailing users) among drivers. The

60% of the regular ridehailing users among active travelers make more than $100,000 a year, which partly explain their relatively high weekly VMD of 95 miles.

As for the weekly VMD, the subgroup of the regular ridehailing users among *drivers* and *active travelers* drove *more* with their personal vehicles compared to those that do not use ridehailing among drivers and active travelers. We interpret that the regular ridehailing users among drivers and active travelers (approximately 3-4 ridehailing trips a month) have high travel demand, so their higher weekly VMD is not a direct effect of their use of ridehailing services. Instead, for various reasons these regular ridehailing users get rides from ridehailing to meet their high travel demand, while also driving a substantial amount of miles. After all, the use of personal vehicles and ridehailing may *directly* affect each other, and these two measures can be also affected by various factors such as individual characteristics, the built environment attributes, the level of services of various travel modes, complex travel demand, attitudes, and lifestyles. For the investigation of complex relationships among these factors, future research needs to model multiple dependent variables in a system of equations while allowing simultaneous causal relationships (e.g., structural equation modeling).

Instead, the subgroup of the regular ridehailing users among *transit riders* and *car passengers* drove *fewer* miles with their personal vehicles compared to those that do not use ridehailing among transit riders and car passengers. This pattern is consistent with a simple expectation that the use of ridehailing will *directly* decrease the use of personal vehicles. However, it is not clear the extent to which the use of ridehailing *causes* a reduction in VMD. While trips made by ridehailing removes the need for driving (more ridehailing → less driving), it is also plausible that a lack of access to private vehicles may lead individuals to ridehailing (less driving → more ridehailing). In this report, we examine the patterns that are present among various subgroups in a sample collected from California with the specific focus on energy consumption and GHG emission from transportation. Further research is necessary to assess the *causality* and estimate the *size* of such effects.

Table 4. Key Sociodemographic/Economic Characteristics by Modality Class and the Use of Ridehailing (N=1,785, Weighted)

Ridehailing group		Modality classes			
		Driver 79.90%	**Active Traveler** 7.90%	**Transit Rider** 6.30%	**Car Passenger** 5.90%
Non-Users	Educational attainment				
	Bachelor's degree	**33%**	22%	18%	20%
	Graduate degree	**13%**	6%	11%	6%
Occasional Users	Educational attainment				
	Bachelor's degree	56%	**57%**	34%	30%
	Graduate degree	15%	**27%**	7%	16%

Ridehailing group		Modality classes			
		Driver 79.90%	**Active Traveler** 7.90%	**Transit Rider** 6.30%	**Car Passenger** 5.90%
Regular Users	Educational attainment				
	Bachelor's degree	**35%**	34%	8%	26%
	Graduate degree	30%	**47%**	18%	31%
Non-Users	Household income				
	Up to 60k	45%	64%	**75%**	62%
	60~100k	24%	24%	15%	**25%**
	Greater than 100k	**30%**	13%	10%	13%
Occasional Users	Household income				
	Up to 60k	25%	37%	**76%**	59%
	60~100k	25%	**31%**	7%	25%
	Greater than 100k	**50%**	33%	17%	15%
Regular Users	Household income				
	Up to 60k	39%	17%	**76%**	36%
	60~100k	27%	24%	6%	**33%**
	Greater than 100k	35%	**59%**	18%	32%
Non-Users	Living arrangement				
	Household size	3.26	3.01	3.33	**3.64**
	Presence of own children	**56%**	43%	37%	44%
Occasional Users	Living arrangement				
	Household size	**2.96**	2.09	2.29	2.61
	Presence of own children	**49%**	41%	21%	23%
Regular Users	Living arrangement				
	Household size	2.70	1.94	3.09	**3.33**
	Presence of own children	51%	28%	**54%**	48%
Non-Users	Mobility patterns				
	Car/driver	**0.96**	0.74	0.74	0.79
	Vehicle Miles Driven	**141**	29	38	50
	# of Ridehailing/month	0.00	0.00	0.00	0.00
Occasional Users	Mobility patterns				
	Car/driver	**0.99**	0.36	0.48	0.78
	Vehicle Miles Driven	**148**	37	39	62
	# of Ridehailing/month	0.50	0.50	0.50	0.50
Regular Users	Mobility patterns				
	Car/driver	**0.96**	0.59	0.66	0.60
	Vehicle Miles Driven	**155**	95	24	15
	# of Ridehailing/month	3.09	3.82	5.29	**9.28**

Note: Bold indicates the highest value in each row.

Computation of Energy Consumption

With the method explained in previous sections, we compute energy consumption associated with both driving personally-owned vehicle and using ridehailing. Table 5 presents a set of estimates for twelve subgroups in the final sample (N=1,785, weighted). The set consists of gasoline consumed in a year (in gallon) from driving (single estimate for each individual), and for driving and ridehailing (with both a minimum and a maximum estimate, obtained using the assumptions previously described). Note that the minimum estimate used a ridehailing trip length equal to the 25th percentile with dead-heading of 0.5 mile per trip, and the maximum estimate uses the 75th percentile value with dead-heading of 2 miles per trip for urban residents and 4 miles per trip for non-urban residents. These values provide a range of estimates that capture possible environmental impacts from travel patterns of the individuals in each group. In the future stages of the research, once more accurate data become available, these estimates can get updated for better accuracy using the same methodology proposed in this report.

Table 5. Energy Consumption (Annual Gasoline Consumed in Gallon, N=1,785, Weighted)

Modality class	Ridehailing User Group	Fuel consumption from Driving	Fuel consumption from Driving & Ridehailing (min.)	Fuel consumption from Driving & Ridehailing (Max.)
Driver	Non-user *	325.8	325.8	325.8
	Occasional User	323.6	324.1	326.5
	Regular user	328.5	332.1	346.5
Active Traveler	Non-user *	63.7	63.7	63.7
	Occasional User	67.1	67.6	69.9
	Regular user	205.0	209.5	227.0
Transit Rider	Non-user *	69.5	69.5	69.5
	Occasional User	85.8	86.4	88.8
	Regular user	35.8	42.0	66.2
Car Passenger	Non-user *	106.0	106.0	106.0
	Occasional User	156.1	156.6	159.0
	Regular user	40.9	51.9	95.2

Note: Fuel consumption estimates for non-users do not differ by column because the estimated fuel consumption associated with the use of ridehailing is zero (by definition).

Estimation of GHG Emissions

This section examines GHG emission from driving and ridehailing by various groups in the California Millennials Dataset. We first divide individuals in the data into four latent classes with distinctive modality styles: driver, active traveler, transit rider, car passenger. Note that these classes are named based on the primary travel mode used by the members of each latent class. Also, individuals are not deterministically identified as belonging to one class or another.

Instead, we employ their class probability as the weight. Second, for each latent class, we further group individuals based on their level of ridehailing use: no use, occasional use (less than once a month), and regular use (at least once a month). As a result, we identify twelve subgroups (four modality styles * three ridehailing use levels) in the dataset. Note that the sample size is smaller after the further exclusion of incomplete cases (e.g., vehicle information or reported vehicle miles driven).

In the same way in which we estimate energy consumption, the minimum GHG emission estimate from ridehailing is computed using the trip length of ridehailing at the 25th percentile from the 2017 NHTS subsample from California (2.11725 miles/ridehailing trip) with dead-heading miles for each ridehailing trip of 0.5 mile. The maximum GHG emission estimate from ridehailing is computed with the trip length of ridehailing at the 75th percentile from the 2017 NHTS subsample from California (10.49175 miles/ridehailing trip) with the dead-heading miles for each ridehailing trip of 2 miles for urban residents or 4 miles for non-urban residents. Figure 2 presents the bar chart with the measures of GHG emissions only from driving for the four latent classes with distinctive modality styles.
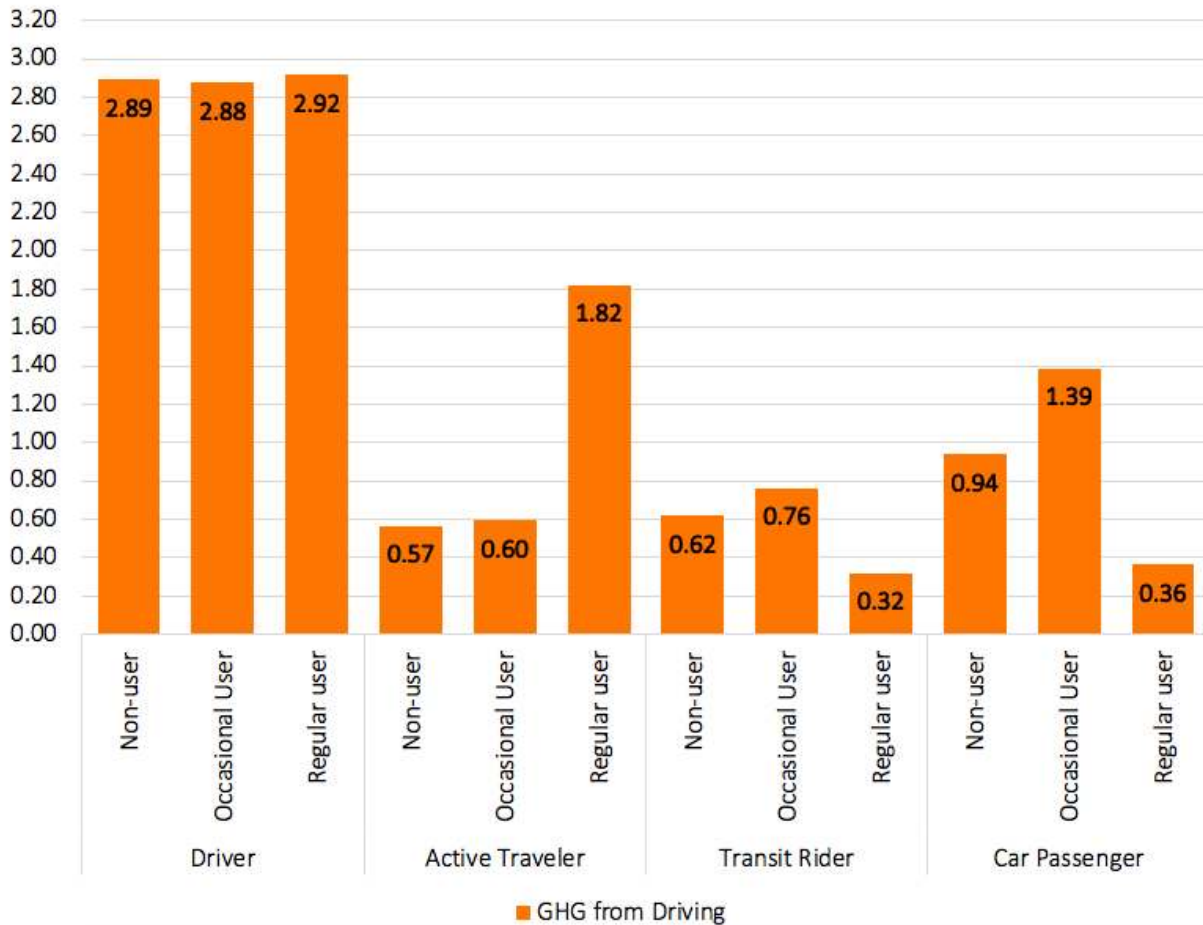
Figure 2. Annual Greenhouse Gas Emission from Driving a Private Vehicle (CO$_2$ in metric ton, N=1,785, Weighted)

Figure 3 shows the GHG emissions from *both* driving a personal vehicle *and* using ridehailing. Apparently, occasional and regular users of ridehailing services in any latent class generate lower GHG emissions from driving; these users drive less than their non-user counterparts (as shown in Figure 2). However, when taking into account the additional GHG emissions associated with ridehailing trips, regular ridehailing users are responsible for a non-negligible additional amount of GHG emissions (even if their combined GHG emissions from both driving and using ridehailing remain substantially below the GHG emissions of the *drivers* group). Figure 3 shows stacked bar charts for the same twelve subgroups with the additional GHG emissions colored in yellow (for the minimum estimate) and green (for the maximum estimate).
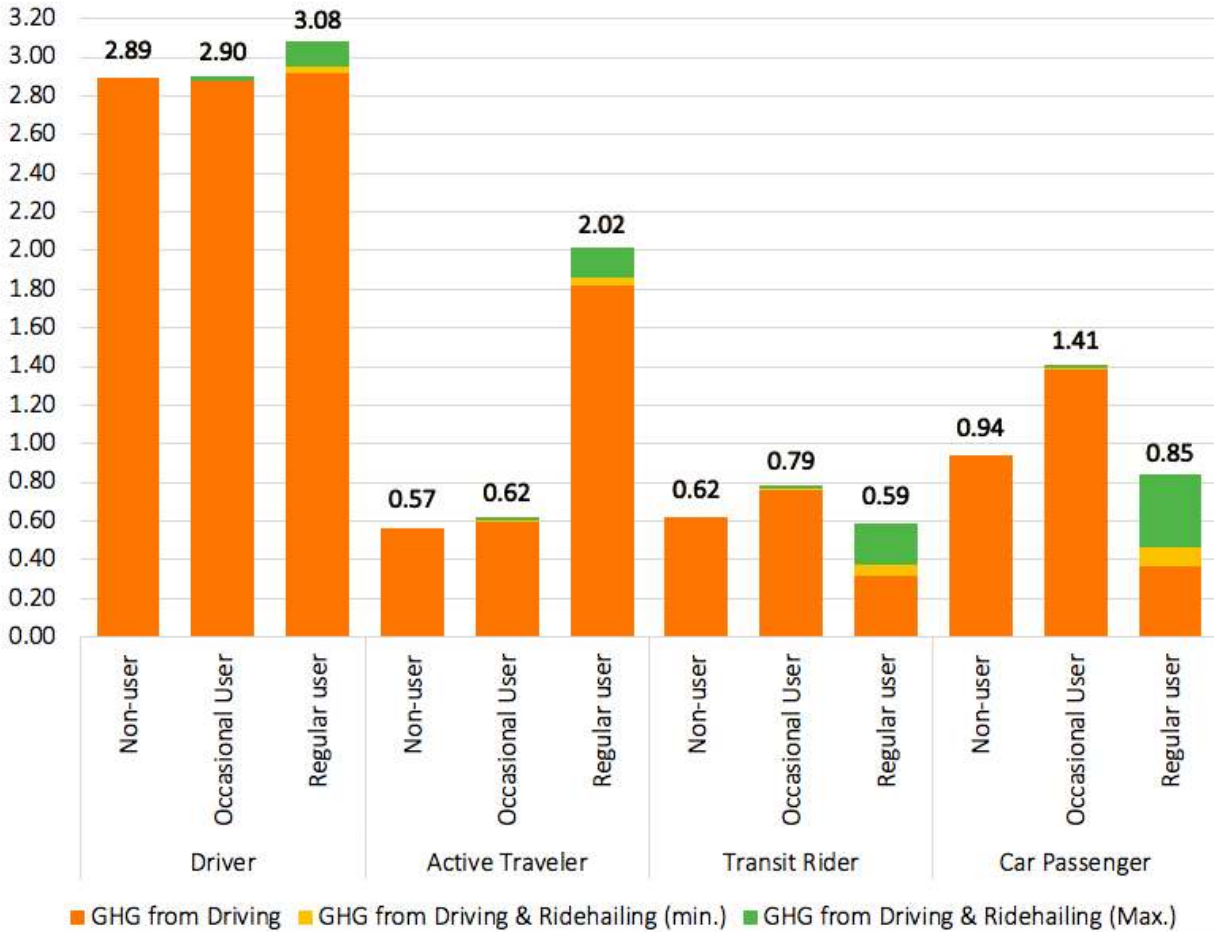
Figure 3. Annual Greenhouse Gas Emission from Passenger Travel (CO$_2$ in metric ton, N=1,785, Weighted)

Note: The number at the end of each bar represents the maximum estimate of the *combined* GHG emissions from both driving and using ridehailing for each group of travelers.

It is important to remind the readers that the reported values are estimates based on the assumptions used in this study, which were informed by existing studies and consulting/industry reports. Not surprisingly, the GHG emissions associated with trips made with ridehailing for the various subgroups in the population would differ substantially varying the assumptions in the study. In this sense, the goal of this report is to explore the extent to which the GHG emission may vary from one group of travelers to another under a simplified approach. In this report, we do not attempt to compute the most accurate estimates, which is beyond the scope of this report due to lack of or insufficiency of relevant data, but to examine the possible variation in GHG emission from transportation. We aim to inform transportation planners and policymakers of the implication of such variation and help them choose a right set of policy and incentives to promote mobility while increasing environmental sustainability in the transportation sector.

Several patterns are present in Figure 3. Not surprisingly, in general drivers produce the most GHG, followed by car passengers, transit riders, and active travelers, although we see substantial variation GHG emission in some of these latent classes by the use of ridehailing. For all travelers, the GHG emissions associated with the use of ridehailing services (even under the highest estimate produced by this research) are still rather small compared to the GHG emissions from driving. This is not surprising, considering the relatively small mode share that ridehailing services still have among most groups of travelers.

Interestingly, among the largest latent class (i.e., *driver*), the variation in GHG emission does not appear to be considerable by the use of ridehailing services. In other words, among drivers, those who should have access to vehicles by definition, their use of ridehailing services is not associated with a noticeable reduction in the use of their own vehicles, but on the contrary ridehailing users tend to also drive their personal vehicles for a substantial amount of miles. Although the regular ridehailing users of the driver class produce more GHG emission in total, the difference with the other members of the *drivers* group is not huge. Even the regular ridehailing users in this group do not seem to use ridehailing very often. That is, we define regular users as using ridehailing *at least* once a month, and the regular users in the drivers class do not show high frequency levels of ridehailing use. These patterns may result from their attitudes (e.g., pro-driving or preferences for being in control) or their travel needs (e.g., frequent/longer/complex trip routines or origin/destinations not being served well by ridehailing) or residential locations that are just more conducive to driving. In short, the ridehailing users among the driver class seem not to use ridehailing services very often due to attitudes, lifestyles, and travel needs. As a result, among the driver latent class, the level of GHG emission does not differ much by their use of ridehailing services.

The *car passenger* class presents unique variations across various estimates of GHG emission. The non-users and occasional users in the car passenger class generate more GHG from transportation than the regular users of the same class. This pattern holds true even the highest GHG estimate from ridehailing is applied to the regular users. That is, the regular ridehailing users in the car passenger class drive their own vehicles very little (or some of the regular users may not have access to cars), while the non-users and occasional users use their vehicles to some extent. Thus, the three user groups in the car passenger class look similar in terms of being driven often by others (i.e., 51% of their trips on average in Table 1), the regular users in the class appear to drive their own vehicles less because of living in a vehicle-deficient household, not preferring driving, or having most destinations in proximity to their home (e.g., urban neighborhood). On the other hand, the increases in GHG emission from ridehailing for the regular users is substantial: from 0.24 CO_2 ton/year (when the GHG from ridehailing is not taken into account) to 0.78 CO_2 ton/year (when the highest GHG estimate for ridehailing use is added) or approximately by a factor of three. Still, the GHG emissions from driving and using ridehailing for regular users in the car passenger class are way lower than the individuals in any of the driver class (however, it should be noted that the approach that we use in this first study does not account for the portion of GHG emissions associated with riding in a privately-owned vehicle as a passenger).

The *transit rider* class shows that, under the highest estimates, its regular ridehailing users produce more GHG emissions than the other members. Within the transit rider class, the ridehailing non-users appear to drive their vehicles to some extent, and the occasional ridehailing users do not use personal vehicles as much as the former group and generate relatively small amounts of GHG emissions from transportation. In comparison, the regular ridehailing users in the class appear to frequently make trips by ridehailing services, generating much higher GHG emissions than their non-ridehailing user counterparts. Again, please note that Figure 3 presents the GHG emission estimates for various subgroups in the California Millennials Dataset, and that these estimates and their relative amounts against other subgroups do not claim any substitution/complementarity effects of ridehailing on public transit. Again, any observed travel patterns might be due to differences in individual attitudes, lifestyles, and travel needs. Further studies are needed to explore the factors associated with the substitution/complementarity patterns of ridehailing and public transit.

The most striking patterns in Figure 3 is the extent to which the regular ridehailing users of the *active traveler* class differ from the GHG emissions of the other members in this class. Their GHG emissions from driving are substantially low, but when the additional GHG emissions from ridehailing are taken into account, the combined GHG emissions are remarkably high for regular users. One important consideration to make for the users in this class is that these estimates are based on a sample (N=1,785) collected in California in 2015, and the regular ridehailing users in the active traveler class is a rather small subgroup in the sample. Having said that, this noticeable pattern is suggestive of a presence of rather high GHG-emitting travelers in the population, who may appear to have more sustainable travel patterns than they actually do if the impacts of their ridehailing trips are not accounted for. Urban residents without access to personal vehicles may fall into this subgroup: e.g., in many cases they walk or bike (64% of trips made by walking, biking, and skateboarding), and in some cases they use ridehailing services (6% of trips being driven by others). Interestingly, the frequency of their ridehailing trips is not negligible, even though they may live in cities where deadheading miles are shorter and pooled ridehailing is more available. One implication is that transportation planners and policymakers need to take a holistic perspective regarding the sustainability implication of various travel patterns: if they ignore the additional GHG emissions generated by active travelers with other non-driving modes (e.g., ridehailing trips), they may not necessarily promote the right policies to increase sustainability and reduce the environmental impacts from transportation. In addition, more accurate analyses should be developed to improve the computation of the environmental impacts from all travel modes (e.g., also including carpooling with others in a private vehicle) as well as more comprehensive data should be used to increase the accuracy and reduce the uncertainty of these estimates, and better support policy-making.

Conclusions and Plans for Future Research

In this report, we propose a novel approach to estimate a combined fuel consumption and GHG emissions associated with both driving a personal vehicle and getting a ride from ridehailing services using data from the individuals in the California Millennials Dataset. The dataset is built out of a transportation survey that collected a wide range of variables in 2015.

We apply latent class cluster analysis and an additional deterministic segmentation to investigate how the levels of fuel consumption and GHG emissions vary for various subgroups in the data, based on two dimensions: the individuals' modality style and their frequency of use of ridehailing. With the latent-class cluster analysis, we identify four latent classes with distinctive modality styles: *drivers*, *car passengers*, *transit riders*, and *active travelers*. We then group individuals in each class by their level of ridehailing use on a typical month as *non-users*, *occasional users* (who use ridehailing less than once a month), and *regular users* (who use it at least once a month).

After applying these two classifications approaches, we examine the variations in the combined fuel consumption and GHG emissions from driving a personal vehicle and using ridehailing. Not surprisingly, the driver class generates the highest GHG emissions among the four latent classes of travelers, and the use of ridehailing services does not make much difference in the GHG emissions (and fuel consumption) among the members of this class. In comparison, the GHG emissions among the members of the other three latent classes vary substantially with the frequency of ridehailing use. In particular, the transit rider class and the active traveler class present relatively high levels of GHG emissions for their regular ridehailing user subgroups. That is, those who travel by walking, biking, and public transit for most of their trips may not appear to be contributing to climate change much compared to drivers. However, if they also use ridehailing frequently, the difference between users of these alternative modes and drivers in terms of combined GHG emissions from these modes becomes substantially smaller.

Ridehailing services have been widely adopted in the last five years or so, and they do enhance mobility of various subgroups in the population (e.g., those residing in areas with poor public transit services). Their total environmental impacts still account for a relatively small percentage of total GHG from transportation as their mode share is still relatively small. Still, the preliminary findings from this report suggest some initial policies that transportation planners and policymakers could start introducing to reduce environmental impacts of such services. Several components would be critical, including the reduction in the total length of ridehailing trips, the improvement of the fuel economy of ridehailing vehicles, and the encouragement of shared rides. Such planning and policy include: (1) the further densification, improvement in land use mix, and supportive street designs of areas with high demand for ridehailing services, as well as strategies to efficiently reduce the deadheading components of the VMT from ridehailing providers; (2) regulations and incentives for cleaner ridehailing vehicles (e.g., policies to promote, or require, electrification of TNC fleets); and (3) the increase in the awareness of the environmental benefits of shared rides (and the safety for such rides) so that the use of pooled ridehailing (instead of single-user ridehailing) becomes prevalent in

most American cities. Further, additional steps could be taken in order to promote the offset of the environmental effects of the use of certain mobility services, such as ridehailing, through other policies and actions (e.g., in the U.S. market, Lyft already pledges to make all its rides be carbon neutral through appropriate steps to offset the GHG emissions produced with its ridehailing activities).

The analysis of this report has several limitations that readers need to be aware of when interpreting its preliminary results. First, the analysis does not aim to identify a relationship of causality between the use of ridehailing services and the use of personal vehicles, and the resulting amount of GHG emissions. Instead, in this study, we limit our analysis to exploring the correlation patterns between the frequency of using ridehailing services and the estimated environmental impacts from driving and using these services. Other approaches, such as the use of longitudinal data (e.g., before/after the introduction of ridehailing services to one's neighborhood/area) or joint estimation techniques (e.g., a joint choice of the use of ridehailing services and the level of vehicle ownership, and modeling of VMD as an outcome of the joint choice) would be more adequate to investigate any causal relationships between the use of ridehailing services and other components of travel behavior (including driving).

Second, while the California Millennials Dataset has several merits over the datasets analyzed in previous studies (e.g., it includes information on personal attitudes and preferences), it does not allow to accurately model the length of ridehailing trips. In response, we use the trip length at 25th, 50th, and 75th percentiles by for-hire vehicle trips in 2017 NHTS California subsample as a proxy. One further step for the improvement in the accuracy of these analyses would be to differentiate the ridehailing trip distance by the socioeconomic, demographic, and built environment characteristics of individuals in the 2017 NHTS data, instead of using these summary values for all individuals in the user groups in the California Millennials Dataset. By doing so, the computation of GHG emissions from transportation would more appropriately take into account that various groups in the population travel over different distances with ridehailing services. However, this approach is still limited in that individuals from the two datasets, the California Millennials Dataset and the 2017 NHTS California subsample, may not present the same travel behavior for various reasons (e.g., sampling bias).

Third, while the analysis of this report aims to compute and compare the *combined* GHG emissions from both driving a personal vehicle and using ridehailing at an individual level, future more refined analyses at a more fine-grained level may be able to reveal behavioral patterns that are not easily examined in this report. For example, the examination of the impacts of using ridehailing services at a trip level may provide a behaviorally richer understanding of the relationships between ridehailing and other travel modes. At the trip level, the response of individuals to the availability and adoption of ridehailing may vary by trip purpose, time of a day, whether the traveler made the trip alone or in a group, other trip-specific characteristics (e.g., whether a trip is part of a two-leg or multi-leg tour), and the attributes of both the origin and destination of the trip. After all, the effect of using ridehailing on other travel modes is the sum of various types of behavioral changes. With a sufficient

sample size, the simulation at a geographically-aggregate level (e.g., Census tract) will be feasible, thus helping transportation planners and policymakers better understand the variations in the impacts of ridehailing; e.g., by region, time of a day and groups of users.

References

Alemi, F., Circella, G., Handy, S., & Mokhtarian, P. (2018a). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society, 13*, 88-104. doi:https://doi.org/10.1016/j.tbs.2018.06.002

Alemi, F., Circella, G., Handy, S. & Mokhtarian, P. (2018b). Exploring the Latent Constructs behind the Use of Ridehailing in California. *Journal of Choice Modelling*, 29, 47-62.

Alemi, F., Circella, G., Mokhtarian, P., & Handy, S. (*forthcoming*). What Drives the Use of Ridehailing in California? Ordered Probit Models of the Usage Frequency of Uber and Lyft, *Transportation Research Part C* (*accepted*).

Alemi, F., Circella, G., & Sperling, D. (2018). *Adoption of Uber and Lyft, Factors Limiting and/or Encouraging Their Use and Impacts on Other Travel Modes among Millennials and Gen Xers in California*. Paper presented at the 97th Transportation Research Board Annual Meeting, Washington, DC.

Ballús-Armet, I., Shaheen, S. A., Clonts, K., & Weinzimmer, D. (2014). Peer-to-peer carsharing: Exploring public perception and market characteristics in the San Francisco Bay area, California. *Transportation Research Record, 2416*(1), 27-36.

Baum-Snow, N., & Hartley, D. A. (2016). *Accounting for central neighborhood change, 1980-2010*. Retrieved from https://www.chicagofed.org/~/media/publications/working-papers/2016/wp2016-09-pdf.pdf (Accessed on September 26, 2018)

Blumenberg, E., Ralph, K., Smart, M., & Taylor, B. D. (2016). Who knows about kids these days? Analyzing the determinants of youth and adult mobility in the US between 1990 and 2009. *Transportation Research Part A: Policy and Practice, 93*, 39-54.

Blumenberg, E., Taylor, B. D., Smart, M., Ralph, K., Wander, M., & Brumbagh, S. (2012). *What's Youth Got to Do with It? Exploring the Travel Behavior of Teens and Young Adults*. Retrieved from https://www.its.ucla.edu/2015/10/20/whats-youth-got-to-do-with-it-exploring-the-travel-behavior-of-teens-and-young-adults/ (Accessed on September 26, 2018)

Buck, D., Buehler, R., Happ, P., Rawls, B., Chung, P., & Borecki, N. (2013). Are bikeshare users different from regular cyclists? A first look at short-term users, annual members, and area cyclists in the Washington, DC, region. *Transportation Research Record: Journal of the Transportation Research Board*(2387), 112-119.

Buehler, R., & Hamre, A. (2014). The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. *Transportation, 42*(6), 1081-1101. doi:10.1007/s11116-014-9556-z

Castiglione, J., Chang, T., Cooper, D., Hobson, J., Logan, W., Young, E., Charlton, B., Wilson, C., Mislove, A., Chen, L., & Jiang, S. (2016). *TNCs Today: A Profile of San Francisco Transportation Network Company Activity*. Retrieved from https://www.sfcta.org/sites/default/files/content/Planning/TNCs/TNCs_Today_112917.pdf (Accessed on September, 2018)

Chen, T. D., & Kockelman, K. M. (2016). Management of a shared autonomous electric vehicle fleet: Implications of pricing schemes. *Transportation Research Record: Journal of the Transportation Research Board*(2572), 37-46.

Circella, G. (2017). ICT-Dependent Life and Its Impacts on Mobility. In J. Zhang (Ed.), *Life-Oriented Behavioral Research for Urban Policy* (1st ed., pp. 149-173). Tokyo: Springer.

Circella, G., & Alemi, F. (2018). Transport Policy in the Dra of Ridehailing and Ohter Disruptive Transportation Technologies. In Y. Shiftan & M. Kamargianni (Eds.), *Advances in Transport Policy and Planning* (First ed., pp. 119-144). Cambridge, MA: Elsevier

Circella, G., Alemi, F., Tiedeman, K., Berliner, R. M., Lee, Y., Fulton, L., Mokhtarian, P. L., & Handy, S. (2017). *What Affects Millennials' Mobility? PART II: The Impact of Residential Location, Individual Preferences and Lifestyles on Young Adults' Travel Behavior in California*. Retrieved from: https://ncst.ucdavis.edu/wp-content/uploads/2015/09/NCST_Report_Millennials_Part_II_2017_March_31_FINAL.pdf (Accessed on September 26, 2018)

Circella, G., Alemi, F., Tiedeman, K., Handy, S., & Mokhtarian, P. L. (2018). *The adoption of shared mobility in California and its relationship with other components of travel behavior*. Retrieved from https://ncst.ucdavis.edu/wp-content/uploads/2016/10/NCST-TO-033.1-Circella_Shared-Mobility_Final-Report_MAR-2018.pdf (Accessed on September 26, 2018)

Circella, G., Fulton, L., Alemi, F., Berliner, R. M., Tiedeman, K., Mokhtarian, P. L., & Handy, S. (2016). *What Affects Millennials' Mobility? PART I: Investigating the Environmental Concerns, Lifestyles, Mobility-Related*. Retrieved from https://ncst.ucdavis.edu/wp-content/uploads/2014/08/05-26-2016-NCST_Report_Millennials_Part_I_2016_May_26_FINAL1.pdf (Accessed on September 26, 2018)

Clewlow, R. R., & Mishra, G. S. (2017). *Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States*. Retrieved from https://itspubs.ucdavis.edu/wp-content/themes/ucdavis/pubs/download_pdf.php?id=2752 (Accessed on September 2018)

Conway, M., Salon, D., & King, D. (2018). Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Science, 2*(3), 79.

Costain, C., Ardron, C., & Habib, K. N. (2012). Synopsis of users' behaviour of a carsharing program: A case study in Toronto. *Transportation Research Part A: Policy and Practice, 46*(3), 421-434.

Coutoure, V., & Handbury, J. (2017). *Urban revival in America, 2000 to 2010*. Retrieved from http://www.nber.org/papers/w24084.pdf (Accessed on September 26, 2018)

Delbosc, A., & Currie, G. (2013). Causes of youth licensing decline: a synthesis of evidence. *Transport Reviews, 33*(3), 271-290.

Feigon, S., & Murphy, C. (2016). *Shared mobility and the transformation of public transit*. Retrived from https://www.apta.com/resources/reportsandpublications/Documents/APTA-Shared-Mobility.pdf (Accessed on September 2018)

Firnkorn, J., & Müller, M. (2011). What will be the environmental effects of new free-floating car-sharing systems? The case of car2go in Ulm. *Ecological Economics, 70*(8), 1519-1528.

Frändberg, L., & Vilhelmson, B. (2011). More or less travel: personal mobility trends in the Swedish population focusing gender and cohort. *Journal of Transport Geography, 19*(6), 1235-1244.

Hall, J. D., Palsson, C., & Price, J. (2017). *Is Uber a substitute or complement for public transit?* Retrieved from http://individual.utoronto.ca/jhall/documents/Uber_and_Public_Transit.pdf (Accessed on September 26, 2018)

Hallock, L., & Inglis, J. (2015). *The Innovative Transportation Index*. Retrieved from http://www.uspirg.org/sites/pirg/files/reports/Innovative_Transportation_Index_USPIRG.pdf (Accessed on September 26, 2018)

Hampshire, R. C., Simek, C., Fabusuyi, T., Di, X., & Chen, X. (2018). *Measuring the impact of an unanticipated suspension of ride-sourcing in Austin, Texas*. Paper presented at the 97th Transportation Research Board Annual Meeting, Washington, DC.

Henao, A. (2017). *Impacts of Ridesourcing-Lyft and Uber-on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior*. (Unpublished doctoral dissertation). University of Colorado at Denver, Denver, CO.

Kolko, J. (2016, March 30). *Urban Revival? Not For Most Americans*. Retrieved from http://jedkolko.com/2016/03/30/urban-revival-not-for-most-americans/ (Accessed on September 26, 2018)

Kuhnimhof, T., Armoogum, J., Buehler, R., Dargay, J., Denstadli, J. M., & Yamamoto, T. (2012). Men shape a downward trend in car use among young adults—evidence from six industrialized countries. *Transport Reviews, 32*(6), 761-779.

Le Vine, S., Adamou, O., & Polak, J. (2014). Predicting new forms of activity/mobility patterns enabled by shared-mobility services through a needs-based stated-response method: Case study of grocery shopping. *Transport Policy, 32*, 60-68.

Lee, H. (2018). Are Millennials Coming to Town? Residential Location Choice of Young Adults. *Urban affairs review*, 1-40. doi:https://doi.org/10.1177/1078087418787668

Lee, Y., Circella, G., Mokhtarian, P. L., & Guhathakurta, S. (2018). *Are Millenials More Multimodal? A Latent-Class Analysis with Attitudes and Preferences*. Paper presented at the 97th Transportation Research Record Annual Meeting, Washington, DC, January 7-11, 2018.

McDonald, N. C. (2015). Are millennials really the "go-nowhere" generation? *Journal of the American Planning Association, 81*(2), 90-103.

Mishra, G. S., Clewlow, R. R., Mokhtarian, P. L., & Widaman, K. F. (2015). The effect of carsharing on vehicle holdings and travel behavior: A propensity score and causal mediation analysis of the San Francisco Bay Area. *Research in Transportation Economics, 52*, 46-55.

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part a-Policy and Practice, 83*, 14-29. doi:10.1016/j.tra.2015.11.001

Polzin, S. E., Chu, X., & Godfrey, J. (2014). The impact of millennials' travel behavior on future personal vehicle travel. *Energy Strategy Reviews, 5*, 59-65.

Ralph, K. M. (2017). Multimodal millennials? The four traveler types of young people in the United States in 2009. *Journal of Planning Education and Research, 37*(2), 150-163.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy, 45*, 168-178. doi:https://doi.org/10.1016/j.tranpol.2015.10.004

Rodier, C. (2018). *The Effects of Ride Hailing Services on Travel and Associated Greenhouse Gas Emissions*. Retrieved from https://ncst.ucdavis.edu/wp-content/uploads/2016/07/NCST-TO-028-Rodier_Shared-Use-Mobility-White-Paper_APRIL-2018.pdf (Accessed on September 26, 2018)

Sadowsky, N., & Nelson, E. (2017). *The impact of ride-hailing services on public transportation use: A discontinuity regression analysis*. Economics Department Working Paper Series, Bowdin College, Retrieved from https://digitalcommons.bowdoin.edu/cgi/viewcontent.cgi?article=1012&context=econpapers (Accessed on September 26, 2018)

Salon, D. (2015). Heterogeneity in the relationship between the built environment and driving: Focus on neighborhood type and travel purpose. *Research in Transportation Economics, 52*, 34-45.

Schaller, B. (2017). *Unsustainable? The Growth of App-Based Ride Services and Traffic, Travel and the Future of New York City*. Retrieved from http://www.schallerconsult.com/rideservices/unsustainable.htm (Accessed on September 26, 2018)

Schaller, B. (2018). *The New Automobility: Lyft, Uber and the Future of American Cities*. Retrieved from http://www.schallerconsult.com/rideservices/automobility.htm (Accessed on September 26, 2018)

Shaheen, S., Chan, N., Bansal, A., & Cohen, A. (2015). *Shared mobility: A sustainability & technologies workshop: definitions, industry developments, and early understanding*. Retrieved from http://innovativemobility.org/wp-content/uploads/2015/11/SharedMobility_WhitePaper_FINAL.pdf (Accessed on September 26, 2018)

Shaheen, S., & Cohen, A. (2018). Is It Time for a Public Transit Renaissance?: Navigating Travel Behavior, Technology, and Business Model Shifts in a Brave New World. *Journal of Public Transportation, 21*(1), 8.

Taylor, B. D., Chin, R., Crotty, M., Dill, J., Hoel, L. A., Manville, M., Polzin, S., Schaller, B., Shaheen, S., Sperling, D., Zafar, M., & Zielinski, S. (2016). *Between Public and Private Mobility: Examining the Rise of Technology-Enabled Transportation Services.* Retrieved from http://www.trb.org/Main/Blurbs/173511.aspx (Accessed on September 2018)

US EPA. (2018a). Fuel Economy Data. Fuel Economy Data Retrieved September 19, 2018, from U.S. Environmental Protection Agency. Retrieved from https://www.fueleconomy.gov/feg/download.shtml (Accessed on September 26, 2018)

US EPA. (2018b, March 13, 2018). Greenhouse Gases Equivalencies Calculator. Retrieved from https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references (Accessed on September 26, 2018)

Zipcar. (2013, February 27th). Millennials & Technology: A Survey Commissioned by Zipcar. Retrieved from http://www.slideshare.net/Zipcar_Inc/millennial-slide-share-final-16812323 (Accessed on September 26, 2018)