



# What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California



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## ABSTRACT

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

## 1. Introduction

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

uncertainty, and potentially replacing the use of other travel modes.

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

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

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

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

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

The remainder of this paper is organized as follows: after a brief literature review in Section 2, Section 3 discusses the data collection and methods of analysis. Then, Section 4 discusses the estimation of two binary choice models and the model results, followed by a discussion of the impact of on-demand ride services on the use of other modes of transportation in Section 5. Finally, conclusions and perspectives for future research are presented in Section 6.

## 2. Literature review

Transportation in the United States is going through an era of rapid transformation, including the disruption of long-standing patterns and the emergence of new ones. Among other trends, total vehicle miles traveled (VMT) and the total number of privately-owned vehicles have started to rise again in the U.S. after a steady decrease in the mid-2000s (FHWA, 2017). The percentage of zero-vehicle households also increased during the period, even as the total number of trips by private vehicle in the country continued to rise (Sivak, 2014). Despite the

continued reliance on private cars, at least some segments of the population are apparently becoming more multimodal (Buehler and Hamre, 2014). In general, people are more open to the use of information and communication technologies (ICT) and the adoption of technology-enabled transportation alternatives, such as new shared-mobility services. On the other hand, the impacts of many of these emerging trends are confounded with other factors affecting travel patterns, including generational differences, changes in household compositions and lifestyles, and the temporary changes associated with the recession that began in 2008. For example, it is not clear whether the increase in the percentage of zero-vehicle households will slow or even reverse now that the economic recession has ended, or whether other factors will sustain it.

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

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

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

Previous research about the early adopters of shared-mobility services (e.g. carsharing, bikesharing and on-demand ride services)

<sup>1</sup> <https://uberexpansion.com/lyft-vs-uber-side-by-side-comparison/> (last accessed on January 28, 2018).

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

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

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

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

Recent studies indicate that the impact of shared-mobility services on other means of transportation may vary based on the type of services available, the local context, and the characteristics of the users (Taylor et al., 2015; Circella et al., 2016a). For example, 40% of TNC users in San Francisco reported that they reduced their driving due to the adoption of on-demand ride services (Rayle et al., 2014). Further, depending on local circumstances, travelers may use on-demand ride services as a substitute for or as a complement to the use of public transit. The Shared-Use Mobility Center (2016) administered a survey among 4500 users of shared-mobility services, revealing that frequent users of shared mobility also tend to be frequent users of public transit and multimodal travelers. Some of this relationship may be due to the correlation of both behaviors with third-party variables such as low car

ownership or living in more accessible locations, and thus it does not imply causality. The same study found that the majority of the trips made by on-demand ride services occurred between 10 pm and 4 am, when public transit either runs very infrequently or does not run at all. This finding suggests a complementarity effect. On the other hand, public transit may be losing riders as the share of ridehailing services increases: a study of seven large U.S. metro areas showed that these services tend to substitute for 6% and 3% of the trips that would have been otherwise made by bus and light rail, respectively (Clewlow and Mishra, 2017). Still, it is not yet clear the extent to which the adoption of shared-mobility services causes an increase (for example) in transit use, as opposed to both of those conditions being caused by other variables such as residential location, age/stage in lifecycle, and vehicle ownership.

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

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

### 3. Data collection and methodology

#### 3.1. The California Millennials Dataset

The California Millennials Dataset was collected in fall 2015 as part of an on-going research project investigating emerging travel patterns and residential location decisions among selected segments of the population. To conduct the project, we designed and administered an online survey to a sample of more than 2400 residents of California recruited through an online opinion panel. The sample included 1400 millennials, i.e. young adults 18–34 years old in 2015, and 1000 members of the preceding Generation X, i.e. middle-aged adults between 35 and 50 years old. We employed a quota sampling approach to ensure that a sufficient number of respondents were included from each of six main geographic regions of California and from three neighborhood types (urban, suburban, and rural). We defined the six regions as (1) the California Central Valley (corresponding to the eight counties in the central San Joaquin Valley); (2) Sacramento, following the boundaries of the Sacramento Area Council of Governments (SACOG); (3) San Diego, following the boundaries of the San Diego Association of Governments (SANDAG); (4) Greater Los Angeles, following the boundaries of the Southern California Association of Governments (SCAG); (5) the San Francisco Bay Area, following the boundaries of the

Metropolitan Transportation Commission (MTC); and (6) the rest of Northern California and Others, comprising the remaining mountain, coastal and rural regions in the state. We also set targets for five socio-demographic characteristics while recruiting the sample: gender, age, household income, race and ethnicity, and the presence of children in the household. We then employed a combination of cell weighting and iterative proportional fitting (IPF) raking to correct for non-representativeness of the sample on various pertinent traits, including age group, neighborhood type, region, race, ethnicity, presence of children in the household, household income, student/employment status, and gender.

A total of 5466 invitations were sent out, and 3018 complete cases were collected. The high response rate of 46.3% is not surprising considering the data collection method used for this project, and the higher propensity of opinion panel members to respond to survey invitations. It is important to note potential concerns with the use of opinion panels. In addition to self-selection bias, which affects most of the studies that use surveys as a main method for data collection, one of the major concerns about the use of an online panel is non-coverage bias (also known as non-/under-representation bias). The concern is that the members of the online opinion panel may not be (fully) representative of the larger population. Studies show that several groups of individuals are more likely to be excluded from online panels than others. For example, elderly women with low educational attainment and people without access to the internet are more likely to be excluded from online panels (e.g., Blasius and Brandt, 2010), although the former group is not a segment addressed by the present analysis. In this study, we used a quota sampling approach to ensure that enough respondents are recruited in each group; however, as also discussed by Blasius and Brandt (2010), quota sampling does not completely resolve this issue given the infeasibility of defining large numbers of categories for the quotas. In our study, we believe that defining quotas based on different regions and neighborhood types as well as five socio-demographic characteristics does a reasonable job of controlling for non-coverage bias. Further, whatever remaining sampling bias(es) may still affect the data, it is reasonable to expect them to affect both age groups in a similar way, thus maintaining the validity of the comparisons between millennials and older adults in the study.

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

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

The California Millennials Dataset is a relevant sample for this study, as millennials and members of Generation X are believed to comprise the majority of the early adopters of Uber and Lyft. In the survey, we asked respondents to indicate whether they are already familiar with various types of emerging shared-mobility services, if these services are available in the area where they live, and what services they have already used. For those services used by respondents, they

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

### 3.2. Analysis

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

The dependent variable is binary: a value of 1 for this variable indicates that the respondent has (already) used on-demand ride services. Fig. 1 shows the distribution of users and non-users of such services by age group (millennials vs. members of the preceding Generation X) in the weighted sample. As shown in this figure, larger shares of millennials have adopted on-demand ride services (31.8%) compared to members of the older cohort (21.3%). To create the dependent variable for the model estimation, we grouped all individuals who reported having used such services in their hometown, away from home, or in both locations, and classified them as “users”. Those who have heard about these services but have not used them yet and those who reported that they have not heard about these services were classified as “non-users”. Table 2 summarizes the key attributes of the individuals who have used these services, who have heard but not used yet, and who have not heard about these services, respectively.

To identify the factors that affect the use of on-demand ride services, we first looked at the differences between users and non-users in the distribution of potential explanatory variables. We selected variables to include in the models by conducting a series of descriptive analyses using one-way analysis of variance (ANOVA) or chi-squared tests to identify variables that differed significantly between the two groups and that were also conceptually meaningful. Table 1 defines, and Table 2 reports the descriptive statistics of the weighted explanatory variables that are included in the final binary logit models (Table 8, in Appendix B, reports the same descriptive statistics for the unweighted dataset). We divided these explanatory variables into four main groups, and we tested different variable transformations in each group to identify the variables most closely associated with the use of Uber/Lyft. The four groups of variables are as follows:

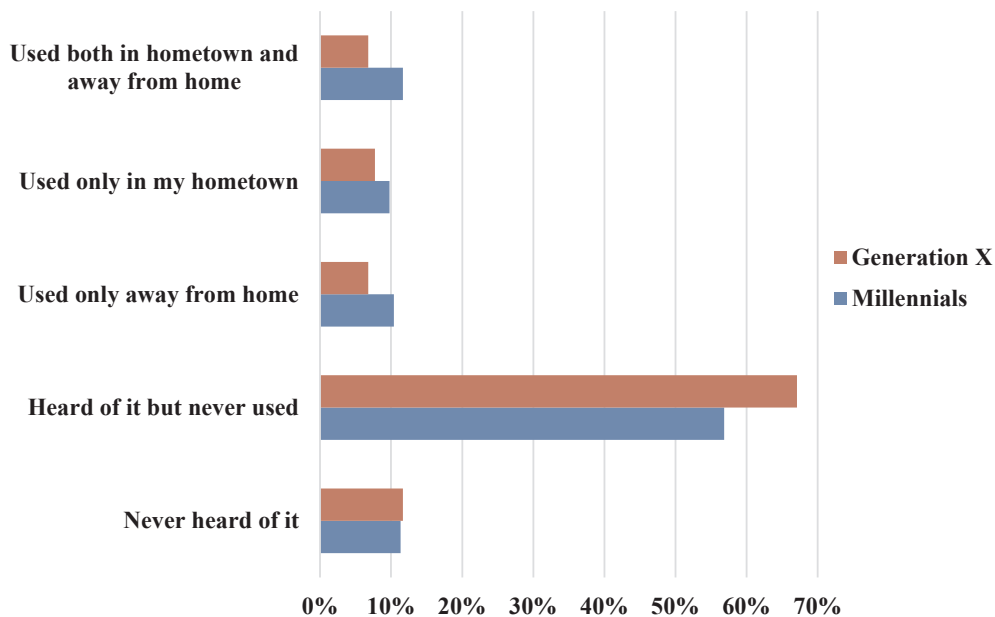


Fig. 1. Awareness and use of on-demand rides (e.g. Uber and Lyft) by age group (Weighted Sample,  $N_{\text{Millennials}} = 1022$ ,  $N_{\text{Gen X}} = 945$ ).

### 3.2.1. Socio-demographics

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

### 3.2.2. Geographic region and built environment

This group of variables includes information on the geographic region where the respondent lives and additional built environment variables that were imported from other datasets. Controlling for the impact of the characteristics of the built environment on the adoption of on-demand ride services is important, as these services are not equally available across all California regions and all neighborhood types. As part of this study, we geocoded the reported home address for each individual in the dataset and classified the residential neighborhood type as predominantly urban, suburban or rural, using the typology defined in *Salon (2015)*.<sup>2</sup> Fig. 2 maps the distribution of the users in different regions of California and neighborhood types. To capture spatial heterogeneity and test the impact of other built environment variables such as land use mix, network connectivity, population density, and regional accessibility on the adoption of on-demand ride services, we integrated the dataset with additional data extracted from the U.S. Environmental Protection Agency (EPA) Smart Location Dataset,<sup>3</sup> based on the respondent’s geocoded home location.

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

<sup>3</sup> The EPA Smart Location Dataset provides various statistical and deterministic built environment indicators, estimated at the Census block group level,

### 3.2.3. Lifestyles and use of technology

This group of variables accounts for individuals’ lifestyles and propensity to use social media (i.e., Facebook), ICT and other technological applications (in general, or to access transportation-related services), as well as the frequency of long-distance travel by purpose (business vs. leisure/personal) and by mode (e.g., car, plane, intercity bus and train). The literature has discussed the role of some of these variables in the context of non-transportation sharing economy services, e.g. their relationships with the use of peer-to-peer lodging services provided by Airbnb. For example, those who are more familiar with the use of technology more often search for (or share) information online, and those who are more active on Facebook or other online social media are more inclined to use Airbnb (*Latitude, 2010*). We hypothesize that these individuals are also more likely to use shared-mobility services. Several variables in our dataset measured the use of smartphones for different purposes. To reduce the dimensionality of the smartphone-related variables, we performed principal component analysis. *Table 3* reports the two principal components and their associated variables. Our hypothesis is that the familiarity with and use of smartphone in connection to transportation and the use of other emerging transportation services (e.g., carsharing, bikesharing) can affect the adoption of on-demand ride services, as technology-oriented users that already benefit from the use of other shared-mobility services might be more inclined also to adopt on-demand ride services.

### 3.2.4. Personal attitudes

Testing the impacts of individual attitudes on the adoption of technological transportation services such as those provided by Uber and Lyft is an important addition. This was possible using the information available in this dataset, whereas attitudinal variables are not commonly available in other datasets available for travel behavior research (such as those collected with national and most regional household travel surveys). As discussed earlier, in this study we estimated two models: the first model only accounts for the first three groups of variables, while the second also includes individual attitudes

(footnote continued)

which were matched to the respondent’s residential location based on the geocoded location of the self-reported street address (<https://www.epa.gov/SMARTGROWTH/SMART-LOCATION-MAPPING>).

**Table 1**  
Description of key variables.

Variable name	Description
<b>Dependent variable</b>	
Adoption of on-demand ride services	1 = Have used on-demand ride services before; 0 = Have heard of these services but have never used them, or have not heard of these services
<b>Explanatory Variables</b>	
<i>Socio-demographics</i>	
Age	
Younger Millennials	1 = Individual 18–24 years old; 0 = Else
Older Millennials	1 = Individual 25–34 years old; 0 = Else
Younger Gen X	1 = Individual 35–41 years old; 0 = Else
Older Gen X	1 = Individual 42–50 years old; 0 = Else
Presence of Children in the Household	1 = Household with child(ren); 0 = Household without children
Household Income	
Low	1 = Annual household income of 0–39,999 USD; 0 = Else
Medium	1 = Annual household income of 40,000–99,999 USD; 0 = Else
High	1 = Annual household income of 100,000 or more USD; 0 = Else
Employment Status	1 = Work as full time or part time employee; 0 = Else
Student Status	1 = Full time or part time student; 0 = Not student
High Education Level	1 = High education (with at least Bachelor's degree); 0 = Else
Non-Hispanic Ethnicity	1 = Non-Hispanic origin; 0 = Hispanic origin
Sex (Female)	1 = Female; 0 = Else
<i>Geographic Region and Built Environment</i>	
Region	
Central Valley	1 = Home address is located in Central Valley; 0 = Else
Northern California and Others	1 = Home address is located in Northern California or Other area; 0 = Else;
Sacramento	1 = Home address is located in Sacramento area; 0 = Else
San Diego	1 = Home address is located in San Diego area; 0 = Else
Greater Los Angeles	1 = Home address is located in Los Angeles area; 0 = Else
San Francisco Bay Area	1 = Home address is located in San Francisco area; 0 = Else
Neighborhood Type (Geocoded Home Address)	
Urban	1 = Respondent lives in urban/central city neighborhood; 0 = Else
Suburban	1 = Respondent lives in suburban neighborhood; 0 = Else
Rural	1 = Respondent lives in rural/rural in urban neighborhood; 0 = Else
Land Use Mix	A continuous variable between 0 and 1 (where higher values mean a more diverse mix), showing 8-tier employment entropy (denominator set to observed employment types in the Census Block Group), obtained from the EPA Smart Location Dataset
Destination Accessibility	A continuous variable between 0 and 1 (where higher values mean greater auto accessibility), showing the Regional Auto Centrality Index, obtained from the EPA Smart Location Dataset
<i>Lifestyles and Use of Technology</i>	
Use of Social Media (Facebook)	
Lower frequency	1 = Checks Facebook less than once a day; 0 = Else
Higher frequency	1 = Checks Facebook at least once or multiple times a day; 0 = Else
Use of Taxi	1 = Has used taxi before; 0 = Else <sup>1</sup>
Use of Carsharing Services	1 = Has used any type of carsharing services (including peer-to-peer carsharing and fleet-based carsharing) before; 0 = Else
Use of Smartphone (see Table 3 for details)	
To Determine Destination and Route	Standardized principal component scores measuring frequency of using smartphone to determine destination and route
For Mode Choice	Standardized principal component scores measuring frequency of using smartphone to choose specific mode(s) and check transit time
Frequency of Long-Distance Business Travel (Log-Transformed)	Continuous variable showing the log of the total number of long-distance trips made for business purposes during the past 12 months
Share of Total Long-Distance Travel by Plane	Continuous variable showing the share of total long-distance trips made by plane during the past 12 months
<i>Personal Attitudes (see Table 4 for details)</i>	
Technology Embracing	Standardized Bartlett factor score measuring attitudes towards the adoption of technology
Variety Seeking	Standardized Bartlett factor score measuring attitudes towards seeking variety in life
Pro-Environmental Policies	Standardized Bartlett factor score measuring pro-environmental policy attitudes

<sup>1</sup> We excluded cases who reported never having heard of taxi services, as likely being frivolous respondents.

using the standardized Bartlett factor scores that were computed through a factor analysis of the original attitudinal variables included in the dataset. Among the 17 factors that were extracted, the *Technology Embracing*, *Variety Seeking*, and *Pro-Environmental Policies* factors had significant effects on the adoption of shared-mobility services and were included in the final model. Table 4 provides more details on the three factor scores that were included in the final model and the attitudinal statements loading on each of them.

Incorporating attitudinal variables into a choice model is an important way to improve the model's ability to explain behavior. The exclusion of attitudinal variables may reduce the explanatory power of the model and may confound the effect of the included explanatory

variables on the adoption of on-demand ride services, wrongly attributing the influence of attitudes to other variables in the model (as discussed in the next section). Thus, neglecting attitudinal variables may lead to omitted variable biases if these variables are correlated with the included independent variables. However, the inclusion of attitudinal variables into a choice model in the form of separately estimated factor scores may introduce some measurement bias because answers to attitudinal questions are not direct measures of attitudes but rather functions of underlying latent attitudes. Although the approach followed in the present paper is a practical way to include attitudes in the model estimation, while retaining simplicity in the model estimation and interpretability of the results, in future phases of the project we

**Table 2**  
Distribution of key explanatory attributes by use of on-demand ride services (Weighted Sample, N = 1967).

Explanatory variables	Users [N = 526]		Heard of but never used [N = 1215]		Never heard of [N = 226]	
	Count	Col. %	Count	Col. %	Count	Col. %
<b>Socio-demographics</b>						
<i>Age</i>						
Younger Millennials	92	17.5%	250	20.6%	58	25.8%
Older Millennials	233	44.3%	331	27.2%	58	25.8%
Younger Gen X	116	22.0%	314	25.9%	46	20.4%
Older Gen X	85	16.2%	319	26.3%	63	28.0%
<i>Presence of Children in the Household</i>						
Yes	248	47.2%	645	53.1%	125	55.3%
No	278	52.8%	569	46.9%	101	44.7%
<i>Household Income [N = 1831]</i>						
Low (\$0–40 K)	108	21.5%	306	27.1%	109	50.5%
Medium (\$40–100 K)	180	35.9%	482	42.8%	62	28.7%
High (\$100 K+)	214	42.6%	339	30.1%	45	20.8%
<i>Employment Status</i>						
Employed	470	89.5%	949	78.1%	165	73.0%
Not Employed	55	10.5%	266	21.9%	61	27.0%
<i>Student Status</i>						
Student	127	24.1%	215	17.7%	60	26.5%
Not Student	400	75.9%	999	82.3%	166	73.5%
<i>Education Level</i>						
Bachelor's Degree or Higher	341	64.8%	547	45.3%	58	25.8%
Associate Degree or Below	185	35.2%	661	54.7%	167	74.2%
<i>Ethnicity</i>						
Hispanic Origin	182	34.6%	490	40.4%	118	52.2%
Non-Hispanic Origin	344	65.4%	724	59.6%	108	47.8%
<i>Sex</i>						
Female	282	53.6%	602	49.5%	124	54.9%
Male	244	46.4%	613	50.5%	102	45.1%
<b>Geographic Region and Built Environment</b>						
<i>Region</i>						
Central Valley	30	5.7%	211	17.4%	60	26.7%
Northern California and Others	3	0.6%	27	2.2%	12	5.3%
Sacramento	21	4.0%	75	6.2%	14	6.2%
San Diego	57	10.8%	108	8.9%	10	4.4%
Greater Los Angeles	295	56.1%	531	43.7%	94	41.8%
San Francisco Bay Area	120	22.8%	262	21.6%	35	15.6%
<i>Neighborhood Type (Geocoded Home Address)</i>						
Urban	220	41.8%	279	23.0%	27	11.9%
Suburban	241	45.8%	568	46.8%	95	42.1%
Rural	65	12.4%	367	30.2%	104	46.0%
<i>Land Use Mix (8-Tier Employment Entropy)</i>						
Mean (Std. Deviation)	0.64 (0.23)		0.59 (0.28)		0.60 (0.27)	
<i>Destination Accessibility (Regional Centrality Index by Auto)</i>						
Mean (Std. Deviation)	0.57 (0.20)		0.51 (0.22)		0.50 (0.25)	
<b>Lifestyles and Use of Technology</b>						
<i>Use of Social Media (Facebook)</i>						
Lower Frequency	137	26.1%	461	37.9%	77	34.2%
Higher Frequency	389	73.9%	754	62.1%	148	65.8%
<i>Use of Taxi</i>						
Used Taxi Before	367	71.5%	438	36.9%	59	35.5%
Never Used Taxi Before	146	28.5%	748	63.1%	107	64.5%

**Table 2 (continued)**

Explanatory variables	Users [N = 526]		Heard of but never used [N = 1215]		Never heard of [N = 226]	
	Count	Col. %	Count	Col. %	Count	Col. %
<i>Use of Carsharing Services</i>						
Used Carsharing Before	93	17.7%	18	1.5%	8	3.6%
Never Used Carsharing Services	432	82.3%	1197	98.5%	217	96.4%
<i>PCA Score: Use of Smart Phone to Determine Destination and Route [N = 1961]</i>						
Mean (Std. Deviation)	0.49 (0.75)		-0.16 (0.99)		-0.28 (1.16)	
<i>PCA Score: Use of Smart Phone for Mode Choice [N = 1961]</i>						
Mean (Std. Deviation)	0.39 (1.04)		-0.16 (0.92)		-0.10 (1.04)	
<i>Frequency of Long-Distance Business Travel (Log-Transformed) [N = 1936]</i>						
Mean (Std. Deviation)	0.50 (0.54)		0.26 (0.44)		0.38 (0.52)	
<i>Share of Total Long-Distance Travel with Plane [N = 1924]</i>						
Mean (Std. Deviation)	0.34 (0.32)		0.18 (0.29)		0.10 (0.23)	
<b>Personal Attitudes</b>						
<i>Factor Score: Technology Embracing [N = 1965]</i>						
Mean (Std. Deviation)	0.42 (0.90)		-0.01 (0.97)		-0.08(0.99)	
<i>Factor Score: Variety Seeking [N = 1965]</i>						
Mean (Std. Deviation)	0.39 (0.88)		-0.03 (0.97)		-0.13(1.08)	
<i>Factor Score: Pro-Environmental Policies [N = 1965]</i>						
Mean (Std. Deviation)	0.46 (1.15)		-0.04 (1.02)		-0.13(1.01)	

plan to use attitudinal indicators as outcomes of latent explanatory variables in the adoption model. This requires a model specification that embeds joint models of revealed (stated) choice(s) and the response to attitudinal statements through latent variables, i.e. a hybrid choice model (Ben-Akiva et al., 2002; Bolduc et al., 2005). Nevertheless, the practicality of Integrated Choice and Latent Variable (ICLV) models have been questioned by researchers (Chorus and Kroesen, 2014). Further, Vij and Walker (2016) showed that an ICLV model can in many cases be reduced to a choice model without latent variables that fits the choice data at least as well as the original ICLV model from which it was obtained. Further, neither of the discussed approaches (i.e. the joint and separate estimation of attitudinal factors in the choice model) can account for the eventual reverse causality and/or bi-directional causality between choice and attitudes. This, particularly, becomes very important if the use (or non-use) of ridehailing over time affects attitudes towards these services, or if personal attitudes simultaneously affect the adoption of ridehailing and at the same time are affected by the adoption of the service.

As indicated in Table 2, the adoption of on-demand ride services is higher among older millennials and those whose education includes a bachelor's degree or higher. About 38% of older millennials reported that they have used on-demand ride services, while the adoption rate is lower among younger millennials and the members of Generation X. We also find a higher adoption rate for individuals who live in high-income households and those with higher levels of education. Similarly, urban dwellers are more likely than others to use these services. With respect to technology adoption, we find that users of on-demand ride services are frequent users of transportation-related smartphone applications and technology-enabled transportation services, while those who have heard about on-demand ride services but never used them, or those who have not heard about these services, are less frequent users of these

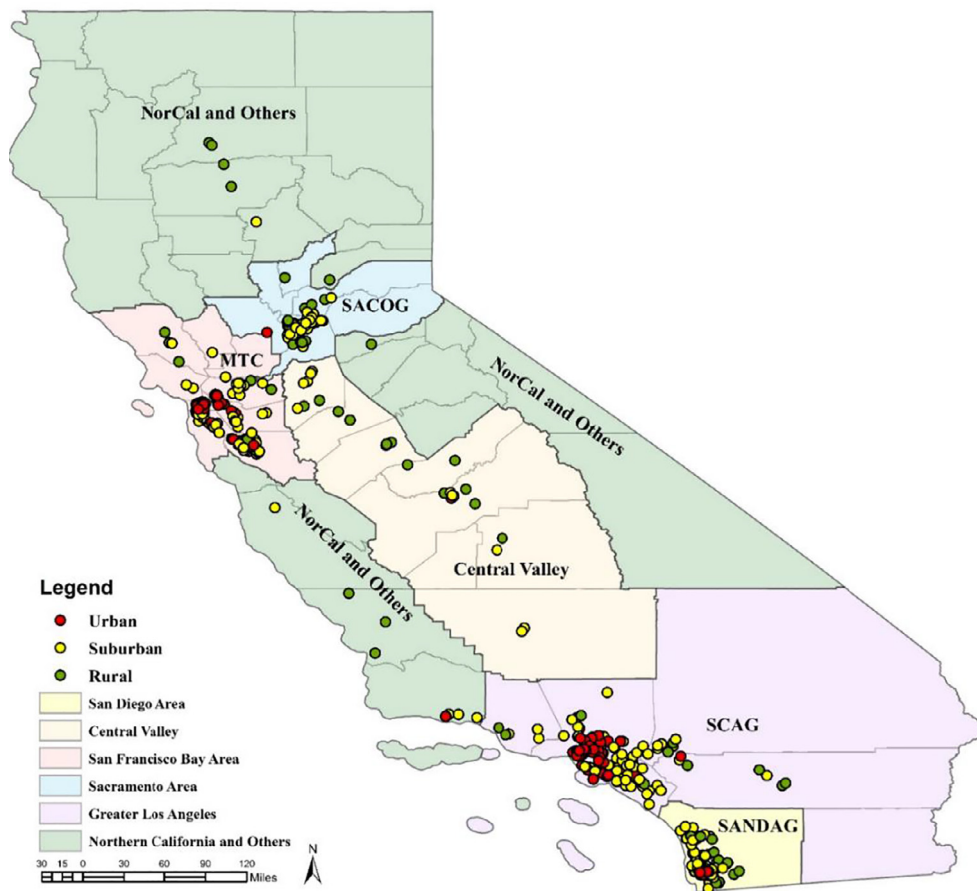


Fig. 2. Distribution of the users of on-demand rides (e.g. Uber and Lyft) by region and neighborhood type.

**Table 3**  
Principal Component Loadings of Use of Smartphone in Relation to Transportation.

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

smartphone-based services. The average scores of all three attitudinal factors are positive among the users of on-demand ride services and higher than for the two groups of non-users, reflecting more positive attitudes toward technology adoption, variety in life and pro-environmental policies.

In other model specifications, not shown in this paper, we included an additional group of explanatory variables measuring the self-reported expected changes in individual travel behavior, such as the expected changes in the use of various transportation modes during the next three years, and the propensity to sell or replace one or more household vehicle(s). The results showed that users of on-demand ride services tend to expect to travel by train and active modes more often and to use a car less often in the next three years, and they are less likely to increase the number of cars in their household. However, we

excluded these variables from the final models, even though they had statistically significant coefficients, because of their likely endogenous nature, which would therefore bias the coefficient estimates. For example, a recent Reuters/Ipsos opinion poll reveals that about 10% of the users of on-demand ride services plan to dispose of their vehicles and turn to on-demand ride services as their primary means of travel (Henderson, 2017), supporting the supposition that the decision to sell a household vehicle in the medium-term future could well be an effect rather than a cause of the adoption of shared-mobility services.

#### 4. Modeling the adoption of on-demand ride services

Table 5 presents the final models of on-demand ride services adoption (user versus non-user) without and with attitudinal variables. The first model, without attitudinal variables, is largely consistent with the results from previous studies based on descriptive statistics, and with our expectations. In the second model, the three attitudinal factors discussed above proved to be significant.

##### 4.1. Model of on-demand ride services adoption – without attitudes

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



**Table 4**  
Relevant factors and their strongly-loading attitudinal statements.

Factors and most strongly-associated attitudinal statements	Loadings from pattern matrix
<i>Pro-environmental Policies</i>	
We should raise the price of gasoline to reduce the negative impacts on the environment	0.94
We should raise the price of gasoline to provide funding for better public transportation	0.84
The government should put restrictions on car travel in order to reduce congestion	0.34
<i>Variety Seeking</i>	
I like trying things that are new and different	0.61
I have a strong interest in traveling to other countries	0.41
<i>Technology Embracing</i>	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me	0.62
Getting around is easier than ever with my smartphone	0.58
Learning how to use new technologies is often frustrating	−0.33
Technology creates at least as many problems as it does solutions	−0.29

highest adoption rate among individuals who both work and study. In early models that we estimated, the presence of children in the household was significant; however, the magnitude of the impact of this variable diminishes after including other variables, and the variable was found not to have statistically significant effects in the final model. In addition, we find that the adoption of on-demand ride services is higher among females and individuals of non-Hispanic origin.

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

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

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

#### 4.2. Model of on-demand ride services adoption – with attitudes

To test for the impact of individual attitudes and preferences on the adoption of on-demand ride services, we incorporate factor scores as explanatory variables in the adoption model. We find that the rate of adoption of on-demand ride services is significantly higher among

individuals with more positive factor scores for technology embracing, pro-environmental policies, and seeking variety in life. These findings are consistent with our expectations about ridehailing users. Interestingly, none of the other attitudes that we tested, including factors measuring attitudes toward (1) *car use and ownership* (e.g. “car as a tool” and “must own a car”); (2) *multitasking while commuting*; and (3) *mode choice* were significant. We speculate that we will see more statistically significant attitudinal variations between users and non-users when analyzing the frequency of use of on-demand ride services (rather than simply their adoption as we do in this paper). We plan to investigate the frequency of use of these services in a future extension of this research.

As shown in Table 5<sup>4</sup>, the inclusion of attitudinal variables improves the goodness of fit of the model but has only a small impact on the coefficients and statistical significance of the variables included in the model, consistent with the low correlations between these factor scores and other variables used in the final model. The small impact indicates that the attitudinal variables mostly add independent explanatory power not captured by other variables.

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

#### 5. Frequency of use of on-demand ride services and impact on the use of other travel modes

How the use of on-demand ride services affects other components of travel behavior, and in particular the use of other means of transportation, is a critical question for understanding the environmental, economic and equity effects of these services. As shown in Fig. 3, the majority of Uber and Lyft users solicit on-demand ride services only occasionally (less than once a month). Millennials tend to use on-demand ride services with higher frequency compared to the older cohorts. Interestingly, about 10% of both groups report they have used these services in the past, but they do not use them anymore. This may indicate dissatisfaction with prior use, or a change in circumstances that has made usage less accessible or desirable.

<sup>4</sup> We further expanded our investigation of the contribution of personal attitudes to the model goodness of fit, through testing the inclusion of these factors as either the first or the last group of variables into the model estimation. The results show that attitudinal factors contribute about 0.23 and 0.12 to the adjusted rho-squared of the model, respectively, compared to the Equally Likely and Market Share models, if this group of variables is included first in the model estimation. Instead, this contribution is only 0.04 and 0.05, respectively, where personal attitudes are entered as the last group of variables in our final model (after controlling for all other variables). Looking at the contribution of each group of variables, we find that attitudinal factors largely shrink the magnitude of the contribution of the socio-demographic variables in the final models, confirming that key sociodemographics act as a proxy for attitudinal variables (thus, taking over some of their explanatory power) in models that do not control explicitly for individuals’ attitudes.

**Table 5**  
 Estimation results for weighted binary logit model of the adoption of on-demand ride services (N = 1702).

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

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

Table 6 shows how users of ridehailing differ with respect to their sociodemographic traits and the geographic location of their residence. We find that frequent users of on-demand ride services (those who reported that they have used these services at least on a weekly basis) are mainly from the Bay Area and Los Angeles regions and are more likely to live in urban neighborhoods. About half of frequent users of these services are between 25 and 34 years old and are more likely to live in low-/medium-income households. Interestingly, we find that a larger percentage of frequent ridehailing users live in zero-vehicle households, compared to non-frequent users. However, it is not clear whether the current number of vehicles in the household is a cause of the higher usage of these services, or an effect of their adoption (e.g. ridehailing users might decide to dispose of a vehicle, as they can fulfil their mobility needs with these services). The cross-sectional nature of the dataset does not allow exploring this topic in more detail, though in future stages of the research (when longitudinal data will become available in this panel study) we plan to investigate this topic.

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

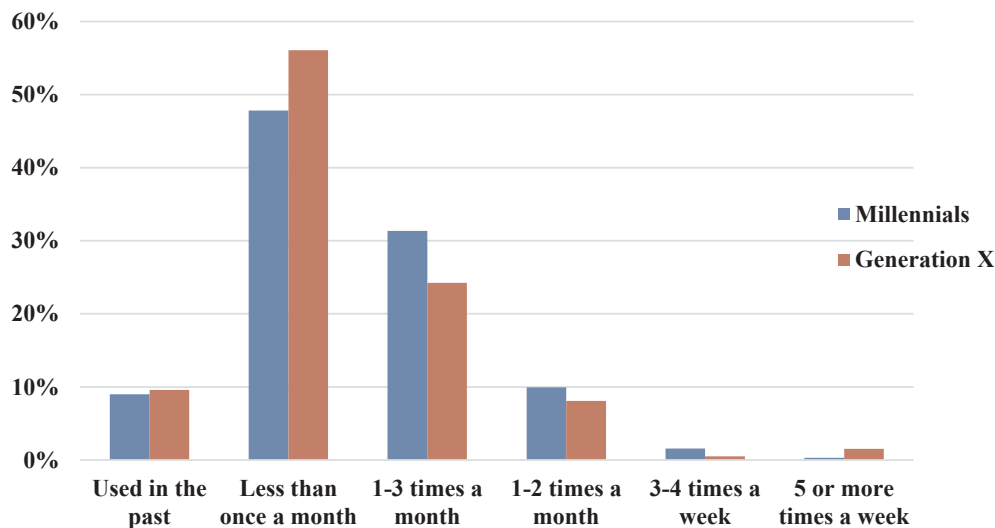


Fig. 3. Frequency of using on-demand ride services (Weighted Sample,  $N_{\text{Millennials}} = 322$ ,  $N_{\text{Gen X}} = 198$ ).

Table 6

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

Explanatory variables	Did not use or used in the past [N = 1491]		Used it less than once a month [N = 265]		Used it 1–3 times a month [N = 148]		Used it at least 1-2 times a week [N = 57]	
	Count	Col. %	Count	Col. %	Count	Col. %	Count	Col. %
<i>Age</i>								
Younger Millennials	321	21.5%	41	15.5%	27	18.3%	11	19.3%
Older Millennials	406	27.3%	113	42.6%	74	50.0%	27	47.4%
Younger Gen X	373	25.0%	60	22.6%	28	18.9%	12	21.0%
Older Gen X	391	26.2%	51	19.3%	19	12.8%	7	12.3%
<i>Household Income [N = 1831]</i>								
Low (\$0-40K)	429	31.0%	43	16.9%	33	23.4%	17	29.8%
Medium (\$40-100K)	561	40.5%	89	34.9%	50	35.5%	24	42.1%
High (\$100K+)	396	28.5%	123	48.2%	58	41.1%	16	28.1%
<i>Education Level</i>								
Bachelor’s Degree or Higher	628	42.4%	190	71.7%	82	55.0%	41	70.7%
Associate Degree or Below	855	57.6%	75	28.3%	67	45.0%	17	29.3%
<i>Region</i>								
Central Valley	279	18.7%	11	4.2%	9	6.0%	0	0.0%
Northern California	40	2.7%	2	0.8%	1	0.7%	0	0.0%
Sacramento	92	6.2%	10	3.8%	4	2.7%	2	3.5%
San Diego	125	8.4%	26	9.8%	20	13.4%	5	8.6%
Greater Los Angeles	647	43.4%	149	56.4%	81	54.4%	42	72.4%
San Francisco Bay Area	308	20.6%	66	25.0%	34	22.8%	9	15.5%
<i>Neighborhood Type (Geocoded Home Address)</i>								
Urban	328	22.0%	79	29.9%	69	46.3%	49	84.5%
Suburban	685	45.9%	150	56.8%	61	40.9%	7	12.1%
Rural	478	32.1%	35	13.3%	19	12.8%	2	3.4%

avoided).

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

Figs. 4 and 5 exhibit similar patterns, such as higher shares of millennials reporting reductions in walking/biking and transit use than for Gen Xers. A close comparison of the two figures is revealing, however. Strictly speaking, the same people who reported that they would

have walked/biked or used public transportation if not for Uber/Lyft (Fig. 5) should also have reported that Uber/Lyft reduced their walking/biking or public transportation use (Fig. 4). Instead, for both of these mode categories and across both cohorts, we see substantially lower shares in Fig. 4 than in Fig. 5.<sup>5</sup> We speculate that these logical

<sup>5</sup> The situation for reducing driving is more complex, because some respondents could conceivably have answered “Reduced the amount of driving I did” with taking a taxi or being a car passenger in mind, since those options were not presented in the first question. The combined shares of people (92% of Gen Xers, 84% of millennials) responding “would have driven a car”, “would have taken a taxi”, “would have used a van/shuttle service”, or “would have gotten a ride from someone” in Fig. 5 is higher in each cohort than the shares (72% Gen Xers, 69% of millennials) responding “Reduced the amount of driving I did” in Fig. 4, suggesting that at least some of these respondents reported a

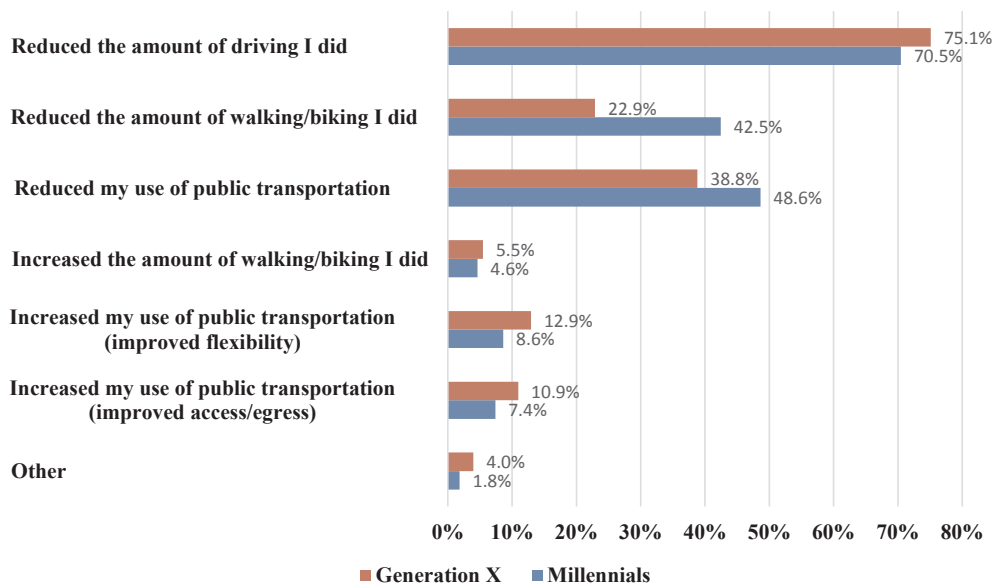


Fig. 4. The impact of Uber/Lyft on the use of other means of transportation by age group (Weighted Sample,  $N_{\text{Millennials}} = 325$ ,  $N_{\text{Gen X}} = 201$ , multiple answers allowed for each respondent).

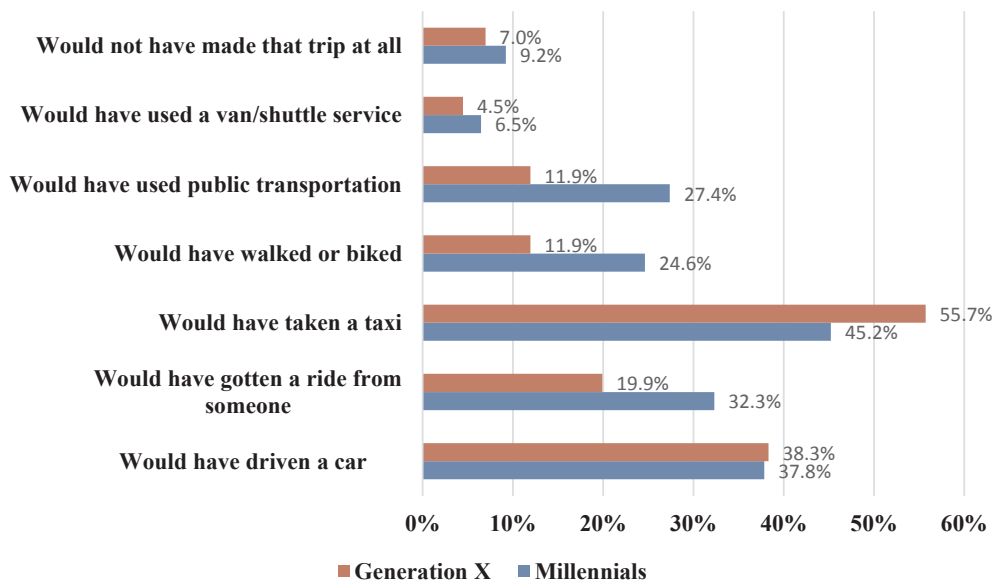


Fig. 5. How users would have traveled in the absence of Uber/Lyft by age group (Weighted Sample,  $N_{\text{Millennials}} = 302$ ,  $N_{\text{Gen X}} = 164$ , multiple answers allowed for each respondent).

inconsistencies are a result of the differences in question format, the multiple answers allowed for each question, and the fact that many users might end up reporting a reduction in some modes (e.g. they walk less because of the use of Uber) as the impact of the substitution with a *third* mode (e.g. users who switch from using public transit to Uber *do* reduce their use of public transit and also the amount of walking they do to/from public transit stations). Further, in Fig. 5, respondents were asked to consider a counterfactual: “what would you have done if Uber/Lyft had not been available?” To answer this question, they must “think backward” and *hypothetically* “change the past”, whereas to respond in Fig. 4 (“how did Uber/Lyft affect your use of other modes?”), they must “think forward” about the *consequences* of an action *actually taken*. Of course, accurately picturing the consequences still requires comparison

(footnote continued)

reduction in “driving” to more generally refer to a reduction in “car use”.

to the counterfactual, but it seems plausible to conjecture that the forward-oriented question format evokes that comparison in a more instinctive fashion.

## 6. Conclusions and discussion

In this study, we investigated the factors that affect the adoption of on-demand ride services such as Uber and Lyft among millennials and members of the preceding Generation X, using data collected in California during fall 2015. Our study is different from previous ones in using multivariate analysis to investigate the joint and separate influence of multiple factors affecting the adoption of on-demand ride services. The availability of Uber and Lyft as well as the share of trips made by these services are continuously growing: even though Uber and Lyft do not share information about their market and characteristics of their users, information disseminated online suggests that the number of cities where these services are available at least doubled from 2015 to

2016. We expect that these services will continue to grow until they become available throughout the U.S. The role of on-demand services will likely increase still more as society transitions toward a future dominated by autonomous vehicles. Accordingly, planners and policy makers have a strong interest in improving their understanding of the factors affecting the use of these services and the potential impacts that these services have on travel behavior.

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

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

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

## Appendix A.

See Table 7

drivers. Hence, the public benefits of single-passenger demand-responsive services are still uncertain.

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

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

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**Table 7**  
Factors and their attitudinal statement loadings.

Attitudinal statements	Factor loadings from pattern matrix
<i>Pro-environmental Policies</i>	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.94
We should raise the price of gasoline to provide funding for better public transportation.	0.84
The government should put restrictions on car travel in order to reduce congestion.	0.34
<i>Variety Seeking</i>	
I like trying things that are new and different.	0.61
I have a strong interest in traveling to other countries.	0.41
<i>Technology Embracing</i>	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.62
Getting around is easier than ever with my smartphone.	0.52
Learning how to use new technologies is often frustrating.	-0.33
Technology creates as least as many problems as it does solutions.	0.29
<i>Traditional Shopper</i>	
I prefer to shop in a store rather than online.	0.99
I enjoy shopping online.	-0.42
<i>Pro-exercise</i>	
The importance of exercise is overrated.	0.82
Getting regular exercise is very important to me.	-0.59
<i>Pleasant Commute</i>	
My commute is stressful.	-0.80
My commute is generally pleasant.	0.69
Traffic congestion is a major problem for me personally.	-0.54
The time I spend commuting is generally wasted time.	-0.50
Getting stuck in traffic does not bother me that much.	0.31
<i>Pro-suburban</i>	
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to.	0.76
I prefer to live close to transit even if it means I will have a smaller home and live in a more crowded area.	-0.69
I like the idea of living somewhere with large yards and lots of space between homes.	0.43
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.	-0.35
<i>Responsive to Environment and Cost of Travel</i>	
The environmental impacts of the various means of transportation affect the choices I make.	0.73
I am committed to using a less polluting means of transportation as much as possible.	0.59
The price of fuel affects the choices I make about my daily travel.	0.53
To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle.	0.38
<i>Established in Life</i>	
I am already well-established in my field of work.	0.70
I am still trying to figure out my career (e.g. what I want to do, where I will end up).	-0.64
I am generally satisfied with my life.	0.38
<i>Long-term Urbanite</i>	
I picture myself living long-term in a suburban setting.	-0.81
A house in the suburbs is the best place for kids to grow up.	-0.57
I picture myself living long-term in an urban setting.	0.32
<i>Must Own a Car</i>	
I definitely want to own a car.	0.72
I am fine with not owning a car, as long as I can use or rent one any time I need it.	-0.49
<i>Materialistic</i>	
I would/do enjoy having a lot of luxury things.	0.42
I prefer to minimize the material goods I possess.	-0.40
I like to be among the first people to have the latest technology.	0.39
For me, a lot of the fun of having something nice is showing it off.	0.39
To me, owning a car is a symbol of success.	0.30
<i>Climate Change Concern</i>	
Greenhouse gases from human activities are creating major problems.	0.79
Any climate change that may be occurring is part of a natural cycle.	-0.66
It is pointless for me to try too hard to be more environmentally friendly because I am just one person.	-0.31
<i>Monochronic</i>	
It's best to finish one project before starting another.	0.51
I like to juggle two or more activities at the same time.	-0.35
<i>Time and Mode Constrained</i>	
My schedule makes it hard or impossible for me to use public transportation.	0.58
I am too busy to do many things I'd like to do.	0.44
Most of the time, I have no reasonable alternative to driving.	0.40
<i>Pro-social</i>	
Social media (e.g. Facebook) makes my life more interesting.	0.50
People are generally trustworthy.	0.43

(continued on next page)

**Table 7** (continued)

Attitudinal statements	Factor loadings from pattern matrix
I enjoy the social aspects of shopping in stores.	0.32
<i>Car as a Tool</i>	
The functionality of a car is more important to me than its brand.	0.58
To me, a car is just a way to get from place to place.	0.48

Note: loadings < 0.29 are omitted.

**Appendix B.**

See [Table 8](#)

**Table 8**

Distribution of key explanatory attributes (Unweighted Sample).

Explanatory variables	Users [N = 472]		Heard but never used [N = 1243]		Never heard [N = 251]	
	Count	Col. %	Count	Col. %	Count	Col. %
<b>Socio-demographics</b>						
<i>Age [N = 1966]</i>						
Younger Millennials	70	14.8%	219	17.6%	45	17.9%
Older Millennials	233	49.4%	419	33.7%	86	34.3%
Younger Gen X	101	21.4%	286	23.0%	57	22.7%
Older Gen X	68	14.4%	319	25.7%	63	25.1%
<i>Presence of Children in the Household [N = 1966]</i>						
Yes	198	58.1%	641	51.6%	140	55.8%
No	274	41.9%	602	48.4%	111	44.2%
<i>Household Income [N = 1831]</i>						
Low (\$0–40 K)	101	22.5%	334	29.0%	122	52.4%
Medium (\$40–100 K)	209	46.7%	586	51.0%	87	37.3%
High (\$100 K+)	138	30.8%	230	20.0%	24	10.3%
<i>Employment Status [N = 1966]</i>						
Employed	376	79.7%	781	62.8%	136	54.2%
Not Employed	96	20.3%	462	37.2%	115	45.8%
<i>Student Status [N = 1966]</i>						
Student	106	22.5%	213	17.1%	47	18.7%
Not Student	366	77.5%	1030	82.9%	204	81.3%
<i>Education Level [N = 1958]</i>						
Bachelor’s Degree or Higher	306	64.8%	519	42.0%	50	20.1%
Associate Degree or Below	166	35.2%	718	58.0%	199	79.9%
<i>Ethnicity [N = 1966]</i>						
Hispanic Origin	91	19.3%	304	24.5%	71	28.3%
Non-Hispanic Origin	381	80.7%	939	75.5%	180	71.7%
<i>Sex [N = 1966]</i>						
Female	275	58.3%	736	59.2%	148	59.0%
Male	197	41.7%	507	40.8%	103	41.0%
<b>Geographic regions and built environment</b>						
<i>Region [N = 1966]</i>						
Central Valley	26	5.5%	180	14.5%	50	19.9%
Northern California	17	3.6%	111	8.9%	54	21.5%
Sacramento	52	11.0%	186	15.0%	41	16.3%
San Diego	103	21.8%	198	15.9%	18	7.2%
Greater Los Angeles	143	30.3%	296	23.8%	51	20.3%
San Francisco Bay Area	131	27.8%	272	21.9%	37	14.8%
<i>Neighborhood Type (Geocoded Home Address) [N = 1966]</i>						
Urban	164	34.7%	196	15.8%	19	7.6%
Suburban	234	49.6%	617	49.6%	111	44.2%
Rural	74	15.7%	430	34.6%	121	48.2%
<i>Land Use Mix (8-Tier Employment Entropy) [N = 1966]</i>						
Mean (Std. Deviation)	0.64 (0.24)		0.59 (0.29)		0.61(0.28)	
<i>Destination Accessibility (Regional Centrality Index by Auto) [N = 1966]</i>						
Mean (Std. Deviation)	0.59 (0.21)		0.51 (0.23)		0.51(0.26)	

(continued on next page)

**Table 8** (continued)

Explanatory variables	Users [N = 472]		Heard but never used [N = 1243]		Never heard [N = 251]	
	Count	Col. %	Count	Col. %	Count	Col. %
<b>Lifestyles and Use of Technology</b>						
<i>Use of Social Media (Facebook) [N = 1966]</i>						
Lower Frequency	119	25.2%	458	36.8%	84	33.5%
Higher Frequency	353	74.8%	758	63.2%	167	66.5%
<i>Use of Taxi [N = 1863]</i>						
Used Taxi Before	325	71.6%	463	38.1%	73	37.8%
Never Used Taxi Before	129	28.4%	753	61.9%	120	62.2%
<i>Use of Carsharing Services [N = 1961]</i>						
Used Carsharing Services Before	79	16.7%	22	1.8%	6	2.4%
Never Used Carsharing Services	393	83.3%	1221	98.2%	245	97.6%
<i>PCA Score: Use of Smart Phone to Determine Destination and Route [N = 1961]</i>						
Mean (Std. Deviation)	0.35 (0.79)		−0.25 (1.01)		−0.50 (1.15)	
<i>PCA Score: Use of Smart Phone for Mode Choice [N = 1961]</i>						
Mean (Std. Deviation)	0.28 (1.02)		−0.21 (0.91)		−0.26 (0.94)	
<i>Frequency of Long-Distance Business Travel (Log-Transformed) [N = 1936]</i>						
Mean (Std. Deviation)	0.42 (0.51)		0.21 (0.41)		0.31 (0.48)	
<i>Share of Total Long-Distance Travel with Plane [N = 1924]</i>						
Mean (Std. Deviation)	0.32 (0.32)		0.15 (0.27)		0.07 (0.18)	
<b>Personal Attitudes</b>						
<i>Factor Score: Technology Embracing [N = 1965]</i>						
Mean (Std. Deviation)	0.41 (1.14)		−0.08 (1.26)		−0.35 (1.26)	
<i>Factor Score: Variety Seeking [N = 1965]</i>						
Mean (Std. Deviation)	0.41 (1.11)		−0.11 (1.27)		−0.26 (1.44)	
<i>Factor Score: Pro-Environmental Policies [N = 1965]</i>						
Mean (Std. Deviation)	0.33 (1.12)		−0.10 (1.02)		−0.17 (0.97)	
<i>Factor Score: Multi-tasking [N = 1965]</i>						
Mean (Std. Deviation)	0.10 (1.33)		−0.05 (1.41)		−0.41 (1.42)	

**Appendix C. Supplementary data**

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.tbs.2018.06.002>.

**References**

Ben-Akiva, Moshe, Walker, Joan, Bernardino, Adriana T., Gopinath, Dinesh A., Morikawa, Taka, Polydoropoulou, Amalia, 2002. Integration of choice and latent variable models. Chapter 21 In: Mahmassani, Hani S. (Ed.), In perpetual motion: Travel behaviour research opportunities and application challenges. Emerald Group Publishing Limited, Bingley, United Kingdom, pp. 431–470.

Belden Russonello Strategist (BRS). 2013. Americans' Views on their Communities, Housing, and Transportation. Report for the Urban Land Institute, Washington D.C. March 2013. <https://uli.org/wp-content/uploads/ULI-Documents/America-in-2013-Final-Report.pdf> (last accessed on January 22, 2018).

Blasius, Jörg, Brandt, Maurice, 2010. Representativeness in online surveys through stratified samples. Bull. Sociol. Method./Bull. Method. Sociol. 107 (1), 5–21.

Blumenberg, Evelyn, Ralph, Kelcie, Smart, Michael, Taylor, Brian, 2016. Who knows about kids these days? Analyzing the determinants of youth and adult mobility in the U.S. between 1990 and 2009. Transport. Res. Part A 93, 39–54.

Bolduc, D., Ben-Akiva, M., Walker, J., Michaud, A., 2005. Hybrid choice models with logit kernel: applicability to large scale models 1. Chapter 12 In: Lee-Gosselin, Martin E.H., Doherty, Sean T. (Eds.), Integrated land-use and transportation models: behavioural foundations. Emerald Group Publishing Limited, pp. 275–302.

Buck, Darren, Buehler, Ralph, Happ, Patricia, Rawls, Bradley, Chung, Pyton, Borecki, Natalie, 2013. Are bikeshare users different from regular cyclists? A first look at short-term users, annual members, and area cyclists in the Washington, DC Region. Transport. Res. Rec. J. Transport. Res. Board 2387, 112–119.

Buehler, Ralph, Hamre, Andrea, 2014. The multimodal majority? Driving, walking, cycling, and public transportation use among American Adults. Transportation 42 (6), 1081–1101.

Cao, Xinyu, Mokhtarian, Patricia L., Handy, Susan, 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. Transport Res. 29 (3), 359–395.

Certify, 2015. Sharing economy Q2 report. Room for more: Business travelers embrace the sharing economy. As cited in Taylor, Brian D., Ryan Chin, Melanie Crotty,

Jennifer Dill, Lester A. Hoel, Michael Manville, Steve Polzin, et al. 2015. Between public and private mobility: examining the rise of technology-enabled transportation services. Transport. Res. Board: Committee Rev. Innov. Urban Mobility Serv.

Chorus, Caspar G., Kroesen, Maarten, 2014. On the (im-) possibility of deriving transport policy implications from hybrid choice models. Transport Policy 36, 217–222.

Circella, Giovanni, Lew Fulton, Farzad Alemi, Rosaria M. Berliner, Kate Tiedeman, Patricia L. Mokhtarian, and Susan Handy, 2016a. What Affects Millennials' Mobility? PART I: Investigating the Environmental Concerns, Lifestyles, Mobility-Related Attitudes and Adoption of Technology of Young Adults in California. Project Report, National Center for Sustainable Transportation. University of California, Davis, May 2016; available at [http://ncst.ucdavis.edu/wp-content/uploads/2014/08/05-26-2016-NCST\\_Report\\_Millennials\\_Part\\_I\\_2016\\_May\\_26\\_FINAL1.pdf](http://ncst.ucdavis.edu/wp-content/uploads/2014/08/05-26-2016-NCST_Report_Millennials_Part_I_2016_May_26_FINAL1.pdf) (last accessed on January 22, 2018).

Circella, Giovanni, Kate Tiedeman, Susan Handy, Farzad Alemi, and Patricia L. Mokhtarian, 2016b. What Affects U.S. Passenger Travel? Current Trends and Future Perspectives. White Paper from the National Center for Sustainable Transportation. University of California, Davis, February 2016; available at [https://ncst.ucdavis.edu/wp-content/uploads/2014/08/06-15-2016-NCST\\_White\\_Paper\\_US\\_Passenger\\_Travel\\_Final\\_February\\_2016\\_Caltrans3.pdf](https://ncst.ucdavis.edu/wp-content/uploads/2014/08/06-15-2016-NCST_White_Paper_US_Passenger_Travel_Final_February_2016_Caltrans3.pdf) (last accessed on January 22, 2018).

Circella, Giovanni, Farzad Alemi, Kate Tiedeman, Rosaria M. Berliner, Yongsung Lee, Lew Fulton, Patricia L. Mokhtarian, and Susan Handy, 2017. What Affects Millennials' Mobility? PART II: The Impact of Residential Location, Individual Preferences and Lifestyles on Young Adults' Travel Behavior in California. Project Report, National Center for Sustainable Transportation. University of California, Davis, March 2017; available at [https://ncst.ucdavis.edu/wp-content/uploads/2015/09/NCST\\_Report\\_Millennials\\_Part\\_II\\_2017\\_March\\_31\\_FINAL.pdf](https://ncst.ucdavis.edu/wp-content/uploads/2015/09/NCST_Report_Millennials_Part_II_2017_March_31_FINAL.pdf) (last accessed on January 22, 2018).

Clewlow, Regina R., Mishra, Gouri Shankar, 2017. Disruptive Transportation: The Adoption, Utilization, and Impacts of Ride-Hailing in the United States. Institute of Transportation Studies, University of California, Davis Research Report UCD-ITS-RR-17-07.

Davidson, Todd, Michael E. Webber, 2017 (October 21). Using Only Uber or Lyft Is Cheaper than Owning a Car for 25% of Americans- Here's How to Know If You Apply. Business Insider. Retrieved from <http://www.businessinsider.com/uber-or-lyft-is-cheaper-than-owning-a-car-for-25-percent-of-americans>



- lyft-could-be-cheaper-than-owning-a-car-2017-10 (last accessed on January 22, 2018).
- Federal Highway Administration (FHWA). 2017. March 2017 Traffic Volume Trends. [https://www.fhwa.dot.gov/policyinformation/travel\\_monitoring/tvt.cfm](https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm) (last accessed on January 22, 2018).
- Frändberg, Lotta, Vilhelmson, Bertil, 2011. More or less travel: personal mobility trends in the Swedish population focusing on gender and cohort. *J. Transport Geogr.* 19 (6), 1235–1244.
- Hallock, Lindsey, and Jeff Inglis. 2015. The Innovative Transportation Index: The Cities Where New Technologies and Tools Can Reduce Your Need to Own a Car. [http://www.uspirg.org/sites/pirg/files/reports/Innovative\\_Transportation\\_Index\\_USPIRG.pdf](http://www.uspirg.org/sites/pirg/files/reports/Innovative_Transportation_Index_USPIRG.pdf) (last accessed on January 22, 2018).
- Henderson, Peter. 2017 (May 25). Some Uber and Lyft riders are giving up their own cars: Reuters/Ipsos poll. Reuters. Retrieved from <https://mobile-reuters-com.cdn.ampproject.org/c/mobile.reuters.com/article/amp/idUSKBN18L1DA> (last accessed on January 22, 2018).
- Kuhnimhof, Tobias, Armoogum, Jimmy, Buehler, Ralph, Dargay, Joyce, Denstadli, Jon Martin, Yamamoto, Toshiyuki, 2012. Men shape a downward trend in car use among young adults—evidence from six industrialized countries. *Transport Rev.* 32 (6), 761–779.
- Latitude. 2010. “The New Sharing Economy: Latitude.” <http://latdsurvey.net/pdf/Sharing.pdf> (last accessed on January 22, 2018).
- Mcbride, Sean, 2015. Ridesourcing and the Taxi Marketplace. Senior honors Economic Thesis. School of Art and Sciences, Boston College University <http://dlib.bc.edu/islandora/object/bc-ir:104530> (last accessed on January 22, 2018).
- McDonald, Noreen C., 2015. Are millennials really the ‘Go-Nowhere’ generation? *J. Am. Plann. Assoc.* 81 (2), 90–103.
- Rayle, Lisa, Susan Shaheen, Nelson Chan, Danielle Dai, and Robert Cervero. 2014. App-Based, On-Demand Ride Services: Comparing Taxi and Ridesourcing Trips and User Characteristics in San Francisco. Working Paper. University of California Transportation Center (UCTC). [https://www.its.dot.gov/itspac/dec2014/ridesourcingwhitepaper\\_nov2014.pdf](https://www.its.dot.gov/itspac/dec2014/ridesourcingwhitepaper_nov2014.pdf) (last accessed on January 22, 2018).
- Salon, Deborah, 2015. Heterogeneity in the relationship between the built environment and driving: focus on neighborhood type and travel purpose. *Res. Transport. Econ.* 52, 34–45.
- San Francisco County Transportation Authority (SFCTA). 2017. “TNCs Today: A Profile of San Francisco Transportation Network Company Activity”. November 2017; available at [http://www.sfcta.org/sites/default/files/content/Planning/TNCs/TNCs\\_Today\\_112917.pdf](http://www.sfcta.org/sites/default/files/content/Planning/TNCs/TNCs_Today_112917.pdf) (last accessed on January 22, 2018).
- Shaheen, Susan, Adam Cohen, Ismail Zohdy, and Beaudry Kock. 2016. Smartphone applications to influence travel choices: practices and policies. Report No. FHWA-HOP-16-023. 2016, April 2016. <https://ops.fhwa.dot.gov/publications/fhwahop16023/fhwahop16023.pdf> (last accessed on January 22, 2018).
- Shaheen, Susan, Adam Cohen, and Ismail Zohdy. 2016. Shared Mobility: Current Practices and Guiding Principles. Report No. FHWA-HOP-16-022, April 2016. <https://ops.fhwa.dot.gov/publications/fhwahop16022/fhwahop16022.pdf> (last accessed on January 22, 2018).
- Shared-Use Mobility Center. 2016. Shared Mobility and the Transformation of Public Transit” <http://www.apta.com/resources/reportsandpublications/Documents/APTA-Shared-Mobility.pdf> (last accessed on January 22, 2018).
- Sivak, Michael, 2014. Has Motorization in the US Peaked? Part 4: Households without a Light-duty Vehicle. Transport Research Institute, University of Michigan, Ann Arbor.
- Taylor, Brian D., Chin, Ryan, Crotty, Melanie, Dill, Jennifer, Hoel, Lester A., Manville, Michael, Polzin, Steve, et al., 2015. Between Public and Private Mobility: Examining the Rise of Technology-Enabled Transportation Services. Special Report 319. Transportation Research Board: Committee for Review of Innovative Urban Mobility Services.
- Vij, Akshay, Walker, Joan L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transport. Res. Part B Method.* 90, 192–217.