Title

Drivers of Change in a World of Mobility Disruption: An Overview of Long Distance Travel, Shared Mobility, and Automated Vehicles

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Drivers of Change in a World of Mobility Disruption:
An Overview of Long Distance Travel, Shared Mobility, and Automated Vehicles

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Abstract

Electrification, automation, and shared mobility, known as the 3 Revolutions (3R) will fundamentally change transportation globally. The 3 Revolutions are coming, and they will change existing travel behavior such as long-distance trips and create new questions such as who will drive for shared mobility and who will buy automated vehicles. Long distance travel, drivers for on-demand ride services, and the adoption of automated vehicles have been of recent interest to researchers, stakeholders, and policy makers but have just begun to be studied.

Long-distance travel research is limited due to the lack of robust data and the complexity of defining a long-distance trip. The patterns of infrequent long-distance trips are poorly understood especially compared to the better studied (and understood) local daily travel patterns. This study contributes to filling that gap by investigating the factors that affect the frequency of long-distance trips of Californian millennials and members of the preceding Generation X. The data used was collected with an online survey administered in fall 2015 to study the mobility of these age groups. The survey collected information on several travel-related variables, including the number of long-distance trips (defined as trips longer than 100 miles, one way) made by various modes during the previous 12 months. Six negative binomial regression models of long-distance travel separated by purpose (business or leisure) and mode (overall travel versus air) are estimated. The study explores the relationship of long-distance trip formation with several sociodemographic, land use and attitudinal variables. Consistent with expectations, individual income positively affects the number of long-distance trips made by each individual. Among the attitudinal variables, the individuals who are adventurers, have higher "variety seeking" attitudes and are more interested in adopting new technologies are found to make a larger number of long-distance trips. On the other hand, those who prefer to shop in brick-and-mortar stores rather than online are found

to have lower levels of long-distance travel.

Lyft and Uber are two on-demand ride-service providers in the current landscape of shared mobility. In this chapter, focus is shifted from on-demand ride-sharing passengers to the drivers – a topic to which little attention has been paid but may have a significant impact on car ownership and the derived environmental and social benefits of shared mobility. For this study, data provided by Kelley Blue Book from its nationwide survey of U.S. residents ages 18 to 64 that collected information on shared mobility awareness and usage, vehicle ownership, aspirations for future vehicle ownership, and attitudes on shared mobility and vehicle ownership is used. An ordinal logit model is estimated to understand the willingness to drive for an on-demand ride-service. The individuals who report higher VMT and have more children are more willing to become drivers. Furthermore, the introduction of attitudinal factors leads to finding that those who have positive attitudes towards ride-sharing are more interested in driving. Those who enjoy driving are also more likely to be interested in driving for an on-demand ride-service.

Research on vehicle automation is one of the most current topics in transportation. Some of the questions plaguing the research community include design, cost, and adoption. Many of these questions will remain unanswered until automated vehicles are available to the consumer. In this study, a sample of California new electric vehicle buyers to understand if and how current adopters of new vehicle technologies will adopt automated vehicles is used. Many respondents are interested in purchasing an automated vehicle but indicate that they only have average knowledge of the technology. Using an ordinal logit model, the interest in purchasing a fully-automated vehicle is studied and find that younger men who purchase higher cost vehicles are more interested in purchasing a fully-automated vehicle. Above all else, those who perceive automated vehicles as being safer than non-automated vehicles have an interest in purchasing an automated vehicle.

Contents

Acknowledgements

For my family and friends.

Introduction

Electrification, automation, and shared mobility, known as the 3 Revolutions (3R) will fundamentally change transportation globally. The 3 Revolutions are coming, and they will change existing travel behavior such as long-distance trips and create new questions such as who will drive for shared mobility and who will buy automated vehicles. My dissertation looks at the transitions focusing on three questions of current and future behavior:

1) What is the current landscape of long-distance travel? How will it change once the 3 Revolutions are realized?
2) Who will drive for shared mobility? More specifically, who will drive for on-demand ride services?
3) Who will adopt automated vehicles once they are introduced to the market? What are these individual's socio-demographic and socio-economic backgrounds?

This work comes at a time when the 3 Revolutions should no longer be considered a possibility but an inevitability. Vehicle electrification has already begun to occur throughout the world, but shared mobility and vehicle automation will take longer.

Long distance travel, drivers for on-demand ride services, and the adoption of automated vehicles have been of recent interest to researchers, stakeholders, and policy makers but have just begun to be studied. Long distance travel is typically underreported and underestimated in many studies, but one study found that long distance road trips of over 100 miles represent about 20% of the VMT in the United States (Gross and Feldman 1998). In a newer study of electric vehicle households, long distance travel constitutes about 10% of the household's VMT and about 20% of the vehicle's VMT (cite LD EV TRB paper). Vehicle automation may change the annual VMT attributed to long distance travel as well as the number of long distance trips taken annually. Fully automated vehicles are not currently available for mainstream consumers but among early adopters of new vehicle technologies, such as electric vehicles, have indicated an interest in purchasing them when they are made available. The availability of automated vehicle will change the dynamic of shared mobility services, in particular, transportation network companies, such as Uber or Lyft. The introduction of automated vehicles into their fleets will deplete the number of drivers in their workforce; however, until then it is important to understand those that are interested in driving for these services as their interests may change vehicle ownership and usage pattern and compete with the introduction of automated vehicles.

In the past, long distance travel had not been thoroughly researched. Historically, the data and models used for travel demand forecasting in the United States have typically been focused on the daily, more routine, trips and/or tours made by individuals in their home regions. This focus is consistent with Metropolitan Planning Organizations' (MPOs) planning interests, as they conduct planning in large urban areas where congestion management has dominated the infrastructure investment priorities since the 1950s. While many states have statewide travel demand models that simulate all components of travel demand (including long-distance travel), limited data are available on long-distance travel to calibrate these models. Interest in long-distance travel behavior has grown among researchers and stakeholders in recent years; but data collection among state agencies has been limited. In 2016, six "add-on" agencies collected limited long-distance data using their extra questions and asked respondents to report the number of trips over 50 or 75 miles they had taken in the previous eight weeks (Westat 2015). To date, only a limited number of states - Utah, Ohio, Michigan and California - have conducted dedicated long-distance travel data collection (California Department of Transportation 2013). In estimating the factors that impact the number of long-distance trips, we hoped to understand how the younger millennial generation traveled differently than the older generation X. Millennials will most likely be among the first to use automated vehicles (cite my Transportation part F paper) and are more likely to be drivers for on-demand ride services (cite transportation letters paper), all of which feeds into the 3 Revolutions: electrification, automation, and shared rides.

Shared mobility services and on-demand ride sharing services are dynamic and quickly changing the mobility needs and desires of many individuals. In a society without automated vehicles, on-demand ride services need to have drivers for these services to operate. On-demand ride service drivers are similar to on-demand ride service users with a caveat – those interested in driving for on-demand ride services have children (cite transportation letters). With more than 40 million monthly riders, many ride service researchers have focused their research on the rider (Clewlow, Mishra, and Laberteaux 2017; Rayle et al. 2014). Some research focuses on driver safety (Feeney 2015) and other research on driver wages (Berger and Frey 2017; Henao and Marshall 2017). To date, there is very little research on driver characteristics. This work begins to fill in that gap by studying individuals interested in becoming drivers for these on-demand ride services. Research on drivers is relatively sparse. Understanding driver characteristics can help transportation planners understand the changing nature of roadway users and potential increases in vehicle-miles traveled (VMT). In terms of the three revolutions, on-demand ride services are akin to automated vehicles – a vehicle is hailed through a smartphone application, like calling your vehicle to pick you up; the vehicle arrives, but it is equipped with a driver; and after the ride is finished, there is no need to park and the vehicle leaves. Furthermore, by understanding the potential drivers and their motivations for driving, the transition to what is most successful for one of the revolutions, shared rides, can be studied – if individuals are interested in driving for social reasons instead of monetary reasons, a social driver may be key to enticing riders to share their ride.

The last revolution, electrification goes hand in hand with automation. If policy makers work with the vehicle manufacturers, automated vehicles will not be introduced to consumers with a gas tank, but instead a plug. In the last section of this work, I am interested in looking at the adoption of automated vehicles. The first step to understanding the adoption of new vehicle technology is to look at those who have already purchased other types of new vehicle technology. Focusing on early adopters of new vehicle technology, instead of surveying the general population, is important for understanding who are more likely to be the potential buyers of automated vehicles. The first buyers of new vehicle technology are different than those who adopt the technology later; therefore, a study of the general population would not be appropriate as these consumers are likely to be unknowledgeable about automated vehicles and are thus unlikely to purchase a new vehicle technology. Buyers of electric vehicles on the other hand have demonstrated that they are early adopters by purchasing a new vehicle technology. By surveying these consumers this study will produce results that are representative of the perceptions of those who are likely to purchase new vehicle technologies, rather than being representative of the general population. This method of surveying early adopters attitudes towards new technologies has been previously used in studies of electric vehicles and fuel cell vehicles (Egbue and Long 2012; Hardman et al. 2016).

Understanding traditional travel behavior such as long-distance travel and learning about new travel behavior such as on-demand ride service drivers and an individual's interest in adoption automated vehicles are all part of the larger three revolutions. The remainder of this dissertation is as follows: the first part looks at long-distance travel among Californian young adults; the second part of this paper presents an in-depth look at potential on-demand ride service drivers; the third part of this dissertation presents an analysis that begins to understand who will adopt automated vehicles in California; and finally, the conclusions will present policy implications based on the research presented.

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PART – I

Paper 1: Exploring the Self-Reported Long-Distance Travel Frequency of Millennials and Generation X in California

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EXPLORING THE SELF-REPORTED LONG-DISTANCE TRAVEL FREQUENCY OF MILLENNIALS AND GENERATION X IN CALIFORNIA

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Abstract
Long-distance travel research is limited due to the lack of robust data and the complexity of defining a long-distance trip. The patterns of infrequent long-distance trips are poorly understood especially compared to the better studied (and understood) local daily travel patterns. This study contributes to filling that gap by investigating the factors that affect the frequency of long-distance trips of Californian millennials (18-34 years old, in 2015) and members of the preceding Generation X (ages 35-50 years, in 2015). We use data collected with an online survey administered in fall 2015 to study the mobility of these age groups. The survey collected information on several travel-related variables, including the number of long-distance trips (defined as trips longer than 100 miles, one way) made by various modes during the previous 12 months. We estimate six negative binomial regression models of long-distance travel separated by purpose (business or leisure) and mode (overall travel versus air). The study explores the relationship of long-distance trip formation with several sociodemographic, land use and attitudinal variables. Consistent with expectations, individual income positively affects the number of long-distance trips made by each individual. Among the attitudinal variables, the individuals who are adventurers, have higher "variety seeking" attitudes and are more interested in adopting new technologies are found to make a larger number of long-distance trips. On the other hand, those who prefer to shop in brick-and-mortar stores rather than online are found to have lower levels of long-distance travel.

Keywords: Long-distance travel, Air travel, Personal attitudes, Millennials, California

1. Introduction

The data and models used for travel demand forecasting in the United States have typically been focused on the daily, more routine, trips and/or tours made by individuals in their home regions. This focus is consistent with Metropolitan Planning Organizations' (MPOs) planning interests, as they conduct planning in large urban areas where congestion management has dominated the infrastructure investment priorities since the 1950s. While many states have statewide travel demand models that simulate all components of travel demand (including long-distance travel), limited data are available on long-distance travel to calibrate these models. For example, the 2009 and 2016 National Household Travel Surveys (NHTS) did not collect information on long-distance or intercity travel within the main surveys. In 2016, six "add-on" agencies collected limited long-distance data using their extra questions and asked respondents to report the number of trips over 50 or 75 miles they had taken in the previous eight weeks (*1*). To date, only a limited number of states - Utah, Ohio, Michigan and California - have conducted dedicated long-distance travel data collection (*2*).

Many recent reports, such as Circella et al. (*3*) have addressed current changes in travel behavior including the leveling of vehicle miles of travel (VMT) per person through the late 2000s. However, few of these evaluations explore the relationship between daily travel and the infrequent, but much longer, trips between regions, many of which include overnight stays. Within this landscape of limited data, indications are that long-distance travel is increasing. In 2016, more than 3.2 trillion miles were driven on U.S. roadways. In December 2016, drivers put more than 263.6 billion miles on roadways which represents an increase of 0.5% from the previous year (*4*). In April 2017, air travel load factors crept up to 84 percent, and enplanements hit 70,000,000 (*5*, *6*). Highway and Interstate congestion and the need for more targeted public planning and investments in airports, intercity rail and other modes necessitates that researchers improve their understanding of the factors influencing long-distance travel.

This paper exploits an existing dataset collected with an online survey of Californians in which questions were added about self-reported annual long-distance travel to answer the following research questions:

1. What are the characteristics of long-distance travel of Californian millennials and Gen Xers?
2. What is the association of sociodemographic, geographic, and attitudinal factors with the frequency of long-distance trips?
3. What is the relationship between the attributes of one's local daily travel and one's long-distance travel?

The remainder of the paper is organized as follows. After a summary of the literature describing the factors that are associated with one's level of long-distance travel, we describe the survey data source and the attitudinal variables used in the study. We then present a set of six negative binomial regression models and discuss the factors that are found to affect the self-reported long-distance trip rates. Finally, the conclusions of the paper present some summary remarks and implications for future research, focusing on the need for additional data to better understand long-distance travel.

2. Literature review

Long-distance travel patterns have received limited attention by researchers and modelers. Challenges, from defining what constitutes a long-distance trip to the availability of robust data, plague researchers. Thus, the gaps in knowledge are numerous especially compared to the better understood local daily travel patterns. There is no standard long-distance trip length definition. Further, long-distance are sometimes defined temporally and sometimes spatially. The American Community Survey (ACS) defines a "long commute" as 60 minutes or longer, in one direction (*7*).

Other studies define long-distance travel spatially where one-way distances range from 50-100 miles (*8–11*). Additionally, some studies take a hybrid temporal-spatial approach that focus on trip distance and trip duration to define long-distance trips that include an "overnight stay" (*8*, *12*). A larger number of long-distance travel studies have been conducted in Europe where long-distance datasets are more common and the smaller physical size of countries allows the definition to be based on whether a destination is out-of-country. In this study, a long-distance trip is defined as a one-way trip of 100 miles or longer, therefore focus is given to previous studies that define long-distance travel in a similar context. Attention is paid to studies that focus on the factors related to long-distance travel (*11–14*). Furthermore, interest is given to studies that separate leisure from business travel as our survey did (*8*, *11*, *12*, *14–17*).

Of great interest to this research are the factors that affect long-distance travel. Many studies rely on nationally available data and trip diaries— to date, no study uses attitudinal factors to estimate long-distance travel. A study of long-distance trips made by residents of the United Kingdom and the Netherlands in 1998, Limtanakool et al. (*13*) used binary logit models, showing that men and individuals with higher income make more long-distance trips by private car and train. They also observed that women are less likely to engage in medium- and long-distance commuting (*13*). Similarly, Aultman-Hall et al. (2016) used data from a longitudinal panel of 628 individuals from the United States and Canada who reported information on their long-distance overnight trips monthly with a series of online surveys for approximately one year between February 2013 and February 2014 (*8*). They found that men make more long-distance work trips and air trips annually than women. However, a different study involving the analysis of 6.4 million flight bookings in 2014 found that women make more long-distance airplane business trips than men (*18*). Using data from the 1995 American Travel Survey, Georggi and Pendyala (*11*) estimated linear regression models of long-distance trip generation, segmented by household income per person, which showed that individuals with higher income made more business trips and overall a higher number of trips per year. Using data from random-day trip diaries and long-distance trips questionnaires from the 2008 national household travel survey "Mobility in Germany" (MID), Holz-Rau et al. (*12*) estimated Heckman models and ordinary least squares regression models which found residents in low-density neighborhoods make fewer long-distance trips than those living in high density neighborhoods. Using an ordered probit to model the frequencies of long-distance business and long-distance leisure trips on data from self-reported retrospective surveys collected from about 1,200 respondents from the United States in 2013, LaMondia et al. (*14*) observed that education and income increased most types of long-distance travel but age generally decreased long-distance trip frequency.

Trip type is also an important factor in long-distance travel: how do business travel and personal travel differ? In some cases, respondents have difficulty separating the two trip types. In their study, Aultman-Hall et al. (*8*) observed that in their dataset 14% of trip tours had mixed purposes. Furthermore, 16% of total tours were spatially complex "hub and spoke" and an additional 4.5% were "circular chains"; meaning that trips are complex in terms of purpose and in terms of space. Using negative binomial regressions, Aultman-Hall et al. (*8*) estimated six models for long-distance travel: all long-distance travel, work travel for full-time workers, work travel for those traveled overnight once during the survey year, personal travel, air travel, and personal air travel. For the air, work, and leisure travel, age and household income over $100,000 positively impacted the number of tours (*8*). Additionally, longer daily commutes indicate a higher number of personal long-distance tours but is insignificant in determining work-related tours (*8*). In another study, Georggi and Pendyala (*11*) observed that the frequency of long-distance trip purposes were different across income and age groups – high income-per-person households made more business trips but less recreational trips and younger age groups made more recreation and business trips than those in older age groups.

In summary, prior literature has generally found that higher income and traveling for work increase overall levels of long-distance tours. Some studies find gender and age are important. Long-distance travel is complex requiring more data and studies to better understand the phenomena.

3. Data and Methods

3.1 Data Description

This paper stems from a detailed study of young adult mobility in California (*19*). As part of this project, a detailed cross-sectional online survey was designed and administered to a sample of more than 1,900 California residents between the ages of 18 and 50 years, recruited through an online opinion panel. The survey was administered between September and December 2015. The survey collected information on personal attitudes and preferences towards travel, technology, social media, the environment, life satisfaction, land use, etc., as well as information on lifestyles, residential location and travel patterns, adoption of shared mobility, current travel behavior, past travel, driver's licensing, level of vehicle ownership, socio-demographic traits and several additional factors that may affect respondents' mobility and vehicle ownership. The final dataset available for the project includes 1,975 valid cases, after removing cases with severely incomplete or inconsistent information. For additional information about the project, the survey content and the data collection process, see (*20*).

We geocoded the data using the US Census Master Address File/TIGER version 2015 (*21*), the ESRI database (*22*), and the Google database (*23*). Using the self-reported information (addresses) on the respondent's residential and work locations, we were able to geocode almost all observations in our sample with a good level of precision (block group, or even individual block, for most respondents). Once we geocoded the respondents' home and work locations, we assigned neighborhood types to each respondent's home and work/school (if applicable) location relying on the classifications from Salon (*24*). Additionally, we imported additional land use data from external sources such as the U.S. EPA's Smart Location data (*25*) based on the geocoded residential location. The additional data allowed us to control for land use characteristics and population densities in the place of residence.

Table 1 summarizes selected descriptive statistics of the final sample used in this paper, which was reduced to 1,512 for this modeling effort based on disqualification metrics described in detail in Section 3.2. The average person in our final dataset is female, employed, almost 34 years old, has a bachelor's degree, and lives in a household with an annual income of $76,879. However, as evident in Table 1, the sample contains a range of income and education levels for adults aged 18 to 50 years old. Most respondents were workers although just over a quarter of the sample did not work.

TABLE 1 Descriptive Statistics of the Final Working Dataset (N=1,512)

Characteristic	N (%)
Gender	
Male	611 (*40.4*)
Age	
18 to 24	260 (*17.2*)
25 to 34	584 (*38.6*)
35 to 44	449 (*29.7*)
45 to 50	219 (*14.5*)
Education level	
Some grade/ high school	23 (*1.52*)
High school diploma	158 (*10.5*)
Some college/ technical school	405 (*26.8*)
Associate's degree	174 (*11.5*)
Bachelor's degree	530 (*35.1*)
Graduate degree (e.g. MS, PhD, etc.)	165 (*10.9*)
Professional degree (e.g. JD, MD, etc.)	52 (*3.44*)
Decline to state	5 (*0.33*)
Neighborhood Type	
Urban	290 (*19.2*)
Suburban	744 (*49.2*)
Rural	478 (*31.6*)
Employment	
Employed full-time	771 (*51.0*)
Employed part-time	261 (*17.3*)
Two or more jobs	34 (*2.25*)
Unpaid work	28 (*1.85*)
Homemaker/unpaid caregiver	258 (*17.1*)
Does not work	160 (*10.6*)

Characteristic (sample/pop. size)	N (%)
Annual Household income	
Less than $15,000	86 (*5.69*)
$15,000 to $24,999	111 (*7.34*)
$25,000 to $34,999	129 (*8.53*)
$35,000 to $49,999	202 (*13.4*)
$50,000 to $74,999	364 (*24.1*)
$75,000 to $99,999	247 (*16.3*)
$100,000 to $149,999	239 (*15.8*)
More than $150,000	134 (*8.86*)

Continuous Variables	Mean	SD
Age (years)	33.9	8.7
Household income	$76,879	$51,192
Household size	3.08	1.56
Number of HH vehicles	1.80	0.97
Long-distance Business Trips	3.77	13.37
Long-distance Leisure Trips	5.74	8.45
Total Long-distance Trips	9.49	18.03
Long-distance Airplane Business Trips	0.69	2.47
Long-distance Airplane Leisure Trips	1.01	1.77
Total Long-distance Airplane Trips	1.70	3.49

3.2 Data Cleaning/Disqualification Metrics

This study tries to gain a deeper understanding of long-distance travel among California millennials. As part of this, we looked at self-reported round-trip long-distance trips by mode, described as one-way trips of over 100 miles, in the last 12 months. While many of the long-distance trips reported fell within a reasonable number of trips, based on prior studies by our team (*8*), we found that several respondents indicated an excessively large number of long-distance trips.

Moreover, a significant number of people indicated no trips as compared to existing databases suggesting respondents skipped these questions that were near the end of the survey due to burden.

To address these issues, the team developed disqualification metrics that were applied to clean the sample. In general, observations with more than 100 long-distance car trips were removed from this analysis if the commute distances and/or self-reported weekly VMT could not explain such large amount of car travel. We recognize that self-reported VMT is typically under-reported for low mileage groups and over-reported for high mileage groups (*23*): in order to account for such good-faith underreporting of a respondent's VMT, we decided that the case would be disqualified if the self-reported VMT did not cover at least 50% of the minimum mileage needed for the reported number of long-distance car trips. For cases where the total long-distance round-trip count was over 100 per year, we reviewed the case to check for validity and consistency throughout the survey (e.g. variables measuring employment and work trips, to check whether the individual is employed and makes work trips, has a driver's license, has access to a vehicle, etc); as a result of this process, in most instances we excluded the cases from the analysis. Additionally, we looked at observations were the total count of long-distance round-trip "non-auto" modes, e.g. train, airplane, etc. was over 30 per year. We also focused on cases where the reported annual household income was below $20,000 but the respondent made more than five commercial airplane trips (for either leisure or business). Similarly, we also identified and investigated households with an annual income below $20,000 who reported any business trips made by plane. The last "over-reported" disqualification metric was aimed at individuals who indicated that they "do not work" and they were not in school but who reported that they made any business trips in the previous 12 months. We included individuals that are homemakers, unpaid caregivers, and volunteers in the analysis since any of these professions could incur "work" (or non-leisure/non-personal) travel. The "over-reported" long-distance trip disqualification metric flagged 100 cases for review; 76 of which resulted in exclusion. The remaining 24 cases were mostly individuals who fell into the low household income category – while we examined these cases for unusual travel, there was nothing in their responses that further disqualified them from being included in our analysis.

Due the coding system used in the online platform, we were unable to distinguish between missing values and inputted zeros for the long-distance questions. Consequently, developing metrics for under-reported long-distance travel proved challenging. While it is reasonable to check for consistency for over-reported trips, data from a recent one-year panel (*8*), showed that while three people in the 628-person panel reported no long-distance travel in their stated responses, their actual monthly travel reported over a year differed – the three people who reported no typical long-distance travel in a year, made at least one overnight trip in the panel year. In looking at under-reported long-distance, the team concluded that all respondents who reported both no long-distance business trips and no long-distance leisure trips would be excluded from the analysis; meaning that an additional 367 individuals were excluded from the analysis. Therefore, the models presented here should be considered analysis of travel frequency for those reporting at least one long-distance trip of more than 100-mile one-way in a year.

4. Model

4.1 Model Specification

For this analysis, we estimated negative binomial regression models to explore the relationships between the number of self-reported long-distance round-trip trips, by purpose and mode, taken within the last 12 months and socio-demographic and socio-economic characteristics, residential location, and personal attitudes.

The authors estimated six negative binomial regression models: 1) total number of long-distance business trips, 2) total number of long-distance leisure trips, 3) total number of long-distance business airplane trips, 4) total number of long-distance leisure airplane trips, 5) total number of long-distance plane trips, and 6) total number of long-distance trips.

4.2 Dependent Variables

Survey respondents were asked to report the number of long-distance round-trip trips made in the past 12 months by either car, airplane, train, bus, or another mode. Long-distance trips were defined as a trip longer than 100 miles, one-way. Those who used multiple modes for the long-distance trip were asked to only report the mode that was used for the longest part of the trip to avoid double counting long-distance trips. For instance, if a respondent drove 110 miles to get to their closest airport to fly 800 miles and did the same for the trip back, that individual would have recorded this trip in the airplane category. Furthermore, respondents were asked to categorized trips as either business/work-related or leisure/personal.

As one might expect, most individuals made very few long-distance trips. Generally, respondents made more leisure trips than business trips. In fact, on average respondents made approximately 3.7 business trips and 5.7 leisure trips. Unsurprisingly, the number of airplane trips was considerably lower than the total number of long-distance trips. An average of 1.0 long-distance leisure airplane trips and 0.7 long-distance business airplane trips were made by respondents. This information is summarized in Table 1.

4.3 Explanatory Variables

We tested the inclusion of several groups of explanatory variables. The final version of the models included a total of 21 variables, distributed throughout the six models. These variables were selected on their expected relationship with long-distance travel and were found to be statistically significant in the estimated models. Additionally, we checked the correlation between predictors and found it to be generally negligible — only rather low correlations (lower than 0.25) were observed among the predictors.

The 21 variables can be grouped into four categories: (1) individual characteristics; (2) residential location neighborhood type; (3) factor scores extracted from attitudinal variables from the dataset; and (4) level of travel including modes used for daily travel and total vehicles-mile traveled in the average week (note this VMT excludes air travel and therefore reduces the risk of endogeneity).

We controlled for socio-demographic characteristics in our models by using variables for age, gender, and individual income. A continuous variable for individual income was used to evaluate if individuals with higher income had a larger number of long-distance trips. We explicitly controlled for residential location using a home neighborhood type variable that was geocoded based on a respondent's home address. We hypothesized that individuals living in urban neighborhood types made more long-distance trips based on background literature.

4.3.1 Attitudinal Variables

There were 65 separate statements in the survey that were included to measure individuals' attitudes about several dimensions related to the environment, travel, technology adoption, multi-tasking, life satisfaction, land use, the role of government in travel, etc. We conducted a multi-round factor analysis using principal axis factoring with an oblique rotation to extract the final 14 factors that combine the information available in the attitudinal sections of the study. More specifically, when we attempted to initially extract factors, we included all 65 attitudinal variables. From this first attempt, 19 factors were extracted. However, there were nine attitudinal variables that did not load heavily (at least 0.25) on to any one factor. We wanted to have a factor analysis where all variables used to extract factors would load onto at least one factor with at least a 0.25

loading. Therefore, we removed those 9 variables and reran the factor analysis with the same factoring method and rotation. We continued this procedure until every attitudinal variable being analyzed loaded onto at least one factor with a 0.25 loading. The factors presented in this paper are the result of a 5-round factor analysis. The final set of 14 factors explains 58.6% of the variance. The final models included 10 factor scores as listed in Table 2.

4.3.2 Levels of Local Routine Travel

In addition to the socio-demographic, residential choice, and attitudinal variables, we also control for a person's overall level of travel in our models. For both leisure and business long-distance trips, we used the self-reported weekly vehicle miles traveled as an explanatory variable. We recognized that there was a potential risk of endogeneity with the inclusion of self-reported weekly VMT variable in the non-airplane models of long-distance travel: in fact, many travelers might report a higher level of self-reported VMT because they make more long-distance trips by car (and not the opposite). Accordingly, we also tested model specifications in which we dropped this variable from the model estimation. Removing the weekly VMT variable from the model had a limited impact on the magnitude of the other coefficients, which remain rather stable, which reassured us about the limited effects that the inclusion of this variable have in affecting the final model solution.

When modeling business long-distance trips, we specifically controlled for primary commute mode and commute distance. For long-distance leisure trips, we controlled for the patterns of short distance trips by mode and the adoption of shared mobility. Further, to uncover a relationship between leisure and business travel, we used a dummy variable to indicate if a business trip had been made when estimating the number of long-distance leisure trips. We hypothesize based on Aultman-Hall et al. (*8*) that long-distance business and leisure travel patterns are related entities.

TABLE 2 Factor analysis loadings table

Factors and associated statements	Factor Loadings
Traditional shopper	
I prefer to shop in a store rather than online	1.029
I enjoy shopping online	-0.368
I enjoy the social aspects of shopping in stores	0.332
Pro-environmental policies	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.918
We should raise the price of gasoline to provide funding for better public transportation.	0.854
To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle.	0.254
The government should put restrictions on car travel in order to reduce congestion.	0.339
Tech-Savvy	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.719
Getting around is easier than ever with my smartphone.	0.594
I like to be among the first people to have the latest technology.	0.38
Social media (e.g. Facebook) makes my life more interesting.	0.359
Traditional Thinking	
Greenhouse gases from human activities are creating major problems.	-0.71
Any climate change that may be occurring is part of a natural cycle.	0.682
It is pointless for me to try too hard to be more environmentally friendly because I am just one person.	0.419
It is more important for men than for women to have a high-paying career.	0.384
At work, it is perfectly fine for women to have authority over men.	-0.371
Adventurer	
I like trying things that are new and different.	0.562
I like to juggle two or more activities at the same time.	0.323

Factors and associated statements	Factor Loadings
Commute loving	
My commute is stressful.	-0.793
My commute is generally pleasant.	0.66
Traffic congestion is a major problem for me personally.	-0.576
The time I spend commuting is generally wasted time.	-0.538
Getting stuck in traffic does not bother me that much.	0.328
Pro-suburban	
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to.	0.771
I prefer to live close to transit even if it means I will have a smaller home and live in a more crowded area.	-0.676
I like the idea of living somewhere with large yards and lots of space between homes.	0.443
I like the idea of having different types of businesses (such as stores, offices, restaurants, banks, library) mixed in with the homes in my neighborhood.	-0.342
Established in life	
I am already well-established in my field of work.	0.733
I am still trying to figure out my career (e.g. what I want to do, where I will end up).	-0.623
I am generally satisfied with my life.	0.409
Long-term suburbanite	
I picture myself living long-term in a suburban setting.	0.829
A house in the suburbs is the best place for kids to grow up.	0.556
I picture myself living long-term in an urban setting.	-0.323
Practical (anti-materialistic)	
I prefer to minimize the material goods I possess.	0.439
To me, a car is just a way to get from place to place.	0.42
I would/do enjoy having a lot of luxury things.	-0.413
The functionality of a car is more important to me than its brand.	0.355
For me, a lot of the fun of having something nice is showing It off.	-0.325
I like to be among the first people to have the latest technology.	-0.289

In future extensions of the research, we plan to expand on this topic, and better capture the relationships between long-distance business and leisure trips through the estimation of joint models of long –distance business and leisure trips.

5. Model Results

Based on initial exploratory analysis and descriptive statistics on the dependent variables, we found that the variables have a negative binomial distribution and thus we used negative binomial regression. We estimated six models (Tables 3 and 4) to understand which factors impact long-distance travel.

Table 3 contains the models for the number of long-distance leisure trips, the number of long-distance business trips, and the number of total long-distance trips. The columns are labeled by dependent variable. The columns labeled exp(β) represent the odds-ratio of the parameter. Interpretation is similar to that of a Poisson model; for dummy variables, if exp(β) is 1.2, this can be interpreted as that group (who has that characteristic) making 20% more long-distance trips. For continuous variables, such as income or age, an exp(β) value of 1.10 means that each unit increase is interpreted as a 10% increase in the number of long-distance trips.

The socio-demographic characteristics used in these models provided interesting insight into long-distance travel. As expected, age is negatively correlated with the total number of long-distance trips and the number of long-distance leisure trips – the older individuals in this sample are not traveling as much as the younger individuals. Gender played a role in the number of long-distance leisure trips; men made fewer long-distance leisure trips than women and not by a trivial amount— approximately, 17.1% fewer trips. Both (*8*, *13*) find that men on average make more long-distance trips than women; however, this analysis yields the opposite result. Individual income is positively correlated with the number of long-distance business trips and the total number of long-distance trips. Those living in an urban neighborhood, when compared to a rural neighborhood, made more long-distance business trips and overall number of trips. Urban workers may work for companies that require more business travel and make more long-distance business trips than those in rural environments.

An individual's overall level of vehicle travel as measured by commuting and VMT also affected the number of long-distance trips made in the prior 12 months. Longer commutes were indicative of more long-distance business travel. Since long-distance travel did not explicitly exclude long commutes, the number of long-distance trips reported may include commute trips. Similarly, the reported weekly VMT had a small but positive impact on the total number of long-distance leisure and overall trips. For the long-distance business trip model, we also considered the primary commute mode. Those who commuted by an active mode (e.g. bike, walk, etc.) made more long-distance business trips than those who commuted by transit/work-provided shuttle (transit). Similarly, those who commuted by private vehicle made more long-distance business trips than those who commuted by transit. Those who have never used carsharing services (e.g. Zipcar) made fewer leisure trips than those who have used them. All these effects might signal the impact of some latent construct associated with more traditional lifestyles and perhaps belonging to less affluent and less dynamic sociodemographic groups.

In this paper, in place of estimating a joint model for long-distance leisure and long-distance business trips (which remains a direction for future research for this study), we used an indicator variable for business trips in the leisure model. We find that those who make no long-distance business trips tend to make 21% fewer long-distance leisure trips. Like the active-mode commuters, those who bike for short distance trips make more long-distance leisure trips than those who do not bike.

To the best of the authors' knowledge, this is the first study that incorporates attitudinal factors into an analysis of long-distance travel. The inclusion of factors extracted from the attitudinal variables provided more insight into further understanding long-distance travel. Individuals who score highly on the traditional thinking factor made fewer long-distance leisure trips, while those who score highly on the "established in life" make more long-distance trips. The "traditional thinker" factor has the largest effect on long-distance business travel. In fact, its effect on long-distance business travel is almost twice as much as the most influential total long-distance travel factor and almost three times more influential than the strongest long-distance leisure factor – both are highly influenced by the "adventurer" factor.

The second most influential factor on long-distance travel is the "tech-savvy" factor. Further, individuals who feel as though they do not have a grasp on their career, life, or are not generally satisfied with the state of their life may not be interested in or able to take long-distance trips. Those who scored highly on the "adventurer" factor made more long-distance trips – adventurers may not be satisfied with business as usual and perhaps look at travel (for whatever reason) for variety. On the other hand, those who scored highly on the "traditional shopper" factor make fewer trips. As in the overall long-distance travel models, those who live in predominantly urban neighborhoods make more long-distance airplane trips; this could be due to the proximity to airports or the emergence of lifestyles that are more common among urban dwellers.

TABLE 3 Parameter estimates for leisure, business, and total long-distance trip models

	Number of total long-distance trips		Number of long-distance leisure trips		Number of long-distance business trips	
	Exp(β)	p	Exp(β)	p	Exp(β)	p
(Intercept)	10.147	<0.0001	12.469	<0.0001	0.549	0.0377
Age of respondent	0.986	<0.0001	0.990	0.0003		
Sex (Male)			0.823	0.0002		
Individual Income (base: $10k)	1.033	0.0005			1.088	<0.0001
Neighborhood type						
Urban	1.517	<0.0001			2.656	<0.0001
Suburban	1.053	0.4119			1.326	0.0573
Commute distance					0.016	<0.0001
Weekly VMT	1.001	<.0001	1.001	<.0001		
Primary commute mode						
Active mode (e.g. walk, bike, skateboard, etc.)					2.494	0.0055
Private vehicle (e.g. drive alone, carpool, etc.)					2.009	0.0039
Never used Car-sharing			0.762	0.0145		
Made no long-distance business trips			0.784	<.0001		
Doesn't bike for short-distance personal trips	0.8070	0.005	0.851	0.0236		
Factor: Traditional thinking	1.057	0.0234	0.936	0.003	1.352	<.0001
Factor: Established in life	1.068	0.0106				
Factor: Long-term suburbanite	0.894	<.0001	0.926	0.0003	0.871	0.0091
Factor: Adventurer	1.137	<.0001	1.090	<.0001	1.173	0.0015
Factor: Commute loving	0.912	0.0002			0.782	<.0001
Factor: Pro-suburban	1.054	0.0406			1.232	0.0007
Factor: Tech Savvy	1.073	0.0034			1.253	0.0001
Factor: Traditional shopper	0.938	0.0163			0.845	0.006
Dispersion	0.8604744	<.0001	0.7066075	<.0001	3.2603912	<.0001
Observations	1,406		1,498		1,034	
Generalized R-square	0.20		0.10		0.17	

Table 4 presents the final models for the business, leisure, and total long-distance airplane trips. These second models are very similar to those in Table 3, in terms of explanatory variables. Socio-demographic characteristics, land use, travel choices, and attitudinal factors all play a role in the number of long-distance trips by airplane for leisure and business purposes. The predictor that has the most influence on long-distance travel by airplane, excluding categorical variables, is the "established in life" factor, followed by household income. Those who feel as though they are established in their career and satisfied with their life make more long-distance business trips by air than those who are pro-suburban. Additionally, higher individual income is associated with a higher number of long-distance airplane business trips.

Age and household income negatively impact the number of long-distance airplane trips. Age has a negative effect for total, leisure, and business trips, whereas household size has a negative impact on total long-distance plane trips. Each additional household member is associated with a reduction in the number of long-distance airplane trips of 12%. This is consistent with prior research showing that children reduce the amount of travel due to the increased household obligations. The decrease for age is not as extreme: an increase in age of one year is associated in 2% reduction in the number of long-distance airplane trips. This finding is unexpected because the age range was capped at 50 years-old, so this requires more investigation.

An individual's general level of travel also has an impact on the number of long-distance airplane trips. As it was for overall long-distance travel, those who make short distance leisure trips by bike have a higher number of long-distance trips by air. Similarly, the number of long-distance air trips for business is positively associated with the number of long-distance air trips for leisure. For example, since many business flyers earn frequent flyer miles for their business trips, they can buy tickets for their vacation travel for little to no cash, instead spending air miles. Higher weekly VMT positively impacts long-distance leisure plane trips. An individual's primary commute mode has an impact on the number of long-distance business plane trips taken. Those who primarily telecommute make more long-distance business trips annually than individuals who commute by transit. A telecommuter's corporate offices or main office may be located in a different city or even state which might require frequent in-person meetings. Those who commute by private vehicle and active modes also take higher numbers of long-distance business plane trips. These findings point to the impact of the knowledge economy and the system of a global mobile elites which include a level of mobility that is not accessible to everyone.

Attitudinal factors affect the number of long-distance airplane trips reported in the 12-month period. Identifying as "established in life" has the greatest influence on the number of long-distance business trips by air and total long-distance trips by air compared to identifying with any other factor. Individuals who scored highly on the "pro-environmental policies" factor make more long-distance trips by air – since we do not explicitly control for education this could be capturing the influence of educated individuals that travel by air. "Traditional shoppers" and those that are "tech-savvy", have opposite trends in long-distance airplane travel. "Traditional shoppers" fewer long-distance airplane trips, whereas those are more "tech-savvy" make more long-distance airplane trips. "Tech-savvy" individuals may have more access to purchasing of air travel online, whereas "traditional shoppers" may dislike travel by airplane and/or purchasing air travel online—online shopping is not something they enjoy doing.

TABLE 4 Parameter estimates for long-distance airplane trips

	Number of total long-distance air trips		Number of long-distance air leisure trips		Number of long-distance air business trips	
	Exp(β)	P	Exp(β)	p	Exp(β)	p
(Intercept)	2.220	0.0003	0.865	0.4334	0.120	<0.0001
Age of respondent	0.979	<0.0001	0.987	0.0079		
Household size	0.875	<0.0001				
Individual Income (base: $10k)	1.140	<0.0001	1.069	<.0001	1.235	<0.0001
Neighborhood type						
Urban	2.122	<0.0001	1.973	<.0001	3.040	<0.0001
Suburban	1.087	0.3808	1.104	0.2942	1.259	0.1799
Weekly VMT			1.001	0.0146		
Primary commute mode						
Active mode (e.g. walk, bike, skateboard, etc.)					2.901	0.0073
Private vehicle (e.g. drive alone, carpool, etc.)					3.144	0.0002
Studies/works exclusively from home					3.252	0.0032
Number of long-distance business trips by air			1.105	<.0001		
Doesn't bike for short-distance personal trips	0.698	0.0007	0.718	0.001		
Factor: Established in life					1.322	<.0001
Factor: Practical (anti-materialistic)	0.921	0.0066			0.893	0.0257
Factor: Long-term suburbanite					1.174	0.0102
Factor: Pro-environmental policies	1.125	0.0015	1.155	<.0001		
Factor: Pro-suburban	0.922	0.0278	0.908	0.0057	0.777	0.0002
Factor: Tech Savvy	1.109	0.0045				
Factor: Traditional shopper	0.898	0.0062	0.888	0.0019	0.855	0.0181
Dispersion	1.283	<.0001	0.838	<.0001	2.826	<.0001
Observations	1,406		1,498		1,034	
Generalized R-square	0.20		0.10		0.17	

6. Conclusions

Long-distance travel is difficult to study. Before this only two year-long measures of long-distance travel had been collected in the United States: the 1995 American Travel Survey and the relatively small Longitudinal Survey of Overnight Travel (8). Presently there are only a handful of states that have collected long-distance travel data usually over 8-12 week time periods. This work aims to help fill the long-distance data gap in the USA by contributing models of annual long-distance travel by California millennials and Generation X members. This study focuses on the effects of socio-demographic traits, residential location, and individual attitudes on long-distance travel. Using data, collected in fall 2015, from the California Millennial Dataset, we model the number of long-distance trips of 1,512 respondents ages 18-50 years who made at least one long-distance trip in the last 12 months.

Californian millennials and Generation X members have a wide range of levels of long-distance travel. The oldest individuals in this sample make, on average, 8.4 total long-distance trips compared to the youngest persons in the sample who make, on average, 13.5 long-distance trips per year. Furthermore, this study suggests women may be starting to make more long-distance trips than men. We are uncertain if future long-distance travel of the younger millennials will remain higher than those in Generation X or if it will decrease to a similar level. It could be that the youngest cohort will always make more long-distance trips or that as individuals age their sense of adventure or desire to travel is reduced. In the meantime, local and regional planners need to balance systems and programs for residents and visitors while preparing to increase consideration of long-distance travel as a growing component of volume and factor in assessing mobility.

Our negative binomial regressions estimated the effect of the explanatory variables on the number of long-distance trips made for business, leisure, and their sum. The results indicate that age, being male, and household size have negative impacts on long-distance trip rates. Individual income positively impacts the number of long-distance trips made. An individual's residential location also impacts the number of long-distance trips made; urbanites make more business trips than rural dwellers. The factors that represent the largest impact on the number of long-distance trips per year are factors developed from our attitudinal questions. This is an important core finding of this study that informs approaches within future data collection and studies. Attitudes are important to long-distance travel. Being a "traditional thinker", "tech savvy", and "established in life" were significant predictors. Those who score highly on the "traditional thinking" factor make fewer trips, while those who score highly on the "established in life" factor make more. While it may seem counterintuitive that climate change deniers make fewer trips, we do not control for employment type and status – it could be that traditional thinkers simply work in industries where business trips are not part of the job. Weekly vehicle-miles traveled, the use of certain modes for short-distance and commute travel also affect long-distance travel.

Another new type of relationship explored, but not large factor in our models, is the one between long-distance and short-distance travel. In the development of the analyses for the study, we analyzed short-distance trip patterns (in particular, for car trips) and compared them to the number of long-distance annual (car) trips and we could not find a statistical significant relationship between the frequency of leisure short-distance car trips and the frequency of leisure long-distance car trips.

This study demonstrates that measuring and modeling long-distance travel is viable and that future data collection efforts and models should incorporate this travel to achieve more accurate overall models of the transportation system and its impact on sustainability and quality of life. Challenges related to the burden of the survey suggest that more streamline measures of long-distance travel may be needed. However, while many are advocating for passive or semi-passive mobile device data collection for long-distance travel measurement, the attitudinal variables and resultant factors, collected and modeled here demonstrate the sustained importance of collecting personal variables that require survey collection to understanding travel and forecasting it.

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8. Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: Rosaria Berliner, Lisa Aultman-Hall, Giovanni Circella; data collection: Rosaria Berliner, Giovanni Circella; analysis and interpretation of results: Rosaria Berliner, Lisa Aultman-Hall, Giovanni Circella; draft manuscript preparation: Rosaria Berliner. All authors reviewed the results and approved the final version of the manuscript.

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PART – II

Paper 2: What Drives Your Drivers: An In-Depth Look at Lyft and Uber Drivers

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WHAT DRIVES YOUR DRIVERS: AN IN-DEPTH LOOK AT LYFT AND UBER DRIVERS

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Abstract

Lyft and Uber are two on-demand ride-service providers in the current landscape of shared mobility. This paper shifts the focus from on-demand ride-sharing passengers to the drivers – a topic to which little attention has been paid but may have a significant impact on car ownership and the derived environmental and social benefits of shared mobility. In this study, we use data provided by Kelley Blue Book from its nationwide survey of U.S. residents ages 18 to 64 that collected information on shared mobility awareness and usage, vehicle ownership, aspirations for future vehicle ownership, and attitudes on shared mobility and vehicle ownership. We estimate an ordinal logit to understand the willingness to drive for an on-demand ride-service. We find that the individuals who report higher VMT and have more children are more willing to become drivers. We introduce attitudinal factors and find that those who have positive attitudes towards ride-sharing are more interested in driving. Those who enjoy driving are also more likely to be interested in driving for an on-demand ride-service.

Keywords: On-Demand Ride Services; Shared mobility; Uber/Lyft drivers; Ordinal Logit

1. Introduction

Lyft and Uber are two of the most well-known, on-demand ride service providers in the current landscape of shared mobility. As of October 2016, Uber had 40 million monthly riders worldwide and that number appears to be growing (Kokalitcheva, 2016). While monthly ridership increases, driver retention remains low at roughly 4% (Efrati, 2017). This means that about 96% of Uber drivers leave the company within a year of their start date (McGee, 2017).

With more than 40 million monthly riders, many ride service researchers have focused their research on the rider (Clewlow, Mishra, & Laberteaux, 2017; Rayle, Shaheen, Chan, Dai, & Cervero, 2014). Some research focuses on driver safety (Feeney, 2015) and other research on driver wages (Berger & Frey, 2017; Henao & Marshall, 2017). To date, there is very little research on driver characteristics. Two fundamental questions on driver characteristics are: What types of individuals want to drive for on-demand ride sharing companies such as Lyft or Uber? And what motivates an individual to drive for one or both of these companies? Answers to these questions will not only assist on-demand ride-service companies but could also allow planners and other stakeholders to estimate fluctuations and increases in vehicle-miles traveled and private vehicle ownership. With the majority of research being done on Lyft/Uber riders, we have little information about the drivers; this paper attempts to fill that gap by providing an in-depth analysis of potential and current drivers. Research on drivers is relatively sparse. Understanding driver characteristics can help transportation planners understand the changing nature of roadway users and potential increases in vehicle-miles traveled (VMT). Similarly, knowing the people that are driving for these services will allow vehicle manufacturers to tailor their vehicles to meet the needs and demands of drivers.

The automotive research company, Kelley Blue Book, provided our sample, which came from a nationwide survey of U.S. residents aged 18 to 64 conducted in August 2015. The sample collected information on shared mobility awareness and usage, personal vehicle ownership, aspirations for future vehicle ownership, and attitudes and opinions on shared mobility and personal vehicle ownership. We estimate an ordinal logit model to understand the willingness to drive for an on-demand ride sharing service (e.g. Lyft/Uber). We find that vehicle ownership plays a significant role in estimating the willingness to drive for an on-demand ride sharing service. Additionally, individuals who have strong and positive attitudes towards ride-sharing services are more likely to drive.

This paper is organized as follows: the following (second) section provides a review of relevant literature. The third section discusses the data used in this analysis and provides summary statistics of respondents in the sample. The fourth section discusses the methodology used. The fifth section presents the modeling results. The final (sixth) section presents conclusions and discusses the next steps of the project.

2. Literature Review

This literature review is split into two parts. It begins by reviewing on-demand shared mobility user characteristics, as well as providing a definition for on-demand shared mobility. The second part discusses taxi driver characteristics, which parallel on-demand ride sharing driver traits.

2.1 On-Demand Shared Mobility

Since 2010, on-demand ride sharing companies have provided rides to tens of millions of users (Goodin, Ginger; Moran, 2016; Kokalitcheva, 2016). They have only continued to grow in popularity, notoriety, and in name. These companies match passengers with drivers through a smartphone application (app) installed on the phones of both parties: the passenger requests a ride in the app and the request is sent to a driver. If the driver denies the request, the request is sent to another driver. This process continues until the request is approved, and then the driver that accepts the request, picks up, transports, and then drops off the passenger. The cashless operation is brokered by the company; fares, and in some cases tips, are collected through the app and paid to drivers accordingly. On-demand ride sharing has many different names: Transportation Network Companies (TNCs), on-demand ride sourcing, ride-hauling, ride-booking, ride-matching, and app-based ride sharing. This paper will use the term “on-demand ride sharing” to describe services such as Lyft and Uber.

Recently, attention has been given to the users of these services—their socio-demographic characteristics, their attitudes, and travel behavior. There have been several studies that explicitly focus on, or paid a great deal of attention to, on-demand ride sharing users and service usage (Clewlow et al., 2017; Rayle et al., 2014; Smith, 2016). In 2016, the five on-demand ride sharing companies licensed in New York City provided 133 million rides (Schaller, 2017). In fall 2016, on-demand ride sharing companies picked up 87% as many rides as yellow taxis (Schaller, 2017). According to a Pew Research Center survey conducted between November and December 2015, roughly 15% of Americans have used on-demand ride sharing apps (Smith, 2016). At a more disaggregate level, the Pew Report finds that about 21% of urbanites, 15% of suburbanites, and 3% of rural-dwellers have used on-demand ride sharing services (Smith, 2016). Using a survey of respondents from seven metropolitan areas in the U.S. administered in fall 2015, Clewlow et al. (2017) found adoption rates between 15% and 29% for individuals residing in suburban and urban neighborhoods, respectively (Clewlow et al., 2017). They also reported the adoption rate of on-demand ride sharing by generation (Clewlow et al., 2017). About 40% of those in Generation Y (adults born between the years 1977 and 1995) had downloaded and used one of the apps, compared to only 3% of those in the silent generation (adults born between the years 1925 and 1942) (Clewlow et al., 2017). A similar study of Millennials in California (those born between the years 1981 and 1997) found that on-demand ride share adopters are more likely to be students and employed and less likely to have children in the household (Alemi, Circella, Handy, & Mokhtarian, 2017). In general, on-demand ride sharing adopters tend to be younger and have higher levels of education compared to non-adopters (Alemi et al., 2017; Clewlow et al., 2017; Rayle et al., 2014).

2.2 Driver Characteristics

Services such as Lyft and Uber serve as matchmakers: matching drivers to riders and vice versa. The quickly changing landscape of these drivers has made it difficult to research and publish studies in a timely manner; however, one study has succeeded. Using a survey of 601 Uber drivers weighted to the entire Uber driver population by average work hours and hourly earnings, Hall and Krueger (2015) were able to describe Uber driver characteristics and socio-demographic traits, and to compare these traits and characteristics to the population of all workers in the United States and to taxi drivers and chauffeurs (Hall & Krueger, 2015). Roughly 30% of Uber drivers are aged 30 to 39, which is a distinctly higher percentage than taxi drivers (19.9%) for the same age group (Hall & Krueger, 2015). Uber drivers have higher education levels than taxi drivers and chauffeurs – in fact, 47.7% of Uber drivers received a college or advanced degree whereas only 18.9% of taxi drivers and chauffeurs achieved the same. Furthermore, only 41.1% of workers (according to the American Community Survey) have received college or advanced degrees, meaning that Uber drivers, in general, are more educated than workers (Hall & Krueger, 2015). In terms of gender, compared to the overall population of workers in the United States, there are far fewer females – only 14% of Uber drivers are female (Hall & Krueger, 2015). Fewer Uber drivers are married than workers, but more have children at home (Hall & Krueger, 2015). Surprisingly, about 7% of Uber drivers are veterans, compared to 5.2% of all workers (Hall & Krueger, 2015). Although Hall and Krueger (2015) have provided the socio-demographic traits of Uber drivers, their report makes no mention of driver attitudes or feelings about vehicle ownership and ride sharing (Hall & Krueger, 2015). Furthermore, the report has no specific data about the drivers' past experiences with Uber as riders, something that the authors believe leads many individuals to become drivers (Hall & Krueger, 2015).

Based on the Hall and Krueger (2015) study, it appears that there are similarities between Lyft/Uber passengers and Uber drivers (Hall & Krueger, 2015). Both drivers and riders are younger and more educated (Alemi et al., 2017; Clewlow et al., 2017; Hall & Krueger, 2015; Rayle et al., 2014; Smith, 2016). This study hopes to further close the gap in research connecting drivers and passengers and to provide a deeper insight into likely drivers for these services.

3. Empirical Context

This study is based on data from an extensive online survey commissioned by Kelley Blue Book, an automotive research company based in Irvine, California, to study the motivations behind shared mobility usage, in addition to opinions and behaviors about current and future transportation. The survey collected information on respondents' involvement in ride sharing and vehicle sharing and how those factors affect other choices relating to shared mobility decisions and the intention to purchase a vehicle. The survey was administered in an online format by a market research firm, from August 3 to 9, 2015 to U.S. residents aged 18 to 64.

The final unweighted sample has 1,916 respondents. The average respondent in the dataset is 37 years old, female, Caucasian, married, has no children, and has a household income of approximately $62,500. Table 1 presents descriptive statistics for the sample population.

It should be noted that the descriptive statistics presented in Table 1 are not entirely representative of the US population. The surveyors over sampled Millennials (18-34 years old in 2015) and under sampled Generation X/Baby Boomers (35-64 years old in 2015). This over sampling allowed us to key into the group of individuals that heavily rely on shared mobility services. In terms of gender and ethnicity, males were slightly under sampled (47.8% vs. 50%) and ethnicity/race had similar over and under sampling.

This national survey collected data on awareness and used of a wide variety of services, including the burgeoning "pooling" offshoots. Respondents were asked about potential pricing schemes, such as their preferences for new shared mobility subscription services, barriers to using these services (if they did not already use them), interest in becoming a driver for ride-sharing, etc.

TABLE 5 Descriptive statistics (unweighted)

Characteristic (sample size)	N (%)	Characteristic (sample size)	N (%)
Gender (1916)		**Household income (1916)**	
Male	908 (47.4)	Less than $25,000	357 (18.6)
		$25,000 to $30,000	135 (7.05)
Age (1916)		$30,000 to $50,000	380 (19.8)
18 to 24	502 (26.2)	$50,000 to $75,000	359 (18.7)
25 to 34	508 (26.5)	$75,000 to $100,000	269 (14.0)
35 to 41	210 (11.0)	$100,000 to $125,000	117 (6.11)
42 to 50	255 (13.3)	$125,000 to $150,000	72 (3.76)
51 to 64	441 (23.0)	$150,000 to $200,000	68 (3.55)
		More than $200,000	42 (2.19)
		Prefer not to answer	117 (6.11)
		Characteristic (sample size)	**Sample mean**
Education level (1916)			
Some grade/high school	49 (2.56)		
High school/GED	341 (17.8)	Number of operational personal vehicles (1569)	1.18
Some college/technical school	531 (27.7)		
Associate's degree	220 (11.5)		
Bachelor's degree	530 (27.7)		
Graduate degree (e.g. MS, PhD, etc.)	202 (10.5)		
Professional degree (e.g. JD, MD, etc.)	31 (1.62)		
Prefer not to answer	12 (0.63)		
Employment (1916)			
Employed full-time	835 (43.6)		
Employed part-time	289 (15.1)		
Student	198 (10.3)		
Homemaker	219 (11.4)		
Other	31 (1.62)		
Unemployed	203 (10.6)		

The questionnaire consisted of 8 sections that collected information on:

A. Socio-demographic information (introduction): This section collected information from respondents and their children (where applicable) about their age, gender, ethnicity, marital status, parental obligations, child information, household location, and neighborhood type.

B. Vehicle ownership: This section collected information about vehicle ownership, including the number of vehicles in the household, general vehicle characteristics, and the respondent's future vehicle purchase timeline.

C. Travel attitudes: The section asked the respondents to provide their beliefs and opinions about driving, personal transportation, and vehicle ownership.

D. Ride sharing and vehicle sharing information: This section collected information about the familiarity and usage of ride sharing and vehicle sharing services. The respondents were asked about each stage of ride sharing and vehicle sharing familiarity: a) had they heard of the service?; b) is the service available in their area?; c) had they used the service?; d) how they first heard about the service?; e) which specific service was available in their area?; and f) when did they first use the service? For those who reported that they had never used any service, respondents were asked about their willingness to try the service.

E. Ride sharing attitudes: This section collected information about ride sharing attitudes by using several likert-scale type questions. In addition to the likert-scale questions, this section presented respondents with questions about different pricing schemes for ride sharing services, what transportation modes would ride sharing replace, and a 4-point likert-scale description of vehicle ownership vs. ride sharing.

F. Vehicle sharing attitudes: This section collected similar information to the previous section but within the context of vehicle sharing.

G. Future transportation: This section asked questions about the respondent's future travel intentions. Specifically, the survey asked about the situations in which respondents would use a certain mode of transportation. Furthermore, for those who indicated that they had not used ride sharing or vehicle sharing, attention was paid to what would encourage them to use these services in the future.

H. Socio-demographics (conclusions): The final section collected information about shared economy usage (e.g., AirBnB, VRBO, Couchsurfing, etc.), in addition to employment status, daily VMT, home parking availability, number of people in the household, level of education, and annual household income.

4. Methodology

Understanding the drive to drive for on-demand ride sharing services can be explained by several factors, including attitudes, socio-demographic characteristics, and personal travel choices. The Kelley Blue Book report (Hall & Krueger, 2015) focused only on driver socio-demographics and did not discuss a relationship between driving and personal attitudes. We aim to bridge this gap by looking to explore the relationship between the desire to drive for an on-demand ride sharing service and an individual's attitude towards vehicle ownership and ride sharing itself.

In the Kelley Blue Book survey, respondents were asked about the likelihood of them driving and their current driver status for on-demand ride sharing services. Figure 1 below presents the histogram of their responses.

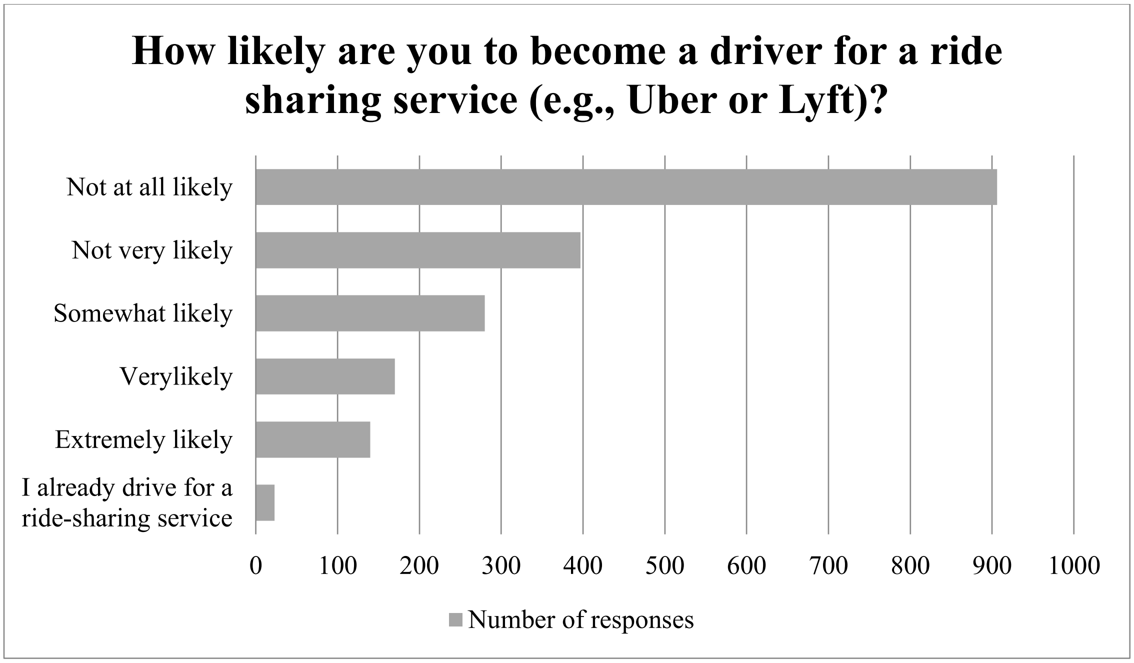

FIGURE 1 Histogram of responses.

While an overwhelmingly large number of respondents (N=1,303) indicated that they are "not very likely" or "not at all likely" to drive for an on-demand ride sharing service, the remaining respondents (N=613) indicated some willingness to drive for an on-demand ride sharing service. In fact, 23 respondents answered that they already drove for such a service; however, no information about the service for which they drove was collected.

As part of this modeling effort, we included several explanatory variables. The final version of the model includes 12 explanatory variables that were selected based on the literature as well as the inclusion of several factors extracted through a two-stage factor analysis. These variables are can be categorized into three groups: socio-demographic characteristics, personal travel, and attitudes.

We include several socio-demographic variables as explanatory variables in our model. We control for age using the age variable. We are also able to control for the number of children in the household. Being a parent or having to look after children means that work and other activities need to be flexible – driving for a service such as Lyft can provide the flexibility needed while allowing parents or guardians to make some (extra) income. We also control for the impact of gender and household income; we expect that with higher household income, the desire to drive for an on-demand ride sharing service would be low.

We also control for personal travel in the model. In general, we hypothesize that variables that are positively associated with travel will lead to a willingness to drive for Uber. Self-reported daily vehicle miles traveled (VMT), the availability of parking at home, and the number of shared mobility services that are used are considered personal travel variables. In this instance, the number of shared mobility services used serves as a proxy for the level of interaction with shared mobility in general. As an individual's experience and interaction with shared mobility increases, it becomes more likely that the individual wants to drive for a service. This reflects a desire to become more integrated into the shared mobility environment. The availability of parking at home could persuade or dissuade an individual from driving; while it may not be the first thought that comes to mind, having parking is almost a necessity when it comes to vehicle ownership, and as a result, having the ability to drive for a service. In terms of daily VMT, individuals who drive more may enjoy the act of driving and therefore would like to drive for a service. In order to collect VMT, respondents were asked the question, "What is the approximate daily mileage you travel during a typical day?"

We also use attitudinal factors derived from likert-type statements in the survey. Using a two-stage factor analysis, seven factors were extracted from 22 variables. Both factor analyses used a maximum likelihood factoring method with an oblique rotation. The first factoring stage included variables related specifically to vehicle ownership attitudes. The second stage focused on variables related to ride sharing attitudes. Our final model incorporates six of the seven factors. The description of those factors is as follows:

a. Ride sharing factor – Pro-ride sharing: Individuals who score high on this factor tended to agree with statements such as “Ride sharing is better than using a taxi or renting a vehicle”, “Ride sharing is safe”, and “Using smartphone applications is a great way to request a ride”.
b. Ride sharing factor – Single item: This factor was a single item, meaning that respondents who “score high” on this factor strongly agreed with the statement “Ride -sharing is better than owning or leasing a vehicle for me”.
c. Vehicle ownership factor – Pro-vehicle ownership: Individuals who score high on this factor tended to agree with statements such as “Owning a vehicle is a smart investment” and “Owning/leasing a vehicle gives you a sense of freedom and independence”.
d. Vehicle ownership factor – Doesn’t need to own a vehicle: Individuals who score high on this factor tended to agree with statements such as “Having transportation is necessary but owning a vehicle is not” and “Owning/leasing a vehicle is too expensive”.
e. Vehicle ownership factor – Single item: This factor was a single item, meaning that respondents who “score high” on this factor strongly agreed with the statement, “If I could, I’d prefer to drive a variety of vehicles rather than always drive the same one”
f. Vehicle ownership factor – Single item: This factor was a single item, meaning that respondents who “score high” on this factor strongly agreed with the statement, “I like the ability to multi-task while in a vehicle”.

Studies suggest that using a linear regression model is appropriate when a “variable has four or more [ordinal] categories,” (Bentler & Chou, 1987). For this study, we use an ordinal logit model to estimate the willingness of an individual to drive for an on-demand ride sharing service such as Lyft or Uber. Our dependent variable, “Willingness to drive”, was aggregated into 3 levels for this analysis: “Not likely to drive”, “Somewhat likely to drive”, and “Likely to drive”. The first level, “Not likely to drive”, includes 1,303 responses, which constitutes approximately 68% of respondents. The second level, “Somewhat likely to drive”, consists of 280 responses, and the final level, “Likely to drive”, included 333 responses. Table 6, below, presents some descriptive statistics for the variables tested to model the willingness to drive, including the mean, median, and standard deviation in age, income, number of children, and VMT for each willingness level. Furthermore, it includes some count information for categorical variables, such as level of education and gender. The average age of the individuals who indicated that they were likely to drive for a ride sharing service is approximately 33 years old with a standard deviation of 10.34 years. Furthermore, those with children indicate a higher willingness to drive than those without. The wealthiest individuals in our sample also indicated that they are likely to drive for an on-demand ride sharing service.

TABLE 6 Sample descriptives of dependent variable

		Willingness to drive level		
		Not likely to drive	Somewhat likely to drive	Likely to drive
Age	Mean	38.86	33.67	32.77
	Median	36	31	31
	Standard Deviation	14.47	12.18	10.34
Income	Mean	$60,547.78	$61,511.19	$71,364.35
	Median	$45,000.00	$62,500.00	$62,500.00
	Standard Deviation	$45,133.18	$45,087.84	$48,427.53
Number of Children	Mean	0.56	0.70	0.98
	Median	0	0	1
	Standard Deviation	0.99	1.12	1.12
VMT	Mean	16.83	19.51	24.23
	Median	8	15	15
	Standard Deviation	18.51	19.20	21.85
RS Factor - Pro-ride sharing	Mean	-0.17	0.16	0.55
	Median	-0.12	0.24	0.56
	Standard Deviation	0.93	0.79	0.81
RS Factor - Ride sharing is better than vehicle ownership	Mean	-0.25	0.27	0.73
	Median	-0.29	0.36	0.86
	Standard Deviation	0.74	0.69	0.67
Single Item – I like the ability to multi-task while in a vehicle	Mean	2.72	3.23	3.56
	Median	3	3	4
	Standard Deviation	1.23	1.15	1.23
Vehicle ownership factor – Doesn't need to own a vehicle	Mean	-0.06	0.02	0.21
	Median	-0.10	0.13	0.26
	Standard Deviation	0.78	0.71	0.78
Single Item – If I could, I'd prefer to drive a variety of vehicles rather than always drive the same one	Mean	2.60	3.16	3.61
	Median	3	3	4
	Standard Deviation	1.20	1.04	1.12
Gender (Column %)	Female	57.79%	43.21%	40.24%
	Male	42.21%	56.79%	59.76%
Education level (Column %)	Some grade/high school	2.15%	2.85%	3.90%
	High school/GED	19.42%	14.64%	14.11%
	Some college/technical school	29.16%	27.15%	22.52%
	Associate's degree	11.97%	9.64%	11.11%
	Bachelor's degree	25.86%	30.36%	32.43%
	Graduate or Professional degree (e.g. MS, PhD, etc.)	10.90%	14.29%	15.31%
	Prefer not to answer	0.54%	1.07%	0.60%

5. Results

5.1 Ordinal Logit Model

For this analysis, we use an ordinal logit model on the unweighted sample using JMP statistical software. While other studies suggest that multinomial logit (MNL) models provide a deeper, more thorough understanding of the dependent variable (Anowar, Yasmin, Eluru, & Miranda-moreno, 2014; Bhat & Pulugurta, 1998; Potoglou & Susilo, 2005), the authors believe that treating this variable as nominal would violate the ordinal relationship of the variable. Moreover, we risked an IIA violation since MNL treats the response variable as purely nominal variables. While there are risks with an ordinal logit model, we employed a parallel lines test to check that the slope parameters stayed the same for all response outcomes and that it is only intercepts (labeled "cut" in Table 3) that change. Since the parallel lines test assumption was met (i.e. the parameter estimates do not change based on the response level, only the intercepts change), we confidently employ an ordinal logit model to model the willingness to drive for an on-demand ride sharing service. The goodness of fit, R-squared, metric is 0.221, meaning that the variables in the model explain approximately 22.1% of the variance in the willingness to drive. Most studies that have investigated on-demand ride sharing usage report only descriptive statistics (Clewlow et al., 2017; Rayle et al., 2014). The parameters of the ordinal logit model estimated for this study are presented in Table 3 below.

TABLE 7 Parameter estimates for ordinal logit model

Term	Estimate	Std Error	Chi Square	Prob> ChiSq
Cut 1 [Not likely to drive]	-1.87	0.27	48.93	<.0001
Cut 2 [Somewhat likely to drive]	-3.01	0.27	120.44	<.0001
Age	-0.03	0.00	36.43	<.0001
VMT	0.01	0.00	10.95	0.0009
Number of Children	0.24	0.05	20.86	<.0001
Female	-0.19	0.06	11.85	0.0006
Vehicle Ownership Factor – Doesn't need to own a vehicle	-0.20	0.08	6.11	0.0135
Vehicle Ownership Factor – I like the ability to multi-task while in a vehicle	0.16	0.05	9.84	0.0017
Vehicle Ownership Factor – If I could, I'd prefer to drive a variety of vehicles rather than always drive the same one	0.37	0.05	52.21	<.0001
RS Factor – Pro-ride sharing	0.29	0.07	17.25	<.0001
RS Factor – Ride sharing is better than vehicle ownership	1.28	0.09	212.84	<.0001
Number of observations	1916			
R-Squared	0.221			

As shown in Table 3, as the age parameter increases, the willingness to drive for on-demand ride sharing services decreases. Older individuals are not as familiar with these services, perhaps because they have white collar jobs that would make driving appear less beneficial than it would to a person in his or her 20s or 30s. Similar to the findings from (Hall & Krueger, 2015), we observe that women are less likely to drive for on-demand ride sharing services. Women, compared to men, may feel more uncomfortable or vulnerable driving or being alone with strangers in their vehicle. We also tested household income, education, and occupation in our model; however, none were statistically significant; as a result, these variables were not included in the final model.

As VMT and the number of children at home increase, the willingness to drive for on-demand ride sharing increases. Having children living in your home and being a parent means finding employment that is flexible and will work with your schedule: driving for a service such as Lyft or Uber provides that flexibility needed in that environment. Those who drive more, on average, are more willing to drive for an on-demand ride sharing service – perhaps it is their increased mobility that leads them towards providing similar levels of mobility to others. Or perhaps it could be that they see their routine driving as a pathway to making some extra money.

Understanding the willingness to drive for these services is aided by understanding attitudes. For instance, those who score highly on the pro-ride sharing factors are more likely to want to drive for Lyft. More specifically, individuals who scored highly on the factor "Ride sharing is better than vehicle ownership" expressed a higher willingness to drive for on-demand ride sharing programs. Surprisingly, those who feel as though they do not need to own a vehicle are more interested in driving for an on-demand ride service. Unsurprisingly, those who like the ability to multi-task while driving are interested in driving for Lyft; the socialness, newness, and excitement could be within their comfort zone and make driving more appealing.

5.2 Previous Experience with On-Demand Ride Sharing Services

Previous experiences with an on-demand ride sharing service can greatly impact an individual's attitudes, opinions, and continuing use of the service. Figure 2 presents a graphical cross-tabulation of the respondents' shared mobility knowledge and their willingness to drive. Shared mobility knowledge is divided into three levels: the respondent had never heard of these services prior to the survey, the respondent had heard of these services but have never used them, and the respondent had used these services (alone, with friends, etc.). Most respondents fell into the second category, having heard of the services but never used them, followed by use of the services. The number within the bar represents the number of respondents who fall in that category. For instance, there are 69 respondents who have never heard of on-demand ride sharing, but indicated they are likely to drive for a service.

The Pearson chi-square value for the contingency table/graph is 355.109, meaning that the willingness to drive is different between the different levels of shared mobility knowledge. In general, most respondents reported that they were not likely to drive for a ride sharing service. As shown by Figure 2, those who have previous experience with on demand ride sharing make up more than 60% of those who indicated that they are likely to drive for ride sharing. Surprisingly, those who have no experience or knowledge of ride sharing indicated at a higher rate than individuals who have heard of it but not used it that they are likely to drive. While the survey tool collects information about how respondents were made aware of these services, it did not collect information on how the information was presented to them: positive press, bad press, negative word of mouth, etc. It could be that some respondents with no firsthand experience with these services have already decided against using the services and will not engage with them in any way.

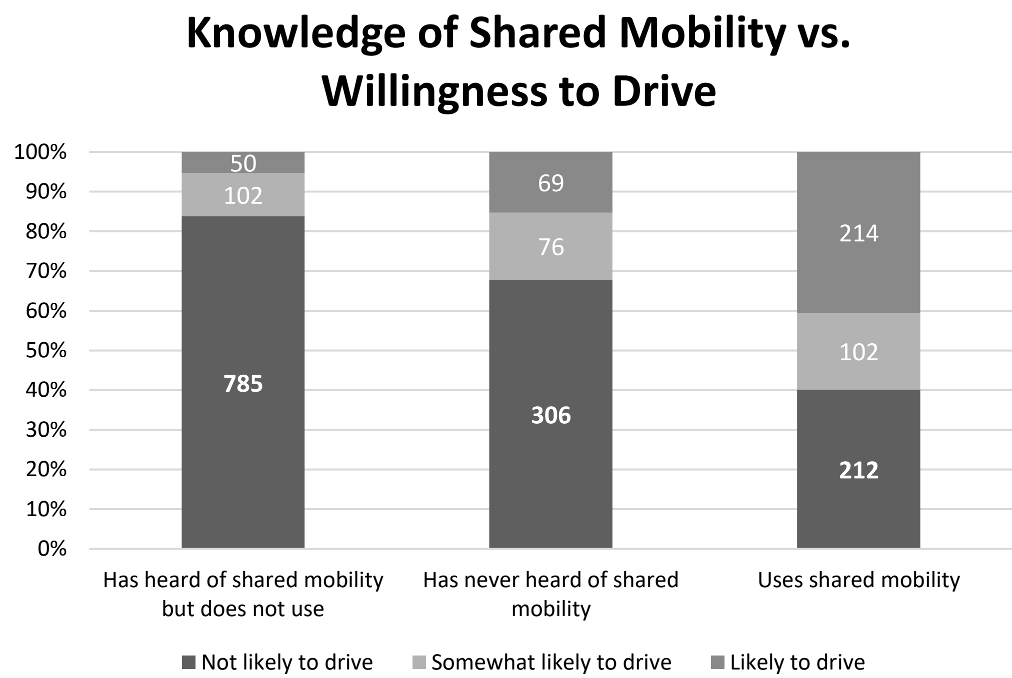

FIGURE 2 Knowledge of Shared Mobility vs. Willingness to Drive.

5.3 Motivations to Drive for an On-Demand Ride Sharing Service

In this subsection, we discuss the motivations to drive for an on-demand ride sharing service. Respondents that answered at least "somewhat likely" to the question "How likely are you to become a driver for a ride sharing service," were given a follow up question that asked about *why* they were interested in driving for these services. Figure 3 presents the graphical depiction of their responses.

The motivations for driving can differ from person to person and Figure 3, to some degree, represents those differences. While not all motivations are accounted for, and reasons undoubtedly exist that were not presented to the respondents, this list includes many of the critical motivations that the on-demand ride sharing companies would, themselves, highlight as reasons to drive. As shown in Figure 3, most respondents that answered this question said that their interest in driving for an on-demand ride sharing service is due to a desire to earn money, regardless of their willingness level. Enjoying the act of driving and meeting new people were overwhelmingly picked by those who indicated they were "likely to drive". Additionally, offsetting the cost of purchasing or leasing a vehicle, in general, is also a popular motivation. When looking at the specific reasons (e.g., offsetting the cost of buying a new car, buying a more expensive car, etc.) it could seem like purchasing or leasing a vehicle? is a less popular motivation – in some cases, individuals are interested in going from 0-car ownership to 1-car ownership, in other cases, individuals want to go from an economy vehicle to a more luxurious vehicle. Many services promote driving as a way to offset the costs of owning a vehicle and even provide vehicle leases for those who do not own a vehicle (Kieler, 2016).

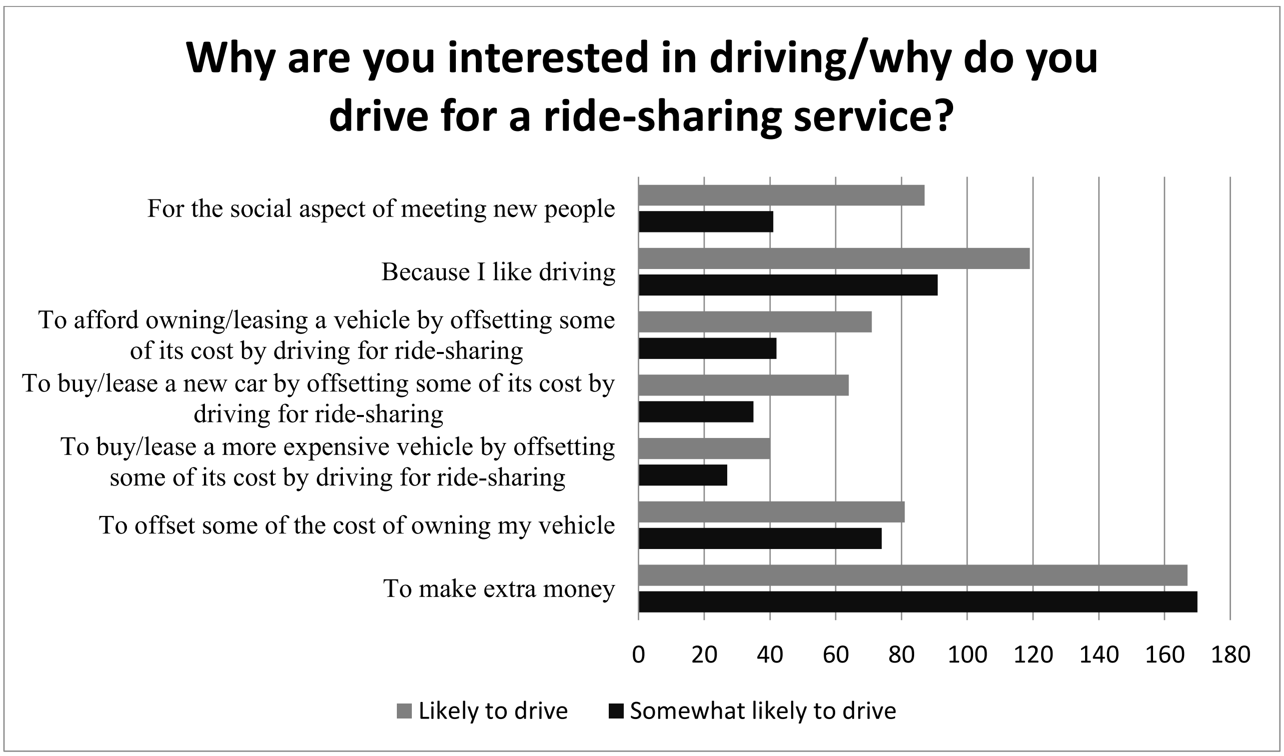

FIGURE 3 Answers to "Why are you interested in driving for a ride-sharing service".

6. Discussion

For this study, we investigated the factors that influence an individual's willingness to drive for an on-demand ride sharing service, the relationship between on-demand ride sharing knowledge and willingness to drive, as well as the motivations for driving, using data collected by the automotive research company Kelley Blue Book in August 2015. As discussed in the literature, most studies have focused on the on-demand ride sharing user. There has been an omission, for the most part, on the drivers. The work discussed in this paper hopes to close that gap.

Using an ordinal logit model, we found that age, number of children, vehicle ownership, gender, and attitudes all play an important role in estimating the willingness to drive for an on-demand ride sharing service. More specifically, those who have positive attitudes towards ride sharing and vehicle ownership are more willing to drive for these services. In general, we hope that individuals with positive attitudes towards ride sharing and negative attitudes towards vehicle ownership would reduce their car ownership if using shared mobility; however, potential part-time or full-time drivers may do the opposite when they join as drivers. Furthermore, personality traits also have an impact; those who are more adventurous or engage in multi-tasking are more willing to drive for Lyft. These individuals may enjoy meeting new people, driving to new places – wherever the ride takes them. While we are the first study to incorporate attitudes, we found that our socio-demographic results were consistent with (Hall & Krueger, 2015). More specifically, those interested in becoming on-demand ride sharing drivers are less likely to be female and younger than those who are not interested.

The contingency table presented in Figure 2 showed that the willingness to drive for shared mobility differs based on an individual's knowledge of shared mobility. The most surprising outcome is that those who had no knowledge of these services prior to the questionnaire appeared to be more willing to drive than those who had heard of the service but not used it; in this case knowledge deterred some individuals from wanting to drive. Those who indicated a willingness to drive were asked about the motivations behind that decision depicted by Figure 3. Earning extra money appears to be the most popular motivation for driving for an on-demand ride sharing service, followed by liking to drive.

The results of this modeling effort could be of interest to on-demand ride sharing services in terms of driver recruitment. The two most well-known companies, Uber and Lyft already provide fiscal incentives to encourage driver enrollment; however, instead of wide-scale public campaigns (e.g., billboard advertisements or social media advertisements), these companies could target individuals with certain socio-demographic characteristic traits, ridership qualities, and vehicle ownership status. Furthermore, the results of this paper suggest that shared mobility services may have a secondary impact on the car market. On the one hand, the general expectations for these services is that they will reduce car ownership, on the other hand the potential drivers, who bring their own cars for the service may increase their household car ownership. Both usage of on-demand ride services and the feeling that an individual does not need to own a vehicle indicate a higher willingness to drive. If an individual wants to drive on a part-time or full-time basis, access to a vehicle, in many cases, vehicle ownership, is paramount. While usage of on-demand ride services may reduce car ownership, since riders may feel as though they do not need a vehicle; driving for these services necessitate vehicle access or ownership, which in turn could increase the number of vehicles sold.

This analysis has a few limitations due to the type of data available from the survey: lack of information about vehicle rental programs, no information about work schedule, and the omission of neighborhood type data. We are unable to comment on retention rate, but if the ride-sharing companies were to track the socio-demographic characteristics and attitudes of their drivers, they may be able to better target drivers that will have higher retention rates and lessen driver turnover. Furthermore, the analysis was limited by the number of variables available. For instance, respondents were not asked about their work schedule flexibility. A flexible work schedule would allow individuals that potential to drive for an on-demand ride sharing service. Shared mobility use is highest in urban centers (Alemi et al., 2017); unfortunately, the data received by Kelley Blue Book only had the respondents' metropolitan area and as a result we were unable to control for neighborhood type, which might have been a good indicator for willingness to drive. The everchanging nature of these services means that having new data is essential to understanding behavior. While the findings in this paper represent the groundwork to understanding who will drive for these services, the driver population continues to grow and change. For instance, Uber's leasing pilot program was not introduced until August 2015, and was introduced mostly in the California market (Uber, 2015). At the time of the study, most respondents were likely unaware of the leasing program and their willingness to drive for these services could have changed because of the program. Moreover, as noted in McGee (2017), the ride sharing service driver retention rate remains low, and respondents that indicated a willingness to drive in 2015 may have different attitudes towards driving today, or may even have become drivers (McGee, 2017).

7. Conclusions

The ordinal logit discussed in this paper highlighted the factors that impact an individual's willingness to drive for an on-demand ride sharing service. Previous studies relied solely on socio-demographic traits (Hall & Krueger, 2015), but this study shows that attitudinal factors also have a significant impact. Most notably, the belief that ride sharing is better than vehicle ownership provides a strong indication that an individual is interested in driving for an on-demand ride sharing service; however, this does not lessen the impact of age, sex, or attitudes towards vehicle ownership – it merely provides more explanatory power to a topic that is under-researched. Those who indicate a willingness to drive for on-demand ride services are overwhelmingly motivated by the opportunity to make extra money.

Furthermore, we want to better understand the motivations for driving and the impact on car ownership. While many respondents indicated that the money earned would be used to offset the cost of maintaining their vehicle or even purchasing a new/more expensive one, without real driver data, we cannot be certain that their stated preference will match their behavior. Therefore, the next phase of this research will be to conduct an intercept survey of drivers in Northern California sometime in late-2018 or early-2019 to update the data and gain deeper insight into vehicle ownership, the effectiveness of vehicle leasing programs, and the motivations for drivers to continue driving.

8. Acknowledgements

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PART – III

Paper 3: Uncovering Early Adopter's Perceptions and Purchase Intentions of Automated Vehicles: Insights from Early Adopters of Electric Vehicles in California

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Uncovering Early Adopter's Perceptions and Purchase Intentions of Automated Vehicles: Insights from Early Adopters of Electric Vehicles in California

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Abstract

Research on vehicle automation is one of the most current topics in transportation. Some of the questions plaguing the research community include design, cost, and adoption. Many of these questions will remain unanswered until automated vehicles are available to the consumer. In this study, we use a sample of California new electric vehicle buyers to understand if and how current adopters of new vehicle technologies will adopt automated vehicles. We find that many respondents are interested in purchasing an automated vehicle but indicate that they only have average knowledge of the technology. Using an ordinal logit model, we model the interest in purchasing a fully-automated vehicle and find that younger men who purchase higher cost vehicles are more interested in purchasing a fully-automated vehicle. Above all else, those who perceive automated vehicles as being safer than non-automated vehicles have an interest in purchasing an automated vehicle.

Keywords: Automated vehicles; driverless vehicles; ordinal logit; electric vehicles; early adopters

1. Introduction

Research on vehicle automation is one of the most current topics in transportation. Some of the questions plaguing the research community include design, cost, and adoption. What will the vehicles look like? How much will they cost? How much are people willing to pay for automated vehicle technology? Who will buy these vehicles? Many of these questions will remain unanswered until automated vehicles are available to the consumer; however, beginning to understand the first adopters of these technologies may be possible by surveying early adopters of transportation technologies such as electric vehicles and semi-automated vehicles. The aim of this study is to better understand the individuals who are more likely to be among the first to purchase automated vehicles focusing on the early adopters of other new technology, electric vehicles.

The first step to understanding the adoption of new vehicle technology is to look at those who have already purchased other types of new vehicle technology. Focusing on early adopters of new vehicle technology, instead of surveying the general population, is important for understanding who are more likely to be the potential buyers of automated vehicles. The first buyers of new vehicle technology are different than those who adopt the technology later; therefore, a study of the general population would not be appropriate as these consumers are likely to be unknowledgeable about automated vehicles and are thus unlikely to purchase a new vehicle technology. Buyers of electric vehicles on the other hand have demonstrated that they are early adopters by purchasing a new vehicle technology. By surveying these consumers this study will produce results that are representative of the perceptions of those who are likely to purchase new vehicle technologies, rather than being representative of the general population. This method of surveying early adopters attitudes towards new technologies has been previously used in studies of electric vehicles and fuel cell vehicles (Egbue & Long, 2012; Hardman, Shiu, Turrentine, &

Steinberger-Wilckens, 2016).

The recent market introduction of electric vehicles began in 2008-2010 when the Nissan Leaf and Tesla Roadster were introduced (Cobb, 2015). In the 8-10 years that followed here vehicles were followed by around 40 other plug-in vehicles. In 2017 electric vehicles made up 181,659 sales, or roughly 5.32% of market share of new vehicles, in California in 2017 (Auto-Alliance, 2018). Diffusion of innovation theory states that the first 16% of buyers of any new technology are early adopters (Rogers, 2003). Therefore, the buyers of PEVs in California are early adopters, and this group is the sample used in this study.

Using a sample of California plug-in electric vehicle households, we consider socio-demographic, socio-economic, and attitudes and opinions towards automated vehicles to evaluate an individual's interest in purchasing an automated vehicle. This paper provides a first look at this issue and is the first study to explore early adopters' perceptions of electric vehicles.

2. Literature Review

Automated vehicles are not yet available for either commercial or private sale or use, apart from vehicle pilot programs (e.g. Waymo, Uber, etc.), and therefore there is no existing literature about actual purchasing behavior. Existing literature shows that the first buyers of new vehicle technologies are often different than those who adopt the technologies later (Axsen, Cairns, Dusyk, & Goldberg, 2018; Campbell, Ryley, & Thring, 2012; Caperello & Kurani, 2011; Carley, Krause, Lane, & Graham, 2013; Gnann, Plötz, Funke, & Wietschel, 2015; Hardman, Shiu, Steinberger-Wilckens, & Turrentine, 2017; Hardman & Tal, 2016; Hidrue, Parsons, Kempton, & Gardner, 2011; Ben Lane & Potter, 2007; Plötz, Schneider, Globisch, & Dütschke, 2014). The single strongest hypothesis is that those who have proven themselves as early adopters of new vehicle technology (i.e. electric vehicle owners) share characteristics with those who will be among the first to purchase automated vehicles.

To understand how innovations are adopted, we first look to the Diffusion of Innovations theory published in 1962 (Rogers, 2003). Simply put, a technology or innovation is not instantaneously introduced and adopted – innovation introduction has been studied and discussed. Next, we look at literature that has investigated the market introduction of other automotive technologies. Researchers have been studying new vehicle technology for over two decades. Most of the research has focused on hybrid electric vehicles (more commonly known as hybrid vehicles), plug-in electric vehicles, and fuel cell vehicles.

2.1 Diffusion of Innovations

Diffusion of Innovations theory, as referred to as "Rogers Theory" was first published in 1962 (Rogers, 2003). Rogers theory explains how new technology and ideas are spread and adopted over time. In his book, he explains that there are four elements that impact the adoption of new technology: the technology itself, communication channels (e.g. the tools a marketer uses to reach the consumer and vice versa), time, and a social system (Rogers, 2003). For this study, the idea of early adopters and relative advantage are crucial.

Early adopters and innovators, typically referred to as early adopters, are the first group of individuals to adopt a new technology and have been found to be different from the general population and majority (Rogers, 2003). In general, early adopters are highly educated, have high income, and have positive attitudes towards new technology. Early adopters are essential for wide-scale new technology adoption as these individuals are more willing to try new technologies. Furthermore, it is necessary to survey those who are most likely to be the first buyers of the new technology to understand their attitudes and opinions towards said technology. If the majority (i.e. later adopters) were to be surveyed about this technology, history shows that their opinions and perceptions would most likely not be similar to those that are most likely to buy the technologies.

Relative advantage is the degree to which an innovation or new technology is considered better than the product it replaces. In general, new technology must have a relative advantage so that early adopters will purchase it (Rogers, 2003). It follows that if the new technology is not perceived as superior to the technology it is replacing, neither early adopters nor the majority will be inclined to purchase it. There are several studies which find that in order for new technologies to succeed they must have valuable qualities (Agarwal & Prasad, 1997; Brockman & Morgan, 1999; Freeman, 1995; Hardman, Steinberger-Wilckens, & van der Horst, 2013; Hsu, Lu, & Hsu, 2007; Johnson, Kiser, Washington, & Torres, 2018; Van Slyke, Ilie, Lou, & Stafford, 2007).

2.2 Adopters of new vehicle technologies

Previous literature has investigated consumers of new vehicle technology – their common socio-demographic and household characteristics. Much of this literature has supported diffusion of innovation theory finding that the first buyers of these technologies are different to the majority of consumers. The first studies focused on hybrid electric vehicles, studies than began to focus on battery electric vehicles as they approached commercialization. We briefly review this literature as it has some relevance to the adoption of automated vehicles, which is another new automotive technology that consumers will interact differently with compared to any previous vehicle technologies.

In general, new vehicle technologies challenge consumers to use their vehicles different compared to the incumbents. In the case of electric and fuel cell vehicles consumers are challenged to refuel their vehicles in ways or locations that are different from gas stations. Electric vehicles also have shorter driving ranges and constrain consumers to shorter driving ranges. The exception to this is hybrid electric vehicles. Consumer interaction with hybrid vehicles is not fundamentally different than it is with conventional gasoline vehicles – the refueling process and driving range is identical for both vehicles. However, the vehicles are still a new technology that consumers will perceive differently. The early adopters of hybrid vehicles in were found to have above average incomes and educations (de Haan, Mueller, & Peters, 2007; Ozaki & Sevastyanova, 2011), they are eager to use new and innovative technologies and are interested in the environmental advantages of owning a hybrid (de Haan et al., 2007; Ozaki & Sevastyanova, 2011; Turrentine & Kurani, 2007).

Plug-in electric vehicles are more different to gas cars than hybrid electric vehicles due to their limited driving ranges and different refueling/recharging system. The early adopters of electric vehicles have been found to be highly educated, high income, mostly male, live in households with more than 1 car, are part of large social groups, and are willing to accept change (Egbue & Long, 2012; Jakobsson, Gnann, Plötz, Sprei, & Karlsson, 2016; Bardlay Lane et al., 2014; Plötz & Gnann, 2011). An individual's propensity or likelihood of purchasing a battery electric vehicle increases with younger individuals, education, and an environmentally friendly lifestyle (Hidrue et al., 2011). Knowledge and perceptions of electric vehicles play a role in adoption. In general, those who are more concerned for the environment are more likely to adopt electric vehicles (Wang, Tang, & Pan, 2018). Electric vehicle early adopters are interested in the performance of the vehicles and would not necessarily consider purchasing an electric vehicle if their performance was seen as inferior to their gasoline counterpart (Egbue & Long, 2012). Similarly, precious experiences with electric vehicles can significantly change a user's perception of BEVs (Bühler, Cocron, Neumann, Franke, & Krems, 2014).

2.3 Prior research on automated vehicles

Prior research on automated and self-driving vehicles focuses on potential users, vehicle safety and perceptions of safety, opinions of consumers, and willingness to pay for vehicle automated vehicle technology. Research in these areas is dynamic and growing quickly. Several researchers believe that younger people will be the first to adopted automated vehicle technology (Abraham et al., 2016; Bansal & Kockelman, 2016; Deloitte, 2014; Lee, Ward, Raue, D'Ambrosio, & Coughlin, 2017). A 2016 survey of Americans ages 12 through 64 years old conducted by Kelley Blue Book, reports nearly 63% of Americans believe that fully automated (or driverless) vehicles are safer and more efficient; however, many believe that total adoption of automated vehicles will not be achieved in their lifetimes (Kelley Blue Book, 2016). Although these beliefs are not shared by all. In a study of 5,000 people from throughout the world, 69% of respondents remarked that fully-automated driving would reach a 50% market share by 2050 (Kyriakidis, Happee, & de Winter, 2015).

A 2014 report by Schoettle and Sivak surveyed consumers in the U.S., U.K., and Australia about opinions on automated and self-driving vehicles. They found that majority of respondents had some prior knowledge of automated vehicle technology but also expressed concerns about riding in self-driving vehicles in terms of safety, security, and performance (Schoettle & Sivak, 2014). However, despite hesitations, a majority of respondents indicated a desire to have this technology in their vehicle (Schoettle & Sivak, 2014). Furthermore, most of the respondents were unwilling to pay extra for the automated technology (Schoettle & Sivak, 2014). In a survey about automated and shared vehicle use among American consumers, (Gurumurthy, Kockelman, & Hahm, 2018) found that Americans are willing to pay, on average, \$2,073 to own an automated vehicle over a conventional gasoline vehicle and pay an additional \$1,078 to include a manual driving option.

In all prior studies on automated vehicles, the sample was drawn from the general population—a group that is not and will not be representative of the first automated vehicle buyers. In general, the majority of consumers are unfamiliar with automated vehicle technology and as a result cannot provide an accurate estimate of their willingness to pay or even a semi-accurate definition for the different levels of autonomy. This study aims to fill the gap left by previous studies by surveying early adopters of new vehicle technology – individuals who are more tech-savvy, familiar with the different vehicle technologies, and in some cases, have personal experience with automated vehicle technology.

3. Data Description and Methods

3.1 Data Description

For this project, we designed and implemented a detailed cross-sectional survey of California residents who participated in the Clean Vehicle Rebate Project (CVRP). The Clean Vehicle Rebate Project is a California funded rebate program in which Californian residents can apply for a rebate of up to \$7,000 for the purchase or lease of an eligible, new zero-emission light duty vehicle ("Clean Vehicle Rebate Project," 2018). The 2017 survey was sent to 31,672 households who applied to the CVRP, of those 15% started the survey and of those 75% completed the survey with an average completion time of 25 minutes. The data collected includes travel data including home location, commute trips, long-distance trips, household vehicles, charging availability and locations, knowledge and opinions of automated vehicle technologies, and experiences with automated vehicle technology (if applicable).

TABLE 8 presents some sample descriptive statistics.

TABLE 8 Sample Descriptive Statistics

Characteristic (sample size)	N (%)	Characteristic (sample/pop. size)		N (%)
Gender (3280)		**Annual Household income (3312)**		
Female	885 (27.0)	Less than $50,000		115 (3.47)
Male	2395 (73.0)	$50,000 to $99,999		466 (14.1)
		$100,000 to $149,999		684 (20.7)
Age (3314)		$150,000 to $199,999		638 (19.3)
18 to 29	172 (5.19)	$200,000 to $249,999		406 (12.3)
30 to 39	759 (22.9)	$250,000 to $299,999		273 (8.24)
40 to 49	818 (24.7)	$300,000 to $349,999		132 (3.99)
50 to 59	727 (21.9)	$350,000 to $399,999		68 (2.05)
60 to 69	552 (16.7)	$400,000 to $449,999		53 (1.60)
70 to 79	236 (7.12)	$450,000 to $499,999		24 (0.72)
80 or older	25 (0.75)	$500,000 or more		74 (2.23)
Decline to state	25 (0.75)	I prefer not to answer		379 (11.4)
Education level (3312)		**Continuous Variables**	**Mean**	**SD**
Grade 8 or less	2 (0.06)	Household income	$185,339	$102,122
Some high school	11 (0.33)	Household size	2.78	1.27
High school graduate or GED	38 (1.15)	HH vehicles	2.34	0.93
Some college	348 (10.5)	Commute distance (miles)	18.85	22.44
College graduate	1039 (31.4)			
Some graduate school	251 (7.58)			
Masters, doctorate, or professional degree	1594 (48.1)			

The average respondent in the sample is male, 49 years old, has a college degree, lives in a household with approximately 1.8 other people, and has 2.34 household vehicles. As shown in TABLE **8**, men constitute roughly 73% of the sample, which is consistent with prior literature. Both (Peters & Dütschke, 2014; Plötz et al., 2014) discuss that electric vehicle buyers are mostly men, middle aged, and come from households with more than one vehicle.

3.2 Survey Design

This detailed cross-sectional survey consisted of 9 sections. The sections and a brief description are described below:

1. **CVRP vehicle information:** Basic vehicle information for the newest plug-in household vehicle including year, make, model, price paid, vehicle financing, current odometer reading, etc. In order to obtain accurate year, make, and model reporting, we used the Edmunds.com API for vehicle identification.
2. **Household vehicle composition:** Basic vehicle information for other household vehicles, if applicable.
3. **Household composition and commute information:** Number of drivers and non-drivers in the household. Commute information such as commute frequency, commute mode, and commute route.
4. **Long-distance road travel:** Number of long-distance trips over 200 miles round-trip in the last 12 months. Specific information about the longest road trip including number of passengers, vehicle used, route taken, trip duration, etc.
5. **Vehicle charging and driving behavior:** Use and frequency of home and out-of-home charging.
6. **Vehicle purchasing process:** Decision process used to purchase/lease the CVRP vehicle.
7. **Utility:** Information about home utility provider, use of renewables (i.e. solar panels), if the utility incentivizes EV charging, etc.
8. **Automated vehicles:** This optional section that collected information about AV awareness and opinions towards vehicle automation. Respondents who had vehicles with automated capabilities, they were asked about their experiences using the software.

9. **Socio-demographic and socio-economic information:** This final section collected information about respondents' income, education, home ownership, etc.

The levels of autonomy were defined using the Society of Automotive Engineers definitions with the aid of Figure 4, presented below.

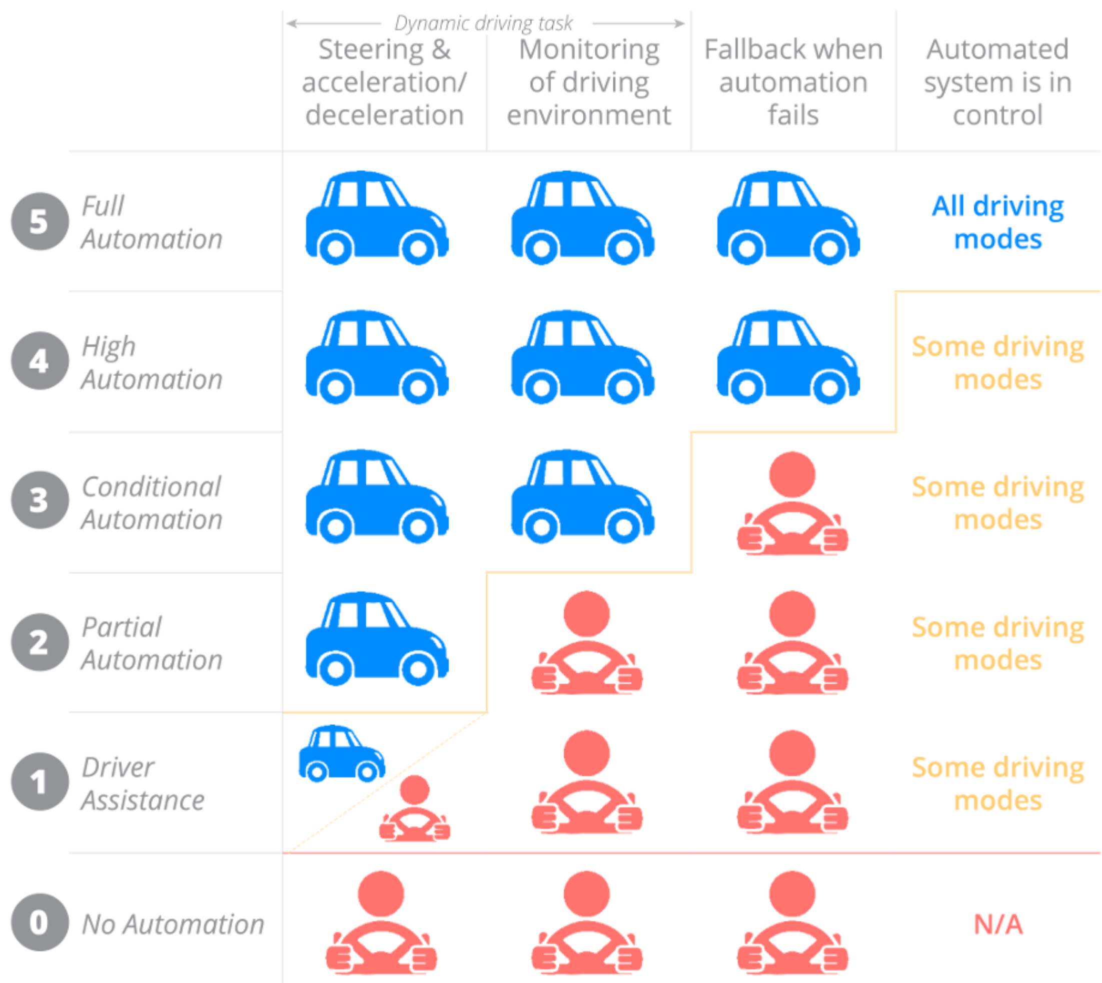

Figure 4. Society of Automotive Engineers Levels of Autonomy (Source: www.sae.org)

More specifically, Levels 0, 1, and 2 were defined as "The driving is entirely operated by a human driver with some assistance system (e.g. Adaptive Cruise Control)". Level three was defined as, "The driving is controlled by an automated driving system, but the human driver must remain fully alert but may have hands and feet off the controls." Level 4 (self-driving cars) was defined as, "The driving is controlled by an automated driving system by the vehicle may request that the human takes control." Level 5 (driverless) was defined as, "The human does not drive the vehicle in any way."

3.3 Modelling

The modeling efforts focus on the information collected in the automated vehicle survey section. Respondents were first presented with a short description of the different levels of autonomy, as defined by the Society of Automotive Engineers, then were asked about their prior knowledge of automated vehicles. Prior to the survey, approximately 97% of respondents indicated some prior knowledge of automated vehicles and most respondents indicated an above average knowledge level. Additionally, several questions tried to compare vehicle characteristics, such as safety, comfort, driver fatigue, energy consumption, environmental impacts, purchase price, etc. of non-automated vehicles to automated vehicles, as well as automated vehicle purchase intentions.

3.3.1 Intentions to Purchase a Level 4/5 Automated Vehicle Model Structure

As part of this project, we estimate the purchase intentions of respondents to buy a level 4 or level 5 automated vehicle. Survey takers were presented with the question, "How likely are you to purchase a vehicle with the following levels of automated driving capabilities when they are available on the market in your price range?" for vehicles with level 3, 4, and 5 automated capabilities. We estimate an ordered logit model of the average likelihood to purchase a level 4 or level 5 automated vehicle. We relied on the average of the two responses, one for level 4 and one for level 5, due to the full automated capabilities afforded by both levels.

In general, an ordinal logit model is defined as:

$$\ln\frac{prob(event)}{1-prob(event)} = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k;$$

Where the odds of a particular event, j, occurring are of the form:

$$\theta_j = \frac{prob(event \leq j)}{prob(event > j)} = \frac{prob(event \leq j)}{1 - prob(event \leq j)}$$

The ordinal logistic model can then be written as:

$$\ln(\theta_j) = \alpha_j - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_j X_j);$$

Where each logit has its own α_i term but has the same coefficient for β_i, which means that the effect of the independent variables is the same for different logit functions. The model relies on the sample that answered questions in this optional section of N = 1,504.

3.3.2 Dependent Variable: Intentions to Purchase a Fully Automated Vehicle

Our study models the average intention to purchase a fully automated vehicle (i.e. level 4 or level 5) using the 5%, 25%, 50%, 75%, 90%, 95%, and 100% quantile values as discrete breaks. The initial scale of both purchase intention variables was -3 to 3, on a continuous, sliding scale. Rather than use equal intervals, quantiles were used as the natural break points. As shown in Figure 5, the average intention to purchase a fully automated vehicle is heavily weighted at end points and the midpoint – respondents were unsure about their purchase intentions, absolutely unwilling to purchase an automated vehicle, or couldn’t wait for them to be introduced to the market.

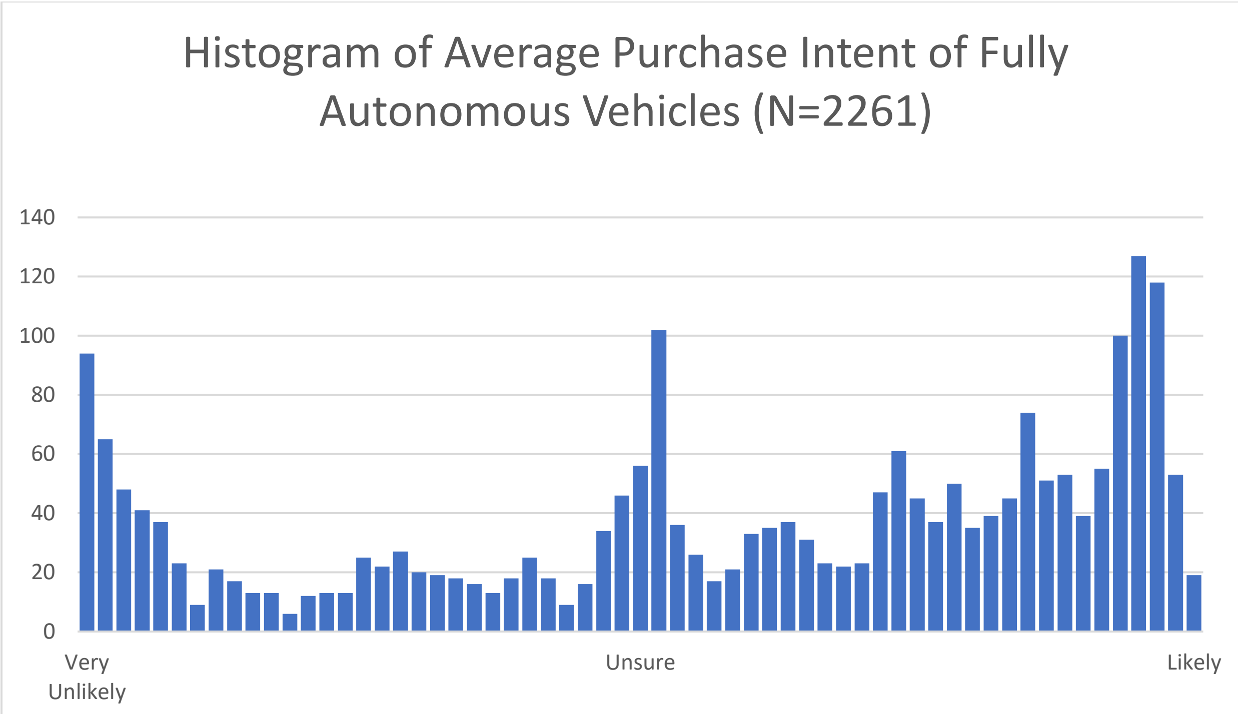

Figure 5. Histogram of Average Purchase Intent of Fully Automated Vehicles

For the question, "How likely are you to purchase a vehicle with the following levels of automated driving capabilities when they are available on the market in your price range," respondents were presented with a slider bar with 5 answer options: Very unlikely, indifferent, very likely, I'm unsure, and no answer. On the -3 to 3, "very unlikely" translates to a value of -3, "unsure" is represented by 0, and "very likely" is represented by a 3. Since this was a continuous scale, unless the respondent had a very strong opinion, their responses did not fall on an integer value. The "I'm unsure" and "No answer" were responses recorded outside the -3 to 3 range and thus were not included in our model.

3.3.3 Independent Variables: Purchase Intentions of Fully Automated Vehicles

In this modeling effort, eight independent variables were found significant in the parsimonious model used to estimate the average purchase intention of fully automated vehicles. Based on the literature, special attention was paid to socio-demographic and perceptions variables. There are three groups of independent variables: socio-demographic, vehicle traits, and attitudes and opinions towards automated vehicles. Socio-demographic variables include age, household size, and gender. The vehicle trait variables include the manufacturer's suggested retail price (MSRP) of the household's newest plug-in electric vehicle and the number of vehicles in the household. We tried to include household income but given the homogeneity of the high household incomes, household income was not a significant variable in the model. Instead, we relied on the MSRP of the new vehicle as a way to describe willingness to pay for a car. The attitudes and opinions towards automated vehicles variables that were tested included perceived knowledge of automated vehicles, the safety of automated vehicles (as compared to non-automated vehicles), the comfort of automated vehicles (as compared to non-automated vehicles), the driver fatigue in automated vehicles (as compared to non-automated vehicles), the purchase price of automated vehicles (as compared to non-automated vehicles), and the environmental impacts of automated vehicles (as compared to non-automated vehicles). More specifically, respondents were asked about their knowledge of automated vehicles and if automated vehicles were better than their non-automated counter parts.

Table 11 presents the sample descriptive statistics of selected independent variables used to estimate the model cross-tabulated with the different levels of the interest in purchasing an automated vehicle.

4. Results and Discussion

4.1 Perceptions About Automated Vehicles

Respondents were asked in question 10.1.2, "Prior to this study how would you rate your knowledge of automated vehicles?" While nearly all respondents indicated that they were aware of automated vehicles prior to the survey, more than a half of respondents felt that they had little to average knowledge about automated vehicles. Figure 6 below provides a distribution of their answers to question 10.1.2.

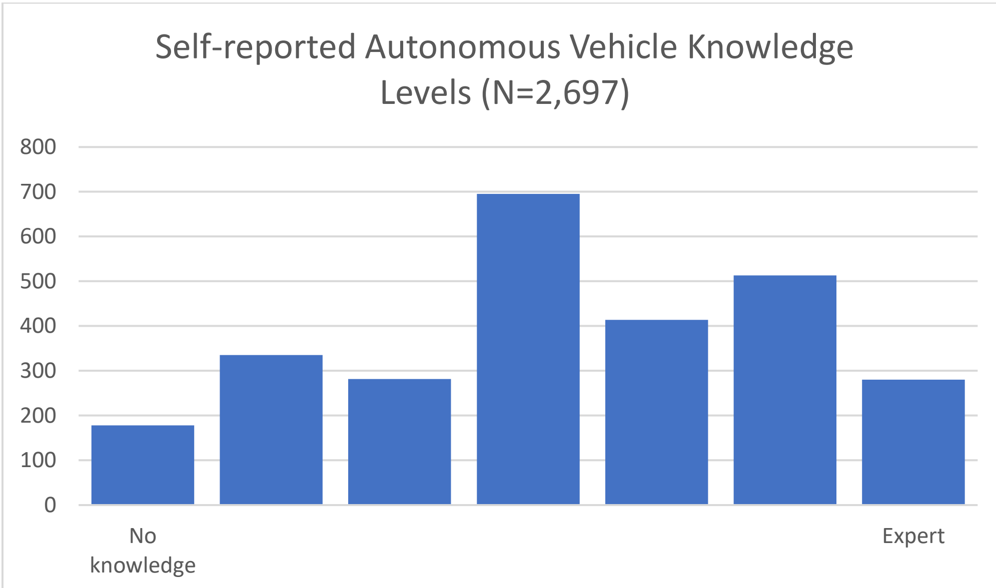

Figure 6 Q10.1.2: Self-reported Automated Vehicle Knowledge Levels

Question 10.1.2 is a continuous scale from -3 to 3, where -3 represents no knowledge, 3 represents expert knowledge, and 0 indicates average knowledge; however, for the purposes of this figure, responses were binned in 7 groups. Roughly 26% of respondents indicated they had average knowledge of automated vehicles. Electric vehicle early adopters tend to be more tech savvy and therefore probably have a higher knowledge than the general population.

As discussed in Section 3.3.3, respondents were asked about their opinions and perceptions towards automated vehicles. For eight perceptions, respondents were asked to compare a vehicle quality between automated and non-automated vehicles, using a continuous scale with end points "Far Worse" (0) to "Far Better" (1), with "No Change" (0.5) at the midpoint. Survey respondents were asked, "How do you think an automated vehicle (Level 3-Level 5) would compare to a non-automated vehicle (Level 0-Level 2) in the following areas?" The areas provided were: Safety, Comfort, Driver Fatigue, Refueling/Recharging Convenience, Energy Consumption, Environmental Impacts, Journey Travel Time, and Vehicle Purchase Price. As shown in Figure 7, below, for all categories, with the exception of purchase price, respondents identified automated vehicles as the "better" option when comparing automated and non-automated vehicles. In Figure 4, if the respondent were to have answered 0, they believed that non-automated vehicles were better than automated vehicles for that specific metric. If they had answered 0.5, the respondent believes that there is no difference between non-automated and automated vehicles for that metric. If the respondent had answered 1 for a specific metric, they believe that automated vehicles were far better than non-automated vehicles for that metric.

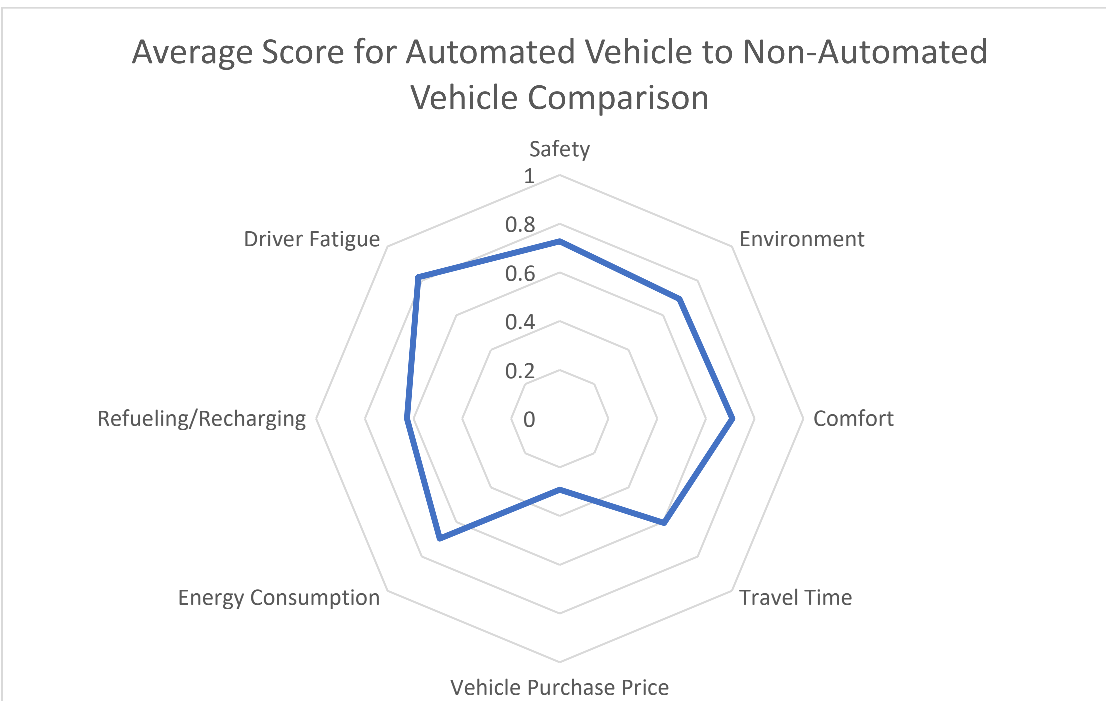

Figure 7 Spider Graph of Average Score for Automated Vehicle to Non-Automated Vehicle Comparison

4.2 Ordinal Logit Model

As mentioned in Section 3, we use an ordinal logit model on the sample of California plug-in electric vehicle households. While multinomial logit (MNL) models may provide a more comprehensive understanding of the dependent variable (Anowar, Yasmin, Eluru, & Miranda-moreno, 2014; Bhat & Pulugurta, 1998; Potoglou & Susilo, 2005), the authors believe that treating this variable as nominal would violate the ordinal quality of the variable. To offset the risk of estimating an ordinal logit model, a parallel lines test was used to check that the slope parameters stayed the same for all response variables and that only the intercepts changed – this is a key assumption of an ordinal logit model. The parallel lines test assumption was met, meaning that the slopes of the independent variables remain the same for the different levels of the dependent variable and only the intercepts change. Having met the parallel lines assumption, an ordinal logit model was confidently estimated to measure the intention of purchasing a fully automated vehicle. The goodness of fit, R-squared, metric is 0.1702, meaning that the variables in the model explain approximately 17% of the variance in the intent to purchase a fully automated vehicle. To the best of the authors' knowledge, this is the first analysis of early-adopters' intention to purchase an automated vehicle. The parameters for the full estimated ordinal logit model are presented in Table 9. The parameters for the estimated final ordinal logit model are presented in Table 10.

Table 9. Parameter estimates for full ordinal logit model

		Estimate	Std. Error	Wald	Sig.
Threshold	5% Quantile	1.818	0.520	12.190	0.0005
	25% Quantile	4.449	0.525	71.720	<.0001
	50% Quantile	6.308	0.539	136.740	<.0001
	75% Quantile	7.979	0.553	208.140	<.0001
	90% Quantile	9.305	0.563	273.060	<.0001
	95% Quantile	10.171	0.572	316.320	<.0001
Location	Automated to non-automated safety comparison	4.482	0.306	213.870	<.0001
	Automated to non-automated driver fatigue comparison	2.089	0.360	33.620	<.0001
	Automated to non-automated environmental impacts comparison	1.367	0.317	18.610	<.0001
	Automated to non-automated purchase price comparison	0.854	0.253	11.400	0.0007
	Number of HH Vehicles	-0.113	0.063	3.220	0.0726
	Age	-0.011	0.004	8.110	0.0044
	Household Size	0.088	0.047	3.460	0.063
	Male	0.156	0.068	5.270	0.0217
	VMT	0.000	0.000	0.040	0.8354
	MSRP of Newest PEV (base $10,000)	0.131	0.023	31.610	<.0001
	Population Density	0.001	0.003	0.220	0.6391
	Household Income (base $10,000)	-0.007	0.005	1.750	0.1859
	Knowledge of Automated Vehicles	0.208	0.044	22.120	<.0001
Number of observations					1,306

Table 10 Parameter estimates for final ordinal logit model

		Estimate	Std. Error	Wald	Sig.
Threshold	5% Quantile	1.791	0.374	22.970	<.0001
	25% Quantile	4.515	0.381	140.740	<.0001
	50% Quantile	6.346	0.397	255.890	<.0001
	75% Quantile	7.991	0.412	376.570	<.0001
	90% Quantile	9.317	0.424	483.680	<.0001
	95% Quantile	10.227	0.435	553.580	<.0001
Location	Automated to non-automated safety comparison	4.570	0.285	257.730	<.0001
	Automated to non-automated driver fatigue comparison	2.081	0.326	40.670	<.0001
	Automated to non-automated environmental impacts comparison	1.336	0.294	20.700	<.0001
	Automated to non-automated purchase price comparison	0.870	0.234	13.820	0.0002
	Number of HH Vehicles	-0.136	0.057	5.800	0.0161
	Age	-0.009	0.004	6.530	0.0106
	Household Size	0.071	0.043	2.670	0.1022
	Male	0.163	0.063	6.570	0.0104
	MSRP of Newest PEV (base $10,000)	0.131	0.023	31.610	<.0001
	Knowledge of Automated Vehicles	0.163	0.041	16.190	<.0001
Number of observations					1,527

Table 11 Sample descriptive statistics of selected independent variables

		5% quantile	25% quantile	50% quantile	75% quantile	90% quantile	95% quantile	>95% quantile
MSRP of Newest PEV	Mean	$ 37,099.49	$ 37,895.43	$ 40,833.59	$ 43,531.13	$ 49,153.74	$ 53,298.11	$ 55,145.68
	Median	$ 33,220.00	$ 33,220.00	$ 34,905.00	$ 35,595.00	$ 37,570.00	$ 37,570.00	$ 40,905.00
	Std Dev	$ 14,386.26	$ 13,504.43	$ 17,978.23	$ 20,570.63	$ 24,575.20	$ 25,338.92	$ 26,534.91
Number of HH Vehicles	Mean	2.41	2.46	2.34	2.33	2.29	2.28	2.18
	Median	2.00	2.00	2.00	2.00	2.00	2.00	2.00
	Std Dev	1.08	1.02	0.94	0.91	0.85	0.97	0.83
Age	Mean	48.69	51.70	48.66	47.45	46.99	47.51	44.95
	Median	45.00	55.00	45.00	45.00	45.00	45.00	45.00
	Std Dev	13.31	13.91	13.52	13.43	12.57	13.57	12.07
Household size	Mean	3.02	2.69	2.74	2.89	2.91	2.79	2.88
	Median	3.00	2.00	2.00	3.00	3.00	2.00	3.00
	Std Dev	2.02	1.22	1.17	1.27	1.28	1.32	1.39
Knowledge of Automated Vehicles	Mean	-0.44	-0.32	0.05	0.47	0.84	1.10	1.17
	Median	0.00	0.00	0.00	0.30	0.96	1.18	1.31
	Std Dev	1.35	1.34	1.24	1.13	1.32	1.08	1.31
Automated to non-automated safety comparison	Mean	0.32	0.50	0.71	0.82	0.86	0.89	0.92
	Median	0.26	0.53	0.74	0.85	0.92	0.95	0.97
	Std Dev	0.30	0.28	0.19	0.14	0.13	0.11	0.13
Automated to non-automated environmental impacts comparison	Mean	0.54	0.61	0.67	0.72	0.75	0.77	0.80
	Median	0.50	0.56	0.64	0.71	0.78	0.81	0.88
	Std Dev	0.17	0.18	0.16	0.17	0.18	0.19	0.19
Gender (Row %)	Female	7.17%	32.90%	28.31%	19.30%	7.72%	1.65%	2.94%
	Male	4.55%	15.72%	24.17%	26.77%	17.20%	6.03%	5.56%
Gender (Column %)	Female	33.62%	40.22%	27.35%	18.82%	12.61%	8.11%	14.55%
	Male	66.38%	59.78%	72.65%	81.18%	87.39%	91.89%	85.45%

4.3 Discussion

As shown in Table 10, as the age increases, the interest in buying a fully automated vehicle decreases. Even though these individuals are early adopters of new vehicle technology, such as electric vehicles, they may not be ready to give up control of the wheel and allow the car to drive for them. Living in a larger household increased an individual's interest in purchasing an automated vehicle. Those PEV owning households that have more people in the household recognize some of the advantages of owning a fully automated vehicle; for instance, while person A is shopping, they can send the vehicle to fetch persons B and C and then have the car retrieve them (person A) at the store. Consistent with earlier literature on early adopters of new vehicle technologies, this model estimates that men are more likely to be interested in purchasing fully automated vehicles than women.

Many early adopter studies find that early adopters typically have high or above average household incomes (de Haan et al., 2007; Egbue & Long, 2012; Jakobsson et al., 2016; Bardlay Lane et al., 2014; Ozaki & Sevastyanova, 2011; Plötz & Gnann, 2011). This study that focus on adoption of new technology among early adopters of electric vehicles would be no exception; however, the household incomes of those in this sample are already high and there is very little heterogeneity exhibited in the sample. Instead, we look at the MSRP of the newest PEV to gain a deeper understanding of how these households use their high incomes. Individuals who paid more for their newest vehicle also indicate a higher interest in purchasing a fully automated vehicle. It could be that these respondents are willing to pay more in general for their vehicle or they are interested in vehicles with automated capabilities. The PEVs with the highest MSRPs in this sample are Tesla vehicles which can be equipped with autopilot software, owners of these vehicles may have experience with semi-automated vehicles which could impact their interest in fully automated vehicles. Those respondents with a higher number of household vehicles expressed a lower interest in purchasing fully automated vehicles; perhaps, these individuals could be 'car enthusiasts' who enjoy the physical act of driving and therefore do not want to relinquish this activity to a computer.

The last set of variables, attitudes and opinions towards automated vehicles, tell an interesting story. Those respondents who indicated a higher level of knowledge of automated vehicles were more interested in purchasing them. These individuals may understand both the advantages and disadvantages of full automation and believe that the positives characteristics of autonomous vehicles outweigh the negatives. Since everyone in this sample was a member of a plug-in vehicle household, the belief that automated vehicles are more environmentally friendly than non-autonomous vehicles indicated a higher interest in purchasing an automated vehicle. Many PEV households own a PEV for the environmental benefits that are associated with zero-emission vehicles and this notion is extended to automated vehicles. A feeling that automated vehicles are safer than non-automated vehicles is the strongest indicator of intent to purchase one. According the Association for Safe International Road Travel, almost 1.37 million people die annually in crashes (ASIRT, 2018). Among those, approximately 37,000 Americans die in road crashes and an additional 2.35 million people are injured (ASIRT, 2018). Many individuals, these respondents included, value road safety and are looking for ways to mitigate crashes and reduce human error – fully automated vehicles can provide a safer driving experience than non-automated vehicles and many consumers prioritize safety above all else.

5. Conclusions and Future Research

The ordinal logit model discussed in this paper highlighted the factors that impact an individual's intention to purchase a fully automated vehicle. This is the first study that looks at early adopters to understand future purchase intentions of automated vehicles and finds that not surprisingly, positive attitudes towards automated vehicles correlate with purchase intentions. Most people in the sample indicated that they had limited knowledge about automated vehicles but did express some interest in purchasing them in the future. Older people are less interested in purchasing automated vehicles but have the financial means to do so. As shown in the model, younger individuals with expensive electric vehicles are likely to be early adopters of automated vehicles. When considering the differences between fully automated (with human controls) and driverless (vehicles without steering wheels), most respondents were hesitant to accept driverless vehicles – most likely due to the fear of using a vehicle that would not let them drive. Overall, Tesla owners (or those with an autopilot experience) are more interested in purchasing automated vehicles.

Based on our survey results, electric vehicle buyers seem likely to purchase automated vehicles. Vehicle automation may make electric vehicles more desirable to consumers which may help grow the electric vehicle market. There is uncertainty about how automated vehicles will be used, which may increase VMT and congestion. More research is needed in this area to assist policy makers to prevent potential VMT growth.

While not much can be said about the general population, based on the literature those who will be first to adopt automated vehicles will be similar to those who are adopting plug-in electric vehicles. In general, early adopters were interested in purchasing fully automated vehicles, a future study could compare the interest in automated vehicles between EV adopters and gas car owners. This study did not investigate the impact of automated vehicle on travel behavior. Future research should investigate how consumers anticipate using the vehicles. Studies could also investigate how semi-automated vehicles (e.g Tesla BEVs with autopilot) are being used today to assess whether there are any change to travel from these vehicles. How will automated vehicles and non-automated vehicles coexist on roadways? Once made available to consumers, how long until the market share of sales of fully automated vehicles reaches 5% or 10%? Will the vehicles be adopted by high income consumers only or will lower income consumers and those with disabilities be able to access and use the vehicles or will they remain a product for high socio-economic status consumers. There are several questions in which this study cannot answer. Finally, this research only focused on one state in the USA, California. Future studies should seek to understand the attitudes of early adopters across the USA.

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Conclusions and Future Work

The 3 Revolutions should no longer be considered a possibility but an inevitability. Vehicle electrification has already begun to occur throughout the world, but shared mobility and vehicle automation will take longer. Reevaluating "old" or traditional behavior patterns such as long-distance travel and learning about new behavior, such as transportation network company drivers and interest in adopting automated vehicles, are all important to evaluating the impact of the 3 revolutions: electrification, automation, and shared rides.

Long distance travel is difficult to study – there are only a handful of states that collect information on long-distance travel. The research conducted aimed to close that gap by studying long-distance travel of millennials and Generation X in California. Californian millennials and Generation X members have a wide range of levels of long distance travel. Those who are tech-savvy, the first to have the newest technology and those who need Wi-Fi or 4G connectivity, make a higher number of long distance trips than those who are not tech savvy. With vehicle automation, long distance travel may grow and become an even larger share of annual VMT. In the future, studies that look at long distance travel should also collect information on potential automated vehicle use, including topics such as frequency, trip purpose, and trip length. Furthermore, these studies should include the electrification of vehicles as well as the potential to share rides, similar to a private shuttle.

Only one study has looked at the characteristics of on-demand ride service drivers (Hall and Krueger 2015). The Hall and Krueger study did not rely on attitudes and opinions, instead it relied solely on socio-demographic and socio-economic data and only presented descriptive statistics. In using an ordinal logit model to understand the factors that impacts an individual's willingness to drive for an on-demand ride service, a deeper understanding of how to identify potential drivers is gained. Furthermore, to better understand the motivations for driving and the impact on car ownership. While many respondents indicated that the money earned would be used to offset the cost of maintaining their vehicle or even purchasing a new/more expensive one, without real driver data, it cannot be certain that their stated preference will match their behavior. Future work on this topic should include focus groups, interviews, or surveys of current on-demand ride service drivers that collect information on why they drive, how long they plan to drive, vehicle technology (to see if there is interest in transitioning to electric vehicles), and shared ride experiences. Learning more about on-demand ride service drivers is one way to better understand how vehicle automation will change the way people travel. In the short term, understanding their experiences and who they are can help move riders towards the more cost effective shared rides.

The introduction of automated vehicles needs to be heavily regulated to ensure that their adoption does not lead to increased congestion and surges in VMT. This first look at the potential adoption of automated vehicles makes use of an ordinal logit model. The model estimates that the first individuals to adopt automated vehicles will be younger plug-in electric vehicle owners who spent more money on their newest plug-in vehicle. In general, early adopters were interested in purchasing fully automated vehicles. In looking at the first wave of potential adopters of automated vehicles, policies can be developed to smooth their introduction into the vehicle fleet. Given their proven dedication to new vehicle technologies as well as high income and education, electric vehicle buyers seem likely to purchase automated vehicles. Vehicle automation may make electric vehicles more desirable to consumers which may help grow the electric vehicle market. There is uncertainty about how automated vehicles will be used, which may increase VMT and congestion. More research is needed in this area to assist policy makers to prevent potential VMT growth. A future study could compare the interest in automated vehicles between EV adopters and gas car owners. This study did not investigate the impact of automated vehicle on travel behavior. Future research should investigate how consumers anticipate using the vehicles. Studies could also investigate how semi-automated vehicles (e.g Tesla BEVs with autopilot) are being used today to assess whether there are any changes in travel with these vehicles. How will automated vehicles and non-automated vehicles coexist on roadways? Once made available to consumers, how long until the market share of sales of fully automated vehicles reaches 5% or 10%? Will the vehicles be adopted by high income consumers only or will lower income consumers and those with disabilities be able to access and use the vehicles or will they remain a product for high socio-economic status consumers. There are several questions in which this study could not answer. This research only focused on one state in the USA, California. Future studies should seek to understand the attitudes of early adopters across the USA.

Understanding long distance travel, on-demand ride service drivers, and the adoption of automated vehicles each represent parts of the path needed to achieve the 3 revolutions: electrification automation and shared rides. Vehicle automation may fundamentally change the way people travel, especially for long distance travel. More long-distance travel and higher mobility may increase overall VMT and congestion. Understanding how vehicle automation will impact long-distance travel is paramount to estimating annual VMT and should be studied before automated vehicles are made available for consumers. On-demand ride service drivers are quintessential to providing rides for on-demand ride service passengers. By understanding their willingness to drive, planners and other stakeholders can be better equipped to incentivize shared rides, not only for the passenger but for the driver as well. Automated vehicles are vehicles of the future; however, policy makers and other stakeholders need to start planning for their introduction to consumers.